Data Fusion in Wireless Sensor Networks

Maen Takruri

Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

Faculty of Engineering and Information Technology
UNIVERSITY OF TECHNOLOGY, SYDNEY

March 2009

Certificate of Authorship/Originality

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text. I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Production Note:
Signature removed prior to publication.

Maen Takruri, March 2009

Acknowledgements

I would like to express my gratitude to my supervisor, Prof. Subhash Challa, whose generosity and commitment are above and beyond the call of duty; words do not describe my gratitude. I appreciate his vast knowledge and skill in many areas and his assistance in completing this thesis. I would like also to thank my co-supervisor, Dr. Tim Aubrey for his assistance and support.

I must also thank the following people from the University of Technology, Dr. Khalid Aboura for his assistance and advice in statistics, Dr. Rami Al-Hmouz, Dr. Mohammad Momani, Dr. Kais Al-Momani, Mr. Mohammad Al-Hattab and Mr. Akram AlSukker for their support and invaluable philosophical debates, exchanges of knowledge, which helped enrich the experience.

I would like to acknowledge the support of the ARC Research Network on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP) through the collaborative work with A/Prof. Marimuthu Palaniswami, A/Prof. Christopher Leckie, Mr. Sutharshan Rajasegarar from the University of Melbourne, to whom I would like to express my deep and sincere gratitude for their valuable contribution in implementing Support Vector Regression with the Drift detection and correction algorithms in chapters 6 and 7 of this thesis. Thanks also go to Dr. Rajib Chakravorty from NICTA Victoria Laboratory for his assistance and advice in estimation theory.

I am deeply grateful to my sisters Ruba, Heba and Sahar and my brother Awn, for their loving support. I owe my loving thanks to my wife Ramah and my beloved daughter Tasneem. Without their love, patience and encouragements I would not have finished this thesis. I wish to extend my deep and warm gratitude to my father

Sadeq and my mother Zeinat. They raised me, taught me, and always supported and loved me. To them I dedicate this thesis.

In conclusion, I acknowledge that this research would not have been possible without the financial support of THALES, Australia through the ARC Linkage grant (LP0561200)/APAI Scholarship. To them, I express my sincere gratitude.

To my father and mother.

Contents

List of Figures

List of Tables

List of Abbreviations

DCM-WD	Drift Corrected Measurement With Drift
DCM-WOD	Drift Corrected Measurement Without Drift
EKF	Extended Kalman Filter
EnKF	Ensemble Kalman Filter
FFT	Fast Fourier Transform
KF	Kalman Filter
IBRL	Intel Berkeley Research Laboratory
IMM	Interacting Multiple Model
R-WD	Reading With Drift
R-WOD	Reading Without Drift
SVM	Support Vector Machine
SVR	Support Vector Regression
UKF	Unscented Kalman Filter
UT	Unscented Transform
WSN	Wireless Sensor Network

Abstract

WIRELESS Sensor Networks (WSNs) are deployed for the purpose of monitoring an area of interest. Even when the sensors are properly calibrated at the time of deployment, they develop drift in their readings leading to erroneous network inferences. Traditionally, such errors are corrected by site visits where the sensors are calibrated against an accurately calibrated sensor. For large scale sensor networks, the process is manually intensive and economically infeasible. This imposes finding automatic procedures for continuous calibration. Noting that a physical phenomenon in a certain area follows some spatio-temporal correlation, we assume that the sensors readings in that area are correlated. We also assume that measurement errors due to faulty equipment are likely to be uncorrelated. Based on these assumptions, we follow a Bayesian framework to solve the drift and bias problem in WSNs.

In the case of densely deployed WSN, neighbouring sensors are assumed to be close to each other that they observe the same phenomenon. Hence, the average of their corrected readings is taken as a basis for each sensor to self-assess its measurement, estimate its drift and to correct the measurement using a Kalman Filter (KF) in the case of smooth drift, and the Interacting Multiple Model algorithm (IMM) in the case of unsmooth drift. The solutions are computationally simple, decentralised and also scalable. Any new node joining the neighbourhood needs only to obtain the corrected readings of its neighbours to find the average and apply the KF iterative procedure.

On the other hand, when the sensors are not densely deployed, Support Vector Regression (SVR) is used to model the interrelationships of sensor measurements

in a neighbourhood. This enables the incorporation of the spatio-temporal correlation of neighbouring sensors, to predict future measurements. The SVR predicted value is used by a KF to estimate the actual drift and correct the measurement. Unfortunately, the KF introduces some system errors when used with nonlinear systems. The use of Unscented Kalman filter (UKF) instead, considerably reduces the system error and results in a better drift correction. The use of IMM with the SVR-UKF framework allows for reducing the sampling rate which eventually reduces the communication overhead among the sensors and saves the communication energy.

In this thesis, we present several solutions for the random and systematic (drift and bias) errors in sensors measurements, for different sensor deployment scenarios. We also consider two drift scenarios, namely smooth and unsmooth drifts. We evaluate the presented algorithms on simulated and real data obtained from the Intel Berkeley Research Laboratory sensor deployment. The results show that our algorithms successfully detect and correct systematic errors (drift and bias) developed in sensors and filters out the noise. Thereby, prolonging the effective lifetime of the network.