Preventing Falls in Hospitals with Body Worn Batteryless Sensor Enabled RFID

by

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in

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Contents

Abstract

Falls prevention in older people is a growing area of study. Multiple studies have employed fixed pressure mats on beds and chairs to detect when a person exits the bed or chair and alert caregivers to intervene and supervise the patient. In general, randomized control trials using these techniques found little variation in the number of falls in older people because of the large number of false alarms producing alarm fatigue among caregivers.

Wearable technology—capable of providing information from locations other than the bed or chair—provides an alternative to pressure mats used in hospitals. However, studies that use wearable technology for falls prevention or alarming approaches is lacking. Moreover, technological approaches focused on activity recognition rarely consider the activities of older people. This is because collecting data from this population is difficult due to the constraints of their age, especially with hospitalized patients. In addition, previous wearable sensor studies considered battery-powered sensing units to provide consistent measurements. However, the use of battery-powered body-worn sensor units for activity recognition of older people in hospital settings face a number of practical limitations such as the unit's size, high cost, attachment method and need for maintenance. Furthermore, older people have expressed interest in using wearable sensors built upon RFID technology that are small and unobtrusive.

This thesis proposes a falls prevention intervention based on the use of a batteryless (passive) wearable sensor platform capable of identifying patients and their movements; the use of such body-worn, passive sensor has not been previously studied with older people for falls prevention. Despite the benefits of the proposed sensor—small, batteryless, and lightweight—the captured data is usually noisy and sparse, an inherent limitation to human activity recognition problems. Therefore, the main aim of this work is to investigate and evaluate methods for the recognition of activities in older people, in particular, hospitalized older people, wearing a passive wearable sensor as part of a technological falls prevention intervention to generate timely alarms to caregivers to assist patients attempting a high-risk activity. Given the use of a novel sensor, this thesis also investigates the acceptability and wearability of the proposed sensor as perceived by older people.

The research in this thesis makes several contributions to the field of human activity recognition. In particular, the formulation and development of methods for human activity recognition to accomplish a technological intervention for the prevention of falls using a novel RFID-based sensor technology, the evaluation of these methods with healthy and hospitalized older populations, the contribution of three datasets for human activity recognition research with different demographics, and the development of a sensor acceptability model to determine acceptability and wearability of the proposed sensor by the trialled cohorts.

This thesis suggests that the deployment of a wearable sensor based falls prevention intervention is feasible, especially in a hospital setting. Furthermore, the use of this technology was considered acceptable by the trialed cohorts as it was unobtrusive to physical movements and easy to use; however, older people were conscious of using the device as it was a highly visible sensor prototype.

Statement of Originality

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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23/10/2018

Signed Date

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"For of him, and through him, and to him, are all things: to whom be glory for ever. Amen."
Romans 11:36

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Publications

During my PhD research, a number of papers were published, accepted or are currently under revision. The content of this thesis is partially based on those papers, as listed below:

Journals

[1] R. Shinmoto Torres, D. C. Ranasinghe, D. Abbott, K. Hill, and R. Visvanathan, "A battery-less and wireless wearable sensor system for identifying bed and chair exits in a pilot trial in hospitalized older people," *PLOS ONE*, vol. 12, no. 10, pp.1–25, 2017.

[2] R. Shinmoto Torres, Q. Shi, A. van den Hengel, and D. C. Ranasinghe, "A hierarchical model for recognizing alarming states in a batteryless sensor alarm intervention for preventing falls in older people," *Pervasive and Mobile Computing*, vol. 40, pp. 1–16, 2017.

[3] R. Shinmoto Torres, D. C. Ranasinghe, Q. Shi, and A. van den Hengel,"Dynamically weighted conditional random fields for learning from imbalanced body worn sensor data streams," *IEEE Transactions on Neural Networks and Learning Systems*, 2017. To be submitted.

[4] R. Shinmoto Torres, R. Visvanathan, S. Hoskins, A. van den Hengel, and D. C. Ranasinghe, "Effectiveness of a battery-less and wireless wearable sensor system for identifying bed and chair exits in healthy older people," *Sensors*, vol. 16, no. 4, pp. 564, 2016.

[5] D. C. Ranasinghe, R. L. Shinmoto Torres, K. Hill, and R. Visvanathan, "Low cost and batteryless sensor-enabled radio frequency identification tag based approaches to identify patient bed entry and exit posture transitions," *Gait & Posture*, vol. 39, no. 1, pp. 118 – 123, 2014.

Conferences

[1] R. L. Shinmoto Torres, D. C. Ranasinghe, and Q. Shi, "Evaluation of wearable sensor tag data segmentation approaches for real time activity classification in elderly," in *Mobile and Ubiquitous Systems: Computing, Networking, and Services* (I. Stojmenovic, Z. Cheng, and S. Guo, eds.), vol. 131 of *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering*, pp. 384–395, Springer, 2014.

[2] R. L. Shinmoto Torres, D. C. Ranasinghe, Q. Shi, and A. P. Sample, "Sensor enabled wearable rfid technology for mitigating the risk of falls near beds," in *Seventh IEEE International Conference on RFID (RFID)*, pp. 191–198, 2013.

[3] D. C. Ranasinghe, R. L. Shinmoto Torres, A. P. Sample, J. R. Smith, K. Hill, and R. Visvanathan, "Towards falls prevention: A wearable wireless and battery-less sensing and automatic identification tag for real time monitoring of human movements," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 6402–6405, 2012.

[4] R. Visvanathan, D. C. Ranasinghe, R. L. Shinmoto Torres, and K. Hill, "Framework for preventing falls in acute hospitals using passive sensor enabled radio frequency identification technology," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 5858–5862, 2012.

Publications not Referred in this Thesis

[1] R. L. Shinmoto Torres, A. Wickramasinghe, V. N. Pham, and D. C. Ranasinghe, "What if your floor could tell someone you fell? A device free fall detection method," in *15th Conference on Artificial Intelligence in Medicine*, pp. 86–95, 2015.

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Chapter 1

Introduction

Falls among older patients in hospitals and nursing homes are common and costly. These falls are estimated to increase hospital bed days by 886 000 per year and cost AU$1375 million annually by 2051 in Australia alone [1]. Moreover, fallers have significantly larger hospitalization costs than non-fallers of a similar age, gender and diagnosis-related group [2]. A 12-month study of 200 000 falls reports in the UK indicates that inpatient falls are the most frequent (40 %) type of safety incident [3]. Falls were directly responsible for 26 patient deaths and about 1500 fractures, including 530 hip fractures [3]. In addition to the falls-related economic costs, there are also falls-associated psychological sequelae to the individual that include anxiety, depression, loss of confidence, fear of falling and, ultimately, a downward spiral of decline in health [4]. Staff and families are also impacted by the occurrence of falls; feelings of distress, guilt and anxiety are contributors to conflict and are often cited in litigations or inquests [5]. Therefore, hospitals and health providers are acutely interested in developing effective falls prevention strategies for older patients in care settings.

1.1 Falls Prevention Strategies in Hospitals

Several intervention strategies for falls prevention have been studied in the literature [5, 6] and recommended as best practice for use in hospitals to reduce the risk of falls and injuries in older patients [1, 3]. Some strategies aim to reduce specific causes of falls. For example, a review of medications used by patients can help identify and modify the use of certain drugs that can increase falls risk such as those that cause drowsiness; the use of non-slippery footwear can help patients avoid slipping on wet floors, especially in the toilet; and the provision of more opportunities for patients to be mobile and exercise in a supervised manner can help improve balance and minimize prolonged bed rest [1, 3]. Other intervention strategies have been developed to reduce the severity of injuries caused by falls such as bone fractures by using hip protectors or modifying floor materials [1, 3]. However, multiple randomized controlled trials (RCTs), focused on the prevention of falls in older people have found no clear evidence of a significant reduction of falls based on any particular intervention [5, 7, 8].

Various clinical studies have determined that most falls of older people, 70 %, occur in hospital bedrooms [9, 10] and about 10 % of falls occur in hospital or nursing home restrooms [9, 10, 11]. Moreover, 80 % of falls in hospital bedrooms occur around the bed [12] and falls from transferring movements, i.e. getting in and out of bed and chair ($\approx$ 40 %), are more common than falls when ambulating ($\approx$ 35 %) [6, 11]. Most falls are also related to the need of the faller to go to or return from the toilet, exiting a soiled bed or getting a tissue [9]. Many falls occur at night when nurse staffing levels are low, patients are in bed and confusion or nocturia occur [13, 9]. Therefore, technology based interventions such as movement sensor alarms on beds or chairs—e.g. pressure mats [14, 15, 16], infra-red beam detectors [14]—are used to monitor unsupervised activities by patients and prevent falls by mitigating the risk of falls associated with patients' circumstances of falls by alerting hospital staff of a patient's bed and chair exits to facilitate a timely supervision. However, recent long term RCTs using pressure sensors on beds and chairs for falls prevention in hospitals have shown not to reduce falls [15, 16]. One of the reasons for this lack of success is attributed to "alarm fatigue" due to the low specificity of pressure sensors (about 0.3 % in [14]) resulting in high number of false alarms. Given the significance of the problem and the lack of evidence supporting the use of pressure sensors on beds and chairs to reduce falls, it is imperative that we explore new technologies to develop more effective movement sensor alarm interventions suitable for older people [17, 18].

1.2 Technology Preference of Older People

Recent studies by Bergmann et al. [19] and Chaudhuri et al. [20] have determined that older people have an interest in small sensors embedded in their clothing over the use of environmental devices (e.g. video cameras) as body-worn sensors are minimally invasive and allow continuous monitoring [19, 20]. Moreover, small body-worn sensors are perceived to preserve the privacy of individuals, as older people have expressed concern regarding their privacy being violated by approaches that rely on cameras [21, 22].

Various studies have investigated the use of body-worn sensors in laboratory settings [23, 24, 25], and free-living environments [26, 27, 28, 29] to detect falls or assess falls risk. However, very few have investigated falls prevention in acute hospitals or residential care environments [30]. Body worn sensors provide an opportunity to re-examine technological interventions to monitor patients and develop more effective movement sensor alarm systems for falls prevention [17, 18]. However, most sensors employed have been battery powered, expensive, large and relatively heavy units [31, 32, 30, 26] requiring the wearer to recharge the unit during sleep or change batteries regularly or replace the sensor unit entirely, as clinically used sensors have an average battery life of 3 to 4 days [33]. These maintenance procedures increase the workload of staff as length of stay of patients can last several weeks to a month or more. Moreover, removal of the sensing device at night for recharging is not practical as nursing levels are lower, patient confusion is increased and fall rates are higher during nighttime [13].

Therefore, lightweight, wearable sensors that can be integrated to clothing can provide new opportunities to monitor older patients without invading their privacy and restricting their movements. Moreover, these sensors are likely to be accepted by older people. Furthermore, sensors that are low-cost and therefore easily disposable are also desirable as a way to prevent health issues due to possible contamination, contact with bodily fluids and spread of highly infectious diseases, as well as to avoid creating a maintenance burden on healthcare staff.

1.3 Proposed Intervention

This thesis investigates a sensor alarm intervention for the prevention of falls in older people based on a wearable sensor that is small, batteryless, inexpensive, lightweight and can be continuously worn. In particular, a Wearable Wireless Identification and Sensing Platform (W^2ISP, see Section 1.3.1)—a low cost passive sensor enabled Radio Frequency Identification (RFID) tag [34] that only requires a single attachment site over clothing and is capable of real time monitoring of a person wearing the device and capturing the person's body movement information—is investigated. This study is part of an ongoing ageing and technology research project at the Basil Hetzel Institute, the Queen Elizabeth Hospital located in Adelaide, Australia, and the Auto-ID Labs at the University of Adelaide.

The proposed movement sensor alarm intervention framework is shown in Fig. 1.1. A patient wears the W^{2}ISP on top of their clothes, the sensor signals are collected by the real time monitoring environment—consisting of the RFID infrastructure: RFID readers and antennas—and sent to the patient monitoring software for processing and analysis. When the patient attempts to perform a high risk activity of interest e.g. exit the bed or chair, the patient monitoring software recognizes this attempt and sends an alarm to hospital staff to facilitate a timely supervision of the patient. Once a hospital staff, wearing an individual RFID tagged name badge, enters the room to help the patient, their identities and presence in the room are recognized by the system and the alarm is automatically turned off.

In terms of high risk activities of interest targeted by the intervention; the researchers, considering where falls occur and the circumstances of falls, have identified the following high risk activities as those leading to a fall in hospitals [35]: i) entering into a toilet or a bathroom facility without the aid of a caregiver, or leaving a patient's room without the aid of a caregiver; ii) getting up from a bed-side chair without the aid of a caregiver; iii) getting out from a bed without the aid of a caregiver; and iv) mobilizing without a walking aid.

The proposed intervention is significantly different to existing approaches where the sensor is in the room infrastructure, e.g. beds and chairs, and monitoring is limited to bed and chair exits where the presence of a caregiver or the likely location or posture of the patient other than the bed or chair cannot be determined. The approach of wearing a sensor allows continuous ambulatory monitoring, is not restricted to a specific piece of furniture and permits the unique identification of patients. Furthermore, in contrast to audible bed side alarms, typical of pressure mat based bed and chair exit methods, clinical staff providing a response receive alert messages on their handheld mobile devices with the following information: i) the identity of the patient (*who* – provided by the unique electronic identifier stored on the W^{2}ISP); ii) the physical location of the patient (*where* – provided by the localization performed by the RFID readers, antennas and W^{2}ISP); iii) the type of high risk activity (*what*); and iv) a timestamp of when the high risk activity was detected (*when*). Notably, only the *what* information is determined by the patient monitoring software; the remaining information is extracted directly from the RFID infrastructure and the W^{2}ISP.

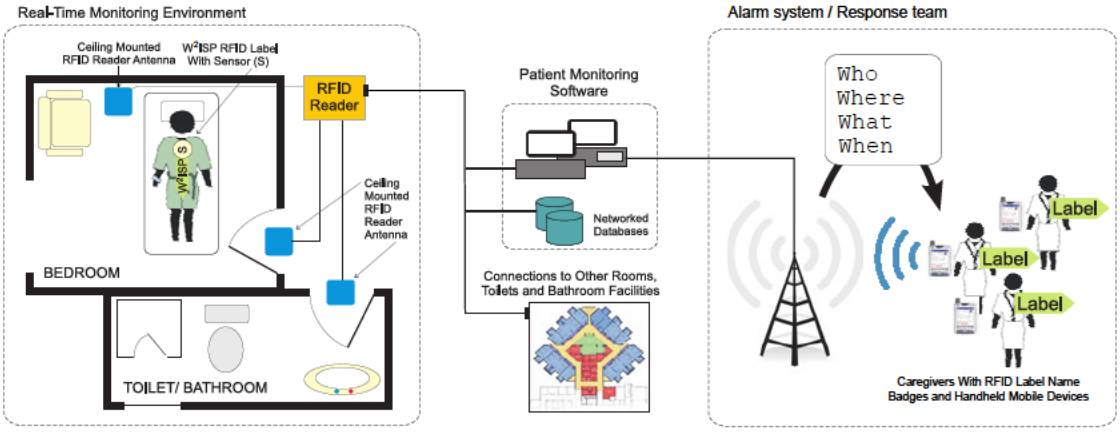


Figure 1.1: Movement sensor alarm intervention concept.

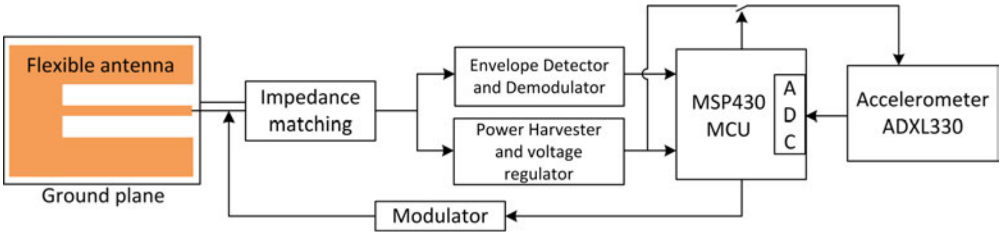
1.3.1 Batteryless Wearable Sensor—W^{2}ISP

In addition to the concept of employing a body-worn device for falls prevention, a key innovative aspect of the proposed intervention is to investigate the use of a wearable batteryless sensor unit.

The Wearable Wireless Identification and Sensing Platform (W^{2}ISP) shown in Fig. 1.2(a) is a batteryless sensor based on RFID—a wireless technology capable of uniquely identifying objects and people [36]—where the exchange of information between an RFID tag and RFID antennas connected to RFID readers is contactless. Similar to passive RFID technology, the W^{2}ISP is a batteryless device and harvests its power from the electromagnetic (EM) radiation produced by off-the-shelf Ultra High Frequency (UHF) RFID reader antennas, and therefore has a potentially indefinite operational life. The W^{2}ISP [37], based on [38], was developed by our group and is suitable for wear over a garment; the dimensions of the W^{2}ISP circuitry are 18 mm × 20 mm and 2 mm (l × w × h) and it weighs approximately 2 g. W^{2}ISPs can be read at moderate range (about 3 to 4 m) and are estimated to cost around US$3 when manufactured in mass quantities [39, 37]. Given the small size, weight and the independence from batteries to function, we expect this device to be accepted by older people wearing the sensor.

The W^{2}ISP, shown in Fig. 1.2(b), contains a tri-axial accelerometer (ADXL330) with a minimum full scale range of $\pm 3\,g$ ($1\,g = 9.8\,\mathrm{m\,s^{-2}}$), low power requirement of 180 µA with a supply voltage of 1.8 V and typical output sensitivity of 300 mV/g. The device also includes a 16-bit, ultra low power microcontroller (MSP430F2132) that also includes a 10-bit 200 kilo-samples-per-second analog to digital converter

(a)



(b)

Figure 1.2: (a): W^{2}ISP and axes of the acceleration sensor. (b): Block diagram of the W^{2}ISP.

(ADC). The firmware executing on the microcontroller is an implementation of the ISO-18000-6C air interface protocol [40] so that the W^{2}ISP can be read by standard commercial off-the-shelf UHF RFID readers. The 10-bit per axis accelerometer data is sampled and embedded in the 96-bit EPC (Electronic Product Code) where a partition of the EPC is used to include a unique identifier [41]. The sensor response is backscattered and subsequently received by an RFID reader antenna and decoded by an RFID reader.

The W^{2}ISP is constructed with a flexible antenna using low-loss flexible foam (C-foam), of dimensions 36 mm × 85 mm and 2 mm (l × w × h), for comfort of the person wearing the sensor. The W^{2}ISP also includes a washable RIPSTOP silver coated nylon fabric (230 mm × 220 mm) to isolate the W^{2}ISP circuitry and antenna from the effects of a human body, i.e. avoid degrading the performance of the W^{2}ISP due to detuning of the W^{2}ISP antenna [37].

1.3.2 RFID Infrastructure

Sensor enabled RFID tags such as the W^{2}ISP cannot work standalone and require other components to capture the sensor information. i.e. RFID readers and backend systems. RFID readers, also called interrogators, are responsible for powering and communicating with the W^{2}ISP.

RFID readers are generally placed at fixed locations with their antennas strategically placed to detect tagged objects passing through their EM field. Typically RFID readers can read multiple co-located RFID tags simultaneously, e.g. up to several hundred tags per second can be read by a modern RFID reader. The reading distance ranges from a few centimetres to more than 10 m, depending on factors such as the operating frequencies of the tags, the transmitted power of readers, antenna gain, and interference from other RF devices [36]. RFID readers can read a W^{2}ISP tag up to a maximum distance of 4 m [37].

RFID readers are generally capable of multiplexing between multiple antennas, which are used for transmitting and receiving RF signals from tags. Readers interface with a local data network (LAN) infrastructure to send the captured information from RFID tags to backend systems, such as the patient monitoring software shown in Fig. 1.1, for processing, storage and sharing of information.

UHF RFID readers operate between 920 and 926 MHz in Australia. The radiated power from RFID reader antennas is reported to be well below the level for human safety published by the International Commission on Non-Ionizing Radiation Protection (ICNIRP) guidelines [42]. Currently, based on present studies, there are no known adverse effects from RFID readers operating in the UHF region on pacemakers or implantable cardioverter-defibrillators. Furthermore, there is no known evidence that RFID systems operating in the far field using the UHF spectrum influence the performance of commonly used medical devices such as physiological monitors, e.g. electrocardiogram monitors, and intravenous pumps.

1.4 Objectives

The objective of this thesis is the investigation and evaluation of methods for the recognition of activities in older people wearing a novel batteryless wearable sensor (W^{2}ISP) as a means to realize the proposed technological intervention for preventing falls in hospitals. The intention is to issue timely and accurate alerts to allow hospital staff to provide assistance when a high-risk activity that can lead to a fall is being attempted by a patient. In particular, this study explores methods for recognizing bed exiting and being out-of-bed or chair exiting and being out-of-chair by analyzing data gathered from the RFID infrastructure and the wearable batteryless sensor, and the generation of timely and accurate alert signals. Given that we are interested in the effective recognition of alerts, the evaluation of these methods focuses on the reduction of false alarms, i.e. generated alerts not caused by a high-risk activity, and missed alarms, i.e. high-risk activities that were undetected.

The main demographic for this study is frail older people in hospitals and nursing homes. Besides the use of pressure mats on chairs and beds, very few technological solutions have been trialled on older patients. Therefore, an objective of this thesis is to evaluate the techniques developed for the recognition of high-risk activities with older people in hospital settings. To the best of the author's knowledge, this is the first study to evaluate wireless batteryless body-worn sensor technology for activity recognition of older people.

Our wearable batteryless sensor device can be used on top of clothes, is lightweight and unobtrusive. Moreover, the device requires no-maintenance from staff and thus staff do not have to remember to recharge batteries. Further, the low-cost nature of the device allows the sensor to be easily disposed to support infection control practices in hospitals and to manage hygienic issues (contact with bodily fluids). Nevertheless, we are interested in investigating the feasibility of our approach by determining the acceptability and understanding the perception of our technological approach by the trialled cohorts, in particular, hospitalized older people. This is an important objective given that few studies studies (1.3 %) using body-worn sensors have considered the perception of users about the technology [19].

1.5 Outline of the Thesis

This document, a *combination thesis*, integrates chapters in the standard format with chapters as publications. This thesis is structured in nine chapters, excluding the conclusion and bibliography, as shown in Fig. 1.3. Given that human activities are by nature sequential, i.e. activities consist of a sequence of movements or motions that the body naturally follows; this thesis focuses mainly on conditional random fields (CRF) based structured prediction methods. CRF is a well-suited technique for activity recognition as it considers the possible complex dependencies between performed motions and the possible transitions from one activity to the next.

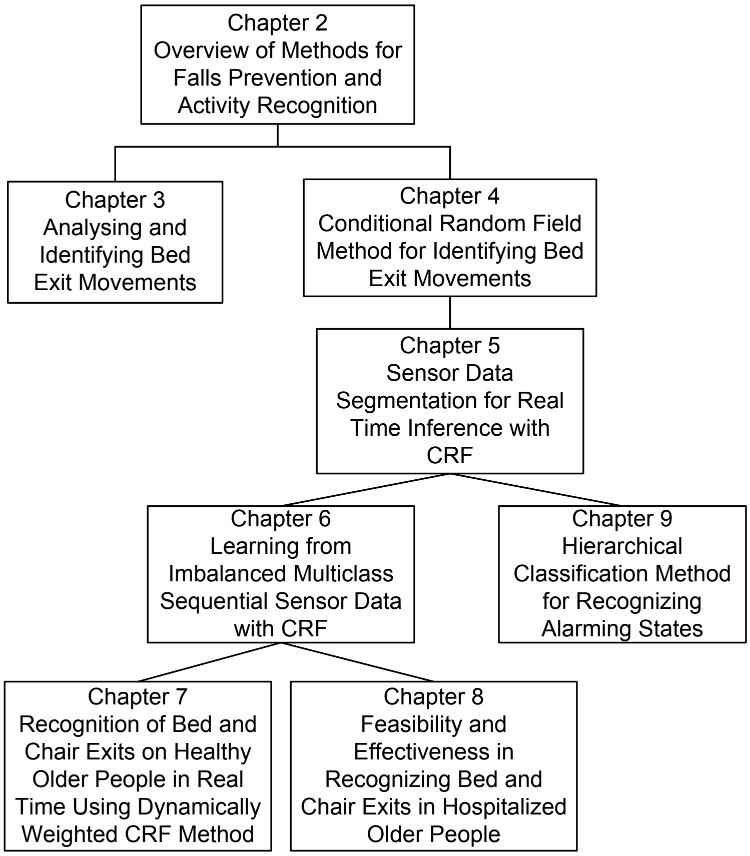


Figure 1.3: Structure of thesis

Chapter 2 reviews previous literature on fall prevention interventions in older people and studies on human activity recognition. Activity recognition studies are reviewed based on the sensor platform and the methods used to make decisions regarding performed activities. This overview highlights the benefits of wearable sensors and the use of growing techniques such as machine learning in the detection of activities of interest.

Chapter 3 develops two approaches for sensor location (on-body and off-body), using a single passive RFID based sensor (WISP—Wireless Identification and Sensing Platform), for the recognition of bed exits on a healthy young adult population. The first method uses the passive sensor as a body-worn sensing unit worn on the chest, the second method places the same sensor unit on the side of a mattress. Both approaches use empirical decision trees to identify bed exits. These approaches demonstrate the feasibility of collecting wearable sensor data from a younger population and are corner stone for further development with older adults.

Chapter 4 introduces the machine learning classification method of conditional random field (CRF) for sequential data, as is the case of sensor data that captures human activities, and is important as various CRF-based methods are developed in this thesis. This chapter is based on a published paper, and sets the initial baseline for analysis using CRF machine learning technique and compares with the empirical methods described in Chapter 3. The CRF method developed in this paper classifies human motion data sequences from healthy older volunteers wearing a W^2ISP to recognize bed exits. This study presents the activity recognition problem formulation as a machine learning problem instead of the empirical method in Chapter 3. This chapter also investigates the acceptability and wearability of the sensor as perceived by the trialled population.

Chapter 5 analyzes two problems related to CRF classification of sensor stream data given the positive results from Chapter 4. The first problem is the study of segmentation methods on sequential data and contextual information features extracted from fixed and dynamic sized sliding window based segments, relevant to the current sensor observation, to improve CRF classification performance. The second problem is the prediction of events in real time; this is because sequential learning algorithms such as CRF usually provide class labels for complete series of data, and in the case of healthcare applications, access to information from patients in real time is essential to make decisions or perform timely interventions.

Chapter 6 addresses the problem of data imbalance in sequential human activity data. Imbalance is a problem as it can affect decisions from a classification model. Imbalance is caused as the time spent performing the activities of interest is small when compared to that of other activities and also due to the increased difficulty to catch sensor readings from older patients while performing activities of short durations. This chapter proposes a dynamically weighted CRF, where class-wise weights are not fixed but are autonomously calculated. This method maintains the integrity of the sequence as modifying the time sequence changes the flow of movements and the relationship between activities. This approach is based on the optimization of the overall F-score as an effective metric to evaluate the reduction of false positives and false negatives during the learning stage of the prediction model in conditions of high data imbalance and low availability of training data.

Chapter 7 presents a technological intervention for the recognition of bed and chair exits based on the concept in Section 1.3. This approach considers a two-stage method to generate bed and chair exit alarms and evaluates its performance with a population of healthy older people in a clinical environment. The first stage is a multi-class classifier based on the dynamically weighted CRF method developed in Chapter 6, followed by a heuristics based stage that considers marginal probability predictions to assign class labels in real time.

Chapter 8 develops a two-stage technological intervention for the recognition of bed and chair exits. This chapter differs from Chapter 7 in the use of available experimental data from hospitalised older patients trialled in their hospital rooms and in the activity recognition methodology. The proposed approach uses weighted SVM for the recognition of bed and chair exits. A second stage follows consisting of a decision function that generates an alarm signal based on the predicted class probabilities. This method is compared with the CRF-based method in Chapter 7. This chapter also presents the results from an investigation of the acceptability and wearability of the sensor among the population of hospitalized older patients.

Chapter 9 introduces a hierarchical classifier as a one-stage technological intervention for the recognition of alarming states in older people. This method avoids the use of empirically determined heuristic methods or multiple processing stage methods such as cascaded classifiers or the two-stage approach in Chapter 7 and Chapter 8 to make a decision regarding the generation of an alarm. The hierarchical classifier formulates the real time recognition of alarm and no-alarm states corresponding to exiting and being out of the bed or chair as high level activities, where low-level activities correspond to observable motions or postures. The methods in this chapter are evaluated on data from healthy and hospitalised older participants.

Chapter 10 summarizes the contributions, discusses the results obtained in this thesis in the context of existing approaches and presents possible future research directions.

Chapter 2

Overview of Methodologies for Falls Prevention Interventions and Activity Recognition

This chapter presents a literature review on falls prevention interventions in older people. We explore recent clinical studies that measured the effects of current alarming procedures for the prevention of falls in hospitals. In addition, we explore technical studies for the recognition of activities that, if performed by older people, have the potential to cause a fall and thus can be used in the context of falls prevention. These approaches are described based on their sensing platform and classification methods. This review serves as background to the methods developed in the following chapters.

2.1 Clinical Interventions for the Prevention of Falls

In recent years, several studies have investigated methods for the prevention of falls in older adults, using multiple types of interventions to reduce the number of falls in hospitals or nursing homes. For example, the Cochrane Database of Systematic Reviews for preventing falls in older people in care facilities and hospitals [43], a review of 60 intervention trials, indicated some of the most widely studied intervention methods were: i) Exercise e.g. improving of balance and gait, strength, physiotherapy, or tai-chi; ii) Medication review, mostly targeting psychoactive medications and decreasing their use; iii) Vitamin D alone or with calcium to improve muscular strength and musculoskeletal function; iv) Staff training on patient-safety to a wide range of healthcare staff; v) Environment/assistive technology such as room adaptations (e.g. carpeted floors, low beds), communication/signalling aids (e.g. identification bracelets, pressure alarm sensors), protection aids (e.g. hip protectors), mobility aids (e.g. walkers, fitted footwear); vi) Various other methods such as olfactory stimulus or exposure to sunlight.

Recent reviews of mostly randomized control trials (RCT) in nursing homes and hospitals [43, 44, 45, 7, 46, 8] have demonstrated that, in few cases, the use of multiple component or multifactorial interventions can achieve a reduction of falls. However the evidence of a decrease of falls or fallers is not significant in all the reviews and thus making their benefits inconclusive. It is also not clear which intervention components are most effective toward the reduction of falls from these studies. Moreover, cases of single intervention studies, reported in these reviews, indicate almost no significant improvement in the reduction of falls.

Following the limited success of RCTs in reducing falls, several limitations remain regarding the restricted success with: i) patients with cognitive impairment; ii) first time fallers; and iii) interventions in acute hospital settings, where the length of stay is shorter as the rate of falls are higher during the first two weeks of hospitalization [47]. Technological interventions provide a way to overcome these limitations; however, little information and limited technological deployment studies can be found in the literature. For example, in the systematic review of Hempel et al. [44] on hospital-based studies about 24 of 59 studies used bed exit alarms; similarly, the review of Goodwin et al. [46] on hospitals, nursing homes and community-based studies only 5 of 18 studies used some type of technological intervention. Section 2.1.1 describes some of the latest studies focused on technological clinical interventions aimed at preventing falls by automatically producing an alert to notify a carer to provide supervision to a patient.

2.1.1 Technological Interventions

As mentioned in Section 2.1, a limited amount of studies are available in the literature that are focused on technological interventions for falls prevention. Moreover, these studies reported only the number of actual falls during the study and failed to report on the performance of the system based on the number of issued alarms in the same period of time. The problem with this approach to measuring performance is that failure to prevent a fall is not only related to a failure of the monitoring system to raise an alert. In fact, multiple causes such as long distance from the patient to the nurses' station, busy personnel, or a delay in response to the alert, can restrict hospital staff from supervising the patient on time.

Most clinical studies that include a technological approach introduced interventions based on localized recognition of activities that can lead to falls, as is the case of bed and chair exits. For instance, various studies have focused solely on the effects of bed and chair exit alarms in the reduction of falls [16, 15, 48] using pressure mats. These devices consisted of sensor enabled mats placed on the bed or chair over the contact areas with the human body where the loss of contact would initiate an alarm.

The studies by Sahota et al. [16] and Shorr et al. [15] reported the number of falls in their respective interventions; whereas the study of Wong Shee et al. [48] was able to report the number of joint bed and chair exit alarms. However, the performance of the alarming system in [48] was not clearly determined; this was due to a mix of alarming and nursing call systems and the dependence on nursing personnel reports to determine data accuracy. Falls prevention results of the studies by Sahota et al. [16] and Shorr et al. [15] are unclear as the use of pressure mats had no significant effect on the number of falls. In the study by Wong-Shee et al. [48] a significant reduction of falls was noted when comparing pre-intervention and intervention periods; however, falls during intervention and post-intervention as well as pre- and post-intervention periods were not significantly different. Some possible explanations for the failure in the reduction in falls include the insufficient response time to alerts from caregivers, a large number of false alarms, patients falling immediately on exiting the bed or chair and multiple organizational factors such as communication, leadership and management that were underestimated during implementation [16, 15].

In addition to using bed and chair exit alarms on high risk patients, the study by Dykes et al. [49], proposed an intervention that also considered a risk assessment tool using health information technology to decrease falls in four urban hospitals in the US. The approach produced personalized care plans and posters; the study was able to reduce falls in people over 65 years old significantly, but failed to prevent repeated falls.

The previous approaches [16, 15, 48, 49] considered only one type of sensor for alarming, i.e. pressure mats; in contrast, the study by Capezuti et al. [14] found that pressure sensor alarms worked better when combined with other sensors such as infra-red (IR) beam detectors. In addition, this research found that pressure sensors were unreliable with low weight patients—less than 45.4 kg [14], a common weight for patients associated with dementia and other conditions; and that sensor location has to be customized to the body and motion of each individual patient. Nonetheless, even with the combined sensors, specificity was very low, i.e. a high rate of false alarms, with a value of 0.3 %.

Other types of sensors to prevent patients from leaving a bed or chair used mechanical activation. One of the simplest methods is a wired clip which is attached to the patient's garment. Once the patient attempts to leave, the clip detaches from the control box and an alarm is activated; however, there is risk associated to this method as there is evidence of death by asphyxia by entrapment due to a cord that failed to detach [50].

These previous approaches have been limited in their scope as these environmental sensors were localized to the bed and chair area. In contrast, wearable technologies have been scarcely studied, although there is an express interest from older people in small wearable sensors (see Section 1.2). For example, the recent study by Wolf et al. [30], the only one to our knowledge to use a wearable sensor in a hospital trial, was able to detect bed exits by using a battery powered accelerometer sensor worn on the thigh and secured with bandages. The study used a commercially available sensor; where the cost of a single unit is about US$400.00. Nurses were required to ensure the cleanliness and powering of the device routinely; in addition, the performance of the equipment was measured by interviewing the nurses who indicated the system was reliable. Thus, this approach is costly to implement and maintain as the recharging of batteries and cleansing of devices are mandatory and are performed by clinical staff. Given this lack of studies focused on monitoring technologies for older people, we expand this review to examine studies focused on the recognition of activities on other demographics that can also be applied to older people for monitoring activities of interest in a hospital room environment.

2.2 Human Activity Recognition Approaches

This section reviews activity recognition approaches on different demographics based on the use of sensing technologies that are capable of recognizing bed or chair exits

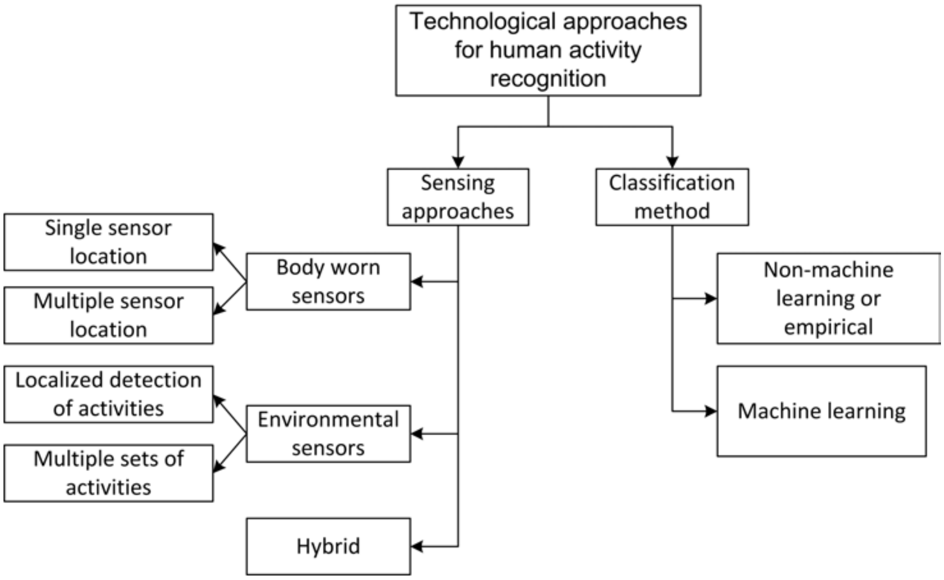


Figure 2.1: Taxonomy of falls prevention studies for the recognition of human activities.

and ambulation movements. In general, these studies characterize the motion of a person performing an activity of interest by using different types of sensors to capture a specific action or a sequence of actions. Although many studies exclusively utilize video feed for patient monitoring, we do not include these methods in this review as the use of cameras can be perceived as a violation of privacy by those being monitored, especially older people [22]. Similarly, we exclude studies that focus only in the detection of falls, as our approach is focused on fall prevention and the detection of activities that can lead to falls; and studies that use smartphones [51, 52, 53, 54] or personal digital assistants (PDA) [55] for recognizing activities as these devices (bulky and with short battery life) are not suitable for hospitalized older people.

We base the categorization of the methods considered in this section according to two different aspects of the proposed solutions, namely: i) sensing approaches as sensors can be body worn or environmental; and ii) a classification or selection methodology used for activity recognition. The taxonomy used to identify the studies is shown in Fig. 2.1.

2.2.1 Sensing Approaches

Depending on the approach, sensors can be placed on the body of the participant, in the environment where measurements are being taken or in a combination of both places.

Body Worn Sensors Using a Single Sensor Location

Early studies applied kinematic sensors such as accelerometers [26, 27] or a combination of accelerometer and gyroscope [31]. The study by Najafi et al. [31], one of the first studies to trial body-worn sensors in an older population, used a battery powered kinematic sensor consisting of a bi-axial accelerometer and a gyroscope. The sensor unit was attached to the chest of a participant and used for ambulatory monitoring of multiple activities such as walking, sitting, standing and lying and posture transitions such as sit to stand and stand to sit. The collected data was stored in a data logger for offline analysis. This method obtained high sensitivity and specificity values of $> 90\,\%$ for activity recognition.

The recent study by Godfrey et al. [26] was an improvement over that of Najafi et al. [31] as it simplified both the use of sensors and the necessary calculations to identify the activities of interest. This research [26] used a single tri-axial accelerometer attached to the chest and connected to a data logger to detect sitting, standing, walking and lying efficiently by using simple digital filters. Godfrey et al. [26] also estimated the body tilting angle by calculating the difference between the actual posture and a previously known posture (standing) of the person, using vector operations. The results from this study [26] point to the feasibility of using a single battery-powered sensor for the detection of participants' postures, obtaining results close to those of Najafi et al. [31]. Both studies [26, 31] secured the sensor unit with straps to the older person's body; while a second unit containing a data-logger, which received data from the sensors with a short cable, was worn by the participant on the waist. This practice, although ideal for data collection, is neither comfortable for the user nor feasible for an elderly patient who has to recharge or change batteries from its unit. In addition, the detection of events was not in real time as analysis was performed offline, after extracting the data from the data-logger.

Later studies by Najafi et al. [29] and Schwenk et al. [32] used a single sensor unit on the chest to help determine the risk of falls in older people. Both studies tested older people with cognitive impairment [32] and diabetes and peripheral neuropathy [29]. The researchers were able to determine the patients' risk of falling after establishing the correlation between the associated risk and the time taken to perform some specified activities, such as stand to sit. Interestingly, Schwenk et al. [32] found that some differences in activity time durations were noticeable between fallers and non-fallers, even when regular tests such as Time Up and Go (TUG) or 5-Chair stand indicated no difference between these groups.

Other studies that placed a single sensor on the chest are those by Brodie et al. [28] and Lee et al. [56]. The study by Brodie et al. [28] used a freely worn pendant sensor housing an accelerometer and a gyroscope to assess the risk of falling of older people living independently. This study measured the number of steps in short and long walks and found a correlation between fallers and the number of steps in their walks in relation to non-fallers, with several days of monitoring being necessary to assess propensity for falling. The study by Lee et al. [56] also placed a single accelerometer on the chest to recognize, in real time, activities such as lying, walking, standing, going upstairs and downstairs. This method performed standalone calculations in a laptop carried by the volunteer wearing the sensor and achieved accuracies $> 86\,\%$. Moreover, after activity detection, [56] was able to provide energy expenditure for the detected activity.

Other studies located the sensor on the waist of the participant such as the studies by Narayanan et al. [27] and Karantonis et al. [57]. The study of Narayanan et al. [27] used a tri-axial accelerometer for the evaluation of falls-risk of older people in independent living using TUG, 5-Chair stand transitions and alternate step (on a platform) tests. This study achieved a high correlation between their results and those of a physiological profile assessment, which estimates the possibility of falling within 12 months of the assessment [27]. Similarly, the research by Karantonis et al. [57] collected data from an accelerometer with a micro-controller and a small memory where a classification algorithm was performed once per second. The unit contains an active transponder that sends the information to a computer using the ZigBee (IEEE 802.15.4) wireless communication protocol for storage, minimal analysis and display. The system was able to detect walking, sitting, standing and lying with high accuracy, where all activities but walking, which was detected by the central computer, were classified within the remote microcontroller unit. In the case of falling, the system issued a "possible fall" alert with $100\,\%$ accuracy. Fall detection accuracy was high because this event was left to further analysis, collecting data for one minute and analysed by a human operator. Results from walking activities were satisfactory for normal and fast paces, but these are not adequate for elderly patients who mostly move at slow paces. Furthermore, some inconsistencies were found due to the sensor location, as in some tests the sensor changed position or rotated.

The pelvic region has also been used to place sensor units. Cho et al. [58] used the information of a tri-axial accelerometer and an image sensor included in a belt buckle to recognize activities such as walking, sitting, standing, turning, running and going up/down stairs. We consider this study in this review, although it uses an image sensor because this signal is combined with that of a kinematic sensor and images were not recorded or transmitted; however, no information was given about the population trialled.

Body Worn Sensors Using a Multiple Sensor Locations

All previously mentioned studies considered a single sensor location for activity recognition; however various other studies placed sensor units on multiple body locations [59, 25, 60, 24]. In the study by Luštrek et al. [59], four location sensors placed on the chest, waist and ankles, and one tri-axial accelerometer placed on the chest of the participant were used to capture motion and location of both the sensor and the participant in an apartment, as well as the height of the sensor with respect to the ground. The approach was able to recognize activities such as lying, sitting and falling with accuracy $\geq 84\,\%$.

The study by Varkey et al. [25] used two wireless battery powered sensor units consisting of a tri-axial accelerometer and tri-axial gyroscope on the wrist and ankle of three young volunteers. This study aimed to recognize two levels of activities; starting from high level activities such as walking, jogging and smoking to a more specific or low level such as arm-moving-up or arm-moving-down. Misclassification for both levels of activities was about 9 %, and 20 % for high level and low level activities respectively.

Other studies used only accelerometers in their multi-sensor approach. The study by Uslu et al. [60] used one or two wearable devices equipped with tri-axial accelerometers worn on the wrist and ankle; this study was able to recognize simple actions such as lying, sitting, walking, standing and using a wheelchair, along with their transitions. This study achieved a detection success rate of above 94 %. Although this study aims to serve older people, no information is given about the tested population. In the case of the study of Banos et al. [24], the dataset of a previous study by Bao et al. [61] was used for the detection of activities such as cycling, running, lying, going upstairs or walking. This dataset uses bi-axial accelerometers located on the hip, wrist, arm, ankle and thigh of young volunteers This method considers that partial decisions can be made at sensor level and activities are recognized at a later stage using these partial decisions achieving $> 95\,\%$ accuracy.

These previously mentioned methods using multiple sensor locations on the body, may not be comfortable for the participant using or wearing them, and these methods have not been trialled with an older population. Moreover, an important consideration when using body worn sensors that is common to the previously mentioned studies is the issue of sensor power as most tested sensors are battery powered and securely encased. This makes the devices bulky and subject to maintenance, which is not a desirable characteristic of monitoring devices for older people [19].

A summary of these methods is shown in Table 2.1

Table 2.1: Details of body worn sensor studies for detection of activities and prevention of falls.

Author(year)	Type of sensors used	Tested population	Performance
Najafi(2003) [31]	Chest attached accelerometer and gyroscope wired to data logger	9 older participants, average age 66 $\pm$ 14	Offline analysis recall $>$ 90%, specificity $>$ 92% for all activities
Karantonis(2006) [57]	Triaxial accelerometer connected via Zigbee to remote computer	5 young (22–23) and one older healthy adult (60)	Real time analysis except for falls (1 m delay), accuracy $>$ 63% for all activities
Cho(2008) [58]	Triaxial accelerometer with embedded one image sensor in a belt	No information	Detection using 2 s windows accuracy $\geq$ 80% for all activities
Narayanan(2010) [27]	Waist mounted triaxial accelerometer with wireless data collection	68 older participants, age: 72–91	Combined falls risk test correlation with physiological profile assessment value, $\rho = 0.81$
Luštrek(2011) [59]	Triaxial accelerometer worn on the chest and up to four tags on different parts of the body for location and velocity calculations	10 healthy participants, tests included falls	Detection using 1 s window; accuracy $>$ 83% for all activities and average accuracy of 94.7%
Godfrey(2011) [26]	Chest strapped accelerometer wired to data logger	10 healthy older participants age: 70–83	Offline analysis recall and specificity $>$ 83% for all activities

Lee(2011) [56]	Triaxial accelerometer attached to the chest and connected to laptop via USB cable	20 healthy young participants age: 22–30	Detection every 5 s accuracy $\geq$ 86% for all activities
Varkey, 2012 [25]	Triaxial accelerometer and gyroscope, on wrist and ankle	3 young participants age: 26–28	Detection every 0.8 s accuracy $>$ 91% for all activities
Banos(2013) [24]	Five biaxial accelerometers distributed on limbs and hip as in [61]	20 young adult participants as in [61] age: 17–48	Detection every 6 s accuracy $>$ 95%
Uslu(2013) [60]	2 sensors attached to ankle and wrist or single sensor attached to leg or wrist	No information	Real time detection; success rate $>$ 94% using multiple sensors
Najafi(2013) [29]	Triaxial accelerometer with embedded logger attached to chest	8 older participants with diabetes and peripheral neuropathy; average age 77 ± 7	TUG activities recognition recall and specificity of 100%
Schwenk(2014) [32]	Similar device used in [31]	77 older patients with cognitive impairment, average age 81.6 $\pm$6.3	Statistical significant difference between physical activity sensor based parameters of fallers and non-fallers (p=0.008) where performance tests showed no difference ($p > 0.23$)
Brodie(2015) [28]	Freely worn pendant sensor housing a triaxial accelerometer and pressure sensor	18 independent living older participants, average age 83.4 $\pm$7.0	Statistical significant difference of gait features between fallers and non-fallers ($p < 0.05$)

Environmental Sensors for localized detection of activities

In this approach, furniture such as a bed, chair or commode were used to place a variety of pressure sensors to detect some important movement transitions, such as bed or chair exiting. For example, a commercially available product consisting of a bed mat to monitor sleep activity and bed exits was trialled in the study by Bruyneel et al. [62]. A bed exit was determined when the presence sensors produced no signal and the measured temperature at the mat was under 33 °C. The performance results for sensitivity and specificity were between 90 and 100 % for their tested population of young and middle aged participants. On the other hand, the time for the sensor to reach a stable temperature was from 70 to 90 min, which means that activities in the first hour can potentially be undetected.

A diverse approach to the use of bed mats includes the use of pressure sensors located in sensitive areas used by patients before and during bed exiting such as bed railings as in the study of Hilbe et al. [63]. In this study [63], the sensor system performed well with sensitivity and specificity values of 96 % and 95.5 % respectively; however, it was tested on a population of nurses acting as older patients and was unable to classify one postural condition in which the patient had both legs on top of the railings. Additional downsides to using pressure sensors are their associated cost, such as maintenance and replacement, which impact on their clinical deployment; moreover, the use of bed rails is not recommended as they can increase the height of a fall [12].

Alternative studies, such as that of Hoque et al. [64] was focused on the study of sleeping behaviour. The researchers used three accelerometer enabled RFID tags, denominated as Wireless Identification and Sensing Platform (WISP), attached to three sides of a mattress (two laterals and close to the legs) and an RFID reader antenna located under the bed. The study was able to detect bed presence and analyse sleep quality and body positioning during sleep by analysing the mattress deformation caused by the participant's body. This method obtained a accuracies of 90 to 100 % for body positioning in the bed.

Environmental Sensors for the recognition of multiple sets of activities

This type of approaches focuses on the recognition of a wider set of activities, distributing the sensing platform around the living environment [65, 66, 67, 68]. In the study by Buettner et al. [66], RFID tags with embedded accelerometers (WISPs as used in [64]) were attached to everyday objects and the RFID reader antennas were located on the ceiling, making the user free of devices. This approach obtained a performance of about 90 % for both precision and recall, and also had an overall better performance when compared to using a portable RFID reader and short range RFID tags on the same objects. However, the system was prone to problems caused by sensor occlusion due to the positioning of the sensors with respect to the reader antennas on the ceiling, the handling of the tagged objects and the increased distance to the RFID reader antenna, causing the tag to receive insufficient power.

The advancement and miniaturization of sensors in general have allowed large scale deployments of sensing and monitoring technologies in smart homes where interactions with the sensing platform are used to monitor or recognize activities. In the study by Cook [65], multiple sensors (e.g. motion, door, temperature, light and water) were installed inside the settings of seven houses of a wide adult age range population. Activity monitoring was of a general context: cook, work, leave home, personal hygiene, sleep, bed-to-toilet and relax were some of the activities of interest. This environment information was used to infer the most probable activity being performed by the house's inhabitant. The results from these methods were not generalizable as accuracy values varied from 32 % in one house dataset, while other datasets achieved 100 % accuracy. In addition, the results are not demographically segmented, making the impact of this study on elderly people unclear.

Other approaches using smart homes have been explored for the recognition of activities, monitoring of patterns and location of participants. For example, the studies of Helal et al. [69, 70] used multiple sensors in a home setting with sensors in electric outlets, floors, bed, bathroom and other locations for the recognition of activities; and an ultrasound positioning system for the location of a user in the home environment. In the study by Tapia et al. [67], a number of state-change sensors were placed on locations such as cabinets, doors, windows and appliances to determine generic activities such as preparing lunch, toileting or doing laundry, with recognition accuracy per activity $> 25\,\%$. The system expects that monitoring possible pattern variations of these activities that can be linked to health problems; however this premise was not trialled. The study by Lu and Fu [68] used wireless sensors integrated into objects such as floors, power outlets and appliances as well as RFID tags on objects. The main approach of the sensing platform is capturing the interaction of humans and objects, and environmental information, whilst also being capable of receiving commands and activate actuators. This method [68] achieved accuracies of over 67 % for detecting activities such as using PC, studying, watching tv, using different appliances, making tea, walking and sitting. None of these four studies [70, 69, 67, 68] reported tests with older adults. Moreover, common challenges for smart home deployments are the presence of multiple inhabitants or the recognition of interleaved activities, which were not addressed in these studies.

We also considered studies where sensors were located on fall prevention apparatus such as in the studies of Hirata et al. [71] and Wakita et al. [72]; both studies developed robotic aids for older people: a walking aid and a supporting cane respectively. Multiple sensors and laser range finders allowed the robotic aids to provide support to the user when the device detected the user was in trouble, for example when the displacement of the person's feet base in relation to the robot was insufficient to provide support to the person. However, there are no reported trials with these devices as they are still heavy, the robotic cane is 50 kg. Moreover, a person with cognitive impairment can easily forget to use such aids. A summary of these environmental sensor based methods are shown in Table 2.2

Table 2.2: Details of environmental sensor studies for detection of activities and prevention of falls.

Author(year)	Type of sensors used	Tested population	Performance
Helal(2003) [70]	Ultrasound location system	Testing robot	Location error < 22 cm within a house setting
Tapia(2004) [67]	State-change sensors in doors, windows, cabinets, drawers, microwave ovens, refrigerators, stoves, sinks, toilets, showers, light switches, lamps, containers, other appliances and locations	2 participants, ages: 30 and 80	Detection every 5 s, accuracy $> 25\%$ for all activities
Helal(2005) [69]	Smart home with sensors in appliances, electric outlets, floors, doors, bed, bathroom, and others	No information	No results presented
Hirata(2007) [71]	Walker type robot with laser range finder and tilt angle sensors	No information	Real time functionality, no quantitative results
Buettner(2009) [66]	Accelerometers embedded in RFID tags attached to everyday items	10 participants	Activity recognition precision $> 73\%$ and recall $> 40\%$ for all activities, overall precision and recall = 90% and 91% respectively
Lu(2009) [68]	Wireless sensors integrated into objects; detection of current flow, voltage, pressure, vibration, motion, acceleration, distance and contact along with IDs from RFID tags	10 participants	Recognition of activities accuracy $> 68\%$ for all activities
Hoque(2010) [64]	Three triaxial accelerometers embedded in RFID tags attached to a bed mattress	11 participants	Body position inference accuracy $> 90\%$
Hilbe(2010) [63]	Pressure sensitive side rails for hospital beds	62 adults (age: 18–60) behaving like older people	Bed exit detection recall = 96.0% and specificity = 95.5%
Bruyneel(2011) [62]	Commercial bed sensor mat to detect body temperature, presence and movement	17 participants older than 18	Bed exit recall = 100%, specificity = 85%, detection considered after 2 minutes of exit
Cook(2012) [65]	Multiple homes equipped with various on-off sensors: doors, switches, light , water and burners and temperature	Young healthy participants and older (healthy and with dementia) participants	Overall activity accuracy $> 34\%$ for all house datasets
Wakita(2013) [72]	Cane robot including force and tilt angle sensors, and laser ranger finders	Intended for elderly and handicapped, 3 participants	Real time functionality testing coincidence of robot and intended direction

Hybrid Approaches

This section reviews studies that combine environmental and body worn devices [23, 73, 54, 74]; body worn devices considered included wearable sensors or RFID readers [23, 73, 74].

A usual configuration includes multiple wearable devices with accelerometer sensor units and portable RFID readers to interact with tags in the environment, as in the study by Wang et al. [74]. This approach achieved real time recognition of activities by recognizing gestures at sensor level and high level (complex) activities at a centralized processing device with an overall 82 % accuracy.

A different approach to wearing sensors consists of the participant using a portable RFID reader in order to recognize activities of interest based on the use of previously tagged objects [23, 73]. These studies mined the web for object terms relative to each activity of interest and used this information to determine the activities performed based on the human interaction with multiple objects. The activities of interest in these studies have different scope. For example, in [23], the activities are focused into specific movements or objects such as make coffee, brush teeth, watch tv, clean table or read a book; whereas in [73], the activities of interest can include various types of movements or objects such as oral hygiene, take medication, housework, washing or leisure activity. Precision and recall for [23] were about 92 %; whereas in [73], metrics were > 64 % and > 33 % respectively.

A special case is the study by Cohn [75], where the authors tried to detect human motion by using only the human body as an antenna to receive the environmental electric noise from the power lines to which we are all exposed. The system reads the changes on this signal while the body is moving, achieving an average accuracy of 92.7 %. Although the participant does not use any sensor, the participant carries the processing unit in a backpack which is connected to the body on the neck. In addition, the system had problems in identifying mirror movements for left and right hand motions.

2.2.2 Classification Approaches

These studies can also be differentiated by their classification or decision methods; clearly, we can distinguish the studies of interest into those that use machine learning or non-machine learning based approaches (empirical) to make a decision. Regardless of the taxonomy, the studies considered analyse physical data in order to make decisions about the postures and/or activities for recognition.

Empirical or Non-Machine Learning Methods

Studies that used non-machine learning methods such as thresholds, in general, used a single constant stream of data from their sensors for analysis. For example the studies by Najafi et al. [31], Godfrey et al. [26], Brodie et al. [28], Bruyneel et al. [62], Hilbe et al. [63], Karantonis et al. [57], and Wolf et al. [30] were able to determine if some activity has occurred by post-processing the sensor data. In the case of kinematic sensor data streams, the information is usually passed through digital filters such as low pass, band pass and high pass filters, or Discrete Wavelet Transforms as in [31] to isolate frequency components that provide movement information or to remove noise from the sensor signal. Some studies do not require filtering post-processing, as in the case of [63] where raw signals from static sensors (fixed on the bed) were immediately classified.

The output of the filtering processes is verified by an empirical threshold-based classifier and an activity was determined if the processed value lies outside an acceptable predefined threshold. The construction of empirical decision trees is common in methods using thresholds as in the aforementioned studies [31, 26, 28, 62, 63, 57, 30], where the division of branches corresponds to the responses to established threshold levels for the different activities of interest. In general, these methods were trained and tested using the same population, hence determining thresholds level using the testing population. For these methods to work, data streams require a constant data sampling as methods rely on digital filtering processes and thus, sensors require a battery powered sensing unit.

Machine Learning Methods

The increasing complexity of human activity recognition tasks, e.g. multiple or simultaneous performed activities, has widened the previous classification methods to the use of machine learning techniques in human activity recognition studies [18]. In this context, the system learns prediction models from training data to recognize the performed actions by the monitored participants. Most commonly used methods were based on Decision Trees (DT), Naïve Bayes Classifiers (NBC), Hidden Markov Models (HMM), Conditional Random Fields (CRF), Emerging Patterns (EP), Neural Networks (NN) and Support Vector Machines (SVM).

We present a brief introduction to the most commonly used machine learning techniques for activity recognition. We do not introduce CRFs as this method will be explained more thoroughly in Chapter 4.

Decision Trees This approach creates a set of rules by examining the discriminatory ability of the data features. This method can be understood as a sequence of questions, where a question depends on the answer to previous questions; creating a tree where each branch from the root to the leaf node is a classification rule. Hence, classification starts at the root where different links from the root represent different values and all links are mutually exclusive, i.e. only one link is to be followed. Each leaf node bears a label; hence, once reached, that label is assigned to the input data [76, 77]. One of the advantages of decision trees is that the models are easy for humans to understand. One of the most popular decision tree algorithms is C4.5; this approach is based on the concept of information gain to select the attributes that should be placed in the top nodes. In addition, this method can handle discrete and continuous attributes as well as missing features [76]. This algorithm uses heuristics for pruning the tree, i.e. deleting redundant antecedents on the learned tree rules.

Naïve Bayes Classifier These are a family of methods that apply the Bayes theorem and assume that every pair of feature observations are independent and identically distributed (i.i.d.). This is, given a feature vector $\mathrm{x} = \{x_1, \cdots, x_n\}$, where n is the number of features, all features are independent variables; and the class variable $y = \{1, \cdots, K\}$ has K possible values. Bayes theorem states the following relationship:

$$P(y = k|\mathrm{x}) = \frac{P(y = k) \prod_{i=1}^{n} P(x_i|y = k)}{P(\mathrm{x})} \tag{2.1}$$

$$y = \arg\max_{y_k} P(y_k)P(x_i|y_k) \tag{2.2}$$

This model learns from the training data the conditional probability of each feature given its class label. However, this classifier oversimplifies the classification problem by assuming that all features are independent given a class value; nonetheless, that assumption does not always hold, e.g. acceleration signals from different axes are highly correlated, as are other physiological signals [18, 78].

Hidden Markov Models Hidden Markov models are generative probabilistic models for representing distributions over data sequences. HMMs have two components, an observable (x) and a hidden component (y); we assume that the hidden process satisfies the Markov property, i.e. the current state y_t depends only on the its previous state y_{t-1} (first-order Markov property). HMMs are trained by determining state transitions, assumed to be first-order Markov chains; and the probabilities of each possible set of observations to be related to a hidden state. In this model, each set of observations depends only on the respective hidden state; considering conditional independence between observed variables [79, 80]. Calculation of the model parameters is usually done with the Baum-Welch algorithm [79].

Given a sequence of class variables $Y = \{y_1, \cdots, y_T\}$ and the sequence of observations $X = \{\mathrm{x}_1, \cdots, \mathrm{x}_T\}$, where T is the number of elements in the sequence. The HMM model is defined as:

$$P(X) = \sum_{y \in \mathcal{Y}} \prod_{i=1}^{T} P(y_i | y_{i-1}) P(\mathrm{x}_i | y_i) \tag{2.3}$$

where $\mathcal{Y}$ is the set of all possible label sequences Y. Two prediction problems can be solved: i) finding the probability of the observations; and ii) finding the most likely state trajectory given the observation. Solutions for these problems require application of the forward-backward and the Viterbi algorithms respectively [79].

Dynamic Bayesian Networks These are Bayesian networks for representing time series, as Bayesian Networks cannot represent temporal dependencies. This means that an event can cause another event in the future, but not viceversa. One of the simplest cases corresponds to the first order Markov model, where each variable is influenced only by its predecessor. In this case, for a sequence of data $Y = \{y_1, \cdots, y_T\}$ the joint probability is given by: $P(Y) = P(y_1)P(y_2|y_1) \cdots P(y_T|y_{T-1})$. Common applications such as Kalman filters and HMMs are particular cases of DBNs. DBNs allow for richer sets of relationships than HMMs as the model can be extended to higher orders or a factored representation, as is the case for factorial HMMs, where the underlying state transitions evolve independently from each other in independent Markov chains [81, 82].

Support Vector Machine This supervised machine learning method finds the optimal separating hyperplane between two classes with the maximum margin between the nearest training data points of the participating classes, see Fig. 2.2, where training data are assumed as i.i.d. SVM can project the data from the original feature space to a higher dimensional space. This way, data from two classes can always be separated given a sufficiently high dimension. Moreover, a linear separation in a higher space is equivalent to a non-linear separation in the original space [83]. Given the training data $\{\mathrm{x}_i, y_i\}$, $i = 1, \cdots, l$, where the d-dimensional feature vector $\mathrm{x}_i \in \mathbb{R}^d$ is associated to the class label $y_i \in \{-1, 1\}$.

The optimal separating hyper-plane

$$\mathbf{w}^T \mathrm{x} + b$$

is obtained by solving the optimization problem:

$$\text{minimize} \quad \tfrac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{l} \xi_i \tag{2.4}$$

$$\text{subject to:} \quad y_i(\mathbf{w}^T \mathrm{x}_i + b) \geq 1 - \xi_i \tag{2.5}$$

$$\xi_i \geq 0;\ i = 1, \cdots, l \tag{2.6}$$

where C is a constant regularization parameter that penalizes margin violations and ξ_i are slack variables and represent error margin from non-separable data classes. This convex constrained optimization problem can be solved using its dual formulation [83, 84] given below.

$$\text{maximize} \quad \sum_{i=1}^{m} \alpha_i - \tfrac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j \mathrm{x}_i^T \mathrm{x}_j \tag{2.7}$$

$$\text{subject to:} \quad 0 \leq \alpha_i \leq C \tag{2.8}$$

$$\sum_i \alpha_i y_i = 0 \tag{2.9}$$

where α_i are Lagrange multipliers and the data samples x_i where $\alpha_i > 0$ are the points on the margin and are called support vectors. Moreover, the inner product $\mathrm{x}_i^T \mathrm{x}_j$ can be replaced with a kernel function $K(\mathrm{x}_i, \mathrm{x}_j)$. The kernel function computes the inner product into a high dimensional feature space, and thus, generating non-linear decision boundaries in the input data space.

Prediction of testing data is done by determining on which side of the hyperplane (H in Fig. 2.2); a test feature vector lies and assigning the corresponding label. This is done with the decision function:

$$\mathrm{sgn}(\mathbf{w}^T \mathrm{x}_{test} + b) \tag{2.10}$$

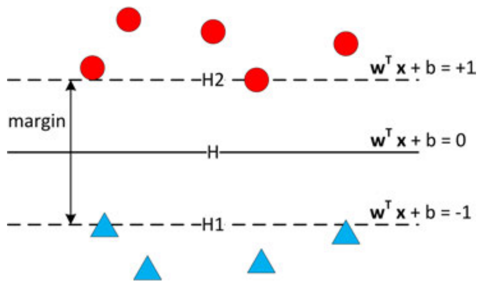


Figure 2.2: Graphical representation of separating hyperplanes for a linear SVM, the samples on the separating hyperplanes are *support vectors*.

Neural Networks These models are inspired by the functioning of the biological nervous system. NNs have two main components: i) processing nodes (or neurons); and ii) weighted connections between nodes. Nodes, typically organized in layers, take inputs (at input layer) or outputs from previous layers and produce a scalar valued response to a non-linear activation function, characteristic of the node. The connection weights between nodes are the model parameters and are determined during training.

NNs can have multiple architectures (e.g. feedforward or recurrent networks) and learning algorithms, such as the back-propagation algorithm. It has been shown that NNs with a sufficient number of nodes and layers can approximate any continuous function; however, in some cases, methods can suffer from slow convergence or reach local minima [85]. The topology of the network is often determined heuristically, as knowledge of the problem can be used to determine the network structure; however, this is not trivial, as poor performance and overfitting can be caused by topologies too simple or complex, respectively. This is also related to the model complexity given by the number of parameters or weights in the network [76].

Most studies base their approaches in the aforementioned methods; Table 2.3 illustrates the classification algorithms in the various activity recognition studies considered.

Table 2.3: Classification algorithms used in fall prevention and human activity recognition studies.

Type	Classifier	Author(year)

Non-machine learning	Thresholding	Najafi(2003) [31], Godfrey(2011) [26], Bruyneel(2011) [62], Hilbe(2010) [63], Karantonis(2006) [57], Wolf(2013) [30], Narayanan(2010) [27], Najafi(2013) [29], Schwenk(2014) [32], Brodie(2015) [28]
Bayesian	NBC, Bayesian Networks	Hoque(2010) [64], Tapia(2004) [67], Lu(2009) [68], Uslu(2013) [60], Cook(2012) [65], Philipose(2004) [73]
Markovian	HMM, CRF	Buettner(2009) [66], Uslu(2013) [60], Cook(2012) [65]
Decision Trees	C4.5	Banos(2013) [24], Luštrek(2011) [59]
Feature Detection	SUSAN	Uslu(2013) [60]
Domain Transformation	SVM	Banos(2013) [24], Luštrek(2011) [59], Cohn(2012) [75], Cho(2008) [58], Varkey(2012) [25]
Instance Based	*K*-Nearest Neighbour	Banos(2013) [24]
Neural Networks	Perceptron	Lee(2011) [56]
Meta Learning	Majority Voting, Hierarchical Decision, Boosting	Banos(2013) [24], Cook(2012) [65]
Similarity Measure	Dynamic Time Warping	Wang(2012) [74]
Pattern Discovery	EP	Wang(2012) [74], Gu(2010) [23]

Simple probabilistic models such as NBC were applied successfully in the studies by Tapia et al. [67], Hoque et al. [64] and Lu et al. [68] for the recognition of activities in home settings. In Tapia et al. [67], sets of activities to recognize for each participant were different, and thus results were participant-specific; moreover the volunteers had to label their activities for days, which was troublesome for system users and can cause potential inaccuracies during training. This study [67] demonstrated that a multiclass NBC and multiple binary NBCs performed similarly with $\pm 5\,\%$ difference. In Hoque et al. [64] the classifier performed better with higher overall accuracy ($1 -$ error) using data from multiple sensors as opposed to any individual sensor using only acceleration sensor readings. The study by Lu et al. [68]

was able to recognize inter-leaved activities by implementing several NBCs in parallel for each activity to recognize; these classifiers were not exclusive, hence two activities may occur simultaneously. Moreover, features were selected for each activity NBC as opposed to making a general feature selection process; in addition, it used a user-defined weighted factor to reduce errors during training.

Other popular techniques for activity recognition applications were the methods of SVM and HMM in the studies of Cohn et al. [75], Cho et al. [58], and Buettner et al. [66] as these methods have achieved good performance in comparative studies [86]. In Cohn et al. [75], DC and frequency components from the AC power signal were used as features for a SVM classifier to identify gestures and location of the person. In this method, participants performed activities of specific duration to synchronize with data segments. However, the classifier can be affected by electrical changes in the environment. Moreover, the authors suggest use of HMM can improve the performance by avoiding imprecise data segmentation that lead to misclassifications and using discrete states for each gesture as in HMMs. In Cho et al. [58], a hybrid classifier using SVM with data from a tri-axial accelerometer in 2 s windows and an image sensor using the grid-based optical flow method was able to determine walking, sitting, up/down stairs, standing and running activities. However, image sensor component was only better when walking and turning. The use of HMM, which, as opposed to NBC and SVM, considers dependencies of the observed states, was successfully applied by Buettner et al. [66] to map the observed data into activities or sequences of activities in a smart home environment.

