Managing Uncertainty in RFID Based Tracking Applications

Rengamathi Sankarkumar

School of Computer Science

University of Adelaide

This dissertation is submitted for the degree of

Master of Philosophy

University of Adelaide November 2015

I would like to dedicate this thesis to my loving family ...

Declaration

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.

I give consent to this copy of my thesis when deposited in the University Library, being made available for loan and photocopying, subject to the provisions of the Copyright Act 1968. The author acknowledges that copyright of published works contained within this thesis resides with the copyright holder(s) of those works.

I also give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library Search and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

Rengamathi Sankarkumar
November 2015

Acknowledgements

This thesis would not be possible without the help and support of kind people, only some of whom is possible to give particular mention here.

I would like to present my sincere gratitude to my co-supervisor Dr. Damith C Ranasinghe for the support to pursue research in RFID and the all time guidance and support. He taught me not only how to do research, but also how to find out why to do research. I could not be prouder of my academic roots and hope that I can in turn pass on the research values and the dreams that he has given to me.

I would like to thank my principal supervisor A/Prof. Michael Sheng for the kind advices enriched with a lifetime of research experience. He has always cared about me and my future and provided great insights for me to pick my path in the best direction. I am so proud of working with you both, thank you.

In this opportunity I'd like to thank my friend, Dr. Sanjeev Arulampalam for his kind help and effort in showing me the path for research studies and for teaching me the basics of particle filters. Without his help I would have not made my research findings possible. I'd also like to thank Sage Hall from Sage Hall Proofreading Services, for providing language proof reading advice for my thesis under the ASEP standard D and E.

I especially thank my mom Devaki, dad Sankar and brother Nivas. My hard-working family have sacrificed their lives for me and provided unconditional love and care. I do believe that I would not have made it this far without them. I know I always have my family to count on when times are rough.

I would not have contemplated this road if not for my lovely husband, Prithvi and my son Jai, who instilled love in all senses within me. They have been the best of friends along this journey. Thanks my dearest for being patient with me, for being beside me when no one could be, and for rekindling my dreams when no one believed in me.

Abstract

Object or people based tracking systems that use RFID have seen increasing usage over the past decade. These systems provide an effective tracking solution by leveraging the non-line-of-sight precise identification capability of RFID technology, however they still have to overcome a number of challenges posed by the nature of the technology to improve their reliability and accuracy, such as uncertain data that leads to location uncertainty. In this thesis, two applications are been concentrated: i) asset tracking; and ii) tracking people. The goal was to develop a generalizable approach for tracking objects or people effectively by managing the location uncertainty problem caused by uncertain RFID data.

In the context of an asset tracking application, we describe an optimized tracking algorithm to predict the locations of objects in the presence of missed reads using particle filters. To achieve high location accuracy we develop a model that characterizes the motion of objects in a supply chain. The model is also adaptable to the changing nature of a business, such as flow of goods, path taken by goods through the supply chain, and sales volumes. A scalable tracking algorithm is achieved by an object compression technique, which also leads to a significant improvement in accuracy.

In the context of a people tracking application for addressing wandering off, one of the common behaviours among cognitively impaired patients, we have developed an approach for identifying the traversing direction and the traversing path used by the patients wearing an RFID tag integrated into clothing for the first time. Our approach uses a particle filtering (PF) based technique with Received Signal Strength Indicator (RSSI) maps obtained from scene analysis to continuously track a person wearing an RFID tag over their attire. Using real-time spatial and temporal data obtained from the PF based tracking approach, we develop two algorithms: i) tag traversing direction (TD) algorithm to identify the tag bearer's moving direction (e.g. moving out of a room); and ii) tag traversing path detection algorithm (TPD) to estimate the traversal path used by the tag bearer.

Furthermore, we propose a generic model for RFID sensing infrastructure using Kernel

Density Estimation (KDE) to eliminate the need of generating an RSSI map for every new environment. The newly developed algorithm can be implemented in practice without the need for further training data. We then integrate Kullback-Leibler (KL) divergence into our sensor model to overcome problems posed by information loss when the RSSI distribution in the training data set is used to generate a generic sensor model based on approximating RSSI distribution over the monitoring region. Moreover, we also utilize a Dynamic Time Warping (DTW) technique to improve the performance of our TPD algorithm by measuring the similarities between the real-time temporal data and the trail walking temporal data. At last, we investigate the accuracy of our algorithms in a multiple-participants environment. A detailed discussion of all the proposed method's performance and accuracy for both applications show that our algorithms are robust.

Statements of Authorships

This thesis contains one journal paper (under review), and three conference papers (all peer reviewed and published). I have provided a statement of authorship for each of these articles to certify that I was actively involved in the process of preparing each article.

The following is the list of all publications included in this thesis.

- R. Sankarkumar, D. C. Ranasinghe, and T. Sathyan. A highly accurate method for managing missing reads in RFID enabled asset tracking. *In 10th International Conference on Mobile and Ubiquitous Systems (MOBIQUITOUS)*, Tokyo, Japan, 2013. Ranked as A according to Core conference ranking 2014.

- R. Sankarkumar, D. C. Ranasinghe, and T. Sathyan. A highly accurate and scalable approach for addressing location uncertainty in asset tracking applications. *In IEEE International Conference on Radio Frequency Identification (IEEE RFID)*, Orlando, USA, 2014. Ranked as B according to Core conference ranking 2014.

- R. Sankarkumar and D. C. Ranasinghe. Watchdog: A novel, accurate and reliable method for addressing wandering-off using passive RFID tags. *In Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems (MOBIQUITOUS)*, London, UK, 2014. Ranked as A according to Core conference ranking 2014.

- R. Sankarkumar and D. C. Ranasinghe. Watchdog: Practicable and unobtrusive monitoring technology for addressing wandering-off with low cost passive RFID. *In the International Journal of Pervasive and Mobile Computing (PMC), Special Issue on Pervasive Computing for Gerontechnology* (Under Review). Ranked as B according to Core journal ranking 2014.

Statement of Authorship

Title of Paper	A Highly Accurate Method for Managing Missing Reads in RFID Enabled Asset Tracking
Publication Status	⦿ Published, ○ Accepted for Publication, ○ Submitted for Publication, ○ Publication style
Publication Details	Sankarkumar, R., D. C. Ranasinghe, and T. Sathyan, "A Highly Accurate Method for Managing Missing Reads in RFID Enabled Asset Tracking", 10th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, Tokyo, Japan, 12/2013

Author Contributions

By signing the Statement of Authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

Name of Principal Author (Candidate)	Rengamathi Sankarkumar		
Contribution to the Paper	Performed simulation, gathered and interpreted data, wrote manuscript and acted as corresponding author.		
Signature		Date	09/07/2015

Name of Co-Author	Damith C Ranasinghe		
Contribution to the Paper	Formulate the problem, supervised development of work, help in data interpretation and manuscript evaluation.		
Signature		Date	10/07/2015

Name of Co-Author	Thuraiappah Sathyan		
Contribution to the Paper	Helped to evaluate and edit the manuscript.		
Signature		Date	03/07/2015

Name of Co-Author			
Contribution to the Paper			
Signature		Date	

Statement of Authorship

Title of Paper	A Highly Accurate and Scalable Approach for Addressing Location Uncertainty in Asset Tracking Applications
Publication Status	⦿ Published, O Accepted for Publication, O Submitted for Publication, O Publication style
Publication Details	Sankarkumar, R., D. C. Ranasinghe, and T. Sathyan, "A Highly Accurate and Scalable Approach for Addressing Location Uncertainty in Asset Tracking Applications", IEEE International Conference on Radio Frequency Identification (IEEE RFID 2014), Orlando, USA, IEEE, 2014.

Author Contributions

By signing the Statement of Authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

Name of Principal Author (Candidate)	Rengamathi Sankarkumar		
Contribution to the Paper	Developed algorithm and performed simulation study for the problem, wrote manuscript and acted as corresponding author.		
Signature		Date	09/07/2015

Name of Co-Author	Damith Ranasinghe		
Contribution to the Paper	Supervised development of work, helped in data interpretation, manuscript evaluation and edit the manuscript.		
Signature		Date	10/07/2015

Name of Co-Author	Thuraiappah Sathyan		
Contribution to the Paper	Helped to develop the algorithm, evaluate and edit the manuscript.		
Signature		Date	03/07/2015

Name of Co-Author			
Contribution to the Paper			
Signature		Date	

Statement of Authorship

Title of Paper	Watchdog: A Novel, Accurate and Reliable Method for Addressing Wandering-off using Passive RFID Tags
Publication Status	⦿ Published, ○ Accepted for Publication, ○ Submitted for Publication, ○ Publication style
Publication Details	Sankarkumar, R., and D. C. Ranasinghe, "Watchdog: A Novel, Accurate and Reliable Method for Addressing Wandering-off using Passive RFID Tags", 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, London, Great Britain, 12/2014

Author Contributions

By signing the Statement of Authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

Name of Principal Author (Candidate)	Rengamathi Sankarkumar		
Contribution to the Paper	Actively involved in the conceptualization of the work, formulation of the problem to a tracking problem, developed algorithm, conduct the experiments, interpreted data, wrote manuscript and acted as corresponding author.		
Signature		Date	09/07/2015

Name of Co-Author	Damith C Ranasinghe		
Contribution to the Paper	Conceptualization of the study, supervised development of work, helped in data interpretation, manuscript evaluation and edit the manuscript.		
Signature		Date	10/07/2015

Name of Co-Author			
Contribution to the Paper			
Signature		Date	

Name of Co-Author			
Contribution to the Paper			
Signature		Date	

Statement of Authorship

Title of Paper	Watchdog: Practicable and Unobtrusive Monitoring Technology for Addressing Wandering-off with Low Cost Passive RFID
Publication Status	○ Published, ○ Accepted for Publication, ⦿ Submitted for Publication, ○ Publication style
Publication Details	Sankarkumar, R., & Ranasinghe, D. C. Watchdog: Practicable and Unobtrusive Monitoring Technology for Addressing Wandering-off with Low Cost Passive RFID. In the International Journal of Pervasive and Mobile Computing, Special Issue on Pervasive Computing for Gerontechnology (Under Review).

Author Contributions

By signing the Statement of Authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

Name of Principal Author (Candidate)	Rengamathi Sankarkumar		
Contribution to the Paper	Conceptualization of the study, formulation of the problem to a tracking problem, developed algorithm, conduct the experiments, interpreted data, wrote manuscript and acted as corresponding author.		
Signature		Date	09/07/2015

Name of Co-Author	Damith C Ranasinghe		
Contribution to the Paper	Supervised development of work and in data interpretation, manuscript evaluation and edit the manuscript.		
Signature		Date	10/07/2015

Name of Co-Author			
Contribution to the Paper			
Signature		Date	

Name of Co-Author			
Contribution to the Paper			
Signature		Date	

Table of contents

List of figures

List of tables

Chapter 1

Introduction

In context of growing advances in lower power microelectronics and sensors, there is a considerable increase in the usage of mobile and ubiquitous computing i.e., where computing is made to appear in any device, in any location and in any form. This has enabled the possibility of tracking and tracing objects or people in widely distributed networks, such as supply chains, surveillance, pharmaceuticals, aged care, military, and postal services. Tracking and tracing a unique object or person with high precision and accuracy is a demanding requirement for all the above said fields, where processes that identify the past and current location of a unique object are needed, as well as other detailed information such as the time spent in each location of transit.

Radio-frequency identification (RFID) technology enables unique identification. RFID systems are capable of automatically identifying people or objects who are connected with

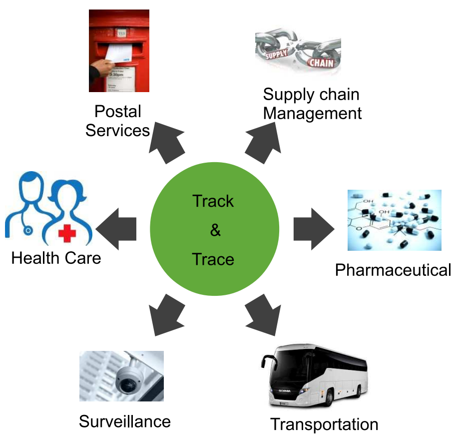


Fig. 1.1 Applications that Utilise Tracking

an RFID tag. Fig.1.1 gives an overview of the applications that utilize RFID systems. RFID uses radio-frequency waves to transfer identifying information between tagged objects and readers without line of sight, providing a means of automatic identification [33]. History shows some evidence that RFID was discovered in 1935, but the first patent rights for RFID tags was received only in 1973. However, the potential benefits of using RFID has only recently been realized [6]. Below is a brief overview of RFID system components and their basic working principles.

An RFID system usually comprises of three key components as shown in Fig. 1.2: i) an RFID tag; ii) an RFID reader; and iii) RFID reader antenna. The RFID reader is a transceiver that transmits the RF (radio frequency) signals using the connected RFID reader antenna. The RF signal can both energize an RFID tag and read the information stored in the tag and transfer the information to a processing device (backend system) through the transceiver. The RFID antenna together with the reader provides the means for not only transmitting its information to a tag but also converts the radio waves scattered back from the RFID tag into digital information that can then be passed on to backend systems for further processing. In RFID systems, the type of tag that is holding the information plays an important role in evaluating the efficiency and performance of the system. RFID tags can be classified into three types: i) active tags; ii) passive tags; and iii) battery-assisted passive tags. In table 1.1, we have compared different types of RFID tags that are currently used in the market.

1.1 Motivation

Due to the low cost nature of passive tags, RFID has become one of the key enabling wireless communication technologies that can provide low cost solutions for various tracking problems. For instance, RFID has a critical role to play in supply chains as they can en-

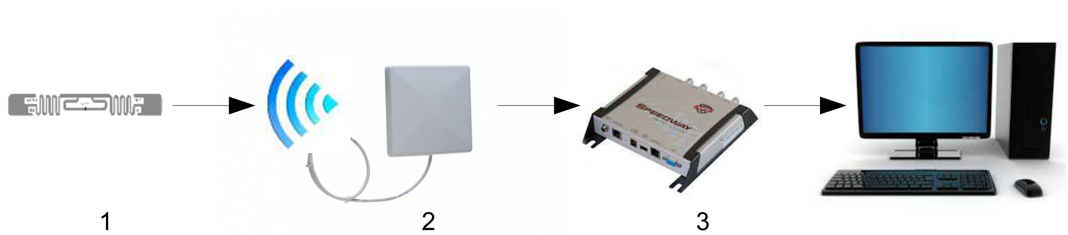


Fig. 1.2 A Simple RFID System: 1) An RFID Tag; 2) An RFID Reader Antenna; and 3) An RFID Reader

Table 1.1 Types of RFID tags

	Active Tag	**Passive tag**	**Battery-assisted tag**
Power source	Internal battery	Energy transferred from the RFID reader via RF	Tag uses internal battery to power electronics but tag responses use load modulated backscatter as in passive tags
Communication Range	Long Range (100 m or more)	Short range (up to 10 m)	Moderate range (up to 100 m)
Price	$25, USD or more	from 0.07 to 0.50 US cents	$ 2 USD or more

able tracking of objects, such as their condition as in cold chain monitoring and location to improve the visibility of the objects traversing through supply chains for inventory management, and can effectively enable targeted recall of products [43]. Further, through better visibility of inventory and whereabouts of goods, process or delivery errors can be identified and rectified in real-time. In addition, automated tracking of goods in the supply chain not only generates a security benefit, but also monitors the company's promises in delivery times which improves customer satisfaction [14].

