Freedom: Online Activity Recognition via Dictionary-based Sparse Representation of RFID Sensing Data

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***Abstract*—Understanding and recognizing the activities performed by people is a fundamental research topic for a wide range of important applications such as fall detection of elderly people. In this paper, we present the technical details behind Freedom, a low-cost, unobtrusive system that supports independent living of the older people. The Freedom system interprets what a person is doing by leveraging machine learning algorithms and radio-frequency identification (RFID) technology. To deal with noisy, streaming, unstable RFID signals, we particularly develop a dictionary-based approach that can learn dictionaries for activities using an unsupervised sparse coding algorithm. Our approach achieves efficient and robust activity recognition via a more compact representation of the activities. Extensive experiments conducted in a real-life residential environment demonstrate that our proposed system offers a good overall performance (e.g., achieving over 96% accuracy in recognizing 23 activities) and has the potential to be further developed to support the independent living of elderly people.**

***Keywords*-Activity recognition, RFID, sparse coding, dictionary, feature selection, sensing data**

I. Introduction

Worldwide, the population is aging due to increasing life expectancy and low birth rate. With recent developments in cheap sensor and networking technologies, it has become possible to develop a wide range of valuable applications such as the remote health monitoring and intervention. These applications offer the potential to enhance the quality of life for the elderly, afford them a greater sense of security, and facilitate independent living [1]. For example, by monitoring the daily routines of a person with dementia, it is possible to track how completely and consistently the daily routines are performed, and determine when the resident needs assistance. Central to realizing these applications is *activity recognition*, which is emerging as an important area of research and development in recent years [2].

Computer vision related human activity recognition is one of the directions, but unfortunately, such solutions demand high computational cost for machine interpretation. In addition, the performance of such vision-based approaches depends strongly on the lighting conditions (e.g., poor performance at night), camera facing angles (e.g., uncovered areas) etc, which greatly restricts its applicability in real environments. Cameras are generally considered to be intrusive to people's privacy.

With the growing maturity of sensor, radio-frequency identification (RFID), and wireless sensor network technologies, activity recognition from inertial, unobtrusive sensor readings has become a popular research area in last few years. Inertial sensors are the most frequently used wearable sensors for human activity recognition [3], [2]. Although sensor-based activity recognition can better address issues such as privacy than conventional computer vision-based approaches, most work from sensor-based activity recognition require people to wear the inertial sensors [4], [3] and RFID tags [2]. The main drawbacks of such solutions is that they need users' cooperation. As a result, these approaches are not always practical, particularly for monitoring elderly persons with cognitive disabilities.

To overcome the aforementioned issues, we have developed an effective and unobtrusive activity recognition system to support independent living of older people by leveraging passive RFID tags—which are maintenance free (no batteries needed for tags) and inexpensive (about 10 cents each and still dropping quickly)—and data mining techniques. Our approach is lightweight in computational cost, and people do not need to wear any devices. Passive RFID tags are deployed in an environment (e.g., on the wall in a room) forming a tag array. By analyzing the Received Signal Strength Indicator (RSSI) fluctuations, our system can successfully recognize different activities performed by a person in the environment.

Recognizing human actions from streaming RFID signals is a challenging problem due to the nature of signal changes in real-world conditions like distraction, diffusion and degradation [5]. Sparse coding aims at modeling data vectors as sparse linear combinations (i.e., *sparse representation*) of basis elements, and has been widely used in image processing and computer vision applications [6]. In this paper, we explore sparse representation for robust activity recognition. The main contributions of our work are summarized below:

- We develop a dictionary-based learning approach to uncover structural information between RSSI signals of different activities. The dictionaries are learned by a sparse coding based algorithm. Compared to the existing activity recognition approaches, our dictionary-based approach achieves more compact representation of activities while preserving richer information, thereby underpinning efficient and robust recognition of human activities.
- We propose a lightweight yet effective feature selection method to extract signal patterns. We particularly exploit an unsupervised and filter-based feature selection ap-