Multiple classifiers have also been used, in chains or simultaneously, to process information from multiple sensors and improve the output of a single classifier. For example, the study of Uslu et al. [60] used a model that considers multiple sensors and a hybrid classifier that uses NBC, HMM and a SUSAN Corner Detector (SCD) to detect transitions between activities in real time. During the classification chain, the NBC processes chunks of sensor information to find the posterior probability; if a decision is not made at this stage, the data is processed by the SCD which maps data and establishes distances to the possible activities. After a non detection at this stage, the HMM determines the activity label. Similarly, the study by Luštrek et al. [59] used multiple methods to build its activity recognition model. For example, the authors use Random Forests to detect activities of interest; and a second stage of classifiers such as SVM and C4.5, which combined with location information, are used to detect activities including falling. The accuracy of using location information sensors, in general, performed better than that of accelerometers sensors. Lee et al. [56] used various NNs to determine, first, a NN was used to determine the state of the participant is either static (lying or standing) or dynamic (walking, driving, up/down stairs). Second, two NNs were used to determine which static or dynamic activity was performed respectively.

Another method to address the recognition of activities with multiple classifiers is using a hierarchical approach where different granularities of the performed activities were recognized at each level of the classifier. In this context, different hierarchical levels recognize different levels of complexity (complex and simple or high-level and low-level activities respectively) from the performed activities. For example, in the study of Varkey et al. [25], the first stage of the activity recognition process detects the activity of interest (high level activity) whereas the second stage finds specific motions (low level activities) within the high level activity. Both stages were based on SVM classifiers. However, the decisions were based on measuring the predictions within a two-window method where a label that identifies the outer window of fixed size is determined by the class of the inner-window, of size predetermine during training, that has the largest distance to the hyperplane.

Similarly, the study of Wang et al. [74] also used two levels of recognition. The first level detected low level activities (gestures) by comparing the collected sequence with a database of template gestures using Dynamic Time Warping, a method that measures the similarities between two time series, not necessarily linearly aligned. The second level combined the gestures and environmental information using an EP based algorithm for real time classification in a mobile device. This method was compared with HMMs achieving better accuracy by up to 35 %. The study of Banos et al. [24] is able to recognize activities using a multiple stages. The first stage consists of multiple simple binary classifiers, per activity and sensor where each classifier applies a one-vs-all strategy. The output of these classifiers were introduced to the different levels of the hierarchy which grouped and ranked the output of the previous stage to decide on the activity level. This way, a decision is made at sensor level and then at a general level using the selected outputs from each sensor. This method achieved better performance than multi-class classifiers even when using a single sensor; in general, good performance is achieved using the SVM classifier.

The use of multiple sensors in a smart home environment can potentially produce large amounts of sensor data streams as these sensors report regularly over time. The study by Cook [65] used data mining techniques in addition to machine learning techniques, where various classifiers (NBC, HMM and CRF) were applied and compared for activity recognition individually and in an ensemble. This study [65] showed that ensemble classifiers and semi-supervised learning models, using the ensemble for labelling new data, performed better than individual classifiers.

Finally, some studies, such as those of Philipose et al. [73] and Gu et al. [23], mined the internet for lists and sequences of objects and actions used in completing an activity and thus avoiding the collection of labelled data and obtaining multiple combinations of activity patterns. In [73], the activities are inferred using a DBN classifier, where the models are based on probabilities extracted from the mined information and the observed data corresponds to the objects that have interaction with the participant. Similarly, in [23] data is mined from how-to-do websites extracting lists of objects related to each activity and determining their weight. Based on the mined activity-object-weight information, a model is constructed using an EP derived algorithm (contrast patterns) that constructs sets of possible objects used (fingerprints); a score function is then used to recognize the activity performed comparing object fingerprints and a sequence of data readings input. One advantage of these models is that model parameters can be learned without supervision due to the data mining-training process.

2.3 Summary

In this chapter, we have presented an overview on previous approaches for the prevention of falls and recognition of activities. Clinical approaches for the prevention of falls have had limited success with interventions focused to provide supervision for hospital patients and face several limitations e.g. patients with cognitive impairment, a high rate of falls in first time fallers and falls in acute hospitals. We also presented methods for the recognition of activities using technological approaches. The benefits of using wearable sensors, in this review, are counterbalanced by their need for batteries and equipment maintenance; on the other hand, environmental sensors leave the participant free of sensors but monitoring is restricted to certain areas and have been only tested with people living independently. Nevertheless, we emphasise on wearable technology as a viable platform for sensor deployment; moreover, older people have indicated their preference in light, wearable devices for monitoring in a previous study [19]. We also underscore the application of emerging techniques such as machine learning for activity recognition and its growing presence in healthcare applications. We consider the advantages of structured classifiers as activities are sequential by nature and not necessarily independent of each other.

In the next chapter we present two technological approaches to identify bed exits using wearable and environmental sensor approaches. The following chapters build methods for the recognition of bed exits and chair exits in the framework of the proposed intervention described in Section 1.3.

Chapter 3

Analysing and Identifying Bed Exit Movements

This chapter, based on a published paper of the author [87], aims to investigate the accuracy of two technological approaches using a wearable, low-cost, passive sensor device, Wireless Identification and Sensing Platform (WISP), to identify posture transitions associated with bed exiting automatically, in order to provide caregivers with the opportunity to intervene when the bed exit is detected. The two different technological methods evaluated are: i) WISP located over sternum; and ii) WISP attached to mattress on the lateral side away from the entry or exit side.

3.1 Methods for Bed Exit Detection

3.1.1 WISP Attached Over Sternum Method

In this method, a WISP tag was located over the sternum of the subjects on top of their attire with double sided adhesive tape as shown in Fig. 3.1(c). The acceleration data used in this approach is expressed in a gravitational scale, i.e. in terms of g ($1\,g = 9.8\,\mathrm{m\,s^{-2}}$), and the data was considered in 20 s segments. The algorithm, shown in Fig. 3.1, uses acceleration readings from the three axes, denoted by: i) y_g: the mediolateral axis; ii) x_g: the anteroposterior axis; and iii) z_g: the dorsoventral axis, which vary with the alignment of the WISP sensor with respect to gravity during postural transitions. The algorithm considers the strength of the wireless signal sent from the WISP tag and received at an RFID reader antenna referred to as the RSSI (Received Signal Strength Indicator) [88, 89] to estimate the location of the subject with respect to the reader's antennas (such as near the bed or chair). A bed exit event is defined as a sequence of two actions; a posture transition (PT) of lying to sitting, shown in Fig. 3.1(a), followed by a PT of sitting to standing as in Fig. 3.1(b). The

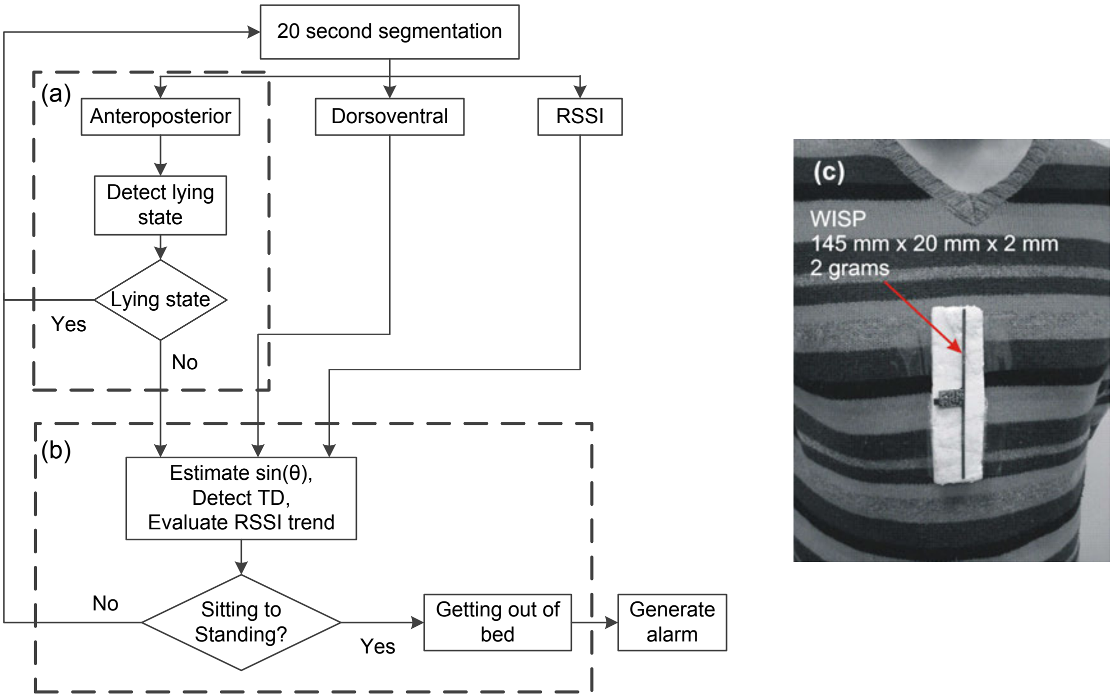


Figure 3.1: Algorithm for bed exiting detection, (a) transition to a lying state: standing to lying was detected using the anteroposterior axis data. (b) Bed exit event detection: PTs of standing-to-sitting and sitting-to-standing were classified in the absence of lying and using $\sin(\theta)$, RSSI and the duration of the posture transition where a bed exit event activates an alarm. (c) WISP is attached over a garment on top of the sternum.

reverse sequence of PTs indicates bed entry. Each of these PTs were differentiated to determine a bed exit or entry event.

Lying to Sitting and Sitting to Lying

A static lying state can be discriminated from a sitting and standing state by analysing acceleration readings from the anteroposterior axis (x_g). Readings from the anteroposterior axis will be approximately $0\,g$ when lying and around $1\,g$ when standing. However to identify possible onset of a bed exit event, lying-to-sitting and sitting-to-lying PTs as described in part (a) of the algorithm presented in Fig. 3.1 must be identified.

PTs of lying-to-sitting and sitting-to-lying were detected based on a threshold based method first established by Najafi et al. [31]. The lying-to-sitting and sitting-to-lying PTs can be detected using the filtered (to remove noise) vertical acceleration (x_g) as shown in Fig. 3.2. The time of occurrence of a PT (t_{PT}) is the estimated time at which

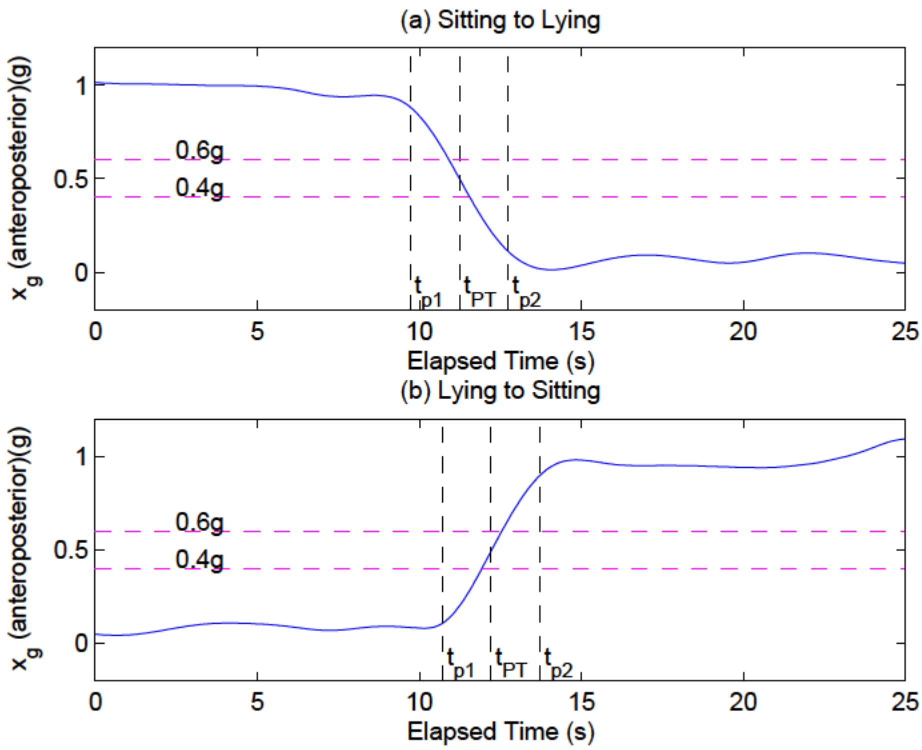


Figure 3.2: (a) Detection of sitting to lying start (t_{p1}) and ending (t_{p2}) points from the anteroposerior axis information and (b) detection of the lying to sitting process.

a posture transition occurs. The PT of sitting-to-lying was confirmed if the mean of (x_g) between $t_{p1} = t_{PT} - 1.5\,\text{s}$ and t_{PT} (before) and between $t_{p2} = t_{PT} - 1.5\,\text{s}$ and t_{PT} (after) was higher than $0.6\,g$ and lower than $0.4\,g$ respectively. The PT of a lying-to-sitting transition was classified if the mean of x_g before and after t_{PT} was below $0.4\,g$ and above $0.6\,g$ respectively, as illustrated in Fig. 3.2(b).

Sitting-to-Standing and Standing-to-Sitting

To classify standing-to-sitting or sitting-to-standing PTs, a threshold based approach using the information from a subject's trunk displacement angle, time duration (TD) of the posture transitions and the RSSI pattern was used.

Both standing-to-sitting and sitting-to-standing transitions have two phases: an initial leaning forwards followed by a leaning backwards. The displacement of θ (angle between trunk and vertical axis) in the mid-sagittal plane for both transitions generates a maximum and then recovers. In contrast to the more accurate but more power consuming gyroscope based method in Najafi et al. [31] we have estimated θ using (eq. 3.1) based only on accelerometer information.

$$\theta \approx \arctan\left(\frac{z_g}{x_g}\right) \tag{3.1}$$

We use the pattern of $\sin(\theta)$ as a classifier [31]. The $\sin(\theta)$ values were filtered using a forward-backward third order Butterworth band pass filter (BPF) with cut-off frequencies at 0.04 and 0.7 Hz to isolate the information signal associated with sitting-to-standing and standing-to-sitting transitions. From the filtered signal, $\sin_F(\theta)$, t_{PT} was considered as the time corresponding to the maximum of $\sin_F(\theta)$. The $\sin_F(\theta)$ at their t_{PT} exceeding a threshold value of 0.16 was observed for sitting-to-standing and standing-to-sitting PTs. TD is measured as the time interval from the beginning, t_{p1}, to the end, t_{p2}, of a PT. For sitting to standing and standing to sitting transitions, TD is measured from the beginning of the leaning forwards phase at t_{p1} to the end of the leaning backwards phase at t_{p2}; t_{p1} and t_{p2} correspond to the minimum of $\sin_F(\theta)$ before and after t_{PT}. PTs of sitting to standing and standing to sitting TDs exceeded a threshold value of 1.725 s. This result confirms that reported by Najafi et al. [31] using a gyroscope to estimate $\sin(\theta)$.

RSSI, which describes the strength of the WISP signal detected at an RFID reader antenna, was used as a method of estimating the distance of the person to the antenna and hence whether the person was standing or sitting at the end of the PT. RSSI is inversely proportional to the quadruple power of distance [88, 89]; this indicates that the distance variation from the antenna due to the displacement of the body will cause an increase or decrease in RSSI, depending on the location of the receiving antenna. In the test environment, antennas were located higher than 1.6 m above floor level; as a result, when standing, the distance from the WISP to the antenna is shorter than that when the person is sitting. This caused an RSSI negative gradient when standing-to-sitting and a positive gradient when sitting to standing. RSSI was reported by the RFID reader for each received signal from a WISP. A sensor at any given time would have different RSSI readings on different RFID reader antennas, making each antenna a reference point for location and displacement purposes.

3.1.2 Mattress Attached WISP Method

In this method, we used only one WISP attached to the side of the bed opposite the side frequently used for getting in or out of bed to avoid damage to the device or occlusion from the subject's body. The signal of interest corresponds to the acceleration readings of the z axis (z_p), perpendicular to both gravity and the side of the mattress, in percentage values (where 50 % is equivalent to 0 g) and its derivative z'_p. If a subject lies or sits on the mattress, the change in the alignment of the sensor as a result of the deformation of the mattress during the activity causes a change in (z_p).

It has been established that if a subject keeps a static posture in bed or if the mattress is empty, the derivative z'_p remains in a defined value range [64]. For this research, it was observed that the value range for z'_p for static posture was $[-20, 20]$. A static state was defined as: i) sitting on the bed; ii) lying on the bed; or iii) an empty bed. Readings from z_p obtained when the mattress was empty were observed to be $49.94 \pm 0.11\%$. The mean value of z_p for empty, sitting and lying conditions were below 50 %, between 50 % and 50.5 %, and above 50.5 % respectively.

An algorithm (Fig. 3.3) was developed considering the changes in z_p and z'_p to identify a significant movement in bed as a PT out of a static state or significant movement made by the subject while remaining in a static state. Detection of getting into and getting out of the bed was realized by monitoring two successive static states. A possible static state is triggered by: i) the occurrence of an out-of-range event (z'_p exiting the static state value range $[-20, 20]$); and ii) if there were no other out-of-range event in the following 5 s. However, if the next out-of-range event duration were shorter than 5 s, the first out-of-range event was discarded and the system waited for the next event. The first event was discarded because the activity was considered a significant movement made by the subject while remaining in a static state and too rapid to qualify as a posture transition. The mean value of z_p during the 5 s period was subsequently used to determine the current static state. A transition was classified as getting into bed if the next state of the patient belonged to either sitting or lying and was preceded by an empty state. Similarly, a posture transition was classified as getting out of bed if the next static state were empty and preceded by a sitting or lying static state. In addition, the next static state was updated with the current static state for the next classification iteration. When a new static state did not match any classification, the current static state was left unaltered.

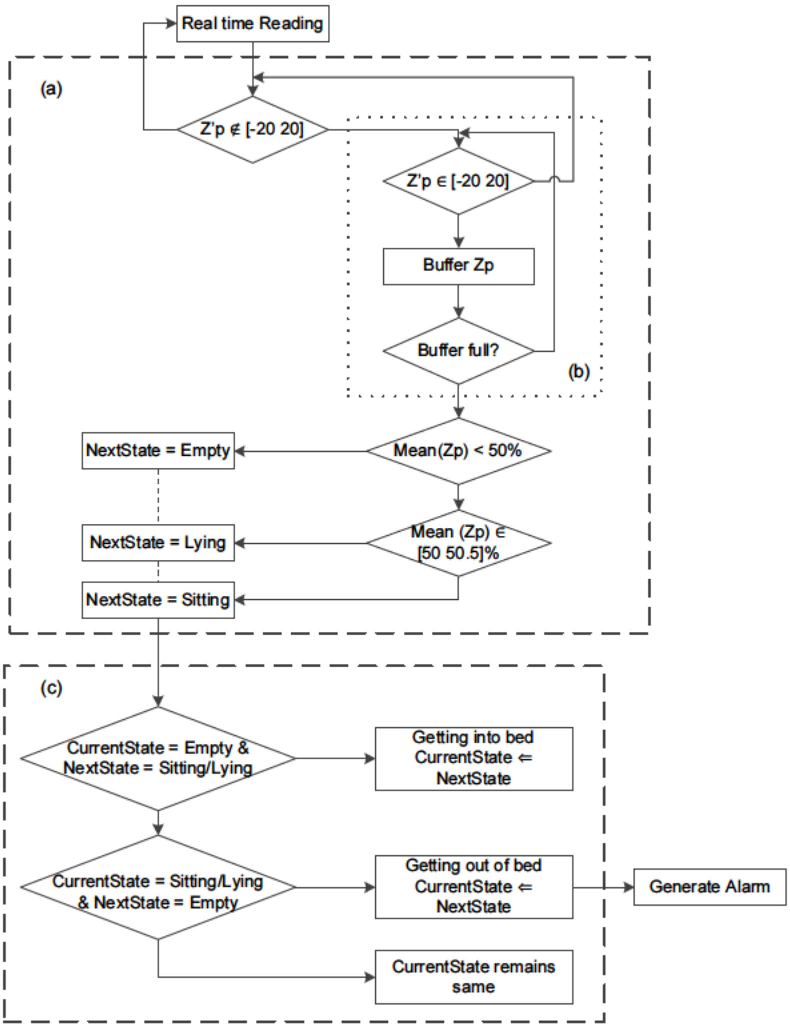


Figure 3.3: Algorithm based on the mattress attached WISP tag: (a) detection of static state given the mean value of buffered acceleration data, resulting states can be empty, lying or sitting. (b) Buffer memory collecting data for 5 s, if another out-of-range event occurs within the 5 s, the buffering is restarted from the new event. (c) Activity classification based on a comparison of static states and an update of the current static state.

3.1.3 Experimental Settings

A cohort of ten healthy adult volunteers aged between 23 and 30 (mean 26.4 ± 2.12) years participated in this study. The study occurred within a clinic trial room in the Basil Hetzel Institute, Woodville, South Australia.

3.1.4 Data Collection

Each subject was given scripted routines of postural transitions that included: i) getting into bed, lying and getting out of bed; ii) walking (for example walking from the bed to the chair and vice versa); and iii) sitting down on or getting up from a chair. Each subject was given three separate scripts with random orderings of these postural transitions. The algorithms were not customized to each subject. The transitions were recorded by the patient monitoring software and annotated simultaneously in the software system by a researcher during the data collection process. This allowed for subsequent evaluation of the results.

3.1.5 Statistical Analysis

True positives were the correctly identified bed exit events (in the case of WISP on sternum algorithm, both lying to sitting followed by sitting to standing were detected correctly). True negatives were events of no-interest that were correctly identified as not bed exits events (for example, getting into bed). False negatives were known bed exit events that were not identified (i.e. misses). False positives are other movements that were identified as a bed exit event. Sensitivity and specificity, (3.2) and (3.3) respectively, of identifying bed entry and exit were then estimated to compare the performance of the two methods. Receiver operating characteristic (ROC) curves were also evaluated.

$$\text{Sensitivity} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}} \times 100 \tag{3.2}$$

$$\text{Specificity} = \frac{\text{true negatives}}{\text{true negatives} + \text{false positives}} \times 100 \tag{3.3}$$

3.2 Results

Subjects performed over 180 PTs including standing-to-sitting, sitting-to-lying, lying-to-sitting and sitting-to-standing for the WISP attached to a body trunk algorithm and 100 PTs for the algorithm based on the WISP sensor attached to mattress including, sitting, standing (implying bed empty) and lying. The results, shown in Table 3.1, suggest that the WISP over the sternum method obtained higher sensitivity in detecting entry into and exit out of bed when compared with the WISP on mattress method. Whilst both methods recorded similar specificity in terms of detecting entry into bed, the WISP on mattress method had marginally better (97.4 % vs. 93.8 %) specificity in terms of identification of bed exit events.

Table 3.1: Performance of two technological methods for the classification of posture transitions (WISP located over sternum vs WISP attached to mattress).

Algorithm	Postural transition	TP	TN	FP	FN	Sensitivity	Specificity
WISP located over sternum	Getting into bed (stand-sit-lying)	39	40	1	3	92.8 %	97.5 %
	Getting out of bed (lying-sit-stand)	38	45	3	4	90.4 %	93.8 %
WISP attached to mattress	Getting into bed (empty-lying/sitting)	32	37	1	6	84.2 %	97.4 %
	Getting out of bed (lying/sitting-empty)	30	37	1	8	79.0 %	97.4 %

Both methods have most of their data scattered close to the left side of the ROC graphs indicating low False Positives (i.e. false alarms) (Fig. 3.4). We calculated the areas under the ROC curves (AUC) by trapezoidal integration of the data. The body worn WISP AUCs were 0.931 and 0.859 for getting in and out of bed respectively and the sensor on bed algorithm had AUCs of 0.882 and 0.855 respectively. The WISP over sternum method demonstrated a better response as its curves depicted closer alignment to optimal performance (top left corner) and a larger AUC for both getting in and out of bed, compared with the WISP on mattress method.

3.3 Discussion

The main finding of this study was that a single WISP placed over the sternum accurately identified movement into and out of bed. The small, battery free and low

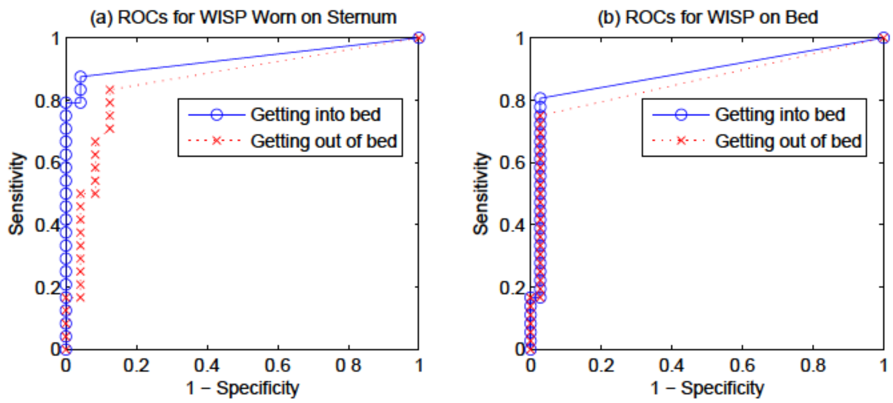


Figure 3.4: ROC curves corresponding to position transitions: (a) ROC curve for the sensor located over sternum method, (b) ROC curve for the case of the sensor attached to mattress method.

cost nature of WISPs are an advantage, especially in settings where there is significant risk of infection such as hospitals where the device offers both disposability and user-friendliness. The WISP located over the sternum method performed better with few false negatives and positives with bed exits. These low error rates are likely to be associated with higher levels of nurse acceptance of the system.

Several bed exit alarms for fall prevention [63, 62] achieved sensitivity and specificity values of $> 90\,\%$ using a pressure sensor on bed rails and a bed mat, respectively. However, bed rails are not recommended as they can cause falls from a higher height, causing injuries [90, 91]; the use of bed mats require constant servicing and cleaning, increasing cost due to the use of multiple sensors and exposure to fluids from incontinent patients. Moreover, the bed mat system and can have a detection delay of up to 2 min, in contrast to a maximum of 20 s for the WISP over sternum method.

There are, nonetheless, limitations associated to WISPs. Wireless transmissions can be blocked in certain positions. For example, readings are absent when subjects lie in a prone position with the WISP over sternum method. It will need to be determined if this is clinically important and should be overcome. Because the WISP harvests its own power from radiofrequency signals, it can only work within a range of 3–4 m of an antenna without intervening RF-opaque materials and, therefore, multiple antennas and readers are likely to be required to provide adequate coverage within a clinical or care area.

Loosely fitted hospital garments may not allow the sensor to follow body movements closely affecting the effectiveness of body worn WISP algorithms to detect bed exit posture transitions. However, since the algorithms are based on thresholds and patients are automatically and uniquely identified by their electronic ID within a WISP, it will be possible for staff to adjust the threshold levels for each patient. Nevertheless the tolerance of the algorithm to inadvertent sensor repositioning and loosely fitted clothing still needs to be investigated. Finally, evaluation was undertaken in healthy adult subjects but frail older patients may not get out of or into bed as quickly or in the same way as younger people. Other types of bed exits, such as shuffling down to the foot of the bed to exit, or exiting over bedrails; and those involving use of support, e.g. walking aids or holding on to a chair or table, also warrant investigation to ensure the system identifies less conventional bed exit methods.

3.4 Conclusions

In this chapter, we have progressed two technological methods involving WISPs to detect bed exits accurately, a postural transition often associated with falls in hospitals and aged care settings. It was demonstrated that the WISP over sternum method was superior and further investigations in older frail people are required. In the following chapters, we evaluate our body worn sensor approach with older people, our population of interest, to determine the feasibility and performance of ambulatory monitoring systems for this population.

Chapter 4

Conditional Random Field Method for Identifying Bed Exit Movements

In previous chapters we have proposed a framework intervention for the prevention of falls in older people based on the use of a passive lightweight sensor embedded RFID tag. We tested two methods for the recognition of bed exits using these sensors on a population of young adults with results favouring a body-worn sensor option. The previously used methods favoured the use of sensor data and received power information from the sensor. Post processing of the data was necessary given the irregular nature of data collection in passive devices; this included interpolation and digital filtering of the signals. These two methods made classification decisions based on empirical decision trees using thresholds achieving high performance. However, these methods were not tested with an older population; who, we expect, perform activities differently than younger people.

In the present chapter we focus on the recognition of bed exits in a group of healthy older people. We introduce a machine learning technique for the classification of sequential data as is the case of human activity. Furthermore, we extract data of interest from raw sensor readings, avoiding interpolation and filtering processes. We demonstrate that the use of machine learning is better suited than threshold based methods in the case of wearable passive sensor data streams from older people. In addition, we present the perception of the sensor by the trialled population regarding wearability and freedom of movement.

This chapter is divided as follows, Section 4.1 introduces a machine learning classifier, Conditional Random Fields (CRF), and its suitability as an appropriate tool for the recognition of human activities from sequential data as is the case of sensor data streams. We describe inference and training of CRFs based on the linear chain structure as used in this thesis. Section 4.2 contains one published article that evaluates the use of machine learning on movement information from older people using our passive wearable sensor, compares its performance with threshold methods and presents the perception of users on the wearability of the device.

4.1 Conditional Random Fields

Conditional random fields (CRF), first introduced by Lafferty et al. [92], are probabilistic models learned for structured classification. Human activity, consisting of complex movements that are always a sequence of actions over time, can be considered a structured domain where CRFs are appropriately efficient tools.

4.1.1 Conditional Random Fields for Human Activity Recognition

Activities performed by humans are by nature sequential, i.e. every activity has a sequence of movements or motions that the body naturally follows and depend on previous body motion. CRF is well suited for the recognition of human activity as CRF takes in consideration complex dependencies between class labels (activities), modelling the possible transitions from one activity to the next. In addition, CRF makes no independence assumptions about the observations; this allows the incorporation of various overlapping and complex features without violating any independence assumption. Hence, CRF can use flexible non-independent feature functions that can incorporate a human expert's knowledge on the problem domain into the model. This discriminative model also allows the use of topologies that allows exact inference over the labels such as chains or trees. This chapter focuses on the case of linear chain conditional random field structure as this model has shown high classification performance in the literature [93, 94].

4.1.2 Graphical Representation

The probability distributions in the model can be represented in a graphical form, where distributions over various variables can be represented as a product of local functions, each depending on a subset of variables. There is a close relationship between this factorization to the conditional independence relationships between variables; where the absence of an edge between two variables, represented by nodes

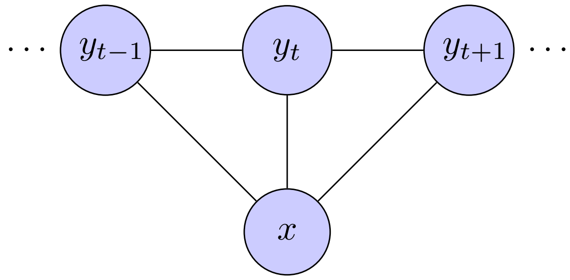


Figure 4.1: Graphical representation of a liner chain conditional random field

in the graph, indicates conditional independence between these two variables. This means that two random variables A and B are said to be conditionally independent given a third random variable C if their conditional probability distributions are also independent

$$p(A = a, B = b|C = c) = p(A = a|C = c)p(B = b|C = c)$$

We use the notation $(A \perp B|C)$ to indicate that A is conditionally independent of B given C [95].

In undirected graphical models such as that of CRF, the model structure has direct consequence on the efficiency of the inference process. For example, exact inference tends to be intractable when the graph structure contains loops. The case of a linear chain CRF, our case of study, is shown in Figure 4.1, where the sequence of observation variables of length T given by $X = \{x_t\}_{t=1}^{T} = \{x_1, x_2, \cdots, x_t, x_{t+1}, \cdots, x_T\}$ corresponds to a label sequence $Y = \{y_t\}_{t=1}^{T} = \{y_1, y_2, \cdots, y_t, y_{t+1}, \cdots, y_T\}$ and any individual variable y_t can take a value from the finite set of class labels $\mathcal{Y} = \{1, \cdots, |y|\}$. The conditional independence in this case, for example, can be seen with variables y_t; which are conditionally independent if all paths between any pair of nodes are blocked by an observed variable. We can see that all paths between nodes through X are blocked. Hence, y_{t-1} is conditionally independent of y_{t+1} for all $t \in \{2, \cdots, T-1\}$; this is equivalent to a first order Markov assumption over the label sequence.

Let $G = (V, E)$ be an undirected graph with edges E and vertices or nodes $V = X \cup Y$. Given the collection of cliques (complete subgraphs) in G, $\mathcal{C} = c \subset V$, the probability distribution of an undirected graphical model is defined as the product of its factors of the form $\phi_c(x_c, y_c)$, where each factor is a function over clique $c \subset V$. This factorization is performed such that conditionally independent variables are not within the same factor, i.e. they belong to different cliques. The joint probability can be written in the form

$$p(X, Y) = \frac{1}{Z} \prod_{c \in \mathcal{C}} \phi_c(x_c, y_c) \tag{4.1}$$

where factor ϕ_c is a non negative function called a potential function of the variables within a clique $c \in \mathcal{C}$. The normalization constant Z, also called partition function, ensures the distribution of p sums to 1 and defined as $Z = \sum_V \prod_{c \in \mathcal{C}} \phi_c(x_c, y_c)$. A challenge in undirected graphs is the calculation of Z as the summation is over all possible variables; this makes the computation of the joint probability $p(X, Y)$ intractable.

Given that graph G is a linear chain where its cliques are the edges and vertices, G meets the local Markov independence criteria as any node $y_t \in Y$ is independent of the rest of nodes in the graph given its immediate neighbours. By the Hammersley-Clifford theorem [96, 97], which states that a strictly positive distribution that follows the Markov independence criteria can be represented by the factorization on cliques that cover all nodes and edges of G. Thus, the distribution over the label sequence Y given X has the form.

$$p(Y|X) = \frac{1}{Z_X} \prod_{c \in \mathcal{C}} \phi_c(x_c, y_c) \tag{4.2}$$

where $\mathcal{C}$ is the set of all cliques defined by the graph and the biggest possible clique is two neighbour nodes; the normalization constant Z_X is computed by summing over all possible label sequences, which is tractable in linear chains, and has the form

$$Z_X = \sum_Y \prod_{c \in \mathcal{C}} \phi_c(x_c, y_c) \tag{4.3}$$

In the case of linear chain CRF, the cliques of the graph contains every pair of nodes of variables Y and the observation sequence, so $c_t = \{y_{t-1}, y_t, X\}$. Moreover, the non-negative potential function can be defined as:

$$\phi_{c_t}(y_{c_t}, x_{c_t}) = \exp\left(\langle \lambda, f\left(y_{t-1}, y_t, X\right)\rangle\right) \tag{4.4}$$

where the weight λ is a weight vector over the number of feature functions $f()$. The weight vector is the model parameter which is learned during training. The feature functions represent properties from the variables and the interactions between them, they operate on a set of variables that form a maximal clique in G.

Feature functions, formally, can be any function that maps both sets of variables, observations X and labels Y, to a real number i.e. $f : X \times Y \rightarrow \mathbb{R}$. However, these are often considered as indicator functions and the value of the feature function is given by the weights these functions are multiplied to. Generally, two types of feature functions are defined; we have transition feature functions which in the case of a chain have the form: $f_t\left(y_{i-1}, y_i, X\right) = \mathbb{1}_{\{y_{i-1}=m\}}\mathbb{1}_{\{y_i=n\}}$ that depends on the previous and current label and state feature functions, $\mathbb{1}$ is the indicator function, and m and n are possible label values from the label set $\mathcal{Y}$. We also have emission or state feature functions which correspond to an observation-label pair of variables and has the form: $f_e\left(y_{i-1}, y_i, X\right) = \mathbb{1}_{\{y_i=n\}}\mathbb{1}_{\{x_i=o\}}$, where o is the value of an observation data. In the case of human activity we can consider for example a transition feature function that assesses the transition between two postures, for example if two possible activity labels are lying on bed and sitting on bed, we have the feature function $f_t\left(y_{i-1}, y_i, X\right) = \mathbb{1}_{\{y_{i-1}=\text{"Lying on bed"}\}}\mathbb{1}_{\{y_i=\text{"Sitting on bed"}\}}$. Similarly, in the case of emission feature functions, if we consider for example the label to be "Lying on bed" when readings of an accelerometer to be $0\,\mathrm{m\,s^{-2}}$, we have the function $f_e\left(y_{i-1}, y_i, X\right) = \mathbb{1}_{\{y_i=\text{"Lying on bed"}\}}\mathbb{1}_{\{x_i=0\,\mathrm{m\,s^{-2}}\}}$.

Finally, the conditional distribution can be written as

$$p(Y|X;\lambda) = \frac{1}{Z(X)}\exp\left(\sum_{t=1}^{T}\langle\lambda, f\left(y_{t-1}, y_t, X\right)\rangle\right) \tag{4.5}$$

where the normalization term or partition function $Z(X)$, is given by

$$Z(X) = \sum_{Y}\exp\left(\sum_{t=1}^{T}\langle\lambda, f\left(y_{t-1}, y_t, X\right)\rangle\right) \tag{4.6}$$

which sums over all possible sequences, which is tractable in chain structures.

4.1.3 Inference

In this section, we seek to find the most likely sequence of labels for Y for a given input sequence of observations X. We also use inference during training as we need to efficiently calculate the normalization function $Z(X)$.

In a linear chain, these tasks can be performed exactly with the belief propagation algorithm [98, 79]. The expression for the partition function in (4.6) can be expanded and summations grouped for variable elimination [95] as

$$Z(X) = \sum_{y_T} \sum_{y_{T-1}} \phi(y_{T-1}, y_T, X) \sum_{y_{T-2}} \phi(y_{T-1}, y_{T-2}) \cdots \\ \sum_{y_2} \phi(y_2, y_3, X) \sum_{y_1} \phi(y_1, y_2, X)\phi(y_0, y_1, X) \quad (4.7)$$

From (4.7), we can iteratively eliminate sums of the internal variables; this approach reduces exponentially the amount of calculations to perform [99]. We define a set of forward variables α_t that store the intermediate summations. Hence, for the first elimination on the inner-most summation, we consider the term $\alpha_1(y_1) = \phi(y_0, y_1, X)$ which is a chain start initialization potential; and the term for the first sum is:

$$\alpha_2(y_2) = \sum_{y_1} \alpha_1(y_1)\phi(y_1, y_2, X) \quad (4.8)$$

The partition function is then of the form

$$Z(X) = \sum_{y_T} \sum_{y_{T-1}} \phi(y_{T-1}, y_T, X) \sum_{y_{T-2}} \phi(y_{T-1}, y_{T-2}) \cdots \sum_{y_2} \phi(y_2, y_3, X)\alpha_2(y_2) \quad (4.9)$$

where calculations are reduced by summing over y_1.

We generalize the term α to be of the form:

$$\alpha_t(y_t) = \sum_{y_{t-1}} \alpha_{t-1}(y_{t-1})\phi(y_{t-1}, y_t, X). \quad (4.10)$$

Therefore recursive computations of alpha results in the calculation of $Z(X)$ as:

$$Z(X) = \sum_{y_T} \alpha_T(y_T) \quad (4.11)$$

Note we can also perform a backwards recursion over (4.7) where the summations are performed in reverse order. We initialize the backwards chain with initialization term $\beta_T(y_T) = 1$, and the recursive term beta is defined as:

$$\beta_t(y_t) = \sum_{y_{t+1}} \beta_{t+1}(y_{t+1})\phi(y_t, y_{t+1}, X). \quad (4.12)$$

Hence, we can also calculate the partition function as $Z(X) = \sum_{y_1} \beta_1(y_1)\phi(y_0, y_1, X)$.

To calculate the marginal probabilities, $p(y_t|X)$, for every element in a sequence, we compute the summation over all other elements in the sequence:

$$p(y_t|X) = \sum_{y^{-t}} p(y|X) \quad (4.13)$$

where y^{-t} denotes all elements of the sequence except t i.e. $y_{1:t-1,t+1:T}$, hence the expanded formulation for the marginal probability $p(y_t|X)$ is:

$$p(y_t|X) = \frac{1}{Z(X)} \sum_{y_1} \cdots \sum_{y_{t-1}} \sum_{y_{t+1}} \cdots \sum_{y_T} \phi(y_0, y_1, X)\phi(y_1, y_2, X) \cdots \\ \cdots \phi(y_{t-1}, y_t, X)\phi(y_t, y_{t+1}, X) \cdots \phi(y_{T-1}, y_T, X) \quad (4.14)$$

reducing variables from the start and the end of the sequence using (4.10) and (4.12), we have the expression for the marginal to be

$$p(y_t|X) = \frac{1}{Z(X)} \alpha_t(y_t)\beta_t(y_t) \quad (4.15)$$

Note this means, that to infer the assignment of a label in a sequence we require past, present and future information for every variable y_t in the sequence.

In particular, we are more interested in calculating the most likely label for each variable y_t, i.e. $\text{argmax}_{y_t} p(y_t|X)$; instead of finding the most likely labelling for the sequence Y, i.e. $\text{argmax}_Y p(Y|X)$. Calculation of the latter is possible using the Viterbi or max-product algorithm [79], which is similar to the forwards and backwards approach previously discussed but instead of using summations in (4.7) these are replaced with maximization.

4.1.4 Training

Let us consider a set of N training sequences $\mathcal{N} = \{X^{(n)}, Y^{(n)}\}_{n=1}^{N}$, where each pair $(X^{(n)}, Y^{(n)})$ is independent and identically distributed to any other pair of training sequences in $\mathcal{N}$. We seek to determine the set of weights λ that maximizes the conditional probability $p(Y|X)$. However, it is more convenient to work with the log-likelihood as we are working with logistic regression functions. Therefore, we maximize the function $\mathcal{L}(\lambda)$.

$$\mathcal{L}(\lambda) = \sum_{n=1}^{N} \log p(Y|X; \lambda) \quad (4.16)$$

$$\mathcal{L}(\lambda) = \sum_{n=1}^{N} \sum_{t=1}^{T} \langle \lambda, f(y_{t-1}^{(n)}, y_t^{(n)}, X^{(n)}) \rangle - \sum_{n=1}^{N} \log \left(Z(X^{(n)}) \right) \quad (4.17)$$

In order to avoid overfitting the likelihood is penalized with a term that affects those weights with large norm [100]. A common regularization method is the square of the ℓ_2 norm of the weight vector multiplied by a regularization parameter $1/2\sigma^2$ that determines the degree of penalization. Other types of regularization are possible such as the ℓ_1 norm; however, throughout this thesis we use the ℓ_2 norm for regularization. The log-likelihood is then the expression:

$$\mathcal{L}(\lambda) = \sum_{n=1}^{N}\sum_{t=1}^{T}\langle \lambda, f(y_{t-1}^{(n)}, y_t^{(n)}, X^{(n)})\rangle - \sum_{n=1}^{N}\log\left(Z(X^{(n)})\right) - \frac{\|\lambda\|_2^2}{2\sigma^2} \tag{4.18}$$

We calculate the gradient of $\mathcal{L}$ with respect to the weights.

$$\frac{\partial \mathcal{L}}{\partial \lambda_k} = \sum_{n=1}^{N}\sum_{t=1}^{T} f_k(y_{t-1}^{(n)}, y_t^{(n)}, X^{(n)}) - \sum_{n=1}^{N}\frac{1}{Z(X^{(n)})}\frac{\partial Z(X^{(n)})}{\partial \lambda_k} - \frac{\lambda_k}{\sigma^2} \tag{4.19}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_k} = \sum_{n=1}^{N}\sum_{t=1}^{T} f_k(y_{t-1}^{(n)}, y_t^{(n)}, X^{(n)}) - \sum_{n=1}^{N}\frac{1}{Z(X^{(n)})}\sum_{Y'}\exp\left(\sum_{t=1}^{T}\langle \lambda, f({y'}_{t-1}^{(n)}, {y'}_t^{(n)}, X^{(n)})\rangle\right) \sum_{t=1}^{T} f_k({y'}_{t-1}^{(n)}, {y'}_t^{(n)}, X^{(n)}) - \frac{\lambda_k}{\sigma^2} \tag{4.20}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_k} = \sum_{n=1}^{N}\sum_{t=1}^{T} f_k(y_{t-1}^{(n)}, y_t^{(n)}, X^{(n)}) - \sum_{n=1}^{N}\sum_{Y'} p(Y'|X^{(n)})\sum_{t=1}^{T} f_k({y'}_{t-1}^{(n)}, {y'}_t^{(n)}, X^{(n)}) - \frac{\lambda_k}{\sigma^2} \tag{4.21}$$

The first term of the gradient corresponds to the sum of the occurrence of each feature in the training set. The second term corresponds to the expectation of each feature under the model distribution $p(Y|X;\lambda)$, which can be computed efficiently using the belief propagation method in the previous section.

In terms of optimization of the log likelihood function, we note the function in (4.18) is concave as the expression of the form $\log\sum\exp()$, found in the second term of (4.18), is convex. Similarly the regularization term is convex, and the first term in (4.18) is linear, assuring the log likelihood to be concave and that there is a global optimum.

There are multiple optimization methods, in the work of Lafferty et al. [92] an iterative scaling algorithm is used to maximize the log likelihood function. However, faster methods based on gradient-based optimization such as conjugate or mixed conjugate gradient descent and the limited memory BFGS (L-BFGS) [101]. L-BFGS is a second order optimization algorithm, faster than conjugate gradient methods which are first order methods. L-BFGS approximates the calculation of the inverse Hessian matrix and uses a limited amount of memory. Therefore, the method is not interested in exactly approximating the Hessian matrix, but to determine the direction of update. Moreover, L-BFGS has performed well compared to conjugate gradient methods [102, 103].

This section provided a brief introduction to CRFs and its suitability for activity recognition; the following section focuses on the application of this sequential learning algorithm into activity recognition methods for falls prevention.

4.2 Recognition of Bed Exits Using CRFs

The article contained in this section is a conference paper that introduces CRFs into motion data from healthy older people in two datasets using the W^2ISP. We compare the prediction of complete sequences of activities from our method with an empirical threshold based method as used in the previous chapter and demonstrate the advantages of using CRFs in the detection of bed exits.

R.L. Shinmoto Torres, D.C. Ranasinghe, Q. Shi and A. Sample. "Sensor enabled wearable RFID technology for mitigating the risk of falls near beds", *7th Annual IEEE International Conference on RFID*, pp.191–198, 2013. (Best paper finalist).

Sensor Enabled Wearable RFID Technology for Mitigating the Risk of Falls Near Beds

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Abstract—**The increasing ageing population around the world and the increased risk of falling among this demographic, challenges society and technology to find better ways to mitigate the occurrence of such costly and detrimental events as falls. The most common activity associated with falls is bed transfers; therefore, the most significant high risk activity. Several technological solutions exist for bed exiting detection using a variety of sensors which are attached to the body, bed or floor. However, lack of real life performance studies, technical limitations and acceptability are still key issues. In this research, we present and evaluate a novel method for mitigating the high falls risk associated with bed exits based on using an inexpensive, privacy preserving and passive sensor enabled RFID device. Our approach is based on a classification system built upon conditional random fields that requires no preprocessing of sensorial and RF metrics data extracted from an RFID platform. We evaluated our classification algorithm and the wearability of our sensor using elderly volunteers (66-86 y.o.). The results demonstrate the validity of our approach and the performance is an improvement on previous bed exit classification studies. The participants of the study also overwhelmingly agreed that the sensor was indeed wearable and presented no problems.**

I. Introduction

Falls occur commonly in residential care and hospitals, especially at night and in the surroundings of the bed [1]–[3]. Falls are costly as patients have a longer length of stay (LOS) at hospitals [4] and can result in anxiety, depression and a loss of independence; similarly, caregivers and nurses may also be affected by psychological trauma [5]. Monitoring the patient and recognizing their high risk falls related activities provide an opportunity to intervene and prevent a fall or provide immediate attention from a caregiver [6], [7] as opposed to falls detection [8], [9]. However, a fall detection strategy does not server as a falls mitigation strategy.

Previous studies were focused on detecting bed exits. In the case of methods in [6], [7], [10]–[12], these were based on one or multiple sensors strategically placed on or around the bed. Most of these methods involved pressure sensors achieving varying performance results as a consequence of the multiple types of sensing units employed. Furthermore, pressure sensors were found unreliable with patients lighter than 45.4 kg, a common weight for frail patients, but improved performance was achieved in combination with other sensors [12]. The location of these units (bed mats, bed rails, floor mats) makes them susceptible to constant mechanical stress, requiring regular maintenance and/or replacement. In addition, these units need thorough cleaning as they may be exposed to body fluids and/or other contaminated material.

Other studies focused on human activity recognition. These methods used different sensor systems, which can be divided either into worn sensors or environment sensors. However, a more accurate categorisation of these studies can be done based on their classification system: i)techniques based on threshold based algorithms; and ii)machine learning based approaches. From the former, in [13]–[16] sensors such as accelerometers and gyroscopes were used to extract physical features as input to a threshold based classification system as first proposed by Najafi [13]. Most methods required the use of bulky battery powered devices with multiple sensors that were attached to the subject's body. This approach implies heavy instrumentation of the subject which is not practicable with frail elderly subjects, and a high maintenance cost [13]–[15]. Furthermore, these methods relied on heavily preprocessed data e.g. multiple filtering stages, prior to the classification algorithms to isolate information content or extract desired features. This results in unwanted delays, added computational overhead and algorithmic complexity; all of which are detrimental to a responsive, scalable system [13]–[16].

Studies based on machine learning based classifiers, such as those of [17]–[22], included hidden Markov models (HMM), conditional random fields (CRFs) and support vector machines (SVMs). Generally, these methods demonstrated better performance than threshold based methods but to varying degrees of success. In the case of [17]–[19], these techniques suffered similar practical deficiencies as those of the threshold based methods i.e. battery powered equipment and subject instrumentation. In contrast, the methods in [20]–[22], all subjects were instrument free but the setting was around independent living, which is not the case for our target population. In addition, results showed great variability, this inconsistency affects the application of these techniques to elder care in a medical environment as result discrepancy leads to poor reliablity and lack of acceptance over time of a proposed strategy.

In order address the shortcomings of previous methods for bed exit detection, in this article, we propose an accurate, low

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computational overhead, low latency and low cost method for mitigating the risk of falls caused by bed exiting of elderly patients in hospitals and residential care environments. Furthermore, have addressed the issues of privacy concerns around using video based approaches [23] by indirectly inferring the activities of patients.

Firstly, our proposed approach utilizes a light, low cost, inexpensive, battery free RFID tag called Wearable WISP (Wireless Identification and Sensing Platform) or W^{2}ISP [24] (see Section II-A). This sensor is worn by elderly patients attached to their clothes (Figure 1(b)). Secondly, in order to improve the system responsiveness we keep the computational cost low by using a single accelerometer per person and minimum data preprocessing by eliminating filtering steps. Responsiveness is a key consideration because of the urgency of attending to a high risk situation (such as bed exiting) requires a prompt system response to provide a timely alert to a caregiver to proceed to an intervention in a hospital environment as described in [25]. Thirdly, to consider the dependency among consecutive activities, we use CRFs [26] to model and predict activities with flexibility of introducing various features to improve the performance of previous approaches [16]. Finally, since the use of video images for monitoring systems has been perceived as intrusive [23] to a patient's privacy, our approach preserves the privacy of a person. In summary, the contributions of this paper are as follows:

- We designed a simple approach for supporting bed exit classification using a single truly wearable device for the first time (to the best of our knowledge). The device is small, low cost, battery-less and can be worn continuously; moreover, the device relies on a single accelerometer sensor and is able to protect a patient's privacy.
- Utilize noisy and incomplete information effectively for activity classification by using conditional random fields based algorithm.
- Present a method that has been proven in elderly population as we have conducted extensive trials with elderly volunteers (66 to 86 years old), closely resembling the target population for this application as opposed to our previous trial using healthy adult volunteers [16].

The rest of the paper is organized as follows, Section II gives a brief overview the overall system and the data sources used; Section III describes the experimental settings and procedures, Section IV describes our experimental results and we present our conclusions in Section V.

II. System Overview

The proposed monitoring system consists on a wireless sensing platform, an activity recognition system (ARS) and a bed exit alert system (BEAS).

A. Wireless Sensing Monitoring Environment

The wireless sensor, W^{2}ISP [24], is a passive RFID tag based on the WISP developed in [27] (see Figure 1(a)). A W^{2}ISP includes a tri-axial accelerometer (ADXL330) and a microprocessor (MSP430F2132) and is powered by the electromagnetic (EM) energy radiated by nearby RFID antennae. The accelerometer works in low power mode and therefore requires minimum power to read the sensor. Although the low power operation mode increases read rate, it also introduces noise. The W^{2}ISP differs mainly from the WISP [27] in its wearability and increased read range as the tag employs an improved flexible antenna that isolates human body effects by using a conductive fabric. Experimentally, the sensor has reported a maximum read range of 4 m from [24] when attached over a person's chest area, on top of their clothing (see Figure 1(b)).

TABLE I
Parameters reported by a read event from the RFID Reader)

Parameter	symbol
Tag Identification	tID
Antenna Identification	aID
Acceleration on X* axis	a_v
Acceleration on Y* axis	a_l
Acceleration on Z* axis	a_f
Frequency Channel	fCH
Phase	ϕ
Received Signal Strength Indicator	$RSSI$

*X, Y and Z axes are relative to the sensor; vertical(v), lateral(l) and frontal(f) axes are relative to the subject.

Three or four antennae located around the patient's room, directed mainly towards the chair, bed and walking area, due to the high risk of falls associated with these areas [1] are used to capture data from W^{2}ISPs. Antennae are powered by an Speedway Revolution reader operating at the regulated Australian RF frequency band of 920-926 MHz operating at a maximum regulated power of 1 W. Antennae were strategically located to closely simulate a real hospital room deployment (see Section III-A). Furthermore, the reader is capable of reading and discriminating multiple tags simultaneously. The information from the reader, shown in Table I, is reported to an in-house designed middleware which formats and timestamps the data for further analysis by the classification algorithms.

B. Classification Problem

We must consider two key issues related to our classification system. First, we need to understand the sequence of activities comprised in bed exiting. Based on observations of elderly subjects we considered the sequence of states:

- Lying
- Sitting on bed
- Out of bed.

Secondly, we need to acknowledge the limiting nature of RFID technology. The effects of variable distance to antenna, destructive interference due to multipath, RF band interference and occlusion by RF opaque objects such as the human body, cause irregular, incomplete and noisy readings which are delivered to the ARS. Hence, the sequence of activities from the sensor that describe a bed exit can be discontinuous

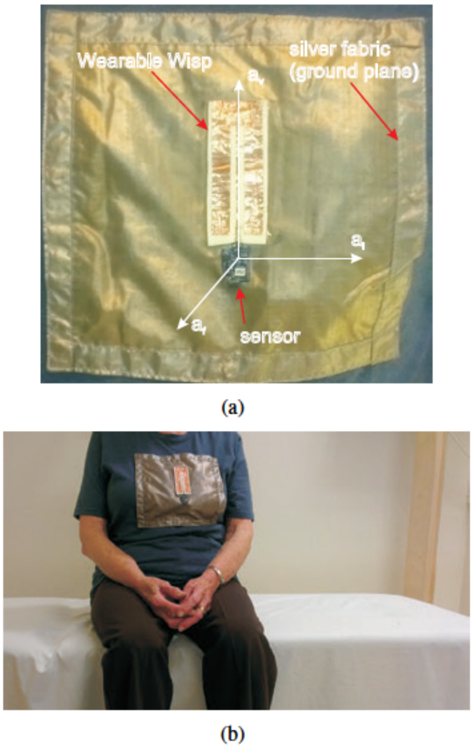

Fig. 1. (a) Wearable WISP showing sensor and accelerometer axes, (b) Elderly volunteer with Wearable WISP attached to garment.

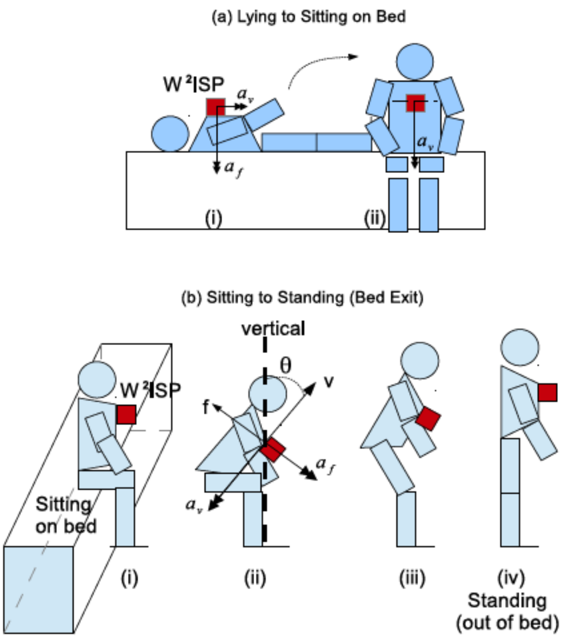

Fig. 2. Process sequence for (a)Lying to sitting, (b) Sitting to standing

(e.g. Lying to Out-of-bed). In addition, we have to consider sensor noise due to the sensor working on inadequate power.

Finally, we can indicate that a bed exit event is recognized as such if an Out-of-bed activity has been predicted, given that the previous activity was either Sitting-on-bed or Lying.

C. Activity Recognition System

Given an observation sequence $X = (x_t)_{t=1}^{T}$, where $x_t \in \mathbb{R}^d$ and T is the length of the sequence. The Activity Recognition System (ARS) is to predict the associated activity sequence (*i.e.* label) $Y = (y_t)_{t=1}^{T}$, where $y_t \in \{1, \cdots, C\}$. Here C is the number of activities (classes).

Here we use CRFs to build our ARS (activity recognition system), because CRFs naturally model the dependencies of the activities in one sequence. CRFs assume the conditional distribution from exponential family below [26],

$$p(Y|X;\lambda) = \frac{1}{Z(X,\lambda)} \exp\left(\sum_k \lambda_k \sum_{t=1}^{T} F_k\left(y_{t-1}, y_t, X, t\right)\right) \tag{1}$$

$$Z(X,\lambda) = \sum_Y \exp\left(\sum_k \lambda_k \sum_{t=1}^{T} F_k\left(y_{t-1}, y_t, X, t\right)\right), \tag{2}$$

where F_k are the feature functions and $\lambda = (\lambda_k)_k$ are the weight vector. $Z(X,\lambda)$ is a normalization constant. The parameter λ of the CRF can be learnt via maximizing the likelihood. Here we use Limited-memory BFGS (LBFGS) [28] to maximizing the likelihood. Given X and λ, ARS predicts the label Y,

$$Y = \operatorname*{argmax}_Y p(Y|X;\lambda), \tag{3}$$

where we use the Viterbi algorithm to get the maximal assignment for the label Y instead of exhaustive search.

D. Model Setting

We consider a CRF model based on the sequence of states determined in Section II-B (Figure 3). Observations are extracted directly from the reader reported data, we consider for each observation the following data $[a_v, a_l, a_f, RSSI, aID]$. The value of RSSI is of interest as an indicator of relative distance to surrounding antennae, a higher RSSI value to a certain antenna would indicate the tag is in closer vicinity than to an antenna with a lower RSSI to the same tag. In addition, we consider the body tilting angle θ towards the front and back from the vertical reference (see Figure 2(b)). The angle θ is a rich source of information for body posture and transition [13], [14], [16], which is approximated from current acceleration values $\theta = arctan\left(\frac{a_f}{a_v}\right)$; furthermore, we consider the $sin(\theta)$ as alternative to θ as is proportional to θ and range limited to [-1,1].

Acceleration and $sin(\theta)$ are continuous signals with infinite amount of possible state sequences; therefore we quantized both signals to steps of 0.05(g for acceleration), and constrained these signals to the range of [-1,1]. This range is enough to include all activities of interest as acceleration values exceeding this range are unlikely for elderly patients with the exception of falling, which can reach high acceleration values.

We include the time difference $(\triangle t)$ between an observation x_t and its prior x_{t-1}. Similarly, this information is quantized into steps of 0.025 s as the minimum $\triangle t$ between consecutive

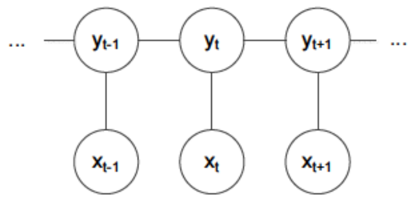

Fig. 3. CRF model: Sequence of labels y_t depend on sequence of observations x_t; in our case y_t can take values: Lying, Sitting on bed or Out of bed.

observations and limited to a maximum $\triangle t = 10$ s, as we consider this time sufficient for a person to be in a steady state.

E. Bed Exit Alert System

We evaluate the recognition of bed exit events in the sequence of observations in an alert setting context. The Bed Exit Alert System (BEAS) is to provide an alert signal, provided the current ARS output $y_t = \{\text{Out-of-bed}\}$, and previous output $y_{t-1} = \{\text{Lying, Sitting-on-bed}\}$, independent of the number of consecutive readings in the current state.

We consider this approach because few identification errors scattered along a test sequence can trigger multiple alarm errors as opposed to multiple recognition errors in a sequence batch that can trigger a single alarm error. This is because we make a prediction per each sample observation. Since the nature of this system is to notify caregivers/nurses of a high risk activity being performed, the alert signal needs to be triggered once only. That is only the first predicted Out-of-bed label in an input sequence after a Lying or Sitting-on-bed state triggers the signal, regardless of the duration of the state.

F. Baseline Method

Our proposed bed exit classification algorithms is evaluated against a threshold based classifier recently developed in [16] to recognize bed exits. This method considers acceleration data processed in multiple stages and was evaluated using only healthy adult volunteers [16].

This algorithm recognized bed exit events after detection of a lying to sitting on bed and sitting to standing postural transition (PT) sequence. The first transition used filtered vertical acceleration (a_v) data while the second considered filtered $sin(\theta)$ where θ is the body tilting angle with respect to the vertical. Another parameter considered was the change in RSSI values with respect to a fixed antenna. As a person sitting or standing becomes farther or closer to the fixed antenna, a perceivable negative or positive difference in RSSI, respectively, is observed.

III. Experimental Setting

A. People and Location

We conducted a trial with fourteen elderly volunteers from 66 to 86 years old. The trials were performed at a clinical room which was instrumented with antennae positioned to closely resemble a hospital room deployment; i.e. antennae

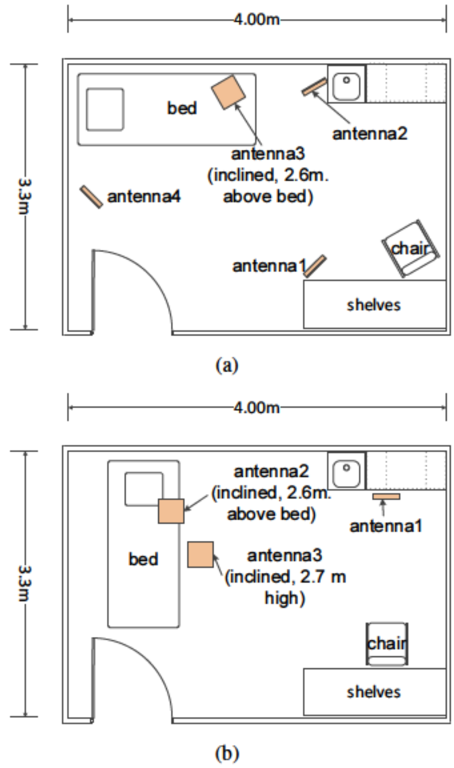

Fig. 4. Different room configurations used for trials (a): First room configuration (*RoomSet1*), (b): Second room configuration (*RoomSet2*).

were located in non-obstructive positions on the walls and ceiling. For this reason, most some activities resulted in the patient being away from the direction of maximum radiation from reader antennas or being too far from the closest antenna. This constraint affected the frequency of samples collected as well as resulting in incomplete data segments.

We considered two different room configurations as practical deployment options. Antennae were strategically located to best fit each of the room arrangements with the constraint of ceiling and wall positioning of antennae. The first room configuration (*RoomSet1*), included one antenna at ceiling level (*antenna3*), and three antennae located on walls, which directly covers the bed area and most of the room area. The second room configuration (*RoomSet2*) included two antennae at ceiling level (*antenna2* and *antenna3*) and dispensed with one wall level antenna, this disposition covered the area of the bed, its vicinity and covered the area over the arm chair as shown in Figure 4.

B. Experimental Procedure

Each volunteer wore a garment with the sensor attached over the sternum, as shown in Figure 1(b). Each subject was directed to perform an average of five sets of activities. Each set of activities included a mixture of the following:

- Lying on bed (in any position of the subject's choosing such as to the side or supine position), sitting on bed, getting out of bed, getting into bed

TABLE II
RoomSet1 AND *RoomSet2* GENERAL INFORMATION.

Characteristic	RoomSet1	RoomSet2
Number of antennae	4	3
Number of activity sets	60	27
Number of subjects*	10	5
Number of observations	52459	22619

*one subject participated in both datasets

- Sitting down on arm chair, getting up from arm chair, sitting on arm chair
- Walking

There were no additional instructions given about the mannerisms for conducting activities and thus resulted in different gait, speed and posture transition time for each subject. Volunteers were also instructed to lie down comfortably. They were either in supine position or on their sides. All the activities were annotated by an observer in real time.

We evaluated two datasets each corresponding to the deployments illustrated in Figure 4. Table II describes the differences in for both datasets. Data from both datasets was used to generate the features described in Section II-D before being processed by the classifier for automatic activity recognition.

We evaluated the performance of the system, accuracy, sensitivity and specificity given in (4), (5) and (6) respectively, to correctly predict observation labels and alert in case of bed exit events. The ARS (activity recognition system) performance was evaluated via a 10-fold cross validation of our two datasets; BEAS (bed exit alert system) was evaluated using ARS test data output from the 10-fold partitioning.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}.100 \qquad (4)$$

$$Sensitivity = \frac{TP}{TP + FN}.100 \qquad (5)$$

$$Specificity = \frac{TN}{TN + FP}.100 \qquad (6)$$

In (4), (5) and (6), for any given activity of interest, true positives (TP) refers to labels correctly classified as the activity of interest; true negatives (TN) are labels of other activities correctly excluded; false positives (FP) are all false alarms or other activities wrongly classified as our activity of interest and false negatives (FN) are all misses or observations of our activity of interest wrongly labelled.

IV. RESULTS

A. Reading Rate Variations

The experimental results are largely dependant on the timely powering of the sensor as explained previously (Section II-B). The translation and body motion of the sensor bearer creates variations in readings due to distance changes to antennae and other factors such as multipath. These factors affect the reading rate due to inadequate power to operate the sensor as well as the resulting extended power-up time.

TABLE III
ANTENNA RANGE FROM COLD START (METERS)

	Response Time Window (s)	
Deviation angle from antenna front (degrees)	2	5
0	1.5	2.0
30	1.37	1.58
60	0.92	1.35
90	0.40	0.47
[90 180>	0	0

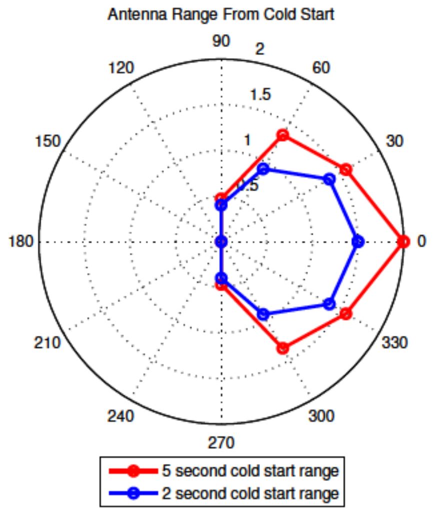

Fig. 5. Antenna range from cold start for two time windows: 2 s (blue) and 5 s (red). Distance measured in the horizontal plane in meters.

We have tested the read range of the W^2ISP from a cold start measures from our critical antennae (those located on the ceiling) over two fixed time windows (see Table III). A cold start is where the reservoir capacitor of the Wearable WISP has been discharged after a time t^* without RF exposure (in our case $t^* \geq 10$ s). We evaluated read range using a ceiling mounted antenna and a W^2ISP located at 2.5 m and 1.4 m, respectively, above ground level. The antenna had an inclination of 50° from the vertical. We considered measurements every 30° from the front of the antenna and two time windows of 2 and 5 s for the sensor to gather power and respond at maximum distance to the antenna as shown in Table III and Figure 5. The sensor can send information from cold start 1.5 m away from the antenna in less than 2 s when directly in front of the antenna; an increase of deviation from the front of the antenna results in a shorter range for the sensor to be able to respond in that time window.