An example supply chain routine is shown in Fig. 1.3. An RFID enabled object (i.e an object with an RFID tag attached) is captured by an RFID reader infrastructure and sends a notification once the goods reach the next stage in the supply chain, such as, the goods are delivered to the packing centre at 11.00 a.m. Here, the location of the goods are captured by the RFID system with the time of arrival information. Therefore, an RFID system ensures that the right quantity of product has been delivered to the right place and at the right time. Consequently, the current location of the goods is clearly visible to all the parties in the supply chain in real-time.

On the other hand, we can also use RFID technology for tracking persons. In Australia, in the period between 2012 to 2060 the population aged 75 or more is expected to rise by 4 million i.e., an increase from about 6.4 to 14.4 per cent of the population [2]. This ageing population across the globe is expected to increase the number of patients with dementia, which might raise a significant need for continuous monitoring among cognitively impaired dementia patients as wandering-off (elopement) from the cared area is quite common among them. The 2013 Alzheimer's Facts and Figures [3] states that, "15.5 million caregivers provided 17.7 billion hours of unpaid care valued at more than $220 billion", which clearly shows the continuous need for monitoring among dementia patients. Consequently, spatial tracking of older people is an emerging area of significance because tracking a person with fine location granularity enable automated supervision of older people in aged care and acute hospital environments.

RFID enabled people tracking has the potential to address wandering off and can tremendously reduce the work pressure of care givers. RFID systems are capable of monitoring patients in real time and send notifications to the caregivers in the event of wandering-off or when a fall is detected [38].

However, using RFID systems to track objects or people is not always reliable because of the uncertainty associated with RFID data, especially those systems based on low cost passive RFID tags. In the next section, we will consider the reasons for the occurrences of uncertainty and its consequences.

1.2 Challenges

In spite of RFID providing a low cost approach to build tracking applications with many promising benefits, there remain some challenges to be overcome before these benefits can be realised. One of the main challenges is uncertainty in the collected raw RFID data.

Uncertainty in RFID networks can occur because of various external and internal factors, such as interference caused by other objects or radio waves in the environment, signal bounce-off from various surfaces in the environment leading to signal cancellation, fading and scattering, distance between the tag and the reader, orientation of the tag and malfunction of RFID components. These factors typically make the raw RFID data inadequate for

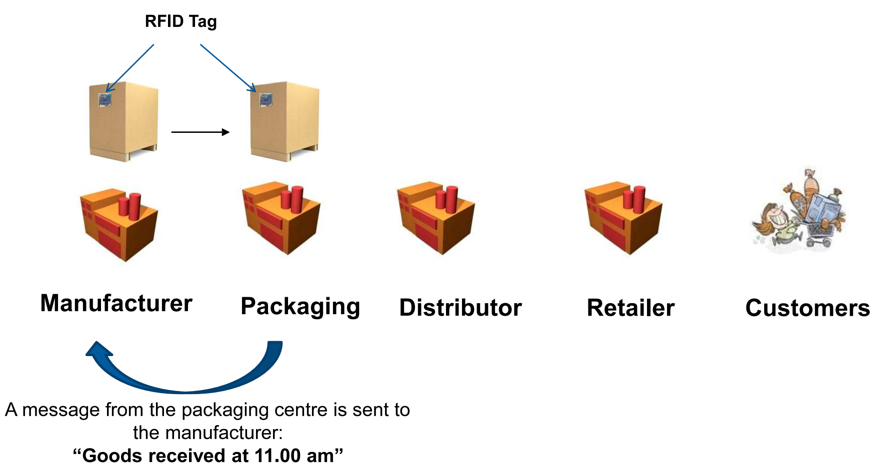


Fig. 1.3 An Example Supply Chain Routine

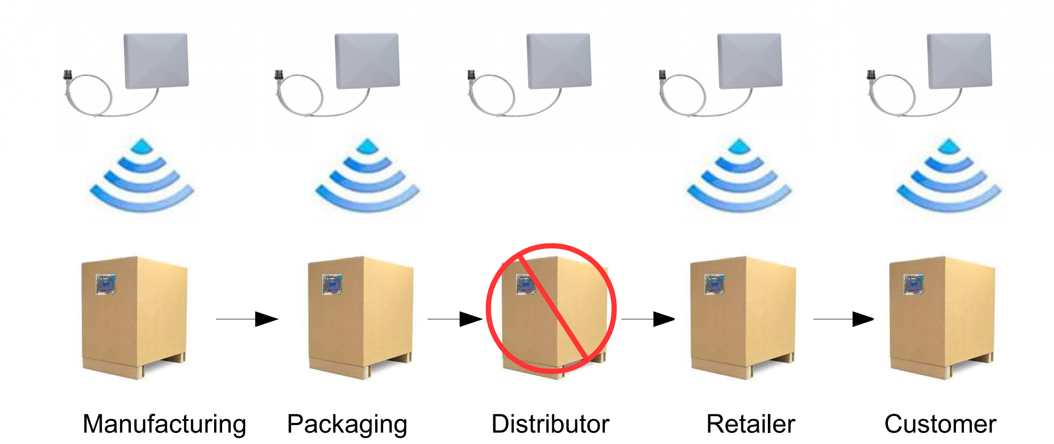


Fig. 1.4 Missed Reads in the Distribution Centre

determining the location in tracking applications. In this thesis, we have broadly classified uncertainty in RFID data into two categories: i) uncertainty resulting from missed reads (false negatives); and ii) uncertainty resulting from noise inherent in the received signals from tags.

Missed reads, also known as false negatives, occur when an RFID tag exists in a readable zone but the RFID readers fail to read the tags due to, for example, environmental factors, such as interference, or internal factors, such as a weak response signals from tags and malfunction of the RFID components [43, 44]. In order to understand the challenge posed by missed reads, consider the example in Fig. 1.4 which shows a supply chain routine followed by an object instrumented with a passive RFID tag. The object's tag was not read in the distribution center due to some environmental factors. Now the status of the object is unknown and the current location of that object could be in the distribution center, in transit between packing to the distribution center, still in the packaging center or even stolen.

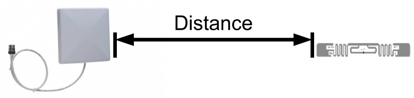
Noisy data is largely due to the intrinsic sensitivity of RF waves to the environment, such as reflection from side walls and floor, occluding metal objects, absorption of liquids, tag orientation, thermal noise produced from the electrical components and object moving speed. Fig. 1.5a & 1.5b shows the effects of the distance between the tag and the reader. It is clear from the Fig. 1.5b that as the distance between the reader and the tag increases, the tag readability decreases. Materials such as liquids or metals occluding the tag has a serious impact on the readability of the tag [12]. In Fig. 1.5c, 1.5d, 1.5e we experimented the effect of liquids that completely and partially block the RFID tags in three positions: (i) directly before or behind the liquid; (ii) directly behind the liquid with a portion of the tag unblocked by the liquid; and (iii) beside the liquid. For each of these positions the tag read rate is calculated using the formula below.

$$Read\ rate = \frac{Number\ of\ reads\ per\ minute}{Average\ read\ rate\ in\ a\ liquid\ free\ environment\ per\ minute}$$

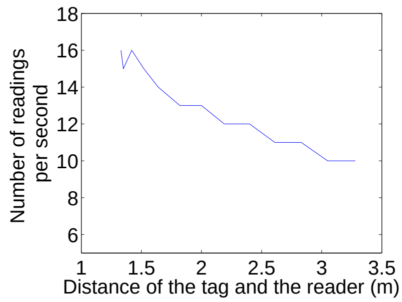
The average read rate in a liquid free environment was 140 per minute. The experimental results shown in Table 1.5f, proves that the environment with liquid near the tag does not have adverse effect on the read rate of the tag unless the tag is partially or completely blocked by the liquid. From one of our previous researcher [12] it is also found that occluding metal objects have similar effects on the read rate of the tag. This sensitivity in RFID systems leads to imprecise, incomplete or even misleading information while inferring the location of an object or people in tracking applications.

For example, in people tracking aged care applications, the Received Signal Strength Indicator (RSSI) of the RFID data can be utilized for fine-grained spatial tracking of the tag bearer. However, due to the highly noisy nature of the received RFID signals, no exact inference about the patient traversing direction (e.g., moving from inside the room to outside) or traversing path (e.g., moving from the left corner of the inner side of the room to right corner of outside the room) can be made, but this is essential for alerting a caregiver when a person leaves a cared area or informing a caregiver the path taken by a person eloping so that they can be subsequently found by the caregiver.

The above examples give an overview of the challenges that are faced by uncertain RFID data. Although, active tags and battery assisted tags provide stronger signal (less noise) and are much less likely to be missed, the price of active and battery assisted tags as well as the need to replace batteries make them the less desirable for wide-scale tracking applications. Therefore, passive tags are an economic solution for tracking, especially where cost of the tags need to be minimized. In addition, passive tags are also lightweight, and passive (batteryless) RFID tags power themselves when they are interrogated by an RFID antenna, which leads to them being maintenance free. However, passive tag based tracking systems have to overcome location uncertainty before deploying them in tracking applications. Consequently, RFID data, especially collected from the passive RFID tags, have to be either cleaned or managed before high level processing can be carried out to ensure the accuracy of the tracking applications.



(a) Distance between the tag and the reader



(b) Impact of the distance between tag and reader

(c) Tag attached before or behind the bottle

(d) Tag attached beside the bottle

(e) Tag attached behind the bottle (3 cm of the tag unblocked from liquid)

Position	**Read rate %**
Before the bottle	100
Behind the bottle	0
Behind the bottle with 3 cms of the tag un-blocked	89
Side of the bottle	99

(f) Readability of tags

Fig. 1.5 Environmental effects on received RFID data

1.3 Author's Main Contributions

In this thesis we have provided solutions to manage location uncertainty, specifically in the context of two RFID based tracking applications using passive RFID tags: i) tracking assets in supply chain management applications which involves coarse-grained location tracking (e.g., packaging area, distribution center); and ii) addressing wandering-off among elderly in aged care settings and hospitals which involves fine grained location (e.g., x and y coordinates of a room) tracking. We have utilized a sampling based inference technique known as particle filtering to manage location uncertainty in both applications.

1.3.1 Addressing Location Uncertainty in Asset Tracking

It is believed that improving visibility of objects in the supply chain routine solves several problems such as cold chain monitoring, counterfeit and inventory management [18]. Even though RFID provides promising benefits in tracking systems, RFID based asset tracking is particularly prone to false negatives, which are also known as missed reads. Missed reads make RFID data incomplete [35] and using such RFID data in object tracking lead to ambiguity in the locations of objects.

Therefore, we have presented an approach to address location uncertainty caused by missed reads in a returnable asset management scenario where the requirements are derived from International Linen Services (ILS) Pvt. (Ltd.). We modelled objects travelling through a supply chain using an object flow graph to capture possible movements of objects and used a PF based object tracking algorithm to continuously track objects, even though raw RFID data is incomplete due to missing reads.

The asset based tracking involves a broader location tracking application similar to the example discussed in Fig. 1.5. The proposed sampling based inference technique is not only scalable for tracking large numbers of items but also accurately determines the most likely location of the objects in the event of missed reads.

1.3.2 Addressing Location Uncertainty in Tracking People

Wandering-off (e.g. elopement) [8] among older people with dementia, Alzheimer's disease (AD) and other cognitive impairments is common [4, 7, 21, 32]. Hospitals and residential homes have a significant need for monitoring and recognizing wandering-off (e.g. elopement) among older people with cognitive impairments because of the serious consequences arising from wandering-off, such as disappearances and serious injuries, for example, from collisions with vehicles in parking lots.

We propose a novel approach to address wandering off by identifying the traversal direction and traversal path used by elderly people instrumented with low cost passive RFID tags on their attire named *Watchdog*. We utilised the PF based technique with the RSSI map generated with the help of scene analysis techniques to develop two algorithms called the tag Traversal Path Detection (TPD) to detect the path used and tag Traversal Direction (TD) algorithm to identify the direction used by the tag bearer.

In the previous asset tracking application, missed reads where the only hurdle for successful location tracking, whereas in this application, accurately determining the fine-grained traversal path used by the tag bearer with the noisy RFID raw data is more challenging. This is because Watchdog has to overcome various sources of noise affecting the received tag response (i.e. RSSI) such as the noise resulting from the limited working range of modulated backscatter Ultra High Frequency (UHF) RFID, noise in the received signal, multi-path effects, fading and scattering to reveal the traversal path used by the tag bearer.

1.4 Document Overview

In this section we give a detailed overview of the contents of each chapter in this thesis.

Chapter 2 discusses the related works in both asset tracking and people tracking applications. This chapter also discusses previous research works upon which our approach is built.

In Chapter 3, we make our first contribution in Section 3.1, where we discuss our initial results while tracking RFID enabled assets in a returnable asset supply chain using a PF based asset tracking algorithm. Later in Chapter 3, Section 3.2 we provide an enhanced algorithm and detailed discussion for the same asset tracking problem. Here, we introduce an object flow graph to adapt the evolving B2B (Business to Business) and B2C (Business to Customer) relationships. We also propose an approach to exploit business related contextual information to aggregate objects that are travelling together to develop an optimised Particle Filter (PF) based tracking algorithm.

In Chapter 4, for the first time, we propose a novel approach to address wandering-off using passive tags. Addressing location uncertainty in tracking people applications is a complex problem. We say this is more complex because of the nature of RF waves.

The emitted RF waves mostly get absorbed by the human body, which therefore reduces the received signal strength or completely eliminates an occurrence of a read. Further the RSSI is highly dependent on environmental factors is thus very noisy. In this work, we use a particle filtering based technique with Received Signal Strength Indicator (RSSI) maps obtained from scene analysis to continuously track a person wearing an RFID tag over their attire. Using real-time spatial and temporal data obtained from the PF based tracking algorithm, we develop two algorithms: i) tag traversing direction (TD) algorithm to identify the tag bearer's moving direction (e.g. moving out of a room); and ii) tag traversing path detection algorithm (TPD) to estimate the traversal path used by the tag bearer.

In Chapter 5, we introduce a system that relies on a PF based algorithm that overcomes the need for acquiring deployment specific models of sensing infrastructure for accurate location monitoring to accurately identify the traversal direction and traversal path used by a person instrumented with a single batteryless (passive) RFID tag over their attire. In particular, we use a generic sensor model with Kullback-Leibler (KL) divergence to accurately identify path and direction. Our approach requires no modification to commercial RFID devices, firmware, hardware, or detailed surveys of deployment scenes and can be implemented in real-time. Furthermore, use of commercial RFID technology not only provides an unobtrusive, battery-less sensing approach to continuously and automatically monitor wandering-off among cognitively impaired older people, but also allows the monitoring of individual persons based on their care needs.

