

Collaborative Information Processing Techniques for Target Tracking in Wireless Sensor Networks

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ABSTRACT

Target tracking is one of the typical applications of wireless sensor networks: a large number of spatially deployed sensor nodes collaboratively sense, process and estimate the target state (*e.g.*, position, velocity and heading). This thesis aimed to develop the collaborative information processing techniques that jointly address information processing and networking for the distributive estimation of target state in the highly dynamic and resources constrained wireless sensor networks.

Taking into account the interplay between information processing and networking, this thesis proposed a collaborative information processing framework. The framework integrates the information processing which is responsible for the representation, fusion and processing of data and information with networking which caters for the formation of network, the delivery of information and the management of wireless channels.

Within the proposed collaborative information processing framework, this thesis developed a suite of target tracking algorithms on the basis of the recursive Bayesian estimation method. For tracking a single target in wireless sensor networks, this thesis developed the sequential extended Kalman filter (S-EKF), the sequential unscented Kalman filter (S-UKF) and the Particle filter (PF). A novel extended Kalman filter and Particle filter hybrid algorithm, named as EKPF was also developed. The simulation results showed that the EKPF outperformed other three algorithms in terms of tracking accuracy and robustness. Moreover, to help evaluate the performance of the developed tracking algorithms, the posterior Cramer-Rao lower bound (PCRLB) which is the theoretical lower bound on the mean square error of the target state estimation was also computed.

To tackle the measurement origin uncertainty in practical target tracking in wireless sensor networks, this thesis designed a Particle filter and probability density association filter (PDAF) hybrid algorithm, named as PF-PDAF for tracking a single target under the dual assumptions of clutter and missed detections. The PF-PDAF combines the advantages of PDAF algorithm in effectively solving the data association problem with the merits of PF that can accommodate the general non-Gaussian, nonlinear state space model. The PCRLB under measurement origin uncertainty was also derived and computed. For

multiple target tracking in wireless sensor networks, this thesis designed a Particle filter and joint probabilistic data association filter (JPDAF) hybrid algorithm, named as PF-JPDAF. The PF-JPDAF algorithm extends the traditional JPDAF to solve the general non-linear non-Gaussian multiple targets tracking problems in wireless sensor networks.

In the highly energy and communication bandwidth constrained wireless sensor networks, a critical consideration is that the information processing needs to be distributive. By adopting the hierarchical network architecture to achieve dynamic sensor nodes clustering and utilizing the Gaussian mixture model (GMM) to propagate estimation results amongst sensor clusters, this thesis developed the distributive PF, the distributive EKPF, the distributive PF-PDAF and the distributive PF-JPDAF tracking algorithms. Moreover, this thesis proposed a composite objective function incorporating both the information utility and the energy consumption measures to facilitate the sensing nodes selection in the distributive tracking algorithms. This composite objective function enables the distributive tracking algorithms to achieve the desirable tracking accuracy while still maintaining the lower energy consumption.

DECLARATION

This work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by other person, except where due reference has been made in the text.

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AUTHOR'S PUBLICATIONS

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