B. Experimental Results

The manually labelled data (truth) was compared with predicted data. Table VII shows overall accuracy for both datasets, and a percentage comparison of the composition of both datasets in terms of collected observations. We can observe that both datasets achieved high overall accuracy. In the case

TABLE V
NEAR BED RELATED ACTIVITY RECOGNITION IN BOTH DATASETS

Activities	RoomSet1 (%)			RoomSet2 (%)		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
Lying	99.62±0.25	99.74±0.21	99.43±0.59	97.45±4.08	98.15±4.17	94.66±5.71
Sitting on bed	96.37±1.94	92.51±6.11	97.78±1.07	94.67±6.55	78.28±11.42	96.08±5.35
Out of bed	96.62±2.02	87.97±4.99	97.76±2.09	96.07±5.64	71.84±12.61	98.04±3.33

TABLE IV
ARS OVERALL ACCURACY AND RELATIVE COMPOSITION OF EACH LABEL IN RESPECTIVE DATASETS (%)

	RoomSet1	RoomSet2
ARS Overall Accuracy	96.34±1.94	94.14±6.56
Composition for Lying	59.04	88.67
Composition for Sitting on bed	28.86	7.11
Composition for Out of bed	12.09	4.21

TABLE VI
BED EXIT RECOGNITION IN BOTH DATASETS, RESULTS IN %

Method	Dataset	Accuracy	Sensitivity	Specificity
BEAS	RoomSet1	84.55±6.78	78.24±12.6	87.33±5.35
	RoomSet2	86.9±8.85	90.14±13.47	86.57±11.11
Baseline [16]	RoomSet1	68.28±5.9	14.45±15.4	91.14±5.85
	RoomSet2	69.6±8.36	19.02±19.72	93.36±4.8

of *RoomSet2* the highly accurate result is partly due to the greater composition of Lying observations ($> 88\%$). Samples from lying states achieve a greater prediction accuracy than other labels in that dataset (see Table VII). This disparity in observations is also due to the lack of observations (sensor reads) in positions other than lying attributed to the change in antenna disposition. The lack of reads result from the distances between the W^2ISP wearer and antennae being maximised as the antenna facing the subject sitting on bed (*antenna4* in *RoomSet1*) is moved to being almost on top of the subject (*antenna3* in *RoomSet2*) as seen in Figure 4. From this ceiling position, readings can be hindered due to obstruction by folds in the clothing breaking the ground plane of the sensor or other body parts such as the head obstructing RF signals.

In addition, we have to consider the reduced number of antennae. The likelihood of having a feeding antenna in range to generate a response from cold start reduces as the subject moves from one position to the next, as demonstrated in SectionIV-A.

Comparison of both datasets clearly indicates that *RoomSet1* data achieves better accuracy ($\geq 96\%$), sensitivity ($\geq 88\%$) and specificity values ($\geq 97\%$) as shown in Table V. All states achieved high accuracy values ($> 94\%$), particularly in *RoomSet1*, in which sensitivity values were noticeably higher than those in *RoomSet2*. These results indicate that the system is able to differentiate between subjects Lying and Sitting-on-bed, which is an added advantage in patients that are not supposed to get up from bed unsupervised, especially at night time where a Sitting-on-bed state implies that the patient is probably attempting to go to the toilet. Another important issue to notice is that in all cases the level of specificity or false alarms is relatively low ($\geq 94.6\%$), explicitly in *RoomSet1* where specificity ranges from 97.8% to 99.4%.

TABLE VII
BED EXIT RESULTS FROM PREVIOUS STUDIES

Study Author	Sensitivity(%)	Specificity(%)
Hilbe [11]	96.0	95.5
Bruyneel [10]	91.0	100.0
Ranasinghe [16]	90.4	93.8

We evaluate the BEAS performance using ARS predictions. The results are shown in Table VI where accuracy for both datasets is $> 84\%$. Results indicate that *RoomSet1* deployment achieves lower performance than that of *RoomSet2*. However, these results seem to contradict those of individual label predictions where *RoomSet1* achieved higher performance values for all labels when compared to data from *RoomSet2*. The explanation lies in the higher numbers of scattered label recognition errors resulting in increased FP and FN values in *RoomSet1*. Furthermore, in *RoomSet2*, the low composition of Out-of-bed observations does not reduce performance of bed exit classifications as only one predicted label is enough to trigger an alarm.

We compare these results with those of the Baseline method applied to both datasets. We notice that accuracy and sensitivity values are much lower than those of BEAS because the baseline method requires detection of PTs in order to perform its threshold based classification. The method fails to detect most PTs due to incomplete data from elderly subjects, producing many FNs.

Furthermore, our proposed bed exit classification algorithm achieved a low false alarm rate (specificity $> 86\%$). This result is important as a high false alarm rate can cause frustration in caregiver staff affecting the acceptance of the intervention. Although the baseline method depicts a larger specificity, it is only because of a general failure to detect possible events to evaluate rather than the classifier not producing FPs.

Moreover, we compare these results with previously developed fall prevention devices [10], [11], [16] shown in Table VII. Hilbe et al. [11] achieved sensitivity and specificity values in the order of 95%. The system is composed of a pressure sensor mounted on the bed rails; however, bed rails are not recommended as a method to prevent falls as it may increase the height of a fall and the risk of related injuries

[3], [29]. Bruyneel et al. [10] used multiple sensors (presence, movement, temperature) built in a bed mat. This method achieved no false alarms but has an increased associated cost due to demands of servicing and cleaning as the product is exposed to body fluids from patients. Moreover, mats are prone to displacement due to body movement and this method confirms a bed absence signal after a 2 minute delay. Similarly, in the baseline method [16] a 20 s data segmentation strategy is employed resulting in maximum response delays of 20 s. In contrast to these methods, our proposed system achieves comparative results and offers additional advantages as it is wearable, wireless, inexpensive, maintenance free and free of heavy data cleaning and conditioning steps such as filtering; therefore, free of processing delays that might withhold the timely execution of a high risk alarm [10], [16].

C. Wearability of the Wireless Sensor Equipment

This section investigates the users perception on the wearability of the device among the elderly volunteers. A short questionnaire filled out by each subject after their trial. The questionnaire was designed based on the work of [30] which identified several factors for evaluating wearable sensors. In our study, we focused on the use of the equipment and the restrictions on freedom of movement of the user while wearing the equipment. The questions were awarded a score from an 11 level point system (0-10). Although the questions are formulated in either positive or negative statements, in all cases a score of 10 demonstrate complete satisfaction on both question sets. The questions for measuring the wearability of the W^2ISP were:

1) Wearing the equipment was no problem.
2) I just forgot I am wearing it.
3) I am satisfied using the equipment.
4) I find the equipment easy to use.

The specific questions for measuring freedom of movement were:

5) How did you experience wearing the equipment while performing activities?
6) Were you hindered by the equipment while walking?
7) Were you hindered by the equipment while sitting?
8) Were you hindered by the equipment while lying?

The tabulated results (Table VIII) show great satisfaction towards the equipment and its wearability. In particular the results indicate that the elderly volunteer participants were not constrained or obstructed by the device while performing their activities. The system achieved average scores of 9.8 and 9.7 for both question sets. In general female subjects provided higher scores on all questions than male subjects with the exception of Question 8. Furthermore female responses to Question 8 has the largest SD as well as the lowest score, perhaps indicating that females may have felt some discomfort when lying with the sensor attached over the breast bone. However, further studies (such as a focus group) will be required to develop a more definitive conclusion. Overall, these results overwhelmingly support the use of the W^2ISP as a wearable and easy to use device, suitable for use with elderly.

TABLE VIII
SCORE AWARDED TO EQUIPMENT ACCEPTANCE AND FREEDOM OF MOVEMENT: AVERAGE ± SD

	Trials Population		
Question	Overall	Males	Females
1	9.88±0.48	9.5±1.00	10±0.00
2	9.7±0.84	9.5±1.00	9.76±0.83
3	9.76±0.66	9.5±1.00	9.84±0.55
4	9.88.±0.48	9.5±1.00	10±0.00
Average Equipment	9.8±0.63	9.5±1.00	9.9±0.5
5	9.7±0.68	9.5±1.00	9.76±0.6
6	9.88±0.48	9.5±1.00	10±0.00
7	9.88±0.48	9.5±1.00	10±0.00
8	9.29±1.57	9.5±1.00	9.23±1.73
Average Freedom of Movement	9.69±0.92	9.5±1.00	9.75±0.92

V. CONCLUSION

In this article, we provide a novel approach to bed exit classification for mitigation the risk of falls. We considered the use of raw signals i.e. with no preprocessing such as filtering, to achieve bed exit alarming capability. We proposed a classification algorithm based on CRFs to correctly predict the label of each observation and ultimately distinguish whether the subject has exited the bed using these labels. The system was successful evaluated using two datasets.

The results demonstrate that the proposed system has similar performance as more expensive, bulky bed exit alarm systems requiring regular maintenance.In addition, our proposed classification algorithm is a significant improvement over the threshold based algorithm. Furthermore our approach achieves high accuracy with incomplete and noisy raw data.

Furthermore, the system can be developed for real time processing as the proposed classification algorithm is capable of making a prediction for every observation. In addition, the system is capable of multi-tag reading, thus, capable of multi-patient monitoring and alarming. In terms of responsiveness our system provides minimal delay, however this does not guarantee a prompt intervention from respondents (carers). Further trials are needed to establish the effectiveness of our approach as a falls prevention strategy.

The use of two room configurations shows that the use of more antennae does not necessarily improve the overall performance of the system. The use of a more focused antenna placement as in *RoomSet2* where antennae were particularly oriented towards high falls risk locations such as the bed and chair achieved higher performance as opposed to *RoomSet1* which covered a wider horizontal plane. Furthermore having a unnecessarily larger area of coverage also lead to more scattered errors due to the relatively large numbers of readings obtained from locations outside the vicinity of the bed. However having a more a more focused area of coverage makes the system more sensitive to a varying room configurations. However, given that clinical rooms in the same hospital or residential care environment have similar layouts, classifier can be trained to adapt to new conditions.

This research also demonstrates the feasibility of using the Wearable WISPs as an activity monitoring device. The use of such device is clearly advantageous as an inexpensive, wireless, maintenance free device can easily be discarded when exposed to a high risk infection environment unlike using bed rails or bed mats. The feedback given from participants in the study confirmed the device to be wearable and non-obstructive.

A practical implementation of the solution will however imply a one time infrastructure cost of deploying commercial UHF readers and antennae. Nevertheless, RFID hardware prices have been falling as RFID technology is more widely adopted. The only recurrent cost component is the tags, however, the cost of the tags are continuing to diminish. At present the W^{2}ISP is expected to cost around $2 to $3 when mass produced [24], [31].

Finally, our group is currently working on collecting information from real patients in their clinical environment to verify the performance of this study with real patient data. Our future work will also involved extending the classification algorithms to include the prediction of other risk related activities such as getting up from a chair, going to the toilet and walking without a walking aid. In order to improve classification accuracy we are currently considering support vector machine based algorithms that incorporate learning so that we can move towards a system that evolves over time.

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References

[1] K. Rapp, C. Becker, I. Cameron, H. König, and G. Büchele, "Epidemiology of falls in residential aged care: analysis of more than 70,000 falls from residents of bavarian nursing homes," *J. Am. Med. Dir. Assoc.*, vol. 13, no. 2, pp. 187.e1–187.e6, 2012.

[2] C. Becker and K. Rapp, "Fall prevention in nursing homes," *Clin. Geriatr. Med.*, vol. 26, no. 4, pp. 693–704, 2010.

[3] H. Hanger, M. Ball, L. Wood *et al.*, "An analysis of falls in the hospital: can we do without bedrails?" *J. Am. Geriatr. Soc.*, vol. 47, no. 5, pp. 529–531, 1999.

[4] K. Hill, M. Vu, and W. Walsh, "Falls in the acute hospital settingimpact on resource utilisation," *Aust. Health Rev.*, vol. 31, no. 3, pp. 471–477, 2007.

[5] D. Oliver, "Prevention of falls in hospital inpatients. agendas for research and practice," *Age Ageing*, vol. 33, no. 4, pp. 328–330, 2004.

[6] C. D. Vass, O. Sahota, A. Drummond, D. Kendrick, J. Gladman, T. Sach, M. Avis, and M. Grainge, "REFINE (Reducing falls in in-patient elderly)-a randomised controlled trial," *Trials*, vol. 10, no. 1, p. 83, 2009.

[7] R. Tideiksaar, C. F. Feiner, and J. Maby, "Falls prevention: the efficacy of a bed alarm system in an acute-care setting." *Mt. Sinai J. Med.*, vol. 60, no. 6, pp. 522–527, 1993.

[8] O. Ojetola, E. Gaura, and J. Brusey, "Fall detection with wearable sensors–safe (smart fall detection)," in *2011 7th Int. Conf. on Intelligent Environments*, july 2011, pp. 318–321.

[9] M. Mubashir, L. Shao, and L. Seed, "A survey on fall detection: Principles and approaches," *Neurocomputing*, vol. 100, no. 0, pp. 144–152, 2013.

[10] M. Bruyneel, W. Libert, and V. Ninane, "Detection of bed-exit events using a new wireless bed monitoring assistance," *Int. J. Med. Inform.*, vol. 80, no. 2, pp. 127–132, 2011.

[11] J. Hilbe, E. Schulc, B. Linder, and C. Them, "Development and alarm threshold evaluation of a side rail integrated sensor technology for the prevention of falls," *Int. J. Med. Inform.*, vol. 79, no. 3, pp. 173–180, 2010.

[12] E. Capezuti, B. Brush, S. Lane, H. Rabinowitz, and M. Secic, "Bed-exit alarm effectiveness," *Arch. Gerontol. Geriatr.*, vol. 49, no. 1, pp. 27–31, 2009.

[13] B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C. Bula, and P. Robert, "Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 6, pp. 711–723, 2003.

[14] A. Godfrey, A. Bourke, G. Ólaighin, P. van de Ven, and J. Nelson, "Activity classification using a single chest mounted tri-axial accelerometer," *Med. Eng. Phys.*, vol. 33, no. 9, pp. 1127–1135, 2011.

[15] D. Karantonis, M. Narayanan, M. Mathie, N. Lovell, and B. Celler, "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring," *IEEE Trans. Inf. Technol. Biomed.*, vol. 10, no. 1, pp. 156–167, 2006.

[16] D. C. Ranasinghe, R. L. Shinmoto Torres, K. D. Hill, and R. Visvanathan, "Low cost and batteryless sensor-enabled radio frequency identification tag based approaches to identify patient bed entry and exit posture transitions," *Gait Posture*, unpublished.

[17] G. Cohn, D. Morris, S. Patel, and D. Tan, "Humantenna: using the body as an antenna for real-time whole-body interaction," in *Proc. 2012 ACM Annu. Conf. Human Factors in Computing Systems*. New York, NY, USA: ACM, 2012, pp. 1901–1910.

[18] C. Doukas and I. Maglogiannis, "Emergency fall incidents detection in assisted living environments utilizing motion, sound, and visual perceptual components," *IEEE Trans. Inf. Technol. Biomed.*, vol. 15, no. 2, pp. 277–289, 2011.

[19] M. Lutrek and B. Kalua, "Fall detection and activity recognition with machine learning," *Informatica*, vol. 33, no. 2, p. 197204, 2009.

[20] M. Buettner, R. Prasad, M. Philipose, and D. Wetherall, "Recognizing daily activities with RFID-based sensors," in *Proc. of the 11th Int. Conf. on Ubiquitous Computing*. ACM, 2009, pp. 51–60.

[21] D. J. Cook, "Learning setting-generalized activity models for smart spaces," *IEEE Intell. Syst.*, vol. 27, no. 1, pp. 32–38, 2012.

[22] N. C. Krishnan and D. J. Cook, "Activity recognition on streaming sensor data," *Pervasive Mob. Comput.*, no. 0, 2012.

[23] S. Londei, J. Rousseau, F. Ducharme, A. St-Arnaud, J. Meunier, J. Saint-Arnaud, and F. Giroux, "An intelligent videomonitoring system for fall detection at home: perceptions of elderly people," *J. Telemed. Telecare*, vol. 15, no. 8, pp. 383–390, 2009.

[24] M. Zhou, D. C. Ranasinghe, T. Kaufmann, and C. Fumeaux, "Wearable quarter-wave microstrip antenna for passive UHF RFID applications," *Int. J. Antennas Propag.*, unpublished.

[25] R. Visvanathan, D. C. Ranasinghe, R. L. Shinmoto Torres, and K. Hill, "Framework for preventing falls in acute hospitals using passive sensor enabled radio frequency identification technology," in *Proc. 2012 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2012, pp. 5858 –5862.

[26] C. Sutton and A. McCallum, *An introduction to conditional random fields for relational learning*. Introduction to statistical relational learning. MIT Press, 2006.

[27] A. Sample, D. Yeager, P. Powledge, A. Mamishev, and J. Smith, "Design of an rfid-based battery-free programmable sensing platform," *IEEE Trans. Instrum. Meas.*, vol. 57, no. 11, pp. 2608–2615, 2008.

[28] D. Liu and J. Nocedal, "On the limited memory bfgs method for large scale optimization," *Math. Program.*, vol. 45, no. 1, pp. 503–528, 1989.

[29] F. Healey and D. Oliver, "Bedrails, falls and injury: evidence or opinion? a review of their use and effects," *Nurs. Times*, vol. 105, no. 26, pp. 20–24, 2009.

[30] R. Fensli, P. E. Pedersen, T. Gundersen, and O. Hejlesen, "Sensor acceptance model - measuring patient acceptance of wearable sensors," *Methods Inf. Med.*, vol. 47, no. 1, pp. 89–95, 2008.

[31] M. Buettner, B. Greenstein, A. Sample, J. Smith, and D. Wetherall, "Revisiting smart dust with rfid sensor networks," in *Proc. 7th ACM Workshop on Hot Topics in Networks (HotNets-VII)*, 2008.

Chapter 5

Sensor Data Segmentation Methods for Real Time Inference with CRF

In the previous chapter we have demonstrated the better performance of a Conditional Random Fields based method in the recognition of bed exits, in complete sequences, when compared to a threshold based classifier tested with healthy older adults. We have also evidenced that the response of a classifier to different populations such as young and older people are very different and that recognizing activities in older people is a harder problem to solve. However, the classification method considered the batch processing of sequences of activities and only considered instantaneous features, extracted from every received sensor observation.

The article contained in this chapter is a conference paper that consider these two limitations. First, we evaluate various segmentation methods and relevant contextual information features extracted from fixed and dynamic sized sliding window based segments to improve the performance of a CRF classifier. Second, based on the sum product algorithm, we modify the class prediction model to obtain marginal probabilities for every incoming sensor observation as opposed to inferring a complete sequence of activities, e.g. using the Viterbi algorithm, as in the previous chapter.

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Evaluation of Wearable Sensor Tag Data Segmentation Approaches for Real Time Activity Classification in Elderly

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Abstract. The development of human activity monitoring has allowed the creation of multiple applications, among them is the recognition of high falls risk activities of older people for the mitigation of falls occurrences. In this study, we apply a graphical model based classification technique (conditional random field) to evaluate various sliding window based techniques for the real time prediction of activities in older subjects wearing a passive (batteryless) sensor enabled RFID tag. The system achieved maximum overall real time activity prediction accuracy of 95 % using a time weighted windowing technique to aggregate contextual information to input sensor data.

Keywords: Conditional random fields · RFID · Feature extraction

1 Introduction

The development of accurate human activity recognition methods is a growing field of study as many applications can be derived from this base. One application is the mitigation of high falls risk activities of older people in hospitals or age care facilities, as falls events occur especially in the bedroom [1]. A correct recognition of such high risk events can lead to an intervention to mitigate an event that can potentially cause further physical injury and mental distress [12]. For high falls risk mitigation the accurate recognition of real time activities is paramount as most falls occur during transfer activities, which are changes of static activities or locations (e.g. sit to stand, stand to sit or ambulating) [1,14]. In this article we consider activity recognition in the context of identifying high falls risk related activities.

Recent work on real time recognition of events have succeeded using body sensors [2,4,8,9,13,17], using tri-axial accelerometers, magnetometers and gyroscopes. These studies along with research using video images [11,18] or environment sensors [7,10] required the use of different time or data (number of

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samples, pixels) based segmentation approaches to extract relevant information for data classification.

The difficulty for real time recognition of activities using sensors is that individual sensor readings are limited in time-space and by themselves provide little additional information about the related activity for the classifier to predict an activity correctly. In order to provide further contextual information to data collected [6], incoming sensor data stream is segmented for feature extraction prior to evaluation.

Using data segments is not precise as there is no pre-defined window size and sizes may differ depending on the application [4,8] or sensor platform used [2,8]. In addition, a passive sensor's data stream is not continuous and data collected can be incomplete or noise distorted. These factors can influence the information quality of the individual data segment. Moreover, the occurrence and information value of future readings are uncertain and the classifier relies exclusively on current and past information to emit a result. The classifier performance is also affected by the presence of data from unrelated activities (e.g. distant past activities' data or sensor readings from unrelated areas or activities) and data from unrelated activities may outweigh current activity information in a given data segment [7].

This paper describes several sliding window segmentation methods for a real time per sensor datum prediction of human activities from a sensor and ID data stream from a battery-less wearable radio frequency identification (RFID) platform, called W^{2}ISP [5]. Our main focus is the implementation and evaluation of the effectiveness of segmentation methods using a multi-class classifier to identify incoming activity data in real time. We used a conditional random field (CRF) classifier because of its desirable sequence dependency modelling capabilities. The main contributions of this study are: (i) development of a real time CRF based classifier for activity recognition of passive sensor and ID data streams; (ii) implementation and testing of multiple fixed and dynamic sized windowing methods for contextual information extraction based on data characteristics; and (iii) experimental demonstration of the accuracy of these methods using data gathered from a trial with older subjects (66–86 years old) in a clinical environment.

The rest of the paper is described as follows: Sect. 2 gives a brief overview of related work, Sect. 3 discusses the methodology for our windowing approaches. Section 4 shows the evaluation results from the various methods in the previous Section and finally conclusions are given in Sect. 5.

2 Related Work

There are several studies with as many approaches for the real time recognition of human activities using threshold and machine learning classification systems. Some real time results [4,8,13] imply the timely recognition of body positions or postures, however, these methods required a data buffer from which the classifier makes a prediction. Hence, results are available periodically rather than having an output per individual sensor reading; some studies considered overlapping of data to provide faster output while having larger data buffers [8]. A study by Wang et al. [17] used a 1 s sliding window and a smartphone processing platform producing a recognition delay (time elapsed from ground truth to prediction of the ground truth) of $\sim$ 5.7 s. Other real time smartphone based studies relied on the sensors embedded in the device [9] or were used as a hub for other worn sensors [2]. Current smartphones are not imperceptible devices and their usage with older populations needs to be studied.

All these methods used different approaches to segmenting and windowing data. Most tried empirically different segment sizes to find that which maximized the resulting accuracy using the same set of features [8,17] or the window selection was arbitrary [9]; while others were limited by the underlying technology itself [4]. In addition, most of these studies produced periodical results only and used battery operated sensors which are bulky and not appropriate for older or frail subjects. Furthermore, none has been evaluated on an older population.

In the work of Krishnan et al. [7], several methods were applied to evaluate the best sliding window method for smart home data sets. Each method provided extra features for added information about the last received sample. The nature of irregular and incomplete data from environment sensors in the smart home is similar to that of passive worn sensors in an RFID platform, as is our case. This research study implements methods adapted from [3,7] to the ID and sensor data stream from sensor enabled passive RFID devices to evaluate time series data segmentation approaches for real time classification of scripted activities from older people.

3 Methodology

In this section, we present the developed windowing methods for feature extraction and describe the datasets and classification system used. These methods are based on the passive sensor platform (W^{2}ISP) constraints where signal collection is irregular, noisy and incomplete. Our RFID deployments used antennae location to obtain readings from targeted areas of high falls risk activities (in and around a bed and a chair) in two clinical rooms (Sect. 3.7).

Using a tri-axial acceleration (ADXL330) data stream from a W^{2}ISP we predicted the activity label (Sect. 3.7) that best represented every datum received. Our feature vector included: $V = [a_f, a_v, a_l, sin(\theta), RSSI, A_{ID}, \triangle T]$ for the recognition of bed exits, where a_f, a_v and a_l are frontal, vertical and lateral components of the tri-axial accelerometer sensor, $sin(\theta)$ refers to the body tilt angle, $RSSI$ is the strength (power) of the signal received from the W^{2}ISP by an RFID reader, $A_{ID} = \{aID_1, .., aID_A\}$ (where A is the number of antennae) is the identifier of the antenna that collected the datum and $\triangle T$ is the time difference between current and previous reading [15]. In [15] we obtained high accuracy for label detection using batch processing of activities sequences segmented by trial and by patient with a CRF classifier. In this study, we use CRF for real time activity recognition and apply different windowing techniques for feature extraction and predict the activity label of the last received sensor reading.

3.1 Activity Windowing (AW)

This approach considers that the system knows in advance the activity that is being performed and segments the data per each activity for both training and testing stages. Although knowing the activities performed beforehand in a real environment is implausible given that the separation of activities is unambiguous, maximum accuracy is expected from the predicted labels. Given this condition, we consider this technique our golden standard. However, this approach does not perform predictions in real-time but predicts samples in different sized pre-segmented batches where each batch represents a single activity. We use the generic set of features V for each observed sensor reading (Sect. 3) as input to the classifier.

3.2 Fixed Sample Windowing (FSW)

This approach considers a sliding window with fixed number of samples. The windowed sample sequence provides contextual information about the last sample in the window to enable the classifier to emit a more accurate prediction [7]. Different window sizes can better fit the duration of different activities (labels) as was the case in Sect. 3.1 when the activities are already known. To illustrate this case, consider resting positions such as lying or sitting on bed or the chair that usually last several minutes or hours when compared to dynamic activities such as walking. The lengths of such events are disproportionate and difficult to segment in real data; whereas a fixed sample segmentation is simple to produce.

The selection of window size is an empirical process, where the best result corresponds to the segment length that best fits all activities. For this analysis additional features are extracted and added to our generic feature vector V as contextual information. In contrast to [7] the set of extra features corresponds to the count of events reported by each antenna in the window, as we can differentiate sensor reading origin by the antenna used. Hence, the number of extra features is equal to the number of antennae present. Moreover, these summed amounts are further normalized to four levels of importance (0: unused, 1: low, 2: medium and 3: high importance) computed as follows:

$$F(i,k) = \left\lceil \frac{3 * c_{i,k}}{\sum_{j=1}^{A} c_{j,k}} \right\rceil \tag{1}$$

where A is the number of antennae and $c_{i,k}$ corresponds to the count of antenna i events in the window for the last reading k.

Two issues are present in this method. First, the window duration can span a long time and readings from distant past activities can affect the classifier decision. Second, a large volume of readings from previous activities unrelated to the current activity or spurious readings from distant antennae covering a distinct area present in the window can also alter the classifier decision. In order to meet these issues, weighted features are considered to balance the influence of unrelated data [7] and are described in Sects. 3.3 and 3.4.

3.3 Time Weighted Windowing (TWW)

This method is based on FSW in Sect. 3.2, as it uses a fixed sample window. However, more importance is given to events closer to the last sample to reduce the effect of historical events on the classifier. This technique gives each sample i in a window a distinct weight $T(i,k)$ which is a function of the time difference $\triangle_{i,k}$ between the last received sample k and sample i in the fixed time window. The evaluation of the weights is defined by an exponential function:

$$T(i,k) = \begin{cases} 0 & \text{if } \triangle_{i,k} >= \frac{1}{D} \\ \exp\left(-D * \triangle_{i,k}\right) & \text{else} \end{cases} \tag{2}$$

where D is the rate of decay, if $D > 1$ elements very close ($\triangle_{i,k}$ <1 s) are given priority as the exponential function decays quickly; smaller values of D allows the function to consider a wider time range of sensor readings. The method also considers a limited amount of time, bounded by $\triangle_{i,k} = \frac{1}{D}$, as larger values of $\triangle_{i,k}$ provide less weight. The extra features now consist of the sum of the weights for the readings corresponding to each antenna in the window and replaces the extra features from FSW method. Hence, the extra features are defined by the vector: $W = [\sum T(i,k)\delta(a_i, aID_1), \ldots, \sum T(i,k)\delta(a_i, aID_A)]$, where $a_i \in A_{ID}$ is the antenna corresponding to the i^{th} sample and the function $\delta(a_m, a_n)$ is defined as:

$$\delta(a_m, a_n) = \begin{cases} 0 & \text{if } a_m \neq a_n \\ 1 & \text{if } a_m = a_n \end{cases} \tag{3}$$

In addition, we normalize vector W to levels of importance using (1).

3.4 Mutual Information Windowing (MI)

Similarly to TWW (see Sect. 3.3), this method uses a fixed sample window (see Sect. 3.2). However, this approach intends to reduce the influence of readings from antennae focused on areas unrelated to the current activity. In general, samples of different activities are collected from antennae depending on the activity location. Nevertheless, readings from distant antennae occur in real data with low received energy ($RSSI$), although these readings are rare. We consider two types of mutual information between the i^{th} sample and the last sample k in a segmented window: (i) MI1: mutual information (MI) of two consecutive readings occurring from any pair of antennae as defined in [7] and given in (4); and (ii) MI2: the MI of two consecutive readings occurring from a given pair of antennae at any time (i.e. disregards the order of antennae occurrence while focusing only on antenna relationships), defined in (5), where N is the number of elements in the training sequence, $a_i \in A_{ID}$ and function $\delta(.)$ is as defined in (3).

$$MI1(m,n) = \frac{1}{N} \sum_{j=1}^{N-1} \delta(a_j, a_m)\delta(a_{j+1}, a_n) \tag{4}$$

$$MI2(m,n) = \frac{1}{N} \sum_{j=1}^{N-1} \left(\delta(a_j, a_m)\delta(a_{j+1}, a_n) + \delta(a_j, a_n)\delta(a_{j+1}, a_m)\right) \tag{5}$$

The mutual information is built from the entire training data set prior to testing where a square matrix ($A \times A$) with all possible antennae pairs and a triangular matrix is obtained for MI1 and MI2 respectively. These MI weights are used to build the extra features, where all sensor readings in a window are weighted in relation to the last reading and summed in relation to their corresponding antenna, obtaining the vector $W = [\sum MIr(i,k)\delta(a_i, aID_1), \ldots, \sum MIr(i,k)$ $\delta(a_i, aID_A)]$ where $r = \{1, 2\}$. Vector W is normalized to levels of importance using (1).

3.5 Dynamic Windowing (DW)

This method considers a time based window of varying size using statistical properties of the data to continually adapt the window size. This method, first devised by Jeffery et al. [3] for cleaning of RFID data streams, was applied because the algorithm balances the need to provide contextual information by increasing the window size and reducing the window size when sensor readings become more sporadic. This method considers a stepped window size increments (0.5 s per sample) but reduction is rapid (halving the window size) when required [3]. We assume a standard epoch[1] duration of 0.25 s and sensor observation probability of 90 % [3]. For this method we use the extra features of the FSW method (see Sect. 3.2).

3.6 Fixed Time Windowing (FTW)

This method considers a sliding window of fixed time duration T^*, as opposed to a dynamic changing time window size as in DW. All readings within the time interval T^* from the last received reading k are considered in a window. Given the irregular collection of data (due to the nature of the passive device), the number of samples per segment will differ. For this method we use the extra features of the FSW method (see Sect. 3.2).

3.7 Datasets

We used data from two clinical room deployments as described in [15]; where both datasets (*RoomSet1* and *RoomSet2*) used four and three antennae respectively. In *RoomSet1* one antenna is placed on top of the bed (ceiling) and three on the walls focusing on the chair and around the bed providing a wide area of coverage. In *RoomSet2* two antennae were placed on top of the bed (ceiling) and one antenna focused on the chair. Fourteen older subjects were trialled (age:74.6 ± 4.9), wearing the W^2ISP on top of their garments. They performed a series of scripted activities which included: (i) lying (in bed); (ii) sitting in bed; (iii) sitting in chair; and (iv) ambulating. The CRF classifier was used to predict these four activity labels. In order to collect the ground truth, activities were annotated in real time by an observer. The same basic features were extracted

[1] Epoch refers to a group of RFID interrogation cycles.

for each dataset; however, the total number of features differed for both datasets as the aggregated extra features are based on their antennae deployment.

3.8 Classifier

In this research, we used a linear chain CRF, a model for structured classification (prediction) [16], as in a previous study [15]. We have preferred this method as it models the dependencies of activities in a sequence. Due to this advantage the system is trained using the complete sequence of activities of each training trial for parameter estimation with the exception of the first method (AW) as it assumes activities are previously known and independent from each other. In CRF, training and testing stages require the probabilistic inference of the target labels (hidden variables). In general, the inference process allows us to obtain: (i) marginal probabilities of the labels (using sum-product algorithm); and (ii) the most probable global state of all our hidden variables i.e. maximum a posteriori (MAP) assignment (using max-product algorithm). Our application requires real time response, thus we use the sum product algorithm (which only propagates the messages forwards) to find the marginal probability of the current hidden variable given the past and current observation efficiently. The prediction is done by maximizing the marginal probability.

The sum product algorithm propagates messages for every edge (i, j) connecting nodes i and j in a graph. In Fig. 1, circles represent the state variables $Y = \{y_1, \ldots, y_k\}$ and squares represent factors (node and edge potentials). The message updating and marginal probability are computed as follows:

$$m_{i,k}(s_k) = \sum_{s_i}(\psi(s_i)\psi(s_i, s_k) \prod_{t \in N_i \backslash \{k\}} m_{t,i}(s_i)) \tag{6}$$

$$p(s_k) = \tfrac{1}{Z}\psi(s_k) \prod_{i \in N_k} m_{i,k}(s_k) \tag{7}$$

where $\psi(s_i)$ and $\psi(s_i, s_k)$ are node and edge potential respectively, s_i represents node i, $N_i \backslash \{k\}$ represents the set of neighbours of node i with the exception of node k, p is the marginal probability and Z is a normalization factor. In the case of our real time application, we are only interested in the marginal probability of the last variable (y_k) given the input observation as shown in Fig. 1, where the marginal probability of variable y_k reduces to:

$$p(y_k \mid x_{1:k}, \lambda) = \tfrac{1}{Z(\lambda, x_{1:k})}\, \psi(y_k; x_{1:k}, \lambda) m_{k-1,k}(y_k; x_{1:k}, \lambda) \tag{8}$$

where messages $m_{i,j}$ are calculated using (6) and $\lambda = \{\lambda_t\}$ represents the parameters estimated in training. Moreover, the message $m_{k-1,k}(y_k; x_{1:k}, \lambda)$ is recursive as it depends on previous messages as in the expression $m_{k-1,k}(y_k; x_{1:k}, \lambda) = \sum_{y_{k-1}} \psi(y_{k-1}; x_{1:k}, \lambda)\psi(y_{k-1}, y_k; x_{1:k}, \lambda)m_{k-2,k-1}(y_{k-1}; x_{1:k-1}, \lambda)$.

This derivation for the sum product is appropriate for real time streaming data as the sequence of information is always increasing and an activity label prediction is required for each datum. Therefore, we apply the expression in (8) for inference during testing.

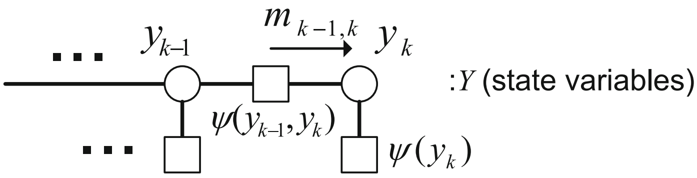

Fig. 1. Message propagation for the probability distribution of y_k

3.9 Statistical Analysis

The analysis of results was obtained using a 10-fold cross validation where general performance was measured using overall accuracy (referred as accuracy and given in (9)), and individual label performance using geometric mean (GM) and $Fscore$ as defined in (9), where N is the number of readings, TP is true positives and recall, specificity and precision are determined as per standard definitions. Results are shown as mean ± standard deviation (SD). Statistical significance is measured using a two-tailed two-sample t-test at 5 % significance level.

$$Accu = \frac{TP}{N} \quad GM = \sqrt{recall.specificity} \quad Fscore = \frac{2.recall.precision}{recall + precision} \tag{9}$$

4 Evaluation

The first evaluation corresponds to labelling a pre-segmented sequence in the AW method. High accuracies ($> 97.7\,\%$) and high $Fscore$ and GM values ($> 87\,\%$ and $> 92\,\%$) are obtained for *RoomSet1* and *RoomSet2* datasets (see Table 2). In $RoomSet2$, metrics for sitting-in-chair are affected by one test fold where only 17 samples were present for that activity which was missed (false negative), affecting all metrics. Accuracies for the FSW method are shown in Table 1(a), which tested sliding windows of 5 to 60 samples. Highest accuracy for $RoomSet1$ is achieved between $N = 10$ and 20; the largest source of error is caused by false negatives (FN) of sitting-in-bed and false positives (FP) in ambulating labels. These errors are minimal in AW approach. $RoomSet2$ is affected by one fold where samples collected during lying and sitting-in-bed caused mutual errors, which also affected the rest of the methods. Given that $RoomSet2$ metrics do not vary in this set of window sizes, we consider the window sample size of 15 as the best parameter for this method.

The TWW method was tested using a fixed window size of 15 samples as found in FSW method. For this study we tested decay rate values of $D = 2^{-7}$ to 2^0 as shown in Table 1(b). Highest accuracy for $RoomSet1$ occurs for $D = 2^{-2}$ and then drops slightly. In contrast, best performance for $RoomSet2$ occurs between $D = 2^{-1}$ to 2^{-3} with some folds affected by mutual error between lying and sitting-in-bed as in FSW method. However, accuracy is not significantly different across $RoomSet2$ ($p > 0.34$). Hence, we consider a decay rate of $D = 2^{-2}$ as the best parameter for this windowing case.

Results for MI windowing indicates that both MI1 and MI2 approaches (see Sect. 3.4) obtained similar results as shown in Table 2, where results are almost identical. From the MI1 matrices shown below, we can see that for $RoomSet1$ there is little interaction between antennae, with higher values for self transition of antennae as found in [7]; in $RoomSet2$ there are strong transition values for antennae aID_2 and aID_3 both of which are located on top of the bed and report most in-bed and around-bed sensor readings.

MI1*RoomSet1* (%)

	aID_1	aID_2	aID_3	aID_4
aID_1	35.12	0.25	2.18	3.28
aID_2	0.22	8.77	0.04	0.06
aID_3	2.23	0.03	16.48	4.33
aID_4	3.24	0.04	4.36	19.26

MI1*RoomSet2* (%)

	aID_1	aID_2	aID_3
aID_1	3.19	0.16	0.31
aID_2	0.17	21.92	18.15
aID_3	0.4	18.14	37.42

The DW method produced high accuracy (94.6 %) results for $RoomSet2$ but for $RoomSet1$ results are comparable to those of previous windowing methods as shown in Table 2. However, $Fscore$ and GM are significantly different compared to MI ($p < 0.01$). Partial results for FTW are shown in Table 1(c), where time durations of 1 to 128 s were tested. The highest accuracies were achieved with a 4 s time window for both datasets. In $RoomSet2$, there is little variation among different time windows. In contrast, for $RoomSet1$ this method achieves the highest accuracy for all tested methods as seen in Table 2 but this result is still significantly different from that of the golden standard ($p \sim 10^{-7}$).

Finally, we combined time and space based segment contextual information extraction with expected performance improvement. Combination of FTW and MI1, introduced mutual information rather than counting events in FTW. The results for $RoomSet1$ lie between the amalgamated methods; however, the overall performance for $RoomSet2$ is lower than FTW and MI1. The combination case of TWW and MI1 introduced extra features from both methods, achieving the highest accuracy for $RoomSet2$ which is comparable with our golden standard ($p = 0.14$). Results for $RoomSet1$ are slightly lower than the best performance with FTW method (see Table 2). This is because TWW+MI1 had a rich extended information. However, in FTW+MI1 the fixed time window did not bring enough mutual information as the number of samples in a segment can be as low as one, performing lower than counting per antenna samples.

Further analysis of Table 2 indicates low $Fscore$ and GM values for $RoomSet1$ created mostly by FNs and FPs (false positives) for sitting-in-bed and ambulating respectively. These errors were reduced in the FTW case but not greatly. Metrics for $RoomSet2$ were affected by two main causes, one fold in particular produced large FN and FP for lying and sitting-in-bed respectively and few readings for sitting-in-chair label which in some folds are ignored produced recall, Fscore and GM values of zero and affected these averages. In both datasets, the low composition of ambulating activity data (not shown) compared to the other states affected individual and average metrics as only a couple of seconds of data are retrieved as a subject walked away from the reading range of antennae near the bed or chair.

These results indicate the real time inference algorithm (marginal inference) found most difficulty predicting ambulating and sitting-in-bed samples for *RoomSet*1. In general, no method was able to produce maximum results for both datasets, although results for FTW and TWW+MI1 methods are comparable ($p > 0.48$) in both datasets. *RoomSet*2 disposition using two antennae focusing on the bed was able to avoid classification error in *RoomSet*1, however there were relatively smaller number of sensor readings for sitting-in-chair as only one antenna powers the tag in *RoomSet*2. In terms of real time analysis, test inference calculation time for both datasets is of 5.12 µs and 7.31 µs per sample respectively and this time is minimal compared with the observed minimum inter-sample duration time of 25 ms. These results were obtained using algorithms implemented in MATLAB scripts and mex code but these algorithms will run faster if developed in a low level language as C/C++ and therefore our results also demonstrate that the classifier is capable of real time sample prediction.

Table 1. Partial accuracies for FSW, TWW and FTW methods

(a) Accuracy for Fixed Sample Window method						
Datasets	N = 5	N = 10	N = 15	N = 20	N = 30	N = 60
RoomSet1	70.6±6.0 %	71.2±6.1 %	72.5±5.9 %	72.2±6.2 %	70.6±6.2 %	70.7±5.9 %
RoomSet2	94.9±4.3 %	91.9±11.5 %	91.8±11.2 %	91.7±11.3 %	91.2±11.6 %	93.5±6.9 %
(b) Accuracy for Time Weighted Window method						
Datasets	$D = 2^0$	$D = 2^{-1}$	$D = 2^{-2}$	$D = 2^{-3}$	$D = 2^{-4}$	$D = 2^{-7}$
RoomSet1	70.3±6.1 %	71.6±6.1 %	73.1±7.5 %	71.8±6.2 %	71.7±6.0 %	71.8±6.1 %
RoomSet2	91.3±11.2 %	94.3±5.0 %	91.7±11.2 %	93.5±4.6 %	92.1±11.1 %	90.2±10.8 %
(c) Accuracy for Fixed Time Window method						
Datasets	$T = 1$	$T = 2$	$T = 4$	$T = 8$	$T = 16$	$T = 128$
RoomSet1	70.5±6.2 %	73.9±7.1 %	78.2±7.3 %	73.6±6.8 %	71.9±6.7 %	70.2±5.7 %
RoomSet2	91.5±11.3 %	91.6±11.4 %	92.3±11.2 %	92.2±11.1 %	92.2±11.0 %	91.2±11.0 %

Table 2. Classification accuracy for all tested methods for both datasets, including average Fscore and GM for all activities.

	RoomSet1 (%)			*RoomSet2 (%)*		
Method	*Accuracy*	*Fscore*	*GM*	*Accuracy*	Fscore	GM
AW	98.1±1.8	93.5±5.5	96.1±3.7	97.7±3.6	87.0±21.0	92.8±16.6
FSW	72.5±6.0	57.9±6.5	76.6±5.5	91.8±11.2	67.5±23.2	82.5±17.7
TWW	73.1±7.5	59.0±9.2	77.1±8.0	91.7±11.2	69.3±21.4	84.4±18.0
MI1	70.8±6.0	55.2±5.0	74.0±4.3	94.4±5.2	68.6±20.5	84.3±17.2
MI2	70.8±6.1	55.3±5.4	74.1±4.9	93.8±5.2	67.5±20.4	83.3±16.8
DW	74.7±8.1	61.2±10.2	79.2±8.4	94.6±4.7	68.4±22.7	83.4±18.6
FTW	**78.2 ± 7.3**	**65.1 ± 11.5**	**82.1 ± 9.2**	92.3±11.2	68.5±23.9	82.8±18.7
FTW+MI1	71.5±6.0	56.6±5.6	75.2±4.8	91.7±11.1	67.1±22.9	82.9±17.8
TWW+MI1	77.1±7.8	63.8±11.5	81.0±9.1	**95.0 ± 4.2**	**71.6 ± 20.2**	**85.8 ± 16.8**

5 Conclusions

In this study we have developed a number of sliding window based data segmentation techniques for real time prediction of human activities where contextual information was introduced as extra features to the input observation to improve classification accuracy. Although no segmentation method exceeded the golden standard for both datasets, methods TWW+MI1 and FTW achieved high performance metrics in both datasets and had comparable results with the golden standard with *RoomSet2* dataset. In general *RoomSet2* achieved better results than *RoomSet1*, due to its more focused antennae disposition which caused less prediction errors as opposed to a wider area coverage as in *RoomSet1*. Moreover, the system can process real time streaming data using fixed or variable windowing approaches on a sample by sample basis with high accuracy as in the case of *RoomSet2*; and using a CRF classifier which learned the model using complete sequences of activities and applied into real time label prediction.

A limitation comes from the scripted nature of the activity datasets. Nonetheless, all related sensor worn research (see Sect. 2) were based on scripted set of activities, where execution order was random or sequential. Further analysis is required to determine whether these segmentation techniques based on scripted models can perform well with unscripted and undirected activities.

Finally, this work sets the foundation for high level applications such as high falls risk activities (bed and chair ingress or exit, room exiting and bathroom access) recognition in real time.

References

1. Becker, C., Rapp, K.: Fall prevention in nursing homes. Clin. Geriatr. Med. **26**(4), 693–704 (2010)
2. Györbíró, N., Fábián, A., Hományi, G.: An activity recognition system for mobile phones. Mob. Netw. Appl. **14**(1), 82–91 (2009)
3. Jeffery, S., Franklin, M., Garofalakis, M.: An adaptive rfid middleware for supporting metaphysical data independence. VLDB J. **17**(2), 265–289 (2008)
4. Karantonis, D., Narayanan, M., Mathie, M., Lovell, N., Celler, B.: Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. IEEE Trans. Inf. Technol. Biomed. **10**(1), 156–167 (2006)
5. Kaufmann, T., Ranasinghe, D.C., Zhou, M., Fumeaux, C.: Wearable quarter-wave microstrip antenna for passive UHF RFID applications. Int. J. Antennas Propag. (2013)
6. Kern, N., Schiele, B., Schmidt, A.: Recognizing context for annotating a live life recording. Pers. Ubiquit. Comput. **11**(4), 251–263 (2007)
7. Krishnan, N.C., et al.: Activity recognition on streaming sensor data. Pervasive Mob. Comput. **10**, 138–154 (2014)
8. Lee, M.W., Khan, A., Kim, J.H., Cho, Y.S., Kim, T.S.: A single tri-axial accelerometer-based real-time personal life log system capable of activity classification and exercise information generation. In: 32nd Annual International Conference IEEE Engineering in Medicine and Biology Society, pp. 1390–1393 (2010)

9. Lee, Y.-S., Cho, S.-B.: Activity recognition using hierarchical hidden markov models on a smartphone with 3D accelerometer. In: Corchado, E., Kurzyński, M., Woźniak, M. (eds.) HAIS 2011, Part I. LNCS, vol. 6678, pp. 460–467. Springer, Heidelberg (2011)
10. Lu, C.H., Fu, L.C.: Robust location-aware activity recognition using wireless sensor network in an attentive home. IEEE Trans. Autom. Sci. Eng. **6**(4), 598–609 (2009)
11. Messing, R., Pal, C., Kautz, H.: Activity recognition using the velocity histories of tracked keypoints. In: IEEE 12th International Conference on Computer Vision, pp. 104–111 (2009)
12. Oliver, D.: Prevention of falls in hospital inpatients. agendas for research and practice. Age Ageing **33**(4), 328–330 (2004)
13. Ranasinghe, D.C., Shinmoto Torres, R.L., Hill, K.D., Visvanathan, R.: Low cost and batteryless sensor-enabled radio frequency identification tag based approaches to identify patient bed entry and exit posture transitions. Gait & Posture (2013)
14. Robinovitch, S.N., Feldman, F., Yang, Y., Schonnop, R., Lueng, P.M., Sarraf, T., Sims-Gould, J., Loughin, M.: Video capture of the circumstances of falls in elderly people residing in long-term care: an observational study. The Lancet **381**(9860), 47–54 (2012)
15. Shinmoto Torres, R.L., Ranasinghe, D.C., Shi, Q., Sample, A.P.: Sensor enabled wearable rfid technology for mitigating the risk of falls near beds. In: 2013 IEEE International Conference on RFID, pp. 191–198 (2013)
16. Sutton, C., McCallum, A.: An introduction to conditional random fields. Found. Trends Mach. Learn. **4**(4), 267–373 (2012)
17. Wang, L., Gu, T., Tao, X., Lu, J.: A hierarchical approach to real-time activity recognition in body sensor networks. Pervasive Mob. Comput. **8**(1), 115–130 (2012)
18. Xia, L., Chen, C.C., Aggarwal, J.: Human detection using depth information by kinect. In: 2011 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, pp. 15–22 (2011)

Chapter 6

Learning from Imbalanced Multiclass Sequential Sensor Data with CRF

The previous chapter introduced segmentation methods for the extraction of contextual information to improve the classification performance in CRF and also the real time inference of sequential data; these contributions are intrinsic to the methods in the remaining chapters of this thesis. However, a major challenge with sensor data streams for human activity monitoring is the occurrence of data imbalance; this is natural in frail older people in a nursing homes or hospitals, as they can spend more time lying on the bed than walking. Other external factors, such as the nature of the sensor platform, can also affect the imbalance problem. In addition, optimization metrics such as accuracy are not representative of the results in the minority classes and are biased towards the dominating class.

The article contained in this chapter is a journal paper that considers the problem of data imbalance in the cases of low availability of training data. The method presented uses class-wise weights that are dynamically determined during the training of the classification model, the weights seek to optimize the overall F-score as opposed to metrics that favours the majority class such as accuracy. Our model avoids cumbersome validation processes to obtain optimal weight parameters such as grid search that requires an exponential number of processes. We tested our approach with two datasets for human activity monitoring using batteryless and battery powered sensor platforms.

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Dynamically Weighted Conditional Random Fields for Learning from Imbalanced Body Worn Sensor Data Streams

Roberto L. Shinmoto Torres, Damith C. Ranasinghe, Qinfeng Shi, and Anton van den Hengel

Abstract—**Data imbalance is an inherent characteristic of human activity data from body worn sensors in a growing number of healthcare applications. Imbalanced data can negatively bias the performance of classifiers favoring majority classes; however, minority classes, corresponding to short duration activities, provide important information for applications such as falls prevention or falls risk assessments. We investigate a probabilistic graphical model based method of Conditional Random Fields (CRF) for improving learning from imbalanced sequential multi-class data streams from body worn sensors. We propose a class-wise dynamically weighted CRF (dWCRF) where weights are automatically determined during training by maximizing the expected overall *F*-score. We tested our method with two datasets using batteryless and battery-powered body worn sensors (BLBW and BPBW respectively) and compared performance and training times with a set of state-of-the-art classification methods. Overall, our method outperformed other CRF based methods and performed similar to or better than SVM based methods. Our method outperformed or performed similar to other classifiers in terms of minority class predictions. Further, dWCRF requires significantly less time to build a prediction model than other state-of-the-art methods evaluated. dWCRF can improve the real-time classification performance of sequential body worn sensor data streams in the presence of data imbalance, especially when labeled training data are scarce, which is often the case in real-world applications such as recognition of activities for falls prevention in older people.**

Index Terms—**Data imbalance, Dynamically Weighted Conditional Random Fields, dWCRF, F-score optimization, Human activity recognition.**

I. INTRODUCTION

DEVELOPMENTS in emerging wearable sensor technologies are enabling a multitude of applications in healthcare such as gait analysis, falls risk assessments, monitoring of heart rate and of Parkinson's symptoms, and falls prevention. [1]–[4]. The recognition of activities in older people is of particular interest as a means of preventing injuries from events such as falls by providing an early intervention, or identification of function decline, as in those with Alzheimer's or Parkinson's disease.

One of the main challenges in human activity recognition is that sensor data is usually imbalanced as data from activities of daily living (ADL) are not necessarily equally distributed. This is because people naturally perform some activities that are of longer duration than others. For example, in the context of patient monitoring in hospitals or nursing homes, resting activities such as lying on bed (i.e. sleeping) or sitting on a chair or the bed are of longer duration than ambulating activities, where destinations, such as the restroom, are very close. Moreover, those performing these short-duration activities (e.g. ambulating) are potentially at risk of falling and injury [5]. This data imbalance in the training information can negatively affect the classifier by being biased to prefer the majority class [6]. Hence, it is important to increase the overall classification performance, in particular, in identifying minority classes.

Another challenge that also contributes to data imbalance in human activity monitoring applications arises from the difficulty of collecting data for the training of activity recognition systems in real-life environments. For instance, it can be more difficult to collect data from certain activities such as those performed closer to the sensing infrastructure, e.g. environmental motion sensors, than those activities performed farther from the sensor as data collected from the latter can be scarcer. Moreover, collection and labeling of a large corpus of training data with frail participants such as hospitalized older patients is difficult due to the physical limitations associated to their older age and ailments [7]. Therefore, a classifier which is highly accurate at predicting all activity classes in datasets where availability of training data is scarce is highly desirable.

This paper presents a novel method for learning from imbalanced data using conditional random fields (CRF) [8], a graphical model for structured classification that captures dependency relationships between performed activities as described by sensor data streams. We propose a class-wise cost parameter based classifier that considers the influence of individual classes for learning from sequential imbalanced multiclass datasets. The cost parameters (weights) are not fixed as they are dynamically adjusted during the training process, while the classifier seeks to optimize the model's expected overall F-score to minimize both false positives (false alarms) and false negatives (missed classifications). Hence, weights are learned during training, avoiding an empirical search for optimal weights which can be time consuming. Further, our approach takes less time to train and validate new parameters than other state-of-the-art methods.

The performance of our approach is evaluated with two human activity recognition datasets: 1) a batteryless body worn sensor worn over clothing of healthy and hospitalised

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older people in the context of a falls prevention application in clinical and hospital settings; and 2) a battery powered body worn sensors on healthy adults in a laboratory environment for the collection of ADLs, in cases of high data imbalance.

A. Related works

This section reviews previous methods developed for improving the classification of imbalanced data, such as data re-sampling [9]–[12], adjusting decision thresholds [13] or the inclusion of cost parameters or weights into the classification algorithm [14]–[21], as in our proposed method.

Re-sampling: These methods consider the removal or introduction of data to modify the levels of imbalance [9]–[11]. However, such approach can modify a sequence structure and its meaning, this is an issue with real world applications that require maintaining the original data structure. For example, in human activity recognition the time sequence is important to determine the flow of movements and modifying the data can change the sequence of activities and the way it is analyzed, e.g. affecting transition probabilities in Markov chains.

Decision threshold: Methods such as that of [13] used receiver operating characteristic (ROC) curves to decide which decision threshold produces the best performance, achieving similar results to re-sampling techniques. However, ROC curves, which depend on specificity, do not reflect the errors in imbalanced data. This is due to specificity of the minority class being conditioned to include the true positives of the majority class and thus leading to over optimistic results.

Cost parameter: This approach requires the inclusion of fixed class-wise costs into the classifier's objective function during training to reinforce the learning of under-represented classes. Generally, cost sensitive learning approaches have been reported to perform better than re-sampling techniques in some applications [6]. Some cost parameters have the form of a cost matrix that weighs each misclassification case, giving higher costs to misclassifications of a minority class observation in comparison to majority classes [14]–[16].

Costs were also used to rescale the data; by re-weighting, re-sampling the training samples or moving decision thresholds according to their costs. These costs are usually user provided, e.g. from a cost matrix [16]. Similarly, fixed class-wise costs were considered in [19], [20] that depended on the class population and misclassification cost per class. The issue with fixed costs [19], [20] is that these are usually given, and optimal costs have to be determined by an extensive validation process. This process can be cumbersome and computationally expensive as a grid search for optimal parameters uses an exponential number of operations, making model training and updating (in case of new training data) difficult.

In contrast, other studies [17], [18], [22] dynamically changed the costs by verifying classification errors on each optimization iteration [18], [22] or in proportion to the participating classes in the training data in incremental learning algorithms [17]. However, model optimization was based on classification error (1-accuracy) minimization [17], [22], which is not ideal for imbalanced data. This is because accuracy is largely favoured by the dominant class and provides little performance information regarding the minority class [23].

Other studies offered alternative methods [24], [25]. Soda [24] decided between an unbalanced or a balanced classifier for every observation and measured its performance based on accuracy; while Beyan et al. [25] proposed a hierarchical method based on clustering and outlier detection that, in general, was not significantly better than other methods. Moreover, both studies did not consider multi-class problems.

Cost parameters methods in CRF: These methods have been applied in [21], [26] to improve CRF classification performance. The study of Gimpel et al. [26] used fixed costs according to specific performance tasks (task-wise) such as improving recall, precision or both (as in F-score) [26] as opposed to classification error minimization as in previous studies. On the other hand, the method of Lannoy et al. [21] considered a fixed set of class-wise weights in its model (WCRF) that were also not learned during training.

The study of Dimitroff et al. [27] considered a learning algorithm for binary classification using a maximum likelihood model (weighted maximum entropy) to optimize the expected F-score during training where weights were calculated autonomously. Our study extends the method in [27], originally proposed for binary classification problems, to multiclass structured prediction using CRF.

Furthermore, previous studies have considered human activity recognition using body worn sensors where few of these datasets are freely available. Moreover, most datasets are produced in controlled conditions presenting little class imbalance. For example, from the UCI machine learning repository, there are few datasets that collected human activities in continuous sequences using wearable devices [28]–[31]. From these, only Opportunity (OPR) [28] and Activity Recognition from Chest Accelerometer (ARA) [30] show some degree of imbalance given by their low ratio between number of elements of minority class and that of the majority class (0.11 and 0.08 respectively). In addition, later studies using these datasets have not addressed the issue of data imbalance during the learning stages of the classification process. In contrast, we consider a dataset of older participants in a clinical environment including hospital patients where data imbalance is implicit in the dataset given the application context of monitoring older people in a hospital setting.

B. Paper Contributions

Our approach extends existing knowledge by formulating an algorithm for sequence learning that relies on maintaining the integrity of the sequential data, while seeking to improve overall harmonic mean of recall and precision. We make the following contributions:

1) We present a novel cost sensitive learning method for imbalanced multiclass data classification in real time, based on weighted conditional random fields (WCRF). The optimization process is based on maximizing the expected overall F-score where class-wise cost parameters are dynamically computed during training. To our knowledge, this is the first attempt for multiclass classifier optimization based on F-score to learn from imbalanced data with dynamically learned cost parameters, in particular, for graphical models such as CRF.

2) We apply our method to two scenarios. The first considers two case studies of sequential data streams from healthy and hospitalized older people using a batteryless body worn sensor over their clothing. The second scenario uses a published dataset, with modified imbalance, that uses a battery powered body worn sensor for collecting ADLs.
3) Our approach achieves, in general, a better performance than other CRF based methods and similar to better performance than SVM based classifiers. Moreover, our approach takes considerably less time to train and validate parameters than other state-of-the art methods

II. Proposed Dynamically Weighted Learning Method

In this section we begin by briefly revisiting CRFs, a probabilistic graphical model for structured classification [8], [32], before defining our method in Section II-A.

Let us assume a set of training data sequences $\mathcal{D} = \{x^{(n)}, y^{(n)}\}_{n=1}^{N}$, where input sequences are i.i.d. to each other — i.e. sequence in $\{x^i, y^i\}$ is independent of that in $\{x^j, y^j\}$ for $i \neq j$. Hence we consider a single training instance $\{x^{(n)}, y^{(n)}\}$ in our formulation as this does not complicate the algorithms, consisting of a sequence of input observations $\{x_t\}_{t=1}^{T}$ and their corresponding labels $\{y_t\}_{t=1}^{T}$, where $y_t \in \{1 \cdots K\}$ and K is the number of classes to infer. The advantage of CRF is that it constructs pairwise relationships between adjacent hidden variables and their corresponding observations, a property from the first order Markov assumption. The probability distribution in CRF is given by:

$$p(y|x, \lambda) = \frac{1}{Z} \exp\left(\sum^{T} \phi_t\left(y_{t-1}, y_t, x; \lambda\right)\right), \tag{1}$$

$$Z(x) = \sum_{y_{1\cdots T}} \exp\left(\sum^{T} \phi(y_{t-1}, y_t, x; \lambda)\right). \tag{2}$$

Here the potential function $\exp(\phi(y_{t-1}, y_t, x; \lambda))$ follows the logistic model function

$$\phi(y_{t-1}, y_t, x; \lambda) = \lambda^1 f(y_{t-1}, y_t) + \lambda^2 f(y_t, x) \tag{3}$$

where $\lambda = \left(\lambda^1, \lambda^2\right)$ are the model parameters to be estimated during training and $f(.)$ are transition and emission feature functions that produce boolean values. The term $Z(x)$ is the partition function and normalizes the conditional probability.

During model training, we seek to maximize the conditional log likelihood (CLL) $\mathcal{L}$, defined as:

$$\mathcal{L}(\lambda) = \log p(y|x), \tag{4}$$

$$\mathcal{L}(\lambda) = \sum^{T} \left(\lambda^1 f(y_{t-1}, y_t) + \lambda^2 f(y_t, x)\right) - \log(Z(x)). \tag{5}$$

Since $\mathcal{L}$ is a convex function we apply a quasi-Newton method for estimation of model parameters λ such as the L-BFGS optimization algorithm. The partition function considers a summation over all possible values of x and y. We calculate the value of $Z(x)$ using the belief propagation (sum–product) algorithm which recursively calculates the passing of messages over all elements in the tree. In the case of linear chain graphical models, belief propagation provides an exact solution for the calculation of $Z(x)$, given by $Z(x) = \sum_{y_T} \alpha_T$, where α_t are the messages propagating forward in the algorithm.

A. Dynamically Weighted Conditional Random Fields (dWCRF)

This section details our dynamically weighted CRF (dWCRF) approach for structured predictions to address the negative effects of imbalanced data on learning.

Let's assume that every training sequence in $\mathcal{D}$ has number of classes $K = 3$ where class k_1 has number of elements T_1, where $T_1 << T_{2,3}$, $T_2 \sim T_3$, and T_2 and T_3 are number of elements of classes k_2 and k_3 respectively. We use a case of imbalance on a single class for simplicity; however, this can be extended to other cases of K and minority classes. In order to balance k_1 with other classes, we replicate k_{min} observations a number of times w_1. The location of replicated samples in a structured sequence is important as randomly allocating them changes the temporal relationships in a sequence. Hence, replicated samples should be adjacent respecting the natural sequence of classes. In a resulting balanced sequence $\{x^{*n}, y^{*n}\}$ of length T^*, larger than T (length of original $\{x^n, y^n\}$), maximization of $\mathcal{L}^*(\lambda)$ will result in a longer training process due to the increased dataset.

The CLL $\mathcal{L}^*(\lambda)$ is given by

$$\sum^{T^*} \left(\lambda^{*1} f(y^*_{t-1}, y^*_t) + \lambda^{*2} f(y^*_t, x^*)\right) - \log(Z(x^*)).$$

Let us divide the first term above by classes y^*_t:

$$\sum^{T_1^*} \left(\lambda^{*1} f(y^*_{t-1}, y^*_t) + \lambda^{*2} f(y^*_t, x^*)\right)\Big|_{y_t^*=k_1} + \cdots$$
$$+ \sum^{T_3^*} \left(\lambda^{*1} f(y^*_{t-1}, y^*_t) + \lambda^{*2} f(y^*_t, x^*)\right)\Big|_{y_t^*=k_3}$$

where $\sum_i T_i^* = T^*$. This is equivalent to multiplying the sequence by a class-wise weight w_k; thus a single value weight does not modify the class imbalance. We have that $T_1^* = w_1 T_1$, $T_2^* = w_2 T_2$ and $T_3^* = w_3 T_3$. Hence we rewrite the above expression as of size T (shorter and faster to train):

$$\sum^{T_1} w_1 \left(\lambda^1 f(y_{t-1}, y_t) + \lambda^2 f(y_t, x)\right)\Big|_{y_t=k_{min}} + \cdots$$
$$+ \sum^{T_3} w_3 \left(\lambda^1 f(y_{t-1}, y_t) + \lambda^2 f(y_t, x)\right)\Big|_{y_t=k_{maj2}}$$

This expression can be generalized to K classes and introduced to $\mathcal{L}^*(\lambda)$ as a weighted CLL.

$$\mathcal{L}(\lambda, w) = \sum_{n=1}^{N} w \log p(y^{(n)}|x^{(n)}, \lambda) \tag{6}$$

Equation (6) considers all training sequences $\mathcal{D}$ to show that w is a scalar weight not dependent on n and affects each element of the sequence of length T (weight vector $[w_t]_{t=1}^{T}$). Our objective function is similar to that in [27]; however, the weight term in [27] equally affects the complete sequence and, therefore, does not address class imbalance.

In addition, classification performance metrics such as accuracy (1-error) are not suitable as results are biased towards the majority class. Hence, we impose the minimization of false positives (FP) or false alarms; and false negatives (FN) or missed classifications. Intuitively, this means increasing both true positives (TP) and true negatives (TN) of all classes. We use the expected F-score [27] as an optimization metric for our model as it considers FN and FP in its definition. In [27], Dimitroff et al. demonstrated using the Pareto optimality concept that there exists a set of weights w_{F_β} for which λ_F, the parameter that optimizes the expected F_β-score, coincides with weighted maximum likelihood optimization parameter λ^w_{ML}. More information on Pareto efficiency can be found in [27], [33]. Although, the approach followed in [27] was for a binary Maximum Entropy classifier; this article extends this previous work to multiclass classification using dWCRF.

The expected overall F_β-score ($\bar{F}$), given by the mean expected F_β-score over all classes has the expression

$$\bar{F} = \frac{1}{K}\sum_{k=1}^{K}\left(\frac{(1+\beta^2)\text{Precision}_k.\text{Recall}_k}{\beta^2\cdot\text{Precision}_k+\text{Recall}_k}\right) \tag{7}$$

where $\beta \in \mathbb{R}$ is non-negative and balances the contributions from precision and recall. Henceforth, for simplicity, we consider $\beta = 1$, where precision and recall have the same influence; i.e. the harmonic mean of both precision and recall. Let us assume $\widehat{\lambda}$ to be the maximizer of $\bar{F}$, and considering that $TP_k = \sum_{i:y_i=k} p(y_i = k|x,\lambda)$ and $FP_k = \sum_{i:y_i\neq k} p(y_i = k|x,\lambda)$; expanding and operating in (7), can be rewritten as

$$\bar{F}(\lambda) = \frac{2}{K}\left[\frac{TP_1}{TP_1+T_1+FP_1}+\cdots+\frac{TP_K}{TP_K+T_K+FP_K}\right] \tag{8}$$

where T_k are the number of elements of class k in the training sequence, i.e. $\sum_k(T_k) = T$. From (8), we want to show that $\widehat{\lambda}$ is an element of the Pareto optimal set of the multicriteria optimization problem (MOP)

$$\max_\lambda\{TP_1, TP_2, \cdots, TP_K\}. \tag{9}$$

We do not consider the FP term from (8) as we are interested in maximizing TPs and reducing FPs; moreover, increasing $TP_{\{1\cdots K\}\setminus u}$ (set of all TPs except that for class u) will reduce $FP_{k=u}$. If we consider that $\widehat{\lambda}$ is not Pareto efficient in the MOP in (9), then there is a λ_0 such that $(TP_1(\lambda_0),\cdots,TP_K(\lambda_0))$ dominates $(TP_1(\widehat{\lambda}),\cdots,TP_K(\widehat{\lambda}))$; i.e. at least one of the objectives is improved by λ_0 compared to that of $\widehat{\lambda}$. Since the expression in (8) increases as TP_k increases, implying that $\bar{F}(\lambda_0) > \bar{F}(\widehat{\lambda})$; this contradicts the initial assumption that $\widehat{\lambda}$ maximizes $\bar{F}$.

We can also observe that the Pareto optimal set of (9) is contained in that of the MOP

$$\max_\lambda\{p(y_1|x,\lambda), p(y_2|x,\lambda)\cdots, p(y_T|x,\lambda)\} \tag{10}$$

this is because if we assume a λ that is Pareto optimal for (9) but not for (10), then we have a λ_0 that improves at least one of the objectives in (10) without decreasing the others. This means the K-tuple $(TP_1(\lambda_0),\cdots,TP_K(\lambda_0))$ dominates $(TP_1(\lambda),\cdots,TP_K(\lambda))$, contradicting the assumption that λ is Pareto optimal for (9). Thus the $\bar{F}$ optimizer $\widehat{\lambda}$ is also Pareto optimal for (10) and therefore $\widehat{\lambda}$ is Pareto optimal for the MOP

$$\max_\lambda\{\log p(y_1|x,\lambda),\cdots,\log p(y_T|x,\lambda)\} \tag{11}$$

given that $\log(.)$ is a strictly increasing function. The expression in (11) is equivalent to the set of potential functions in (3) for $t = 1\cdots T$. Moreover, the Pareto optimal set of (11) can be obtained by maximizing non-negative linear combinations of its objectives [33]. This means there is a set of weights $w_t\mid_{t=1}^T$ such that

$$\begin{aligned}\widehat{\lambda_F} &= \arg\max_\lambda\,(w\log p(y|x,\lambda))\\ &= \arg\max_\lambda(\ell(\lambda,w))\end{aligned} \tag{12}$$

where the rightmost expression corresponds to the weighted log-likelihood as expressed in (6) when training sequences are i.i.d. to each other. Our work above expands the proof in [27] from binary to multiclass classification.