Chapter 6, discusses the utilization of Dynamic Time Warping (DTW), a pattern recognition technique, in our wandering-off problem. In Chapter 4 and Chapter 5, in order to infer the path used by the patient, the TPD algorithm directly utilizes the location estimates from the particle filter. As a result of the inference, the prediction either ends up in a defined path (e.g. Straight in to Straight out) or in an undefined path (Further explanation about paths can be found in Chapter 4.) In contrast the approach pursued here uses the DTW algorithm if an undefined path is identified where DTW is used to measure the similarities between the possible reference paths and the real time walking data to make an inference about the real path used. Furthermore, we have examined the possibility of tracking multiple people simultaneously in the given state space.

In Chapter 7, we review our work and conclude our thesis. We also discuss some of the possible future work in this area.

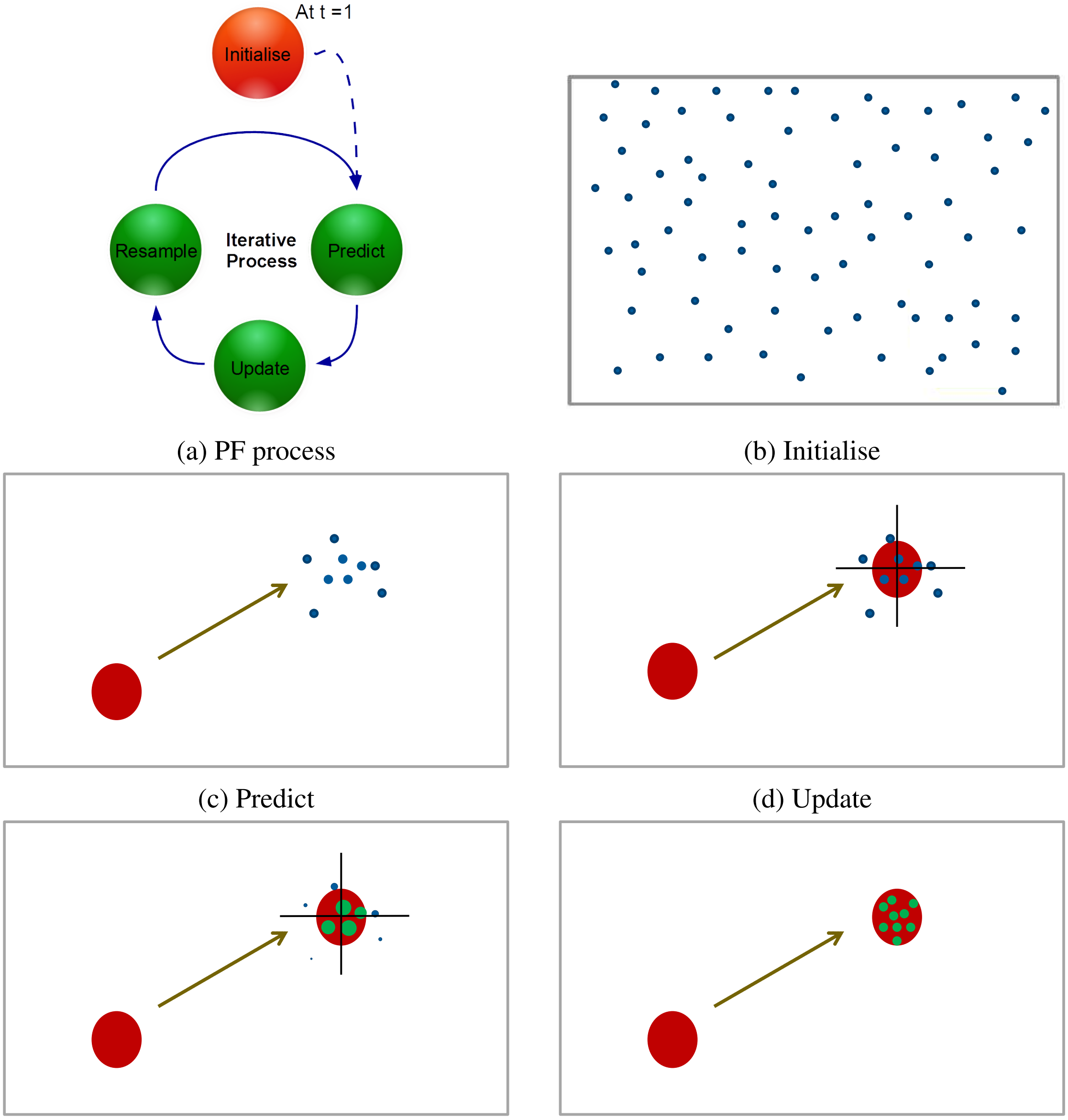
Chapter 2

Literature Review

In the past decade, number of research papers have been published regarding managing location uncertainty caused by raw RFID data. This is one of the key research areas for many researchers in the field of mobile and ubiquitous computing. A number of existing publications have demonstrated various methods to clean or manage uncertain RFID data. Here, uncertainty can be any of the following such as false negatives or missed reads, inconsistent data, and redundant data [52]. In the following sections we discuss some of the literature which deals with managing location uncertainty in two RFID based tracking applications: i) asset tracking in supply chain networks applications; and ii) tracking people in indoor environment applications. Before discussing the related literatures, in the next section we give a general overview of the particle filtering technique which is a central approach we have employed to address location uncertainty in the tracking applications. The PF overview helps the reader to understand this thesis more clearly.

2.1 General Overview of Particle Filters

A number of location tracking applications, either RFID based or non RFID based technologies, have utilized particle filters [45, 50, 56]. Particle filtering is a sequential Monte Carlo method that uses a set of particles for state estimation, where the motion model can be non-linear or non-Gaussian. PF in tracking applications is capable of computing the conditional probability of a hidden state, i.e., the current location of the object or person in our application context, given some noisy observations. In our tracking application we are interested in determining the traversal path used by an object or person given some noisy



(a) PF process (b) Initialise

(c) Predict (d) Update

(e) Weight (f) Resample

Fig. 2.1 PF Process and an Example for the PF Steps raw RFID readings. There are several reasons for choosing PF in our tracking algorithm rather than other filters like Kalman and Unscented Kalman Filters (UKF): 1) Kalman filter are effective in linear systems with Gaussian noise. However, in a non-linear system such as the changing dynamics of a moving person or an object attached with an RFID tag, which has non-Gaussian noise, for example, noise from various sources like reflection from side walls, ceiling and floor, occluding metal objects and absorption of liquids, PF can generate more accurate results [46]; and 2) UKF estimates the hidden state of a non-linear system by utilising a deterministic sampling technique to pick a minimal set of sigma points i.e., possible state estimations around a mean estimate, to determine the unknown state. UKF has some similarities with PF in that it transforms a set of points from the previous state through a known non-linear equation and combines the results to estimate the current state [46]. However the method of choosing these points in PF is non-deterministic in contrast, UKF follows a specific algorithm. This eventually leads to the estimation errors which can converge to zero in PF when the number of particles are increased but the error convergence is not possible in UKF [46]. Lets see below how PF operates in a recursive fashion to estimate the unknown state of the object in Fig. 2.1a.

Here we discuss an example to illustrate the motivation for using PF in object tracking problems. We are going to track the red object (e.g., a balloon) in shown in Fig. 2.1. If we know the current location and speed of this object then we can predict the future location by assuming the balloon moves with a uniform linear motion. But our prediction might be wrong due to external noise, such as wind, causing the balloon to have moved to a different location than predicted. So instead of having a single prediction, if we could have had slightly different prediction locations then at least one of them might be near to the right location. Here the particles are used to predict probable locations and on receiving an observation these particles are validated by weighting. Before analysing the steps involved in the PF we give an overview of the two critical models used in the PF.

The Motion Model: The motion model formulates the evolution of an object's current state from its previous state. In the example scenario, the object was considered to move with a uniform linear motion with possible process noise from the wind.

The Measurement Model: The measurement model describes how the true observation relates to the predicted particles.

Steps of PF:

Initialize: The initialisation step is done only in the first iteration as we do not know the true location of an object at the first time step. In this step the particles are scattered all over the given state space, as shown in Fig. 2.1b.

Predict: At the current time, using the motion model we predict the location of the object by considering the state of the object in the previous time step and the observations obtained so far, as shown in Fig. 2.1c.

Update: On receiving an observation, the location of predicted particles are updated by weighting the particles using the measurement model to obtain importance weights, where high weights are given to the particles nearer to the measurement, as shown in Fig. 2.1d and 2.1e.

Resample: The resampling step eliminates the particles that have lower weights and replicates the particles that have higher weights within a probabilistic framework. This results in a new set of same number and equally weighted particles for the next iteration, as shown in Fig. 2.1f. In the next section, we see some of the works that address uncertainty in RFID networks in the supply chain networks.

2.2 Asset Tracking in Supply Chain Applications

Tracking is essential in industrial applications such as supply chain management, to monitor the traveling objects. In supply chain management, the motivation behind using RFID is to eliminate the barriers in visibility, which is the key for many problems [15, 18, 31, 51] such as those associated with inventory control. According to [27], one of the most important benefits of such improved information visibility is realized in inventory management and asset utilization. According to the results in [27], the qualitative factors account for over half of the anticipated total benefits of RFID technology. However, the barrier they are facing to obtain a genuine location tracking system is the uncertainty in RFID networks [13].

Uncertainty in RFID based asset tracking are particularly prone to false negatives, which is also known as missed reads. Missed reads make RFID data incomplete [35] and using such RFID data in asset tracking lead to ambiguity in the locations of objects. Hence, managing missed reads in raw RFID data is important for developing effective asset tracking applications.

2.2.1 Data Cleaning Techniques

Previous research on managing uncertainty in RFID systems [22–24] proposed an adaptive smoothing window to clean raw RFID data. The basic idea of the method is that they assume that, if there is a tag in the segmented window then the tag is present for the whole time span of that window. In this case, a larger window is able to overcome missed reads but prone to redundant data and inconsistent data. On the other hand, smaller windows are less affected by the redundant data (which are caused by frequently read tags that are within the vicinity of the reader for a long time, which might require significant amount of memory) and inconsistent data (is a factor where no inference about the object can be made because of the object being read by different readers in different position) but prone to missed reads. Therefore, the system is dependent on choosing an appropriate window size for an application.

In [53], the authors define an adjustable smoothing window that adjusts the size of the window with respect to the rate of missing RFID data in the traceability supply chain applications. The adaptable window helps in distinguishing missed and inconsistent data, however, these data cleaning techniques are not applicable to estimate the location of objects in a supply chain because they cannot predict a missed object's likely location.

2.2.2 Managing Location Uncertainty

A number of existing publications [16, 28, 48, 56] have used Bayesian techniques to manage the location uncertainty problem in tracking applications. In [16] authors have only addressed uncertainty caused by false positives. In [56] authors' aim is not addressing missed reads, nevertheless they reduce the effect of missed reads by aggregating an object's readings to a single read during a pre-defined time period. However, they need at least one reading during that time period to avoid missing an object. Thus, the accuracy of their technique reduces when an object is completely missing (i.e. unobserved) for a period of time.

In [28], the authors designed a transition model that depicts the probable flow of objects and serves as a base for their predictions of past, current and future locations of RFID tagged objects, even in the case of missed reads. However, these methods need a detailed transaction history of a business to develop the transition model. Also, this approach cannot be used for continuous object tracking.

The work in [48] aims to precisely locate an object placed on a shelf using a mobile reader. However, the accuracy of their approach to find the precise location of static objects relies on accurate measurement of the sensor model obtained from training data. In widely distributed supply chains, obtaining training data for each location is a tedious process. In addition, their algorithm does not predict the motion of the object in the case of missed reads and thus their approach cannot predict the possible location of a moving object.

In [35], the authors demonstrate how containment relationships of objects enable object localization. Their proposed method relies on packaging level information and forms coloured time-varying graphs that depict inter-object containment relationships. The data inference technique estimates the most likely location of an object if there is a missed read. The inference techniques infer edges and nodes (objects) in the graph, building a probabilistic distribution over all possible locations for each node. Iterative inference combines both edge and node inference estimates to find the most probable location of an object. However, the ability to address missed reads is highly dependent on the inter-object containment relationships, such as the data association that a particular set of cases are on a particular pallet.

In Chapter 3, we propose a tracking algorithm that is capable of estimating an object's location in the case of missed reads. In contrast to [28], we continuously track objects in a large scale supply chain and our dynamic motion model is flexible to adapt to changes in object flow and can be used in any widely distributed supply chains with large volumes of complex transactions. Unlike [56], once an object is detected by a reader, our approach is capable of estimating an object's location throughout the supply chain even if the object is missed by multiple readers. In contrast to [48], we are not interested in a precise location estimation and so we do not need training data to build an accurate sensor model that predicts the location of missed objects. Although we could have used a measured sensor model at each location, this requires extra effort. Finally, the ability of the proposed algorithm to predict the location of missed objects is independent of inter-object relationships. In addition, our approach can also be applied to contained objects (e.g. cases on a pallet aggregated and tracked as a single object instead of multiple cases), as in [35].

2.3 Tracking People in Indoor Environments

Object or people based indoor tracking has shown its importance in various areas such as hospitals, aged care, shopping malls, offices and many other structures [56]. Existing out-door location based tracking technologies [30, 42] cannot be directly implemented indoors as these techniques use GPS or cellular positioning to evaluate user location. GPS or cellular positioning techniques cannot be used efficiently in a covered indoor space where fine granularity in the spatial details is required. Furthermore these technologies are power hungry and thus pose problems in terms of size and maintenance of batteries. Passive RFID can be considered one of the efficient systems for indoor based tracking. However, the readings from the RFID tags are highly noisy and no exact inference about the tracking person can be made with raw data. If the uncertainty problem can be resolved passive RFID can provide a low cost and effective solution for indoor based tracking [47] problems.

People tracking is vital in hospital and aged care environment to track patients suffering from cognitively impaired diseases. Exact fine grain inference about the location and the previous locations used by the patients is significant in these kind of applications. Hence, managing noisy readings in the raw RFID data can help develop low cost and effective people tracking applications.

2.3.1 Identifying Traversing Direction and Traversal Path Used in an Indoor Environment

Number of works that utilise passive tags for determining tag traversal direction are limited. In [25], authors use several antennas and record the tag events as they are detected. Then using the order of events, tag direction is determined. However, their research is conducted using relatively more expensive active (battery powered) RFID tags to determine the traversing direction of a tag. In [37], time intervals between tag detections by static reader antennas are used to find the tag traversal direction, however, this method has only been successful with dense tags (10 or more) and cannot be implemented with single tag. In [57], direction of arrival (DoA) is used to find the moving direction of a tag, however, real-time evaluation of this method is not reported in the paper. In [59], we developed two methods using tag phase and its radial velocity to determine the direction of a passive tag worn by a person. However, the accuracy of identifying the tag traversal direction is less than 90% and it is also likely to be adversely affected by higher walking speeds of a tag bearer.