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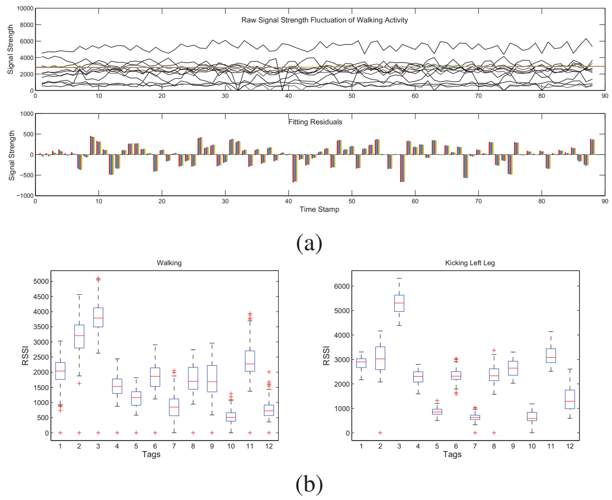


Fig. 1. (a) Signal strength fluctuation of activity *walking* and its corresponding linear/quadratic/cubic/polynomial fittings and residuals, (b) the signal distribution pattern of activities *walking* (left) and *kicking left leg* (right)

proach based on the canonical correlation analysis (CCA), which not only retains the natural assignment of feature components but also uncovers the interdependency between feature components.

- We validate and evaluate our proposed system by a prototype application and experiments using a real dataset. In particular, we set up our experimental environment in a cluttered office room, and 6 subjects participate in the data collection for 23 predefined activities. Our experimental results on these real dataset demonstrate the effectiveness and efficiency of the proposed techniques.

We formulate the research problem in Section II and the technical details are described in Section III. In Section IV, we report the experimental results. We overview the related work in Section V and wrap up the paper in Section VI.

II. Observations and Problem Formulation

In this section, we discuss two observations, which hold key groundings for the proposed recognition algorithms.

Observation 1. It is well known that RSSI is quite complicated in real environments due to signal reflection, diffraction, and scattering, especially for the passive tags. It is often affected by the propagation environment and the tagged object properties or human movements in the signal coverage area. The signal strength of passive RFID tags is uncertain and non-linear [7], [5]. As shown in Figure 1 (a), the RSSI variations cannot be easily fitted using generic linear and polynomial regressions since the fitting residuals are quite big. It is therefore not possible to directly use raw RSSI data in activity recognition.

Observation 2. Although RSSI reflects the uncertainty and non-linear distributed patterns, we still can observe some interesting characteristics. More specifically, we discover that the variations of signal strength reflect different patterns, which can be exploited to distinguish different activities. Figure 1 (b) shows the distinctive fluctuation patterns of signal strength collected from *walking* and *kicking left leg*, respectively.

From above observations, we believe that RSSIs of passive RFID tags embody certain patterns for different activities, which can be exploited for effective activity recognition. We therefore formulate our problem as follows.

Let $\mathcal{S} \subset \mathbb{R}^t$ (t is the number of tags) be the domain of observable signal strength fluctuation (RSSI indicator in this work), $\mathbf{s}$ and $\mathcal{L} \in \{1, ..., K\} \subset \mathbb{R}$ be the domain of output activity label l (K is the number of activities). Suppose we have n RSSI and activity label pairs $\{(\mathbf{s}_i, l_i)|\mathbf{s}_i \in \mathcal{S}, l_i \in \mathcal{L}, i = 1, ..., n\}$. The training dataset can be represented as:

$$\begin{aligned} \mathbf{S} &= [\mathbf{s}_1, ..., \mathbf{s}_n] \in \mathbb{R}^{t \times n} \\ \mathbf{l} &= [l_1, ..., l_n]^T \in \mathbb{R}^n \end{aligned} \tag{1}$$

Our goal is to learn a predictor $\mathcal{F} : \mathcal{S} \to \mathcal{L}$ using training dataset, which can assign the most appropriate activity label for a given query sample.

III. The System and the Techniques

Our system (see Figure 2) consists of three main stages:

- Processing the raw signal streaming data from various RFID tag inputs into individual segments, and then extracting low-level statistical features from each segment,
- Learning the overcomplete dictionary for each activity using the extracted features, and
- Given a new signal streaming data, finding the dictionary from the learned activity dictionaries that best approximates the testing sample.

A. Segmentation

The first major task is to divide the continuous sequence of RSSI data stream into a set of individual segments, where each segment corresponds to a specific concept or an activity (e.g., one segment corresponds to *Sitting*, and another segment corresponds to *Standing* etc). We incorporate the temporal information during the segmentation process of feature transformation. We particularly divide the raw streaming signal data into segments where each segment is generated by a sliding window based method. Relevant information can be extracted as features from each single segment. It should be noted that different activities have different mean temporal lengths. To incorporate the activity duration, we use a *one-sliding-window-per-activity* strategy and the length of each window corresponds to the activity duration as carried out by the subject. In this way, our method takes the temporal dependency into account for constructing each activity's dictionary.