B. Weights Estimation

Now we are interested in computing the set of weights w in dWCRF that maximizes the function $\bar{F}$. We use the previous result in (12), which indicates that the objective functions $\bar{F}$ and weighted log-likelihood have gradients equal to zero at the optimal $\widehat{\lambda}$. We have the gradient of the function $\bar{F}$

$$\begin{aligned}\nabla_\lambda\{\bar{F}(\widehat{\lambda})\} = &\sum_{t:y_t=1}\partial_{TP_1}\bar{F}(\widehat{\lambda})\nabla_\lambda p(y_t|x,\widehat{\lambda})+\cdots\\ &+\sum_{t:y_t=K}\partial_{TP_K}\bar{F}(\widehat{\lambda})\nabla_\lambda p(y_t|x,\widehat{\lambda})\end{aligned} \tag{13}$$

and the gradient of the log-likelihood function:

$$\nabla_\lambda\ell(\widehat{\lambda}) = \frac{w}{p(y|x,\widehat{\lambda})}\nabla_\lambda p(y|x,\widehat{\lambda}) \tag{14}$$

where $\nabla_\lambda\{\bar{F}(\widehat{\lambda})\} = \nabla_\lambda\ell(\widehat{\lambda}) = 0$ at the optimal parameter $\widehat{\lambda}$.

Considering the expression in (13) we can obtain the partial derivative:

$$\begin{aligned}\frac{\partial F(\lambda)}{\partial TP_k} = q\Bigg[&\frac{d}{dTP_k}\left(\frac{TP_1}{TP_1+N_1+FP_1}\right)+\cdots\\ &+\frac{d}{dTP_k}\left(\frac{TP_K}{TP_K+N_K+FP_K}\right)\Bigg]\end{aligned} \tag{15}$$

where $q = 2/K$ and given that previously we have considered FP_k to be a function of all TPs other than k, (15) can be expressed as:

$$\begin{aligned}\frac{\partial F(\lambda)}{\partial TP_k} = &\,q\frac{N_k+FP_k}{(TP_k+N_k+FP_k)^2}\\ &+q\sum_{j:1\cdots K\setminus k}\frac{-TP_j\frac{dFP_j}{dTP_k}}{(TP_j+N_j+FP_j)^2}\end{aligned} \tag{16}$$

we consider that the derivative term in (16) are close to zero at the optimal ($\lambda \to \widehat{\lambda}$) and that the derivative is much smaller than its quadratic denominator term; hence we eliminate the summation term from (16), resulting in

$$\frac{\partial F(\widehat{\lambda})}{\partial TP_k} \simeq q \frac{N_k + FP_k}{(TP_k + N_k + FP_k)^2}. \tag{17}$$

The resulting weights for optimizing the weighted maximum likelihood and the corresponding expected overall F-score can now be defined as:

$$w_t = \begin{cases} p(y_t = 1|x, \widehat{\lambda})\partial_{TP_1}\bar{F}(\widehat{\lambda}) & \text{if } y_t = 1 \\ \cdots & \\ p(y_t = K|x, \widehat{\lambda})\partial_{TP_K}\bar{F}(\widehat{\lambda}) & \text{if } y_t = K. \end{cases} \tag{18}$$

We also consider a parameter $\tau > 0$ that corresponds to the number of times ℓ is computed during the optimization process. We use this parameter to apply λ considerations for (17), by executing first homogeneous weights as in linear chain CRF. Hence the resulting weights have the form:

$$w_{t,\tau} = \begin{cases} q & \text{if number interations} < \tau \\ w_t, \text{ as in (18)} & \text{if number interations} \geq \tau. \end{cases} \tag{19}$$

C. Real Time Inference

Usually, class inference process for CRF is performed for complete sequences of data where methods as the forward-backwards or Viterbi algorithms are applied to the test segment and complete sequence of labels is returned [34]. In a previous study, we have underscored the importance of real time prediction of activities [35] where we applied the belief propagation method to obtain the marginal probabilities of the last received observation; we use the current sensor observation and the information from the last inference made on the previous observation. This is given by the form:

$$\begin{aligned} &m(y_t) \\ &= \frac{1}{Z_t}\Big(\exp\left(\phi\left(y_t, x\right)\right)\sum_{y_{t-1}}\left(\exp\left(\phi\left(y_{t-1}, y_t\right)\right) m\left(y_{t-1}\right)\right)\Big) \end{aligned} \tag{20}$$

where $m(y_t)$ is the marginal probability corresponding to the t^{th} observation x_t and Z_t corresponds to the normalizing term so the marginals at a given time t sum to unity and prevents floating point underflow. The assigned label corresponds to the activity with the highest marginal probability.

III. Experimental Studies

We evaluate our dWCRF method using datasets from two different human activity recognition approaches: i) using batteryless body worn sensors (BLBW); and ii) battery powered body worn sensors (BPBW).

A. Problem Formulation

Both scenarios, BLBW and BPBW, consider sequential data from the sensors; these are time series of the form $\{x_t\}_{t=1}^T$, where $x_t \in \mathbb{R}^d$, and associated with a sequence of activity labels $\{y_t\}_{t=1}^T$, where $y_t \in \mathcal{Y} = \{1 \cdots K\}$, and K is the number of activity labels to predict. In sequence learning problems, we assume that training sequences $\mathcal{D} = \{(x^{(n)}, y^{(n)})\}_{n=1}^N$ are i.i.d. from each other. However, dependency relationships between variables in a sequence cannot be assumed. Hence, given a testing sequence $\mathcal{T} = \{(x, y)\}$, we are interested in predicting individual class labels $\hat{y}_t$ for every observation x_t using our trained dWCRF model.

B. Batteryless Body Worn Sensor Datasets (BLBW)

These datasets were obtained in the context of a larger project by our research group directed at the ambulatory monitoring of hospitalized older patients to prevent falls [36], and have ethics approval by the Human Research Ethics Committee of the Queen Elizabeth Hospital, South Australia, Australia (protocol number 2011129).

We evaluate two case studies based on motion information from healthy and hospitalized participants using a batteryless wearable sensor [37]. Trial participants were requested to perform a series of broadly scripted ADLs which included: i) Sitting on bed; ii) Sitting on chair; iii) Lying on the bed; and iv) Walking to the bed, chair or door. A researcher, present during the trials, annotated the labels directly into the middleware for reference as ground truth.

We consider that posture transitions such as sit to stand and stand to sit are integrated into the ambulation or sitting movements. For example, we consider that a person starts ambulating as soon as the body stops contact with the bed or chair. Ambulation, in this case, also includes standing and any motion the person performs while walking around the room.

Given the limitations imposed by the physical space and motion of our target demographics, the BLBW datasets consider four classes ($K = 4$) to distinguish whether a person is in or has exited a resting posture. These classes are: i) Sit-on-bed; ii) Sit-on-chair; iii) Lying; and iv) Ambulating. Details of the sensor platform and the case studies are explained below.

Sensor platform: The participants wore a flexible Wearable Wireless Identification and Sensing Platform (W^{2}ISP) device, developed by our team [37], over a garment on top of the sternum. The W^{2}ISP, based on [38], encases a tri-axial accelerometer (ADXL330) and a 16 bit microcontroller (MSP430F2132). The W^{2}ISP is a batteryless sensor that harvests its energy using the electromagnetic field illuminating the tag from RFID antennas, which also collect the W^{2}ISP sensor data. The main motivations for using this passive (batteryless) sensor compared to using battery powered sensors are twofold: i) the device requires no maintenance as it is battery free, lightweight, inexpensive and easy to replace; and ii) frail older people, especially those with conditions such as delirium or dementia, require easy-to-use equipment [39].

We collect tri-axial acceleration signals and the received signal strength indicator (RSSI) data from the sensor signals. RSSI is used as a measure of relative distance to the antenna receiving a sensor observation, especially over short distances as in our case studies [40]. Further, due to the passive device, sensor observations are not regularly collected in time, and thus increasing the complexity of the problem (see Figure 2).

Case Study 1: Fourteen healthy older volunteers, with average age of 74.6 ± 4.9 years old, completed around five trials each, based on their ability and level of fatigue. Participants

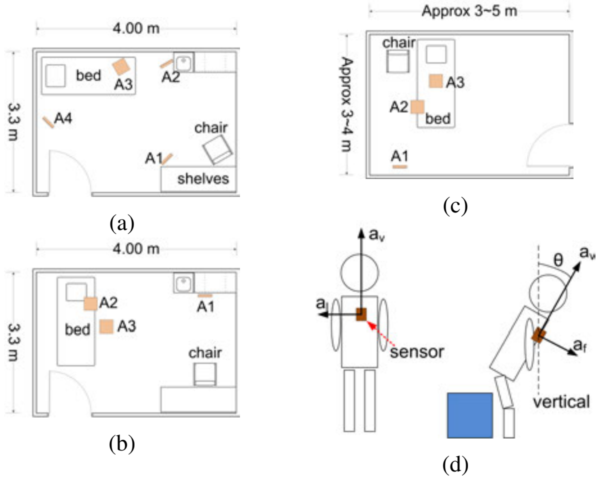

Fig. 1: Physical deployments of an RFID antenna infrastructure (antennas A1...A4) for collecting three datasets: (a): healthy older people (Room1); (b): healthy older people (Room2) and (c): hospitalized older people (Room3). (d): Front and lateral view of sensor axes for a participant standing and sitting/standing with respect to vertical.

were allocated into two different room configurations: Room1 and Room2, each a dataset with 4 and 3 antennas deployments, shown in Figure 1(a) and (b), respectively. Datasets available at http://autoidlab.cs.adelaide.edu.au/research/ahr.

Case Study 2: Twenty six hospitalized patients, with average age of 84.4 ± 5.3 years old, performed a short sequence of ADLs due to the frailty of the participants. Patients were trialled in their respective rooms, constituting dataset Room3. However, data from three patients was removed due to sensor malfunction and insufficient data collection. In this hospital room configuration, see Figure 1(c), the displayed measurements are approximate due to differences between rooms used in the experiments (single or double bed), and the bed and the chair were always next to each other. Both populations were tested using the extracted features described in Appendix A.

C. Battery Powered Body Worn Sensor Dataset (BPBW)

To further validate our approach, we consider the Opportunity activity recognition dataset (OPR) [28]. The large size of OPR ($609\,651$) allows us to modify its levels of imbalance. In this dataset, four participants with multiple sensors attached to their body and the environment perform multiple ADLs. From the features provided (243), we select those related to the trunk of the participant, i.e. sensors located on the hip and the back of the participant. Therefore, we use 19 trunk-related features and a time related feature shown in Appendix B.

Trunk-worn sensors are considered due to similarity with our real world scenario (hospital). Moreover, dataset BPBW has modes of locomotion labels: Stand, Walk, Sit, Lie, similar to the BLBW datasets. The null class was considered as an additional class where we assume the participant is doing something other than the four basic locomotion activity labels. We considered observations where readings from both trunk sensors were present, otherwise the observation was discarded. Finally, we subdivided the data into 5 datasets where each dataset contains data from the 4 participants. The main objective of this test is not to compare with the established benchmarks, but to compare different methods in situations of high data imbalance not present in the original data.

The levels of imbalance are modified for all classes except the majority class (Stand), to create imbalance levels similar and greater than those of our BLBW dataset. Three levels of data removal are used as shown in Figure 3(c), Op1: remove up to 9 of 10 consecutive sensor readings for each activity; Op2: remove up to 11 of 12 consecutive sensor readings for each activity; and Op3: remove up to 14 of 15 consecutive sensor readings for each activity.

D. Statistical Analysis

We determine class specific performance measurements: TP are the correctly predicted activity labels. FP are those predicted labels that do not match the ground truth. FN correspond to those ground truth classes that were missed. TN are those non-target (not intended) classes that were correctly identified.

In addition, we evaluate the performance of each class k using the harmonic mean of Precision (Pr) and Recall (Re):

$$\text{Precision}_k(Pr) = TP_k/(TP_k + FP_k) \tag{21}$$

$$\text{Recall}_k(Re) = TP_k/(TP_k + FN_k) \tag{22}$$

$$F\text{-score}_k = \frac{2\times Pr_k \times Re_k}{Pr_k + Re_k}. \tag{23}$$

In terms of overall performance, we use the average of the class-specific performance metrics i.e. $F\text{-score}_{Overall} = \sum_k F\text{-score}_k/|k|$.

Note we do not evaluate metrics depending on TN such as specificity [4], [41] as, mentioned previously, specificity does not appropriately reflect the performance of the minority class.

We are interested in comparing the F-score results of our classifier with other classifiers. We compare the significance between results using a two-tailed independent t-test. A p-value (p) <0.05 is considered statistically significant.

Evaluation of these metrics in the case of the BLBW datasets was performed using a 10-fold cross validation procedure, where each fold considered complete sequences of activities (a trial) of different people. We considered 6 folds for training 2 folds each for testing and validation. In the case of the BPBW datasets, these were evaluated using a 4-fold cross validation for each dataset, due to the reduced number of trials per dataset; we use two folds for training and one for testing and validation respectively.

E. Performance Evaluation

The performance of our dWCRF model is compared with linear chain CRF [8]; a weighted CRF with fixed weight values (fWCRF) given by the inverse of the class distribution [21]; and a cost parameter based CRF such as the softmax-margin model (C-CRF) [26], we use the L2 regularized model for each classifier of the form $\theta\|\lambda\|^2$. Regularization parameter θ was evaluated in the range $[10^{-4}, 10^{-1}]$. Parameter τ was chosen from the range limited by the lowest number of iterations for linear chain CRF.

In addition, we also compare with multiclass SVM for linear and radial basis function (RBF) kernels (L-SVM and R-SVM respectively) and the weighted SVM for both classifiers (L-WSVM and R-WSVM) [42], [43]. Selection of hyperparameters for the SVM classifiers' regularization, C, and RBF kernel, γ, were evaluated using a grid search in the range $[2^{-5}, 2^{5}]$ for both parameters. SVM algorithms were evaluated using libSVM [44] toolbox in Matlab, which performs a one-vs-one approach for multiclass classification.

The weight parameters for C-CRF, L-WSVM and R-WSVM, are found through cross-validation, evaluating the validation set. Notably, for fWCRF, the weights are fixed and determined solely on the class distribution. In the case of C-CRF, the parameters are selected to optimize F-score as in [45]; we applied an extensive grid search to obtain the optimal parameters in the value range $[0, 20]$. For weighted SVMs, the algorithms require a weight per class, $K = 4$ in our case, requiring a larger grid-search evaluation of the order of N^4 operations, where N is the number of elements in the range to evaluate. Instead we use the covariance matrix adaptation evolution strategy (CMA-ES) [46], a widely used evolutionary optimization algorithm, to find the optimal set of per-class parameters. Given the stochastic nature of the initial parameter selection for the iterative CMA-ES process, we require evaluating multiple starting values; in our case, we evaluated 350 random initial points uniformly distributed in the range $[0, 20]$ for each classifier. In all cases, the set of parameters that produced the highest F-score was chosen.

Hyperparameter validation for the tested methods was performed on a cluster of Intel 8 core E5 series Xeon microprocessors.

IV. Results and Discussion

A. Class Imbalance in BLBW Datasets

Two main sources of imbalance affect the BLBW dataset. The first is the duration of different activities. This is expected, for example, lying on bed is of longer duration than ambulating. The second source of imbalance is due to the passive nature of the W^{2}ISP sensor; this affects the device powering and the regularity of sensor readings. Sensor positioning and proximity to RFID antennas, posture of the participant (causing occlusion) can also affect the powering of the sensor; moreover, these conditions can change from person to person and room to room.

From the room settings, we can see that Room1 intends to collect sensor observations from the complete room, whereas Room2 and Room3 are focused on obtaining data from specific areas around the bed and chair while saving on hardware infrastructure. In Room3, the small dimensions of the path between bed and chair cause ambulation time to be minimal.

Figure 2 illustrates the resulting data imbalance from sensor observations. Data from Room1, see Figure 2(a), indicates that sensor inter-reading times when the participant is sitting on bed range from 0.2 to 1.3 s, from 0.5 to 4.2 s, when the person is ambulating and 0.5 to 6 s when sitting on a chair. In addition, the first observation corresponding to Ambulating and Sit-on-chair are received after 0.7 s and 4.5 s respectively.

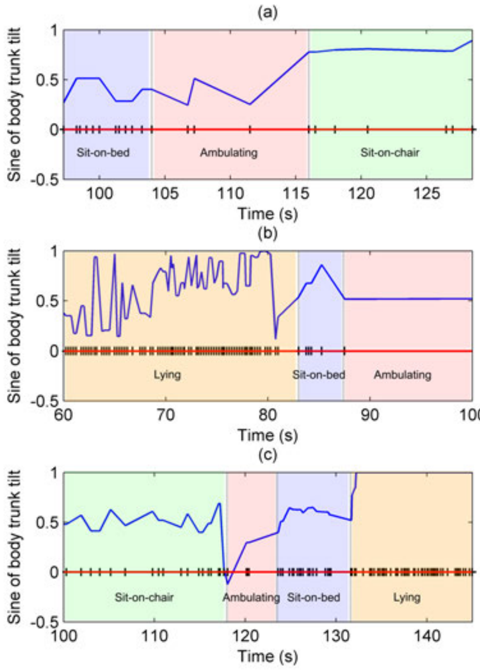

Fig. 2: Raw data corresponding to body tilting, see Figure 1(d), with respect to the vertical for the three datasets (a) Room1, (b) Room2 and (c) Room3 where black vertical marks represent sensor readings and classes are: Sit-on-bed (blue), Ambulating (red), Sit-on-chair (green) and Lying (orange).

In the case of Room2 and Room3, shown in Figure 2(b) and (c) respectively, sensor observations from a person lying in bed (orange background) are more frequently collected due to the location of the antennas when compared to a person sitting on bed (blue background) or ambulating (red background).

Class imbalance of the datasets are shown in Figure 3(a). Datasets Room1 and Room3 show similar imbalance where Lying is the dominant class and the minority class Ambulating has the lowest proportion in both datasets. However, Room1, has more than double the number of sensor observation of Room3—see Figure 3(a); and the minority class (Ambulating) for both datasets has a similar number of observations. Dataset Room2 is dominated by one class (Lying) and the remaining classes have decreasing values of participation with Ambulating being the minority class. Room2 has almost the same amount of sensor readings as Room3; albeit Room3 having collected data from more participants than the other datasets.

B. BLBW Datasets

First, we demonstrate the overall results corresponding to the datasets from Case Study 1 (Room1 and Room2) and Case Study 2 (Room3). These were obtained by averaging all participating classes' individual F-score and are shown in Figure 4. For Room1, the maximum F-score variation between classifiers is about $7\,\%$ between fWCRF and R-WSVM; the

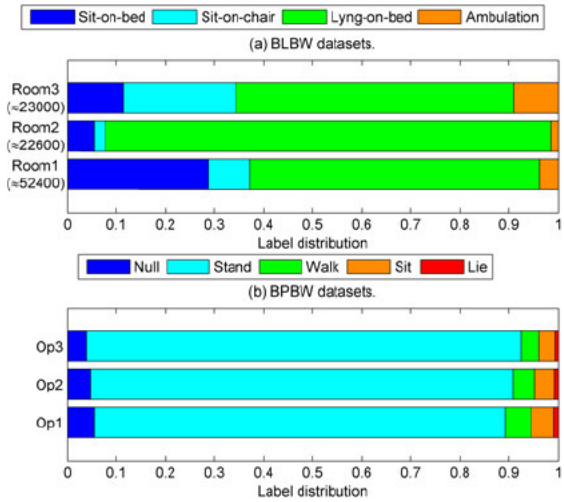

Fig. 3: Overview of data imbalance in our tested populations. (a) BLBW datasets corresponding to healthy and hospitalized patients, the approximate number of sensor observations per dataset is shown in parenthesis. (b) Three cases (Op1, Op2, Op3) of data imbalance from the BPBW dataset.

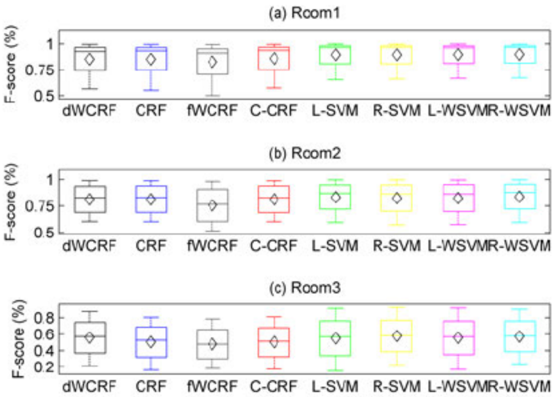

Fig. 4: Overall F-score performance of our three datasets (a): Room1, (b): Room2 and (c): Room3 using our dWCRF, linear chain CRF, fixed weighted CRF (fWCRF), softmax margin CRF (C-CRF), linear SVM (L-SVM), RBF kernel SVM (R-SVM) and their corresponding weighted algorithms: L-WSVM and R-WSVM respectively. Results are shown as boxplots (averages shown as diamonds).

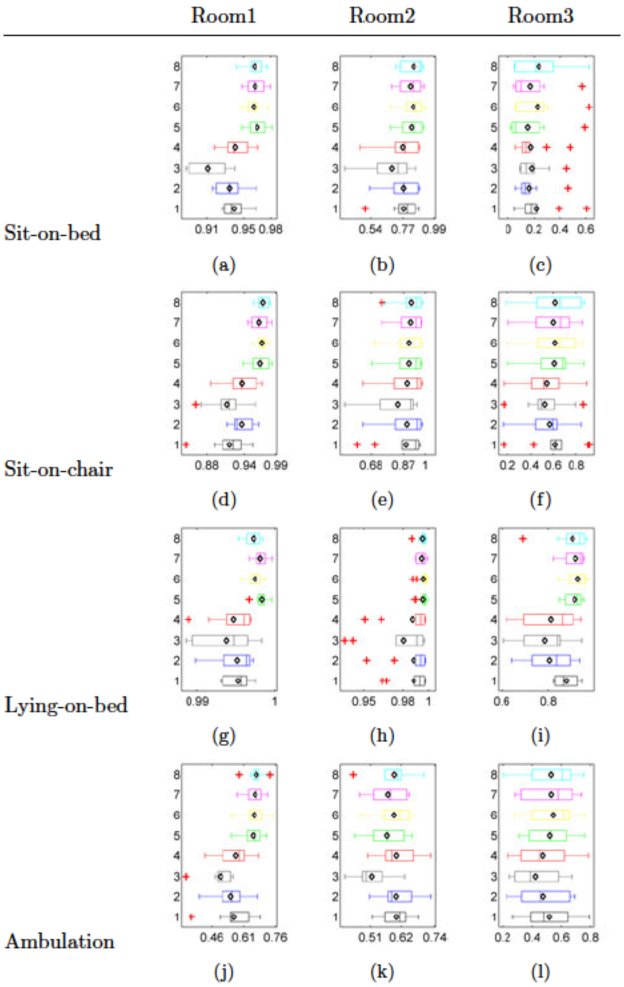

Fig. 5: F-score performance of all classes and datasets. Results are shown as boxplots (averages shown as diamonds). Classifiers tested are: 1: dWCRF, 2: CRF, 3: fWCRF, 4: C-CRF, 5: L-SVM, 6: R-SVM, 7: L-WSVM, 8: R-WSVM.

variation of our dWCRF with the best performing classifier, R-WSVM, is 4.6 % (85.4 % and 90 % respectively). For Room2, the maximum F-score variation is $\approx 8\,\%$ where the difference between our dWCRF (81.3 %) and best performing R-WSVM (83.8 %) is 2.5 %. In Room3, the maximum F-score variation is $\approx 10\,\%$, where the difference between dWCRF (55.7 %) and best performer R-SVM (57.8 %) is 2.1 %. Overall, dWCRF results are not statistically significantly different to those of all other algorithms with $p > 0.67$. Average F-score results are, in general, higher than those of other CRF-based methods and similar to those of SVM-based methods.

In terms of individual classes from the datasets corresponding to Case Study 1 and Case Study 2, we observe differing behaviours. For Room1, see Figure 5 (left column), the SVM classifiers achieve statistically significantly better results than those of dWCRF ($p \leq 0.015$). In particular, for the minority class (Ambulating), the difference in performance is $\approx 10\,\%$ in comparison to R-WSVM—see Figure 5(j). For the remaining classes the differences are $< 5\,\%$. In comparison to other CRF based algorithms, dWCRF has, in general, higher results in terms of mean F-score.

The results for Room2, shown in Figure 5 (middle column), indicate that all results are similar and no classifier is statistically significantly different from dWCRF ($p \geq 0.08$) except Ambulation where dWCRF is better than fWCRF with significance ($p = 0.003$). For the minority class Ambulation, dWCRF mean performance is higher by 3 % compared to both L-SVM classifiers and 0.5 % compared to R-SVM classifiers. This is important as dWCRF improves performance on Ambulation, the most imbalanced class as shown in Figure 3(a). Similarly to Room1, dWCRF, in general, outperformed the other CRF based classifiers ($p \geq 0.20$).

The results for individual classes in Room3, shown in Figure

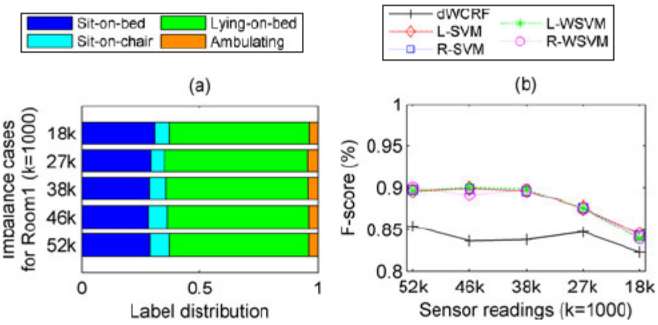

Fig. 6: (a): Class distribution for different dataset populations showing that classes distributions remain almost unchanged during testing. (b): Results from reducing the population of Room1 dataset to verify its effect on different classifier results.

5 (right column), indicates that, the only statistically significant differences correspond to majority class Lying-on-bed being where dWCRF is higher than fWCRF by 9 % and lower than R-SVM by 5 % ($p \approx 0.02$ for both). For minority classes there is no statistical significant difference between dWCRF and other classifiers ($p > 0.192$). In the case of minority class Ambulation, dWCRF, with F-score performance of 52.2 %, is higher than other CRF related methods and similar to SVM-based methods; and for minority class Sit-on-chair, dWCRF achieved the highest F-score performance (61.7 %).

These results indicate that dWCRF performs in general better than other CRF based methods, and in the cases of Room2 and Room3, dWCRF has a similar to better performance than SVM based methods.

Learning with scarce training data: In the previous results for Room1, see Figure 5 (left column), SVM-based methods performed better than dWCRF. A probable reason for the lower performance of dWCRF compared to SVM methods is that Room1 contains more than double the information than the other datasets—see Figure 3(a), providing more than enough support vectors to perform reliable classification. We confirm our proposition by experimenting with Room1 dataset by repeatedly reducing one sequence of activities (or trial) from each fold in order to affect each fold evenly. This process also does not affect the class distribution of the remaining population as illustrated in Figure 6(a). Given that in Case Study 1 and 2, the best performing classifiers were dWCRF and SVM based methods, in our experiment each reduced dataset is tested with the classifiers dWCRF, L-SVM, L-WSVM, R-SVM and R-WSVM. For simplicity of dWCRF calculations, we consider parameter $\tau = 1$. The overall performance, shown in Figure 6(b), indicates that the difference between classifier performances reduces as the dataset reduces.

The results in Figure 6 indicate that the performance of SVM based classifiers do not vary between each other; moreover, the performance declines after the 38k population marker. In contrast, dWCRF performance remains almost unchanged for all population markers. The performance difference between SVM classifiers and dWCRF also reduces; between 27k and 18k population markers, this difference is minimal, ≈ 4 % and 2 %, respectively. More importantly, the differences between classes are no longer statistically significant after the first reduction (46k) with $p \geq 0.41$.

We can see that sensor observation populations, for both Room2 and Room3, are within the population segment between 27k and 18k; and in these datasets, dWCRF results are shown to be similar or better than all other classifiers. Notably, dWCRF classifier performance is not significantly different than SVM based methods after reducing Room1 population levels to those of Room2 and Room3.

We also note that the Room3 dataset corresponds to a real world scenario with hospitalized patients in a hospital environment. Under these real world conditions, we gathered much fewer observations for Room3 than Room1 dataset, although having recruited 26 patients (more than the other two datasets) over a period of more than six months. In fact, under most practical situations, collecting and labelling data is difficult and cumbersome. Therefore the ability of our dWCRF classifier to learn from imbalanced data when available training data is scarce is a significant result.

Furthermore, dWCRF has an added advantage over other weighted methods in that dWCRF does not require a search for optimal weights during validation (see Section IV-D). This makes it a faster approach than using a grid search for optimizing the weights or using techniques such as CMA-ES, which requires multiple training initializations while providing no guarantee of achieving optimal results; and where the complexity of the optimization problem increases with the number of classes.

C. BPBW Dataset

The BPBW datasets, see Section III-C, were tested with best performing classifiers in Case Study 1 and 2. The results are shown in Figure 7. In general, no method is statistically significantly better than dWCRF with $p \geq 0.137$. Nonetheless, the average overall F-score for dWCRF is in general higher than all other methods, with exception of L-WSVM, which has a higher overall F-score in 5 of the 15 imbalanced dataset cases (DS3 and DS4 in Op1, DS3 in Op2, and DS3 and DS5 in Op3) with a maximum difference of 6.5 % in Op2.

In addition, the average F-score between datasets indicate that for all minority classes dWCRF achieves higher F-score than all other methods, except the Null class. Comparing with second best overall performing method of L-WSVM, dWCRF has better per-class average performance with F-score differences of 2 to 20 % for classes other than Null. These results validate the improved ability of our dWCRF method to learn from multiclass sequential data with high imbalance.

D. Empirical Comparison of Parameter Validation Time

We use the BLBW and BPBW datasets to compare training times (including parameter selection) of our proposed dWCRF and other well performing methods. From the BPBW datasets, we randomly select one dataset from each imbalance case: DS5 from Op1, DS3 from Op2 and DS3 from OP3.

The resulting times are shown in Figure 8, where time represents the total time taken for evaluating the range of validation parameters. In this case, we evaluate dWCRF with

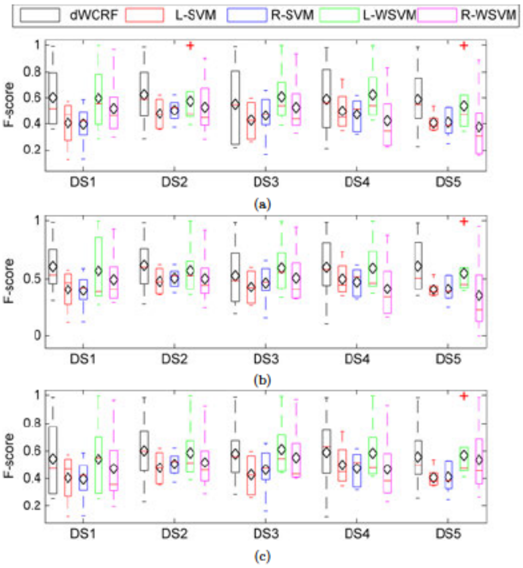

Fig. 7: Overall performance for five datasets, DS1…DS5, on imbalance case (a) Op1, (b) Op2, and (c) Op3.

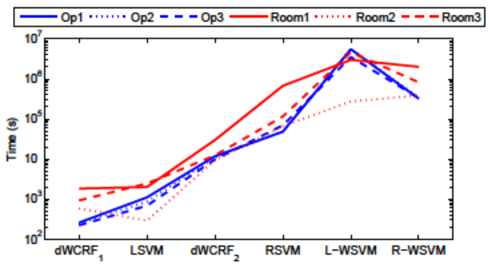

Fig. 8: Comparison of validation times for the tested methods (time axis is in logarithmic scale).

one parameter, regularization parameter θ in dWCRF$_1$, and two parameters, θ and τ in dWCRF$_2$, with cardinalities of 10 and 121 respectively. LSVM had one parameter to validate with a cardinality of 11. RSVM had two parameters to validate with a total combination cardinality of 121. L-WSVM and R-WSVM also included the times of the CMA-ES processes to validate the values of class specific weight parameters.

It is clear that, increasing or decreasing the number of CMA-ES operations has an impact on the total time; however, a large number of operations are necessary to obtain a closer to optimal result as a single CMA-ES operation does not guarantee an optimal solution. We can see in Figure 8 that the time to validate parameters in dWCRF is, in general, significantly lower than that of SVM methods, where in average validation time for dWCRF$_2$ was $0.37\,\%$ of the time used by L-WSVM; the only exception is Room2, where LSVM has a lower training time and performance than that of dWCRF$_1$. These results suggest the advantage of our method in terms of a significantly reduced time to learn a model for a multiclass classifier process with imbalanced data.

V. Conclusion

The present study has established that dWCRF, using a class-wise cost parameter in the objective function, improves the overall F-score performance when compared to other CRF based classifiers and performs similar to better than other SVM based classifiers in our tested datasets in conditions of high data imbalance. We tested our method with two datasets: i) batteryless body worn sensor used by healthy and hospitalized older people in the context of a falls prevention intervention related dataset where labeled data is scarce and imbalanced (BLBP); and ii) a laboratory environment dataset (BPBW) with increased imbalance.

This study also presents a method to obtain a class-wise weighted classifier for optimizing the expected overall F-score from imbalanced multiclass data. In contrast to previous approaches our method dynamically calculates class-wise cost parameters, i.e. requires no previous knowledge of the data to assign cost parameter weights or evaluate cost parameters in the validation stage. In addition, our method obtained F-score performance results comparable with or better than other state-of-the-art classifiers such as SVM based classifiers, but with a significant reduction in learning time. This is because weighted SVM methods have more than two parameters to optimize; thus require an exponential number of validation iterations in order to compare and obtain the best set of parameters.

Appendix A
BLBW Features

We use a fixed time sliding window of duration of 4 s (referred henceforth as segment) from which we extract instantaneous sensor data, contextual information from the segment and inter-segment information. We selected this window method and length as it is simple to deploy and performs as well as more complex windowing methods for feature extraction [35]. The three different types of features are:

Instantaneous Features: These features are strictly obtained from the last received observation corresponding to the current performed activity, shown in Table I, and the gender of the participant which is known. We consider the sine of the body tilting angle $\sin(\alpha)$ on the midsagittal plane towards the front or back of the participant from the vertical reference [4]. Angle α is approximated from current acceleration values $\alpha \approx \arctan\left(\frac{a_f}{a_v}\right)$. The value of RSSI is of interest as a reference of relative proximity to a surrounding antenna. We also consider the time difference (Δt) between sensor observations as in previous research [47]. Also included are the body rotation angles approximated from current acceleration readings: $yaw = \arctan(\frac{a_l}{a_f})$ and $roll = \arctan(\frac{a_l}{a_v})$.

Contextual Information Features: These are extracted from each segment, see Table II, and provide information of what is occurring during the segment duration, i.e. complementary information to the instantaneous features in the temporal vicinity of the last received sensor observation [48].

We include the basic contextual information of the number of events per antenna in the segment; we also include the identification of the antenna that registered the highest and lowest RSSI in the segment, which serve as a location

TABLE I: Instantaneous features.

Feature	Description
a_f	frontal acceleration
a_v	vertical acceleration
a_l	lateral acceleration
$\sin(\alpha)$	sine of body tilting angle
aID	receiving antenna identification
$RSSI$	received signal strength indicator
Δt	time difference with previous observation
yaw	trunk yaw angle
$roll$	trunk roll angle
sex	participant's gender

TABLE II: Contextual information features.

Feature	Description
$aSUM_{1..M}$	number of events per antenna
$a_{max}RSSI$	antenna collecting maximum received power
$a_{min}RSSI$	antenna collecting minimum received power
$Vdisp$	vertical displacement
$MI_{bed-chair}$	mutual information of bed and chair areas
$r_{[fv,fl,vl]}$	Pearson correlation coefficient for acceleration axes

TABLE III: Inter-segment features.

Feature	Description
$\Delta Max[a_f, a_v, a_l]$	Difference of acceleration maxima per axis
$\Delta Min[a_f, a_v, a_l]$	Difference of acceleration minima per axis
$\Delta Med[a_f, a_v, a_l]$	Difference of acceleration median per axis
$\Delta MaxRSSI_{1..M}$	Difference of power maxima per antenna
$\Delta MinRSSI_{1..M}$	Difference of power minima per antenna
$\Delta MedRSSI_{1..M}$	Difference of power median per antenna

marker as a participant is more likely to occupy an area near the antenna reporting a higher RSSI during the segment duration. Other feature is the vertical displacement measured from acceleration readings in the vertical axis (a_v) in the segment. The mutual Information between bed and chair areas considers the occurrences of consecutive observations from two antennas focused towards the chair and bed occurring in either directions as used in [35]. We also consider the Pearson correlation coefficient of all combinations of the three acceleration components of all observations in the segment.

Inter-Segment Features: These features, see Table III, aim to capture information trend variations from consecutive segments and are useful as these variations are insensitive to noise in unfiltered raw sensor data. We include the difference of the maxima, minima and median of the segments' acceleration readings in the three axes with respect to the participant: vertical, frontal and lateral axes. In addition, we are interested in the changes of RSSI, as an indicator of position shifting, given by the difference of the segments maxima, minima and median of the RSSI readings per antenna.

Appendix B
BPBW Features

These features were extracted from body worn sensors as determined in [28] and shown in Table IV.

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TABLE IV: OPR features.

Feature	Description
Δt	Time difference between readings
$Acbh_{[x,y,z]}$	On-body accelerometer (3 axes) on hip
$Acbb_{[x,y,z]}$	On-body accelerometer (3 axes) on back
$Acgb_{[x,y,z]}$	Garment accelerometer (3 axes) on back
$Gygb_{[x,y,z]}$	Garment gyroscope (3 axes) on back
$Mfgb_{[x,y,z]}$	Garment magnetic field sensor (3 axes) on back
$Qugb_{1-4}$	Garment quaternions (1-4) on back

References

[1] J. Andreu-Perez, D. R. Leff, H. M. D. Ip, and G. Z. Yang, "From wearable sensors to smart implants–toward pervasive and personalized healthcare," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 12, pp. 2750–2762, Dec 2015.

[2] Y. L. Zheng, X. R. Ding, C. C. Y. Poon, B. P. L. Lo, H. Zhang, X. L. Zhou, G. Z. Yang, N. Zhao, and Y. T. Zhang, "Unobtrusive sensing and wearable devices for health informatics," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 5, pp. 1538–1554, May 2014.

[3] M. Brodie, S. Lord, M. Coppens, J. Annegarn, and K. Delbaere, "Eight weeks remote monitoring using a freely worn device reveals unstable gait patterns in older fallers," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 11, pp. 2588–2594, 2015.

[4] B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C. Bula, and P. Robert, "Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 6, pp. 711–723, 2003.

[5] K. Rapp, C. Becker, I. D. Cameron, H. H. König, and G. Büchele, "Epidemiology of falls in residential aged care: analysis of more than 70,000 falls from residents of bavarian nursing homes," *Journal of the American Medical Directors Association*, vol. 13, no. 2, pp. 187.e1–187.e6, 2012.

[6] H. He and E. A. Garcia, "Learning from imbalanced data," *IEEE Trans. Knowl. Data Eng.*, vol. 21, no. 9, pp. 1263–1284, Sept 2009.

[7] S. Chernbumroong, S. Cang, A. Atkins, and H. Yu, "Elderly activities recognition and classification for applications in assisted living," *Expert Systems with Applications*, vol. 40, no. 5, pp. 1662–1674, 2013.

[8] J. D. Lafferty, A. McCallum, and F. C. N. Pereira, "Conditional random fields: Probabilistic models for segmenting and labeling sequence data," in *18th International Conference on Machine Learning*. USA: Morgan Kaufmann Publishers Inc., 2001, pp. 282–289.

[9] G. E. A. P. A. Batista, R. C. Prati, and M. C. Monard, "A study of the behavior of several methods for balancing machine learning training data," *SIGKDD Explorations Newsletter*, vol. 6, no. 1, pp. 20–29, 2004.

[10] M. A. Tahir, J. Kittler, and F. Yan, "Inverse random under sampling for class imbalance problem and its application to multi-label classification," *Pattern Recognition*, vol. 45, no. 10, pp. 3738–3750, 2012.

[11] B. Das, N. C. Krishnan, and D. J. Cook, "Handling imbalanced and overlapping classes in smart environments prompting dataset," in *Data Mining for Service*, ser. Studies in Big Data, K. Yada, Ed. Springer, 2014, vol. 3, pp. 199–219.

[12] J.-H. Xue and P. Hall, "Why does rebalancing class-unbalanced data improve auc for linear discriminant analysis?" *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 5, pp. 1109–1112, May 2015.

[13] M. A. Maloof, "Learning when data sets are imbalanced and when costs are unequal and unknown," in *ICML-2003 Workshop on Learning from Imbalanced Data Sets II*, vol. 2, 2003, pp. 2–1.

[14] P. Domingos, "Metacost: a general method for making classifiers cost-sensitive," in *Fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. USA: ACM, 1999, pp. 155–164.

[15] X.-Y. Liu and Z.-H. Zhou, "The influence of class imbalance on cost-sensitive learning: an empirical study," in *Sixth International Conference on Data Mining.*, Dec 2006, pp. 970–974.

[16] Z.-H. Zhou and X.-Y. Liu, "On multi-class cost-sensitive learning," *Computational Intelligence*, vol. 26, no. 3, pp. 232–257, 2010.

[17] S. Pang, L. Zhu, G. Chen, A. Sarrafzadeh, T. Ban, and D. Inoue, "Dynamic class imbalance learning for incremental LPSVM," *Neural Networks*, vol. 44, no. 0, pp. 87–100, 2013.

[18] J. Gama, "Iterative bayes," *Theoretical Computer Science*, vol. 292, no. 2, pp. 417–430, 2003.

[19] L. Jiang, C. Li, and S. Wang, "Cost-sensitive bayesian network classifiers," *Pattern Recognition Letters*, vol. 45, no. 0, pp. 211–216, 2014.

[20] Y.-M. Huang and S. xin Du, "Weighted support vector machine for classification with uneven training class sizes," in *International Conference on Machine Learning and Cybernetics.*, vol. 7, 2005, pp. 4365–4369.
[21] G. de Lannoy, D. Francois, J. Delbeke, and M. Verleysen, "Weighted conditional random fields for supervised interpatient heartbeat classification," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 1, pp. 241–247, 2012.
[22] P. Pletscher, C. S. Ong, and J. M. Buhmann, "Entropy and margin maximization for structured output learning," in *Machine Learning and Knowledge Discovery in Databases*, ser. Lecture Notes in Computer Science, J. L. Balcázar, F. Bonchi, A. Gionis, and M. Sebag, Eds. Springer, 2010, vol. 6323, pp. 83–98.
[23] N. V. Chawla, "Data mining for imbalanced datasets: An overview," in *Data Mining and Knowledge Discovery Handbook*, O. Maimon and L. Rokach, Eds. Springer, 2005, pp. 853–867.
[24] P. Soda, "A multi-objective optimisation approach for class imbalance learning," *Pattern Recognition*, vol. 44, no. 8, pp. 1801 – 1810, 2011.
[25] C. Beyan and R. Fisher, "Classifying imbalanced data sets using similarity based hierarchical decomposition," *Pattern Recognition*, vol. 48, no. 5, pp. 1653 – 1672, 2015.
[26] K. Gimpel and N. A. Smith, "Softmax-margin crfs: Training log-linear models with cost functions," in *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*. USA: Association for Computational Linguistics, 2010, pp. 733–736.
[27] G. Dimitroff, G. Georgiev, L. Toloşi, and B. Popov, "Efficient f measure maximization via weighted maximum likelihood," *Machine Learning*, vol. 98, no. 3, pp. 435–454, 2015.
[28] D. Roggen, A. Calatroni, M. Rossi, T. Holleczek, K. Förster, G. Tröster, P. Lukowicz, D. Bannach, G. Pirkl, A. Ferscha, J. Doppler, C. Holzmann, M. Kurz, G. Holl, R. Chavarriaga, H. Sagha, H. Bayati, M. Creatura, and J. d. R. Millán, "Collecting complex activity data sets in highly rich networked sensor environments," in *Seventh International Conference on Networked Sensing Systems*, 2010, pp. 233–240.
[29] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, "A public domain dataset for human activity recognition using smartphones." in *21th International European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning*, 2013, pp. 437–442.
[30] P. Casale, O. Pujol, and P. Radeva, "Personalization and user verification in wearable systems using biometric walking patterns," *Personal and Ubiquitous Computing*, vol. 16, no. 5, pp. 563–580, 2012.
[31] A. Stisen, H. Blunck, S. Bhattacharya, T. S. Prentow, M. B. Kjærgaard, A. Dey, T. Sonne, and M. M. Jensen, "Smart devices are different: Assessing and mitigating mobile sensing heterogeneities for activity recognition," in *13th ACM Conference on Embedded Networked Sensor Systems*. USA: ACM, 2015, pp. 127–140.
[32] C. Sutton and A. McCallum, "An introduction to conditional random fields for relational learning," in *Introduction to Statistical Relational Learning*, L. Getoor and B. Taskar, Eds. The MIT Press, 2006, pp. 93–127.
[33] M. Ehrgott, *Multicriteria Optimization*. USA: Springer, 2005.
[34] C. Sutton and A. McCallum, "An introduction to conditional random fields," *Foundations and Trends in Machine Learning*, vol. 4, no. 4, pp. 267–373, 2012.
[35] R. L. Shinmoto Torres, D. C. Ranasinghe, and Q. Shi, *Evaluation of Wearable Sensor Tag Data Segmentation Approaches for Real Time Activity Classification in Elderly*. Springer, 2014, pp. 384–395.
[36] R. Visvanathan, D. C. Ranasinghe, R. L. Shinmoto Torres, and K. Hill, "Framework for preventing falls in acute hospitals using passive sensor enabled radio frequency identification technology," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2012, pp. 5858–5862.
[37] T. Kaufmann, D. C. Ranasinghe, M. Zhou, and C. Fumeaux, "Wearable quarter-wave microstrip antenna for passive UHF RFID applications," *International Journal of Antennas and Propagation*, vol. 2013, 2013.
[38] A. P. Sample, D. J. Yeager, P. S. Powledge, A. V. Mamishev, and J. R. Smith, "Design of an rfid-based battery-free programmable sensing platform," *IEEE Trans. Instrum. Meas.*, vol. 57, no. 11, pp. 2608–2615, 2008.
[39] P. Topo, "Technology studies to meet the needs of people with dementia and their caregivers: A literature review," *Journal of Applied Gerontology*, vol. 28, no. 1, pp. 5–37, 2009.
[40] P. Nikitin, R. Martinez, S. Ramamurthy, H. Leland, G. Spiess, and K. V. S. Rao, "Phase based spatial identification of uhf rfid tags," in *2010 IEEE International Conference on RFID*, 2010, pp. 102–109.
[41] A. Godfrey, A. K. Bourke, G. M. Ólaighin, P. van de Ven, and J. Nelson, "Activity classification using a single chest mounted tri-axial accelerometer," *Medical Engineering & Physics*, vol. 33, no. 9, pp. 1127–1135, 2011.
[42] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995.
[43] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers," in *Fifth Annual Workshop on Computational Learning Theory*. USA: ACM, 1992, pp. 144–152.
[44] C.-C. Chang and C.-J. Lin, "LIBSVM: A library for support vector machines," *ACM Transactions on Intelligent Systems and Technology*, vol. 2, pp. 27:1–27:27, 2011, software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm.
[45] K. Gimpel and N. A. Smith, "Softmax-margin training for structured log-linear models," Carnegie Mellon University, Tech. Rep. CMU-LTI-10-008, 2010.
[46] N. Hansen, "The CMA evolution strategy: A comparing review," in *Towards a New Evolutionary Computation*, ser. Studies in Fuzziness and Soft Computing, J. A. Lozano, P. Larrañaga, I. Inza, and E. Bengoetxea, Eds. Springer, 2006, vol. 192, pp. 75–102.
[47] R. L. Shinmoto Torres, D. C. Ranasinghe, Q. Shi, and A. P. Sample, "Sensor enabled wearable rfid technology for mitigating the risk of falls near beds," in *Seventh IEEE International Conference on RFID*, 2013, pp. 191–198.
[48] N. C. Krishnan and D. J. Cook, "Activity recognition on streaming sensor data," *Pervasive and Mobile Computing*, vol. 10, pp. 138–154, 2014.

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Chapter 7

Recognition of Bed and Chair Exits in Real Time Using a Dynamically Weighted CRF Method

The previous chapter introduced a classification (dWCRF) method that considers the imbalance present in the data using class-wise weights that are autonomously calculated. Although result at the classifier were encouraging, we have not tested this approach in the recognition of more complex activities such as bed exits or chair exits.

The published article contained in this chapter presents a monitoring system to generate bed and chair exits alarms in real time from healthy older people. The participants use the W^2ISP on top of their clothes and were trialled in a clinical environment. This study presents a technological intervention that is based on the data collected from the wireless sensor and applies the classifier introduced in Chapter 6 (dWCRF) to improve performance in the presence of imbalanced data. This method also applies a score function to reduce false positives in the recognition of bed and chair exits when compared to our previous approaches.

R.L. Shinmoto Torres, R. Visvanathan, S. Hoskins, A. van den Hengel, and D.C. Ranasinghe. "Effectiveness of a batteryless and wireless wearable sensor system for identifying bed and chair exits in healthy older people", *Sensors*, vol. 16, no. 4, pp. 546, 2016.

sensors

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Article

Effectiveness of a Batteryless and Wireless Wearable Sensor System for Identifying Bed and Chair Exits in Healthy Older People

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Abstract: Aging populations are increasing worldwide and strategies to minimize the impact of falls on older people need to be examined. Falls in hospitals are common and current hospital technological implementations use localized sensors on beds and chairs to alert caregivers of unsupervised patient ambulations; however, such systems have high false alarm rates. We investigate the recognition of bed and chair exits in real-time using a wireless wearable sensor worn by healthy older volunteers. Fourteen healthy older participants joined in supervised trials. They wore a batteryless, lightweight and wireless sensor over their attire and performed a set of broadly scripted activities. We developed a movement monitoring approach for the recognition of bed and chair exits based on a machine learning activity predictor. We investigated the effectiveness of our approach in generating bed and chair exit alerts in two possible clinical deployments (Room 1 and Room 2). The system obtained recall results above 93% (Room 2) and 94% (Room 1) for bed and chair exits, respectively. Precision was >78% and 67%, respectively, while F-score was >84% and 77% for bed and chair exits, respectively. This system has potential for real-time monitoring but further research in the final target population of older people is necessary.

Keywords: fall prevention; bed exits; chair exits; weighted conditional random fields; older people

1. Introduction

Falls occur commonly in hospitals, especially in older people with dementia or delirium, where about 30% of falls result in some type of injury [1]. Falls in hospitals have been reported in the literature to occur inside the patient's rooms (84%) and during ambulation (19%) [1]. Moreover, the majority of falls occur around the bed and chair area [2,3]. Falls are costly as patients have a longer length of stay in hospital wards and other related expenses. The estimated cost of a fall related hospitalization in the United States of America is US$50 534 per person (inflation adjusted since 2006) [4]. Randomized controlled trials showcasing multiple component interventions have had limited success in the reduction of falls. The interventions used include patient assessments, exercise, medication or fixed bed or chair exit alarms where motions such as bed and chair exits trigger an alarm to provide caregivers an opportunity to provide assistance [5,6]. Moreover, there is no clear indication of which component contributed most to the reduction of falls.

Other clinical studies, such as that of Shorr *et al.* [7] and the recent study of Sahota *et al.* [8] focused on fall prevention using only the technological components of fixed bed and chair exit alarms. In these approaches, motions such as bed and chair exits trigger an alarm to provide caregivers an opportunity to provide assistance when such activities are being attempted without supervision. These studies reported no changes in falls after using pressure sensors. Although the performance of the sensors was not reported, a contributing factor for these results may be the high rate of false alarms leading to "alarm fatigue" in caregivers [7]. The study of Wong-Shee *et al.* [9] used similar bed and chair alarms achieving significant reduction of falls when compared to the pre-intervention period; however, there was no significant reduction of falls when compared to the post-intervention period. This study reported the number of alarms, producing as many false alarms as approximately 80% of true detected alarms. Additionally, other recent approaches such as the use of bed mats with multiple sensors [10] or side rails with pressure sensors [11] obtained high performance but were tested on young and middle-aged volunteers rather than on older participants. Moreover, it has been reported that the use of bed rails to prevent falls actually increases the risk of injury as it raises the height of a fall [12]. Multiple studies have also used video images for fall prevention; however, previous research has manifested privacy concerns with the use of cameras in older people's living environments [13].

The use of wearable sensors provide new opportunities for monitoring patients [14,15]. However, most studies are focused on the monitoring of activities or gait [16–19], or the assessment of falls risk [20,21], which evaluates the long term risk of the person by using a self-evaluation tool and targets mostly older people living independently. Researchers have investigated sensor units on the torso consisting of an accelerometer, in some cases in combination with other sensors such as gyroscopes, magnetometers and barometers. Nonetheless, these wearable units were bulky as they were battery operated and in some cases required the patient to be wired, which is not recommended for older people. Other wearable sensor based studies used more than one sensing device attached to the participant's body; for example, in [22], a participant wore wearable sensors (IMOTE2, (sensor node platform developed by Intel Research) and radio frequency identification (RFID) readers on both wrists and a third mote on the body, an approach that is uncomfortable for older people as they are heavily instrumented.

There is a lack of studies using wearable technology to prevent falls that are capable of notifying a caregiver [23]. A recent successful study by Wolf *et al.* [24] trialled a commercial sensor unit—Shimmer (Shimmer, Dublin, Ireland) equipped with a tri-axial accelerometer—With hospital patients for the detection of bed exits. Like previous studies, the sensing unit is expensive, relatively heavy, battery powered and needed to be strapped to the leg, which can be uncomfortable to some patients. In this study, we are interested in investigating a batteryless and lightweight wearable data collection platform that has the potential to be inconspicuous to the person wearing it, while also able to collect and transmit data from the user. Moreover, recent studies have demonstrated that older people have an interest in lightweight sensors that can be embedded in their clothes for monitoring [25], and that chest-located sensors [26] are better able to capture upper-body movements to effectively determine postures in older people [16,17].

The present work focuses on methods for the monitoring of activities in older people using a batteryless wearable sensor which is part of a larger technological intervention to prevent falls (see Figure 1). This study builds on previous research from our team for the detection of bed exits using wearable technology; in [27], we investigated the use of an empirical algorithm on a cohort of young people. In [28], we used a batteryless sensor enabled RFID device, called W^2ISP (Wearable Wireless Identification and Sensing Platform) [29,30], with a cohort of healthy older people where the W^2ISP was worn over their clothing for the collection of human motion information and was found to be acceptable and non-obstructive among the cohort of older people that took part in the trials. Unlike in [28], this study focuses on the recognition of both bed and chair exits and the real-time prediction of activities from streaming sensor data. This characteristic is important for clinicians [25] as a way for them to make instant assessments, prioritize supervision as well as provide a timely intervention to prevent a fall.

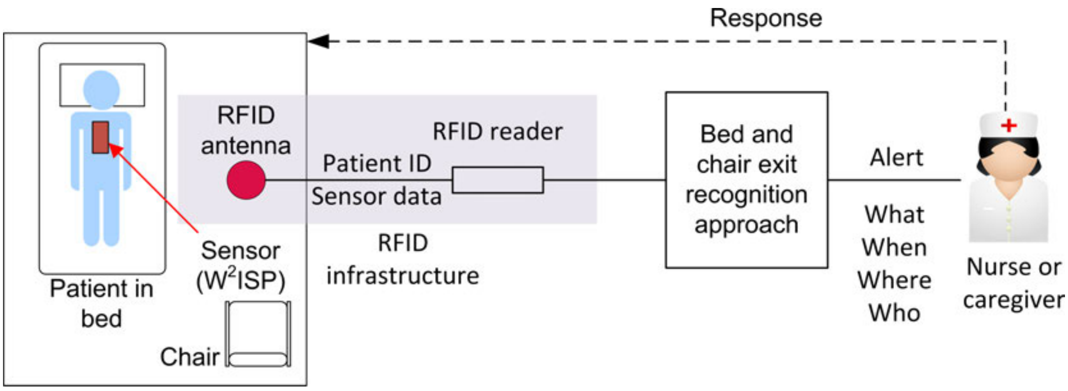


Figure 1. Overview of the proposed fall prevention technological intervention. Data collected by the radio frequency identification (RFID) infrastructure is sent in real-time to the bed and chair exit recognition approach stage. Caregivers can be notified via alert messages to assist the electronically identified patient (*who*) that is performing a bed or chair exit (*what*), the alert is issued in real-time (*when*) and the RFID antenna and reader identifiers can indicate the room occupied by the patient (*where*).

The main objective of the present study is to evaluate the performance of our batteryless sensor based bed and chair exit recognition approach for real-time identification of bed and chair exits. We investigate the application of our wearable device in a population of healthy older people using two different deployment options suitable for hospitals. The bed and chair exit recognition approach consists of: (i) a feature extraction stage; (ii) an activity prediction model built based on a statistical learning method called dynamically weighted conditional random fields (dWCRF) that learns class related weight parameters during training; and (iii) a bed and chair exit recognition algorithm. In order to support future research in the area of wearable sensors for human activity recognition in older populations, we have also made the data used in this study publicly available (http://autoidlab.cs.adelaide.edu.au/research/ahr).

The rest of the paper is organized as follows. Section 2 presents the concept of our technological intervention for fall prevention; Section 3 details our trial and data processing methods. Results and discussion are described in Section 4, and Section 5 presents our conclusions and future work.

2. Technological Intervention

This study is part of a proposed general deployment, shown in Figure 1, that is part of a larger and ongoing intervention strategy being researched for fall prevention for hospitalized older people [31]. Our approach is based on RFID, a technology used in various healthcare applications [32,33], where passive RFID tags—Batteryless, small and inexpensive devices—Can be easily replaced or disposed to prevent possible spread of infections. Moreover, RFID platforms are increasingly being deployed in hospitals, a current reality for monitoring the location of equipment, patients and personnel [34,35]; therefore, integration with an existing RFID infrastructure (*i.e.*, RFID antennas and readers) can result in ease of integration with existing systems and the reduction of operational costs.

In our proposed intervention, the participants, using a batteryless wearable sensor, have data corresponding to their movements and their identification being collected in real-time via the RFID infrastructure (see Figure 1). The data is received at the bed and chair exit recognition approach stage for processing and analysis (shown in detail in Figure 2); this stage issues an alert to caregivers to assist the identified patient after a bed or chair exit has been recognized.

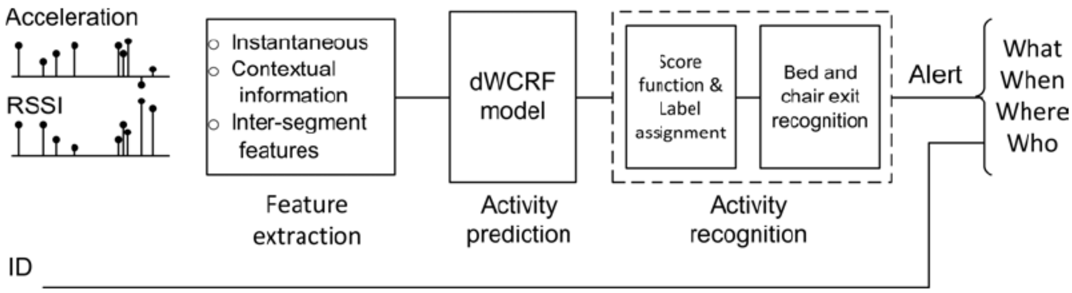


Figure 2. Proposed bed and chair exit recognition approach. Acceleration data from the sensor and additional information such as the received strength of the signal (RSSI) evaluated by the RFID reader are inputs to the recognition approach.

2.1. Sensor Technology

We used a flexible Wearable Wireless Identification and Sensing Platform (W^{2}ISP) device developed by our team, based on [29], suitable for wear over a garment anterior to the sternum as shown in Figure 3A [28]. The W^{2}ISP is a passive RFID tag that includes an accelerometer and a microcontroller unit. The 3-axis accelerometer (ADXL330) has a minimum full scale range of ± 3 g and low power requirement of 180 µA with a supply voltage of 1.8 V and typical output sensitivity of 300 mV/g. The microcontroller (MSP430F2132) is a 16-bit flash, ultra low power consumption unit that also includes a 10-bit, 200 kilo-samples-per-second Analog to Digital Converter (ADC). A block diagram of the W^{2}ISP platform displaying main components is shown in Figure 3C.

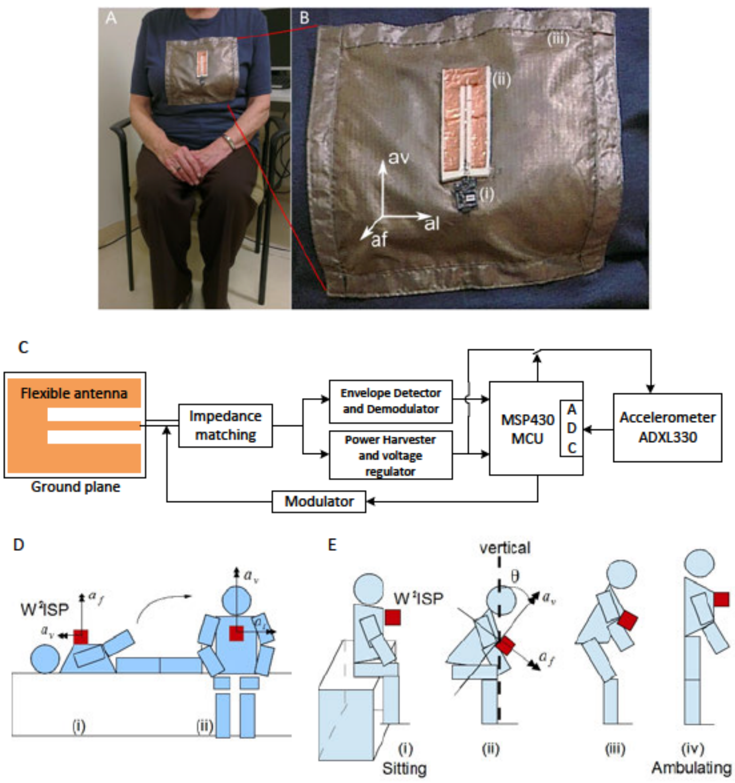


Figure 3. Wearable Wireless Identification and Sensing Platform (W^{2}ISP). **(A)** older volunteer wearing device on top of clothing; **(B)** W^{2}ISP parts: (i) circuitry, $18 \times 20 \times 2$ mm; (ii) flexible antenna, $36 \times 85 \times 2$ mm; and (iii) isolating silver coated fabric, 230×220 mm; **(C)** block diagram of W^{2}ISP platform; **(D)** process of lying on bed to sitting on bed; and **(E)** process of sitting (in bed or chair) to ambulating.

The W^2ISP includes a printed circuit board based RFID circuitry module and sensing unit with a flexible antenna (referred to as sensor hereafter) for patient comfort and a washable RIPSTOP silver coated nylon fabric to isolate device and human (Figure 3) [30]. The W^2ISP communicates with off-the-shelf UHF RFID readers and harvests its power using the electromagnetic (EM) field illuminating the tag from the RFID reader antennas. The RFID reader transmits interrogation signals to the passive tags using the 920–926 MHz ISM (industrial, scientific and medical) band under Australian electromagnetic compatibility regulations. The W^2ISP responds with its unique ID and sensor information by backscattering and modulating the incident RF signal from the reader [36]. The strength of the received backscattered signal captured by an RFID reader antenna and processed by a reader is called received signal strength indicator (RSSI); other information relative to the RF signal such as frequency channel is also collected.

2.2. Bed and Chair Exit Recognition Approach

The approach shown in Figure 2 consists of three main stages: (i) feature extraction; (ii) activity prediction; and (iii) activity recognition process. Feature extraction refers to obtaining essential information from the sensor data stream from which the activity predictor can accurately infer the likelihood of the performed activity; the set of predicted activities (classes) in this study are: (i) Sitting-on-bed; (ii) Sitting-on-chair; (iii) Lying; and (iv) Ambulating. The activity recognition process collects the output of the activity predictor, assigns an activity to each sensor observation using a score function and generates an alert using the activity recognition algorithm in the event a bed or chair exit is recognized. The use of a score function is important to reduce the number of misclassification errors as discussed in Section 3.2.3.

3. Methods

3.1. Data Collection

3.1.1. Study Participants

This study had ethics approval by the Human Research Ethics Committee of the Queen Elizabeth Hospital (protocol number 2011129). Fourteen volunteers participated in the study, they were 65 years and older with no cognitive impairment and able to mobilize independently. Participants were recruited from geriatric clinics or from lists of interested volunteers who had participated in other geriatric research studies. Request for participation was over the phone. Written informed consent was obtained and no honorarium was provided. During the trial, a researcher was present to instruct the participants the activities that needed to be performed from a script. The same researcher also annotated the activities in the sensor data capturing software built by the research team. Participants were informed of the activities contained in the script to ensure that they had no objections to any of the proposed activities but were not informed of the order before the trial start.

3.1.2. Clinical Setting and Procedure

The study was undertaken within two different clinic room configurations: (i) Room 1, with one antenna located on a high stand at ceiling level facing down to the bed, and three other antennas located on vertical stands facing front; and (ii) Room 2, with two antennas located on high stands at ceiling level facing towards the bed area and an antenna on a vertical stand facing the chair (Figure 4). These settings were designed to closely resemble two single room configurations common in a hospital environment (single bed and arm chair in the room). Each room configuration yielded a dataset. We refer to the corresponding data set obtained from each room as Room 1 dataset and Room 2 dataset.

Each participant was assigned to one room setting and randomly allocated to undertake approximately five trials using one of two broadly scripted lists of activities of daily living that included walking to the chair, sitting on the chair, getting off the chair, walking to bed, lying on bed, getting off the bed and walking to the door. Participants were instructed at the beginning of the trial to perform each activity at their own pace and as comfortably as possible; no other instruction was given as to how to perform each activity. In general, participants performed more in-bed activities, *i.e.*, sitting and lying in bed, than sitting on the chair, and, typically, the trials included twice as many lying on bed activities as sitting on chair activities. Consequently, the participants spent more time sitting or lying than ambulating. This is also reflective of hospitalized older people where rooms are small and furniture such as chairs and bed are in close proximity and where patients spend more time on the bed than on the chair. Participants were also instructed to request a trial termination if they were distressed or in discomfort. The duration of the trials per participant was between 90 to 120 min and was performed during the day between 10 am and 3 pm. A researcher annotated in real-time the activities being undertaken (ground truth), and this was later contrasted with activities as determined by the algorithm to measure the system performance.

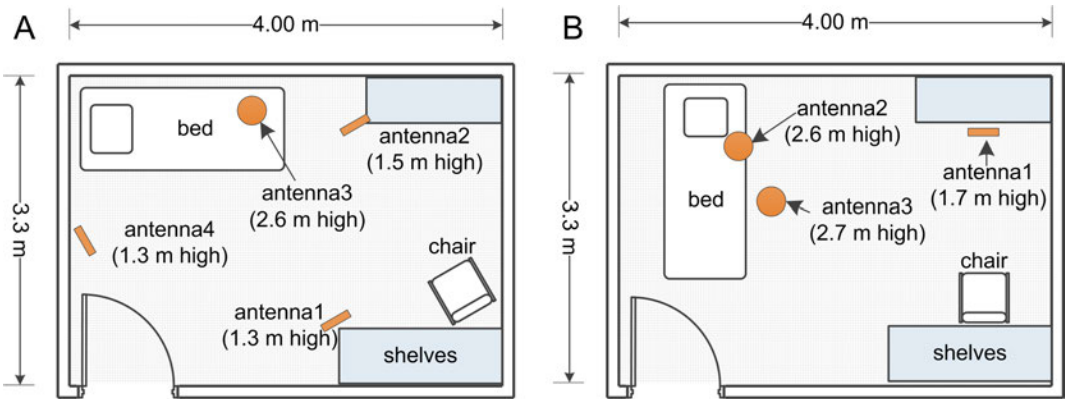


Figure 4. The two room configurations used in the study. Configuration of equipment with antennas on ceiling level shown as circles and vertical antennas shown as rectangles facing either the bed or chair. (**A**) Room 1, antenna3 is at ceiling level on top of the bed and the rest of the antennas are on a vertical stand. Antenna2 is inclined towards the chair and antenna1 and antenna4 face front (chest level) towards the bed area; and (**B**) Room 2, antenna2 and antenna3 are at ceiling level tilted towards the bed and antenna1 is on a vertical stand inclined towards the chair.