To the best of our knowledge, in Chapter 4, we are the first to study traversing path of a tag bearer using passive RFID tags attached to their outfit using fixed antennas. Although mobile robots' trajectories were investigated in [19, 26] by utilising mobile antennas and fixed tags, mobile robots are mounted with RFID antennas and their trajectories are determined from the location of static (fixed) tags attached to walls. These techniques relies on dense tag deployments on walls to determine the trajectory used by the robot and have been specifically designed for scenarios such as stock taking in supermarkets [26] where static tags are placed on shelving. If these approaches are directly implemented in our problem context then more resources are needed than what we currently use, for example, multiple tags have to be attached to the ground over the monitoring area. Also, patients have to carry wrist worn battery powered RFID readers [38] instead of low cost, lightweight and battery-less tags. In contrast, our developed algorithms are capable of accurately and reliably identify the traversal direction and path used by a person instrumented with a single passive RFID tag.

2.3.2 Localisation Methods

Nevertheless, a number of localisation methods exist that may be used to infer a tag bearer's location. These RFID based localisation techniques can be broadly classified into three main categories [11]:

1. *Distance based estimation:* This kind of estimation depends upon the use of properties of triangles such as triangulation and trilateration [11, 29]. The range measurement parameters are obtained from Received Signal Strength Indicator (RSSI) [17], Time of Arrival (ToA) [25], Angle of Arrival (AoA) [49], Time Difference of Arrival (TDoA) [37] and Received Signal Phase (RSP) [59].

2. *Proximity based estimation:* Proximity based estimation is a kind of sensing technique which determines how close an object is from a known priori location. If a tag is detected by a reader antenna, then the location of the tag is assumed to be within the readable zone of that particular antenna [29].

3. *Scene analysis:* Scene analysis consists of two distinct steps [17, 34, 40, 58]. In step 1, information about the features of the environment is collected and in step 2, obtained real-time measurements are compared with the previously collected data (from step 1) to infer the current location of the object.

A fine-grained RFID positioning system that is robust under multi-path and non-line of sight is proposed in [49]. The algorithm is specifically designed to identify the position of an RFID tagged missed object in the given space. For example, to identify a misplaced book in a library where books, racks and shelves have a passive RFID tag on them. This algorithm uses a pre-defined hierarchical algorithm to first identify the rack and then the shelf holding the book and then use a dynamic time warping technique to pinpoint a tag location. Therefore, localizing a static object can be determined with such systems.

Landmarc [34] utilises the scene analysis technique to identify the spatial position of a desired tag from the reference tags whose locations are known previously. They first locate the reference tags that are near to the desired tag and then using their RSSI value and the k-NN algorithm, the nearest tag location is calculated.

Some of the other works that utilise scene analysis to localise the desired tag location with the help of reference tags are discussed in [40, 54, 58]. In [58], the authors localise the desired tag's location by utilising a 2D grid of reference tags and proximity, while in [40], the Kalman filter based technique is used in locating the desired tag and in [54] weighted centroid localisation and PF are employed to track the objects. However, all of the above discussed methods, regardless of the technique they use, rely on reference tags to localise the position of the desired tag.

Quite different to the above discussed methods, in [20, 39], the authors have proposed a device-free tracking method using passive reference RFID tags. In Twins [20], the authors utilize the critical state i.e, the interference caused by the object/person moving in the state space to the fixed tags to identify that a motion has occurred and to track the motion. In the Tag Track [39], however, a new fingerprinting based tracking system is introduced that utilizes k-NN and Gaussian mixture model based HMM to identify the reference tag that is near to the moving object. Unlike the other reference tag based localization discussed previously, [20] and [39] have proposed a method for device-free tracking, however, they still depend upon reference tags to localize the position of the moving object and no evidence for continuous path detection is found.

In [56] indoor spatial queries are evaluated from a PF based method. In contrast to other studies discussed, this work does not need reference tags but introduces nodes and edges all along the state space and assume that the object is moving only along the nearest edge by compromising on fine-grain localization. Also, the discontinuity in their antenna set-up does not allow continuous tracking of objects. Instead, objects missing over a period of time are assumed to be in one of the rooms that are nearest to the last seen location. Although such methods can be beneficial in estimating spatial queries, it cannot be directly implemented in continuous tracking applications. However, the research methods used in [56] serve as a basis for our work, which also does not rely on reference tags. In contrast to [56] we are interested in continuous and accurate monitoring of temporal and spatial coordinates of a tag bearer.

Other than [20, 39, 56], all other localisation techniques discussed above successfully localise a tag using more expensive active RFID tags, in contrast, we use low cost, lightweight, passive (battery-less) RFID tags which power themselves when they are interrogated by an RFID antenna. Therefore the received signals in our system are often noisier and can only be used in a limited working range. We are interested in using passive RFID tags because they are maintenance free (batteryless), unobtrusive and can be easily integrated into clothing as washable passive RFID tags are already a commercial reality [5]. Also, hospitals are places where hygiene is a top priority, so these low cost tags can be easily disposed if required.

Chapter 3

Addressing Location Uncertainty in Asset Tracking

There are two articles included in this chapter where each of section contains one paper.

3.1 An Accurate Method for Managing Missing Reads in RFID Enabled Asset Tracking

This section includes a short paper containing preliminary results obtained for the managing location uncertainty in the context of the returnable asset tracking application.

R. Sankarkumar, D. C. Ranasinghe, and T. Sathyan. A highly accurate method for managing missing reads in RFID enabled asset tracking. *In 10th International Conference on Mobile and Ubiquitous Systems (MOBIQUITOUS)*, Tokyo, Japan, 2013. Ranked as A according to Core conference ranking 2014.

Variables s, m and q are clearly defined in this thesis version of the paper (not found in the published paper) in order to address the reviewer comments.

Sankarkumar, R., Ranasinghe, D. & Sathyan, T. (2014). A Highly Accurate Method for Managing Missing Reads in RFID Enabled Asset Tracking. In Stojmenovic I., Cheng Z. & Guo S. (eds). *Mobile and Ubiquitous Systems: Computing, Networking, and Services. MobiQuitous 2013*. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 131. Springer.

NOTE:
This publication is included on pages 22 - 27 in the print copy of the thesis held in the University of Adelaide Library.

It is also available online to authorised users at:

http://dx.doi.org/10.1007/978-3-319-11569-6_53

3.2 An Accurate and Scalable Approach for Addressing Location Uncertainty in RFID Enabled Asset Tracking

The article included in this section is a conference paper which is an extension of the previous article with an improved tracking algorithm formulated in the context of a two dimensional tracking problem with detailed simulation based experiments and results.

R. Sankarkumar, D. C. Ranasinghe, and T. Sathyan. A highly accurate and scalable approach for addressing location uncertainty in asset tracking applications. *In IEEE International Conference on Radio Frequency Identification (IEEE RFID)*, Orlando, USA, 2014. Ranked as B according to Core conference ranking 2014.

Sankarkumar, R., Ranasinghe, D.C. & Sathyan, T. (2014). A highly accurate and scalable approach for addressing location uncertainty in asset tracking applications. *2014 IEEE International Conference on RFID (IEEE RFID)*, Orlando, FL, 2014, pp. 39-46.

Chapter 4

Addressing Location Uncertainty in Tracking People

The article included in this chapter is a conference paper that proposes a novel method for addressing wandering-off by revealing the traversal direction and path used by the tag bearer in fine-grained precision.

R. Sankarkumar and D. C. Ranasinghe. Watchdog: A novel, accurate and reliable method for addressing wandering-off using passive RFID tags. *In Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems (MOBIQUITOUS)* London, UK, 2014. Ranked as A according to Core conference ranking 2014.

The address of the University is changed from North Adelaide to Adelaide in this published paper in order to address the reviewer's comments.

Sankarkumar, R. & Ranasinghe, D.C. (2014). Watchdog: A novel, accurate and reliable method for addressing wandering-off using passive RFID tags. In *Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems (MOBIQUITOUS)*, London, UK.

NOTE:
This publication is included on pages 38 - 47 in the print copy of the thesis held in the University of Adelaide Library.

It is also available online to authorised users at:

http://dx.doi.org/10.4108/icst.mobiquitous.2014.258040

Chapter 5

Development of a Generic Sensor Model

The article included in this chapter is a journal paper that proposes a generic sensor model using Kernel Density Estimation to eliminate the need for a training data collection phase while deploying the *watchdog* system in a new environment.

R. Sankarkumar and D. C. Ranasinghe. Watchdog: Practicable and unobtrusive monitoring technology for addressing wandering-off with low cost passive RFID. *In the International Journal of Pervasive and Mobile Computing (PMC), Special Issue on Pervasive Computing for Gerontechnology* (Under Review). Ranked as B according to Core journal ranking 2014.

Watchdog: Practicable and Unobtrusive Monitoring Technology for Addressing Wandering-off with Low Cost Passive RFID

Rengamathi Sankarkumar*, Damith C Ranasinghe

Auto ID Labs, The University of Adelaide, Adelaide SA 5005, Australia
**email: rengamathi.sankarkumar@adelaide.edu.au*
**ph:+61 8 8313 4727, *fax:+61 8 8313 4366*

Abstract

Given ageing populations around the world, wandering-off, or elopement, by older people at acute hospitals and nursing homes is a growing problem. Wandering-off incidents can lead to serious injuries and even accidental morbidity. Although various intervention technologies exist for monitoring wandering-off behaviour (such as door alarms), they are expensive, often lead to false alarms, and are unable to differentiate patients and carers, or patients with different needs. In this article we introduce a system that relies on a particle filtering (PF) based algorithm for accurate location monitoring to accurately identify the traversal direction and traversal path used by a person instrumented with a single batteryless (passive) RFID tag on their attire. We use commercial RFID technology and provide an unobtrusive battery-less sensing approach to continuously and automatically monitor wandering-off among older people, but also facilitate individualized monitoring based on their care needs.

Keywords: Dementia; person tracking; particle filter; wandering off; RFID.

1. Introduction

Technologies such as alarms on exit doors [1] or battery powered, body-worn sensors that rely on proximity based sensing approaches [1, 2, 3] are often employed to provide an alarm based intervention to prevent older people from eloping from cared areas. Numerous drawbacks have been reported with these types of sensors; some are inefficient in differentiating caregivers from patients (e.g. alarms on doors), leading to unnecessary alarms, falsely detecting that a person has crossed the threshold of care giving area when they are still within a cared area (false alarms) [1], and maintenance issues such as the need to monitor and replace batteries. Caregivers using such technologies have reported the misleading nature of alarms, such as the alarm being unable to differentiate whether the resident has left the room or has simply opened the door, as well as the tendency to turn alarming systems off due to 'false alarms'or alarm fatigue from large number of false alarms [1]. A particular drawback of existing approaches is the inability to support individualized interventions to prevent wandering-off.

Radio Frequency Identification (RFID) is a wireless, automatic and unique identification technology [4] capable of addressing indoor tracking and monitoring problems using batteryless transponders that can be *unobtrusively* integrated in clothing, such as in linen tracking applications and also capable of continuously monitoring current and past spatio-temporal information of an individual. In [5], we first proposed the use of a single commercial-off-the-shelf (COTS) body-worn RFID (Radio Frequency Identification) tag for developing an approach to address elopement. This was done by automatically detecting the direction of travel as well as the unique identification of individuals, using a novel system capable of individualized interventions. Subsequently, in [6] we proposed a new algorithm that was both highly accurate and fast for not only identifying the traversal direction but also the path used by a person instrumented with a COTS RFID tag attached on their attire. The accuracy of the system relies on a measured sensor model developed by conducting extensive scene analysis of the deployment environment to obtain highly accurate results with low false alarms.

The ability to employ an unobtrusive batteryless sensor is specifically significant since wearable devices have been intentionally damaged as a way of evading existing alarming technologies [1]; therefore our approach using passive RFID with the ability to integrate into textiles is highly practicable. In this paper, we demonstrate that the limitation posed by extensive scene analysis needed for accurate traversal path and direction tracking to develop a wandering-off alarm intervention can be eliminated to achieve a practicable system capable of being deployed in real-life without the need for site specific investigations. Consequently, our proposed approach can reduce the cost of deploying our system in practice without compromising accuracy. The key contributions of this paper are:

- We propose a learnt model for RFID sensing infrastructure using Kernel Density Estimation (KDE) that considers the nature of radio wave propagation as well as the limitations of RFID technology [7]. The proposed model, developed using a training data set consisting of an RSSI (receive signal strength) map of the monitoring environment, forms the sensor model for our generalisable particle filtering based monitoring algorithm so that the algorithm can be implemented in practice without the need for further training data and site investigations.
- We integrate Kullback-Leibler (KL) divergence into our sensor model to overcome problems posed by information loss when the RSSI distribution in the training data set is used to generate a learnt sensor model based on approximating RSSI distribution over the monitoring region.
- Finally, we implement and evaluate the developed algorithm for wandering-off monitoring through experimental deployments with 10 volunteers to evaluate the performance and accuracy of our PF based algorithm in a supervised and unsupervised environment, with and without a learnt sensor model. Furthermore, we investigate and demonstrate the need for the proposed four antenna configuration for monitoring a large spatial region by comparing our results with a setting with two antennas. We show that our apporoach using a COTS RFID tag attached to clothing can eliminate false alarms when detecting wandering-off incidents and can subsequently provide a highly accurate estimate of the path followed by a wandering-off person to facilitate search efforts by caregivers.

The rest of the paper is summarised as follows: The next section gives an overview of the existing technologies that address wandering off and research works that identify traversal direction. Section 3 gives a system overview. Section 4 describes our generalisable PF based monitoring algorithm to determine the traversal path and direction used by the tag bearer and Section 5 provides experimental evidence to demonstrate the feasibility of our system. We summarise our contributions and discuss future work in the Section 6.

2. Related Work

Uses of alarms on door exits is a well known technology in monitoring elderly. There are two types of alarm systems [1]: i) alarms that sound when the door is opened; and ii) alarms that sound when a person wearing a sensor (e.g. a battery powered wrist bracelet) approaches the door. However, these kinds of alarms have several drawbacks such as caregivers not hearing the alarm, inability to identify the room immediately, older people removing the bracelet, or battery of the worn device being flat [1, 8]. Some of the recent researchers have used android powered phones [2] and battery powered WiFi tags [3] to address wandering. However, a common drawback for all the above mentioned technologies is the need to carry bulky battery powered devices. Furthermore, automatically identifying an individual uniquely is still a challenging task because door alarms sound simply when a person enters its readable range and are not capable of differentiating caregivers from patients. As reported in [1], even in the case of hearing an alarm, caregivers show negligence as they assume that an employee would have triggered the alarm. In contrast to the existing methods, our PF based tracking algorithm is robust and accurate in finding the tag traversing direction and thus drastically reducing the false alarm rate.