Some existing segmentation methods (e.g., online time series segmentation) apply an adaptive model on one dimensional data [8], which are not applicable to build segmentation for multi-dimensional streaming data (e.g., N-dimensional RFID RSSI data in our case). In our approach, we design a *slope variation* based sliding window segmentation algorithm by analyzing a distance criterion and the geometrical content of the RSSI data. The algorithm aims to follow the shape of the RSSI fluctuation curve. We first read the samples into a buffer and for each buffer, we mark points with slope change on each dimensional data. In other words, they indicate the changes from peak to trough of the curve, which represent the trend of changes from one posture to the other.

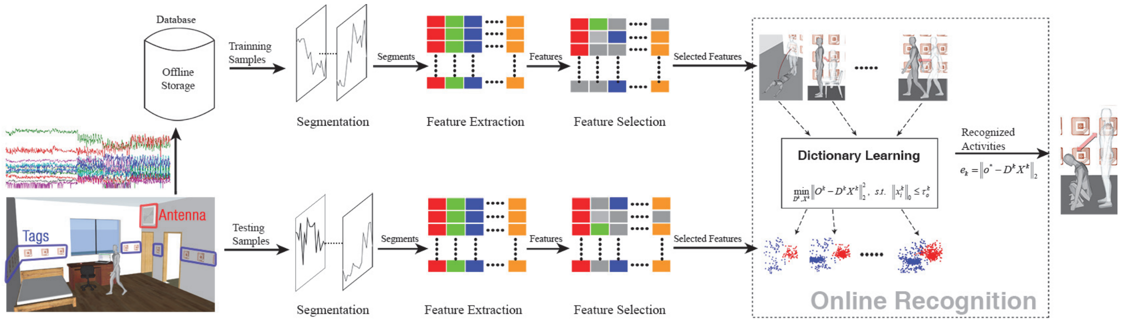


Fig. 2. The architecture of our proposed activity recognition system

We adopt the *majority voting* rules to integrate the segmentation points which are calculated from each dimensional data within each buffer. In terms of all potential segment points of each dimension in one buffer, we count times of each potential point and select the points with the most repeating times as the final segmentation point for the multi-dimensional RSSI in each buffer. If some points have the same repeating times, these points could be regarded as the *center* points and then we respectively calculate the sum of horizontal geometric distances between other potential points and these center points in one buffer. The potential points with the lowest sum of horizontal geometric distances between itself and others would be set as the best segmentation point. We also design a backtrack mechanism to eliminate the troughs or peaks resulted from outliers. After the segmentation process, the continuous $\mathbf{S}$ will be divided as a set of individual segments.

B. Feature Extraction

The feature extraction process focuses on transforming each segment into feature vectors. In our approach, we design seven types of lightweight statistical feature vectors for this purpose, as listed in Table I.

TABLE I
STATISTICAL FEATURES AND BRIEF DESCRIPTIONS

No.	Feature	Description
1	Min	Minimal value of $\mathbf{S}_i$
2	Max	Maximal value of $\mathbf{S}_i$
3	Mean	Average value of $\mathbf{S}_i$
4	Variance	The square of standard deviation of $\mathbf{S}_i$
5	Root Mean Square	The quadratic mean value of $\mathbf{S}_i$
6	Standard Deviation	Measure of the spreadness of $\mathbf{S}_i$
7	Median	The median $\mathbf{S}_i$

The extraction process in our approach yields a total of m feature vectors $\mathbf{O} = \{\mathbf{o}_1, ..., \mathbf{o}_i\}$, where $\mathbf{o} \in \mathbb{R}^m$, here $m = 7 \times t$ where t is the number of tags. However, some features might confuse, rather than help, the classifier to discriminate activities. Also, due to the "curse of dimensionality", the performance may degrade sharply as more features are added when there is no enough training data to reliably learn all the parameters of the activity models. To achieve the best classification performance, the dimensionality of the feature vector should be as small as possible, keeping only the most salient and complementary features.