3.2. Data Processing

3.2.1. Feature Extraction

This stage extracts from the sensorial data the features that describe the underlying signal patterns of body motions as input to the activity prediction stage. We consider time domain features extracted from the W^2ISP readings such as: acceleration, time, phase, frequency channel and RSSI.

A challenging aspect of feature extraction is the formulation of features given noisy and irregular sensor observations. A limitation of RFID technology originates in the tag powering, as it depends on EM illumination from RFID antennas to collect and transfer data from the sensor. Hence, the effects of variable distance to antenna, destructive interference due to multipath, radio frequency band interference and occlusion by RF opaque objects such as the human body cause irregular, incomplete and noisy readings that are delivered to the bed and chair exit recognition approach shown in Figure 2. We can see in Figure 5 some of these effects as incomplete signals are collected from a study participant wearing the sensor where some readings are separated by several seconds, as is the case when the participant is sitting on the chair. This irregularity can cause the loss of sensor readings during posture transitions, e.g., getting out from bed, and can cause a person to have similar sensor readings before and after changing posture. For instance, a person with the sensor on the chest is first sitting on a chair and later stands up, or *vice versa*, these two postures can potentially have similar sensor readings as the person's body has similar chest orientation during both sitting on chair and standing.

We are interested in using acceleration data from the W^2ISP as they contain information about the performed movement. Common features in the literature consider the use of frequency-domain features (e.g., frequency components, energy and entropy) [37], which require regularly sampled data or interpolation methods that add post-processing stages to our method. Hence, we consider time-domain features from acceleration signals and additional sources of information from the received RF signal.

We are particularly interested in RSSI as an indicator of relative proximity to a reading antenna as low values can represent the participant being further from the reading antenna than higher RSSI values. This is because RSSI (1) is inversely proportional to the direct distance (d_o) from transmitting and receiving antennas [38], given by the equation:

$$\mathrm{RSSI} = \frac{KP_t G_t \lambda^4 |H|^4}{(4\pi d_o)^4} \quad (1)$$

where K is the tag backscatter gain, P_t is the output power of the reader, G_t is the gain of the monostatic reader antenna and H is the channel response to multipath [38]. Previous studies have established the importance and utility of RSSI based features. In [39], the combined use of RSSI with acceleration based features improved the classifier performance compared to using acceleration based features by themselves; this study [39] also demonstrated that the combination of features provided similar or better performance to using time and frequency domain features from acceleration readings alone. In [27], variations in RSSI data were useful to determine changes in postures that would otherwise be difficult to discriminate using only acceleration based data, e.g., a person sitting in the chair and standing has the participant's trunk to be upright in both postures. Other information such as RF phase measures the phase angle between the RF carrier (at a given frequency channel) transmitted by the RFID reader and the returned signal from the sensor [40]. Similar to RSSI measurements, phase changes are sensitive to variations in distance and motion of the sensor [40].

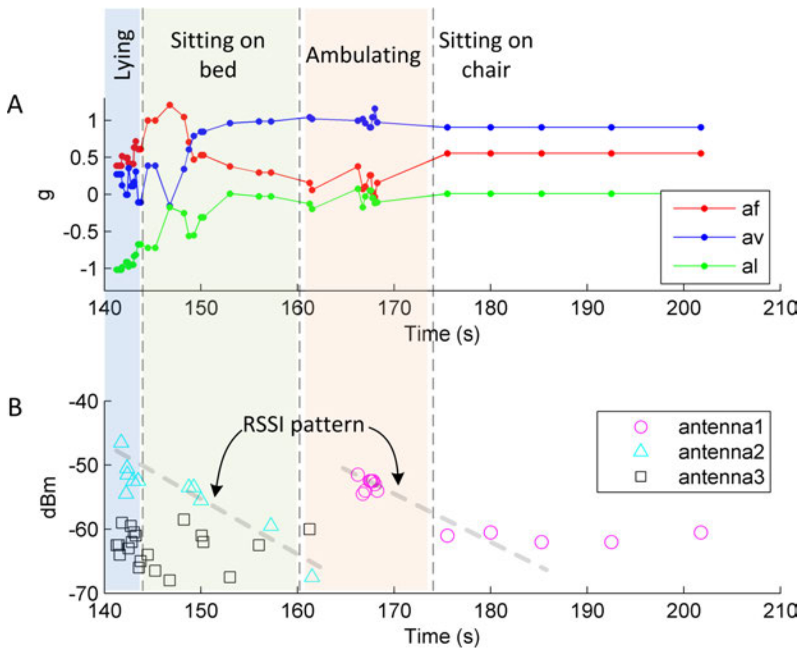


Figure 5. Sample of collected sensor data. (**A**) Raw accelerometer readings along the three axes; and (**B**) RSSI (received signal strength indicator) received from three antennas in the room and RSSI pattern changes across four activities.

Despite the irregular and noisy nature of RFID data, we can see in Figure 5A that the transfer of a person from lying to sitting on bed is evident in the acceleration readings and the RSSI patterns from the readings from antenna2 (see Figure 5B). In contrast, the transition from ambulating to sitting on chair cannot be clearly determined by using acceleration alone; however, the RSSI patterns for antenna1 can help discriminate this transition.

Therefore, we combine time domain information in RSSI, phase, frequency channel and acceleration sensor data and employ three categories of features based on studies in [16,28,39–41]; we describe them in detail below.

Instantaneous features:

These features are obtained from the current reported sensor observation and provide information about the action being performed as reported by the sensor and the participant information. However, no general information of what is occurring in the temporal vicinity is provided. Features included are:

- Accelerometer readings in the three axes: av, al and af shown in Figure 3B;
- Body tilting forwards and backwards given by $\sin(\theta) = \sin(\arctan(\frac{af}{av}))$, θ shown in Figure 3E [16,28];
- Rotational angle yaw $= \arctan(\frac{al}{af})$;
- Rotational angle roll $= \arctan(\frac{al}{av})$;
- ID of the antenna receiving the sensor data (aID) [28];
- Received power from the sensor (RSSI) [28];
- Time difference with the previous observation; and
- Gender of the person.

Contextual information features:

These features are obtained from a 4 s fixed time sliding window segment where the first element in the segment corresponds to the current sensor observation. This segmentation method was evaluated in Shinmoto Torres *et al.* [41] for extraction of contextual information returning good prediction performance and is easily implemented [41]. These features provide an insight into the temporal variations of the sensor information during the segment, hence covering the deficiencies of instantaneous features. The segment information is important as events distant in time (outside the segment) become less relevant to the current activity. Features included are:

- Importance of each antenna in collecting sensor observations given by the relative number of readings per antenna in the segment [41];
- Mutual information between bed and chair areas given by: $\frac{1}{n}\sum_{k=1}^{n-1} \mathbb{1}_{[\{aID_k,aID_{k+1}\}=\{chair,bed\}]} + \mathbb{1}_{[\{aID_k,aID_{k+1}\}=\{bed,chair\}]}$, where $\mathbb{1}_x$ is the indicator function and n the number of elements in the segment [41];
- IDs of antennas receiving maximum and minimum RSSI in segments;
- Displacement in the av axis (Figure 3B), given by: $\iint_{t1-4s}^{t1} av\, dt^2$;
- Mean† and standard deviation† of acceleration readings av, al and af;
- Mean† and standard deviation† of RSSI for all antennas;
- Pearson correlation between pairs of acceleration axes;
- Standard deviation† of variable frequency phase rate (VFPR) [40]; and
- Sum of modulus† of constant frequency phase rate (CFPR) [40].

Inter-segment features:

These features are obtained from the differences in information from consecutive segments. These features characterize the acceleration and received signal power variation trends over successive segments. These pattern variation trends provide information about motion and relative proximity to the area of interest, *i.e.*, bed or chair, that is not affected by noise. The inter-segment information trends are obtained using the features:

- Difference of median, maximum and minimum of acceleration readings av, al and af from consecutive segments; and
- Difference of median, maximum and minimum of RSSI per antenna from consecutive segments.

We also performed feature selection using the data from each room configuration, Room 1 and Room 2, before introducing the data to the Activity predictor stage. We selected simple classifiers such as random forests and probabilistic models such as Bayes network and logistic regression, eliminating low ranked features. Hence, the features above are used for both room configurations, except those of the form $f^{\dagger}$ which are used by Room 1 alone.

3.2.2. Activity Predictor

The activity prediction stage is based on the probabilistic modeling method of linear chain conditional random fields (CRF) [42], a structured classifier that models the dependencies of activities in a sequence, *i.e.*, takes into consideration the information from adjacent observations rather than considering each observation as independent of each other. Moreover, our data is class imbalanced because human activities, by nature, have some activities of longer duration than others e.g., lying on bed is of longer duration than ambulating in the room; another reason is the availability of sensor readings within those activities due to the use of passive devices, as shown in Figure 5.

A recent study from our group introduced dynamically weighted CRF (dWCRF), a method that improves classification performance in class imbalanced data when training information is limited [43]. The classifier introduces a class related weight parameter into the objective function to give a higher cost to errors in minority classes. Therefore, given a training sequence $\{x_t\}_{t=1}^{T}$ associated with a label sequence $\{y_t\}_{t=1}^{T}$, where $y_t \in \mathcal{Y} = \{1 \cdots K\}$; the weighted log-likelihood function has the form

$$\mathcal{L}(\lambda, w) = \sum_{t=1}^{T} w_t \log p(y_t|x_t, \lambda) \tag{2}$$

where λ are the model parameters, w_t are the dynamically calculated class related weight parameters that maximize the overall harmonic mean of recall and precision (F-score). Our dWCRF model evaluates in real-time the extracted features and produces marginal probabilities for each possible activity class. This approach, as opposed to our previous study in [28], takes into consideration the effects of class imbalance without adding complexity to the resulting model and is able to evaluate the occurrence of activities of interest in real-time. In our study, the dWCRF model was implemented based on the crfChain toolbox by Schmidt *et al.* [44]. Furthermore, obtaining an activity prediction model that maximizes recall and precision as opposed to accuracy is important because metrics based on the number of true negatives (*i.e.*, accuracy, specificity) do not give a fair metric in the case of imbalanced data, as true negatives for the minority class are the true positives of the other classes including the majority class, which usually dominates the prediction model.

In general, during activity prediction, a learned CRF model is used to classify complete series of observations described by their extracted features into a sequence of activities as in our previous study [28]. This approach cannot be used in our scenario where activity prediction is required in real-time as an alarm signal must be generated as soon as a bed or chair exit occurs. Therefore, we implemented a real-time activity prediction algorithm that produces the desired marginal probabilities for each class for each received observation by using the sum-product algorithm [45], and is described previously in [41]. The marginal probability inference has the form

$$m_k(y_{k,t}|x_t)\Big|_{k=1}^{K} = \frac{1}{Z_t}\left(\exp(F(y_t, x)) \sum_{y_{t-1}} \exp(F(y_{t-1}, y_t)) m_k(y_{k,t-1}|x_{t-1})\right) \tag{3}$$

Term $m(y_t|x_t)$ are the predicted marginal probabilities for all K possible values of y given the observed sensor data x_t, Z_t is a normalizing term and F is the potential function determined by feature functions from the data. In general, it is expected that inference of complete sequences will be more accurate than real-time inferencing; in the latter case, decisions are based on the current and past sensor observations, whereas, in a sequence, the inference process has disposition of past, current and future information about every observation in the sequence.

We consider that individual activity predictions (*i.e.*, activity with the highest marginal probability for each observation) are not of interest as raw noisy data is used and can induce single prediction errors resulting in emitting an unwanted alert to caregivers (Figure 1). Instead, in the activity recognition process, we use the marginal probabilities that represent the degree of confidence in each possible predicted activity for each sensor observation. Hence, marginal probabilities can be considered as normalized scores for each possible activity.

3.2.3. Bed and Chair Exit Recognition

In this stage, an alert signal is triggered on the occurrence of a recognized bed exit or chair exit as shown in Figure 6. To evaluate this occurrence, we propose a score function that first sums the normalized scores per activity over 1 s of data from the last processed observation (at time t') from the activity prediction stage. The assigned label $y_{t'}$ is given by the expression:

$$y_{t'} = \arg\max_{y_k} \sum_{t=t'-1\,\mathrm{s}}^{t'} m_k(y_{k,t}|X) \tag{4}$$

where m_k is the marginal probability from the activity predictor stage, $y_{k,t}$ are all possible labels at time t and X are the observed sensor readings. The goal of the score function is to assign an activity class that is dominant in the 1 s of data and as a consequence is less affected by activity prediction errors caused by noise. We used a period of 1 s as we want to consider enough data to recognize a posture transition, but not exceed the minimal posture transition duration of 1.75 s, as periods longer than this can overlap valid posture transitions [27]. The score function then selects the activity with the highest sum and assigns that activity to the last processed sensor observation. This scoring function implements a noise removal process, filtering those erroneous predicted activities with high marginal probabilities that could potentially produce false alarms if unfiltered. In addition, performed activities are mostly represented by multiple predictions from multiple sensor observations, hence single predicted activities that are dissimilar to those predicted readings close in time are likely to be erroneous and noise induced. We compare the effectiveness of using our score function in Section 4.

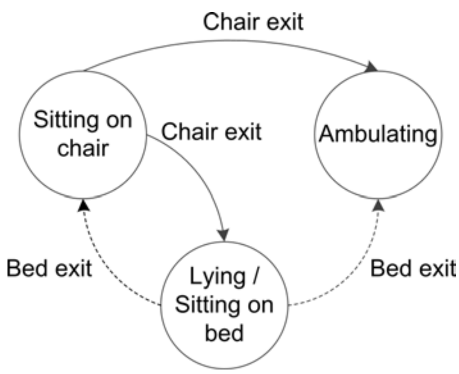


Figure 6. Bed and chair exit recognition. State machine transition model used to recognize a bed or chair exit.

The activity recognition process uses a simple finite state machine, as illustrated in Figure 6, and triggers an alert signal when either a bed or chair exit is identified in real-time by the activity recognition algorithm. Bed exit alerts are generated if an Ambulating or Sitting-on-chair predicted activity is preceded by either Lying or Sitting-on-bed. Similarly, Chair exit is identified if the previous predicted activity is Sitting-on-chair is followed by any other activity. We have included the recognition of bed exit when the participant transfers from bed to the chair and chair to bed for chair exit without ambulation, as it is possible to miss sensor observations while ambulating. After an alert is issued, we consider that it is physically impossible for an alert of the same type to occur in the next 1.75 s as this is the minimum time for a posture transition to take place; therefore we disregard any subsequent alert within the next 1.75 s period [27].

3.2.4. Statistical Analysis

In this study, true positives (TP) were correctly recognized bed or chair exit alerts when: (i) the alert occurs when the person is actually performing an activity of interest; or (ii) the real activity (ground truth) occurs no more than a time $T = 5$ s after the alert signal. False positives (FP) are recognized bed or chair exits that do not follow the TP criteria, *i.e.*, incorrectly identified as target activity. False negatives (FN) are bed and chair exits that were missed.

The performance of the system was evaluated using the metrics:

$$\text{recall (sensitivity)} = TP/(TP + FN) \tag{5}$$

$$\text{precision} = TP/(TP + FP) \tag{6}$$

$$\text{F-score} = (2 \times \text{recall} \times \text{precision}) \;/\; (\text{recall} + \text{precision}) \tag{7}$$

We focus on these metrics as they consider the occurrence of errors in relation to TP. Given that we are focused on evaluating the occurrence of alarming activities, we do not focus on true negative metrics.

Evaluation of these metrics was performed using a 10-fold cross validation procedure that divides the data of a given dataset (*i.e.*, Room 1 dataset or Room 2 dataset) into 10 subsets, where six of these subsets were used for training (learning the dWCRF model in Figure 2), two subsets (validation set) for parameter selection and two subsets for testing which reports the test results of the model selected. In our case, each subset contains data from more than one participant; hence, it is possible that different trials of the same person are distributed in the training, testing and validation subsets, and, therefore, our results are not participant independent. However, use of 10-fold cross validation does allow us to obtain results that are less sensitive to the partitioning of the data. Best parameters were selected from the validation set of returned F-scores. Results are presented as mean ± standard deviation (STD).

For comparison of results, we use a two-tailed independent t-test; a p-value of $p < 0.05$ is considered statistically significant.

4. Results and Discussion

Fourteen healthy participants (average age of 74.6 ± 4.9 years) and male to female ratio of 2:5 participated in the study. In general, when using the score function, our method achieved a consistently higher F-score performance for all activities as shown in Table 1, with dWCRF [43] parameters τ (number of iterations) and ϑ (L2 regularization parameter) of values $\tau = 8, \vartheta = 3.1 \times 10^{-4}$ for Room 1 and $\tau = 1, \vartheta = 3 \times 10^{-4}$ for Room 2. As expected, the score function improves the overall F-score and precision (reducing false positives) at the expense of decreasing recall. This is because some short duration activities can be under-represented in a window and erroneously assigned to a more dominant class label in the window. Although there is overall improvement in mean performance metrics when using the score function, the differences are not statistically significant with $p \geq 0.14$ for all metric comparisons; p-values not shown in Table 1.

These results show that room configuration Room 2 performs better for real-time bed exit recognition with statistical significance ($p \leq 0.001$) as it obtains higher recall, *i.e.*, low missed bed and chair exits, and precision, *i.e.*, low false alarms, while having a more practical deployment than Room 1. In contrast, Room 1 achieved, in general, higher mean performance metrics for chair exits although only recall results were statistically significant ($p < 0.001$). These results are important as they indicate that a smaller deployment as that of Room 2, with two antennas facing the bed, achieves better results recognizing bed exits than a larger deployment as that of Room 1, with three antennas facing the bed.

Table 1. Bed and chair exit recognition results for two room configurations. Comparison of recognition of bed and chair exits with and without the use of a score function. p-value corresponds to comparison between Room 1 and Room 2 using score function.

		Without Score Function		**Using Score Function**		
		Room 1 (%)	**Room 2 (%)**	**Room 1 (%)**	**Room 2 (%)**	**p-value (p)**
Bed Exit	Recall	67.07 ± 9.6	94.16 ± 8.1	64.24 ± 8.9	93.45 ± 9.8	<0.001
	Precision	48.96 ± 9.9	72.07 ± 14.4	57.24 ± 11.0	78.83 ± 13.9	0.001
	F-score	55.98 ± 8.2	80.50 ± 8.7	$\mathbf{59.77 \pm 7.7}$	$\mathbf{84.4 \pm 7.9}$	<0.001
Chair Exit	Recall	95.98 ± 7.0	61.75 ± 22.5	94.87 ± 7.2	60.50 ± 21.2	<0.001
	Precision	61.05 ± 17.7	67.92 ± 27.4	67.02 ± 16.6	70.74 ± 22.6	0.68
	F-score	73.35 ± 14.5	63.03 ± 22.1	$\mathbf{77.64 \pm 13.4}$	$\mathbf{63.78 \pm 18.7}$	0.07

We also present the results of our previous method in [28] where we evaluated a machine learning approach, specifically CRF, in contrast to the empirical approach in [27] to detect bed transfers. In [28], we only considered detection of bed exits, sequence prediction and a reduced number of classes and features. For this comparison, we detect chair exits and bed exits as illustrated in Figure 6, and we use the features, class labels and real-time inference algorithm used for this study. The results shown in Table 2, with CRF parameter $\vartheta = 0.1$ for both Room 1 and Room 2, indicate that our method achieves higher performance than the method in [28] for bed and chair exits in Room 2 and bed exits for Room 1; however, our method has a lower performance for chair exits in Room 1. Differences between F-scores are not statistically significant for all cases ($p > 0.13$) except for bed exits for Room 2 ($p = 0.047$), where our method significantly outperforms that of [28].

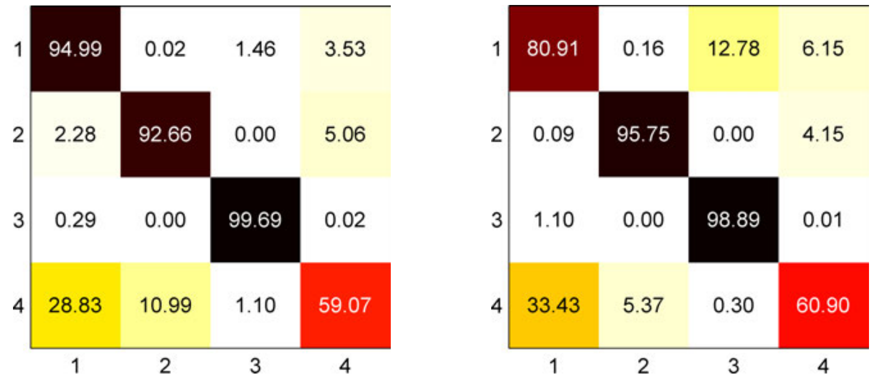
A fair comparison of our results with other studies is difficult as environmental settings and cohorts of people participating are not the same. In an earlier study, Capezuti *et al.* [46] used pressure sensors on beds to detect bed exits in nursing home residents; the tested system achieved recall metric of 71% and a low specificity of 0.3% [46]. This high false alarm rate might be one reason why pressure sensors have been found to be ineffective in recent clinical trials [7,8]. Other studies in the literature that focused on bed exits have reported recall and specificity values over 90%, but these studies were undertaken with young and middle aged adults which is a significant limitation [10,11].

Table 2. Bed and chair exit recognition using previous method in [28].

		Room 1 (%)	**Room 2 (%)**
Bed Exit	Recall	72.64 ± 8.90	91.91 ± 9.70
	Precision	43.22 ± 8.70	66.93 ± 13.10
	F-score	53.96 ± 5.84	76.40 ± 8.80
Chair Exit	Recall	96.98 ± 4.90	61.75 ± 22.50
	Precision	71.13 ± 21.80	63.99 ± 30.10
	F-score	80.51 ± 16.14	60.55 ± 24.30

There are various causes that affect the performance of the system given in Table 1 in both Room 1 and Room 2. Firstly, class imbalance due to the heterogeneous duration of activities, such as lying on bed and ambulating and the passive nature of our sensor affect the learned model of the classifier. Although we use a classifier that considers the effects of imbalance (dWCRF), the classifier is unable to completely discriminate minority class labels (especially Ambulating) as evidenced in the confusion matrix shown in Figure 7. Here, only about 60% of Ambulating sensor observations are correctly predicted. This problem resulted in the Ambulating class being incorrectly identified in approximately

30% and 5%–10% of cases as Sitting-on-bed, and Sitting-on-chair, respectively, see Figure 7. In both room configurations, Ambulating class is about 3.7% and 1.5% of total labels in Room 1 and Room 2, respectively, and correctly predicting these sensor readings as Ambulating is important to determine a bed or chair exit event as illustrated in Figure 6.



(a) Room 1. **(b)** Room 2.

Figure 7. Confusion matrix for data of (**a**) Room 1 and (**b**) Room 2. Output of dynamically weighted conditional random field (dWCRF) classifier for labels 1: Sitting-on-bed, 2: Sitting-on-chair, 3: Lying and 4: Ambulating. Results in %.

Secondly, the inadequate powering of the W^{2}ISP and the random access nature of the air interface protocol EPC Class 1 Gen 2 [47] used by the RFID technology produces a variable number of readings per second [48], as evidenced in Figure 5. Inadequate powering maybe caused by incident RF power variations due to the sensor being occluded from the RFID reader antenna by the human body in different postures. Moreover, in [28], we demonstrated that placing the W^{2}ISP at different distances and angles from the reader antenna affected the time required for the sensor to transmit data as a result of the variable levels of incident RF energy on the W^{2}ISP. These causes aggravate the imbalance problem and also result in missing some posture transitions (sit-to-stand or stand-to-sit) or transitions being unobserved. Hence, the classifier has to discriminate between a person sitting and ambulating, where the trunk of the person is upright in both postures, and the failure of the current features to totally disassociate both postures lead to misclassifications. This is evident in the confusion matrix (Figure 7), where 3%–6% of readings for classes Sitting-on-chair and Sitting-on-bed were predicted as Ambulating. These errors caused false alerts (false positives) in Room 1, producing low precision (<60%) in bed and chair exit recognition. Room 2 is also affected, particularly the low performance of chair exits where classes Sitting-on-chair and Ambulating have the lowest amount of readings in the dataset (2.3% and 1.5% of the data, respectively).

Thirdly, at the end of some trials where the participant was required to exit the chair or bed and exit the room in Room 1, the participant exits the bed occluding the sensor with his body during the posture transition. In such occurrences, while walking a short distance towards the door, antenna1 and antenna4 facing the bed, fail to adequately energize the W^{2}ISP and capture sensor readings. This caused misses (false negatives) for both chair and bed exits.

We also analyze the bed and chair exit recognition delays to understand the effects of using a passive sensor and our activity recognition method. The results in Table 3 show the average and median delay for recognized bed and chair exit events in relation to the ground truth data for both room settings. We can see that for both rooms the average delay is smaller than 3.3 s. We can also see that the average delays for bed exits are larger than those for chair exits. These longer delays are due to a lack of readings between the participant starting to ambulate after exiting the bed and sitting on the chair as the participant wearing the sensor is facing away from the RFID antennas. However, in general, the delay is low (median $\leq$ 1.25 s), especially for chair exits for Room 2 with median = 0. Absence of a delay, *i.e.*, delay $= 0$ s, is possible when the last observation in the score function, corresponding to the first observation out of the chair, correctly determines an actual chair exit.

Table 3. Delay in recognition of bed and chair exit. Time in seconds.

		Room 1	**Room 2**
Bed Exit	Mean$\pm$STD	2.63 ± 4.08 s	3.22 ± 6.05 s
	Median	1.20 s	1.25 s
Chair Exit	Mean$\pm$STD	1.93 ± 2.55 s	2.15 ± 1.56 s
	Median	1.13 s	0.00 s

5. Conclusions

This technological development study for real-time activity monitoring to recognize bed and chair exits that incorporates a single RFID sensor worn by healthy older participants suggests promising preliminary results. In particular, Room 2 antenna positioning demonstrated that a smaller deployment designed to illuminate specific areas of interest can obtain significantly higher F-score (84%) for bed exits compared to that of Room 1 (59%), albeit a lower F-score (63%) for chair exits, although statistically not significantly different from that of Room 1 (77%). This is important in a practical context, as a reduction of antennas suggests a decrease of deployment cost for improved performance in bed exit recognition. This is because most of the cost corresponds to RFID infrastructure as RFID tags are inexpensive and maintenance free. Although RFID infrastructure costs can be relatively high compared to the cost of a sensor, it is important to note that RFID infrastructure is increasingly deployed in hospitals for applications such as patient and equipment tracking [34,35] and our proposed approach can easily leverage upon such existing infrastructure.

We have improved upon our previous study in [28] by enhancing the set of extracted features using a dynamically weighted classifier that considers class imbalance and produces real-time predictions of both bed exits and chair exits. The results of this initial study with older people to determine bed and chair exits in real-time are important due to the lack of methods in the literature that use wearable batteryless sensors for fall prevention on older people. In addition, the results are important, as they investigate the use of batteryless body worn sensors for activity recognition, especially with a cohort of older people.

Our study is not short of limitations, and thus further research must consider various areas of development for improvement. A system limitation, as evidenced in previous discussion, is the antennas' positioning as it affects the collection of sensor observations. The lower chair exit performance for Room 2 indicates that further study is needed to secure better performance from chair exit events by improving antenna positioning strategies. Future studies should also consider placing the sensor on the shoulder to reduce occlusions from ceiling mounted antennas and evaluate its performance. Such an arrangement can potentially increase the data collected when the participant is sitting and ambulating, and thus contribute to increasing the performance of our approach as well as reducing delays to detect bed and chair exits.

Another area for future work is the development of inconspicuous sensors that are textile integrated, and smaller in size without losing performance [49]. In this direction, our group is using washable conductive textile material (RIPSTOP silver fabric) [50,51] to build the antenna of the sensor. Future work in the area of machine learning methods must investigate additional sources of information to extract robust features to help discriminate similar postures. Moreover, the short duration of the trials in this study may not represent the duration of a complete day at a hospital. Therefore, long term trials, including both day and night times, must be considered with a larger sample of hospitalized older participants to validate our approach and evaluate the acceptability of the device after wearing the sensor for long periods of time.

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References

1. Hitcho, E.B.; Krauss, M.J.; Birge, S.; Claiborne Dunagan, W.; Fischer, I.; Johnson, S.; Nast, P.A.; Costantinou, E.; Fraser, V.J. Characteristics and circumstances of falls in a hospital setting. *J. Gen. Intern. Med.* **2004**, *19*, 732–739.
2. Vassallo, M.; Amersey, R.A.; Sharma, J.C.; Allen, S.C. Falls on integrated medical wards. *Gerontology* **2000**, *46*, 158–162.
3. Oliver, D.; Hopper, A.; Seed, P. Do hospital fall prevention programs work? A systematic review. *J. Am. Geriatr. Soc.* **2000**, *48*, 1679–1689.
4. Heinrich, S.; Rapp, K.; Rissmann, U.; Becker, C.; König, H.H. Cost of falls in old age: A systematic review. *Osteoporos. Int.* **2010**, *21*, 891–902.
5. Goodwin, V.; Abbott, R.; Whear, R.; Bethel, A.; Ukoumunne, O.; Thompson-Coon, J.; Stein, K. Multiple component interventions for preventing falls and fall-related injuries among older people: Systematic review and meta-analysis. *BMC Geriatr.* **2014**, *14*, doi:10.1186/1471-2318-14-15.
6. Cameron, I.D.; Gillespie, L.D.; Robertson, M.C.; Murray, G.R.; Hill, K.D.; Cumming, R.G.; Kerse, N. Interventions for preventing falls in older people in care facilities and hospitals. *Cochrane Database Syst. Rev.* **2012**, *12*, doi:10.1002/14651858.CD005465.pub3.
7. Shorr, R.I.; Chandler, A.M.; Mion, L.C.; Waters, T.M.; Liu, M.; Daniels, M.J.; Kessler, L.A.; Miller, S.T. Effects of an intervention to increase bed alarm use to prevent falls in hospitalized patients: A cluster randomized trial. *Ann. Intern. Med.* **2012**, *157*, 692–699.
8. Sahota, O.; Drummond, A.; Kendrick, D.; Grainge, M.J.; Vass, C.; Sach, T.; Gladman, J.; Avis, M. REFINE (REducing Falls in In-patieNt Elderly) using bed and bedside chair pressure sensors linked to radio-pagers in acute hospital care: A randomised controlled trial. *Age Ageing* **2014**, *43*, 247–253.
9. Wong Shee, A.; Phillips, B.; Hill, K.; Dodd, K. Feasibility, Acceptability, and Effectiveness of an Electronic Sensor Bed/Chair Alarm in Reducing Falls in Patients With Cognitive Impairment in a Subacute Ward. *J. Nurs. Care Qual.* **2014**, *29*, 253–262.
10. Bruyneel, M.; Libert, W.; Ninane, V. Detection of bed-exit events using a new wireless bed monitoring assistance. *Int. J. Med. Inform.* **2011**, *80*, 127–132.
11. Hilbe, J.; Schulc, E.; Linder, B.; Them, C. Development and alarm threshold evaluation of a side rail integrated sensor technology for the prevention of falls. *Int. J. Med. Inform.* **2010**, *79*, 173–180.
12. Healey, F.; Monro, A.; Cockram, A.; Adams, V.; Heseltine, D. Using targeted risk factor reduction to prevent falls in older in-patients: A randomised controlled trial. *Age Ageing* **2004**, *33*, 390–395.
13. Demiris, G.; Hensel, B.K.; Skubic, M.; Rantz, M. Senior residents' perceived need of and preferences for "smart home" sensor technologies. *Int. J. Technol. Assess. Health Care* **2008**, *24*, 120–124.
14. Pantelopoulos, A.; Bourbakis, N.G. A survey on wearable sensor-based systems for health monitoring and prognosis. *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* **2010**, *40*, 1–12.
15. Lara, O.D.; Labrador, M.A. A survey on human activity recognition using wearable sensors. *IEEE Commun. Surv. Tutor.* **2013**, *15*, 1192–1209.
16. Najafi, B.; Aminian, K.; Paraschiv-Ionescu, A.; Loew, F.; Bula, C.J.; Robert, P. Ambulatory system for human motion analysis using a kinematic sensor: Monitoring of daily physical activity in the elderly. *IEEE Trans. Biomed. Eng.* **2003**, *50*, 711–723.
17. Godfrey, A.; Bourke, A.K.; Ólaighin, G.M.; van de Ven, P.; Nelson, J. Activity classification using a single chest mounted tri-axial accelerometer. *Med. Eng. Phys.* **2011**, *33*, 1127–1135.

18. Rodríguez-Martín, D.; Pérez-López, C.; Samà, A.; Cabestany, J.; Català, A. A wearable inertial measurement unit for long-term monitoring in the dependency care area. *Sensors* **2013**, *13*, 14079–14104.
19. Brodie, M.A.; Lord, S.R.; Coppens, M.J.; Annegarn, J.; Delbaere, K. Eight weeks remote monitoring using a freely worn device reveals unstable gait patterns in older fallers. *IEEE Trans. Biomed. Eng.* **2015**, *62*, 2588–2594.
20. Narayanan, M.R.; Redmond, S.J.; Scalzi, M.E.; Lord, S.R.; Celler, B.G.; Lovell, N.H. Longitudinal falls-risk estimation using triaxial accelerometry. *IEEE Trans. Biomed. Eng.* **2010**, *57*, 534–541.
21. Schwenk, M.; Hauer, K.; Zieschang, T.; Englert, S.; Mohler, J.; Najafi, B. Sensor-derived physical activity parameters can predict future falls in people with dementia. *Gerontology* **2014**, *60*, 483–492.
22. Wang, L.; Gu, T.; Tao, X.; Lu, J. A hierarchical approach to real-time activity recognition in body sensor networks. *Pervasive Mob. Comput.* **2012**, *8*, 115–130.
23. Delahoz, Y.S.; Labrador, M.A. Survey on fall detection and fall prevention using wearable and external sensors. *Sensors* **2014**, *14*, 19806–19842.
24. Wolf, K.H.; Hetzer, K.; zu Schwabedissen, H.M.; Wiese, B.; Marschollek, M. Development and pilot study of a bed-exit alarm based on a body-worn accelerometer. *Z. Gerontol. Geriatr.* **2013**, *46*, 727–733.
25. Bergmann, J.H.M.; McGregor, A.H. Body-worn sensor design: What do patients and clinicians want? *Ann. Biomed. Eng.* **2011**, *39*, 2299–2312.
26. Yang, C.C.; Hsu, Y.L. A review of accelerometry-based wearable motion detectors for physical activity monitoring. *Sensors* **2010**, *10*, 7772–7788.
27. Ranasinghe, D.C.; Shinmoto Torres, R.L.; Hill, K.; Visvanathan, R. Low cost and batteryless sensor-enabled radio frequency identification tag based approaches to identify patient bed entry and exit posture transitions. *Gait Posture* **2014**, *39*, 118–123.
28. Shinmoto Torres, R.L.; Ranasinghe, D.C.; Shi, Q.; Sample, A.P. Sensor enabled wearable RFID technology for mitigating the risk of falls near beds. In Proceedings of the 7th IEEE International Conference on RFID, Orlando, FL, USA, 30 April–2 May 2013; pp. 191–198.
29. Sample, A.P.; Yeager, D.J.; Powledge, P.S.; Smith, J.R. Design of a passively-powered, programmable sensing platform for UHF RFID systems. In Proceedings of the IEEE International Conference on RFID, Grapevine, TX, USA, 26–28 March 2007; pp. 149–156.
30. Kaufmann, T.; Ranasinghe, D.C.; Zhou, M.; Fumeaux, C. Wearable quarter-wave microstrip antenna for passive UHF RFID applications. *Int. J. Antennas Propag.* **2013**, *2013*, doi:10.1155/2013/129839.
31. Visvanathan, R.; Ranasinghe, D.C.; Shinmoto Torres, R.L.; Hill, K. Framework for preventing falls in acute hospitals using passive sensor enabled radio frequency identification technology. In Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), San Diego, CA, USA, 28 August–1 September 2012; pp. 5858–5862.
32. Alemdar, H.; Ersoy, C. Wireless sensor networks for healthcare: A survey. *Comput. Netw.* **2010**, *54*, 2688–2710.
33. Finkenzeller, K. *RFID Handbook: Fundamentals and Applications in Contactless Smart Cards, Radio Frequency Identification and Near-Field Communication*; Wiley: West Sussex, UK, 2010.
34. Swedberg, C. Group Health Reinvents Patient Care with RTLS. Available online: http://www.webcitation.org/6O7ywg1ps (accessed on 17 March 2014).
35. Fry, E.A.; Lenert, L.A. MASCAL: RFID tracking of patients, staff and equipment to enhance hospital response to mass casualty events. In *AMIA Annual Symposium Proceedings*; American Medical Informatics Association: Bethesda, MD, USA, 2005; Volume 2005, pp. 261–265.
36. Su, Y.; Wickramasinghe, A.; Ranasinghe, D.C. Investigating Sensor Data Retrieval Schemes for Multi-Sensor Passive RFID Tags. In Proceedings of the IEEE International Conference on RFID, San Diego, CA, USA, 15–17 April 2015; pp. 158–165.
37. Bao, L.; Intille, S.S. Activity Recognition from User-Annotated Acceleration Data. In *Pervasive Computing*; Ferscha, A., Mattern, F., Eds.; Springer: Berlin, Germany, 2004; Volume 3001, pp. 1–17.
38. Nikitin, P.V.; Martinez, R.; Ramamurthy, S.; Leland, H.; Spiess, G.; Rao, K.V.S. Phase based spatial identification of UHF RFID tags. In Proceedings of the IEEE International Conference on RFID, Orlando, FL, USA, 14–16 April 2010; pp. 102–109.
39. Wickramasinghe, A.; Ranasinghe, D.C. Recognising activities in real-time using body worn passive sensors with sparse data streams: To interpolate or not to interpolate? In Proceedings of the 12th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MOBIQUITOUS), Portugal, Coimbra, 22–24 July 2015.

40. Li, H.; Ye, C.; Sample, A.P. IDSense: A human object interaction detection system based on passive UHF RFID. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Seoul, Korea, 18–23 April 2015; pp. 2555–2564.
41. Shinmoto Torres, R.L.; Ranasinghe, D.C.; Shi, Q. Evaluation of wearable sensor tag data segmentation approaches for real-time activity classification in elderly. In *Mobile and Ubiquitous Systems: Computing, Networking, and Services*; Stojmenovic, I., Cheng, Z., Guo, S., Eds.; Springer International Publishing: Berlin/Heidelberg, Germany, 2014; Volume 131, pp. 384–395.
42. Lafferty, J.D.; McCallum, A.; Pereira, F.C.N. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In Proceedings of the 18th International Conference on Machine Learning; Morgan Kaufmann Publishers Inc.: San Francisco, CA, USA, 2001; pp. 282–289.
43. Shinmoto Torres, R.L.; Ranasinghe, D.C.; Shi, Q.; van den Hengel, A. Learning from Imbalanced Multiclass Sequential Data Streams Using Dynamically Weighted Conditional Random Fields. Available online: http://xxx.lanl.gov/abs/arXiv:1603.03627 (accessed on 11 March 2016).
44. Schmidt, M.; Swersky, K. crfChain, 2008. Available online: http://www.webcitation.org/6O9mlPgo4 (accessed on 18 March 2014).
45. Yedidia, J.S.; Freeman, W.T.; Weiss, Y. Understanding belief propagation and its generalizations. In *Exploring Artificial Intelligence in the New Millennium*; Lakemeyer, G., Nebel, B., Eds.; Morgan Kaufmann Publishers: Amsterdam, Netherlands, 2003; pp. 239–236.
46. Capezuti, E.; Brush, B.L.; Lane, S.; Rabinowitz, H.U.; Secic, M. Bed-exit alarm effectiveness. *Arch. Gerontol. Geriatr.* **2009**, *49*, 27–31.
47. International Organization for Standardization. ISO/IEC 18000-6:2013—Information technology—Radio Frequency Identification for Item Management—Part 6: Parameters for Air Interface Communications at 860 MHz to 960 MHz General, 2013. Available online: http://www.webcitation.org/6ghl0sdLv (accessed on 31 January 2015).
48. Dong, Y.; Wickramasinghe, A.; Xue, H.; Al-Sarawi, S.F.; Ranasinghe, D.C. A novel hybrid powered RFID sensor tag. In Proceedings of the IEEE International Conference on RFID, San Diego, CA, USA, 15–17 April 2015; pp. 55–62.
49. Chen, S.J.; Fumeaux, C.; Ranasinghe, D.C.; Kaufmann, T. Paired snap-on buttons connections for balanced antennas in wearable systems. *IEEE Antennas Wirel. Propag. Lett.* **2015**, *14*, 1498–1501.
50. Kellomäki, T.; Virkki, J.; Merilampi, S.; Ukkonen, L. Towards Washable Wearable Antennas: A Comparison of Coating Materials for Screen-Printed Textile-Based UHF RFID Tags. *Int. J. Antennas Propag.* **2012**, *2012*, 1–11.
51. Scarpello, M.L.; Kazani, I.; Hertleer, C.; Rogier, H.; Vande Ginste, D. Stability and efficiency of screen-printed wearable and washable antennas. *IEEE Antennas Wirel. Propag. Lett.* **2012**, *11*, 838–841.

Chapter 8

Feasibility and Effectiveness of Recognizing Bed and Chair Exits in Hospitalized Older People

The previous chapter introduced a fall prevention technological intervention based on the recognition of bed and chair exits with a population of healthy older people. However, these alarming conditions have not been investigated with real patients who, we expect, perform activities in a different manner due to their frailty and due to the hospital settings.

The article contained in this chapter is a journal paper that presents a technological intervention for the generation of bed and chair exit alerts from frail hospitalized older people using our W^2ISP sensor on top of their clothes. This study presents a monitoring system based on weighted SVM that recognizes the high risk activities of bed exits and chair exits from motion data from hospitalized older people, trialled in their respective hospital bedrooms. The collected data is irregular and noisy. Alerts are generated for both bed and chair exits using a score function that processes prediction within a fixed time window to determine the occurrence of an alerting event. Results are compared with the method in Chapter 7.

This study also demonstrates the acceptance of this technology in the population of interest, i.e. hospitalized frail older people, considering several acceptance factors.

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RESEARCH ARTICLE

A battery-less and wireless wearable sensor system for identifying bed and chair exits in a pilot trial in hospitalized older people

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Abstract

Falls in hospitals are common, therefore strategies to minimize the impact of these events in older patients and needs to be examined. In this pilot study, we investigate a movement monitoring sensor system for identifying bed and chair exits using a wireless wearable sensor worn by hospitalized older patients. We developed a movement monitoring sensor system that recognizes bed and chair exits. The system consists of a machine learning based activity classifier and a bed and chair exit recognition process based on an activity score function. Twenty-six patients, aged 71 to 93 years old, hospitalized in the Geriatric Evaluation and Management Unit participated in the supervised trials. They wore over their attire a battery-less, lightweight and wireless sensor and performed scripted activities such as getting off the bed and chair. We investigated the system performance in recognizing bed and chair exits in hospital rooms where RFID antennas and readers were in place. The system's acceptability was measured using two surveys with 0–10 likert scales. The first survey measured the change in user perception of the system before and after a trial; the second survey, conducted only at the end of each trial, measured user acceptance of the system based on a multifactor sensor acceptance model. The performance of the system indicated an overall recall of 81.4%, precision of 66.8% and F-score of 72.4% for joint bed and chair exit recognition. Patients demonstrated improved perception of the system after use with overall score change from 7.8 to 9.0 and high acceptance of the system with score $\geq$ 6.7 for all acceptance factors. The present pilot study suggests the use of wireless wearable sensors is feasible for detecting bed and chair exits in a hospital environment.

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Introduction

Falls are the leading cause of preventable injuries in hospitalized older people, especially those with dementia or delirium, where 30% of falls result in injury, and 4 6% in serious injury including death [1]. Moreover, about 2.5 million older people are hospitalized annually due to a fall related injury in the U.S. alone [2]. Apart from physical injury and added financial bur den from related expenses, falls cause psychological trauma such as fear, loss of confidence, anxiety and depression, which in turn impact on an older person's independence [3, 4]. In monetary terms, the U.S. Centers for Disease Control and Prevention (CDC) estimates for 2016 the hospital cost of a single fall related injury at US$35 777 and the direct medical costs for falls injuries to reach US$34.8 billion (both amounts adjusted for inflation since 2013) [5].

Falls are reported to commonly occur in patients' rooms (84%) including those around the bed and chair [6, 7] or in the toilet (11%); in terms of activities at the time of the fall, most falls occur when ambulating (19%), especially without the necessary walking aid [1]. In addition, risk of falling increases as cognitive functions decline in older people [8, 9]. Best practice stan dards for falls prevention in hospitals and nursing homes include the use of safe footwear, review of medications or use of bed and chair exit alarm systems for patients at risk of falling to provide timely alerts to staff to lend assistance to patients attempting to ambulate unsuper vised [10]. However, falls rates remain high [11 13].

Two recent long term fall prevention trials using pressure sensors on beds and chairs by Sahota et al. [14] and Shorr et al. [15] have reported no decrease in falls rate; this lack of success can be partially attributed to "alarm fatigue" due to the very low specificity of pressure sensors (about 0.3% in Capezuti et al. [4]) resulting in high number of false alarms. In addition to the poor performance of pressure mats placed over the chair or mattress, these sensors require constant maintenance such as cleaning and disinfection as pressure mats are likely to be in contact with body fluids, and thus increasing the workload of staff. Moreover, audible alarms [15] result in 'noise' that distresses patients, especially those with cognitive impairment. Multi ple studies have also used video images for preventing falls [16 18]. However, previous research has shown the manifestation of privacy concerns with the use of cameras in older peo ple's living environment [19]. The study in [19] among community dwelling older people reports that cameras raised greater privacy concerns than other technologies, even when meth ods for extracting silhouettes were in place to preserve privacy. Further, the robustness of vision based recognition techniques can be challenged due to multiple reasons such as chang ing illumination, clutter, dynamic backgrounds, occlusions and, in a hospital context, multiple people, patients or visitors in a single ward room.

Wearable sensors as part of a falls prevention alarm system can provide new opportunities for individualized monitoring of patients [20 22] where human motion data can be collected and transmitted in real time for analysis. More importantly, recent studies [23, 24] suggest that older people have demonstrated interest in small sensors embedded in their clothing. In addi tion, as sensors are decreasing in size and power consumption, the inclusion of multiple sen sors can further extract physiological signals of interest [20 22] along with motion data. Most studies using wearable sensors that target older people have mainly focused on the recognition of activities of daily living [25, 26], gait analysis [27] or the assessment of future falls risk against a validated clinical scale in older people [28 30].

Our study, based on the use of a batteryless werarable sensor device, focuses on methods for the recognition of unassisted bed and chair exits as part of a larger intervention strategy for falls prevention as illustrated in Fig 1 [31]. We propose the use of wearable battery less sensor enabled radio frequency identification (RFID) devices [32], placed on top of patient's clothes, to collect human motion information [33]. The use of wearable sensors is advantageous as it is

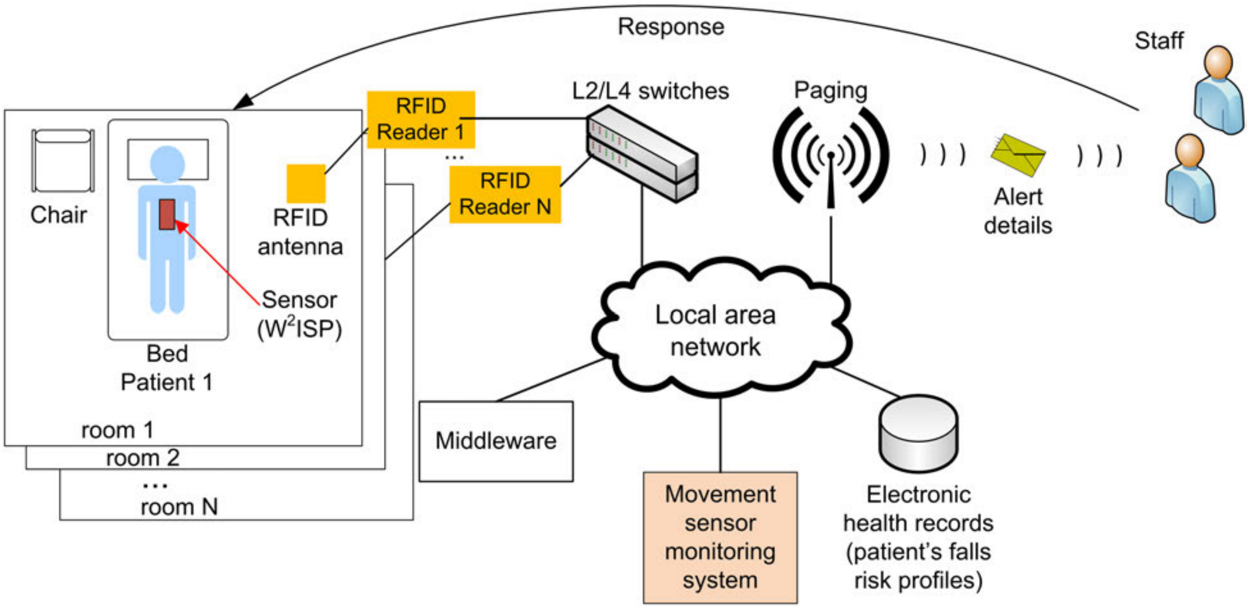

Fig 1. Overview of our technological approach for falls prevention. A patient wears our wearable batteryless sensor, namely a Wearable Wireless Identification and Sensing Platform (W^2ISP), on top of their clothing. The sensor device sends movement information to the movement monitoring sensor system which issues an alarm to staff when a bed or chair exit is recognized.

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low cost, disposable, easy to replace and is maintenance free. Data from the sensor is collected through the RFID infrastructure (wall or ceiling mounted antennas, and readers) connected to a local area network. The system identifies which patient, via their unique RFID tag identifier, requires clinical supervision to move out of a bed or chair. An alert is issued to staff once an unsupervised bed or chair exit is recognized. Staff responding to the individual patient's alert may then intervene and prevent a fall from occurring or provide immediate assistance in the event of a fall incident to prevent a 'long lie'.

We have tested our proposed batteryless sensor device worn on the chest on top of the participant's clothes in young volunteers [34] and healthy older people [35, 36]. High recognition accuracy of bed exits using a heuristics based approach in [34] achieved with young people did not perform well in healthy older people. Using machine learning techniques, we were better able to identify bed exits and chair exits in real time [36]. Our studies in healthy younger and older people confirmed the feasibility of using batteryless wearable sensors and the use of a 3 antenna deployment as an effective method to collect motion data from the batteryless wearable sensor. More significantly, our preliminary work has highlighted the need to develop algorithms for the intended target population i.e. frail hospitalized patients because of observed differences in posture transitions and ambulation of frail older people and the consequential inability of learned models developed in the domain of healthy older people to adapt effectively to the domain described by frail hospitalized patients. Furthermore, an evaluation of a system's ability to detect risk movements such as bed and chair exits has not been reported with hospitalized older people, except for the studies by Capezuti et al. [4] where a combination of pressure mats and infrared beams was investigated and Wong et al. [37] which used pressure mats. Most studies to date have focused solely on reporting the occurrence of falls as a metric to determine the efficacy of the tested falls prevention method [13, 38 40]. Unfortunately, the occurrence of falls cannot directly reveal the underlying performance of the tested falls prevention technology; for example other factors such as staffing levels and timeliness of staff to attend to patients can also influence the reported number of falls and thus we cannot determine whether non prevented falls were caused by failure of the alarming method or other causes. Nevertheless, from the two studies that have measured the performance of the alarming system with hospitalized older people, the study in [4] found that pressure mat based systems generated a large number of falls alarms a specificity of 0.3% was reported in the study; whereas the system of [37] obtained almost similar false alarms to true alarms, especially at night.

In addition, less than 1.3% of current literature on body worn sensors have considered the perception of end users (e.g. patients) [23] but yet we know that ultimately, the opinion of the end user matters most if the technology is to be successfully translated. Hence, it is also imperative that we investigate the patient's perception as well as the acceptability of our system. Therefore, the aims of this pilot study are twofold: i) to explore the performance of our wearable sensor based system in identifying the movement transitions of bed and chair exits in hospitalized older people; and ii)to explore the acceptability of the system to inpatients. This is a vital developmental step prior to investigating the system within a randomized control trial (RCT) to confirm cost effectiveness of the intervention in preventing falls in hospitals.

Materials and methods

Ethics statement

This pilot study is designed as a prospective, non randomized clinical study. The study is approved by the Human Research Ethics Committee of the Queen Elizabeth Hospital (protocol number 2011129) located in Adelaide, South Australia, Australia.

Technology

Wearable sensor technology. We employed a flexible Wearable Wireless Identification and Sensing Platform (W^2ISP) device developed by our team, suitable for wear over garments at the sternum level as shown in Fig 2(a) [33, 35] (picture obtained with patient's consent, patient's face is blurred for anonymization). The W^2ISP, referred to as simply the *sensor* henceforth, is an RFID tag that integrates a tri axial accelerometer (ADXL330) and microprocessor (MSP430F2132) with a flexible antenna for patient comfort and a silver fabric to isolate the antenna from the patient; see Fig 2(a). The sensor does not require batteries (i.e. passive device) as it harvests its energy from the electromagnetic (EM) field generated by the RFID reader antennas illuminating it during the interrogation cycles performed by the RFID reader. When adequately powered, the sensor simply backscatters the unique ID and accelerometer information using the incident RF signal from an RFID reader antenna [41]. A consequence of wirelessly powering the sensor with the incident EM fields is that information can only be obtained when the sensor has gathered sufficient power for powering the W^2ISP circuitry and backscatters data back to the RFID reader. Number of factors, including distance to RFID reader antennas, destructive interference due to multipath, radio frequency band interference and occlusion by RF opaque objects such as the human body can alter the amount of power gathered by our sensor. Hence, we have an irregular reading rate where the time interval between sensor readings varies. In our practical deployment of the sensor, we obtained a sensor read rate of less than 20 reads per second. We can observe the sparse and irregular nature of the sensor data stream from the extract of sensor data recorded from a hospitalized patient shown in Fig 3.

The movement monitoring sensor system collects: i) acceleration readings from the tri axial accelerometer a_v, a_f, a_l shown in Fig 2(a) where acceleration components are corrected based on calibration data and converted to g values; ii)the measured strength of the received

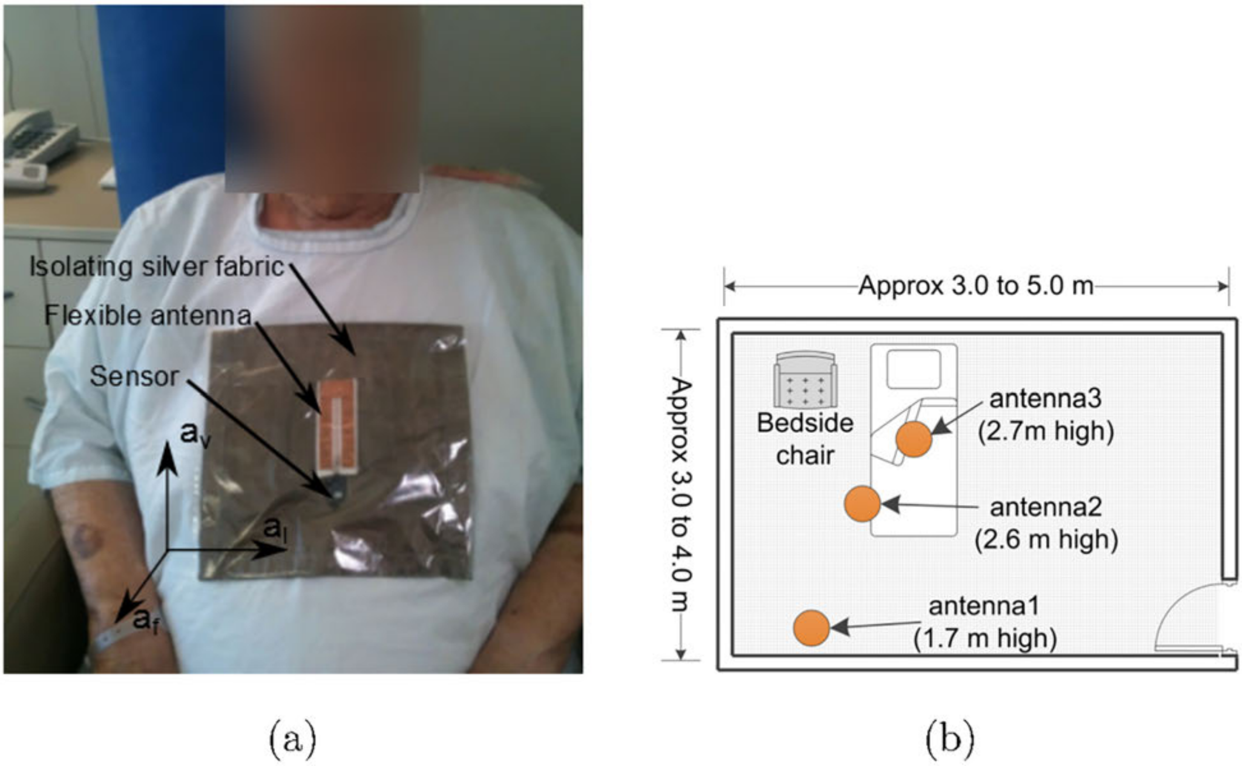

Fig 2. Wireless wearable sensor W²ISP and hospital room configuration. (a) Hospital patient wearing a W²ISP sensor (≈ 3 g, dimensions: 18 × 20 × 2 mm), flexible antenna (36 × 85 × 2 mm) and isolating silver fabric (230 × 220 mm) on top of a gown for illustrative purposes; also shown are the axes of the accelerometer embedded in the W²ISP. (b) Layout of furniture and equipment with antennas shown in circles; antenna2 and antenna3 are at ceiling level on top of bed and antenna1 inclined towards the chair.

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backscattered signal at the RFID reader antenna, called received signal strength indicator (RSSI); iii) RFID reader antenna receiving sensor information; iv) F represents frequency val ues in MHz of the channels used by the RFID reader to query the sensor; and v) RF phase (ϕ), the phase angle between the transmitted RF carrier frequency F and the backscattered signal from the sensor. The acceleration data captures body trunk movement information related to the activities performed by the participant. RSSI is used as a measure of change in distances of a patient wearing the sensor to the RFID reader antenna (aID) receiving the sensor reading [35]. This is because a sensor located closer to the antenna reports higher RSSI values than a sensor located further away. The phase ϕ is used as a source of spatial information (e.g. tag's velocity and distance) to analyze patient movements [42]. Thus, the collected data for every reading has the information: (a_v, a_f, a_l, RSSI, aID, F, ϕ). We provide detailed description of the features we have used in Feature extraction section.

Although the use of a passive wearable sensor approach provides the distinct advantages of lightweight, low cost, and battery free; a limitation originates in the wireless powering, as it depends on the sensor gathering sufficient power from EM signals from RFID reader antennas for powering W²ISP circuitry and backscattering data from the sensor. Hence, the effects of variable distance to RFID reader antennas, destructive interference due to multipath, radio fre quency band interference and occlusion by RF opaque objects such as the human body cause irregular, incomplete and noisy readings that are delivered to the movement monitoring sen sor system (see Fig 4).

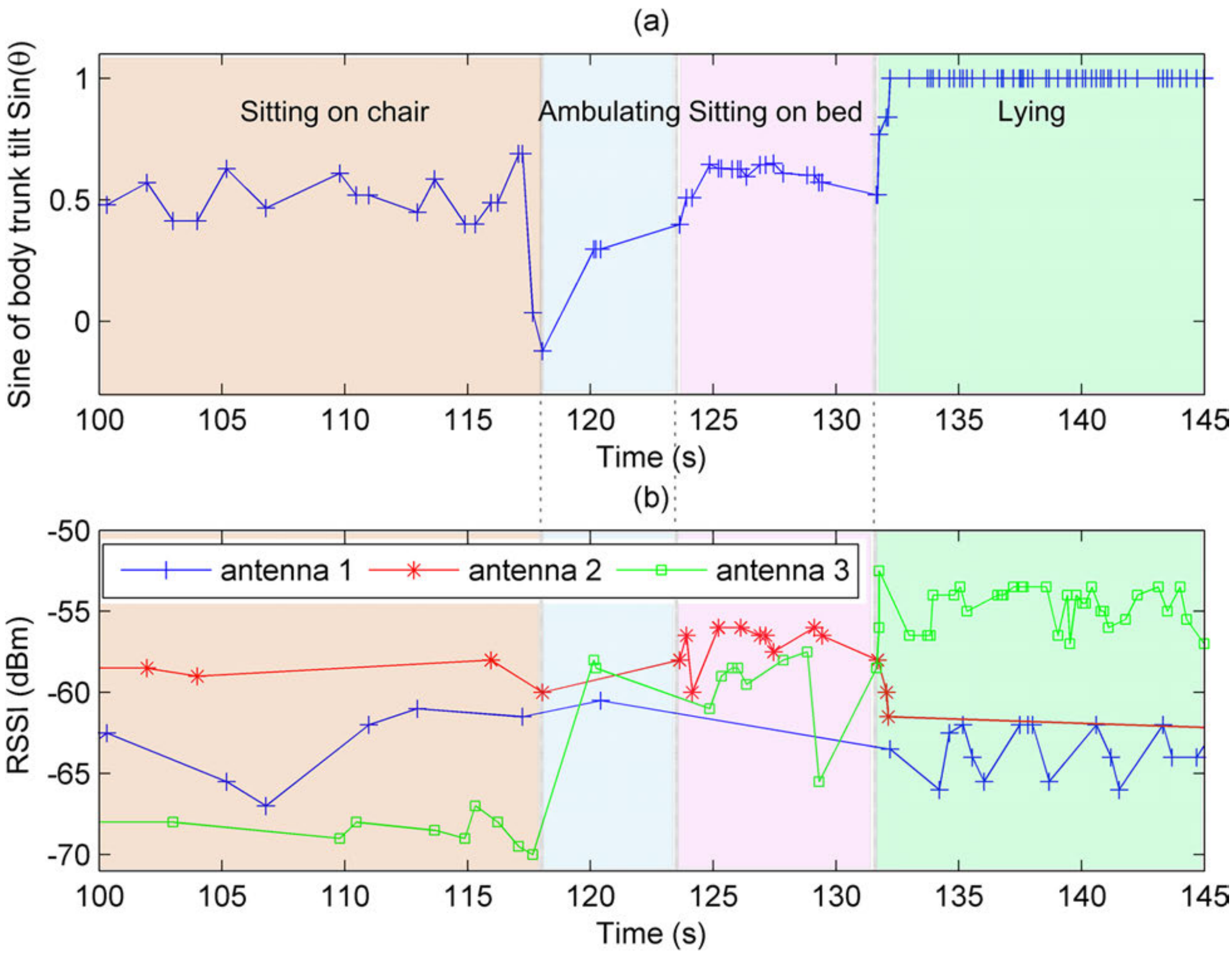

Fig 3. Sensor readings of patient obtained during trial. (a) shows the sine of the body tilting angle (shown in Fig 5(a)) with respect to the vertical. We can also see the sparsity of the sensor readings and the irregular time intervals between sensor readings during activity performance, noted by the varying time intervals between markers on the plot. (b) shows RSSI values for the 3 antennas used in the hospital deployment, we can see the changes in RSSI values across activity boundaries, most notable change is that of antenna 3 (in green) when the patient moves from sitting on chair to ambulating.

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Movement monitoring sensor system. The proposed system considered activities of high risk of falling that are performed by older patients without supervision in a hospital room con text [31]. Previous research [31] has determined that exiting the bed and exiting the chair are high falls risk movements that have to be identified for falls preventing falls. Hence, we pro posed a movement monitoring sensor system, shown in Fig 4(a), that consists of three main stages: i) feature extraction; ii) activity classification; and iii) bed and chair exit recognition process.

Feature extraction refers to obtaining essential information from the sensor and RFID data stream from which the activity classification stage, based on the class sensitive classification method of weighted support vector machine (WSVM), can accurately classify the performed activity. The present work has considered a set of activities (classes) representative of those per formed by patients in a hospital ward room setting to support our wearable falls prevention intervention. As a consequence, we considered the activities: i) Sitting on bed; ii) Sitting on chair; iii) Lying; and iv) Ambulating. Although the number of activities are naturally limited by

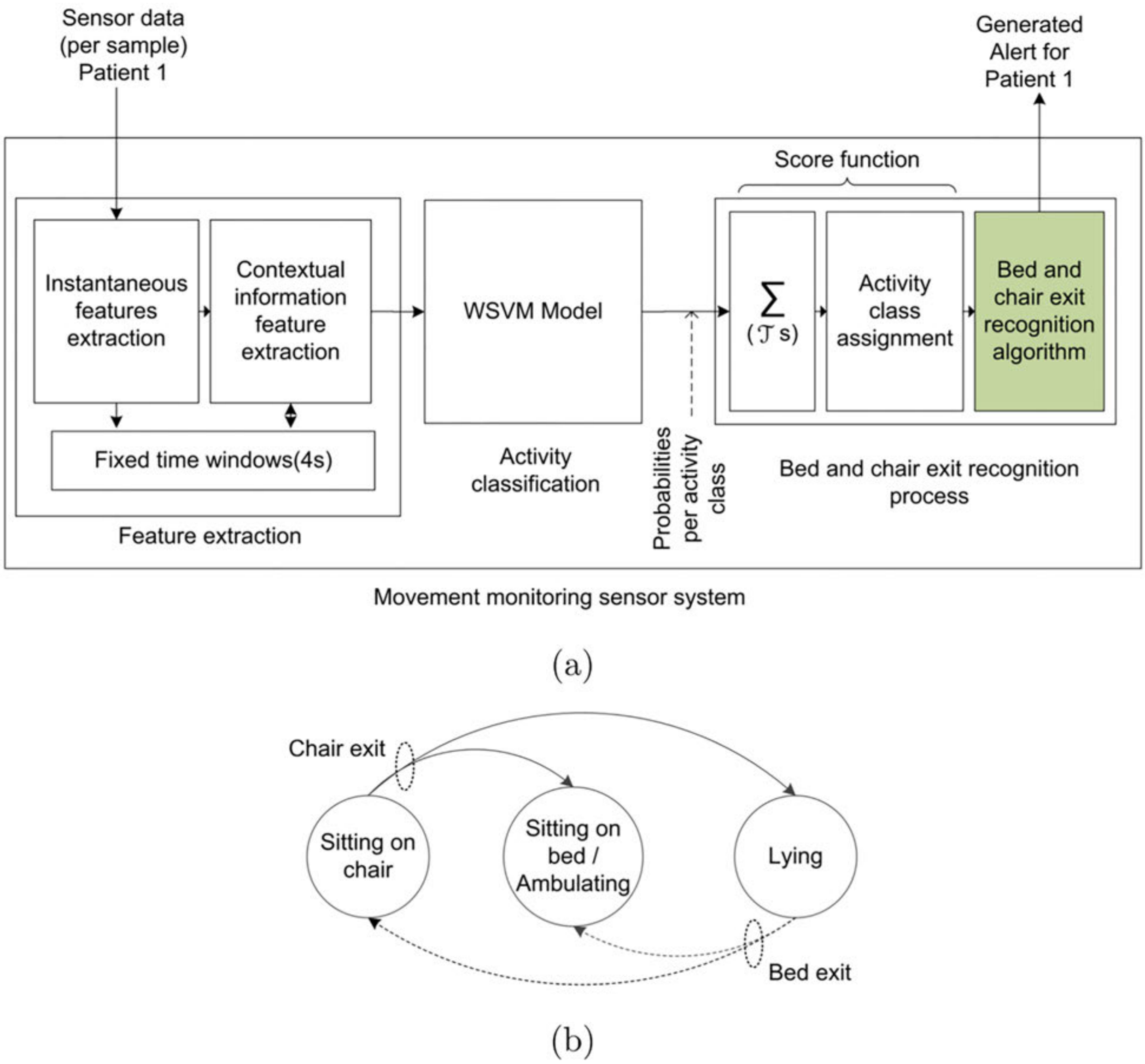

Fig 4. Proposed movement monitoring sensor system. (a): bed and chair exit recognition system and (b): patient state transition model used by the bed and char exit recognition algorithm (green block in (a)).