The number of works that utilise passive tags for determining tag traversal direction is limited. In [9], authors use several antennas and record the tag events as they are detected. Then, using the order of events, tag direction is determined. However, their research is conducted using expensive active RFID tags to determine the traversing direction of a tag. In [10], the time interval between tag detections by the static reader antennas is used to find the tag traversal direction, however, this method has only been successful with dense tag deployments (10 or more tags) and cannot be implemented with a single tag. In [11], a direction of arrival technique is proposed to discover the moving direction of a tag, however, experimental evaluation of their method is not presented. In [5], we developed two methods using tag phase and its radial velocity to determine tag direction of a passive tag worn by a moving person. However, the accuracy of this system is below 90% and it is also likely to be affected by walking speed of the tag bearer. To the best of our knowledge, we were the first to study the traversing direction and path of a tag bearer using passive RFID tags attached to their attire and using fixed antennas [6]. In this paper, we have extended our work by eliminating the need for the site specific scene analysis technique by developing a learnt sensor model integrated with KL divergence to develop a generalisable algorithm.

A related research problem can also be found in research works in the area investigating Mobile robots' trajectories [12, 13] by utilising mobile antennas and fixed tags. Mobile robots are mounted with RFID antennas and their trajectories are determined from the location of the static tags attached to walls or fixed infrastructure. These techniques rely on dense tag deployments to determine the trajectory used by the robot. They have been specifically designed for scenarios such as inventorying stocks in supermarkets [12] where static tags are placed in a shelf. If these approaches are directly implemented in our problem context then more resources are needed than what we currently use, for example, multiple tags have to be attached to the ground over the monitoring area. Also, patients have to carry wrist worn battery powered RFID readers [8] instead of light weight tags. In contrast, our approach is capable of accurately and reliably identifying the traversal direction and path used by a person instrumented with a single passive RFID tag.

Alongside research into continuous path estimations, a number of existing RFID tag localisation methods may be used to infer the tag bearer's location over time. These localisation techniques can be broadly classified into three main categories [14] summarised and discussed below.

Distance based estimation: This kind of estimation depends upon the use of the properties of triangles such as triangulation and trilateration [14, 15]. The range measurement parameters are obtained from Received Signal Strength Indicator (RSSI) [16], Time of Arrival (TOA) [9], Angle of Arrival (AOA) [17], Time Difference of Arrival (TDOA) [10] and Received Signal Phase (RSP) [5]. For instance, in [10] the authors proposed a method using time difference of signal arrival, which is measured by the strength of the received signal at two antennas, to estimate the tag TDOA.

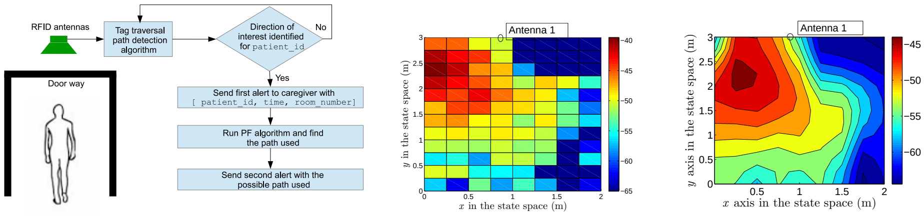
Scene analysis: Scene analysis consists of two distinct steps [16, 18, 19, 20]. In step 1: information about the features of the environment is collected; and in step 2: obtained real-time measurements are compared with the previously collected data (from step 1) to infer the current location of the object. Landmarc [18] utilises the scene analysis technique to identify the spatial position of a desired tag from the reference tags whose locations are known previously. They first locate the reference tags that are near to the desired tag and then using their RSSI value and the k-NN algorithm, the nearest tag location is calculated. Some of the other works that utilise scene analysis to localise the desired tag location with the help of reference tags are discussed in [19, 20, 21]. In [19], the authors localise the desired tag's location by utilising a 2D grid of reference tags and a proximity map, while in [20], a Kalman filter based technique is used in locating the desired tag and in [21] weighted centroid localisation together with a PF is employed to track objects. However, all of the above discussed methods, regardless of the technique they use, rely on reference tags to localise the position of the desired tag.

In [22] indoor spatial queries are evaluated from a PF based method. In contrast to other studies discussed, this work does not need reference tags but introduces nodes and edges all along the state space and assume that the object is moving only along the nearest edges by compromising on fine-grain localisation of objects. Also, the discontinuity in their antenna setup does not allow continuous tracking of an object. Instead, if the object is missing for a while, then it is assumed that the object should be in one of the rooms that are nearest to the last seen location. Although such methods can be beneficial in a localisation system, it cannot be directly implemented in determining the traversal direction and path. However, the research approach used in [22] which deviated from the use of a reference tag to model the sensor for a PF in a localisation technique serve as a basis for our work.

Our Watchdog system identifies the tag traversing direction (e.g. moving out of a room) and tag traversal path from the raw RSSI readings obtained from a passive tag by tracking the tag in real time and preserving the information gathered in the past. Except [22], all the localisation techniques discussed above successfully localise a tag only using expensive active RFID tags. In contrast to active (battery-powered) RFID tags, we use low cost, passive (battery-less) RFID tags which power themselves when they are interrogated by an RFID reader, however, they often generate noisy signals and can only be used in a limited working range. We are interested in using passive RFID tags for our study because of their low-cost, lightweight, unobtrusiveness, and battery-less nature. Also, hospitals are places where hygiene is a high priority and these low cost tags can be easily disposed. In the next section we give an overview of our system.

3. An Overview of Watchdog

We briefly introduce our approach named *Watchdog*, a real-time approach capable of reliably identifying the traversal direction and traversal path used by a person wearing a passive RFID tag on their attire. We named our approach *Watchdog* because usually watch dogs are trained to protect people from hazardous situations and, furthermore, their keen sense of smell is capable of identifying the traversing path used by a particular person. The components we used in Watchdog to address wandering off are: i) a four port RFID reader; ii) four RFID antennas; iii) a passive RFID tag attached over clothing; and iv) two



(a) (b) (c)

Figure 1: (a) Overview of our system (b) Measured sensor model (c) Learnt sensor model

algorithms, detecting the tag traversal direction and the traversing path used while eloping. Fig. 1 (a) depicts an overview of our system.

When a passive RFID tag enters the monitoring zone (e.g., the doorway in Fig. 1 (a)), the 4 mounted RFID antennas power and interrogate the tag in order to obtain the time of the read, t, EPC (Electronic Product Code) assigned for each person, $patient_{ID}$, antenna ID, ant, that identifies the antenna reading the tag and the RSSI value, $rssi$. Thus, raw RFID reads r obtained here can be represented by the schema: [t, $patient_{ID}$, ant, $rssi$]. In contrast to the existing RFID localisation systems, Watchdog accurately identifies the traversal path and direction used by a tag bearer without any reference tags deployed in the state space. Instead, Watchdog employs $RSSI$ readings obtained from interrogating passive RFID tags attached to clothing. Typically, and as we have illustrated [6], RSSI based derivations of location information is highly noisy; therefore, Watchdog uses a particle filtering based approach to overcome the location uncertainty emanating from noisy RSSI measurements to provide a highly reliable approach for monitoring older people in real-time. We describe the particular approach investigated in this article in the following sections.

4. Generalisable Particle Filtering based Monitoring Algorithm

Our approach based on a particle filter works in an iterative fashion to estimate the posterior distribution of a hidden state (e.g., location of a patient) using the observations obtained (e.g., RSSI value) from the RFID infrastructure [23]. Our system explores an approach that is capable of continuously tracking the location of the tag bearer. Our approach is also capable of overcoming missed reads (false negatives) common in raw, real-time RFID data streams [24, 25]. Next, we explain the two critical models that are used to infer the location of a tag (i.e. person) in a dynamic system. They are: i) motion model; and ii) sensor model.

4.1. Motion Model

Motion model or system dynamics describe how the system evolves from the time step $t-1$ to the time step t.

$$l_t = f_t(l_{t-1}, v_{t-1}) \tag{1}$$

where l_t is the true state of the tag, and v_{t-1} is the independently and identically distributed (i.i.d.) process noise.

$$p(l_t|l_{t-1}) = p(l_t|s, \theta, l_{t-1}) \tag{2}$$

The motion model used in our system is shown in (2), where $l = (x, y)$ is the coordinate revealing the state of a tag. The conditional probability p$(l_t|s, \theta, l_{t-1})$ specifies the possible motion of the tag from the previous iteration to the current iteration, given the learning velocity factors: speed, s; and direction, θ. We have considered building a model that can dynamically adapt to the walking speed and direction of a person. Initially we considered the moving speed s to be the mean gait speed reported in [26] for people aged 40 and above and the probability of moving in any of the given direction θ to be equiprobable where θ = $\{0^o$, 45^o, 90^o,..., $315^o\}$. After every iteration we consider the difference between the predicted location and the estimated location to additively increase the speed s to adapt to increasing walking speeds and multiplicatively decreasing speed to adapt to the decreasing walking speeds and halts. The direction θ is updated by multiplicative increases in the probability in the direction of traversal in the previous time *t-1* and decreases in the probability of moving in all other directions.

4.2. Sensor Model

Before explaining the sensor model we give an overview of the development of our learnt model. In general, we can consider RFID tag readings reported by an RFID reader as a time series. In practice, a time series of tag readings $r_{1:m}$ $= \{(t_i, rssi_i, ant_i)\}_{i=1}^{m}$ is partitioned into non-overlapping fixed time segments of duration δt for a given $patient_{ID}$ where t is the time stamp of a tag read, $rssi$ is the Received Signal Strength Indicator (RSSI) value and ant is the ID of the antenna that captured the tag read at time t. From the sequence $r_{1:m}$, we obtain the observation z_t by calculating the mean and standard deviation RSSI value $\overline{rssi}_{ant}$ for each antenna, ant, that obtained a tag read; or

$$z_t = \{\overline{rssi}_{ant}\}_{ant=1}^{ant=w}$$

where the first time stamp t_1 in $r_{1:m}$ is used as the time t for the observation z and w denotes the number of antennas that captured a tag response in the sequence $r_{1:m}$.

Then, to develop a sensor model specific to the deployment settings of the sensing infrastructure, in our case the RFID reader antennas, we estimate the RSSI characteristics of the state space (the region or the area over which we are interested in monitoring a person). In our application context, we divided the state space with an equidistant grid [6]. The approximate distance of each grid is 25 cm $\times$ 25 cm. We obtained the training data by collecting the RSSI values in each of these grid intersections, as described in [6]. Using the data collected over a period of 4 seconds at each of the intersection points, we generate a RSSI map $rssi\_map$ that holds both mean and standard deviation for each of these grid locations. (Note: In [6], $rssi\_map$ only holds mean RSSI values whereas in this paper $rssi\_map$ holds both mean RSSI and standard deviation)

In [6], we demonstrated that the RSSI value reported by an RFID reader of a tag used to instrument a person, $\overline{rssi}_{ant}$, can be used in conjunction with the previousl y developed RSSI map, $rssi\_map$, to obtain an accurate location estimate of a person over time to infer the tag bearer's location and then subsequently determine traversal direction and traversal path of the person using a

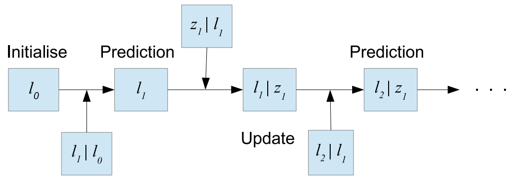


Figure 2: Particle filtering algorithm

particle filter [6]. However, this approach is limited by the need to conduct a laborious scene analysis to develop the RSSI map *rssi_map* for each deployment setting; therefore such an approach is not suitable for practical deployments which ideally require a learnt model that is agnostic to the deployment environment. We describe how we derived an effective learnt sensor model in the following section.

4.2.1. Learn a generic model

Our sensor model is built on a finite training data set collected using the scene analysis technique which we refer to as supervised environment. Now our goal is to learn a generic model using the collected data set, so that the algorithm can be implemented in practice without the need for further site investigation. So, we chose to smooth the finite data using Kernel Density Estimation (KDE).

KDE is a method used to estimate the probability density function of a random variable [27] given a finite data sample. A bivariate Kernel is often used in estimating probability densities in two dimensions. Using the training data (*rssi_map*) and by utilising the bivariate KDE method we learn the generic sensor model which we refer to as learnt model. For a bivariate random sample $\boldsymbol{X}_1, \ldots, \boldsymbol{X}_n$ drawn from a probability density f, the kernel density estimate is defined by

$$\widehat{f}_m(\boldsymbol{x}) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{m^2} \mathcal{K}\left(\frac{\boldsymbol{x} - \boldsymbol{X}_i}{m}\right) \tag{3}$$

where $\boldsymbol{x} = (x_1, x_2)^\top$ and $\boldsymbol{X_i} = (X_{i1}, X_{i2})^\top$, $i = 1, 2, \ldots, n$. Overall, from Eqn. 3 we estimate the probability density of our 2-dimensional random vector,

(X_{i1}, X_{i2}), where we use X_{i1} to represent the x axis of our state space and X_{i2} to represent the y axis of our state space centered at (x_1, x_2), $\mathcal{K}$ denotes a multivariate kernel function operating on the random variables. As we assume that the training data set's distribution is Gaussian and we use a Gaussian kernel, it can be shown that the optimal value of m is $m = 1.06\sigma n^{\frac{-1}{5}}$ [7], where σ is the sample standard deviation, i.e, the standard deviation of the training dataset ($RSSI\_map$).

The $\hat{f}_m(x)$ is our learnt model, which is the joint PDF of the random variables X_{i1} and X_{i2}. The measured sensor model of Antenna 1 and its corresponding generic sensor model learnt using Antenna 1 training data are shown in Fig. 1 (b) and (c), respectively. The rest of this section discusses how we utilise the learnt sensor model in our tracking algorithm.