We develop a canonical correlation analysis (CCA) based method to compute initial rankings for each pair of features, where two feature vectors are given and a projection is computed for feature vector such that they are maximally correlated in the dimensionality-reduced space. We first apply CCA for all pairs of the extracted features. The result is a similarity matrix of canonical correlations. For each pair of feature vectors $\{\mathbf{o}_i, \mathbf{o}_j\}$ that can be linearly mapped into: $\mathbf{o}_i \rightarrow \mathbf{w}_{\mathbf{o}_i}^T \mathbf{o}_i$ and $\mathbf{o}_j \rightarrow \mathbf{w}_{\mathbf{o}_j}^T \mathbf{o}_j$, where $\mathbf{w}_{\mathbf{o}_i} \in \mathbb{R}^m$ and $\mathbf{w}_{\mathbf{o}_j} \in \mathbb{R}^m$, their correlation coefficient ρ can be obtained by maximizing the following equation:

$$\rho = \frac{\mathbf{w}_{\mathbf{o}_i}^T \mathbf{o}_i \mathbf{o}_j^T \mathbf{w}_{\mathbf{o}_j}}{\sqrt{\mathbf{w}_{\mathbf{o}_i}^T \mathbf{o}_i \mathbf{o}_i^T \mathbf{w}_{\mathbf{o}_i}} \sqrt{\mathbf{w}_{\mathbf{o}_j}^T \mathbf{o}_j \mathbf{o}_j^T \mathbf{w}_{\mathbf{o}_j}}} \tag{2}$$

After we deploy CCA for all pairs of features, we can generate an initial ranking for all feature pairs. A higher rank is assigned to those weakly correlated and thus complementary feature pairs. Strongly correlated and thus redundant feature pairs get lower ranks. The initial ranking facilitates the selection of descriptive and complementary features.

We then employ a forward searching strategy to search the feature subsets based on their pairwise rankings, which traverses the full search space provided by the initial ranking of canonical correlation coefficients of the feature pairs to find the optimal feature set, and the searching process will be terminated when either the predefined dimensionality of features is reached or all features are already considered.

C. Activity Dictionary Learning

Recent research shows that learning a dictionary by fitting a set of overcomplete basis vectors to a collection of training samples can generate more compact and informative representation from given data and achieve better recognition results [9]. We propose a sparse representation based approach to recognize human activities by investigating RSSI fluctuations. We learn one single dictionary for each activity, which is formed by a set of basis vectors learned by solving a sparse optimization problem. Each basis vector can effectively capture part of key structural information of given training data from each activity.

There are several advantages in learning activity dictionaries. First, the dictionary for each activity is learned from a collection of training samples via solving ℓ_1 optimization problem [10], which represents structural information of RSSI data in a more compact and informative way. Second, the dictionary learning process of each activity is independent from other activities, which makes an activity recognition system flexible and scalable, as no change is needed on the existing activity dictionaries when a new activity is added. Third, each dictionary can be trained and learned by using only very small training samples, which can effectively relax the heavy workload on labeling and annotating training data in the activity recognition, as required by most existing approaches.

Assuming we have K types of activities, and we construct K dictionaries (one dictionary for each activity). After that, a new signal strength vector is reconstructed using the K dictionaries. The reconstruction errors using different dictionaries are compared and the smallest reconstruction error indicates that the new testing signal sample fits better to the specific corresponding dictionary than others. In what follows, we present the details of the proposed algorithm.

Let $\mathbf{O}^k = \{\mathbf{o}_1^k, \mathbf{o}_2^k, ..., \mathbf{o}_i^k\}$ be the training sample from activity class $\mathcal{C}^k$, to learn and encode the information of the testing samples belonging to a particular activity class, we first construct an overcomplete dictionary $\mathcal{D}^k$ for each class $\mathcal{C}^k$. Recall the set of training samples from the k^{th} activity as $\mathbf{O}^k = \{\mathbf{o}_1^k, \mathbf{o}_2^k, ..., \mathbf{o}_N^k\}$, where $\mathbf{o}_i^k \in \mathbb{R}^m$, m is the feature dimensions. We intend to find a dictionary matrix $\mathbf{D}^k \in \mathbb{R}^{m \times K}$ having $K(K > m)$ vectors $\{\mathbf{d}_1^k, ..., \mathbf{d}_K^k\}$, over which $\mathbf{O}^k$ has a sparse representation $\mathbf{X}^k = \{\mathbf{x}_1^k, ..., \mathbf{x}_N^k\}$, where $\mathbf{x}_i^k \in \mathbb{R}^K$. In this case, the original training matrix $\mathbf{O}^k$ can be represented as a linear combination of no more than $\tau_0^k(\tau_0^k << K)$ dictionary vectors. The optimization problem can be formalized as:

$$\min_{\mathbf{D}^k, \mathbf{X}^k} ||\mathbf{O}^k - \mathbf{D}^k\mathbf{X}^k||_2^2, \ \text{ s.t. } \ ||\mathbf{x}_i^k||_0 \leq \tau_o^k \tag{3}$$