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the context of our application, there is clear intra class diversity, for example, patients lying on bed were watching TV, resting or reading; similarly, during ambulation a patient can be either walking with or without a walking aid. The bed and chair exit recognition process collects the output of the WSVM model, assigns an activity to each sensor observation using a score func tion and generates an alert using the bed and chair exit recognition algorithm in the event a bed or chair exit is recognized following the patient state transitions described in Fig 4(b).

Data collection

Study participants. We trialled a cohort of hospitalized older people, inpatients in the geriatrics ward of the Queen Elizabeth Hospital in Adelaide, South Australia. The patients were 71 years and older, a male to female ratio of about 1 : 2, with no cognitive impairment and with the ability to mobilize independently or use a walking aid. The patients were recruited directly from the hospital, informed written consent was obtained and no honorar ium was provided. We trialled 26 patients in our pilot study. However, data related to three patients were discarded from the performance evaluation study because of poor signal collec tion from the sensor caused by a false contact at an antenna junction point due to mechanical wear and tear. The mechanical failure is because of the laboratory prototype nature of the sen sor developed for the study. Therefore, data from 23 patients were used to evaluate the perfor mance of our system; patient's data is available at S1 Dataset. However, the 26 patients participated in two surveys which included one incomplete post trial survey.

The patients were informed of the activities contained in the script to ensure that they had no objections to any of the proposed activities but were not informed of the order before the trial start.

Hospital settings. The study was undertaken in the rooms of each patient; rooms were single or double bed, hence the room dimensions in Fig 2(b) are approximate. Although every room was different, beds and chairs and their respective setting were uniform for all trials. Our investigation in [35] confirmed that in a clinical setting it was possible to achieve high perfor mance for activity classification using three antennas focused on areas of interest rather than more antennas covering a wider area. Therefore, this study in a hospital setting used a deploy ment with two antennas located on ceiling level inclined towards the bed and one antenna on the wall opposite the chair inclined towards it as shown in Fig 2(b); the bedside chairs were located at either left or right side of the bed and the patient always exited the bed on the side of the bed that was next to the chair. No other furniture was added or removed, and overbed tables were placed outside the walking route during the trials.

The patients performed a set of scripted lists of activities of daily living (ADL) that included walking to the chair, sitting on the chair, getting off the chair, walking to the bed, lying on the bed, getting off the bed and walking to the door. The patients were instructed at the beginning of the trial to perform each activity at their own pace and as comfortable as possible; no other instruction was given as to how to perform each activity. The patients were also instructed to request a trial termination if they were distressed or in discomfort. During the trials two mem bers of the research team were present, the first member instructed the patients with the activi ties that needed to be performed from the script and annotated the activities being undertaken, the ground truth, in the sensor data capturing software; the ground truth was later contrasted with the activities determined by our proposed method to measure the sys tem's performance. The second member was present to ensure the safety of the patient due to their frail condition and could interrupt at any time.

Hospital trial procedure. Each patient was trialled in his/her respective room. Patients only performed the ADLs described above, which were repeated two or three times, depending on the patient's ability to continue the trial. The duration of the trials for this cohort was about 20 to 25 minutes per patient and was performed during the day between 2 pm and 4 pm.

The patients were required to complete a pre trial survey and two post trial surveys, imme diately before and after the trial respectively, to measure the changes of perception and their level of acceptance of the system.

During trials, patients were not always lying flat on the bed. Patients in their bed had the position of the movable head rest of the bed either flat or inclined as patients were resting, receiving visits, watching television or reading. Hence, during the trials, multiple postures in bed were captured when the patient was lying on the bed. Moreover, all the patients that par ticipated in the trials when sitting on the bed, sat with legs off the bed as opposed to sitting straight up with their legs still on the bed; thus we consider a patient sitting with legs off the bed as having the intention of getting out of bed after a period of lying on the bed.

Acceptability study survey design. Two surveys were designed to evaluate equipment acceptability based on the Sensor Acceptance Model developed by Fensli et al. [43]. The first survey is based on the "pre trial expectation" factor identified and used by Fensli et al. [43]. The questions measured the perception of the patients about the system to recognize bed and chair exits and their apprehension towards the use of the equipment. Unlike in Fensli et al. [43] where the first survey was only administered before the trial, in our study the survey was completed by each patient before and after their trials to enable the measurement of change in perception.

The second survey was completed after each trial to measure acceptability and privacy con cerns perceived by the users. The Sensor Acceptance Model [43] identified five key factors (hygienic aspects, physical activity, skin reactions, anxiety, equipment) to determine the patients' acceptance of wearable sensor based systems worn in contact with the skin. We selected three of the factors identified by Fensli et al. [43]: "physical activity", "anxiety" and "equipment" as they are relevant to our study and our sensor is not worn against the skin. We added "privacy" as an acceptability factor due to the importance of privacy violation concerns identified in previous studies [19]. The questions were formulated as positive or negative state ments and used an eleven point semantic differential scale (0 10) where answers indicated agreement/disagreement and no problem/problem. Both surveys are shown in the Results sec tion, where a score of 10 indicates full agreement or satisfaction with the system.

Data processing

Feature extraction. This stage generates from the sensorial data the features engineered to capture the underlying body motions as input to the activity classification stage illustrated in Fig 4. Each reading, $v_i = (a_f, a_v, a_l, RSSI, aID, F, \phi)$ where $i \in \mathbb{N}$ we obtain, contains informa tion from the sensor and RFID infrastructure described previously in Section Wearable Sensor Technology. We are interested in RSSI as its measurements are proportional to $1/d^4$ where d is the line of sight distance between a sensor and an RFID antenna [44]. The hypersensitivity of RSSI to distance implies that patterns in changes in RSSI values with relation to a given RFID antenna can potentially help discriminate between postures, such as sitting and standing as well as a change in posture from sitting to standing see Fig 3(b), that may not be noticeable using acceleration information alone. This is because as acceleration measurements are often similar for sitting and standing postures where the body trunk is likely to be upright as shown in Fig 5(b). We also use RF phase (ϕ) as previous studies [42, 44] have demonstrated that phase measurements computed by an RFID reader based on a received signal from an RFID tran sponder provides spatial information such as a tag's distance from an RFID antenna, and velocity. Therefore we include RF ϕ based features that can potentially capture movements and activities performed by hospitalized patients wearing the sensor. In addition to sensor information v_i, we also use the patient's gender and the timestamp t_i at which the sensor read ing was captured. Hence we consider a sensor reading as the $x_i = (t_i, gender, v_i)$ from which we derive two types of features: i) instantaneous features; and ii) contextual information features.

Instantaneous features. These features are obtained directly from the most recent sensor reading and provide useful information related to the patient and the action being performed as captured by the accelerometer sensor and the RFID infrastructure. For every sensor reading, now defined by $x_i = (t_i; gender; v_i)$, we calculate a set of features directly derived from the values observed in v_i, i.e. instantaneous features, described in Table 1. In addition to considering ele ments of v as features (i.e. $a_f, a_v, a_l, RSSI, aID$); we also consider the resultant acceleration

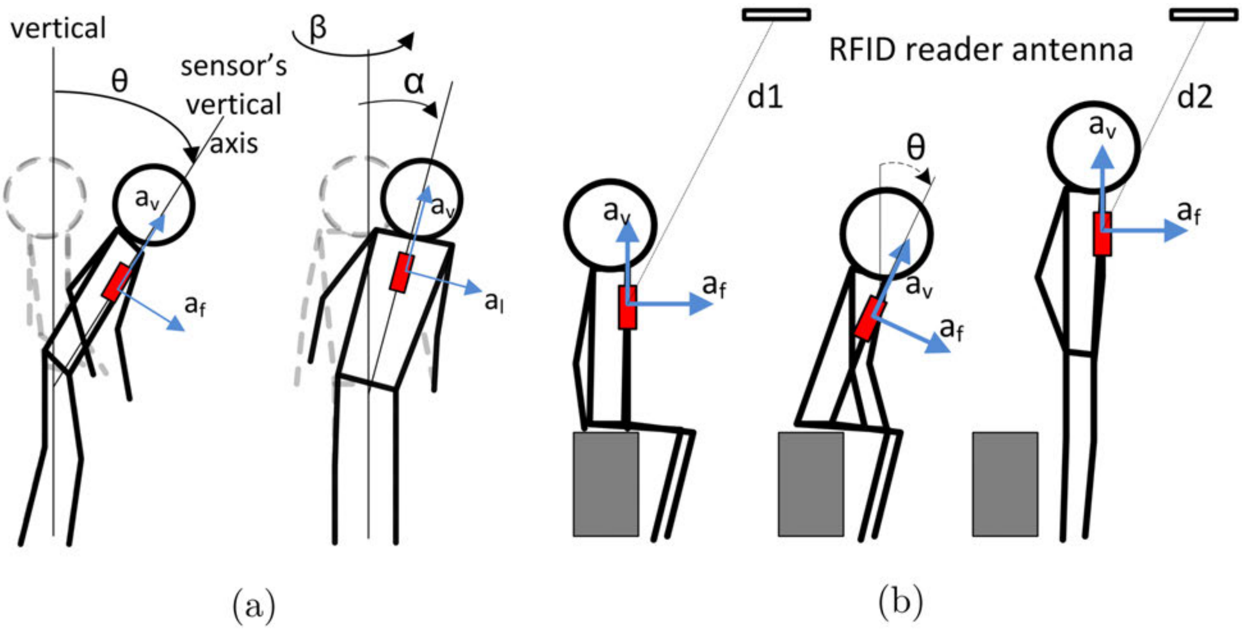

Fig 5. Body motion of person wearing W^{2}ISP. (a) body rotational angles for a person using the W^{2}ISP (in red) that are approximated using acceleration information; (b) sequence of sitting to standing showing distance to antenna, where distance to a person standing (d2) is shorter to when the person is sitting (d1); this also means that RSSI readings are higher when the person is closer to the antenna (standing).

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(feature item 6), the sine of body tilting angle (θ) [26], and body rotation angles yaw (β) and roll (α) determined as shown in Fig 5(a). Given that the W^{2}ISP only includes an accelerometer, these angular measurement values were approximated from the raw accelerometer readings (feature items 4, 9 and 10 in Table 1). We also consider the time difference with the previous reading $\Delta t_i = t_i - t_{i-1}$ as the rate of received sensor readings are irregular i.e. $\Delta t_i \neq \Delta t_{i-1}$ and can

Table 1. List of instantaneous features extracted of interest to system. (* indicates feature used.)

Features		Description
1.	Frontal acceleration (a_f)*	Dorsoventral axis acceleration values in g (i.e. range −1:1)
2.	Vertical acceleration (a_v)*	Anteroposterior axis acceleration values in g
3.	Lateral acceleration (a_l)	Left-right axis acceleration values in g
4.	Sine of body tilting angle (pitch)*	Sine of body tilting angle (θ) towards the front or back with respect to vertical in the midsagittal plane [26], approximated as $\sin\left(\arctan\left(\frac{a_f}{a_v}\right)\right)$
5.	Received signal power (RSSI)*	Received signal power from the sensor as received at reading antenna. RSSI is calculated as: $P_t G_t^2 G_{path}^2 K$ where P_t is the output power of the RFID reader, G_t is the RFID antenna gain, K is the W^{2}ISP backscatter gain and G_{path} is the one-way path gain of the deterministic multipath channel [44] which is inversely proportional to the square of the direct path distance (i.e. d_0^2). Hence, RSSI is inversely proportional to d_0^4.
6.	Resultant acceleration*	Magnitude of acceleration vector given by $a_t \quad \sqrt{a_f^2 + a_v^2 + a_l^2}$.
7.	Time difference Δt	Time difference with previous sensor observation (regardless of receiving antenna).
8.	Participant's gender*	
9.	Trunk yaw angle*	Rotational angle from dorsoventral axis, approximated as: $\beta \approx \arctan\left(\frac{a_l}{a_f}\right)$
10.	Trunk roll angle*	Tilting angle in the coronal plane, approximated as: $\alpha \approx \arctan\left(\frac{a_l}{a_v}\right)$
11.	Antenna ID (aID)	RFID antenna receiving current tag reading.

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provide potential information based on the EM illumination levels of the sensor based on its orientation and distance from the studied fixed antenna configuration.

Contextual information features. These features are generated from segments obtained from partitioning the time series of sensor readings. We generated contextual information features since a single sensor reading is insufficient to capture adequate information regarding underlying activities of duration longer than a single sensor reading and to benefit from information in the temporal vicinity of an activity. Hence, contextual information features overcome the limited ability of instantaneous features to capture information. In general, these features provide an insight into the physical motions and changes in location of a patient by using information from the recent past sensor readings in a segment. In previous research [45] we found that using a partitioning or segmentation approach for extracting contextual features using a fixed time window method improved the performance to be better or similar to more complex segmentation methods; moreover fixed time window based segmentation method is easily implemented. Here, limiting the size of the segment is important as events distant in time become less relevant to the current activity.

More formally, we define a segment as $S_{[t_i - T, t_i]} = \{(t_o, gender, v_o)\}|_{o \;\; t_i - T}^{t_i}$ which contains all received sensor readings during a period of T seconds from the sensor observation at time t_i where $t_i - T < t_i$. Using these sensor readings within the segment $S_{[t_i - T,\, ti]}$, we calculate the contextual features which are shown in Table 2. Subsequently, these features are calculated for the next received reading at t_{i+1} and for every t_j, where $j > i$. We have used T = 4s in our work.

In particular, we considered readings captured by each antenna (feature item 12) and mutual information from bed and chair areas (feature item 16) as developed in [45]. We also calculate features that can provide information about the variations of movement by the patients as provided by the values in v_i; for example, we consider the Pearson correlation coefficient (r), the approximate displacements from the acceleration component of the sensor's vertical axis a_v and the mean and standard deviation of acceleration values within the segment

Table 2. List of contextual information features extracted of interest to system. (* indicates feature used, p.a. = per antenna.)

Features		Description
12.	Readings p.a.*	Indicator of number of readings per antenna in the segment, in our case we consider antenna2.
13.	Antenna collecting maximum power	ID of antenna (aID) with maximum received power in segment.
14.	Antenna collecting minimum power*	ID of antenna (aID) with minimum received power in segment.
15.	Vertical displacement* (d)	Cumulative body displacement in the sensor's vertical axis during a segment, calculated as: $d \quad \iint_0^{\delta t} a_v dt^2$.
16.	Mutual information of bed and chair areas* ($m_{bed-chair}$)	Events occurring between these two areas given by the number of consecutive readings captured in both bed and chair areas, calculated as: $m_{bed \quad chair} \quad \frac{1}{n}\sum_{i \quad 1}^{n \quad 1}(\mathbb{1}_{[\{bed,chair\} \quad \{ant_i, ant_{i+1}\}]} + \mathbb{1}_{[\{chair,bed\} \quad \{ant_i, ant_{i+1}\}]})$; where $\mathbb{1}_x$ assumes 1 if x is true and 0 otherwise and ant_i refers to the antenna receiving the i^{th} sensor reading in a 4 s segment with n sensor readings, used in [45]. In our case we use bed and chair antenna pairs (antenna3, antenna1) and (antenna2, antenna1).
17.	Pearson correlation coefficient* (r)	Correlation between axes information, calculated as: $r_{a,b} \quad \frac{1}{n \quad 1}\sum_{i \quad 1}^{n}\left(\frac{a_i \quad a}{s_a}\right)\left(\frac{b_i \quad b}{s_b}\right)$; where we considered a, b = $\{a_v, a_f\}$, $a \,/\, b$ and s_x is the standard deviation of the samples x in the window.
18.	Mean and standard deviation of RSSI*	Mean and standard deviation of received power received per antenna during 4 s time window. In our case, we consider antenna1 and antenna3.
19.	Median, sum of absolute value and standard deviation of CFPR*	Constant Frequency Phase Rate (CFPR) defined as $CFPR = \phi_{aID,\,F}(i) - \phi_{aID,\,F}(i-1)$, for each antenna. Measured during a 4 s segment as defined in [42]. We consider median of antenna1 and antenna3; absolute value of antenna2 and standard deviation of antenna2 and antenna3.
20.	Standard deviation of VFPR*	Variable Frequency Phase Rate (VFPR) defined as $VFPR \quad \frac{\phi(i) \quad \phi(i \quad 1)}{F(i) \quad F(i \quad 1)}$, for antenna3 during a 4 s segment; features as defined in [42].
21.	Mean and standard deviation of acceleration*	Mean and standard deviation of acceleration values during 4 s time window; we consider the mean of a_v, a_f, a_l and standard deviation of a_l.

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(feature items 15, 17 and 21). We also consider features that provide insight into the variations in RSSI; we consider the mean and standard deviation of RSSI as well as identify the antennas that capture minimum and maximum RSSI values within the segment (feature items 13, 14 and 18). Furthermore, we consider the features engineered in [42] which use phase information to determine possible small scale movements of the patient (feature items 19 and 20).

We performed feature selection to eliminate those features that are less relevant to our activity classification problem without loss of information. From the complete feature vector that considers instantaneous and contextual information features, we performed feature selection using the WEKA data mining tool [46]. We selected two simple statistical classifiers logistic regression and Bayes network and eliminated features that were low ranked for both methods. The features selected are indicated in Tables 1 and 2.

Activity classification. The activity classification stage is based on the machine learning method of weighted support vector machines (WSVM) [47], a classifier based on SVM [48] originally designed for a two class problem (binary). In SVM, the model treats all training samples with equal importance, and this can lead to misclassification in the case of imbalanced data as is our case. Class imbalance is inherent to our problem because some activities performed by people are of longer duration than others; for example, a hospital patient will spend more time lying in bed than ambulating. Moreover, data is more easily collected from some activities than others; for example activities closer to the RFID antenna are easier to collect than those performed farther from the RFID antennas, also the sensor can be occluded from RFID antennas by the patient's body during some movements affecting the sensor's powering and data collection.

Given the training data $\mathcal{D}_l = \{(x_i, y_i, s_i)\}_{i=1}^{l}$, where each training sample x_i is a feature vector associated to a two class label $y_i \in \{-1, +1\}$, WSVM, as opposed to SVM, treats each observation x_i differently according to its known weight $s_i \in \mathbb{R}$. The classification model w, is learned by minimizing the convex objective function:

$$\begin{aligned} \text{minimize} \quad & \Phi(w) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l} s_i \xi_i \\ \text{subject to} \quad & y_i(\langle w, x_i \rangle + b) \geq 1 - \xi_i, i = 1, \cdots, l \\ & \xi_i \geq 0, i = 1, \cdots, l \end{aligned} \tag{1}$$

where C is a constant determined by model parameter selection (see Section Statistical Analysis), ξ_i are error margins and b is the offset of the hyperplane from the origin. Weights s_i are only considered during the training stage as they are used to affect the model w treatment of each individual class; the values of s_i are not determined autonomously by WSVM during training, but are parameters to the model.

Nonetheless, there are two main limitations in using this model in our problem. The first limitation is that our problem requires a multiclass classification model given our set of activities i.e. $y_i \in \mathcal{K} = \{\text{Sitting-on-bed}, \text{Sitting-on-chair}, \text{Lying}, \text{Ambulating}\}$. We use a one against one method for multiclass SVM as it has been demonstrated to perform better than other methods for multiclass SVM [49]. In our study, we implemented the multiclass WSVM model from LIBSVM [50].

The second limitation is that weights are unknown at the time of training. Therefore, we formulate a second optimization problem to find the best set of weights s_i^k for $k \in \mathcal{K}$ that maximizes the overall F score for the training set. We use covariance matrix adaptation evolution strategy (CMA ES) [51], a state of the art evolutionary algorithm, for optimization of the set of weights. This method determines the optimal solution by iteratively estimating an optimal set of parameters from an initial set of weights. In our study, we used the software of [51] to optimize the set of class wise weights. We chose the best set of weights s_i^k, during model parameter selection (see Section Statistical Analysis), after analyzing 200 random sets of initial weights.

Bed and chair exit recognition process. In this stage, an alert signal is triggered on the occurrence of a recognized bed or chair exit. These exiting events from both bed and chair occur in a common area around the bed and the chair as illustrated in Fig 2(b). Hence, the intervening staff is directed to the same area of the bed and chair.

To evaluate the occurrence of bed and chair exits, we propose a score function that first sums the estimated classification probabilities for each activity (class), considered as normalized scores per activity, over a non overlapping time window of duration $\mathcal{T}$ of data produced from the activity classification stage. The goal of the score function is to assign an activity class that is dominant in the time window $\mathcal{T}$ and is therefore less affected by activity classification errors from the underlying WSVM model. The score function then selects the activity class with the highest sum and assigns that activity to the complete data window $\mathcal{T}$.

The scoring function mitigates the resulting effect of those misclassified sensor readings that could produce undesirable false alarms if they were considered in the decision to issue an alarm without the score function. The score function reduces possible false alarms by evaluating the dominant class label of multiple sensor readings over a short time period as a more accurate representation of the activity being performed to generate an alarm signal. We have considered a fixed time window approach of duration $\mathcal{T}$. We consider the value of $\mathcal{T}$ in the range of 0.1 to 5.0 s where the limit value of 5.0 s is more than double the minimum time a posture transition takes place [34] so that a complete transfer is included in a single window. The value of $\mathcal{T}$ was chosen during model parameter selection (see Statistical Analysis) such that it maximizes the overall F score.

When a bed or chair exit has been identified by the algorithm, an alert signal is issued as detailed in Fig 4(b). Exits from a bed are detected when the classified activity of Lying on bed is followed by a Sitting on bed or Ambulation. In the case of exits from a chair, we identify such an event when a Sitting on chair activity is followed by any other activity. After an alert is issued, we consider that it is physically impossible for another alert to occur in the next 1.75 s, which corresponds to the minimum time for a posture transition to take place and longer periods can possibly overlap with other valid posture transitions. Hence, we cancel any additional alerts within that period. Pseudocode is presented in Supporting Information S1 Pseudocode.

Statistical analysis. In this study, true positives (TP) were correctly recognized bed and chair exit alerts when: i) the alert occurs when the person is actually performing an activity of interest as illustrated in Fig 6(a); or ii) the real activity (ground truth) occurs no more than a time $T = 5$ s after the alert signal as illustrated in Fig 6(b). False positives (FP) or false alarms are recognized bed and chair exits that do not follow the TP criteria, i.e. incorrectly identified as target activity. False negatives (FN) are unrecognized bed and chair exits (misses).

We evaluate the performance of the proposed system using recall (also known as sensitivity in the literature), precision and F score, the harmonic mean of recall and precision, as these metrics consider the occurrence of errors (misses and false alarms) in relation to true alarm events (TP). These are defined as: i) recall = TP/(TP+FN); ii) precision = TP/(TP+FP) and iii) F score = (2×precision×recall)/(precision+recall).

We consider evaluating our approach using a leave one out cross validation because this approach gives a clear indication of the performance of the system when tested with data from a patient not known to the algorithm, as is the case in a practical deployment of the system in a hospital. In this validation process, the data of a patient is used for testing (testing set); the data

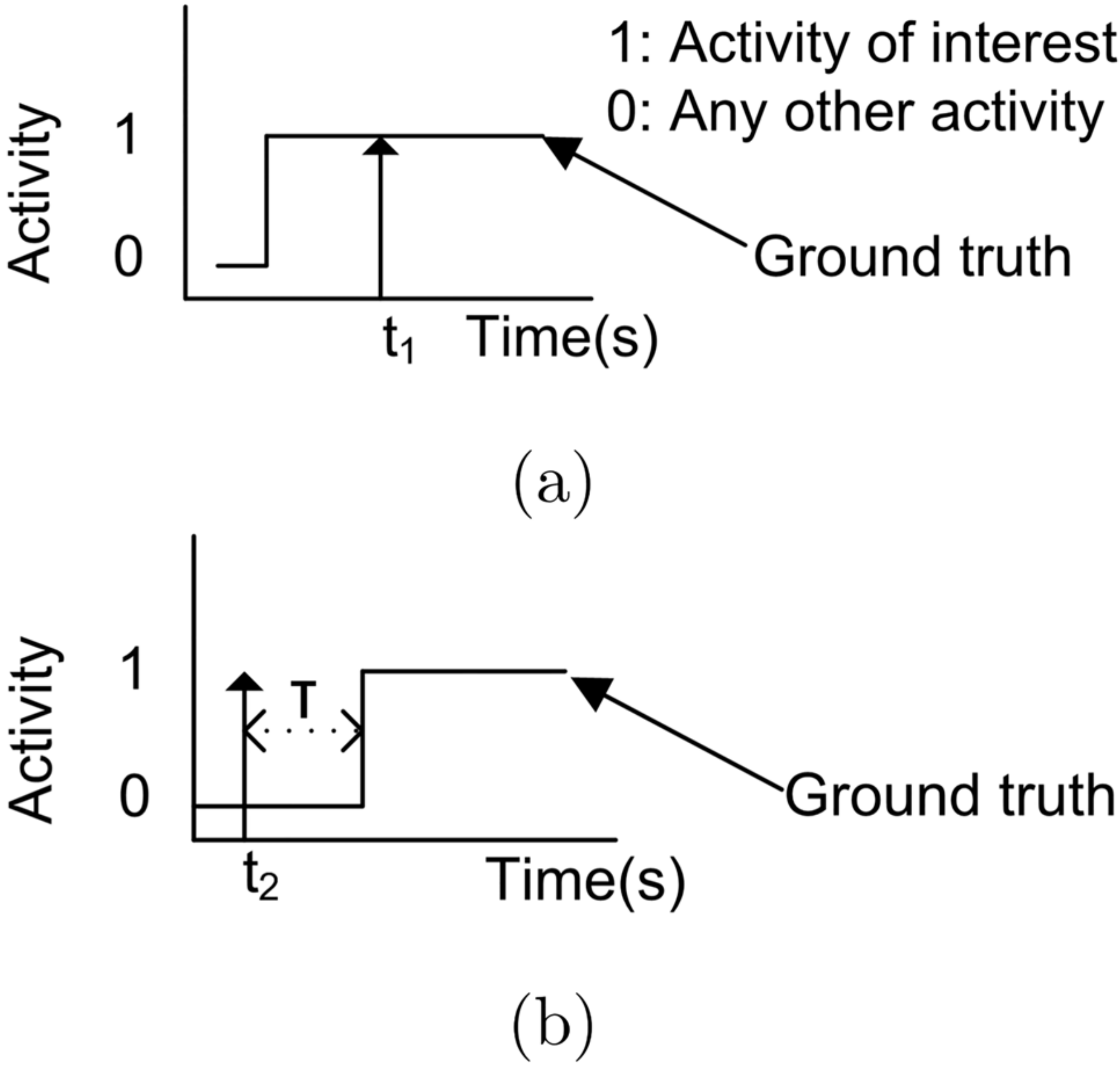

Fig 6. True positive of bed and chair exit recognition. A TP of bed and chair exit is said to occur when an alert (arrow) is triggered at t_1 and t_2 for: (a) a real activity is occurring; (b) real activity occurs less than 5 s after an alert.

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of a different patient is used for parameter validation (validation set) and the rest of the patients' data (21 patients) is used for training the system (training set). This process is repeated sequentially where each of the 23 patients are selected one by one for testing. Hence, the data of the patient used for testing is always unknown to the system as it was trained with data of other patients. We performed model parameter selection using the validation set, where the model with the highest F score was selected for testing.

We compare performance metrics (precision, recall, F score) of the movement monitoring sensor system with other methods using an independent *t* test where our null hypothesis (H_0) is that the performance of our movement monitoring sensor system and other tested method are the same. To compare the pre and post survey responses, we use the Mann Whitney U test, a non parametric test adequate for evaluating ordinal non normal data as is the case of our surveys [52]. The non normality of the data was confirmed by the using the Shapiro Wilk test. The null hypothesis (H_0) of the Mann Whitney U test is that there is no difference between the tested sets of data.

Results

Bed and chair exit recognition system performance results

We used sensor and RFID data from 23 patients as three patients were removed as explained in Section Data Collection   Study Participants. Recognition of bed and chair exits, shown in Table 3, illustrates the results for our windowing method for all trialled patients. We used a fixed time window of duration $\mathcal{T}$ = 4.8s where the overall F score metric is > 72%, as shown in Table 4. We also compare with our study in [36], where we used a dynamically weighted CRF model [53] to classify activities for the recognition of bed and chair exits as in Fig 4(b), using the features developed in this research to make a fair comparison. We have determined that the median delay for the recognition of bed and chair exits is of 4.09 s; also the mode of all delays, rounded to the nearest second, is of 4 s. This indicates that the majority of recognized alarms are not generally longer than the duration of the time window used for determining a bed and chair exit alarm.

Table 3. Recognition of bed and chair exits in the hospital setting. TP = true positives, FP = false positives or false alarms and FN = false negatives or misses.

Patient ID	Total bed & chair exits	Fixed time window $\mathcal{T}$ 4.8 s			Method of [36]		
		TP	FP	FN	TP	FP	FN
p.1	5	2	3	3	2	28	3
p.2	6	4	3	2	5	5	1
p.3	5	4	2	1	5	1	0
p.4	4	4	0	0	4	13	0
p.5	6	6	4	0	5	3	1
p.6	4	3	3	1	3	4	1
p.7	2	2	0	0	2	3	0
p.8	3	3	1	0	3	3	0
p.9	6	5	2	1	3	3	3
p.10	6	3	5	3	2	12	4
p.11	3	2	0	1	2	0	1
p.12	5	3	6	2	5	7	0
p.13	6	6	6	0	6	46	0
p.14	5	4	2	1	4	4	1
p.15	6	6	1	0	6	22	0
p.16	7	5	3	2	6	4	1
p.17	3	2	2	1	2	1	1
p.18	4	4	0	0	4	4	0
p.19	6	4	3	2	5	16	1
p.20	6	4	3	2	6	33	0
p.21	6	6	3	0	6	9	0
p.22	6	6	3	0	6	4	0
p.23	5	5	1	0	5	19	0

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Table 4. Performance metrics for tested methods. Including fixed size window and the method of [36] modified for bed and chair exit detection. Results in %.

	Recall	Precision	F-score
Fixed time window	81.44 ± 18.89	66.82 ± 20.24	72.48 ± 17.84
Method of [36]	84.67 ± 20.69	42.80 ± 23.60	52.75 ± 21.09

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Acceptability study results

Twenty six patients participated in the surveys, with one patient that partially completed the second post trial survey. Analysis of the first survey responses in Fig 7, where each radial axis indicates the mean score of a question, indicates in general an improved perception of the sen sor equipment by the patients after participating in the trial. The pre trial assessment of the system had an overall average score of 7.83 with partial overall scores $\geq$ 6.65 as shown in Fig 7 (red line). On the other hand, the post trial assessment achieved an overall average score of 9.03 (larger outer plot with scores higher than the smaller inner plot). However, patient's pre and post trial response score to question Q6: "I am afraid the equipment will harm me" had a marginal overall score decrease of 0.2.

Survey I	
Q1	I expect this investigation can help prevent falls.
Q2	I believe if I wear this device I will have difficulties doing daily activities.
Q3	I am worried the equipment will not give good enough signals for the research.
Q4	I am afraid the equipment will fall from its attached position if I move too much.
Q5	I am afraid the equipment will break if I move too much.
Q6	I am afraid the equipment will harm me.

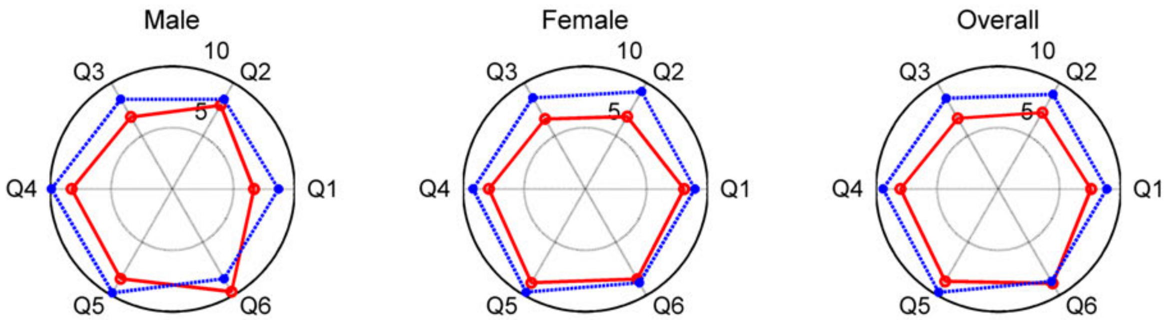

Fig 7. Results from first survey. Radar charts of pre-trial (red line) and post-trial (blue line) responses to the first survey, showing average scores for overall and male and female participant cohorts. Score range from 0 to 10, where 10 indicates full satisfaction with the equipment.

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Comparing pre and post trial response scores using Mann Whitney test (see Section Statistical analysis), for overall results, show that the medians for questions Q2 ($U = 225.5$, $P = 0.019$), Q3 ($U = 215.5$, $P = 0.016$) and Q4 ($U = 237.5$, $P = 0.022$) are statistically significantly different. Considering gender differences in our patient group, the difference in response among male participants were not statistically significant ($P > 0.08$). However, the female participants' pre and post trial response differences for question Q2: "I believe if I wear this device I will have difficulties doing daily activities" ($U = 90.5$, $P = 0.030$), and Q3: "I am worried the equipment will not give good enough signals for the research" ($U = 84$, $P = 0.023$) were statistically significant. For all other questions, the median differences were not significant ($P \geq 0.11$) although having consistently higher average scores in the post trial responses.

Analysis of the second survey shown in Fig 8 indicates an overall average score of 8.99 for all four factors (≥ 6.68 overall) of the Sensor Acceptance Model (physical activity, anxiety, equipment and privacy). The lowest score was for question E2: "I just forgot I am wearing it" in the overall, and gender based analysis, demonstrating an overall concern for the high visibility of the sensor during the trials.

Discussion

This pilot study to evaluate a new technological intervention for preventing falls in hospitals and nursing homes completed with frail hospitalized older people suggests that it is possible to undertake the monitoring of movements associated with bed and chair exits using a single batteryless sensor loosely worn over clothing by a patient. Furthermore, the sensor was found to be acceptable to the hospitalized patients that participated in this pilot study.

Movement monitoring sensor system

This research builds on previous studies from our group focused on bed exits [34 36] in healthy old and young people as opposed to hospitalized older people. In the current study, we adopted a 3 antenna deployment since this arrangement performed well in [35, 36] for bed exit detection. It is important to undertake research within hospitalized older people who are frail as, unlike healthier cohorts, hospitalized older people perform shorter ambulations and move differently when exiting beds and chairs. For example, during our trials, they made several attempts before successfully exiting a bed and their postural changes occurred much more slowly. In addition, furniture tend to be placed in close proximity of each other given the illness and frailty of hospitalized patients and their limited mobility limiting the time patients ambulate between, for example, the bed and the chair. We therefore applied classification methods that consider the effects of minority classes, present in our data because of short duration activities and reduced sensor data collection during postures where the sensor is occluded. We used a score function based on the use of a fixed time window to determine classes and generate alarms to reduce errors from possible misclassifications.

Although our results demonstrate, for the first time to the best of our knowledge, the possibility of using a batteryless wearable sensor to detect bed and chair exits in hospitalized older people, the resulting precision is below expected and thus the number of false alarms (FPs) remains relatively high. This is shown in Table 3 where some of the FPs are caused by the classifier not being able to discriminate among sitting on chair, sitting on bed and ambulating in the space between a bed and a chair. This is caused by lack of sensor observations during transitions, which are usually of short duration as the chair is placed next to the bed as shown in Fig 2(b). Moreover, a patient's posture while sitting in the bed or chair or ambulating might not vary much as they keep an upright posture. This effect can be seen in Fig 9 showing the output from the classifier where ambiguity between sitting in bed and in the chair is shown.

Survey II
Physical Activity
P1 – How did you experience wearing the equipment while performing activities?
P2 – Were you hindered by the equipment while lying?
Anxiety
A1 – I was frightened by this technology.
A2 – I don't want the equipment to be seen by others.
A3 – I don't like the feeling of being monitored.
Equipment
E1 – Wearing the equipment was no problem.
E2 – I just forgot I am wearing it.
Privacy
V1 – How did you experience wearing the equipment knowing that someone could be aware of some of your activities?

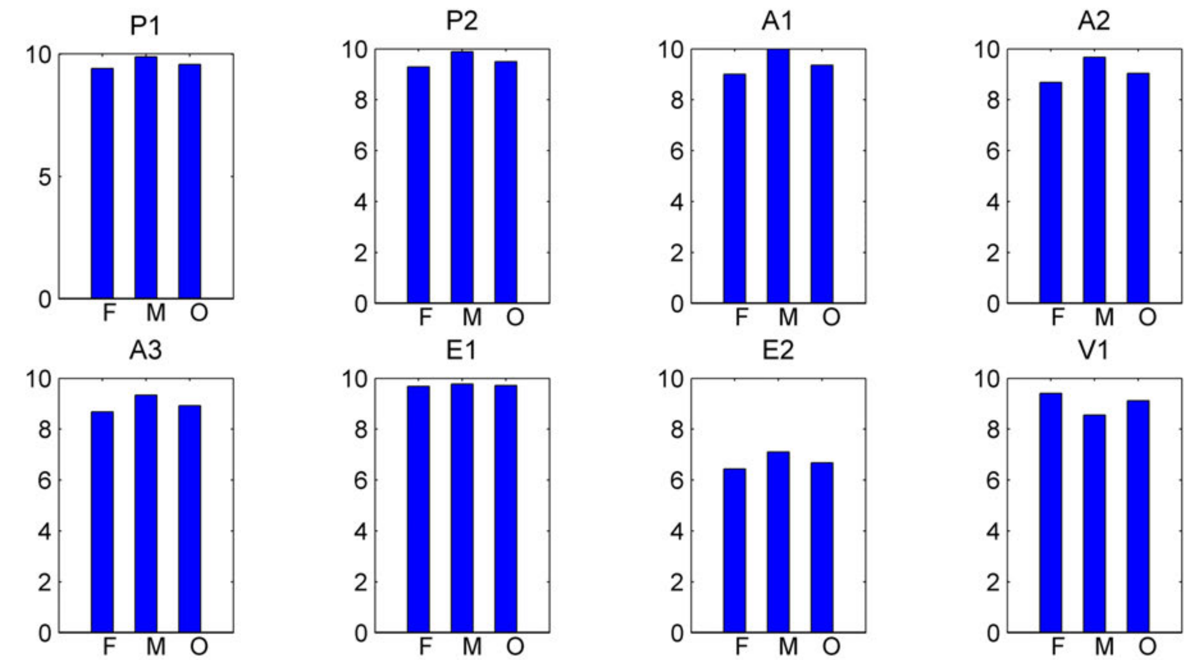

Fig 8. Results from second survey. Second survey conducted post-trial only, showing average score responses in the bar graph. F: female, M: male O: overall.

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Although this problem was reduced using non overlapping windows, it is the case for patients p.1, p.6, p.12, p.13, p.16, p.19, p.20, p.22 where most FPs are caused by the classifier's inability to discriminate between these activities i.e. sitting on chair, sitting on bed and ambulating in the relatively small area next to the bed and chair. However, as expected, the use of non

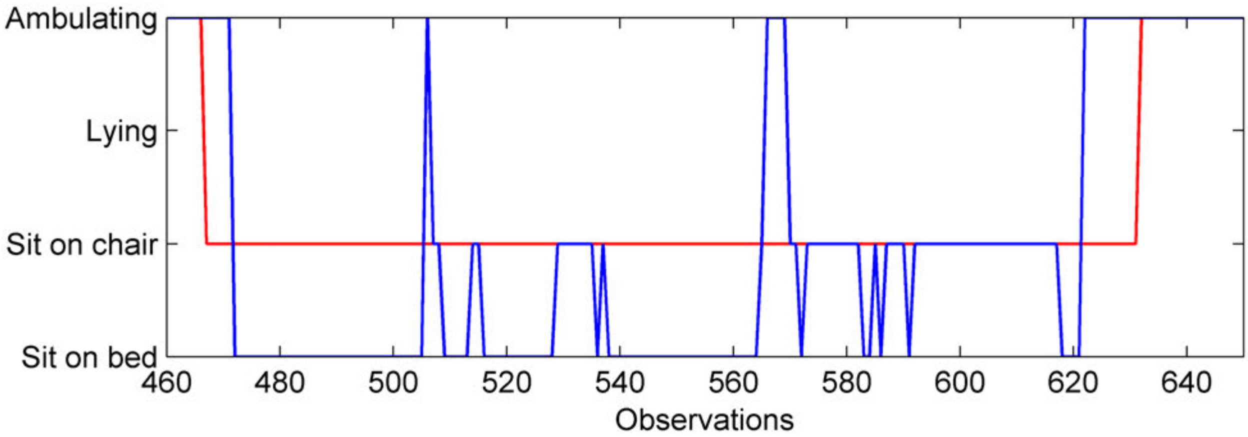

Fig 9. Classified activity contrasted with the ground truth for a patient near a chair. In red: ground truth, in blue: classified activity.

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overlapping windows produced most detection delays within the first processing time window. In the case of patient p.10, misclassifications occurred when the patient was lying in bed, as some readings were classified as sitting or ambulating.

The location of antenna1 focused on the chair on the wall opposite the chair collected few sensor observations. In the case of people sitting on the chair, adequate powering of the sensor is difficult due to the possibility of the chair or the patient being not directly illuminated by this RFID reader antenna as the patient may sit leaning forward or not face the RFID antenna (antenna1) directly. Thus, both ambulation ($\approx$ 9% of total sensor observations) and sitting on chair ($\approx$ 22%) activities were captured with less sensor observations than lying ($\approx$ 56%). For example, patient p.9 has only one sensor observation of the patient sitting on the chair. In the case of ambulation, sensor observations are obtained until the person walks by antenna1 when going to the door and, similarly, in the opposite direction, readings are col lected when the patient is close to antenna1. Past the location of antenna1, when going to the door, none of the antennas illuminate the sensor as the patient's body obstructs the sensor. Moreover, ambulation events can also be of short duration as the patient can access the chair located next to the bed in few short steps. This limited amount of data, especially for ambula tion, manifests as poor quality information and features extracted by such sparse sensor obser vations do not provide adequate information about the underlying patient movements to discriminate activities and, consequently, poor activity recognition performance.

We were not able to find studies reporting both bed and chair exit results to compare with our results, and a fair comparison is indeed difficult given the often different settings, e.g. demographics of participants, sensor type and location, used by different studies. Therefore, there is difficulty in comparing our approach with previous long term studies [4, 14, 15] as these are longitudinal trials with larger populations of hospitalized older people monitored during both on day and night time conditions that reported occurrence of falls and not alarm recognition effectiveness. For instance, the recent long term RCT from Sahota et al. [14] used bed and chair pressure sensors, their results did not report the alarming performance per apparatus but the resulting falls rate. However, the study of Capezuti et al. [4] used pressure sensors on beds in a longitudinal study to measure and report bed exit detection performance in older people where the recall of the system was of 71% and specificity 0.3% [4]. This high false alarm rate might be one reason why pressure sensors have been found to be ineffective in recent clinical trials [14, 15].

There have been other studies [54, 55] that considered only bed exits and reported recall and specificity values over 90%. However, these studies were undertaken with young and mid dle aged adults and that is a limitation of those studies [54, 55]. Furthermore, the empirical methods in [54, 55] were developed and tested with the same dataset, yielding optimal thresh olds for heuristic measures for the particular dataset.

We compared our proposed method performance, F score of 72%, to the results from pre vious studies in [36] as shown in Table 4. Comparing with the method in [36], where a weighted classifier was used to address the problem of imbalanced data, only recall was slightly lower for our method with a non statistically significant difference of $P = 0.58$. However, preci sion and F score, were higher for our method with statistically significant difference ($P < 0.0013$) than those of [36]. A possible cause is the use of a sliding window in [36] that fails to filter some false alarms, affecting the overall F score, albeit producing slightly more true alarms.

Acceptability study

Results from the acceptability study indicate that the sensor system appears acceptable to the hospitalized older people that participated in this pilot study. Results from the first survey denote, in general, increased confidence after the patients experienced the equipment as the overall score increased to 9.0 in the post trial survey. Although post trial response scores for Q6: "I am afraid the equipment will harm me" decreased after the trials for male patients and slightly improved for female patients, this indicates a concern about their safety (see Q6 in Fig 7). This is possibly due to the visible infrastructure to keep RFID antennas in place in patient's rooms as well as the highly visible sensor prototype used in the study. The results from the sec ond survey suggest a general acceptance of the equipment; however, lower scores regarding the patients being conscious of wearing the device (E2) were most probably due to the experi mental nature of the highly visible sensor device. In terms of privacy, the overall score was high (9.1), suggesting that the patients that participated in the trial were comfortable with being monitored using the wireless sensor device in the hospital setting. Overall, the results from the two surveys indicate that: i) the participants of the trial found the sensor acceptable to use; ii) initial anxiety about the equipment can be overcome by allowing older people to experi ence the equipment; and iii) the development of our sensor device must aim to eventually be integrated into textile such as a vest or the hospital gown so it is less obtrusive and unnotice able to a patient.

Overall, our results agree with previous study findings [19] and show that, despite the very visible nature of our particular sensor, wearable sensors are an acceptable technology for mon itoring older people. Further, wearable sensors have the potential to overcome privacy issues raised around the use of video monitoring of older adults in previous studies [16 18]. The study in [17] recommends the avoidance of using video images for more ethical practices such as silhouette extraction; however, this technology is still not widely accepted by older adults [16, 19]. The study in [19] states that, among community dwelling older people, cameras raised greater privacy concerns than other technologies, even when methods for extracting sil houettes were in place to preserve privacy. The study in [16] using a camera for capturing depth information (i.e. a person's body silhouette) for assessing gait parameters in a home set ting highlighted that 6 out of 15 eligible participants contacted did not want to participate in the study despite being provided an explanation and a picture of the privacy preserving silhou ette images collected from the depth sensor.

In addition to our body worn sensor being able to mitigate privacy concerns, our approach also provides technical and economic advantages over video images: i) RFID hardware is increasingly deployed to support asset tracking in hospitals and our approach provides a dual use for an existing infrastructure [56]; ii) the same technology can provide solutions to monitoring not only falls risk but other conditions such as 'wandering off' [31] of individual patients; iii) sensors can be capable of capturing more health related information such as heart rate [57]; and iv) the automatic unique identification provides the ability to individualize alarms to suit the monitoring needs of individual patients.

Limitations and future work

Our approach is not without limitations. Although the use of the non overlapping windows method reduces some errors such as false alarms, it also bounds the delay to produce an alert for staff to intervene, as most alarms are issued within the first time window of duration 4.8 s. In addition, there will always be delays before a staff member is able to assist a patient unless the staff is stationed very near to the patient's room, and therefore, a timely intervention also depends on the human response time. However, in the case of bed exiting, our problem formulation to consider the patient sitting on the bed as attempting to exit the bed gives extra time for staff to intervene.

The proposed intervention for falls prevention has no direct method to detect a fall. However, staff already notified of a bed or chair exit event can act upon a fall incident in the event the fall is not averted and prevent the damaging effects of a 'long lie' condition where life expectancy can be severely reduced as a result of an old person staying more than one hour on the floor after a fall. In relation to the completed surveys, the unbalanced distribution of male to female population and the small size of the trialled population is a limitation to our study. Future trials must consider these population issues as well as resolution of the points raised by our surveys, i.e. highly visible sensor device and RFID infrastructure, to derive more reliable conclusions.

In terms of extending the study, given that some patients used walking aids, it would be relevant to assess ambulation without a required walking aid and alarm when an un aided unsupervised patient attempts ambulation. This can be carried out once a bed or chair exit has been recognized, and the system can then assess whether a previously sensor tagged walking aid associated with the patient is being used. The continuous improvement of innovative techniques such as robust classifiers for activity classification using machine learning techniques, the introduction of improved motion descriptive features or the addition of extra sensors (e.g. barometers) may further improve the performance of the present pilot study and are currently being investigated. It should be highlighted that our approach is proposed for a hospital environment; applying these methods to an independent living environment, such as an older person living in their own homes, will require further development due to the greater variety of activities performed, and multiple bedroom furniture settings possible in a home environment.

Future work in the development of the intervention must address the limitation of the current study and verify improvements over the results obtained in this study. First, having all antennas ceiling mounted can help focus on specific room locations and improve powering of the sensor as well as a simple deployment option for different rooms. Second, placing the sensor on the shoulder rather than the chest is likely to achieve better illumination from ceiling mounted antennas, avoid occlusion from objects and the patient's body and reduce the sparsity in the sensor data, especially during ambulation. Third, in terms of sensor improvements, further research needs to improve resistance to wear and tear and reduce its size and visibility, as was also suggested by the results from the acceptability study, without losing performance. We have already made progress toward that end [58]. Future research must consider a trial with a larger cohort of hospitalized older people wearing a less obtrusive and more robust sensor prototype for longer periods and include scenarios such as staff interacting with patients and people visiting patients and changing the location of the chair. Ultimately, we need to evaluate the efficacy of this system to reduce falls in acute hospital settings using a RCT.

Conclusions

We have described a movement monitoring sensor system incorporating a single RFID sensor worn by hospitalized older people that recognizes bed and chair exits and its preliminary pilot study results are promising. We have identified areas of future development to improve our system's performance, such as placing sensors on the shoulder and RFID reader antennas on the ceiling and improving sensor performance by reducing size and energy consumption by embedded sensors. Further research may be undertaken to include a pilot study for a longer period of time with further developed infrastructure to improve our result metrics and overcome the limitations of our pilot study, and increase the activities of interest (using walking aids). Finally, the system was perceived acceptable to the patients performing the trials on all factors of the sensor acceptance model and showed, in general, an increased confidence after use.

Supporting information

S1 Pseudocode. Pseudocode of algorithms. Algorithm used in this study.
(PDF)

S1 Dataset. Dataset hospital. Data corresponding to the sensor observations for hospitalized older people participating in the trials; data anonymized except for gender.
(ZIP)

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References

1. Hitcho EB, Krauss MJ, Birge S, Claiborne Dunagan W, Fischer I, Johnson S, et al. Characteristics and circumstances of falls in a hospital setting. J Gen Intern Med. 2004; 19(7):732 739. https://doi.org/10.1111/j.1525-1497.2004.30387.x PMID: 15209586
2. Centers for Disease Control and Prevention. Important facts about falls; 2016. http://www.webcitation.org/6gREJTEgu.
3. Abreu C, Mendes A, Monteiro J, Santos FR. Falls in hospital settings: a longitudinal study. Rev Lat Am Enfermagem. 2012 Jun; 20:597 603. https://doi.org/10.1590/S0104-11692012000300023 PMID: 22991124
4. Capezuti E, Brush BL, Lane S, Rabinowitz HU, Secic M. Bed-exit alarm effectiveness. Arch Gerontol Geriatr. 2009; 49(1):27 31. https://doi.org/10.1016/j.archger.2008.04.007 PMID: 18508138
5. Centers for Disease Control and Prevention. Cost of falls among older adults; 2015. Available from: http://www.webcitation.org/6hanayMoC.
6. Oliver D, Hopper A, Seed P. Do hospital fall prevention programs work? A systematic review. J Am Geriatr Soc. 2000; 48(12):1679 1689. https://doi.org/10.1111/j.1532-5415.2000.tb03883.x PMID: 11129762
7. Vassallo M, Amersey RA, Sharma JC, Allen SC. Falls on integrated medical wards. Gerontology. 2000; 46(3):158 162. https://doi.org/10.1159/000022152 PMID: 10754374
8. Allan LM, Ballard CG, Rowan EN, Kenny RA. Incidence and prediction of falls in dementia: A prospective study in older people. PLoS ONE. 2009 May; 4(5):e5521. https://doi.org/10.1371/journal.pone.0005521 PMID: 19436724
9. Mirelman A, Herman T, Brozgol M, Dorfman M, Sprecher E, Schweiger A, et al. Executive function and falls in older adults: New findings from a five-year prospective study link fall risk to cognition. PLoS ONE. 2012 Jun; 7(6):e40297. https://doi.org/10.1371/journal.pone.0040297 PMID: 22768271
10. Australian Commission on Safety and Quality in Healthcare. Preventing Falls and Harm From Falls in Older People: Best Practice Guidelines for Australian Hospitals; 2009.
11. Vassallo M, Vignaraja R, Sharma JC, Hallam H, Binns K, Briggs R, et al. The effect of changing practice on fall prevention in a rehabilitative hospital: The hospital injury prevention study. J Am Geriatr Soc. 2004; 52(3):335 339. https://doi.org/10.1111/j.1532-5415.2004.52102.x PMID: 14962145
12. Dykes PC, Carroll DL, Hurley A, Lipsitz S, Benoit A, Chang F, et al. Fall prevention in acute care hospitals. JAMA: The Journal of the American Medical Association. 2010; 304(17):1912 1918. https://doi.org/10.1001/jama.2010.1567 PMID: 21045097
13. Cameron ID, Gillespie LD, Robertson MC, Murray GR, Hill KD, Cumming RG, et al. Interventions for preventing falls in older people in care facilities and hospitals. Cochrane Database Syst Rev. 2012; 12. https://doi.org/10.1002/14651858.CD005465.pub3 PMID: 23235623
14. Sahota O, Drummond A, Kendrick D, Grainge MJ, Vass C, Sach T, et al. REFINE (REducing Falls in InpatieNt Elderly) using bed and bedside chair pressure sensors linked to radio-pagers in acute hospital care: a randomised controlled trial. Age Ageing. 2014; 43(2):247 253. https://doi.org/10.1093/ageing/aft155 PMID: 24141253
15. Shorr RI, Chandler AM, Mion LC, Waters TM, Liu M, Daniels MJ, et al. Effects of an intervention to increase bed alarm use to prevent falls in hospitalized patients: A cluster randomized trial. Ann Intern Med. 2012; 157(10):692 699. https://doi.org/10.7326/0003-4819-157-10-201211200-00005 PMID: 23165660
16. Newland P, Wagner JM, Salter A, Thomas FP, Skubic M, Rantz M. Exploring the feasibility and acceptability of sensor monitoring of gait and falls in the homes of persons with multiple sclerosis. Gait & Posture. 2016; 49:277 282. https://doi.org/10.1016/j.gaitpost.2016.07.005
17. Liu L, Stroulia E, Nikolaidis I, Miguel-Cruz A, Rincon AR. Smart homes and home health monitoring technologies for older adults: A systematic review. International Journal of Medical Informatics. 2016; 91:44 59. https://doi.org/10.1016/j.ijmedinf.2016.04.007 PMID: 27185508
18. Stone EE, Skubic M. Fall detection in homes of older adults using the Microsoft Kinect. IEEE Journal of Biomedical and Health Informatics. 2015 Jan; 19(1):290 301. https://doi.org/10.1109/JBHI.2014.2312180 PMID: 24733032
19. Demiris G, Hensel BK, Skubic M, Rantz M. Senior residents' perceived need of and preferences for "smart home" sensor technologies. Int J Technol Assess Health Care. 2008; 24:120 124. https://doi.org/10.1017/S0266462307080154 PMID: 18218177
20. Pantelopoulos A, Bourbakis NG. A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis. IEEE Transactions on Systems, Man, and Cybernetics Part C: Applications and Reviews. 2010 Jan; 40(1):1 12. https://doi.org/10.1109/TSMCC.2009.2032660

21. Lara OD, Labrador MA. A survey on human activity recognition using wearable sensors. IEEE Communications Surveys Tutorials. 2013; 15(3):1192 1209. https://doi.org/10.1109/SURV.2012.110112.00192

22. Delahoz YS, Labrador MA. Survey on fall detection and fall prevention using wearable and external sensors. Sensors. 2014; 14(10):19806. https://doi.org/10.3390/s141019806 PMID: 25340452

23. Bergmann JHM, McGregor A. Body-worn sensor design: What do patients and clinicians want? Ann Biomed Eng. 2011; 39(9):2299 2312. https://doi.org/10.1007/s10439-011-0339-9 PMID: 21674260

24. Chaudhuri S, Kneale L, Le T, Phelan E, Rosenberg D, Thompson H, et al. Older Adults' Perceptions of Fall Detection Devices. J Appl Gerontol. 2015; PMID: 26112030

25. Godfrey A, Bourke AK, Ólaighin GM, van de Ven P, Nelson J. Activity classification using a single chest mounted tri-axial accelerometer. Med Eng Phys. 2011; 33(9):1127 1135. https://doi.org/10.1016/j.medengphy.2011.05.002 PMID: 21636308

26. Najafi B, Aminian K, Paraschiv-Ionescu A, Loew F, Bula CJ, Robert P. Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly. IEEE Trans Biomed Eng. 2003; 50(6):711 723. https://doi.org/10.1109/TBME.2003.812189 PMID: 12814238

27. Brodie MA, Lord SR, Coppens MJ, Annegarn J, Delbaere K. Eight weeks remote monitoring using a freely worn device reveals unstable gait patterns in older fallers. IEEE Trans Biomed Eng. 2015; 62 (11):2588 2594. https://doi.org/10.1109/TBME.2015.2433935 PMID: 25993701

28. Schwenk M, Hauer K, Zieschang T, Englert S, Mohler J, Najafi B. Sensor-Derived Physical Activity Parameters Can Predict Future Falls in People with Dementia. Gerontology. 2014; 60(6):483 492. https://doi.org/10.1159/000363136 PMID: 25171300

29. Najafi B, Armstrong DG, Mohler J. Novel Wearable Technology for Assessing Spontaneous Daily Physical Activity and Risk of Falling in Older Adults with Diabetes. J Diabetes Sci Technol. 2013; 7(5):1147 1160. https://doi.org/10.1177/193229681300700507 PMID: 24124940

30. Redmond SJ, Scalzi ME, Narayanan MR, Lord SR, Cerutti S, Lovell NH. Automatic segmentation of triaxial accelerometry signals for falls risk estimation. In: 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2010. p. 2234 2237.

31. Visvanathan R, Ranasinghe DC, Shinmoto Torres RL, Hill K. Framework for preventing falls in acute hospitals using passive sensor enabled radio frequency identification technology. In: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2012. p. 5858 5862.

32. Sample AP, Yeager DJ, Powledge PS, Smith JR. Design of a passively-powered, programmable sensing platform for UHF RFID systems. In: 2007 IEEE International Conference on RFID; 2007. p. 149 156.

33. Kaufmann T, Ranasinghe DC, Zhou M, Fumeaux C. Wearable quarter-wave microstrip antenna for passive UHF RFID applications. International Journal of Antennas and Propagation. 2013; 2013. https://doi.org/10.1155/2013/129839

34. Ranasinghe DC, Shinmoto Torres RL, Hill K, Visvanathan R. Low cost and batteryless sensor-enabled radio frequency identification tag based approaches to identify patient bed entry and exit posture transitions. Gait Posture. 2014; 39(1):118 123. https://doi.org/10.1016/j.gaitpost.2013.06.009 PMID: 23850327

35. Shinmoto Torres RL, Ranasinghe DC, Shi Q, Sample AP. Sensor enabled wearable RFID technology for mitigating the risk of falls near beds. In: 2013 IEEE International Conference on RFID; 2013. p. 191 198.

36. Shinmoto Torres RL, Visvanathan R, Hoskins S, van den Hengel A, Ranasinghe DC. Effectiveness of a Batteryless and Wireless Wearable Sensor System for Identifying Bed and Chair Exits in Healthy Older People. Sensors. 2016; 16(4):546. https://doi.org/10.3390/s16040546

37. Wong Shee A, Phillips B, Hill K, Dodd K. Feasibility, acceptability, and effectiveness of an electronic sensor bed/chair alarm in reducing falls in patients with cognitive impairment in a subacute ward. Journal of Nursing Care Quality. 2014; 29(3):253 262. https://doi.org/10.1097/NCQ.0000000000000054 PMID: 24487696

38. Vlaeyen E, Coussement J, Leysens G, Van der Elst E, Delbaere K, Cambier D, et al. Characteristics and Effectiveness of Fall Prevention Programs in Nursing Homes: A Systematic Review and Meta-Analysis of Randomized Controlled Trials. J Am Geriatr Soc. 2015; 63(2):211 221. https://doi.org/10.1111/jgs.13254 PMID: 25641225

39. Goodwin V, Abbott R, Whear R, Bethel A, Ukoumunne O, Thompson-Coon J, et al. Multiple component interventions for preventing falls and fall-related injuries among older people: systematic review and meta-analysis. BMC Geriatr. 2014; 14(1):15. https://doi.org/10.1186/1471-2318-14-15 PMID: 24495705

40. Bunn F, Dickinson A, Simpson C, Narayanan V, Humphrey D, Griffiths C, et al. Preventing falls among older people with mental health problems: a systematic review. BMC Nurs. 2014; 13(1):4. https://doi.org/10.1186/1472-6955-13-4 PMID: 24552165

41. Finkenzeller K. RFID Handbook: Fundamentals and Applications in Contactless Smart Cards, Radio Frequency Identification and Near-Field Communication. Wiley; 2010.

42. Li H, Ye C, Sample AP. IDSense: A human object interaction detection system based on passive UHF RFID. In: 33rd Annual ACM Conference on Human Factors in Computing Systems. CHI'15. USA: ACM; 2015. p. 2555 2564.

43. Fensli R, Pedersen PE, Gundersen T, Hejlesen O. Sensor acceptance model Measuring patient acceptance of wearable sensors. Methods Inf Med. 2008; 47(1):89 95. PMID: 18213434

44. Nikitin PV, Martinez R, Ramamurthy S, Leland H, Spiess G, Rao KVS. Phase based spatial identification of UHF RFID tags. In: 2010 IEEE International Conference on RFID; 2010. p. 102 109.

45. Shinmoto Torres RL, Ranasinghe DC, Shi Q. Evaluation of wearable sensor tag sata segmentation approaches for real time activity classification in elderly. In: Stojmenovic I, Cheng Z, Guo S, editors. Mobile and Ubiquitous Systems: Computing, Networking, and Services. vol. 131 of Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering. Springer; 2014. p. 384 395.

46. Hall M, Frank E, Holmes G, Pfahringer B, Reutemann P, Witten IH. The WEKA data mining software: An update. ACM SIGKDD Explorations Newsletter. 2009 Nov; 11(1):10 18. https://doi.org/10.1145/1656274.1656278

47. Lin CF, Wang SD. Fuzzy support vector machines. IEEE Transactions on Neural Networks. 2002 Mar; 13(2):464 471. https://doi.org/10.1109/72.991432 PMID: 18244447

48. Cortes C, Vapnik V. Support-vector networks. Machine Learning. 1995; 20(3):273 297. https://doi.org/10.1007/BF00994018

49. Hsu CW, Lin CJ. A comparison of methods for multiclass support vector machines. IEEE Transactions on Neural Networks. 2002 Mar; 13(2):415 425. https://doi.org/10.1109/72.991427 PMID: 18244442

50. Chang CC, Lin CJ. LIBSVM: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology. 2011; 2:27:1 27:27. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm. https://doi.org/10.1145/1961189.1961199

51. Hansen N. The CMA Evolution Strategy: A Comparing Review. In: Lozano JA, Larrañaga P, Inza In, Bengoetxea E, editors. Towards a New Evolutionary Computation. vol. 192 of Studies in Fuzziness and Soft Computing. Springer Berlin Heidelberg; 2006. p. 75 102. Software available at https://www.lri.fr/~hansen/cmaes inmatlab.html.

52. McKnight PE, Najab J. In: Mann-Whitney U Test. John Wiley & Sons, Inc.; 2010.

53. Shinmoto Torres RL, Ranasinghe DC, Shi Q, van den Hengel A. Learning from Imbalanced Multiclass Sequential Data Streams Using Dynamically Weighted Conditional Random Fields. ArXiv e-prints. 2016;.

54. Hilbe J, Schulc E, Linder B, Them C. Development and alarm threshold evaluation of a side rail integrated sensor technology for the prevention of falls. Int J Med Inform. 2010; 79(3):173 180. https://doi.org/10.1016/j.ijmedinf.2009.12.004 PMID: 20083427

55. Bruyneel M, Libert W, Ninane V. Detection of bed-exit events using a new wireless bed monitoring assistance. Int J Med Inform. 2011; 80(2):127 132. https://doi.org/10.1016/j.ijmedinf.2010.10.007 PMID: 21051278

56. Swedberg C. Journal R, editor. Group health reinvents patient care with RTLS. RFID Journal; 2012. http://www.webcitation.org/6O7ywg1ps. Available from: http://www.rfidjournal.com/articles/view?9828.

57. Agezo S, Zhang Y, Ye Z, Chopra S, Vora S, Kurzweg T. Battery-free RFID heart rate monitoring system. In: 2016 IEEE Wireless Health (WH); 2016. p. 1 7.

58. Chen SJ, Fumeaux C, Ranasinghe DC, Kaufmann T. Paired snap-on buttons connections for balanced antennas in wearable systems. IEEE Antennas and Wireless Propagation Letters. 2015; 14:1498 1501. https://doi.org/10.1109/LAWP.2014.2363852

1 Pseudo code

Algorithm 1 Activity class assignment

Require: Output from classifier (probability for each class) Pr_k, Number of non-overlapping windows M

for m=1 to M (M can be ∞) **do**

  $y_{tmp} \leftarrow \sum_q (Pr_{k,q}); q \leftarrow (m-1) \times \mathfrak{T}$ to $m \times \mathfrak{T}$.

  $y_{pred,m} \leftarrow$ index of $\max_k(y_{tmp})$

Algorithm 2 Bed and chair exit recognition from assigned classes

```
Require: predicted output y_pred
for n=2 to N (N can be ∞ ) do
    if y_pred(n − 1) = Sit_on_bed then
        if y_pred(n) = Sit_on_chair then
        else if y_pred(n) = Lying then
        else if y_pred(n) = Ambulating then
    else if y_pred(n − 1) = Sit_on_chair then
        if y_pred(n) = Sit_on_bed then
            if previous predicted bed/chair exit occurred more than 1.75 s ago then
                BedChairExitPred(n) ← 1
        else if y_pred(n) = Lying then
            if previous predicted bed/chair exit occurred more than 1.75 s ago then
                BedChairExitPred(n) ← 1
        else if y_pred(n) = Ambulating then
            if previous predicted bed/chair exit occurred more than 1.75 s ago then
                BedChairExitPred(n) ← 1
    else if y_pred(n − 1) = Lying then
        if y_pred(n) = Sit_on_chair then
            if previous predicted bed/chair exit occurred more than 1.75 s ago then
                BedChairExitPred(n) ← 1
        else if y_pred(n) = Sit_on_bed then
            if previous predicted bed/chair exit occurred more than 1.75 s ago then
                BedChairExitPred(n) ← 1
        else if y_pred(n) = Ambulating then
            if previous predicted bed/chair exit occurred more than 1.75 s ago then
                BedChairExitPred(n) ← 1
    else if y_pred(n − 1) = Ambulating then
        if y_pred(n) = Sit_on_bed then
        else if y_pred(n) = Lying then
        else if y_pred(n) = Sit_on_chair then
```

Chapter 9

Hierarchical Classification Method for Recognizing Alarming States

In previous chapters, we have introduced intervention methods for the generation of bed and chair exit alerts on two populations of healthy and hospitalized older people. Both studies used two-stage methods that evaluated the occurrence of these high risk events in heuristics post-processing stages following a classification stage that predicted class labels in real time.

The article contained in this chapter is a journal paper that considers the problem of recognizing alarm or no-alarm states (high-level activity) which are derived from basic activities or postures (low-level activities). This method uses a graphical model hierarchical classifier, based on CRFs, to recognize both levels of activities simultaneously in real time. This model recognizes alarming states by constructing relationships between the high-level activities, current sensor observations and the predicted low-level activities e.g. sitting on chair, sitting on bed, lying and ambulating. This method avoids the use of empirically determined heuristic approaches or cascaded classifiers for the recognition of alerts , and takes less time to train and validate parameters as opposed to other state-of-the-art approaches .

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A hierarchical model for recognizing alarming states in a batteryless sensor alarm intervention for preventing falls in older people

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ABSTRACT

Falls are common among older people, especially in hospitals and nursing homes. The combination of pervasive sensing and statistical learning methods is creating new possibilities for automatic monitoring of activities of hospitalized older people to provide targeted and timely supervision by clinical staff to reduce falls. In this paper we introduce a hierarchical conditional random fields model to predict alarming states (being out of the bed or chair) from a passive wearable embodiment of a sensor worn over garment to provide an intervention mechanism to reduce falls. Our approach predicts alarm states in real time and avoids the use of empirically determined heuristics methods alone or in combination with machine learning based models, or multiple cascaded classifiers for generating alarms from activity prediction streams. Instead, the proposed hierarchical approach predicts alarms based on learned relationships between alarms, sensor information and predicted low-level activities. We evaluate the performance of the approach with 14 healthy older people and 26 hospitalized older patients and demonstrate similar or better performance than machine learning based approaches combined with heuristics based methods.

1. Introduction

Falls among older people in hospitals and nursing homes are a significant problem and a leading cause of unintentional injury-related death for people over 65 in Australia [1] and USA [2]. These are costly events as the hospital expenses alone of a single fall-related injury is estimated at US$35 777 and the direct medical costs of fall injuries in USA is expected to reach US$34.8 billion annually by 2016 (both amounts adjusted for inflation since 2013) [3].