4.2.2. KL divergence enhanced sensor model

Once there is an observation, the sensor (or measurement) model describes how the observation z_t relates to the true state l_t of the system.

$$z_t = h_t(l_t, u_t) \tag{4}$$

where h_t is a possible non-linear function, and u_t is i.i.d. measurement noise. Now we define the sensor model that we used in our system as shown below.

$$p(z_t|l_t) = p(\overline{rssi}_{ant}|l_t, ant, learnt\_model) \tag{5}$$

where $p(z_t|l_t)$ specifies the likelihood of obtaining a measurement z_t given the predicted state l_t. The conditional probability $p(\overline{rssi}_{ant}|l_t, ant, learnt\_model)$ specifies the mean RSSI and standard deviation of the raw reads, r, which is $\overline{rssi}_{ant}$, given given the predicted states of the tag, l_t, antenna ID, ant and learnt map, $learnt\_model$. Since $\overline{rssi}_{ant}$ and each of the grid intersections in $learnt\_model$ are two different probability distributions and we are interested in measuring the most similar probabilistic distribution in $learnt\_model$ of $\overline{rssi}_{ant}$, we employ the metric called Kullback-Leibler (KL) divergence. KL divergence is an effective metric used to measure the difference between two different probabilistic models [22]. For two probability distributions P and Q, KL divergence is defined to be,

$$D_{KL}(P||Q) = \sum_i P(i)\ ln\ \frac{P(i)}{Q(i)} \tag{6}$$

where $D_{KL}(P||Q)$, measures the information lost when the probability distribution Q is given to approximate the probability distribution P [22]. Therefore, in our sensor model, KL divergence is used to find the maximum-likelihood location by replacing $p(\overline{rssi}_{ant}|rssi\_map_{area})$ in Eqn. (5) as shown below.

$$p(z_t|l_t) = D_{KL}(\overline{rssi}_{ant}||learnt\_model) \tag{7}$$

The *learnt_model* is the learnt sensor model generated for the whole of the state space. Using the predicted current location we can determine the area of interest in the learnt sensor model, $learnt\_model_{area}$, which is the region that specifies the most probable tag movement in the learnt sensor model, *learnt_model*. We identify the area of interest, $learnt\_model_{area}$, in order to neglect the trivial area in the *learnt_model* while determining the final location after an observation z_t. In the motion model we defined how l_t specifies the possible probability of the current state given speed, s, direction θ and previous location of the tag l_{t-1}. Since the area of interest, $learnt\_model_{area}$, strongly depends on l_t, the tag bearers speed, direction and previous location decides the area of interest's boundaries. Also, by replacing *learnt_model* as $learnt\_model_{area}$ in the KL Divergence Eqn. 7, we can minimize the area to be calculated for information lost.

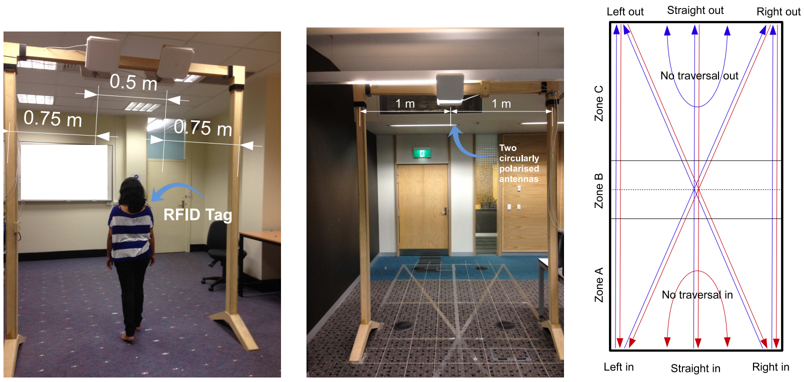
$$p(z_t|l_t) = D_{KL}(\overline{rssi}_{ant}||learnt\_model_{area}) \tag{8}$$

4.3. Recursive Filter

Below we discuss briefly the steps involved in one iteration of the PF. The flow of the PF based algorithm is illustrated in Fig. 2 (a).

Initialise: Particles corresponding to the state of an object are initialised according to $l_0^N \sim p(l_0)$, $N = 1, .., n$, where n is the number of particles used to represent the posterior state distribution of the object.

Predict: Predict the location of an object using the motion model at each time step. At t the state particles l are predicted to be in a location considering



(a) (b) (c)

Figure 3: (a) Four antenna setup (b) Two antenna setup (c) Traversal path

the state at $t-1$ and the observations obtained so far $z_{1:t}$. For $N = 1, ..., n$, predict particles, $l_t^N \sim q(l_t|l_{t-1}^N, z_{1:t})$, where q(.) is an importance function[23].

Update: On receiving an observation z_t, the predicted particles' locations are updated by weighting the particles using the measurement model to obtain importance weights w_t, $w_t^N = p(z_t|l_t^N)$, where high weights are given to the particles nearer to the measurement.

Normalize: The weights are normalised. For $N = 1, .., n$, normalize the importance weight, $w_t^N = w_t^N / \sum_{j=1}^{n} w_t^j$.

Resample: Increasing number of PF iterations leads to sample degeneracy, which means only few particles would have non-negligible weights while the remaining would have near-zero weights [23]. The resampling step eliminates the lower weighted particles and replicates higher weight particles to generate a new set of particles with equal weights [22]. The new set of particles thus obtained is equal to the original number of particles. For $N = 1, .., n$, set, $w_t^N = 1/n$.

4.4. Traversing Path Detection and Traversing Direction Algorithms

The traversing path detection algorithm and the traversing direction algorithms used in this paper follow algorithms 1 and 2 used in [6]. However, the sensor model in [6] utilizes a scene analysis based technique for building a measured sensor model. Instead, our algorithm utilizes the *rssi_map* that has RSSI mean and standard deviation to develop a learnt model with the help of KDE. In our proposed PF algorithm, on an observation, the KL divergence is used to measure the difference between a real time reading and the learnt model to obtain a better description of the relationship between the given observation and the true state of the person.

5. Experiments and Results

We conducted extensive experiments in two laboratory environments (supervised and unsupervised) to evaluate the ability of our algorithms with and without learnt models and with and without KL divergence to accurately identify the traversing path and the traversal direction used by the tag bearer. We further compared the results of our four antenna setup PF based TD and TPD algorithm with a two antenna setup PF based TD and TPD algorithm for to investigate the performance of our approach using a lower cost deployment option.

5.1. Settings and Data Collection

Our state space includes an area with 6 m length, 2 m width and 2.65 m height from the ground level. We considered the wooden frame (shown in Fig. 3 (a) and (b)) of 2 m width and 2.65 m height as the threshold that partitioned the inside (cared area) and the outside. Two antennas were deployed on the inner side of the frame and two were deployed on the outer side. The antennas were located 0.75 m from the side of the frame. All four antennas were inclined at 45° from the horizontal plane because a better illumination of the state space was obtained at this angle. The four antennas employed are circularly polarised antennas of model no: Impinj IPJA1000-USA. We used an Impinj Speedway Revolution UHF (Ultra High Frequency) RFID reader (R420) and 'Squiggle' passive tags. In the learnt model we rely on KDE where the value of d is 13 and n is 9 in Eqn. 3.

We considered 12 paths illustrated in Fig. 3 (c) where *Right-out to Left-in*, *Right-out to Right-in*, *Straight-out to Straight-in*, *Left-out to Left-in* and *Left-out to Right-in* were considered as moving in paths and *Left-in to Right-out*, *Left-in to Left-out*, *Straight-in to Straight-out*, *Right-in to Left-out* and *Right-in to Right-out* were considered as moving out paths. Two non-traversal paths, namely *No-traversal out* and *No-traversal in* were included to consider situations that involve activities inside the room or simply walking towards the outside and turning back.

We conducted our experiments first with two sensor models, namely learnt and measured. Then we integrated KL divergence into our sensor model and conducted experiments to evaluate the use of KL divergence in the above two sensor models. Our experiments investigated all the possible combinations of KL divergence and sensor models in the two environments, namely supervised (where initial measurements were taken) and unsupervised (a new, similar but different environment), in order to evaluate the robustness of our algorithms in different environments and using different models. Further, we have developed and used two approaches to evaluate the accuracy of the path estimation algorithm.

Then, we also utilized a new antenna setup with one antenna on either side (inside and outside) to evaluate the accuracy of the TPD and TD algorithms using a lower cost RFID infrastructure deployment (i.e fewer antennas and a 2 port RFID reader as opposed to a 4 port reader). The experimental setup is shown in Fig. 3 (b) where the antennas are placed in the center 1 m apart from either end of the wooden frame.

Fourteen healthy, young adults aged between 25 to 35 participated in the laboratory experiments. The mean±SD height of our participants was 169±8 cm. However, only the first 6 participants were involved in both the experiments. The passive RFID tag was attached to each participant's attire using double sided adhesive tape over the right shoulder as shown in Fig. 3 (a). Our participants performed a routine of 25 moving in path trials (a list of 25 paths randomly selected from *moving in* paths), a routine of 25 moving out path tri-

Table 1: Performance of our proposed TPD algorithm in the 2 antenna setting

Scenarios	TPD Algorithm	TP	FN	TN	FP	Recall	Precision	Accuracy
Two ant. with 9 segments	`Without KL`	108	392	47	153	$21.6 \pm 3\%$	$41.5 \pm 3\%$	$22.3 \pm 2\%$
Two ant. with 9 segments	`With KL`	113	387	51	149	$23.0 \pm 3\%$	$43.7 \pm 3\%$	$23.9 \pm 2\%$
Two ant. with 6 segments	`Without KL`	130	370	60	140	$26.6 \pm 3\%$	$48.5 \pm 2\%$	$27.7 \pm 3\%$
Two ant. with 6 segments	`With KL`	138	362	65	135	$28.4 \pm 2\%$	$51.2 \pm 3\%$	$29.2 \pm 2\%$

Table 2: Performance of our Proposed TPD Algorithm using Learnt Model in the Four Antenna Settings

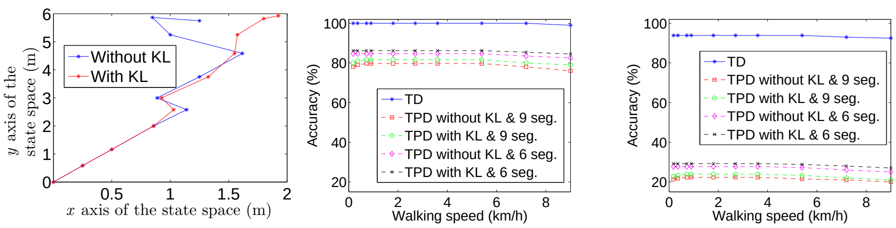
Scenarios	TPD Algorithm	TP	FN	TN	FP	Recall	Precision	Accuracy
In a supervised envi.	`Without KL`	366	134	141	59	$73.2 \pm 6\%$	$86.0 \pm 3\%$	$72.4 \pm 5\%$
In an unsupervised envi	`Without KL`	313	187	125	76	$62.6 \pm 4\%$	$80.5 \pm 2\%$	$62.5 \pm 3\%$
In a supervised envi	`With KL`	371	129	146	50	$74.2 \pm 5\%$	$88.2 \pm 3\%$	$74.3 \pm 4\%$
In an unsupervised envi	`With KL`	325	175	129	71	$65.0 \pm 3\%$	$82.1 \pm 2\%$	$66.9 \pm 3\%$
6 segmented supervised envi.	`Without KL`	393	107	161	39	$78.6 \pm 3\%$	$91.0 \pm 2\%$	$79.1 \pm 2\%$
6 segmented unsupervised envi.	`Without KL`	350	150	157	43	$70.0 \pm 3\%$	$89.1 \pm 2\%$	$72.4 \pm 3\%$
6 segmented supervised envi.	`With KL`	398	102	163	37	$79.6 \pm 2\%$	$91.6 \pm 2\%$	$80.1 \pm 2\%$
6 segmented unsupervised envi.	`With KL`	363	137	161	39	$72.6 \pm 5\%$	$90.4 \pm 3\%$	$74.9 \pm 4\%$

als (25 randomly selected from *moving out* paths) and 20 non-traversing path trials in total. All the participants were asked to walk at their normal speed and were not instructed to walk at any specified speed or manner.

5.2. Statistical Analysis and TPD Algorithm Evaluation Method

In this study, we evaluated the performance of both TPD and TD algorithms by determining: i) Recall = True Positives / (True Positives + False Negatives) and ii) Precision = True Positives / (True Positives + False Positives); and iii) Accuracy = True Positives + True Negatives / (True Negatives + True Positives + False Positives + False Negatives).

Since we are interested in determining if the supervised environment is similar to the unsupervised environment, we evaluated if the results in the supervised environment were statistically significantly different from the unsupervised environment. We used a two-tailed t-test where statistical significance was at p-values less than 0.05. In order to evaluate the performance of our TPD algorithm we partition our state space $2\,\text{m} \times 6\,\text{m}$ into 9 equal partitions as explained



(a) (b) (c)

Figure 4: (a) Performance of our algorithm with and without KL Divergence (b) Accuracy in terms of speed for four antennas deployment (c) Accuracy in terms of speed for two antennas deployment

in [6] and evaluated accuracy by counting the number of final location estimations in each of these partitions.

5.2.1. *Traversing Path Detection Algorithm*

When evaluating the TPD algorithm: True positives (TP) were the paths that were correctly identified (e.g. *Right-in* to *Left-out*); True negatives (TN) were paths of no interest that were correctly identified (e.g. *No-traversal in*); False negatives (FN) (i.e. missed reads) were paths that were not identified due to lack of readings reported from the reader antennas (e.g. *Left-in* to *Left-out* is being reported as *No-traversal out*); and False positives (FPs) are other movements that were identified as a moving direction of interest.

5.2.2. *Traversing Direction Algorithm*

Here, we define the terms used in TD algorithms. TPs were movements that were correctly identified (e.g. *moving out*). TNs were movements of no interest that were correctly identified (e.g. *No-traversal in*). FNs were movements that were not identified (i.e. *moving out* not being reported). FPs are other movements that were identified as a moving direction of interest (e.g. *No-traversal in* being identified as *moving out*).

5.3. Results

To evaluate the performance of our TPD algorithm in both the antenna setups we initially divided our state space into 9 equal parts. However, in most of the incorrect path detections the first segment prediction was wrong because our motion model is still dynamically adapting to the walking speed and moving direction of a tag bearer during the entry of the person to the cared area. After few iterations our PF based algorithm closely adapts to the moving person's direction and speed which resulted in better prediction. Further, when we are analysing data to identify the path used by a person we are only interested in the direction in which the person has left (i.e. eloped) the cared area as opposed to their entry. Therefore, we performed a further evaluation with six segments where the first three horizontal segments were removed from the evaluation without loss of information.

In Table 1 we introduce the results for the two antenna setup evaluated with the measured sensor model. From the Table 1 it is clear that the algorithm with KL divergence performed better than the algorithm without KL and 6 segment results are always slightly better than the 9 segment scenarios in two antenna setup. However, from the results it is clear that the two antenna setup are highly prone to false alarm rate of up to 59%.

The results from Table 2 and Table 3 show the performance of our TPD algorithm (detecting the path used by the tag bearer) using a learnt and measured model in various scenarios for four antenna setup. In four antenna setup, overall, measured model results in Table 3 performed better compared to the learnt model because measured models are concise formulation whereas learnt models are approximations made using KDE.