We adopt the K-SVD algorithm [9] to solve this problem, which performs two steps iteratively until converged. The first stage is the sparse coding stage, $\mathbf{D}^k$ is kept fixed and the coefficient matrix $\mathbf{X}^k$ is computed by orthogonal matching pursuit algorithm, and then the dictionary $\mathbf{D}^k$ is updated sequentially allowing the relevant coefficients to be unique to K-SVD and resulting in a faster convergence. The dictionary learning algorithm is detailed in Algorithm 1.

D. Reconstruction-based Classification

As mentioned above, one advantage of having class-specific dictionaries is that each class is modeled independently and hence the painful repetition of the training process can be avoided when a new type of activity is added to the system. After constructing the dictionary for each activity, for a given query feature vector of signal samples $\mathbf{o}^*$, its reconstruction error for the k^{th} activity ($k \in [1, K]$) can be calculated as:

$$e_k = ||\mathbf{o}^* - \mathbf{D}^k\mathbf{X}^k||_2 \tag{7}$$

Then the activity label of $\mathbf{o}^*$ can be assigned using:

$$l_{\mathbf{o}^*} = l(\min_k e_k) \tag{8}$$

Our proposed activity classification is summarized in Algorithm 2.

Algorithm 1: Activity-Specific Dictionary Learning

Input: Training sample matrix $\mathbf{O} = \{\mathbf{o}_1, ..., \mathbf{o}_N\}$, dictionary size d
Output: Dictionary $\mathbf{D}$ and sparse coefficients $\mathbf{X}$

Initializing dictionary matrix $\mathbf{D}^{(0)} \in \mathbf{R}^{m \times K}$ with ℓ_2 column normalization and $J = 1$;
while *(!= stopping criteria)* **do**
  Using orthogonal matching pursuit to compute the sparse coefficients $\mathbf{x}_i$ for each training sample $\mathbf{o}_i$ by solving the optimization problem;

$$\min_{\mathbf{D}, \mathbf{x}_i} ||\mathbf{o}_i - \mathbf{D}\mathbf{x}_i||_2^2, \quad \text{s.t.} \quad ||\mathbf{x}_i||_0 \leq \tau_o \tag{4}$$

  % Update $\mathbf{d}_j$, the j-th column of $\mathbf{D}^{J-1}$;
  for *j=1:N* **do**
    1. Finding a group of vectors:

$$\xi_j \leftarrow \{i : 1 \leq i \leq N, \mathbf{x}_i(j) \neq= 0\} \tag{5}$$

    2. Computing the overall representation error matrix $\mathbf{E}_j$ by ;

$$\mathbf{E}_j \leftarrow [\mathbf{o}_|, ..., |\mathbf{o}_N] - \sum_{i \neq j} \mathbf{d}_i \mathbf{x}_\tau^i \tag{6}$$

    3. Extracting the i-th column in $\mathbf{E}_j$ where $i \in \xi_j$ to form $\mathbf{E}_j^R$;
    4. Applying SVD to obtain $\mathbf{E}_j^R = \mathbf{U\Delta V}$, and $\mathbf{d}_i$ is updated with the first column of $\mathbf{U}$. The non-zero elements in $\mathbf{x}_\tau^i$ are updated with the first column of $\mathbf{V} \times \Delta(1, 1)$
  end
  J $\leftarrow$ J+1;
end

Algorithm 2: Activity Classification

Input: Signal samples $\mathcal{S} = \mathbf{S}_1, ..., \mathbf{S}_K$, where K is the number of activity classes; Querying signal samples $\mathbf{S}^* = \{\mathbf{s}_1^*, ..., \mathbf{s}_I^*\}$
Output: Activity label $\mathbf{l}^* = \{l_1^*, ..., l_I^*\}$ of $\mathbf{S}^*$