Falls are reported to occur mostly in patients' rooms (84%) [4], where unsupervised near bed and chair activities such as bed exits, chair exits and ambulation have been identified as potential activities and locations of falls related injury for older people [4–6]. Current best practice recommendations, which include interventions based on exercise, nutrition, medication and the use of bed or chair exit alarms [7] contribute to falls prevention in hospitals. Nevertheless, falls rates still remain

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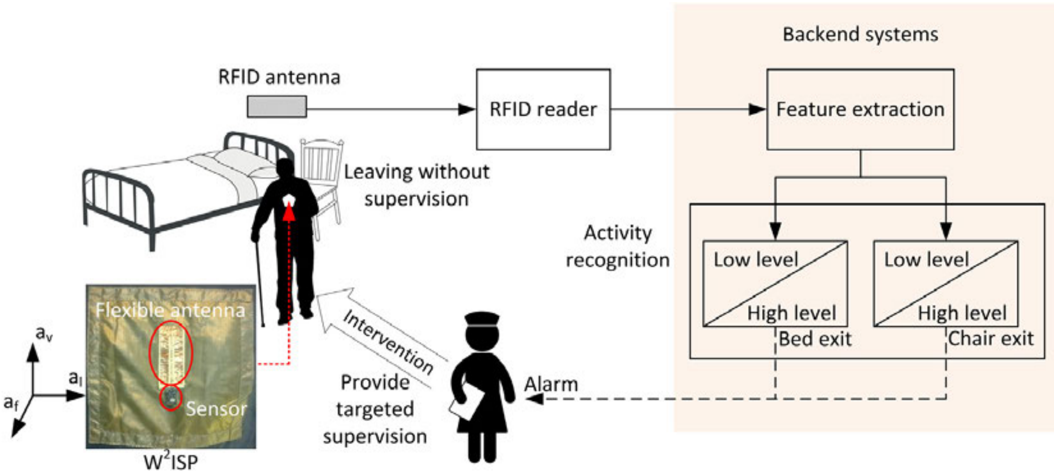

Fig. 1. General description of the intervention for reducing falls and recognition of bed and chair exits. The patient is wearing the batteryless wireless sensor, when exiting the bed or chair an alarm informs the caregiver to provide assistance to the patient. The W^{2}ISP unit is shown on the bottom-left and consists of a flexible antenna, a tri-axial accelerometer and a microcontroller that contains a firmware implementation of ISO-18000-6C RFID air interface protocol.

high [8,9]. For example, a 10-year audit on in-hospital falls recorded only at public hospitals in the State of Victoria, Australia, with a population of over 5 million people, determined that falls increased yearly at a rate of about 160 falls per year with more than 21 000 falls recorded in that 10-year period [8]. Recent falls prevention clinical studies in hospital settings [10–12] based on pressure pads to generate an alarm after detecting a bed or chair exit to provide caregivers an opportunity to assist patients found, in general, little to no reduction of falls. One reason may be attributed to "alarm fatigue" [11] due to false alarms. For instance, the long term clinical study of Capezuti et al. [13] showed that approaches using pressure mats alone or in combination with other sensors (infrared beam detectors) were confronted by high false alarm rates (low specificity of 0.3%). This study [13] also found that nursings staff must evaluate the size and body movements of the patients in order to best locate and configure the mat and possibly include other sensors [13], making pressure mat-based approaches more time consuming in practice and potentially cumbersome for nursing staff [14].

Wearable sensors provide new opportunities to monitor patients and develop more effective movement sensor alarm systems for falls prevention [15,16] as continuous motion data can be collected and analyzed in real time. Moreover, as sensors keep reducing in size, more vital medical data can also be gathered from these devices [15,16]. Wearable devices also eliminate privacy violation concerns raised by older people related to the use of intrusive technologies such as cameras [17]. Wearable sensor-based studies have explored the areas of recognition of activities of daily living (ADL) [18–23], falls detection and assessment of the risk or propensity for falls in older people [24–28]. However, the use of this technology in a clinical intervention to prevent falls remains under-explored.

Most studies using body worn sensors for human activity recognition [18–20,22,23,29] used a single or multiple battery powered sensors attached or strapped to the body. This approach can cause discomfort to older people whom have shown a preference for lightweight wearable devices [30,31]; in particular garment-embedded wearable sensors so that they do not need to remember to use them [30]. Moreover, recharging or changing batteries of sensor devices increases the workload of nursing staff as the length of stay of some patients can last several weeks to a month or more. In contrast to the use of battery-powered sensor methods [18–20,22,23,29], we demonstrated in [32], for the first time, the possibility of using a single batteryless, i.e. lightweight, radio frequency identification (RFID) tag with an integrated accelerometer sensor as a bed exit movement sensor alarm with young people.

RFID, as a wireless and unique identification technology, provides the capability to simultaneously monitor multiple patients; moreover, RFID platforms are increasingly being deployed in hospitals for monitoring equipment, patients and personnel [33]. Therefore, integration with existing RFID infrastructure can result in the reduction of operational expenses. Our RFID-based approach for monitoring patients and providing timely alarms to caregivers in a technological intervention to prevent falls is illustrated in Fig. 1. In this proposed intervention, a patient wears the sensor over a loosely worn garment at sternum level, as chest-located sensors [34] are better able to capture upper-body movements to effectively determine postures in older people. The sensor, an accelerometer embedded passive RFID tag in a wearable embodiment (bottom-left of Fig. 1), collects motion information from the patient in a sparse data stream which is processed by our proposed approach for the recognition of alarms of interest associated with high-risk activities, such as getting out of bed, in real time. Hence, once an unsupervised patient performs a given high-risk activity (i.e. exits the bed or chair), our approach recognizes an alarming condition and issues an alarm for hospital staff to quickly access the room to supervise the patient and prevent a fall. To our knowledge, there is no previous literature that uses a batteryless, wireless sensor device with healthy and hospitalized older people for the prevention of falls.

In the context of our clinical intervention, we are interested in discriminating between alarming and no-alarming states of a patient in a hospital setting, where an alarm state corresponds to a bed exit and being out-of-bed or a chair exit and being out-of-chair whereas a no-alarm encompasses any other state. In our previous studies in [21,32], our approach was to identify posture transitions, for example getting out of bed. The method in [32] was purely heuristics-based with empirically determined threshold levels and produced an output from 20 s segment windows, causing delays in alarm activation and response from caregivers. In [21] we used a two-stage approach where we: (i) predicted an activity label sequence, such as: lying, sitting-on-bed, ambulating from a time series of sensor observations; and (ii) subsequently used a heuristic based empirical method to determine changes from previous and current predicted activity labels to identify alarming activities, for example, sitting-on-bed to ambulating to recognize bed exits. This method [21] achieved better performance than that of [32] when tested on older people. In the present study, our motivation is to formulate the alarm and no-alarm states as high-level activities to be recognized using a hierarchical classifier where the model learns relationships between the alarm and no-alarm states, the current sensor observation and the sequence of predicted low-level activities.

Other studies have also considered the recognition of high-level activities with body worn sensors. For example, walking, running and cycling, in Banos et al. [20] and making coffee, toileting or watching television in Wang et al. [23], were derived from the low-level activities of body or limb movements. In general, methods to determine high-level activities have considered:

- Heuristic methods for the recognition of high level activities [18,32] (see Section 2.1); and
- Multiple stage classifiers [19–23,29] (see Section 2.2).

The use of heuristic methods implies that thresholds or other parameters are empirically determined, i.e. not learned by the model, and calculated or pre-determined for the available testing data [18,23,32]. Often, these parameters must be reevaluated to match the conditions of new testing data. Similarly, for cascaded classifiers [19,20,22], multiple classifiers in sequence are trained where each prediction model requires the evaluation of model parameters (e.g. SVM's trade-off parameter C and kernel parameters). The use of multiple stages can extend the training time, significantly increasing the time required to find optimal parameters. In addition, most studies do not consider the natural relationships between sequential activities during classification.

Therefore, this article proposes a classification algorithm for learning to recognize in real time high level activities, corresponding to the alarming states of a patient exiting a bed and being out-of-bed, or exiting a chair and being out-of-chair. We expect this model to reduce training time from previous multi-stage classification approaches, reinforce the learning of our alarming states, and eliminate the need to rely on empirically determined heuristic stages where real time inference is required. In this study, our contributions are:

1. We develop a novel hierarchical classifier based on the probabilistic method of conditional random fields (CRF) capable of modeling dependencies of activities in a sequence to learn to predict alarming states instead of using empirically determined heuristic approaches or cascaded classifiers and thus avoiding the use of multiple processing stages. In particular, our hierarchical CRF (HCRF) classifier incorporates the decision function to determine when to generate an alarm by discriminating alarming states—which we refer to as our high-level activities—by constructing relationships between high-level activities, current sensor observation and predicted low-level activities from sensor observations (e.g. sitting, lying, ambulating). Furthermore, inferencing in our HCRF approach is achieved in real time using a sum–product algorithm based method that computes the marginal probabilities for every received sensor data as opposed to inferencing complete sequences as is typical in CRFs.
2. Our learning algorithm utilizes time-domain based information from the accelerometer and RFID data obtained from the RFID infrastructure. This allows the rapid calculation of features in contrast to the use of frequency-domain accelerometer information where data interpolation, given the sparse and irregular reading intervals of our passive sensor data, and transformation to frequency domain are necessary.
3. We evaluate the real-time alarming performance of our approach with cohorts of 14 healthy older people and 26 older hospitalized patients from a geriatrics evaluation and management (GEM) unit since we are interested in reducing falls in hospitals.

2. Related works

This section describes previous methods formulated for human activity recognition. These approaches can be broadly categorized based on their method to recognize activities of interest: (i) heuristics-only approaches; and (ii) multiple-stage approaches, usually consisting of a single or sequence of classifiers followed by a heuristics method for activity recognition. We also describe other studies based on hierarchical approaches using CRFs.

2.1. Heuristics-only approaches

In these methods [18,27,32,35] the activities of interest were transitions such as sitting to standing and standing to sitting [18,27,35] or in-bed to out-of-bed [32]. These approaches used a heuristic decision-tree model based on thresholds where the sensor data has to be interpolated and filtered various times according to the activity of interest; moreover, thresholds and other parameters were empirically determined with the testing population and thus are not learned. None of these methods were implemented in real time as [32], our previous approach evaluated with young adult volunteers, considered non-overlapping windows of 20 s duration and [18,27,35] used data-loggers and processed each participant's data in a single batch.

2.2. Multiple stage approaches

These methods [19–23,29,36] usually considered a two-stage solution, where the first stage, a machine learning classifier, predicted low-level activities followed by a second stage for post-processing the prediction stream to determine a label corresponding to a high-level activity. In [21], we considered a two-stage approach where the first stage predicted postures from a sequence of sensor data and the second heuristic-based stage evaluated change of postures from that of being in-bed to out-of-bed to generate an alarm. The studies of Lee et al. [36], Lee et al. [29], Varkey et al. [19], and Wang et al. [23], used cascaded classifier based processes to discriminate between two levels of activities from sensor information, where an identified action, motion or type of movement (e.g. static or dynamic [29], arm moving up or down [19], or stand and walk [36]) is followed by the recognition of the high-level activity of interest (e.g. driving, going upstairs [29]; writing, jogging or walking [19]; and shopping or taking the bus [36]). In Banos et al. [20] multiple binary classifiers were hierarchically ranked and combined, first at individual sensor level and then from multiple sensor sources to recognize an activity being performed.

In the cascaded classifier models of [20,23,36] the high-level classifier waits for the output of the previous level (low-level) classifier in order to perform classification. This can cause some processing delay; for example in [36] the high-level model considers up to 5 min of collected data to make a decision. Other models [19,29] used the sensor data stream for input to the classifiers; however, multiple classification models are trained and used on the high-level classification stage depending on the output of the low-level classifier. In these methods, the high-level activity was determined directly by the high-level classifier [19,29,36]; or a decision stage that decided on the weighted-sum of the outputs of the high-level classifiers where weights were learned; or used a simple heuristics-based score function exceeding a threshold level that was empirically predetermined [23]. Similarly, our approach in [21] used a heuristics method that considered the previous and current predicted activity to issue an alarm.

2.3. CRF-based approaches

Our approach is based on a hierarchical model based on CRFs. Recent approaches using multi-level graphical models, also named hierarchical CRF [37–41] were mostly focused on solving computer vision and imaging problems and did not require real time prediction in their problem formulation as is our case. Moreover, these methods were not intended for sequential time-series data where inference is based on temporal data which is never complete.

Other methods included multilayer approaches such as hidden conditional random fields [42–44] which considers a linear chain model where a layer of variables, in contrast to our approach, is latent and inference of this layer is not required as it is unknown. The study of Chatzis et al. [45] infers labels for two non-latent layers of variables as in our approach. However, these studies [42,45] provide a single classification value for a complete series of observations. As a consequence, these processes [42,45] require the complete set of inputs to perform inference which makes these algorithms unsuitable for our problem which requires a prediction of alarm or no-alarm state for every received sensor observation to meet real time requirements of our application.

In contrast to previous approaches, we develop a method that predicts in real time high level activities in a single classification process without relying on empirically determined parameters or expensive post processing stages. Moreover, all parameters are learned and not determined by testing data. This is the first attempt, to our knowledge, to investigate the use of hierarchical CRFs in the recognition of high-level activities in real time, in our case corresponding to alarming states. We describe the study's approach and algorithms in the following sections.

3. Description of the proposed intervention

This study's proposed intervention is illustrated in Fig. 1 where older people use a wearable sensor device called Wearable Wireless Identification and Sensing Platform (W^2ISP) attached on top of their clothing and described in detail in Section 4.2. Once the patient exits the bed or chair without supervision, (i) data from upper-body motion; (ii) patient identification; and (iii) radio frequency (RF) information such as RSSI (received signal strength indicator), phase and frequency; are collected via the RFID reader infrastructure, i.e. RFID antennas and readers, and transmitted for high-level activity (alarms) recognition in real time. The focus of this paper is the extraction of features from the received data and the recognition of alarming events using two parallel hierarchical conditional random field classifiers.

The first hierarchical model recognizes the out of bed alarming state (exiting the bed and being out of bed), referred to as bed exit henceforth for simplicity. For example, a bed exit considers a person leaving the bed after sitting or lying on it; however, the change of a person lying to sitting on the bed does not generate an alarm as the person is still on the bed. The second hierarchical model recognizes the out of chair alarm state (exiting a chair and being out of chair), referred to as chair exit for simplicity. The hierarchical models predict an alarm or no-alarm state using an associated confidence level for each

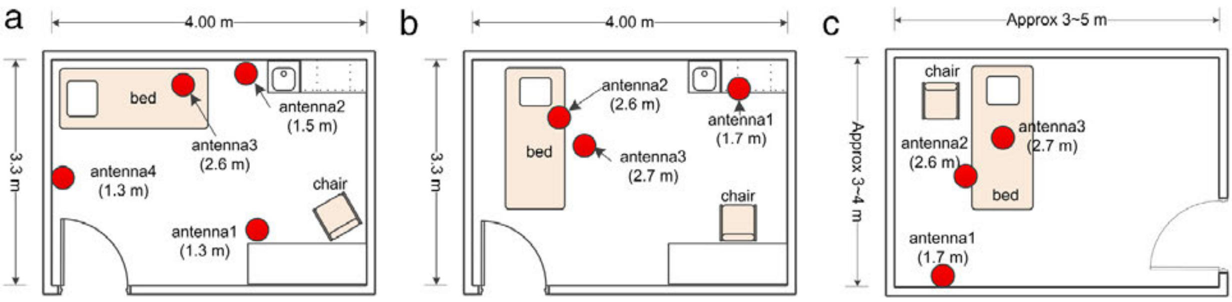

Fig. 2. Description of the experimental settings. (a) Room1, (b) Room2 and (c) Room3.

Table 1
Number of executed bed exits and chair exits during trials.

Room1		Room2		Room3	
Bed exit	Chair exit	Bed exit	Chair exit	Bed exit	Chair exit
83	48	52	20	67	51

prediction based on the marginal probability of the alarm state. Hence, a high confidence indicates a high likelihood of an occurrence of a high-level activity, corresponding to an alarm signal.

The issued alarm is received by hospital staff, who also wear RFID embedded identification tags and can be uniquely identified by the RFID platform, to access the room and perform necessary intervention to prevent a fall from the identified patient [46]. The RFID name badges allow the system to automatically determine the provision of care to infer when a person is being supervised or being cared for.

4. Data collection

4.1. Participants and environment

In this study, we trialled 14 healthy older volunteers aged between 66 and 86 years old and 26 older patients from the geriatrics ward of an Australian hospital, patients were aged between 71 and 93 years old. The participants had no cognitive impairment, were able to mobilize independently or use a walking aid and signed consent for the trials. The trials for the healthy volunteers were performed in a clinical room which was instrumented to resemble two different clinical settings, called Room1 and Room2 and shown in Fig. 2. The healthy older volunteers were assigned to either clinical setting Room1 or Room2. The setting of Room1, shown in Fig. 2(a), used four RFID reader antennas: one on top of the bed on ceiling level and three at wall level covering the areas a person using the sensor device is likely to walk through, with one of these three antennas facing the chair. In the case of Room2, see Fig. 2(b), two antennas are facing the bed and surrounding areas at ceiling level and one antenna is facing the chair. In the case of the hospitalized patients, the trials were performed in their own hospital rooms. Fig. 2(c) shows a general deployment in a hospital room where three antennas were used: two directed to the area next to the bed and one tilted towards the chair. The chairs were located at either side of the bed. The dimensions for Room3 were not fixed since the experiments were carried out in the rooms occupied by participating hospital patients.

The participants performed a set of predefined activities such as lying on the bed, sitting on the bed, sitting on the chair, walking from bed to chair and chair to bed and walking to and from the door. The participants were informed of the activities to perform and were told to perform these activities as comfortably as possible and no indication was made as to how to do each movement. The duration for the trials for healthy volunteer was of about 90–120 min and about 20–25 min for hospitalized volunteers. Healthy participants performed about 5 trials each and completed on average 2 bed exits and 1 chair exit per trial. Hospitalized participants performed one trial each and completed on average 2–3 chair exits and bed exits, depending on their physical condition. The total number of bed and chair exits performed during trials are shown in Table 1. The data of 3 trials from a single volunteer from the healthy cohort in Room1 and the data of 3 patients from the hospitalized cohort of Room3 were not used due to sensor malfunction and insufficient data collection; hence we use the data of 23 patients in Room3. The data of these trials are available at http://autoidlab.cs.adelaide.edu.au/research/ahr.

4.2. Sensing platform

The sensing technology proposed for our intervention is a batteryless wearable sensor device called W^{2}ISP [21,47], see Fig. 1 (bottom left). The W^{2}ISP consists of a sensor module embedded in a flexible antenna constructed from C-Foam [47] for comfort of the user and a silver fabric to isolate the device from the person wearing it. The W^{2}ISP includes a tri-axial accelerometer (ADXL330) and a 16-bit ultra-low power consumption microcontroller (MSP430F2132). The W^{2}ISP powers its components with the energy harvested from the electromagnetic (EM) field produced by off-the-shelf Ultra High Frequency

(UHF) RFID reader antennas. The accelerometer, in particular, has a minimum full scale range of $\pm 3\ g$ and low power requirement of 180 μA with a supply voltage of 1.8 V. The firmware executing on the microcontroller is an implementation of the ISO-18000-6C air interface protocol [48] so that the sensor can be read by standard commercial off-the-shelf UHF RFID readers. The 10-bit per axis accelerometer data is sampled and embedded in the 96-bit EPC (Electronic Product Code) that also includes a unique identifier [49]. The sensor response is backscattered and subsequently received by an antenna and decoded by an RFID reader.

The RFID reader antennas are powered by an Speedway Revolution reader operating at the regulated Australian RF frequency band of 920–926 MHz and at a maximum regulated power of 1 W. The RFID reader collects information from all antennas and is capable of sending this data in real time via a connection to a local area network to back-end systems for processing.

The passive nature of the device powering also constrains the amount of data collected as sensor readings are produced when the sensor and micro-controller have sufficient power from the RFID reader antennas, this depends on factors such as the distance to the antenna or if there is direct exposure or occlusion to the EM signals from the antennas. Hence, the number of readings obtained from the sensing platform is variable and the sensor data stream is characterized by both noise and sparsity [50].

We are interested in using the three axes acceleration data from the sensor as it contains movement information; previous methods used frequency-domain features (frequency components, energy and entropy) [20,22,51,52], where extracting this information requires processing regularly sampled data or interpolating irregular data. However, we have previously shown in [50] that the combined use of RSSI and acceleration based features in the time domain can improve the performance of a classifier compared to when using acceleration and RSSI based features independently, and achieve similar or better performance than features extracted from only acceleration data in time and frequency domain. In addition, extracting frequency domain features produces processing delays; therefore, in this study, we consider time-domain only features from acceleration data and data obtained from the RFID infrastructure, such as RSSI and phase.

We consider the received signal strength indicator (RSSI), which corresponds to the received strength of the signal returned by the sensor. RSSI is an indicator of relative distance to the RFID antenna as a sensor closer to the antenna has higher RSSI readings than a sensor located further away. Previous studies have determined the importance of RSSI for activity recognition [21,32,53]. For example, our study in [21] determined that relative changes in RSSI values can help determine posture variations that may not be noticeable with acceleration information alone.

We can observe the patterns in RSSI and acceleration data in Fig. 3, which shows a bed exit (a)–(b) and chair exit (c)–(d) of a hospitalized person. We can see on all cases that sitting and ambulating postures have scarcer sensor observations than when lying on bed. Fig. 3(a) shows a bed exit, where sitting on bed has very few sensor observations and transferring to ambulating can only be clearly seen in a_f values; however, RSSI values in Fig. 3(b) show that changes for antenna1 can also help determine an exit from the bed. Similarly, Fig. 3(c) shows there is a fast acceleration change when exiting the chair, then acceleration values recover to previous state; however, RSSI values have a clear variation (antenna3) to help discriminate sitting on chair from ambulation. The sine of the body tilting angle (see Section 5.1) follows closely the variations of a_f. Other RF information collected is RF phase, which measures the phase angle between a sent RF carrier (frequency channel) and returned signal from the sensor [53].

5. Feature extraction

We are interested in extracting relevant human movement information from the sensor's raw data as well as the data captured by the RFID infrastructure such as RSSI and phase. We have considered three types of features in this study: (i) instantaneous features; (ii) contextual information features; and (iii) inter-segment features. Since we have exploited information dependent on the number of antennas in the room, we have variable feature vector dimensions $\mathbb{R}^{78}$ for Room1, $\mathbb{R}^{68}$ for Room2 and $\mathbb{R}^{70}$ for Room3.

5.1. Instantaneous features

These features capture information about the actions being performed by a person at a given instant. These features are derived directly from the sensor, RFID infrastructure and user information. The included features are:

- Acceleration readings from three axes: a_v, a_f, and a_l shown in Fig. 1;
- Sine of body tilting angle in the sagittal plane, $\sin(\theta) = \sin(\arctan(\frac{a_f}{a_v}))$ as in [34];
- Rotational angle yaw $= \arctan(\frac{a_l}{a_f})$;
- Rotational angle roll $= \arctan(\frac{a_l}{a_v})$;
- ID of antenna receiving data (*aID*) [21];
- Received signal strength indicator (RSSI) [21];
- Time difference between observations as in [21];
- Resultant acceleration†, $a_{total} = \sqrt{a_f^2 + a_v^2 + a_l^2}$;
- Gender of the participant.

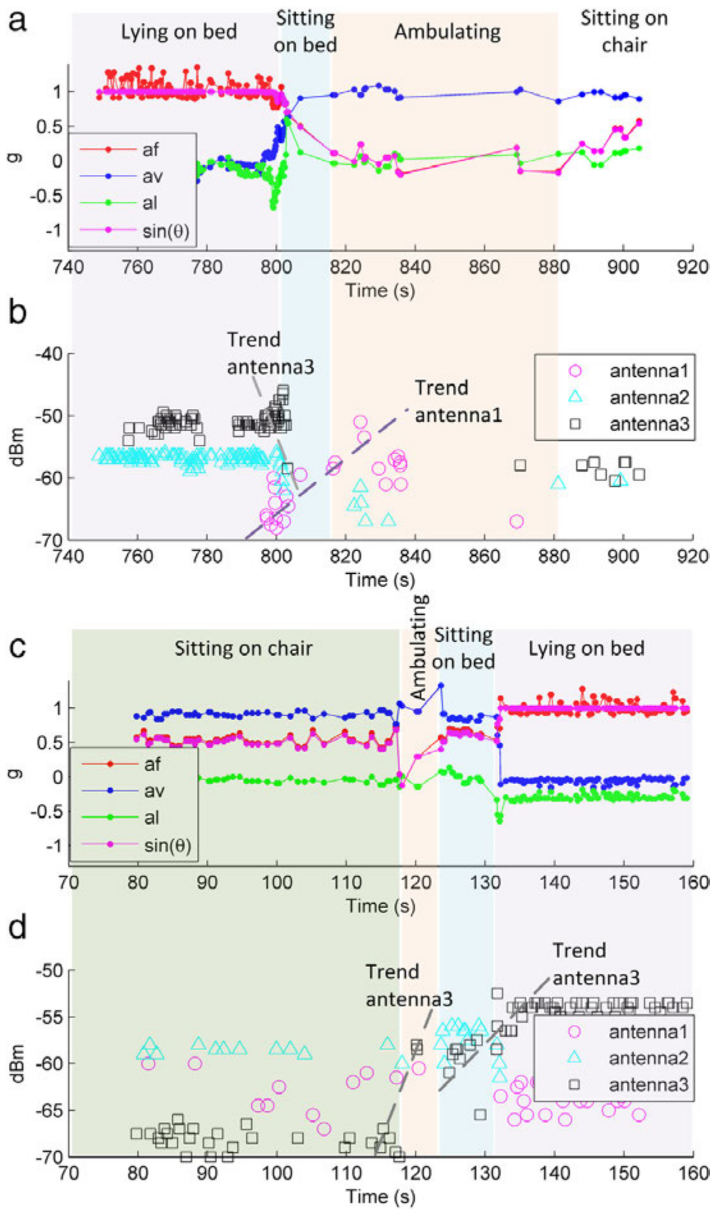

Fig. 3. Variations of acceleration readings, sine of body tilting angle and received signal strength indicator (RSSI), for a set of activities in the hospital setting in Room3. (a) Acceleration readings for a bed exit, where readings for Lying on bed are clearly different to those of other activities while readings for Sitting on bed and Sitting on chair are similar. (b) Variations of RSSI showing trend changes for readings captured by specific antennas during transitions between activities. (c) Acceleration readings during a chair exit, also showing similar readings during sitting postures. (d) RSSI variations, mainly from antenna1, provide trend variation information during changes in posture.

5.2. Contextual information features

These features provide recent temporal context on the action being performed; this is because activities that occurred recently have an impact on the current action as opposed to earlier movements. These are obtained from a fixed time sliding window of 4 s duration. In previous research [54], we found that using this segmentation method produced performance as high as that of other more complex methods for context extraction. The included features are:

- Number of readings per antenna in a segment [54];
- Mutual information from bed and chair area antennas [54] (used antenna2–antenna4 in Room1, antenna1–antenna2 in Room2, and combinations of pairs of antennas in Room3, due to bed and chair being next to each other);
- ID of antennas receiving higher and lower RSSI from tag responses;
- Displacement in the a_v axis, given by $d_{av} = \iint_{t-4s}^{t} a_v dt^2$;
- Mean and standard deviation of three acceleration axes[†];
- Mean and standard deviation of RSSI from all antennas[†];
- Pearson correlation between acceleration readings in the time window;

- Total velocity during segment[†], $v_{a_{total}} = \int_{t-4s}^{t} a_{total} dt$;
- Displacement with total acceleration[†], $d_{a_{total}} = \iint_{t-4s}^{t} a_{total} dt^2$;
- Standard deviation of variable frequency phase rate (VFPR)[†] as used in [53];
- Standard deviation, median and sum of modulus of constant frequency phase rate (CFPR)[†] as used in [53].

5.3. Inter-segment features

These types of features exploit trends and relationships between two segments. Hence, they provide an insight into the long term variations that are consistent with posture changes.

- Difference of maximum, minimum and median of three acceleration axes from consecutive segments;
- Difference of maximum, minimum and median of sine of body tilting angle from consecutive segments[†];
- Difference of maximum, minimum and median of RSSI per antenna from consecutive segments.

We performed feature selection using the WEKA data mining tool [55] using the simple classifiers: random forest; the probabilistic models of Bayes network; and logistic regression, to rank the features based on each classifier evaluated with each dataset. Then we eliminated features ranked low across the datasets. In general, we are interested in using or eliminating complete sets of features as we aim to compare all datasets with the same sets of features. For example, we use the values of the 3 acceleration axes in Section 5.1, but we eliminated the mean and standard deviation of these 3 acceleration axes in a segment in Section 5.2 as these were ranked low by the datasets. Features above with † were eliminated for the general evaluation in Section 7.2.

6. Activity recognition

This section provides detail of the formulation of our hierarchical classifiers, describing training, inference and alarm activation methods. From the collected data, let $x_{1:T}$ denote $x_1, x_2, \ldots, x_T$, a sequence of observations of length T associated to two sets of variables $y_{1:T}$ and $h_{1:T}$ that correspond to performed low and high level activities respectively. Low level activities are observable motions such as lie, sit or ambulate, whereas high level activities correspond to an alarm or no-alarm state, which are related to the low level activities. We assume K classes for the low level activities and H classes for the high level activities; hence $y_t \in \mathcal{Y} = \{1, \ldots, K\}$ and $h_t \in \mathcal{H} = \{1, \ldots, H\}$. The proposed two layer HCRF model is given by the conditional distribution $p(h, y|x)$ and partition function Z.

$$p(h, y|x) = \frac{1}{Z(x)} \exp\left(\sum_{t=1}^{T} \phi_t(h_t, y_t, y_{t-1}, x)\right) \tag{1}$$

$$Z(x) = \sum_{h'_{1:T}} \sum_{y'_{1:T}} \exp\left(\sum_{t=1}^{T} \phi_t\left(h'_t, y'_t, y'_{t-1}, x\right)\right). \tag{2}$$

We decompose the potential function into a set of smaller potential functions (3) resulting in a loop-free factor graph, which is convenient as is simpler to solve and inference is exact. The factor graph is shown in Fig. 4.

$$\phi_t(h_t, y_t, y_{t-1}, x_t) = \phi_{1,t}(y_t, x) + \phi_{2,t}(y_{t-1}, y_t, h_t) + \phi_{3,t}(h_t, x). \tag{3}$$

6.1. Training

During training, we aim to maximize the conditional log likelihood $\mathcal{L}$

$$\mathcal{L} = \log p(h_{1:T}, y_{1:T}|x) \tag{4}$$

$$\mathcal{L} = \sum_{t=1}^{T} \phi_{1,t}(y_t, x) + \phi_{2,t}(y_{t-1}, y_t, h_t) + \phi_{3,t}(h_t, x) - \log(Z(x)) \tag{5}$$

where $\phi_{1,t}(y_t, x) = \langle \theta_1, f_{1,t}(y_t, x) \rangle$, $\phi_{2,t}(y_{t-1}, y_t, h_t) = \langle \theta_2, f_{2,t}(y_{t-1}, y_t, h_t) \rangle$ and $\phi_{3,t}(h_t, x) = \langle \theta_3, f_{3,t}(h_t, x) \rangle$, here $\theta = \{\theta_1, \theta_2, \theta_3\}$ are parameters to be estimated and $f(.)$ is a boolean value transition or emission feature function. In the case of emission parameters, the trained model assigns a weight parameter for each possible discrete feature value (e.g. for feature body tilting angle discrete values between -1 and 1 in steps of 0.05 are considered), for every possible value of variable y in the case of θ_1 and of variable h in the case of θ_3.

An intra-class transition feature function example is $f_{2,t}(y_{t-1} = \text{“Lying”}, y_t = \text{“Sitting on bed”}, h_t = \text{“No Alarm”}) = \mathbb{1}_{y_{k-1}=\text{“Lying”}} \cdot \mathbb{1}_{y_k=\text{“Sitting on bed”}} \cdot \mathbb{1}_{h_k=\text{“No alarm”}}$, where $\mathbb{1}_{\{.\}}$ is the indicator function. Finally to exemplify an emission feature function, consider the example of current observation x_t containing a single feature of acceleration a, where $a = 0\,g$, when currently the person is lying, then $f_{3,t}(y_t = \text{“Lying”}, x_t[a] = 0\,g) = \mathbb{1}_{y_{k-1}=\text{“Lying”}} \cdot \mathbb{1}_{x_k[a]=0\,g}$.

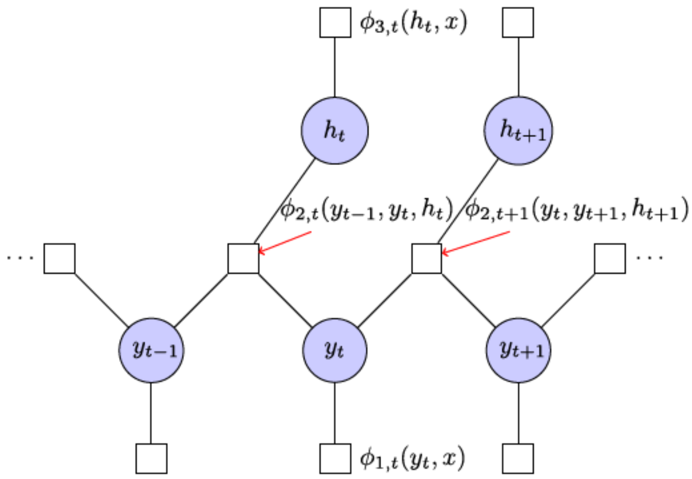

Fig. 4. Graphical model representing our HCRF formulation, indicating inter-class transition potential function $\phi_{2,t}(.)$ and emission potential functions $\phi_{1,t}(.)$ and $\phi_{3,t}(.)$.

We calculate the gradient of the conditional log likelihood with respect to the model parameters θ; below we show gradients with respect to the inter-class transition parameters θ_2, the gradient with respect to intra-class transition and emission parameters are calculated similarly.

$$\frac{\delta \mathcal{L}}{\delta \theta_2} = \sum_{t=1}^{T} f_2(y_{t-1}, y_t, h_t) - \frac{1}{Z(x)} \frac{\delta Z(x)}{\delta \theta_2}. \tag{6}$$

Given that:

$$\frac{\delta Z(x)}{\delta \theta_2} = \sum_{h'_{1:T}} \sum_{y'_{1:T}} \Big(\exp \sum_{t=1}^{T} \left(\langle \theta_1, f_1(y'_t, x) \rangle + \langle \theta_2, f_2(y'_{t-1}, y'_t, h'_t) \rangle + \langle \theta_3, f_3(h'_t, x) \rangle \right) \Big) \sum_{t=1}^{T} f_2(y'_{t-1}, y'_t, h'_t) \tag{7}$$

$$\frac{\delta \mathcal{L}}{\delta \theta_2} = \sum_{t} f_2(y_{t-1}, y_t, h_t) - \mathbb{E}\left[\sum_{t} f_2(y'_{t-1}, y'_t, h'_t) \right] \tag{8}$$

in our study we estimate the parameters $\theta = \arg\max \mathcal{L}$ using L-BFGS [56], a quasi-Newton optimization algorithm widely used in CRF [57], we initialize our model's parameters to $\sim$0 and stop optimization when the gradient is less than the tolerance value of 1×10^{-10}. Note that in (5) we require calculation of the partition function Z, we have from (1) and (2)

$$Z(x) = \sum_{h'_{1:T}} \sum_{y'_{1:T}} \exp \sum_{t} \langle \theta_1, f_1(y'_t, x) \rangle + \langle \theta_2, f_2(y'_{t-1}, y'_t, h'_t) \rangle + \langle \theta_3, f_3(h'_t, x) \rangle. \tag{9}$$

Which can be solved using the sum–product algorithm where messages going forward from the first, y_1, to the last received variable, y_T, are defined as $m_{\alpha_t}(y_t) = m_{y_t \phi_{2,t+1}}(y_t)$. This corresponds to the message propagating from node y_t to factor $\phi_{2,t+1}$. Using the sum–product algorithm this message is equivalent to:

$$m_{\alpha_t}(y_t) = \prod_{j \in N_{y_t} \setminus \{t+1\}} m_{\phi_j y_t}(y_t) \tag{10}$$

$$m_{\alpha_t}(y_t) = \sum_{y_{t-1}} \sum_{h_t} \exp\left(\phi_{1,t}(y_t, x) + \phi_{2,t}(y_{t-1}, y_t, h_t) + \phi_{3,t}(h_t, x) \right) m_{\alpha_{t-1}}(y_{t-1}) \tag{11}$$

where $N_{y_t} \setminus \{t+1\}$ represents all neighbors of node y_t with the exception of nodes indexed with $t+1$. From (9) and (11) we have then the expression for the partition function $Z(x) = \sum_{y'_T} m_{\alpha_T}(y'_T)$.

6.2. Inference

We are not interested in the maximum a posteriori (MAP) assignment of labels but in the marginal probabilities for the labels of both variables. However, we separate two different inference processes corresponding to training and validation or testing stages.

During training, we want to obtain the marginal probabilities of variables h and y, and to calculate the partition function Z. The marginal probability for variables y_t and h_t are given by:

$$p(y_t|x_{1:T}) = \sum_{y^{-t}} \sum_{h} p(h, y|x) \tag{12}$$

$$p(h_t|x_{1:T}) = \sum_{h^{-t}} \sum_{y} p(h, y|x) \tag{13}$$

where y^{-t} denotes $y_{1:t-1,t+1:T}$, similarly for h^{-t}. As in the case of the partition function, the marginal probability can be solved using the sum–product algorithm. Given that messages from all neighbors to the variable nodes are required, we also calculate messages passing backwards from the end of the sequence given by variable, y_T, onto the first element of the chain, y_1, and also messages going to the leaves of the chain represented by variables h_t. In the case of backward propagation we have:

$$m_{\beta_t}(y_t) = \sum_{y_{t+1}} \sum_{h_{t+1}} \exp\left(\phi_{1,t+1}(y_{t+1}, x) + \phi_{2,t+1}(y_t, y_{t+1}, h_{t+1}) + \phi_{3,t+1}(h_{t+1}, x)\right) m_{\beta_{t+1}}(y_{t+1}). \tag{14}$$

Hence the marginal probability for variable y_t in (12) is given by: $p(y_t|x) \propto m_{\alpha_t} m_{\beta_t}$, or defined by the expression:

$$\begin{aligned} p(y_t|x_{1:T}) = \frac{1}{Z_t} \sum_{h_t} \sum_{y_{t-1}} \sum_{y_{t+1}} \sum_{h_{t+1}} \exp\Big(&\phi_{1,t}(y_t, x) + \phi_{2,t}(y_{t-1}, y_t, h_t) + \phi_{3,t}(h_t, x) \\ &+ \phi_{1,t+1}(y_{t+1}, x) + \phi_{2,t+1}(y_t, y_{t+1}, h_{t+1}) + \phi_{3,t+1}(h_{t+1}, x)\Big) m_{\beta_{t+1}}(y_{t+1}) m_{\alpha_{t-1}}(y_{t-1}) \end{aligned} \tag{15}$$

where Z_t is a normalizing parameter. In similar manner the equation in (13) is defined as: $p(h_t|x_{1\ldots T}) \propto \exp(\phi_{3,t}(h_t, x)) m_{\phi_{2,t} h_t}(h_t)$, where $m_{\phi_{2,t} h_t}(h_t) = \sum_{y_{t-1}} \sum_{y_t} \exp\left(\phi_{2,t}(y_{t-1}, y_t, h_t)\right) \cdot m_{y_t \phi_{2,t}}(y_t) m_{y_{t-1}\phi_{2,t}}(y_{t-1})$. Therefore Eq. (13) is given by:

$$p(h_t|x_{1:T}) = \frac{1}{Z_t} \sum_{y_t} \sum_{y_{t-1}} \exp\left(\phi_{1,t}(y_t, x) + \phi_{2,t}(y_{t-1}, y_t, h_t) + \phi_{3,t}(h_t, x)\right) m_{\alpha_{t-1}}(y_{t-1}) m_{\beta_t}(y_t). \tag{16}$$

Inference for the cases of testing or validation differs from that of training in that we require real time inference for each received sensor reading as opposed to performing label inference on the complete input sequence. We have previously defined a label inference method using the message propagation from the sum–product algorithm [54]. Given that we only need to infer the current received datum, calculation of the backwards propagation is not necessary to obtain the marginal probabilities of variables y_t and h_t at time t, which are given by the expressions:

$$\begin{aligned} p(y_t|x_{1:t}) &= \sum_{y_{1:t-1}} \sum_{h_{1:t}} p(h, y|x) \\ &= \frac{1}{Z_t} \sum_{h_t} \sum_{y_{t-1}} \exp\left(\phi_{1,t}(y_t, x) + \phi_{2,t}(y_{t-1}, y_t, h_t) + \phi_{3,t}(h_t, x)\right) m_{\alpha_{t-1}}(y_{t-1}) \end{aligned} \tag{17}$$

$$\begin{aligned} p(h_t|x_{1:t}) &= \sum_{h_{1:t-1}} \sum_{y_{1:t}} p(h, y|x) \\ &= \frac{1}{Z'_t} \sum_{y_t} \sum_{y_{t-1}} \exp\left(\phi_{1,t}(y_t, x) + \phi_{2,t}(y_{t-1}, y_t, h_t) + \phi_{3,t}(h_t, x)\right) m_{\alpha_{t-1}}(y_{t-1}). \end{aligned} \tag{18}$$

6.3. Alarm activation

Our HCRF model determines if the current sensor observation corresponds to an alarming state based on considering the confidence level (marginal probability) associated with alarming state predictions i.e. bed exits and chair exits. We consider a confidence model of the form $\mu_c + \gamma_c \sigma_c$, where μ_c is the mean confidence probability of an alarming state (i.e. bed exit or chair exit), σ_c is the standard deviation and γ_c is a confidence parameter. Both μ_c and σ_c are determined from the alarming state marginal probabilities of the training data; whereas γ_c is a model parameter evaluated during parameter selection (see Section 7.1). Therefore the alarming state for our model at any time t is given by:

$$\text{alarm}_t \begin{cases} 1 & p(h_t|x_{1:t}) \geq \mu_c + \gamma_c \sigma_c \\ 0 & \text{otherwise.} \end{cases} \tag{19}$$

This allows us to exploit the confidence level provided by marginal probabilities associated with alarm states to only send alerts for those alarm predictions with high confidence levels. Hence the confidence model parameter allows us to potentially reduce possible false alarms from alarm state predictions where the probability associated with the predicted class labels cannot provide conclusive evidence to generate an alarm.

7. Evaluation

To evaluate our method we consider each room individually as RSSI and phase features depend on the number of antennas and the relative distribution of antennas with respect to the furniture in the room. In addition, people of different demographics perform activities differently, for instance, in contrast to healthy older people, some frail hospitalized patients made several attempts before transitioning out of bed while others preferred to roll out of bed.

In consideration of the actions performed, we determine the sets of labels for the HCRF classifiers to predict as $\mathcal{Y}$ = {sitting on bed, sitting on chair, lying on bed and ambulating} and $\mathcal{H}$ = {alarm or no-alarm}, where the set of labels $\mathcal{H}$ corresponds to a bed or chair exit alarm as shown in Fig. 1. The alarming process performance was evaluated with respect to bed and chair exits on all datasets. We evaluate the performance of our hierarchical method and compare it with three baseline methods. The first baseline method uses a multiclass CRF classifier followed by a heuristics based stage to decide an alarm or no-alarm label for each observation. The second method is a multiclass SVM classifier using a one-vs-one approach; and the third method is the multiple-stage classifier of Banos et al. [20], described in Section 2.2. We also demonstrate the use of high-level activity specific feature sets to improve performance with the proposed HCRF classifier; and compare training times required by our HCRF method with the baseline methods to further validate our approach in contrast to using cascaded, multi-stage classifiers.

7.1. Statistical analysis

In this study, true positives (TP) are those correctly identified alarms corresponding to bed or chair exits when: (i) the person is actually exiting or has exited the bed or chair (ground truth); and (ii) the ground truth alarm indicator occurs no more than 5 s after the predicted alarm signal. False positives (FP) are those actions that are incorrectly recognized bed or chair exits (false alarms). False negatives (FN) are those ground truth bed and chair exits that were not recognized by the system (missed).

We evaluate the performance of the proposed system using recall, precision and F-score, the harmonic mean of precision and recall; as these metrics consider the occurrence of errors in relation to TPs. These measurements are defined as: (i) recall (RE) = TP/(TP + FN); (ii) precision (PR) = TP/(TP + FP); and (iii) F-score (FS) = (2 × precision × recall)/(precision + recall).

We evaluated these metrics using a 10-fold cross validation with around 60% of sequences used for training, and 20% used for testing and validation each. We use a 10-fold cross validation as it allows us to obtain results that are less sensitive to the partitioning of the data. In the datasets from healthy older people cohorts (Room1 and Room2), the training, testing and validation subsets contain data from more than one participant, where it is possible that different trials of the same person are distributed in these subsets. However, in the case of older patients (Room3), given that each patient only performed a single trial due to their frailty, data for training, testing and validation correspond to different patients. Therefore, the testing results are a good indication of the results that can be expected from the HCRF classifier in a real-life deployment. We used the validation sequences for parameter selection i.e. SVM's C parameter in the range $\{2^{-5}, \dots, 2^{5}\}$, regularization parameter for CRF and HCRF in the range $\{0, 10^{-5}, 5\times10^{-5}, \dots, 5\times10^{-2}, 10^{-1}\}$, and confidence parameter γ_c for the alarm activation stage in the range $\{0.01, \dots, 1\}$. We chose the parameter that produced highest F-score. We compared results using a two tail t-test. A p-value $(P) < 0.05$ is considered statistically significant.

7.2. Performance comparison

This scenario compares the results of our approach with the three previously mentioned baseline methods. In the case of the first baseline multiclass CRF method, the predicted labels are those of our label set $\mathcal{Y}$ and from this output a heuristics based stage sums all previously predicted marginal probabilities in a sliding window of 1 s duration where the first element is the prediction to the last received sensor observation. We then determine the low-level activity with the largest sum in the sliding window as the corresponding label for the last received sensor reading and the corresponding alarming condition. We use this time duration as we have previously determined that the minimum time for a posture transition is about 1.7 s [32]; hence a window size larger than 1.7 s can potentially overlap more than one posture change.

The comparison between our proposed method and the baseline methods is shown in Table 2, for a fair comparison we used the same subset of the features described in Section 5 for all classification models. Comparing results of our HCRF method with the CRF-based heuristics method, for Room1, the HCRF model has statistically significantly better performance for recall for chair exits ($P = 0.026$) and precision for bed exits ($P = 0.024$), whereas the heuristic method had statistically significantly better performance for recall for bed exit ($P = 0.031$). In the case of Room2 and Room3, none of the resulting metrics were statistically significantly different ($P > 0.29$ for Room2 and $P > 0.10$ for Room3) compared to our HCRF model. However, in general, the HCRF model provided higher mean performance for bed exits than the heuristics model.

Comparing HCRF results with the SVM multiclass model, for Room1, bed exit results are higher for the SVM model with statistical significance ($P < 0.028$), whereas chair exits results are not significant ($P > 0.15$). Results for Room2 and Room3 indicate an overall higher performance for our HCRF model ($P > 0.06$), except for recall for bed exits in Room2 where the SVM model has higher performance with significance ($P = 0.014$).

Comparing results with the method of Banos et al. [20], for Room1 and Room2, the results are not significantly different ($P > 0.09$ for both rooms). However, our model showed higher mean F-score performance measures for Room2. In the

Table 2
Comparison between hierarchical approach and two baseline methods: CRF-based heuristic method, SVM multiclass model and SVM-based multiple-stage classifier of Banos et al. [20] (results in %). RE: recall, PR: precision, and FS: F-score. Highest F-scores for each high-level activity are shown in bold.

	HCRF model		CRF-based Heuristics model		SVM multiclass model		SVM-based model Banos et al. [20]	
	Bed exit	Chair exit	Bed exit	Chair exit	Bed exit	Chair exit	Bed exit	Chair exit
	Room1							
RE	57.13 ± 13.01	100.00±0.00	71.13±13.78	96.04 ± 5.18	67.71 ± 5.37	98.26 ± 3.68	63.20 ± 7.89	100.00 ± 0.00
PR	42.26 ± 12.53	51.60±17.31	30.96 ± 7.24	58.06 ± 19.85	55.89 ± 5.42	56.55 ± 16.93	49.42 ± 5.32	60.84 ± 10.56
FS	48.11 ± 11.94	66.62±14.23	42.79 ± 8.56	70.96 ± 16.94	**60.97 ± 3.48**	**70.53 ± 13.63**	55.09 ± 4.41	**75.16 ± 8.33**
	Room2							
RE	84.92 ± 11.41	68.42±22.97	88.93±11.44	68.42 ± 16.75	95.89 ± 5.55	67.58 ± 26.89	89.47±10.38	68.42 ± 25.82
PR	79.29 ± 9.89	57.50±24.34	73.70±13.24	66.20 ± 27.69	72.13±19.04	50.56 ± 27.32	67.04±19.36	56.14 ± 27.27
FS	**81.66 ± 8.99**	60.68±22.01	79.39 ± 6.54	**63.05 ± 16.23**	80.82±12.81	55.74 ± 26.87	74.68±13.00	59.34 ± 24.24
	Room3							
RE	71.73 ± 16.12	93.57 ± 8.33	63.77±10.89	90.48 ± 11.39	62.84±16.06	91.07 ± 13.74	79.24±14.23	87.14 ± 17.11
PR	23.24 ± 16.31	18.66 ± 5.42	21.71±10.62	24.04 ± 8.35	18.22±13.39	14.25 ± 4.98	18.27±13.88	12.50 ± 4.95
FS	**31.70 ± 12.90**	30.67 ± 7.40	30.48±10.66	**36.96 ± 9.11**	26.55±14.92	24.26 ± 7.34	27.57±16.16	21.44 ± 7.30

Table 3
Hierarchical approach results with improved model (%).

	Improved HCRF		HCRF (Table 2)	
	Bed exit	Chair exit	Bed exit	Chair exit
	Room1			
RE	57.13 ± 13.01	98.26 ± 3.68	57.13 ± 13.01	100.00 ± 0.00
PR	42.26 ± 12.53	61.11 ± 18.15	42.26 ± 12.53	51.60 ± 17.31
FS	**48.11 ± 11.94**	**74.15 ± 14.39**	48.11 ± 11.94	66.62 ± 14.23
	Room2			
RE	86.38 ± 10.29	69.25 ± 25.59	84.92 ± 11.41	68.42 ± 22.97
PR	79.65 ± 14.76	62.50 ± 27.85	79.29 ± 9.89	57.50 ± 24.34
FS	**82.22 ± 10.52**	**64.23 ± 24.73**	81.66 ± 8.99	60.68 ± 22.01
	Room3			
RE	66.99 ± 14.90	87.26 ± 11.87	71.73 ± 16.12	93.57 ± 8.33
PR	26.76 ± 20.14	26.12 ± 10.58	23.24 ± 16.31	18.66 ± 5.42
FS	**33.63 ± 13.08**	**39.19 ± 12.53**	31.70 ± 12.90	30.67 ± 7.40

case of Room3, our HCRF model has a better performance with statistical significance for precision ($P = 0.016$) and F-score ($P = 0.012$) for chair exits; all other results were not significantly different ($P > 0.28$).

A reason for the better performance of the SVM methods in Room1 than the other methods is that Room1 has more data collected to train its model (≈52 000 sensor observations) than those of Room2 and Room3 (≈22 000 and ≈23 000 sensor observations respectively). SVM models have a lower performance with datasets with low data availability where our HCRF model outperforms the SVM models in both Room2 and Room3. Room3 dataset represents a study in a real life scenario in the context of our application, where data collection for training is difficult due to the difficulty in recruiting participants, their frail condition and limited movements patients can perform safely; in this context our HCRF approach has outperformed the SVM-based methods.

In summary, comparison results from Table 2 indicate that, in general, our model shows comparable or better performance than the heuristics based model, according to F-score comparison and in general achieved better performance than a SVM multiclass model and the SVM-based method of [20].

7.3. Model adjustment

In the previous performance comparison evaluated in Table 2, all methods used the same set of features for all datasets to determine both chair exits and bed exits. Given that our proposed formulation allows us to influence the learned models by having a specific set of features to describe the high-level activities; we used feature selection methods outlined in Section 5 to craft two feature sets for bed exit alarms and chair exit alarms. Certainly, feature selection can also be employed with the heuristics based baseline model; however, feature selection for the classifier in the baseline method can only improve performance based on the recognition of low-level activities as high-level activities are determined in the heuristic stage. The results from the evaluation of the improved and the previous HCRF model are shown in Table 3.

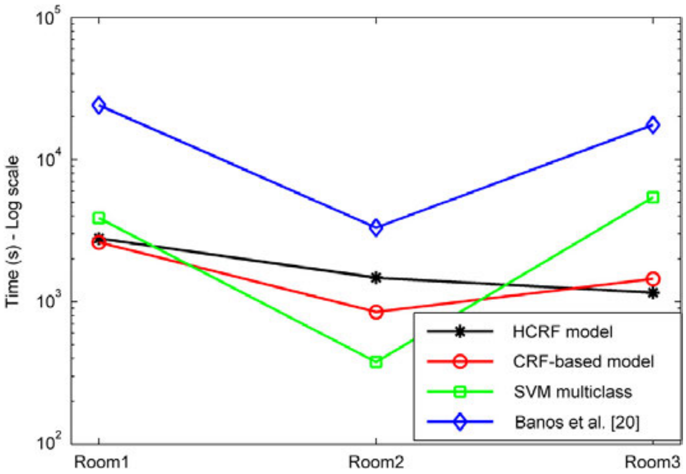

Fig. 5. Total training times for the models including parameter selection: (in black) our HCRF model, (in red) the CRF-based heuristic model, (in green) the SVM multiclass model; and (in blue) the SVM-based model from [20]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The improved HCRF increased the performance for chair exits for Room1 and both bed and chair exit for Room2 and Room3. Room1 has an approximate F-score increase of about 7.5% ($P = 0.18$). In the case of bed exits for Room1, the performance did not increase when compared to the use of the original subset of features, hence we use the previous feature set for bed exits. In the case of Room2 and Room3, F-scores for bed exits and chair exits were increased up to 8.5% for both room sets.

7.4. Training time evaluation

We show in Fig. 5 the different total training times, including parameter selection, for each classification method tested in Table 2. Fig. 5 shows that on average our HCRF model takes as much as the CRF-based heuristic model whereas the SVM-based model of [20] takes at most 1400% longer to train than the respective HCRF model. Our model also takes less time to train than the SVM multiclass model for Room1 and Room3; however, for Room2, SVM multiclass achieves the fastest total training time but the model obtained does not translate to better performance. In the case of Room3, which has almost as many sensor observations as in Room2, training times for SVM-based models are almost as long as those for Room1. The training times for SVM-based models are affected by the evaluation of, mainly, two values of $C = \{2^4, 2^5\}$ that together take about 60% and 67% of the total training time for SVM multiclass (in green) and the method of Banos et al. [20] (in blue) respectively.

7.5. Discussion

The proposed HCRF method achieved, in general, similar to higher F-score performance in comparison with those other baseline methods. The HCRF formulation leads to a number of methodological improvements of HCRF compared to our baseline methods: (i) HCRF avoids the use of multi-stage approaches where usually one or more stages are empirically determined heuristic methods with parameters that are not learned, but determined by the user (e.g. size of the sliding window in CRF-based heuristic method); however, parameters for HCRF are learned and determined during validation; (ii) previous studies for human activity recognition with a single body-worn sensor have only considered battery-powered sensor devices, generally testing their approaches with a young population; whereas our research is the first to study the use of wireless, batteryless body-worn sensors in older people and in particular, hospitalized older people; (iii) HCRF was compared with an SVM multiclass classifier and a recent published paper [20] that used a cascaded classification method. HCRF performed better for datasets Room2 and Room3, and HCRF was, in general, faster to train than SVM-based methods as shown in Fig. 5.

However, the overall results are not desirably high enough for a clinical application for the recognition of bed and chair exits. These lower than expected results were driven mainly by the passive nature of the sensor, leading to a lack of observations during ambulation for the three datasets that caused difficulty to appropriately distinguish between sitting and ambulating activities as body trunk postures are similar. In Room1, although the antenna setting covered a broad area around the room, there is a lack of sensor readings when sitting on bed and standing next to the bed as there are few readings in this position and the posture transition of getting out of the bed is not captured. In Room2, which has the highest performance of all datasets, the antennas focused around the bed allow to capture more readings while the person is lying on bed; however, few readings are still captured while sitting on the bed as illumination of the sensor from the antennas are obstructed by the person's body. In addition, while approaching the chair, older people give their back to the RFID antenna facing the chair and may not face the antenna while sitting on the chair. In Room3, which has the same distribution as Room2 in terms of number

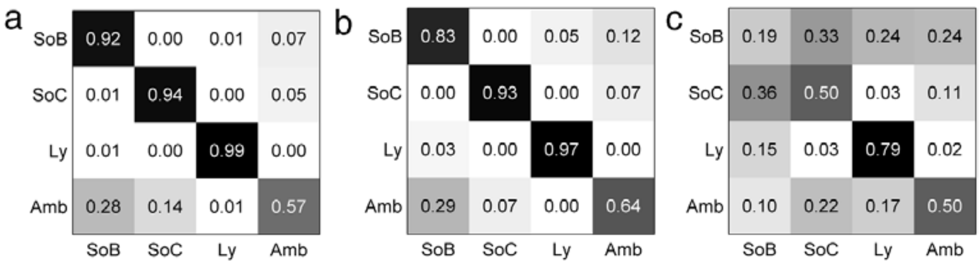

Fig. 6. Confusion matrices from first layer of hierarchical classifier (a): Room1, (b): Room2 and (c): Room3, where SoB: Sitting on bed, SoC: Sitting on chair, Ly: Lying and Amb: Ambulation.

of RFID reader antennas and direction of these antennas, the performance is lower than the other two datasets caused by lack of sensor observations while ambulating and sitting. Moreover, the short distance between bed and chair reduces the number of sensor readings collected while ambulating. Further, body posture of frail patients occlude the sensor as they arch forward when ambulating or sitting.

We can see in Fig. 6 the affect of lack of sensor readings and the similarity of sitting and standing postures on the classifier. Fig. 6(a) and (b) show the confusion matrix from the first layer of the HCRF for Room1 and Room2. Here Ambulating activities were labeled as Sitting-on-bed ($\leq$29%) and Sitting-on-chair ($\leq$14%); these misclassification errors are possible causes for bed exit and chair exit alarm errors as shown in Table 2. These effects are also observed in Room3, shown in Fig. 6(c); in addition, the short distance between the bed and chair cause misclassification between Sitting-on-bed and Sitting-on-chair ($\leq$36%). Moreover, about 80% of Sitting-on-bed labels were incorrectly predicted due to lack of readings while sitting on the bed as ceiling mounted RFID reader antennas were unable to read the sensor when a patient was in a sitting posture and arching forwards. Some patients were lying on bed with raised bed head boards as they read or watched TV during the day and these non-horizontal postures while lying affected Sitting-on-bed label classification.

8. Conclusions

The present study presents a novel hierarchical classification model for a falls prevention intervention that can successfully predict bed and chair exits in real time with better or similar performance than a heuristics based model and SVM-based models, as tested with healthy and hospitalized older people. We have described additional advantages to using our hierarchical classification approach such as the ability to adjust the trained model to the different high level activities of interest and the lower training time required in relation to cascaded classification models. Although the proposed system is not intended to detect falls but to issue an alarm to caregivers when a hospitalized older person is out of the bed or chair, these alarms will allow an attending caregiver to act quickly if a fall has already occurred and prevent consequences arising from a 'long lie'.

There are however, limitations to be dealt with in future research. For example, the lack of sensor observations obtained from our passive sensor approach. This occurs especially when transitioning between activities, due to the RFID antennas not being able to power the sensor. This inadequate powering of the sensor is caused by the human body occluding the sensor or misalignment of the body worn sensor antenna with the RFID reader antennas. This leads to reduced data while performing some activities (sparse data shown in Fig. 3), affecting the performance from the classifier.

Although we use features, such as RSSI, that depend on the antenna deployment; this is not a limitation in our application context of preventing falls in hospitals as the relative positioning of furniture does not change from room to room. However, changing the settings from, for example, a hospital context to a nursing home context may require gathering new training data and re-training.

The present work has considered a set of activities representative of those performed by patients in a hospital setting to support our wearable falls prevention intervention. As a consequence, the number of activities considered is limited and if extended to monitoring older people outside of a hospital context, such as older people living independently at home, a wider set of activities as well as RFID infrastructure deployments should be considered and evaluated. Future work should consider improving the amount of data collected from the sensor by: (i) exploiting recent lower power consuming sensing components such as the micro-controller and accelerometer to improve the sensor unit by reducing its power consumption; (ii) considering the use of textile integrated antennas for the reducing the size of the sensor unit without decreasing performance [58]; and (iii) improving the illumination of the sensor by RFID antennas and thereby energy harvesting by, for example, changing the location of the sensor from the chest to the shoulder of the person and placing all RFID reader antennas on the ceiling. This deployment strategy is a compromise between collecting more sensor readings and capturing upper body motion information as previously used in [18,34], which we have found is not optimal for a passive sensor deployment. These sensor location changes can reduce occlusions from the participants' body during activities and ensures the illumination of the sensor from ceiling located antennas.

Other future work in the context of the application should consider the implementation of a randomized control trial (RCT) with a larger cohort of older patients to determine the effectiveness of our approach to reduce the rate of falls in older patients. Moreover, such a long term trial can also indicate the alarming performance of the system over longer periods of time (during day and night) as opposed to that of short trials, as is the case for our datasets. In addition, we can evaluate the impact of the alarming system on staff and investigate the burden of false alarms to develop a quantitative understanding of 'alarm fatigue'.

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References

[1] C. Bradley, Hospitalisations due to falls by older people, Australia: 2009–10, 2013, http://www.webcitation.org/6fkpL17FD.
[2] Centers for Disease Control and Prevention, Important facts about falls, 2016, http://www.webcitation.org/6gREJTEgu.
[3] Centers for Disease Control and Prevention, Cost of falls among older adults, 2014, http://www.webcitation.org/6h6GwcvHd.
[4] E.B. Hitcho, M.J. Krauss, S. Birge, W. Claiborne Dunagan, I. Fischer, S. Johnson, P.A. Nast, E. Costantinou, V.J. Fraser, Characteristics and circumstances of falls in a hospital setting, J. Gen. Intern. Med. 19 (7) (2004) 732–739.
[5] C. Abreu, A. Mendes, J. Monteiro, F.R. Santos, Falls in hospital settings: a longitudinal study, Rev. Lat. Am. Enfermagem 20 (2012) 597–603.
[6] K. Rapp, C. Becker, I.D. Cameron, H.H. König, G. Büchele, Epidemiology of falls in residential aged care: analysis of more than 70,000 falls from residents of Bavarian nursing homes, J. Am. Med. Dir. Assoc. 13 (2) (2012) 187.e1–187.e6.
[7] Australian commission on safety and quality in healthcare, Preventing falls and harm from falls in older people: Best practice guidelines for australian hospitals, 2009.
[8] C.A. Brand, V. Sundararajan, A 10-year cohort study of the burden and risk of in-hospital falls and fractures using routinely collected hospital data, Qual. Saf. Health Care 19 (6) (2010) e51.
[9] I.D. Cameron, L.D. Gillespie, M.C. Robertson, G.R. Murray, K.D. Hill, R.G. Cumming, N. Kerse, Interventions for preventing falls in older people in care facilities and hospitals, Cochrane Database Syst. Rev. 12 (2012) 1–118.
[10] O. Sahota, A. Drummond, D. Kendrick, M.J. Grainge, C. Vass, T. Sach, J. Gladman, M. Avis, Refine (reducing falls in -patient elderly) using bed and bedside chair pressure sensors linked to radio-pagers in acute hospital care: a randomised controlled trial, Age Ageing 43 (2) (2014) 247–253.
[11] R.I. Shorr, A.M. Chandler, L.C. Mion, T.M. Waters, M. Liu, M.J. Daniels, L.A. Kessler, S.T. Miller, Effects of an intervention to increase bed alarm use to prevent falls in hospitalized patients: A cluster randomized trial, Ann. Intern. Med. 157 (10) (2012) 692–699.
[12] A. Wong Shee, B. Phillips, K. Hill, K. Dodd, Feasibility, acceptability, and effectiveness of an electronic sensor bed/chair alarm in reducing falls in patients with cognitive impairment in a subacute ward, J. Nurs. Care Qual. 29 (3) (2014) 253–262.
[13] E. Capezuti, B.L. Brush, S. Lane, H.U. Rabinowitz, M. Secic, Bed-exit alarm effectiveness, Arch. Gerontol. Geriatr. 49 (1) (2009) 27–31.
[14] S. Applegarth, M. Rowe, W. Kearns, M. Bowen, Activation thresholds and operating characteristics of commercial alarm products to provide surveillance for dementia caregivers, Gerontechnology 11 (3) (2013) 480–487.
[15] A. Pantelopoulos, N. Bourbakis, A survey on wearable sensor-based systems for health monitoring and prognosis, IEEE Trans. Syst. Man Cybern. Part C Appl. Rev. 40 (1) (2010) 1–12.
[16] O. Lara, M. Labrador, A survey on human activity recognition using wearable sensors, IEEE Commun. Surv. Tutor. 15 (3) (2013) 1192–1209.
[17] G. Demiris, B.K. Hensel, M. Skubic, M. Rantz, Senior residents' perceived need of and preferences for "smart home" sensor technologies, Int. J. Technol. Assess Health Care 24 (2008) 120–124.
[18] A. Godfrey, A. Bourke, G. laighin, P. van de Ven, J. Nelson, Activity classification using a single chest mounted tri-axial accelerometer, Med. Eng. Phys. 33 (9) (2011) 1127–1135.
[19] J.P. Varkey, D. Pompili, T.A. Walls, Human motion recognition using a wireless sensor-based wearable system, Pers. Ubiquitous Comput. 16 (7) (2012) 897–910.
[20] O. Banos, M. Damas, H. Pomares, F. Rojas, B. Delgado-Marquez, O. Valenzuela, Human activity recognition based on a sensor weighting hierarchical classifier, Soft Comput. 17 (2) (2013) 333–343.
[21] R.L. Shinmoto Torres, D.C. Ranasinghe, Q. Shi, A.P. Sample, Sensor enabled wearable rfid technology for mitigating the risk of falls near beds, in: IEEE International Conference on RFID, 2013, pp. 191–198.
[22] Ó.D. Lara, A.J. Pérez, M.A. Labrador, J.D. Posada, Centinela: A human activity recognition system based on acceleration and vital sign data, Pervasive Mob. Comput. 8 (5) (2012) 717–729.
[23] L. Wang, T. Gu, X. Tao, J. Lu, A hierarchical approach to real-time activity recognition in body sensor networks, Pervasive Mob. Comput. 8 (1) (2012) 115–130.
[24] F. Bianchi, S. Redmond, M. Narayanan, S. Cerutti, N. Lovell, Barometric pressure and triaxial accelerometry-based falls event detection, IEEE Trans. Neural Syst. Rehabil. Eng. 18 (6) (2010) 619–627.
[25] P. Pierleoni, A. Belli, L. Palma, M. Pellegrini, L. Pernini, S. Valenti, A high reliability wearable device for elderly fall detection, IEEE Sens. J. 15 (8) (2015) 4544–4553.
[26] M. Brodie, S. Lord, M. Coppens, J. Annegarn, K. Delbaere, Eight weeks remote monitoring using a freely worn device reveals unstable gait patterns in older fallers, IEEE Trans. Biomed. Eng. 62 (11) (2015) 2588–2594.
[27] M. Schwenk, K. Hauer, T. Zieschang, S. Englert, J. Mohler, B. Najafi, Sensor-derived physical activity parameters can predict future falls in people with dementia, Gerontology 60 (6) (2014) 483–492.
[28] M. Narayanan, S. Redmond, M. Scalzi, S. Lord, B. Celler, N. Lovell, Longitudinal falls-risk estimation using triaxial accelerometry, IEEE Trans. Biomed. Eng. 57 (3) (2010) 534–541.
[29] M.-W. Lee, A.M. Khan, T.-S. Kim, A single tri-axial accelerometer-based real-time personal life log system capable of human activity recognition and exercise information generation, Pers. Ubiquitous Comput. 15 (8) (2011) 887–898.
[30] J. Bergmann, A. McGregor, Body-worn sensor design: What do patients and clinicians want? Ann. Biomed. Eng. 39 (9) (2011) 2299–2312.
[31] S. Chaudhuri, L. Kneale, T. Le, E. Phelan, D. Rosenberg, H. Thompson, G. Demiris, Older adults' perceptions of fall detection devices, J. Appl. Gerontol. (2015) 1–16.
[32] D.C. Ranasinghe, R.L. Shinmoto Torres, K. Hill, R. Visvanathan, Low cost and batteryless sensor-enabled radio frequency identification tag based approaches to identify patient bed entry and exit posture transitions, Gait Posture 39 (1) (2014) 118–123.
[33] C. Swedberg, Group health reinvents patient care with RTLS - RFID Journal, 2012, http://www.webcitation.org/6O7ywg1ps.
[34] B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C. Bula, P. Robert, Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly, IEEE Trans. Biomed. Eng. 50 (6) (2003) 711–723.