Similar to two antenna setup, it is clear from the Table 2 and Table 3 that our scenarios with KL divergence performed better in all the settings. In Fig. 4 (a), we have given the performance result of the sensor model with and without KL divergence for the same data set where the ground truth is *Left-in* to *Right-out*. This shows that our sensor model embedded with the KL divergence can better overcome problems posed by information loss when the RSSI distribution

Table 3: Performance of our Proposed TPD Algorithm using Measured Model in the Four Antenna Settings

Scenarios	TPD Algorithm	TP	FN	TN	FP	Recall	Precision	Accuracy
In a supervised envi.	`Without KL`	397	103	161	39	$79.4 \pm 5\%$	$91.1 \pm 3\%$	$79.7 \pm 4\%$
In an unsupervised envi	`Without KL`	343	157	143	57	$68.6 \pm 4\%$	$85.8 \pm 3\%$	$69.4 \pm 4\%$
In a supervised envi	`With KL`	404	96	167	33	$80.8 \pm 5\%$	$92.5 \pm 2\%$	$81.6 \pm 4\%$
In an unsupervised envi	`With KL`	367	133	150	50	$73.4 \pm 5\%$	$88.0 \pm 3\%$	$73.9 \pm 4\%$
6 segmented supervised envi.	`Without KL`	417	83	175	25	$83.4 \pm 3\%$	$94.4 \pm 2\%$	$84.6 \pm 3\%$
6 segmented unsupervised envi.	`Without KL`	385	114	159	41	$77.2 \pm 3\%$	$90.4 \pm 2\%$	$77.8 \pm 3\%$
6 segmented supervised envi.	`With KL`	424	76	179	21	$84.8 \pm 3\%$	$95.3 \pm 2\%$	$86.14 \pm 3\%$
6 segmented unsupervised envi.	`With KL`	392	108	166	34	$78.4 \pm 2\%$	$92.2 \pm 3\%$	$79.7 \pm 2\%$

in the training data set is used to generate a learnt sensor model based on an approximating RSSI distribution over the monitoring region. The results of our 6 segmented scenarios for both the models, with and without KL divergence, are also included in the Table 2 and Table 3. The evaluated results show that 6 segmented scenarios reduce the false alarm rate in path detection by 4% to 9% in the four antenna setup. This shows that our sensor model is considerably feasible in adapting to the walking pattern of the tag bearer after few iterations.

On comparing the results in the context of antenna setup, the results with the four antenna setup in Table 2 and Table 3, clearly out performs those obtained with the two antenna setup (e.g. highest false alarm rate of 59%). This is because the readable area covered by two antennas was significantly lower when compared with four antennas setup. Moreover, the four antenna setup has several areas covered by two or more overlapping read zones from multiple antennas so the tag bearer's position was more precisely calculated with the mean estimation. In contrast, the two antenna setup yielded low read rates in some areas and the rest of the areas were covered by only single antenna, so the lack of information had led to often imprecise location estimations.

Table 4 gives an overview of our TD algorithm results in all our possible settings discussed above. Our four antenna setup resulted in 100% accuracy in finding the tag traversal direction in all the circumstances. However, our two antenna setup resulted in a number of incorrect direction prediction in the

Table 4: Performance of our proposed TD algorithm

Scenarios	TD Algorithm	TP	FN	TN	FP	Recall	Precision	Accuracy
Four ant. with 9 & 6 segments	`With & without KL`	500	0	200	0	100%	100%	100%
Two ant. with 9 & 6 segments	`With & without KL`	453	47	200	0	90.6%	100%	93.9%

traversal paths that resulted in 93.3% in accuracy and 90.6% in recall due to the limited area readability of tags offered by the use of only two antennas. However, since the *non-traversal* paths were all correctly identified 100% precision was still maintained in the two antenna setup.

We also evaluated the effect of a tag bearer's traversing speed with the accuracy of our algorithms. We varied the walking speed from approximately 0.18 km/h (0.05 m/s) to 9 km/h (2.5 m/s). As shown in Fig. 4 (b) and (c) walking speed had some impact on the accuracy of our algorithm in both antenna setups. When the speed was increased from 0.18 km/h to 0.9 km/h there is a small reduction in the accuracy of all our TPD algorithms in both antenna setups. This is because our motion model is initialized with a constant speed with additive increases or multiplicative decreases to adapt to the walking speed of the tag bearer over several iterations. Therefore, the first few iterations may not accurately model the speed of the tag bearer and consequently resulted in poor location estimates. However, our TD algorithm was able to maintain 100% accuracy in determining the tag direction with walking speeds less than 7.2 km/h, beyond which the accuracy fell slightly lower to 99%. Although walking speed had some impact on the accuracy of our algorithms, our results were consistent in the normal walking speed (approx. 4.5 km/h to 5.25 km/h) according to mean gait speed reported in [26] for people aged 40 and above.

6. Conclusions

We developed a highly practicable and unobtrusive monitoring technology for addressing wandering off with a low cost passive RFID tag. Our proposed learnt model using KDE performed well by providing 100% accuracy in terms of detecting eloping incidents and virtually eliminating all false alarms. In particualr there was no change in performance when employing the measures sensor model and the learnt model in either supervised or unsupervised environments. In terms of detecting the eloping path, our learnt PF based TPD algorithm provided a false alarm rate $\leq 8\%$ in a 6 segmented supervised environment in conjunction with the KL divergence algorithm. It is also clear from the results in Table 2 and Table 3 that after integrating KL divergence into the sensor model the false alarm rate decreased by at least 2%.

Our approach is a considerable enhancement when compared to existing approaches. The new KL divergence integrated generalised sensor model is likely to result ease of deployment and therefore reduced cost of deploying the Watchdog system. Furthermore, given the elimination of false alarms in correctly identifying eloping incidents and being able to provide individualized interventions is likely to find higher levels of acceptance among caregivers. Even though our algorithm performed well throughout the study, certain path results such as *Right-in* to *Right-out* still performed poorly due to the higher occurrences of missed reads. Furthermore, compared to the results obtained in our previous work [6] our current results with KL in a 6 segmented analysis has improved by 4% to 6% in all three analysis in a supervised environment. Whereas, in an unsupervised environment our current results with KL in a 6 segmented analysis were comparable to the results obtained in our previous work [6].

One approach to overcome the limitations posed by the occlusion of the tag resulting in missed observations is to consider employing another tag above the second shoulder. Future work, should also investigate the accuracy of our algorithms with multiple participants and evaluate the system in a longitudinal trial in a clinical environment. These activities will form our future work.

7. Acknowledgment

This research was supported by a grant from the Hospital Research Foundation (THRF) and the Australian Research Council (DP130104614).

References

[1] M. A. Aud, Dangerous wandering: elopements of older adults with dementia from long-term care facilities, American Journal of Alzheimer's Disease and Other Dementias 19 (6) (2004) 361–368.

[2] F. Sposaro, A geriatric suite of medical applications for Android powered devices.

[3] J. Wan, M. J. O'Grady, G. M. O'Hare, Towards holistic activity modeling and behavioral analyses, 6th Int. workshop on Ubiquitous health and wellness, Newcastle, UK, 2012.

[4] P. H. Cole, D. C. Ranasinghe, Networked RFID systems and lightweight cryptography, London, UK: Springer. doi 10 (2008) 978–3.

[5] M. Zhou, D. C. Ranasinghe, A novel approach for addressing wandering off elderly using low cost passive RFID tags, in: Int. Conf. on MOBIQUITOUS, Tokyo, Japan, 2013.

[6] R. Sankarkumar, D. C. Ranasinghe, Watchdog: A novel, accurate and reliable method for addressing wandering-off using passive RFID tags, in: 11th Int. Conf. on MOBIQUITOUS, London, Great Britain, 2014.

[7] P. Vorst, Mapping, localization, and trajectory estimation with mobile robots using long-range passive rfid, Ph.D. thesis, University of Tuebingen (2011).

[8] D. C. Ranasinghe, R. L. Shinmoto Torres, A. P. Sample, J. R. Smith, K. Hill, R. Visvanathan, Towards falls prevention: A wearable wireless and battery-less sensing and automatic identification tag for real time monitoring of human movements, in: 34th Int. IEEE EMBS Conference, San Diego, USA., 2012.

[9] Y. Jian, Y. Wei, Y. Zhang, Estimating the direction of motion based on active RFID, in: 5th IEEE Int. Conf. on NISS, Vol. 2, 2011, pp. 286–290.

[10] Y. Oikawa, Evaluation of tag moving direction detection in a UHF RFID gate system, Journal of Circuits, Systems, and Computers 21 (06).

[11] Y. Zhang, M. G. Amin, S. Kaushik, Localization and tracking of passive RFID tags based on direction estimation, Int. Journal of Antennas and Propagation 2007.

[12] D. Joho, C. Plagemann, W. Burgard, Modeling RFID signal strength and tag detection for localization and mapping, in: ICRA'09, IEEE, 2009, pp. 3160–3165.

[13] D. Hahnel, W. Burgard, D. Fox, K. Fishkin, M. Philipose, Mapping and localization with RFID technology, in: ICRA'04, Vol. 1, IEEE, 2004, pp. 1015–1020.

[14] M. Bouet, A. L. Dos Santos, RFID tags: Positioning principles and localization techniques, in: Wireless Days, 2008. 1st IFIP, 2008, pp. 1–5.

[15] S. C. Kim, Y. S. Jeong, S.-O. Park, RFID-based indoor location tracking to ensure the safety of the elderly in smart home environments, Personal and ubiquitous computing 17 (8) (2013) 1699–1707.

[16] M. Goller, C. Feichtenhofer, A. Pinz, Fusing RFID and computer vision for probabilistic tag localization, in: IEEE RFID, Orlando, USA, 2014.

[17] J. Wang, D. Katabi, Dude, where's my card?: RFID positioning that works with multipath and non-line of sight, in: Proc. of the Conf. on SIGCOMM 2013, ACM, 2013, pp. 51–62.

[18] L. M. Ni, Y. Liu, Y. C. Lau, A. P. Patil, Landmarc: indoor location sensing using active RFID, Wireless Networks 10 (6) (2004) 701–710.

[19] Y. Zhao, Y. Liu, L. M. Ni, Vire: Active RFID-based localization using virtual reference elimination, in: ICPP, IEEE, 2007, pp. 56–56.

[20] S. S. Saad, Z. S. Nakad, A standalone RFID indoor positioning system using passive tags, IEEE Trans. on Industrial Electronics, 58 (5) (2011) 1961–1970.

[21] L. Yang, J. Cao, W. Zhu, S. Tang, A hybrid method for achieving high accuracy and efficiency in object tracking using passive RFID, in: PerCom, IEEE, 2012, pp. 109–115.

[22] J. Yu, W.-S. Ku, M.-T. Sun, H. Lu, An RFID and particle filter-based indoor spatial query evaluation system, in: Proc. of the 16th Int.Conf. on EDBT, ACM, 2013, pp. 263–274.

[23] M. S. Arulampalam, S. Maskell, N. Gordon, T. Clapp, A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking, IEEE Tran. on Signal Processing, 50 (2) (2002) 174–188.

[24] R.Sankarkumar, D. C. Ranasinghe, and T. Sathyan, A highly accurate method for managing missing reads in RFID enabled asset tracking, in: 10th Int. Conf. on MOBIQUITOUS, Tokyo, Japan, 2013.

[25] R. Sankarkumar, D. C. Ranasinghe, T. Sathyan, A highly accurate and scalable approach for addressing location uncertainty in asset tracking applications, in: IEEE RFID, Orlando, USA, 2014.

[26] R. W. Bohannon, Comfortable and maximum walking speed of adults aged 20–79 years: reference values and determinants, Age and Ageing 26 (1) (1997) 15–19.

[27] D. N. Politis, J. P. Romano, Multivariate density estimation with general flat-top kernels of infinite order, Journal of Multivariate Analysis 68 (1) (1999) 1–25.

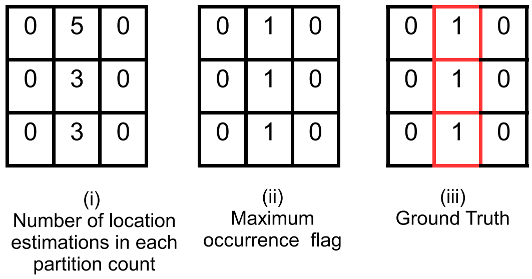
Chapter 6

Tracking in a Complex Multiple People Environment

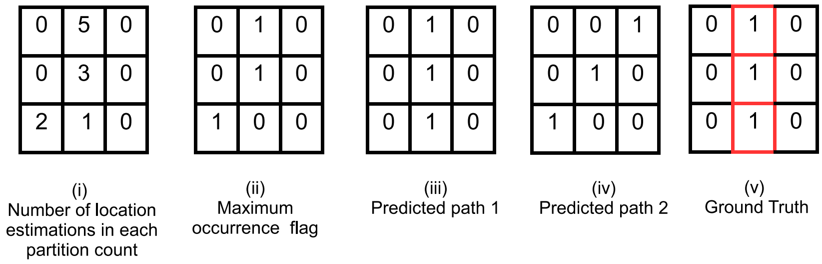
6.1 Introduction

Tracking multiple people present in a tracking area is vital in aged care and hospital environments as the presence of two or more people at the same time in the given region is quite common in these applications. Wandering-off is common behavior among cognitively impaired patients and there may be several reasons for this, such as changed environment, searching for the past, and expressing boredom [2]. It is also noted that if one patient has the intention to wander out of the cared area then that can be a catalyst for others to follow them [1]. Therefore, in an aged care or hospital environment there is a high chance of having two or more patients leaving or entering the cared area at the same time. There is also a possibility of patients trailing at the back of the carer to escape from the cared area. Therefore, it is vital to identify critical circumstances like when two or more patients leave the cared area, or to identify the act of an escaping patient who is hiding and trailing behind a care giver.

In this chapter, we evaluate the performance of our developed algorithms that were discussed in the previous chapters to successfully track multiple persons. We utilize the sensor model used in Chapter 5 for our PF based multiple people tracking algorithm. In addition, in order to improve the recognition of the path used by the tag bearer, we have utilized a well established speech pattern recognition technique called Dynamic Time Warping (DTW) [41, 49].



(a) Defined path



(b) Undefined path

Fig. 6.1 Motivation for DTW (Dynamic Time Warping)

6.2 Dynamic Time Warping

In Chapter 4, Section 6.3 we have defined how we evaluate the path used by a person. We divide the state space into 9 partitions and evaluated accuracy by counting the number of location estimations in each of these partitions and flag that partition as shown in Fig. 6.1a which shows the defined path *Straight-in* to *Straight-out*. On the other hand, there is a possibility for the partition results to show an undefined path as shown in Fig. 6.1b (ii). Now the chance of having a final path prediction closely relates to two possible paths as shown in Fig. 6.1b (iii) & (iv). In this situation, DTW is used to efficiently identify the path used by the tag bearer.

Dynamic Time Warping (DTW) is a method to measure the similarity between any two temporal data. DTW allows two time series that are locally out of phase to align in a non-linear manner in order to overcome the weakness of Euclidean distance metric [10]. In designing our people tracking profiles, DTW have a list of trial walking paths as reference paths and these were collected during the initial training phase. On receiving real time readings, the new path readings are compared with the possible paths as shown in Fig. 6.1b (iii) & (iv) to make an inference about the real path used by the tag bearer.