Extracting N^k feature vectors of signal samples from each activity class C^k using the proposed feature representation (see Section of "Feature Extraction");
Constructing K activity-specific dictionaries $\mathbf{D} = \{\mathbf{D}^1, ..., \mathbf{D}^K\}$ (one dictionary for each activity) using Algorithm 1 ;
for *i = 1: I* **do**
  Transform $\mathbf{S}^*$ to features $\mathbf{O}^*$;
  Computing sparse representation x_i^* of $\mathbf{s}_i^*$ using K dictionaries $\mathbf{D}$;
  Computing reconstruction errors $\mathbf{e} = \{e_1, ..., e_K\}$, where $e_k = ||\mathbf{o}^* - \mathbf{D}^k\mathbf{X}^k||_2, k \in [1, K]$;
  Output activity label by $l_i^* = l(\min_k e_k)$;
end

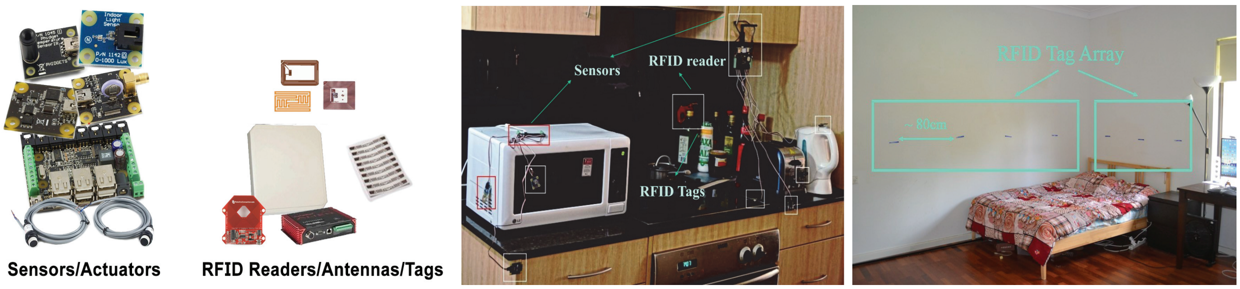
IV. EXPERIMENTS

A. Experimental Settings

Hardware Setup. We used one Alien 9900+ RFID reader, four circular antennas (each antenna for one room) and multiple Squig inlay passive RFID tags in our study. The tags were placed along the walls, where each grid is roughly $0.8m \times 0.8m$. The antennas were arranged between $\approx 1.3m \sim 1.6m$ height with angle $\approx 70°$. Figure 3 shows part of the setup and hardware used in our experimental environment.

Sampling Rate. Passive RFID tags tend to be noisy. For example, one of the challenges in existing RFID systems is false negative readings, caused by missed detections (i.e., a tag is in the antenna's reading range, but not detected). Meanwhile, RSSI data is much sensitive to environments. Appropriate sampling rates can reduce the aforementioned problems. However, too small sampling rates make our method more sensitive to the noise of RFID readings, while too big sampling rates blur the inter-class activity boundaries. In our implementation, we collected the continuous RSSI data streams at the sampling rate of ≈ 0.5 second.

Data Collection. The data acquisition process involves six subjects (five males and one female), and the set of 23 fine-grained, orientation-sensitive activities (including 6 postures and 17 actions). The 23 postures and activities are the most common ones in people's daily lives. Each subject performed each posture or action for 120 seconds and all 23 different activities performed sequentially by one subject were regarded as one set of activity data.



(a) (b) (c)

Fig. 3. (a) hardware devices, and example experimental setup: (b) kitchen and (c) bedroom

Validation Strategy. We validated our approach using a *subject-dependent* strategy, where partial samples of a subject were used for testing and the remaining samples of the same participant were used for training. This is reasonable since that elderly people often live alone.

B. Comparison With Other Methods

We report our experiments that focus on two aspects. First, we implemented four heuristics based on sparse representation proposed in [11], in which the training samples are directly used to construct the dictionaries. Suppose the matrix $\mathbf{B}$ formed by training feature vectors is transformed from K activities, $\mathbf{B} = [\mathbf{B}_1, ..., \mathbf{B}_K]$, where $\mathbf{B}_i$ is the subset of training samples from activity i. Given query samples $\mathbf{o}^*$, the overall process includes two main steps. The first step is about finding sparse representation of $\mathbf{o}^*$ on $\mathbf{B}$. We computed its sparse representation, i.e., the coefficient vector $\mathbf{w}_i$ associated with different activities which can be used to recover $\mathbf{o}^*$. In other words, the querying sample $\mathbf{o}^*$ can be represented as a linear span of $\mathbf{B} \in \mathbb{R}^{m\times d}$.

$$\mathbf{o}^* = \mathbf{b}_{11}\hat{w}_1 + \mathbf{b}_{12}\hat{w}_2 + ... + \mathbf{b}_{1n}\hat{w}_n = \mathbf{B}\hat{\mathbf{w}} \tag{9}$$

The equation can be reformulated as:

$$\hat{\mathbf{w}} = \arg\min_{\mathbf{w}} ||\hat{\mathbf{w}}||, \text{ s.t. } \mathbf{o}^* = \mathbf{B}\hat{\mathbf{w}} \tag{10}$$

where the sparse solution of $\hat{\mathbf{w}}$ can be found via ℓ_1 minimization using truncated Newton interior point method [12].