[35] B. Najafi, D.G. Armstrong, J. Mohler, Novel wearable technology for assessing spontaneous daily physical activity and risk of falling in older adults with diabetes, J. Diabetes Sci. Technol. 7 (5) (2013) 1147–1160.

[36] Y.-S. Lee, S.-B. Cho, Activity recognition using hierarchical hidden markov models on a smartphone with 3D accelerometer, in: Hybrid Artificial Intelligent Systems, in: Lecture Notes in Computer Science, vol. 6678, Springer, 2011, pp. 460–467.

[37] L. Ladický, C. Russell, P. Kohli, P.H.S. Torr, Associative hierarchical random fields, IEEE Trans. Pattern Anal. Mach. Intell. 36 (6) (2014) 1056–1077.

[38] Y. Ding, H. Wang, Adaptive Web Wrapper Based on Hybrid Hierarchical Conditional Random Fields for Web Data Integration, Springer London, London, 2013, pp. 795–801.

[39] T. Liu, X. Wang, X. Dai, J. Luo, Deep recursive and hierarchical conditional random fields for human action recognition, in: IEEE Winter Conference on Applications of Computer Vision (WACV), 2016, pp. 1–9.

[40] B. Ahmed, T. Thesen, K. Blackmon, Y. Zhao, O. Devinsky, R. Kuzniecky, C.E. Brodley, Hierarchical conditional random fields for outlier detection: An application to detecting epileptogenic cortical malformations, in: Proceedings of The 31st International Conference on Machine Learning, 2014, pp. 1080–1088.

[41] Y. Zhu, N.M. Nayak, A.K. Roy-Chowdhury, Context-aware activity modeling using hierarchical conditional random fields, IEEE Trans. Pattern Anal. Mach. Intell. 37 (7) (2015) 1360–1372.

[42] A. Quattoni, S.B. Wang, L.-P. Morency, M. Collins, T. Darrell, Hidden conditional random fields, IEEE Trans. Pattern Anal. Mach. Intell. 29 (10) (2007) 1848–1852.

[43] S.B. Wang, A. Quattoni, L.-P. Morency, D. Demirdjian, T. Darrell, Hidden conditional random fields for gesture recognition, in: IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Vol. 2, 2006, pp. 1521–1527.

[44] L. van der Maaten, M. Welling, L.K. Saul, Hidden-unit conditional random fields, in: International Conference on Artificial Intelligence and Statistics, 2011, pp. 479–488.

[45] S.P. Chatzis, D.I. Kosmopoulos, P. Doliotis, A conditional random field-based model for joint sequence segmentation and classification, Pattern Recognit. 46 (6) (2013) 1569–1578.

[46] R. Visvanathan, D.C. Ranasinghe, R.L. Shinmoto Torres, K. Hill, Framework for preventing falls in acute hospitals using passive sensor enabled radio frequency identification technology, in: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2012, pp. 5858–5862.

[47] T. Kaufmann, D.C. Ranasinghe, M. Zhou, C. Fumeaux, Wearable quarter-wave microstrip antenna for passive UHF RFID applications, Int. J. Antennas Propag. (2013).

[48] International Organization for Standardization, ISO/IEC 18000-6:2013 - information technology – radio frequency identification for item management – part 6: Parameters for air interface communications at 860 MHz to 960 MHz general (2013).

[49] Y. Su, A. Wickramasinghe, D.C. Ranasinghe, Investigating sensor data retrieval schemes for multi-sensor passive RFID tags, in: IEEE International Conference on RFID, San Diego, USA, 2015, pp. 158–165.

[50] A. Wickramasinghe, D.C. Ranasinghe, Recognising activities in real time using body worn passive sensors with sparse data streams: To interpolate or not to interpolate?, in: Proceedings of the 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, MOBIQUITOUS, ICST, Belgium, 2015, pp. 21–30.

[51] L. Bao, S. Intille, Activity recognition from user-annotated acceleration data, in: A. Ferscha, F. Mattern (Eds.), Pervasive Computing, in: Lecture Notes in Computer Science, vol. 3001, Springer, 2004, pp. 1–17.

[52] S.A. Muhammad, B.N. Klein, K. Laerhoven, K. David, Constructing Ambient Intelligence, Springer, 2012, pp. 101–109. Chapter A Feature Set Evaluation for Activity Recognition with Body-Worn Inertial Sensors.

[53] H. Li, C. Ye, A.P. Sample, Idsense: A human object interaction detection system based on passive UHF RFID, in: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, CHI'15, ACM, USA, 2015, pp. 2555–2564.

[54] R.L. Shinmoto Torres, D.C. Ranasinghe, Q. Shi, Evaluation of wearable sensor tag data segmentation approaches for real time activity classification in elderly, in: 10th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, Springer, 2013, pp. 384–395.

[55] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, I.H. Witten, The weka data mining software: An update, SIGKDD Explor. Newsl. 11 (1) (2009) 10–18.

[56] J. Nocedal, Updating quasi-Newton matrices with limited storage, Math. Comp. 35 (151) (1980) 773–782.

[57] C. Sutton, A. McCallum, An introduction to conditional random fields for relational learning, in: L. Getoor, B. Taskar (Eds.), Introduction to Statistical Relational Learning, The MIT Press, 2006, pp. 93–127.

[58] S.J. Chen, C. Fumeaux, D.C. Ranasinghe, T. Kaufmann, Paired snap-on buttons connections for balanced antennas in wearable systems, IEEE Antennas Wirel. Propag. Lett. 14 (2015) 1498–1501.

Chapter 10

Conclusions and Future Work

10.1 Conclusions

This thesis is focused on the development of a technological intervention for preventing falls in older people living in nursing homes or in hospitals by employing passive sensor enabled RFID technology to monitor their activities. In particular, the research presented is focused on methods for recognizing bed and chair exits as high risk activities where the older person performing these activities is at risk of falling. For this purpose, this study evaluated an accelerometer embedded RFID tag named W^2ISP in a wireless, wearable and lightweight sensor device embodiment that was worn over clothing at sternum level. Body worn passive sensor embedded RFID technology for activity recognition has not been previously investigated; therefore, this thesis: i) presents methods to exploit noisy, low and variable sampling interval data and sparse sensor embedded RFID data streams in a body worn passive sensor for activity recognition; ii) evaluates methods for generating alarms on the occurrence of high-risk activities in real-time with healthy and hospitalized older people; and iii) investigates the acceptability and wearability of the proposed W^2ISP sensing platform by the trialled cohorts.

There are clear benefits to using an RFID technology-based sensing approach as the devices are small, lightweight, cable-free, battery-free, inexpensive and unobtrusive to performed motions of older people. In addition to acceleration sensor information, RFID technology provides convenient access to RFID data such as the user identifier as well as RFID environment measurements such as the Received Signal Strength Indicator (RSSI). This thesis exploits these benefits and sources of information for the recognition of high risk activities of interest.

The study in Chapter 3 used RFID technology based batteryless wireless sensor approach to detect bed exits using acceleration and RFID measurements such as RSSI. This study determined the feasibility of using such sensor as a body-worn device, showing better performance than using a fixed-bed sensor approach to detect bed exits with a population of young volunteers. The body-worn sensor approach detected bed exits using an empirical threshold-based method where data was interpolated and digitally filtered with frequencies determined by a time-frequency motion analysis as described by Najafi et al. [31]. Following this study, the use of the W^{2}ISP loosely worn over clothing at sternum level was considered adequate as opposed to a strapped approach [31] to secure the sensor to the body which can be considered uncomfortable for older people. Though this method achieved good results with young adults, similar results were not achieved with older populations, our target demographics; hence the need to develop solutions in the domain of machine learning to identify high risk activities.

Chapter 4 introduced the machine learning method of Conditional Random Fields, a graphical model classification algorithm well suited for learning from sequential data. This chapter proposed an alternative problem formulation to the method used in Chapter 3. The proposed approach used a CRF-based approach for recognizing bed exits using features engineered from raw sensor data i.e. acceleration and RSSI (see instantaneous features in Appendix A). This CRF-based approach was tested on a population of healthy older people in two clinical settings that resemble a hospital environment. This approach achieved better performance than the empirical method in Chapter 3 based on interpolation and digital filtering processes applied to acceleration sensor data.

Chapter 5 developed several data segmentation methods and contextual information features using fixed and dynamic sized windowing methods from a sensor data stream for the extraction of contextual information, related to the current sensor observation. These approaches improved the performance of a CRF classifier by providing temporal information to the classifier given that individual sensor readings provide limited information about the related activity for the classifier to make correct inference. Moreover, given that inference methods in CRF consider the evaluation of the complete sequence e.g. Viterbi algorithm or sum-product; a real time CRF inference method based on the sum-product algorithm that allows the prediction of the marginal probabilities for each label for each incoming sensor reading was also developed therein. This inference approach allows the rapid inference of the current sensor observation, avoiding the need to analyze complete data sequences in order to determine the activity being performed and the timely activation of an alert.

The problem of data imbalance was studied in Chapter 6. Data imbalance is an inherent issue in activity recognition as activities performed by humans are of different durations. In particular with older patients who stay in resting positions (lying or sitting) longer than ambulating. Data imbalance can bias classification models to favor a majority class. However, the correct classification of minority classes is important. For example, detecting a person performing the minority class ambulating is important given the associated high risk of falling while ambulating. In the light of this problem, a dynamically weighted CRF (dWCRF) method that considers the effects from imbalanced data was developed. This approach dynamically calculates the cost parameters during training while optimizing overall F-score to improve overall activity recognition performance (i.e. minimize both false alarms and misses). The approach was evaluated with two datasets for human activity recognition using batteryless and battery-powered body worn sensors, respectively, where the latter corresponds to an external publicly available dataset. This study established that dWCRF improves the overall F-score when compared to other CRF-based methods and performed similar to better than other SVM-based classifiers. In addition, dWCRF achieved a significant reduction in training and model selection time when compared to other fixed-weight methods that require extensive validation to obtain optimal parameters.

Two methods to recognize bed and chair exits and generate alarms in real time was proposed in Chapter 7 and Chapter 8. The alarming performance (true alarms and false alarms) was evaluated with a cohort of healthy older people (66 to 86 years old) in Chapter 7, and a cohort of hospitalized older people (71 to 93 years old) in Chapter 8. Both alarm generation methods were based on a two-stage activity recognition approach where in the first stage, a classifier identified the activities performed, and a second stage using a heuristics-based decision function generated the alarms. The method in Chapter 7 considered the use of the dWCRF method from Chapter 6 and a heuristics stage to determine bed exits and chair exits in real time with a population of healthy older people. The method in Chapter 8 considered a weighted SVM classifier in addition to a heuristic stage to determine bed and chair exits jointly with a population of hospitalized older people and is compared with our approach from Chapter 7. These methods for the recognition of bed and chair exits, with a healthy and hospitalized population of older people, suggest that the use of wearable batteryless sensors for fall prevention on older people is feasible as results are promising given the improvements over the previous method in Chapter 4. Moreover, these results are important as these are the first studies to use wireless batteryless sensors on a population of older people.

Chapter 9 formulated a hierarchical CRF (HCRF) model that is able to recognize alarming states corresponding to a bed exit and being out of bed, and a chair exit and being out of chair, based on the simultaneous recognition of simple activities and modelling dependencies between both alarming states and performed activities. HCRF provides and end-to-end method of learning a model to predict alarming states from sensor enabled RFID data streams without the need for heuristic methods commonly employed to decide on an event from underlying classifications of sensor observations (as in Chapter 7 and Chapter 8), and generate an alarm based on a learned confidence parameter. HCRF performed, in general, similar to better than other heuristic-based approaches or SVM-based activity recognition methods with a population of healthy and hospitalized older people. Moreover, training and model selection time for HCRF was, in general, lower than other multi-stage state-of-the-art SVM-based activity recognition methods that require evaluation of multiple binary classifiers and hence longer training and validation times.

Given that the proposed falls prevention strategy relies on patients using the body-worn passive sensor to monitoring their activities, this thesis evaluated the acceptability and wearability of the proposed sensor device, as perceived by the participants in the studies. This analysis is necessary as final user opinion is paramount for transferring to a hospital deployment; moreover, only 1.3 % of previous body-worn sensor studies have considered the interest of their users [19]. The approach used a modified sensor acceptability model consisting of two surveys, the first survey was administered to older people before and after the trials to measure the changes in perception of the device after use. The second survey was administered after the trials and measured the acceptability and privacy concerns of the users towards the sensor platform. In general, the trialled cohorts found the device to be easy to wear and unobtrusive to their movements (Chapter 4 and Chapter 8). These results are in agreement with the findings of Bergmann et al. [19] where older people showed preference for small, unobtrusive sensor devices. However, older patients were conscious of wearing the device as it was highly visible on top of their garment (Chapter 8). This indicates the need to reduce the size of the W^2ISP for future clinical applications.

Considering the performance of other falls prevention interventions, several recent RCTs focused on falls prevention in hospitals reported their effectiveness in reducing the number of falls in older patients [16, 15]. However, no alarming performance information was given in terms of detected bed exits or chair exits [16, 15]. There has been, however, recent technological studies focused on falls prevention [63, 62, 14], mainly bed exit detection, that reported the performance of their monitoring systems. Table 10.1 shows the results for bed exit detection from the methods of Hilbe et al. [63] and Bruyneel et al. [62] using fixed sensors on hospital beds. These methods, although aimed at older patients, were not tested with older people. The study of Capezuti et al. [14] achieved 71 % recall but a low specificity of 3 %; thus not shown in Table 10.1. This study [14] is the only long term study with older people that report the performance of pressure sensors (together with infra red beam) for the detection of bed exits. Moreover, this study demonstrates the problem of using pressure sensors i.e. high false alarms, unreliability with light-weight patients and need to individualize sensor location for each patient [14]. We also show in Table 10.1 the results for bed exit detection from the important studies of Najafi et al. [31] and Godfrey et al. [26] based on a battery powered sensor strapped to the chest with a population of older people. In these studies [31, 26], the authors focused on detecting posture transitions; and thus we consider the results for detecting sit-to-stand posture transitions as similar to a bed exit movement as normally a bed exit is the progression from lying to sitting to standing. Table 10.1 has not considered specificity $\left(\frac{\text{true negative}}{\text{true negative + false positive}}\right)$, reported in previous studies [31, 63, 62, 26], as activities regarded as true negatives were not clearly established across the studies and also was not considered in the evaluation of the methods in this thesis.

Table 10.1 also shows the results from the methods presented in this thesis for bed exit recognition. Chair exit recognition results are not shown due to the lack of studies reporting this activity in the literature, and the purpose of Table 10.1 is to draw similarities and differences between methods reporting a common activity (bed exits). It should be made clear that direct comparisons between previous methods cannot be made as populations, sensors and experimental settings, and procedures are different. Further, for the trials in this thesis, the sensor was worn over clothing, attached to a loosely fitted garment.

We can see that performance of our approach with healthy young volunteers in Chapter 3 is similar to those studies conducted by Hilbe et al. [63] and Bruyneel et al. [62] with a healthy adult population. In the case of healthy older participants, the methods in Chapter 7 and Chapter 9 also provide similar results to those of Najafi et al. [31] and Godfrey et al. [26]. Notably, there are no quantitative performance measures of bed and chair exits in a hospital context. Therefore the approaches in Chapter 8 and Chapter 9 present benchmarks for future intervention implementations in hospital settings. The different results between the approaches in Chapter 8 and Chapter 9 are due to their distinct methodologies. In particular: i) the approach in Chapter 8 considers the effects of class specific data imbalance whereas the method in Chapter 9 considers each class to equally affect the classifier. ii) Chapter 8 reports on the alarming performance where the method does not discriminate between bed and chair exits; however, the HCRF (Chapter 9) classifier is able to discriminate between bed and chair exits alarms. iii) In Chapter 8, the bed exit alarm component includes the intention to exit the bed i.e. sitting on bed, previous to leaving the bed, whereas the method in Chapter 9 considers a bed exit from the moment the person leaves the bed.

Table 10.1: Performance of bed exit studies

Approach	Detected Exit	Sensor device	Precision	Recall	Participants' age (years)
Fixed bed sensor location					
Hilbe et al. [63]	bed exit	pressure rail		96 %	18 to 60
Bruyneel et al. [62]	bed exit	presence and temperature mat	100 %	91 %	37 ± 9 and 45 ± 11
Battery Powered Sensor Device (worn strapped over chest)					
Najafi et al. [31]	sit-to-stand transfer considered as bed exit	accelerometer and gyroscope		93 %	66 ± 14
Godfrey et al. [26]		accelerometer		83 %	77.2 ± 4.3
Batteryless Sensor Device—W^{2}ISP (worn attached to loosely fitted garment)					
Chapter 3	bed exit	accelerometer		90.4 %	26.4 ± 2.1
Chapter 7[a]	bed exit	accelerometer	78.8 %	93.5 %	66 to 86
Chapter 8[bc]	bed and chair exit	accelerometer	66.8 %	81.4 %	71 to 93
Chapter 9[ac]	bed exit	accelerometer	79.3 %	84.9 %	66 to 86
	bed exit	accelerometer	23.2 %	71.7 %	71 to 93

[a]Participants in age group 66 to 86 are healthy older adults. Here are considered results for the room setting with 3 antennas (Room2), as is similar to that of hospital deployment

[b]Bed and chair exits recognized together

[c]Participants in age group 71 to 93 are older hospitalized patients.

Therefore, the results from this thesis strongly suggests that the deployment of a wearable sensor based falls prevention intervention is feasible, especially in a hospital environment; although further research is required to develop a deployable system. The CRF-based classification methods developed in this thesis can perform better than other CRF-based methods and similar to better than SVM-based methods using sequential data from a wearable passive sensor. Moreover, this thesis determined that the use of this technology appears acceptable to users and it does not restrict older peoples' movement, in particular for hospitalized older people; however the sensor was considered conspicuous to the user given the highly visible sensor prototype. This thesis adds to the knowledge in the areas of falls prevention in older people using wearable sensors, machine learning techniques for sequential sensor data streams, sets benchmarks and opens up new avenues for future work in these fields.

10.2 Thesis Contributions

The main contributions of this thesis are summarized as follows:

- *Investigate a new sensor technology to realize a novel technological intervention to prevent falls in hospitals and nursing homes.* This thesis investigates a single wireless, wearable sensor device consisting of an accelerometer embedded RFID tag, called W^2ISP which is loosely worn on top of clothing. Sensor signals are collected by the RFID infrastructure and sent for processing in real time. Once an alerting event is detected, hospital staff are notified of the event and are able to supervise the patient. Based on the falls prevention framework in Section 1.3, different methods for the recognition of bed exits and chair exits were developed and tested with young people (Chapter 3); healthy older people (Chapters 4 and 7); hospitalized older people (Chapter 8); and both healthy and hospitalized older people (Chapter 9).
- *Investigate and evaluate two approaches for sensor location (on-body and off-body) for the recognition of bed exits.* The study in Chapter 3 studied two possible locations for bed exit detection with young participants. The first approach considers a body-worn sensor device located on top of clothes at sternum level to collect information about the upper body motion of the participant; this approach differs from previous studies where sensor devices were strapped to the body and were battery-powered. The second approach considers the same sensor located on the side of a mattress to detect the mattress deformation due to the weight of the person sitting or lying on the mattress. This experiment, using digital filtering where parameters are based on the time-frequency analysis of motion data and an empirical decision tree suggested that a body-worn sensor approach was better able to detect bed exits. This study also demonstrated that the recognition of activities, in particular bed exits, was possible using a wearable, batteryless sensing device including a single accelerometer sensor, and RFID measurements such as RSSI to provide relative location of the participant with respect to antennas.

- *Reformulate the activity recognition problem to a multi-class classification problem using CRF.* Chapter 4 formulated a machine learning-based method for the recognition of bed exits in healthy older people using Conditional Random Fields (CRFs), a structured classifier that models the dependencies of activities in a sequence. This method engineered features based on the raw acceleration data and RSSI measurements from received sensor observations (see Appendix A), and detected bed exits in complete sequences using the Viterbi algorithm for inferencing class labels. This method outperformed the empirical body-worn sensor method, described in Chapter 3, with a population of healthy older people. In addition, this method demonstrated that machine learning is better suited for sparse and noisy data available from the RFID and sensor data stream than using empirical methods to recognize activities from older people.
- *Investigate segmentation methods for the extraction of contextual information features from wearable batteryless sensor data streams.* Chapter 5 developed and tested various data segmentation methods and contextual information features using fixed and dynamic sized windowing methods to extract contextual information related to the current sensor observation from a sensor data stream to improve performance of a CRF classifier. Given that human motion is closely related to the previous actions in recent past, this study considered such information (recent past) in terms of time and space—i.e. windows delimited by time (duration) or number of sensor observations—to increase the information quality of data segments and provide temporal context to the last received observation from body-worn passive sensors. Results achieved using contextual information features (see Appendix A) from a fixed-time windowing method with were similar or better than those using more sophisticated segmentation methods.
- *Real time inference of streaming sequential data using CRF.* In linear chain CRF, class inference is performed on complete sequences using methods such as the Viterbi algorithm or the sum-product algorithm. This approach is not convenient for real time applications such as falls prevention, where the timely recognition of high risk activities is paramount. Chapter 5 proposed a method based on the sum-product algorithm to determine the marginal probabilities of the last received sensor reading in real time. This method only requires the current and previous sensor observations in order to make a prediction as we

are only interested in the last received sensor observation, as opposed to using complete sequences.

- *Learning method for imbalanced sequential data—dynamically weighted CRF (dWCRF).* Chapter 6 developed a novel learning method based on linear chain CRFs that considers the influence of individual classes in the training process, called dynamically weighted CRF (dWCRF). The prevalence of imbalanced data in human activity recognition problems is an issue as data imbalance can bias classification models to favor the selection of the majority class. The proposed dWCRF uses dynamically calculated class-wise cost parameters in the learning process of the classifier. These cost parameters are not fixed as they are dynamically calculated during training. Simultaneously, the training process seeks to optimize the overall F-score as a way to reduce both false alarms and missed predictions, as opposed to metrics that are biased towards the majority class such as accuracy. This approach was evaluated with two datasets using batteryless and battery-powered body-worn sensors. The proposed dWCRF, in general, outperformed CRF-based methods and achieved similar to better performance to SVM-based approaches where dWCRF also improved F-score performance for the recognition of minority classes. In addition, the training and model selection of dWCRF is faster when compared with other methods that require extensive validation to obtain optimal fixed class-wise cost parameters.
- *Hierarchical CRF classifier for the recognition of alarming states from sequential sensor data in real time.* Chapter 9 proposed a hierarchical CRF (HCRF) classifier that learns to recognize alarming states corresponding to bed exits and being out of bed and chair exits and being out of chair in real time. Alarms are normally decided using two or more processing parametric stages, such as empirically determined heuristic methods or multiple classification stages, e.g. cascaded classifiers or those presented in Chapter 7 and Chapter 8. HCRF considers alarming events as high-level activities, the labeled sensor observations as low-level activities, and predicts both high- and low-level activities simultaneously. The HCRF model constructs relationships between sensor observations, low-level activities and high-level activities to determine the alarming state of the current sensor observation. Moreover, the model incorporates its decision function based on a learned alarm confidence level (marginal probability). Therefore, HCRF avoids the use of empirically determined heuristic

methods or multiple classification stages for the recognition of alarm events. The proposed HCRF, in general, produced similar to better performance than other multi-stage classification methods for human activity recognition. Further, HCRF requires less training time than the multi-stage classification methods.

- *Collected and made publicly available three datasets for human activity recognition research with different demographics.* This study collected data from young volunteers (aged 23 to 30) as well as healthy and hospitalized older people (aged 66 to 86 and 71 to 93 respectively) performing broadly scripted activities of daily living that are common in a hospital or nursing home context such as lying on a bed, sitting on the bed, sitting on a chair, and ambulating between the door, bed and chair. All participants wore a wireless batteryless sensor device to capture body motion information while performing activities. This data is significant as previous studies for activity recognition have mainly used battery-powered sensor devices and very few have considered older people, especially hospitalized older patients, in their approaches. Further details about settings are described in Appendix B. These datasets are available at: `http://autoidlab.cs.adelaide.edu.au/research/ahr`.
- *Develop a modified sensor acceptance model to determine the acceptability and wearability of a body-worn sensor platform.* This study used a quantitative survey instrument based on a modified validated instrument to measure the acceptability and wearability of the equipment on three factors: physical activity; anxiety; and equipment. In addition, the developed sensor acceptance model considered a factor for privacy, to evaluate the importance of privacy violation concerns that could be raised. The model consisted of two surveys where the first survey was administered before (pre-survey) and after (post-survey) to evaluate the changes in perception of the sensor after use; and the second survey, administered after the trial only, to measure the acceptability and wearability of the sensor as perceived by the users (Chapters 4 and 8). The complete sensor acceptance model instrument is shown in Appendix C.

10.3 Future Work

From the work in this thesis, various future research directions can be developed. First, further investigations and development of the RFID infrastructure can potentially improve the activity recognition performance. In particular:

- Investigate changing the location of the sensor to the shoulder as an alternative to the attachment over the sternum. Although an attachment over the sternum is considered in the literature as a better location to obtain upper-body movement sensor readings, an attachment over the shoulder has not been investigated. This modification can allow the positioning of all antennas on the ceiling and may significantly reduce the occlusion of the sensor by the human body.
- Modification of different RFID deployment conditions and parameters such as: i) modification of RFID reader parameters, such as the antenna receiving sensitivity to discriminate spurious readings from sensors far from the area of interest; ii) use of different types of antennas; for example, antennas with different radiation patterns, specifically, directive antennas can be considered to achieve a more focused antenna illumination in some areas such as the bed or chair.
- Conduct experiments to evaluate any changes in performance due to the presence of different furniture in various locations of the room as well as the presence of visitors and clinical staff, as these variations can have an impact on the reading rate of the tags present in the room and the type of movements performed by the patient.

The study of these conditions is not trivial and ideally a long term in-hospital deployment is necessary with a large cohort of patients to validate the results of each study.

Second, further developments in the sensor platform are necessary. The trials and evaluations in this thesis were performed with a prototype sensor device, which was found to be highly visible by the trialled hospitalized population. Therefore, reduction in size and visibility without affecting sensor powering must be paramount for clinical application and acceptability of this technology. For example, textile integrated sensors can embed a fabric antenna into the patient's garment, reducing the visibility of the sensor, and can be considered for future studies. These sensor platform developments should also consider decreasing production costs when mass produced, to successfully commercialize the technology.

In addition, the falls prevention systems can benefit from the aggregation of more sensors on the device, such as pressure sensors (barometers) and magnetometers; these can improve the data sources from which to capture relevant human movements and provide further information about the activities being performed. However, this will both increase the cost of the sensor and the overall power consumption. Nevertheless, augmenting additional power harvesting methods and the utilization of components with reduced power consumption can minimize the occurrence of sudden drops in harvested power (brownouts) due to occlusion, or antenna misalignment, as well as increase the reading range of the sensor device. Early work on an approach to overcome brownout through intelligent power management is demonstrated in [104].

Third, the performance of future movement sensor alarm systems must be evaluated in long term clinical and hospital trials during both day and night with a larger cohort of hospitalized older people. Eventually, a randomized controlled trial (RCT) must be conducted with a newly developed sensor and further optimized hospital RFID infrastructure. Planned RCTs must not only report the efficacy of the technology for preventing falls, but also the performance of the monitoring system in recognizing high risk activities, e.g. bed exits or chair exits, in terms of recognized true alarms and generated false alarms. The reason for reporting the performance of the monitoring system, as opposed to reporting the occurrence of falls as in most RCTs in the literature, is to analyze and better understand the contribution of the monitoring system to the reduction (or not) of the number of falls and that of other external factors such as the time clinical personnel takes to respond to an alert, the number of healthcare personnel available and the time of day, and the effect of false alarms such as alarm fatigue.

Fourth, future research must consider further development of machine learning approaches to improve the accuracy of event identification given the constrains of the hospital environment. In particular, the development of dynamically calculated class-wise weights for improving the performance of the hierarchical conditional random fields (HCRF) approach in the presence of data imbalance. In addition, future research can investigate learning methods such as active learning to update models to benefit from possible healthcare staff feed-back of alarms from a deployed system.

Fifth, an extended monitoring system should recognize all four high risk activities determined in Section 1.3. Therefore, further studies must consider the recognition of other high risk activities not considered in the present thesis; i.e. entering or exiting the toilet without the aid of a caregiver and mobilizing or ambulating without a walking aid. Moreover, extending the context of the present thesis to that of independent living in a home environment would reach a wider demographics of older people while presenting different challenges to those present in a hospital context.

Sixth, future studies must validate the sensor acceptance model developed in this thesis with a larger cohort of hospitalized patients.

Appendix A

Features Extracted from Sensor Data

This appendix shows all features used for the development of this thesis. These features were extracted from the sensor, shown in Figure A.1, using sensor's acceleration data, ID, and RFID measurements (e.g. RSSI and phase). Features are divided according to the method of extraction. i) Instantaneous features, shown in Table A.1, are those extracted directly from the information of every received sensor observation. ii) Contextual information features, shown in Table A.2, are extracted from a fixed 4 s sliding window segment; these features provide an insight of the temporal variations of sensor information during the segment. iii) Inter-segment features, shown in Table A.3, are extracting from comparison between two consecutive segments; these features characterize pattern variation trends about motion and relative proximity to the area of interest.

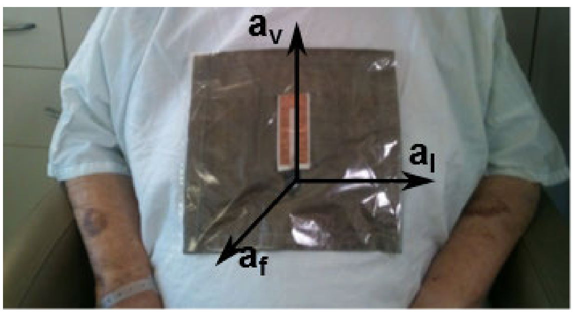

Figure A.1: sensor used showing parts and sensor axes with respect to the body.

Table A.1: **List of instantaneous features extracted from sensor data stream.**

Features		Description
1.	Frontal acceleration (a_f)	Dorsoventral axis acceleration values in range -1:1
2.	Vertical acceleration (a_v)	Anteroposterior axis acceleration values in range -1:1
3.	Lateral acceleration (a_l)	Left-right axis acceleration values in range -1:1
4.	Sine of body tilting angle (pitch)	Sine of body tilting angle towards the front or back with respect to vertical in the midsagittal plane, calculated as: $\sin(\arctan(\frac{a_f}{a_v}))$
5.	Received signal power (RSSI)	Received signal power from the sensor as received at reading antenna.
6.	Acceleration modulus (a_T)	Magnitude of acceleration vector or total acceleration, calculated as $a_T = \sqrt{a_v^2 + a_f^2 + a_l^2}$.
7.	Time difference	Time difference with previous sensor observation (regardless of receiving antenna) in the range 25 ms – 10 s.
8.	Participant's gender	
9.	Trunk yaw angle	Rotational angle from dorsoventral axis, calculated as: $\arctan(\frac{a_l}{a_f})$
10.	Trunk roll angle	Tilting angle in the coronal plane, calculated as: $\arctan(\frac{a_l}{a_v})$
11.	Antenna ID	RFID antenna receiving current tag reading.

Table A.2: List of contextual information features extracted from sensor data stream. (p.a. = per antenna)

Features	Description
12. Events reported p.a.	Indicator of number of readings per antenna in the window.
13. Antenna collecting maximum power	ID of antenna with maximum received power in segment.
14. Antenna collecting minimum power	ID of antenna with minimum received power in segment.
15. Vertical displacement (d)	Cumulative body displacement in the vertical axis during a segment, calculated as: $d = \iint_0^{\delta t} a_v dt^2$.
16. Mutual information of bed and chair areas ($m_{bed-chair}$)	Events occurring between these two areas given by the number of consecutive readings captured in both bed and chair areas, calculated as: $m_{bed-chair} = \frac{1}{n} \sum_{k=1}^{n-1} (\mathbb{1}_{[\{bed,chair\}=\{ant_k,ant_{k+1}\}]} + \mathbb{1}_{[\{chair,bed\}=\{ant_k,ant_{k+1}\}]})$; where $\mathbb{1}_x$ assumes 1 if x is true and 0 otherwise and ant_k refers to the antenna receiving the k^{th} sensor reading in a segment of size n, used in [105].
17. Pearson correlation coefficient for frontal and vertical acceleration axes (r)	Correlation between axes information, calculated as: $r_{a,b} = \frac{1}{n-1} \sum_{i=1}^{n} (\frac{a_i - \bar{a}}{s_a})(\frac{b_i - \bar{b}}{s_b})$; where we considered $a, b = \{a_v, a_f, a_l\}$, $a \neq b$ and s_x is the standard deviation of the samples x in the window.
18. Mean and standard deviation of RSSI	Mean and standard deviation of received power received per antenna during 4 s time window.
19. Median, sum of absolute value and standard deviation of CFPR	Constant Frequency Phase Rate (CFPR) defined as $CFPR = phase(t) - phase(t-1)$, for each antenna. Measurements from all frequencies during the segment as defined in [106].

20. Standard deviation of VFPR	Variable Frequency Phase Rate (VFPR) defined as $VFPR = \frac{phase(t)-phase(t-1)}{frequency(t)-freqeuncy(t-1)}$; features as defined in [106].
21. Mean and standard deviation of acceleration	Mean and standard deviation of acceleration values (a_v, a_f, a_l) during the segment.
22. Total velocity during segment	Total velocity during the segment, calculated as $v_{a_T} = \int_0^{\delta t} a_T dt$.
23. Total displacement during segment.	Cumulative displacement during the segment, calculated as $d_{a_T} = \iint_0^{\delta t} a_T dt^2$.

Table A.3: List of inter-segment features extracted from sensor data stream. (p.a. = per antenna)

Features	Description
24. Difference of acceleration maxima	Inter-segment difference of acceleration (a_v, a_f, a_l) maxima.
25. Difference of acceleration minima	Inter-segment difference of acceleration (a_v, a_f, a_l) minima.
26. Difference of acceleration median	Inter-segment difference of acceleration (a_v, a_f, a_l) median.
27. Difference of power maxima p.a.	Inter-segment difference of received signal power maxima per antenna.
28. Difference of power minima p.a.	Inter-segment difference of received signal power minima per antenna.
29. Difference of power median p.a.	Inter-segment difference of received signal power median per antenna.
30. Difference of sine of body tilting angle maximum, minimum and median	Inter-segment difference of sine of body tilting angle maximum, minimum and median.

Appendix B

Released Datasets

For the completion of this thesis different datasets have been collected. These correspond to healthy and hospitalized older people for data analysis to validate the methods for the recognition of activities that can lead to falls. These trials had ethics approval from the human research ethics committee of the Queen Elizabeth Hospital (TQEH), South Australia, with ethics reference number 2011129. All participants were able to move independently, consented to the trials and also participated in surveys about the perception and acceptability of the sensor technology. Datasets are available at: `http://autoidlab.cs.adelaide.edu.au/research/ahr`.

Healthy Young People

Seven young healthy volunteers aged between 23 to 30 years old participated in this study at the Basil Hetzel Institute, Woodville, South Australia. The volunteers, wearing the WISP on top of their clothes at sternum level, performed random and scripted lists of activities that are more likely to be performed by hospitalized older people, such as: i) go to bed, lie down in the bed and exit the bed; ii) go to the chair, sit on the chair and exit the chair; and iii) ambulate between bed and chair.

The activities were recorded and annotated in real time by an observer using middleware software developed in-house. The activities were labeled as: i) sit-on-bed; ii) sit-on-chair; iii) lying; iv) standing; and v) walking.

Healthy Older People

For this study, fourteen participants, aged between 66 to 86 years old, were recruited from geriatrics clinics and volunteers lists from previous studies. The participants were able to live and mobilize independently, and able to consent to participate in the trial. The participants were contacted by phone and participation information sheets were mailed to them. Before the trial, consent was obtained from the participants and the process of the trial was explained, including the activities to be performed, and the equipment to be used including the sensor. Each participant wore the W^{2}ISP on top of their clothes and performed about five series of broadly scripted activities that included: i) walking to the chair, ii) sitting on the chair, iii) getting off the chair, iv) walking to bed, v) lying on bed, vi) getting off the bed and vii) walking to the door. The participants were instructed to perform the activities as comfortably as they could and no honorarium was provided. The participants were able to terminate the trial at any time and were routinely asked about their condition to continue. The activities were recorded and annotated in real time by a researcher present during the trials. In general, a trial with each participant lasted between 90 to 120 min and was performed during the day between 10 am and 3 pm.

The participants were allocated in two clinical room settings (Room1 and Room2) at the Basil Hetzel Institute, Woodville, South Australia, shown in Fig. B.1, with different distribution of furniture and RFID infrastructure. The rooms were designed to resemble general deployments of different hospital room settings. Room1 was deployed with four antennas, one of them at ceiling level facing down to the bed and the rest of antennas placed on the walls to illuminate the whole room. In contrast Room2, used three antennas focused in areas of interest, i.e. two antennas on ceiling level facing the bed and surrounding area and a third antenna at wall level facing the chair.

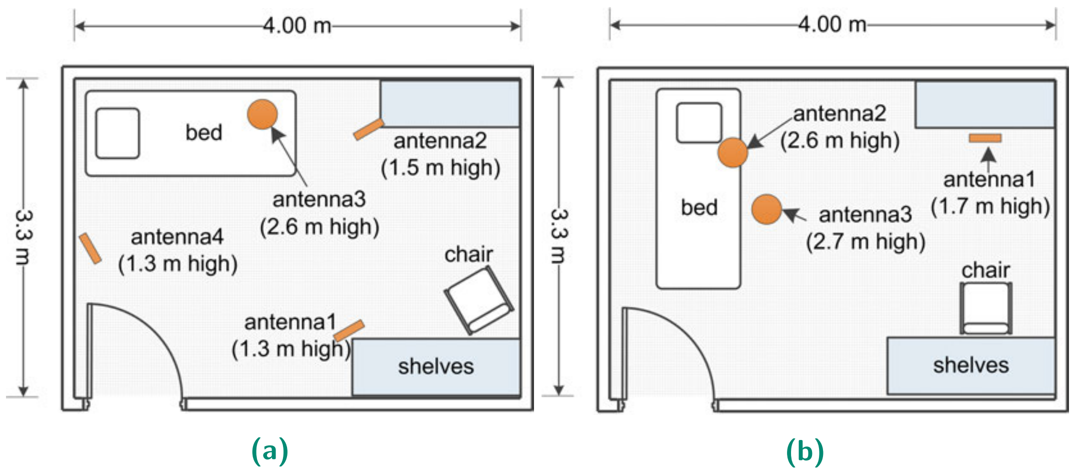

Figure B.1: Two room configurations used with healthy older people. (a): Room1. (b): Room2.

Hospitalized Older People

For this study, 26 patients, aged between 71 to 93 years old, were recruited from the geriatrics evaluation and management (GEM) unit at the TQEH. The patients were able to mobilize with or without a walking aid, had no cognitive impairment and were able to consent to participate in the study.

The patients wore the W^2ISP on top of their hospital gowns and were trialled in their own hospital rooms—single or double rooms—with two antennas at ceiling level facing the bed and a single antenna at the opposite wall facing the armchair as shown in Fig. B.2. Trials were performed between 2 pm and 4 pm and had a duration of about 20 to 25 min due to the frail condition of the participants. The patients performed a broadly set of activities that included i) walk to the chair; ii) sit on the chair; iii) get out of the chair; iv) walk to the bed; v) lie on the bed; vi) get out of the bed; and vii) walk to the door. The patients were not instructed on how to perform the activities, and were told to perform activities at their own pace and request the termination of the trial if they felt discomfort or could not continue. Two researchers were present during trials, one researcher annotated the activities in real time and the second researcher made sure the patient was not hurt and acted if the patient seemed at risk of falling as patients could get easily tired.

During the trials, the position of the movable head rest of the bed was either flat or inclined as patients were resting or awake receiving visits, watching television or reading prior to starting of the trials. Hence, multiple postures were captured when the patient was on the bed during the trials.

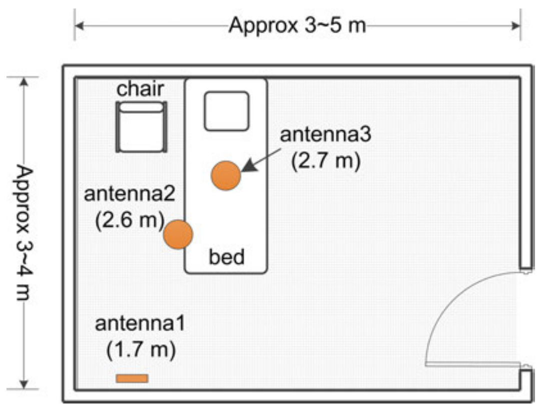

Figure B.2: Hospital room configuration for trials.

Appendix C

Developed Sensor Acceptance Model

This sensor acceptance model was developed based on that of Fensli et al. [107], originally for measuring the patients' acceptance of a wearable skin-attached ECG sensor. The developed sensor acceptance model, for this thesis, consists of two surveys described below.

First Survey

This survey is based on the "pre-trial expectations" factor from the model of Fensli et al. [107]. These questions measured the perception of people about the activity recognition system and their apprehension towards its use. This model considered the application of the survey before and after the trials (pre- and post-trial) to measure the changes of perception after usage. The survey questions are:

1. I expect this investigation can help prevent falls.
2. I believe if I wear this device I will have difficulties doing daily activities.
3. I am worried the equipment will not give good enough signals for the research.
4. I am afraid the equipment will fall from its attached position if I move too much.
5. I am afraid the equipment will break if I move too much.
6. I am afraid the equipment will harm me.

Second Survey

This survey was designed for administration after the trials. The questions are designed to measure acceptability and wearability about the system as perceived by users. The model for this thesis considered three key acceptance factors from [107], i.e. “physical activity”,“anxiety” and “equipment” which determine the users’ acceptance of the device. This study also considered a new factor “privacy”, given the importance of previous privacy violation concerns manifested in other studies [22]. The survey questions, divided by acceptance factors, are:

Physical Activity

1. How did you experience wearing the equipment while performing activities?
2. Were you hindered by the equipment while walking?
3. Were you hindered by the equipment while sitting?
4. Were you hindered by the equipment while lying?

Anxiety

1. I was frightened by this technology.
2. I don’t want the equipment to be seen by others.
3. I don’t like the feeling of being monitored.

Equipment

1. Wearing the equipment was no problem.
2. I just forgot I am wearing it.
3. I am satisfied using the equipment
4. I find the equipment easy to use.

Privacy

1. How did you experience wearing the equipment knowing that someone could be aware of some of your activities?

In the analysis of Chapter 4, a short set of the above questions were considered, as the focus of the study was to study the use of the equipment and freedom of movement of the users while wearing the sensor device; hence this study used factors “Equipment” and “Physical”, correspondingly.

The analysis in Chapter 8 considered most questions above, except questions Physical-2 and Physical-3 because activities such as walking and standing can be considered already included when responding question Physical-1—a more general question. In addition, this analysis did not include questions Equipment-3 and Equipment-4 because of the short time of the trials with older patients (20 to 25 min), which is insufficient for patients to determine satisfaction or easiness to use with the sensor device. Instead, this analysis focused on their general experience of wearing the sensor.

Bibliography

[1] Australian Commission on Safety and Quality in Healthcare, "Preventing falls and harm from falls in older people: Best practice guidelines for Australian hospitals," 2009.

[2] K. D. Hill, M. Vu, and W. Walsh, "Falls in the acute hospital setting - impact on resource utilisation," *Australian Health Review*, vol. 31, no. 3, pp. 471–477, 2007.

[3] F. Healey, S. Scobie, B. Glampson, A. Pryce, N. Joule, and M. Willmott, "The third report from the patient safety observatory. slips, trips and falls in hospital," *London: National Patient Safety Agency*, 2007.

[4] D. Oliver, "Evidence for fall prevention in hospitals," *Journal of the American Geriatrics Society*, vol. 56, no. 9, pp. 1774–1775, 2008.

[5] D. Oliver, F. Healey, and T. P. Haines, "Preventing falls and fall-related injuries in hospitals," *Clinics in Geriatric Medicine*, vol. 26, no. 4, pp. 645–692, 2010.

[6] C. Becker and K. Rapp, "Fall prevention in nursing homes," *Clinics in Geriatric Medicine*, vol. 26, no. 4, pp. 693–704, 2010.

[7] F. Bunn, A. Dickinson, C. Simpson, V. Narayanan, D. Humphrey, C. Griffiths, W. Martin, and C. Victor, "Preventing falls among older people with mental health problems: a systematic review," *BMC Nursing*, vol. 13, no. 1, p. 4, 2014.

[8] E. Vlaeyen, J. Coussement, G. Leysens, E. Van der Elst, K. Delbaere, D. Cambier, K. Denhaerynck, S. Goemaere, A. Wertelaers, F. Dobbels, E. Dejaeger, K. Milisen, the Center of Expertise for Fall, and F. P. Flanders, "Characteristics and effectiveness of fall prevention programs in nursing homes: A systematic review and meta-analysis of randomized controlled trials," *Journal of the American Geriatrics Society*, vol. 63, no. 2, pp. 211–221, 2015.

[9] E. B. Hitcho, M. J. Krauss, S. Birge, W. Claiborne Dunagan, I. Fischer, S. Johnson, P. A. Nast, E. Costantinou, and V. J. Fraser, "Characteristics and circumstances of falls in a hospital setting," *Journal of General Internal Medicine*, vol. 19, no. 7, pp. 732–739, 2004.

[10] R. Cumming, C. Sherrington, S. Lord, J. Simpson, C. Vogler, I. Cameron, and V. Naganathan, "Cluster randomised trial of a targeted multifactorial intervention to prevent falls among older people in hospital," *British Medical Journal*, vol. 336, no. 7647, pp. 758–760, 2008.

[11] K. Rapp, C. Becker, I. D. Cameron, H. H. König, and G. Büchele, "Epidemiology of falls in residential aged care: analysis of more than 70,000 falls from residents of bavarian nursing homes," *Journal of the American Medical Directors Association*, vol. 13, no. 2, pp. 187.e1–187.e6, 2012.

[12] H. Hanger, M. Ball, and L. Wood, "An analysis of falls in the hospital: can we do without bedrails?," *Journal of the American Geriatrics Society*, vol. 47, no. 5, pp. 529–531, 1999.

[13] G. R. Murray, I. D. Cameron, and R. G. Cumming, "The consequences of falls in acute and subacute hospitals in australia that cause proximal femoral fractures," *Journal of the American Geriatrics Society*, vol. 55, no. 4, pp. 577–582, 2007.

[14] E. Capezuti, B. L. Brush, S. Lane, H. U. Rabinowitz, and M. Secic, "Bed-exit alarm effectiveness," *Archives of Gerontology and Geriatrics*, vol. 49, no. 1, pp. 27–31, 2009.

[15] R. I. Shorr, A. M. Chandler, L. C. Mion, T. M. Waters, M. Liu, M. J. Daniels, L. A. Kessler, and S. T. Miller, "Effects of an intervention to increase bed alarm use to prevent falls in hospitalized patients: A cluster randomized trial," *Annals of Internal Medicine*, vol. 157, no. 10, pp. 692–699, 2012.

[16] O. Sahota, A. Drummond, D. Kendrick, M. J. Grainge, C. Vass, T. Sach, J. Gladman, and M. Avis, "Refine (reducing falls in in-patient elderly) using bed and bedside chair pressure sensors linked to radio-pagers in acute hospital care: a randomised controlled trial," *Age and Ageing*, vol. 43, no. 2, pp. 247–253, 2014.

[17] A. Pantelopoulos and N. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 40, pp. 1–12, Jan 2010.

[18] O. Lara and M. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Communications Surveys Tutorials*, vol. 15, no. 3, pp. 1192–1209, 2013.

[19] J. Bergmann and A. McGregor, "Body-worn sensor design: What do patients and clinicians want?," *Annals of Biomedical Engineering*, vol. 39, no. 9, pp. 2299–2312, 2011.

[20] S. Chaudhuri, L. Kneale, T. Le, E. Phelan, D. Rosenberg, H. Thompson, and G. Demiris, "Older adults' perceptions of fall detection devices," *Journal of Applied Gerontology*, 2015.

[21] S. Londei, J. Rousseau, F. Ducharme, A. St-Arnaud, J. Meunier, J. Saint-Arnaud, and F. Giroux, "An intelligent videomonitoring system for fall detection at home: perceptions of elderly people," *Journal of Telemedicine and Telecare*, vol. 15, no. 8, pp. 383–390, 2009.

[22] G. Demiris, B. K. Hensel, M. Skubic, and M. Rantz, "Senior residents' perceived need of and preferences for "smart home" sensor technologies," *International Journal of Technology Assessment in Health Care*, vol. 24, pp. 120–124, 2008.

[23] T. Gu, S. Chen, X. Tao, and J. Lu, "An unsupervised approach to activity recognition and segmentation based on object-use fingerprints," *Data & Knowledge Engineering*, vol. 69, no. 6, pp. 533 – 544, 2010.

[24] O. Banos, M. Damas, H. Pomares, F. Rojas, B. Delgado-Marquez, and O. Valenzuela, "Human activity recognition based on a sensor weighting hierarchical classifier," *Soft Computing*, vol. 17, no. 2, pp. 333–343, 2013.

[25] J. P. Varkey, D. Pompili, and T. A. Walls, "Human motion recognition using a wireless sensor-based wearable system," *Personal Ubiquitous Comput.*, vol. 16, pp. 897–910, Oct. 2012.

[26] A. Godfrey, A. Bourke, G. Ólaighin, P. van de Ven, and J. Nelson, "Activity classification using a single chest mounted tri-axial accelerometer," *Medical Engineering & Physics*, vol. 33, no. 9, pp. 1127–1135, 2011.

[27] M. Narayanan, S. Redmond, M. Scalzi, S. Lord, B. Celler, and N. Lovell, "Longitudinal falls-risk estimation using triaxial accelerometry," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 3, pp. 534–541, 2010.

[28] M. Brodie, S. Lord, M. Coppens, J. Annegarn, and K. Delbaere, "Eight weeks remote monitoring using a freely worn device reveals unstable gait patterns in older fallers," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 11, pp. 2588–2594, 2015.

[29] B. Najafi, D. G. Armstrong, and J. Mohler, "Novel wearable technology for assessing spontaneous daily physical activity and risk of falling in older adults with diabetes," *Journal of Diabetes Science and Technology*, vol. 7, no. 5, pp. 1147–1160, 2013.

[30] K.-H. Wolf, K. Hetzer, H. zu Schwabedissen, B. Wiese, and M. Marschollek, "Development and pilot study of a bed-exit alarm based on a body-worn accelerometer," *Zeitschrift für Gerontologie und Geriatrie*, vol. 46, no. 8, pp. 727–733, 2013.

[31] B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C. Bula, and P. Robert, "Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 6, pp. 711–723, 2003.

[32] M. Schwenk, K. Hauer, T. Zieschang, S. Englert, J. Mohler, and B. Najafi, "Sensor-derived physical activity parameters can predict future falls in people with dementia," *Gerontology*, vol. 60, no. 6, pp. 483–492, 2014.

[33] A. Chan, N. Selvaraj, N. Ferdosi, and R. Narasimhan, "Wireless patch sensor for remote monitoring of heart rate, respiration, activity, and falls," in *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 6115–6118, July 2013.

[34] A. Ruhanen, M. Hanhikorpi, F. Bertuccelli, A. Colonna, W. Malik, D. Ranasinghe, T. S. López, N. Yan, and M. Tavilampi, "Sensor-enabled rfid tag handbook," *BRIDGE, IST-2005-033546*, January 2008.

[35] R. Visvanathan, D. C. Ranasinghe, L. Stewart, A. Khoo, T. M., G. D., S. Hoskins, J. Wood, and K. D. Hill, "AMBIGeM: Innovative use of technology to monitor humans and possibily prevent falls in acute care." Available: http://autoidlab.cs.adelaide.edu.au/sites/default/files/publications/papers/12207-CALHN-A1-posterAmbiGeMVer0.4.pdf, 2012.

[36] K. Finkenzeller, *RFID handbook: fundamentals and applications in contactless smart cards, radio frequency identification and near-field communication*. Wiley, 2010.

[37] T. Kaufmann, D. C. Ranasinghe, M. Zhou, and C. Fumeaux, "Wearable quarter-wave microstrip antenna for passive UHF RFID applications," *International Journal of Antennas and Propagation*, vol. 2013, 2013.

[38] A. Sample, D. Yeager, P. Powledge, A. Mamishev, and J. Smith, "Design of an rfid-based battery-free programmable sensing platform," *IEEE Transactions on Instrumentation and Measurement*, vol. 57, no. 11, pp. 2608–2615, 2008.

[39] M. Buettner, B. Greenstein, A. P. Sample, J. R. Smith, and D. J. Wetherall, "Revisiting smart dust with rfid sensor networks," in *Proceedings of the 7th ACM Workshop on Hot Topics in Networks (HotNets-VII)*, 2008.

[40] International Organization for Standardization, "Iso/iec 18000-6:2010 - information technology – radio frequency identification for item management – part 6: Parameters for air interface communications at 860 mhz to 960 mhz," 01 2013.

[41] Y. Su, A. Wickramasinghe, and D. C. Ranasinghe, "Investigating sensor data retrieval schemes for multi-sensor passive rfid tags," in *2015 IEEE International Conference on RFID (RFID)*, (San Diego, USA), pp. 158–165, 2015.

[42] L. Fung, K. Chan, W. Lam, S. Leung, Y. Wong, P. Wu, and C. Tang, "Electromagnetic assessment on human safety of rfid system at hong kong international airport," *Microwave and Optical Technology Letters*, vol. 49, no. 4, pp. 924–928, 2007.

[43] I. D. Cameron, L. D. Gillespie, M. C. Robertson, G. R. Murray, K. D. Hill, R. G. Cumming, and N. Kerse, "Interventions for preventing falls in older people in care facilities and hospitals," *Cochrane Database of Systematic Reviews*, no. 12, 2012.

[44] S. Hempel, S. Newberry, Z. Wang, M. Booth, R. Shanman, B. Johnsen, V. Shier, D. Saliba, W. D. Spector, and D. A. Ganz, "Hospital fall prevention: A systematic review of implementation, components, adherence, and effectiveness," *Journal of the American Geriatrics Society*, vol. 61, no. 4, pp. 483–494, 2013.

[45] I. M. Miake-Lye, S. Hempel, D. A. Ganz, and P. G. Shekelle, "Inpatient fall prevention programs as a patient safety strategy: A systematic review," *Annals of Internal Medicine*, vol. 158, no. 5˙Part˙2, pp. 390–396, 2013.

[46] V. Goodwin, R. Abbott, R. Whear, A. Bethel, O. Ukoumunne, J. Thompson-Coon, and K. Stein, "Multiple component interventions for preventing falls and fall-related injuries among older people: systematic review and meta-analysis," *BMC Geriatrics*, vol. 14, no. 1, p. 15, 2014.

[47] J. Sutton, P. Standen, and W. Wallace, "Patient accidents in hospital: incidence, documentation and significance," *The British journal of clinical practice*, vol. 48, no. 2, pp. 63–66, 1994.

[48] A. Wong Shee, B. Phillips, K. Hill, and K. Dodd, "Feasibility, acceptability, and effectiveness of an electronic sensor bed/chair alarm in reducing falls in patients with cognitive impairment in a subacute ward," *Journal of Nursing Care Quality*, vol. 29, no. 3, pp. 253–262, 2014.

[49] P. C. Dykes, D. L. Carroll, A. Hurley, S. Lipsitz, A. Benoit, F. Chang, S. Meltzer, R. Tsurikova, L. Zuyov, and B. Middleton, "Fall prevention in acute care hospitals," *JAMA: the journal of the American Medical Association*, vol. 304, no. 17, pp. 1912–1918, 2010.

[50] S. Miles and K. Parker, "Pictures of fatal bedrail entrapment," *American Family Physician*, vol. 58, pp. 1759–1760, 1998.

[51] N. Györbíró, A. Fábián, and G. Hományi, “An activity recognition system for mobile phones,” *Mobile Networks and Applications*, vol. 14, pp. 82–91, Feb. 2009.

[52] A. J. A. Majumder, I. Zerin, M. Uddin, S. I. Ahamed, and R. O. Smith, “smartprediction: A real-time smartphone-based fall risk prediction and prevention system,” in *Proceedings of the 2013 Research in Adaptive and Convergent Systems*, RACS ’13, (USA), pp. 434–439, ACM, 2013.

[53] M. Uddin, A. Salem, I. Nam, and T. Nadeem, “Wearable sensing framework for human activity monitoring,” in *Proceedings of the 2015 Workshop on Wearable Systems and Applications*, WearSys ’15, (New York, NY, USA), pp. 21–26, ACM, 2015.

[54] N. Roy, A. Misra, and D. Cook, “Ambient and smartphone sensor assisted adl recognition in multi-inhabitant smart environments,” *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–19, 2015.

[55] N. Ravi, N. Dandekar, P. Mysore, and M. L. Littman, “Activity recognition from accelerometer data,” in *Proceedings of the National Conference on Artificial Intelligence*, vol. 3, pp. 1541–1546, 2005.

[56] M.-W. Lee, A. M. Khan, and T.-S. Kim, “A single tri-axial accelerometer-based real-time personal life log system capable of human activity recognition and exercise information generation,” *Personal and Ubiquitous Computing*, vol. 15, no. 8, pp. 887–898, 2011.

[57] D. Karantonis, M. Narayanan, M. Mathie, N. Lovell, and B. Celler, “Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring,” *IEEE Transactions on Information Technology in Biomedicine*, vol. 10, no. 1, pp. 156–167, 2006.

[58] Y. Cho, Y. Nam, Y. Choi, and W. Cho, “SmartBuckle: human activity recognition using a 3-axis accelerometer and a wearable camera,” in *Proceedings of the 2nd International Workshop on Systems and Networking Support for Health Care and Assisted Living Environments*, pp. 7:1–7:3, 2008.

[59] M. Luštrek, H. Gjoreski, S. Kozina, B. Cvetković, V. Mirchevska, and M. Gams, “Detecting falls with location sensors and accelerometers,” in *Proceedings of the 23rd Innovative Applications of Artificial intelligence*, pp. 1662–1667, 2011.

[60] G. Uslu, H. I. Dursunoglu, O. Altun, and S. Baydere, “Human activity monitoring with wearable sensors and hybrid classifiers,” *International Journal of Computer Information Systems and Industrial Management Applications*, vol. 5, pp. 345–353, 2013.

[61] L. Bao and S. Intille, “Activity recognition from user-annotated acceleration data,” in *Pervasive Computing* (A. Ferscha and F. Mattern, eds.), vol. 3001 of *Lecture Notes in Computer Science*, pp. 1–17, Springer, 2004.

[62] M. Bruyneel, W. Libert, and V. Ninane, “Detection of bed-exit events using a new wireless bed monitoring assistance,” *International Journal of Medical Informatics*, vol. 80, no. 2, pp. 127–132, 2011.

[63] J. Hilbe, E. Schulc, B. Linder, and C. Them, “Development and alarm threshold evaluation of a side rail integrated sensor technology for the prevention of falls,” *International journal of Medical Informatics*, vol. 79, no. 3, pp. 173–180, 2010.

[64] E. Hoque, R. F. Dickerson, and J. A. Stankovic, "Monitoring body positions and movements during sleep using WISPs," in *Proceedings - Wireless Health 2010, WH'10*, pp. 44–53, 2010.

[65] D. J. Cook, "Learning setting-generalized activity models for smart spaces," *IEEE Intelligent Systems*, vol. 27, no. 1, pp. 32–38, 2012.

[66] M. Buettner, R. Prasad, M. Philipose, and D. J. Wetherall, "Recognizing daily activities with RFID-based sensors," in *Proceedings of the 11th international conference on Ubiquitous computing*, pp. 51–60, ACM, 2009.

[67] E. Tapia, S. Intille, and K. Larson, "Activity recognition in the home using simple and ubiquitous sensors," *Pervasive Computing*, vol. 3001, pp. 158–175, 2004.

[68] C.-H. Lu and L.-C. Fu, "Robust location-aware activity recognition using wireless sensor network in an attentive home," *IEEE Transactions on Automation Science and Engineering*, vol. 6, no. 4, pp. 598–609, 2009.

[69] S. Helal, W. Mann, H. El-Zabadani, J. King, Y. Kaddoura, and E. Jansen, "The gator tech smart house: a programmable pervasive space," *Computer*, vol. 38, no. 3, pp. 50–60, 2005.

[70] S. Helal, B. Winkler, C. Lee, Y. Kaddoura, L. Ran, C. Giraldo, S. Kuchibhotla, and W. Mann, "Enabling location-aware pervasive computing applications for the elderly," in *Proceedings of the First IEEE International Conference on Pervasive Computing and Communications. (PerCom 2003).*, pp. 531–536, 2003.

[71] Y. Hirata, A. Hara, and K. Kosuge, "Motion control of passive intelligent walker using servo brakes," *IEEE Transactions on Robotics*, vol. 23, no. 5, pp. 981–990, 2007.

[72] K. Wakita, J. Huang, P. Di, K. Sekiyama, and T. Fukuda, "Human-walking-intention-based motion control of an omnidirectional-type cane robot," *IEEE/ASME Transactions on Mechatronics*, vol. 18, no. 1, pp. 285–296, 2013.

[73] M. Philipose, K. P. Fishkin, M. Perkowitz, D. J. Patterson, D. Fox, H. Kautz, and D. Hahnel, "Inferring activities from interactions with objects," *IEEE Pervasive Computing*, vol. 3, no. 4, pp. 50–57, 2004.

[74] L. Wang, T. Gu, X. Tao, and J. Lu, "A hierarchical approach to real-time activity recognition in body sensor networks," *Pervasive and Mobile Computing*, vol. 8, no. 1, pp. 115 – 130, 2012.

[75] G. Cohn, D. Morris, S. Patel, and D. Tan, "Humantenna: using the body as an antenna for real-time whole-body interaction," in *Proceedings of the 2012 ACM annual conference on Human Factors in Computing Systems*, CHI '12, (USA), pp. 1901–1910, ACM, 2012.

[76] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*. John Wiley & Sons, 2012.

[77] J. R. Quinlan, "Improved use of continuous attributes in c4. 5," *Journal of artificial intelligence research*, vol. 4, pp. 77–90, 1996.

[78] P. Langley, W. Iba, and K. Thompson, "An analysis of bayesian classifiers," in *Proceedings of the international conference on artificial intelligence*, vol. 90, pp. 223–228, AAAI, 1992.

[79] L. Rabiner, "A tutorial on hidden markov models and selected applications in speech recognition," *Proceedings of the IEEE*, vol. 77, no. 2, pp. 257–286, 1989.

[80] T. G. Dietterich, "Machine learning for sequential data: A review," in *Structural, Syntactic, and Statistical Pattern Recognition* (T. Caelli, A. Amin, R. Duin, D. de Ridder, and M. Kamel, eds.), vol. 2396 of *Lecture Notes in Computer Science*, pp. 15–30, Springer, 2002.

[81] Z. Ghahramani, "Learning dynamic bayesian networks," in *Adaptive Processing of Sequences and Data Structures* (C. Giles and M. Gori, eds.), vol. 1387 of *Lecture Notes in Computer Science*, pp. 168–197, Springer, 1998.

[82] Z. Ghahramani and M. Jordan, "Factorial hidden markov models," *Machine Learning*, vol. 29, no. 2-3, pp. 245–273, 1997.

[83] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995.

[84] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers," in *Proceedings of the Fifth Annual Workshop on Computational Learning Theory*, COLT '92, (USA), pp. 144–152, ACM, 1992.

[85] S. Haykin, *Neural Networks: A Comprehensive Foundation*. Upper Saddle River, NJ, USA: Prentice Hall PTR, 2nd ed., 1998.

[86] A. Mannini and A. M. Sabatini, "Machine learning methods for classifying human physical activity from on-body accelerometers," *Sensors*, vol. 10, no. 2, pp. 1154–1175, 2010.

[87] D. C. Ranasinghe, R. L. Shinmoto Torres, K. Hill, and R. Visvanathan, "Low cost and batteryless sensor-enabled radio frequency identification tag based approaches to identify patient bed entry and exit posture transitions," *Gait & Posture*, vol. 39, no. 1, pp. 118 – 123, 2014.

[88] P. Nikitin, R. Martinez, S. Ramamurthy, H. Leland, G. Spiess, and K. V. S. Rao, "Phase based spatial identification of uhf rfid tags," in *2010 IEEE International Conference on RFID*, pp. 102–109, 2010.

[89] A. Faheem, R. Virrankoski, and M. Elmusrati, "Improving RSSI based distance estimation for 802.15.4 wireless sensor networks," in *2010 IEEE International Conference on Wireless Information Technology and Systems. ICWITS 2010*, pp. 1–4, 2010.

[90] R. Tideiksaar, C. F. Feiner, and J. Maby, "Falls prevention: the efficacy of a bed alarm system in an acute-care setting.," *The Mount Sinai journal of medicine, New York*, vol. 60, no. 6, pp. 522–527, 1993.

[91] F. Healey and D. Oliver, "Bedrails, falls and injury: evidence or opinion? a review of their use and effects," *Nursing Times*, vol. 105, no. 26, pp. 20–24, 2009.

[92] J. D. Lafferty, A. McCallum, and F. C. N. Pereira, "Conditional random fields: Probabilistic models for segmenting and labeling sequence data," in *Proceedings of the 18th International Conference on Machine Learning*, ICML '01, (USA), pp. 282–289, Morgan Kaufmann, 2001.

[93] T. L. M. van Kasteren, G. Englebienne, and B. J. A. Kröse, "An activity monitoring system for elderly care using generative and discriminative models," *Personal and Ubiquitous Computing*, vol. 14, no. 6, pp. 489–498, 2010.

[94] E. Nazerfard, B. Das, L. B. Holder, and D. J. Cook, "Conditional random fields for activity recognition in smart environments," in *Proceedings of the 1st ACM International Health Informatics Symposium*, IHI '10, (USA), pp. 282–286, ACM, 2010.

[95] D. Koller and N. Friedman, *Probabilistic graphical models: principles and techniques*. MIT press, 2009.

[96] J. M. Hammersley and P. Clifford, "Markov fields on finite graphs and lattices," 1971.

[97] J. Besag, "Spatial interaction and the statistical analysis of lattice systems," *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 36, no. 2, pp. 192–236, 1974.

[98] J. Pearl, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. Morgan Kaufmann, 1988.

[99] C. Sutton and A. McCallum, "An introduction to conditional random fields for relational learning," in *Introduction to Statistical Relational Learning* (L. Getoor and B. Taskar, eds.), pp. 93–127, The MIT Press, 2006.

[100] S. Chen and R. Rosenfeld, "A survey of smoothing techniques for me models," *IEEE Transactions on Speech and Audio Processing*, vol. 8, pp. 37–50, Jan 2000.

[101] J. Nocedal and S. Wright, eds., *Numerical Optimization*. Springer, 1999.

[102] F. Sha and F. Pereira, "Shallow parsing with conditional random fields," in *Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology - Volume 1*, NAACL '03, (USA), pp. 134–141, Association for Computational Linguistics, 2003.

[103] R. Malouf, "A comparison of algorithms for maximum entropy parameter estimation," in *Proceedings of the 6th Conference on Natural Language Learning - Volume 20*, COLING-02, (USA), pp. 1–7, Association for Computational Linguistics, 2002.

[104] Y. Dong, A. Wickramasinghe, H. Xue, S. F. Al-Sarawi, and D. C. Ranasinghe, "A novel hybrid powered rfid sensor tag," in *2015 IEEE International Conference on RFID*, pp. 55–62, 2015.

[105] R. L. Shinmoto Torres, D. C. Ranasinghe, and Q. Shi, "Evaluation of wearable sensor tag data segmentation approaches for real time activity classification in elderly," in *Mobile and Ubiquitous Systems: Computing, Networking, and Services* (I. Stojmenovic, Z. Cheng, and S. Guo, eds.), vol. 131 of *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering*, pp. 384–395, Springer International Publishing, 2014.

[106] H. Li, C. Ye, and A. P. Sample, "Idsense: A human object interaction detection system based on passive uhf rfid," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, CHI '15, (New York, NY, USA), pp. 2555–2564, ACM, 2015.

[107] R. Fensli, P. E. Pedersen, T. Gundersen, and O. Hejlesen, "Sensor acceptance model - measuring patient acceptance of wearable sensors," *Methods of Information in Medicine*, vol. 47, no. 1, pp. 89–95, 2008.