Statement of Originality

The thesis contains no material which has been accepted for the award of any other degree or diploma in any other university or other tertiary institution, 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. I give consent to the final version of my thesis being made available worldwide when deposited in the University’s Digital Repository**, subject to the provisions of the Copyright Act 1968. **Unless an Embargo has been approved for a determined period.

Signature : __________________________
Name : Majid Hosseini
Date : __________________________
Abstract

Wireless sensor networks have gained considerable attention from both academia and industry in last few years due to their crucial and advantageous applications including localising and tracking variety of objects and phenomena in different environments. Using a fleet of inexpensive sensor nodes is substituted the old fashion of the expensive nodes in the technology of autonomous sensing and tracking. The existing works are heavily based on state-space systems of a linear motion model along a nonlinear measurement. Due to nonlinearity in measurements, non-linear state estimation methods, like particle filtering, has become more popular in this field. There are three issues highlighted on using such tools in wireless sensor networks consist of heavy computation, lack of good knowledge of motion model, and initialization. This research has proposed solutions to all three problems. The tracking problem is divided into two categories of static and dynamic tracking. In the former, the main proposed method is a maximum likelihood estimator which is initialised via a least squares estimation. In this case, there is no assumption about target motion and it is independent from sampling rate. For the latter group, a nearly-constant-acceleration linear model is assumed for target movement along a nonlinear measurement model. First, this work derives a linear form of the nonlinear measurement. Then, a Kalman filter estimator initialised by maximum likelihood is designed for tracking purposes. For analogy to Kalman model, a particle filter estimator is also designed on the original nonlinear measurement. During this research, it is also found that most of existing works are assuming independent measurement noise, probably for problem simplification. Therefore, a similar tracking system is proposed considering dependent noise measurement. The analysis and numerical proof is presented in this research and both cases are compared together. The results show that the proposed tracking system with dependent measurement noise highly overtake the other method with independent measurement noise. At last, due to importance of distributed techniques in wireless sensor networks, a quasi distributed tracking method is developed through applying a naive extended Kalman filtering on each sensor’s measurements. However, the final coordinate estimation is done in the fusion center using standard least squares estimation. The simulation results show a great improvement on the accuracy of estimation over the standard least squares.
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LIST OF ABBREVIATIONS

AoA - Angle of Arrival
CRB - Cramér-Rao Bound
DV-Hop - Distance Vector-Hop
EKF - Extended Kalman Filter
ELSE - Extended kalman filtered Least Squares Estimation
GPS - Global Positioning System
KFE - Kalman Filter Estimation
LOS - Line-Of-Sight
LSE - Least Squares Estimation
MCL - Monte Carlo Localization
MEMS - Micro Electro-Mechanical System
MKF - Maximum likelihood Kalman Filter estimation
MLE - Maximum Likelihood Estimation
MMWSN - MultiMedia Wireless Sensor Network
MWSN - Mobile Wireless Sensor Network
PFE - Particle Filter Estimation
QoS - Quality of Service
RF - Radio Frequency
RFID - Radio-Frequency IDentification
RSSI - Received Signal Strength Indication
SMC - Sequential Monte Carlo
TDoA - Time Difference of Arrival
TL - Transmission Loss
ToA - Time of Arrival
TUKF - Truncated Unscented Kalman Filter
TWSN - Terrestrial Wireless Sensor Network
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