The second step is about classification. Given a query sample $\mathbf{o}^*$, the four heuristics utilize the reconstruction coefficients to perform activities classification by harnessing the subspace structure of coefficients $\hat{\mathbf{w}}$, detailed as the following:

- Maximal Coefficients (**MC**). The testing sample label associates with the largest coefficient of $\mathbf{o}_i$. So the predicted activity label l_i for the query sample is:

$$l_{\mathbf{o}^*} = \arg\max_k(\delta_k(\mathbf{o}^*)) \tag{11}$$

  where $\delta_k(\mathbf{o}^*)$ represents the coefficients in $\mathbf{o}^*$ only associated with label l_k.
- Maximal Coefficients Sum (**MCS**). The predicted label of the query sample is the label whose sum of coefficients of $\mathbf{o}^*$ is maximized:

$$l_{\mathbf{o}^*} = \arg\max_k(\sum_k \mathbf{o}^*) \tag{12}$$

  For a given testing RSSI, the label with the largest sum value is the predicted activity.
- Minimal Residual (**MR**). For each activity k, we define a characteristic function $\delta_k : \mathbb{R}^n \rightarrow \mathbb{R}^n$, which selects the coefficients associated with the k^{th} posture class. For $\hat{\mathbf{w}} \in \mathbb{R}^d$, $\delta_k(\hat{\mathbf{w}})$ is a new vector whose only non-zero entries are the entries in $\hat{\mathbf{w}}$ that are associated with k^{th} posture class. We can reconstruct the given query sample $\mathbf{o}^*$ as $\hat{\mathbf{o}^*} = \mathbf{B}\delta_k(\hat{\mathbf{w}})$. Thus, we can classify $\mathbf{o}^*$ to the posture class based on reconstruction approximations from each activity class that has the minimal residual between the real $\mathbf{o}^*$ and the estimated $\hat{\mathbf{o}^*}$:

$$r_k(\mathbf{o}^*) = ||\mathbf{o}^* - \mathbf{B}\delta_k\hat{\mathbf{w}}_k||_2 \tag{13}$$

  Then $\mathbf{o}_i$ can be classified to activity k that has the minimal residual value using the following equation:

$$l_{\mathbf{o}^*} = \arg\min_k r_k(\mathbf{o}^*) \tag{14}$$

- Maximal Number of Nonzero Coefficients (**NonZero**). The predicted activity label of sample $\mathbf{o}^*$ is denoted as:

$$l_{\mathbf{o}^*} = \arg\max_k |\delta_k(\mathbf{o}^*)| \tag{15}$$

  where $\delta_k(\mathbf{o}^*)$ represents the coefficients in $\mathbf{o}^*$ only associated with label l_k. $|\cdot|$ denotes the length of $\delta_k(\mathbf{o}^*)$.

Second, we employed multiple classifiers to evaluate the quality of the generated feature subsets. The following classification techniques were selected since they have already been successfully applied for activity recognition applications.

- Multinomial Logistic Regression with ℓ_1 (**MLGL1**) is a modification of linear regression that is able to predict dependent variables based on the logistic function. Given our multi-class activity recognition problem, we combine the ℓ_1 regularization with multinomial logistic regression, which models the conditional probability $P_{\mathbf{w}}(l_j = \mp 1|\mathbf{o}_i)$ The prime problem with ℓ_1 regularization can be calculated by optimizing the log likelihood:

$$\min_{\mathbf{w}} \sum_{k=1}^{K} ||\mathbf{w}_k||_1 - \sum_{i=1}^{n}\sum_{k=1}^{K} l_{ik}\mathbf{w}_k^T\mathbf{o}_i + \sum_{i=1}^{n} \log\left(\sum_{k=1}^{K}\exp(\mathbf{w}_k^T\mathbf{o}_i)\right) \tag{16}$$

- k-Nearest Neighbor (k**NN**) is a common classifier for a variety of classification problems. It predicts the class of a sample by a majority voting of the class labels of the K nearest training instances.
- Linear Support Vector Machine (**LSVM**) aims at finding the best separation of binary-labeled instances by determining a hyperplane which maximizes the margin between support vectors of different classes. Given the

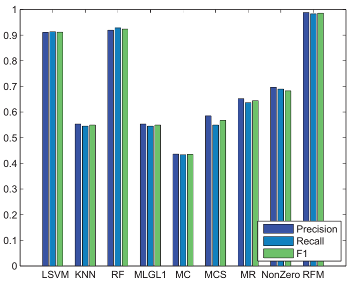


Fig. 4. Overall comparison our approach (RFM) with other methods

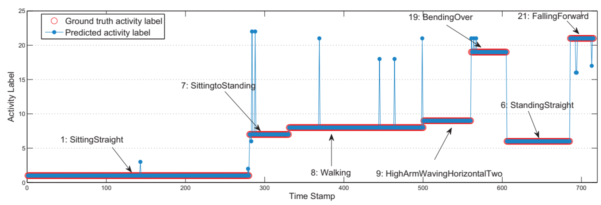


Fig. 5. An example of detected activity sequence

sequence of training RSSI and corresponding posture labels $\mathcal{O} = \{(\mathbf{o}_1, l_i), ..., (\mathbf{o}_n, l_n)\}$, where $\mathbf{o} \in \mathbb{R}^D$ and $l \in \{1, ..., k\}$. The objective function is formulated as:

$$\begin{aligned} &\min_{\mathbf{w},b,\xi} \mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{n}\xi_i \\ &\text{s.t. } l_i(\mathbf{w}^T\phi(\mathbf{o}_i) + b) \geq 1 - \xi_i, i = 1, 2, ..., n \\ &\quad \xi_i \geq 0, i = 1, 2, ..., n \end{aligned} \tag{17}$$

where ξ_i is the slack variables, C is the penalty of error term, $K(\mathbf{o}_i, \mathbf{o}_j) = \phi(\mathbf{o}_i)^T\phi(\mathbf{o}_j)$ is the kernel function.

- Random Forest (**RF**) builds a forest of decision trees that have the same distribution but independent output classes.

Figure 4 shows the overall performance comparison results. We can observe that our method (RFM, RFID-based Activity Monitoring) significantly outperforms all of the other approaches, which shows a good potential and effectiveness in activity classification. From the results, our method can accurately recognize most of orientation sensitive activities in a cluttered real living environment. Figure 5 shows a detailed example of a sequences of activities, our proposed method can identify a series of activities only with minor misclassification during the activity transitions.

V. Related Work

RFID has been increasingly explored in the area of human activity recognition. Some research efforts propose to realize human activity recognition by combining passive RFID tags with traditional sensors (e.g., accelerometers). In this way, daily activities are inferred from the traces of object usage via various classification algorithms such as Hidden Markov Model, boosting and Bayesian networks [2]. Other efforts dedicate to exploit the potential of using "pure" RFID techniques for activity recognition [5]. For example, Wang et al. [13] use RFID radio patterns to extract both spatial and temporal features, which are in turn used to characterize various activities. However, such solutions require people to carry RFID tags or even readers (e.g., wearing a bracelet).

Recently, there have emerged research efforts focusing on exploring *device-free* activity recognition. Such approaches require one or more radio transmitters, but people are free from carrying any receiver or transmitter. Most device-free approaches concentrate on analyzing and learning distribution of radio signal strength (RSSI) or radio links. For instance, Youssef et al. [14] propose to pinpoint people's locations by analyzing the moving average and variance of wireless signal strength. Zhang et al. [7] develop a sensing approach using an RFID tag array. However, most of these efforts focus on localization and tracking. There are not much work on study device-free activity recognition.

VI. Conclusion and Future Research

We have presented in this paper the technical details underneath a device-free, unobtrusive human activity recognition system with location support that holds the potential to support independent living of older people, which is a critical research and development area given the significant challenges presented by the aging population in most countries. We particularly investigate a dictionary-based approach for sparse representation of noisy and unstable radio frequency identification (RFID) streaming signals. Our approach achieves a more compact representation of the activities while preserves richer information, thereby supporting efficient and robust recognition of human activities. Our future work will focus on two main directions: (1) we plan to evaluate our system on larger datasets along with more subjects via incorporating with local aged care centers; (2) we will work on identifying complex human activities is one main goal of our future work, e.g., inferring a person is eating or watching TV.

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