6.3 Generalizable PF based Monitoring with DTW

The generalizable PF based tracking algorithm used in Chapter 5 is utilized with the DTW algorithm for the multiple people tracking scenario. When a situation, such as that shown in Fig. 6.1b (ii), arises as a result of the TPD algorithm, then the DTW algorithm is triggered i.e., since the TPD algorithm resulted in an unknown path (do not resemble any of the predefined paths) the DTW algorithm is involved to infer the path used by the tag bearer. In this case, the possible predefined paths that would match with the unknown path are first identified. For example, consider Fig. 6.1b (ii) coming from top to bottom of the figure, the first two partions are believed to be true and the third partition is believed to be false. In order to finish the path, and assuming that the first two partition are true, we conclude that the third partition should be in the middle (see Fig. 6.1b (iii)). Also, as shown in Fig. 6.1b (iv), we can see that the first partition may be incorrect. This process leads to a collection of possible paths. After having a collection of possible paths, RFID tag read data for each path obtained from training data is individually compared with the real time RFID tag read data using DTW as described below.

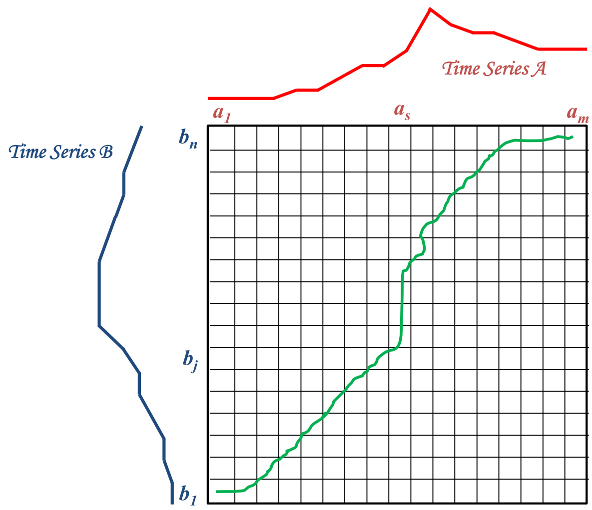


Fig. 6.2 Warping Cost Matrix

This figure is adapted from this presentation www.psb.ugent.be/cbd/papers/gentxwarper/DTWAlgorithm.ppt, created by Elena Tsiporkova

6.3.1 DTW Algorithm

Given two sequences from real time unknown path A and a possible path B_u from the collection of possible path B, composed respectively of m and n feature vectors,

$$A = a_1, a_2, a_3, ..., a_i, ...a_m$$

$$B_u = b_1, b_2, b_3, ..., b_j, ...b_n \; where \; B_u \in B$$

DTW searches for the best alignment that minimizes the total cost C [41] calculated using a cost matrix that defines the cost of mapping two points c_s as the euclidean distance in each cell.

$$C = c_1, c_2, c_3, ..., c_s, ...c_k$$

$$c_s = |a_i - b_j|$$

The algorithm is better explained using Fig. 6.2. The two time sequences that are being compared are shown along the two axes of c. Each cell in c_s gives the cost of aligning a_i and b_j. Since we are interested in the path that has close alignment with a predefined path, we find the sum of all the cell values and the lowest among all the possible routes is the final cost of the matrix. The green dots in Fig. 6.2 shows the smallest value of c_s for each sequence and the final cost for the sequence B_u is calculated using

$$Cost_u = \sum C \; where \; Cost_u \in Cost$$

. Then, $Cost_u$ will result in the cost of mapping the two sequences A and B_u. Now DTW is performed for the next pair of sequences i.e., A and another element in B. Once the cost of all the sequences in B are computed, the sequence that holds the minimum cost in $Cost$ will be concluded as the path used by the tag bearer.

6.3.2 Multi People Tracking Algorithm

We extended our algorithm to track multiple people instrumented with a passive RFID tag entering and leaving our state space. Multiple people tracking formulation can be efficiently implemented since each person of interest can be uniquely identified using the worn passive RFID tag's identifier and hence we not do have a data association problem. Whenever a person instrumented with a tag enters the monitoring area an independent PF based tracking algorithm is triggered to track the particular tag ID i.e., an independent PF based TPD and TD algorithm is spawned for the first observation of every new tag ID currently not being monitored. Here we have made the simplifying assumption that the motion of each individual is completely independent from any other individual.

For example, in Fig. 6.3a, person 1 with a tag ID $patient_1$ started walking in the path *Straight-in* to *Straight-out* at time 9.01. Now a PF based TPD and TD algorithm is run for every δt observation for that patient ID $patient_1$. Later, at time 9.03, we observe a reading for person 2 with a tag ID $patient_2$ in the left corner. Now a new PF based tracking algorithm is triggered with an initializations step, where particles are scattered all over the state space except the current position of $patient_1$. The TPD and TD algorithm is now initiated to track the path and direction of $patient_2$. The tag reading partition in Chapter 4, Section 4.1 works as below.

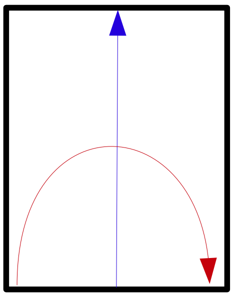
We partition a sequence of tag reading $r_{1:m} = \{(patient_{ID}, t_i, rssi_i, ant_i)\}_{i=1}^{m}$ in a non-overlapping fixed time segment δt for a given $patient_{ID}$ where $patient_{ID}$ is the patient identification number, t is the time stamp of a tag read, $rssi$ is the Received Signal Strength Indicator value and ant is the ID of the antenna that captured the tag read at time t. This is the same partitioning technique used in Chapter 4 and 5 except for the introduction of $patient_{ID}$ as one of the partitioning variable in addition to t and ant. From the sequence $r_{1:m}$, we obtain the observation z_t for each $patient_{ID}$, by calculating the mean RSSI value $\overline{rssi}_{ant}$ for each antenna ant that obtained a tag read.

$$z_{t(patient_{ID})} = \{\overline{rssi}_{ant}\}_{ant=1}^{ant=w}$$

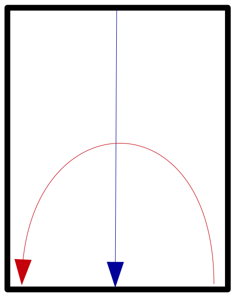
where, the first time stamp t_1 in $r_{1:m}$ is used as the time t for the observation z, and w denotes the number of antennas that captured a tag response in the sequence $r_{1:m}$. The obtained mean RSSI value $\overline{rssi}_{ant}$ is compared with the previously developed *rssi_map* to infer the tag bearer's location and then subsequently determine TD and TPD.

6.4 Experiments and Results

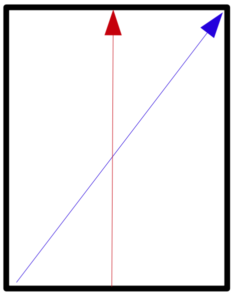
We conducted extensive experiments in a laboratory environment to evaluate the ability of our DTW included multi-people tracking algorithm to accurately identify the traversing path and the traversal direction used by the tag bearers.



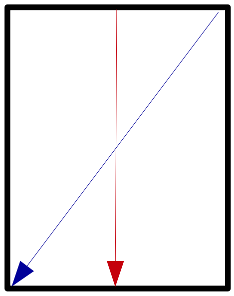
(a) **Path 1**
$patient_1$ - Straight in to Straight out
$patient_2$ - No Traversal left in to right in



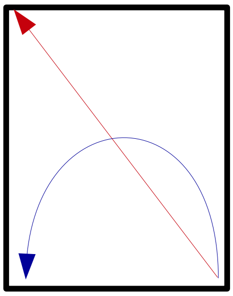
(b) **Path 2**
$patient_1$ - Straight out to Straight in
$patient_2$ - No Traversal right in to left in



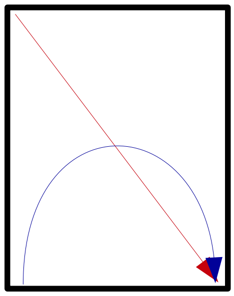
(c) **Path 3**
$patient_1$ - Left in to Right out
$patient_2$ - Straight in to Straight out



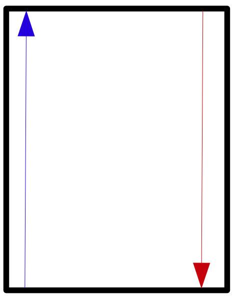
(d) **Path 4**
$patient_1$ - Right out to Left in
$patient_2$ - Straight out to Straight in



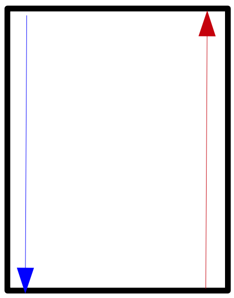
(e) **Path 5**
$patient_1$ - No Traversal Right in to Left in
$patient_2$ - Right in to Left out



(f) **Path 6**
$patient_1$ - No Traversal Left in to Right in
$patient_2$ - Left out to Right in

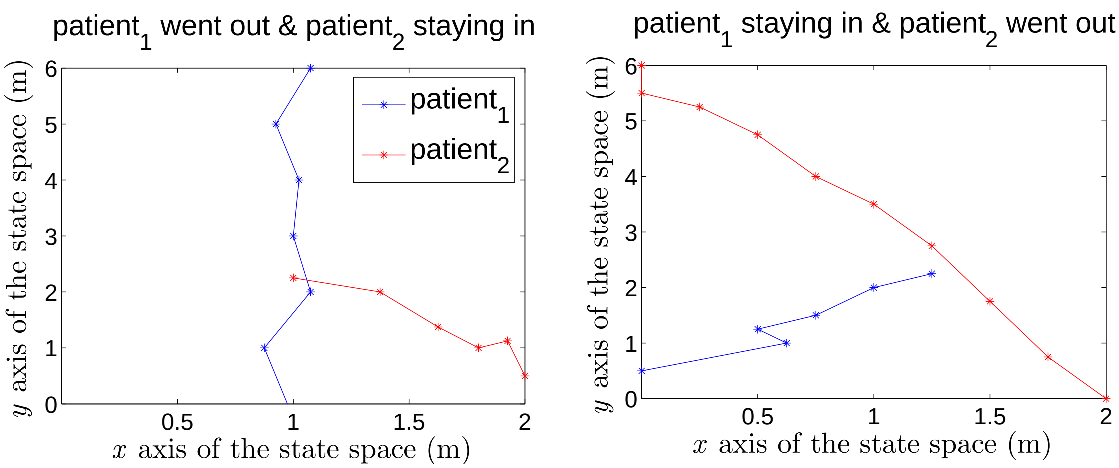


(g) **Path 7**
$patient_1$ - Left in to Left out
$patient_2$ - Right out to Right in



(h) **Path 8**
$patient_1$ - Left out to Left in
$patient_2$ - Right in to Right out

Fig. 6.3 Path Used by the Tag Bearers



(a) Path 1 (b) Path 5

Fig. 6.4 Performance of our TPD Algorithm in the Detection of Path 1 & 5

6.4.1 Settings

We have utilized the same state space that has been used in Chapter 4 and 5. We also conducted our experiment in the same environment described in Chapter 4 and 5.

The state space includes an area with length = 6 m, width = 2 m and height = 2.65 m from the ground level. We considered the same wooden frame of 2 m width and 2.65 m height as the threshold that partitioned the inside (cared area) and the outside. Two antennas were deployed on inner side of the frame and two were deployed on the outer side. The antennas were located 0.75 m from the side of the frame. All four antennas were inclined at 45° because a better illumination of the state space was obtained at this angle. The four antennas employed are circularly polarised antennas of model no: Impinj IPJA1000-USA. We used an Impinj Speedway Revolution UHF (Ultra High Frequency) RFID reader (R420) and 'Squiggle' passive tags.

The detailed paths that have been used by $patient_1$ and $patient_2$ in different scenarios are listed in Fig. 6.3. These scenarios are designed to take into consideration some of the possible movements in a hospital or aged care environment. For example, Path 5 explains the possible trailing behind a caregiver, where caregiver is the $patient_1$ (blue path) moving inside the cared path and the patient is the $patient_2$ who is trailing behind the caregiver until he reaches the door and then escapes by moving out using the *Right-in* to *Left-out* path.

Table 6.1 Multi-People Tracking Results with and without DTW

	Person	TD	TPD Accuracy (without DTW)	TPD Accuracy (with DTW)	Heading Out Accuracy
Path 1	$patient_1$	100%	36%	44%	**60%**
	$patient_2$	100%	0%	4%	-
Path 2	$patient_1$	100%	36%	40%	-
	$patient_2$	100%	0%	0%	-
Path 3	$patient_1$	100%	41%	52%	**64%**
	$patient_2$	100%	32%	36%	-
Path 4	$patient_1$	100%	44%	48%	-
	$patient_2$	100%	24%	32%	-
Path 5	$patient_1$	100%	0%	4%	-
	$patient_2$	100%	36%	40%	**60%**
Path 6	$patient_1$	100%	0%	0%	-
	$patient_2$	100%	36%	44%	-
Path 7	$patient_1$	100%	52%	60%	**72%**
	$patient_2$	100%	52%	56%	-
Path 8	$patient_1$	100%	48%	56%	-
	$patient_2$	100%	56%	60%	**68%**

6.4.2 Statistical Analysis

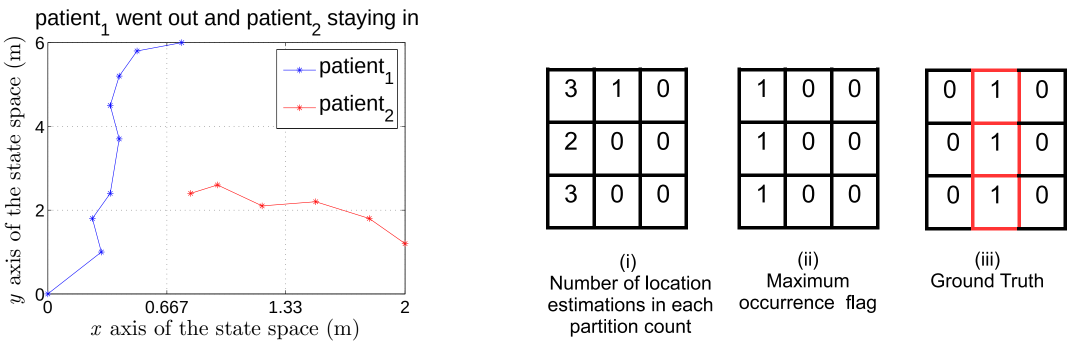
The evaluation of both TPD and TD algorithms follow the same statistical analysis as described in Chapter 4, Section 6.4 in the explanation of TP, TN, FP and FN for the TPD and TD algorithms. However, we have only evaluated the accuracy of the algorithm and did not calculate the recall or precision because of the nature of the evaluation. To evaluate recall and precision we need all four factors (TP, TN, FP, FN). However, while interpreting the results in terms of paths, it is possible to have all four factors in a single path shown in Fig. 6.3. Therefore, we have only evaluated the accuracy. In Table 6.1, we have provided the results for the multi-people tracking experiments in terms of the path used by $patient_1$ and $patient_2$.

6.4.3 Results

The results from Table 6.1 show that our multi-people tracking algorithm with a DTW algorithm performs better than the multi-people tracking algorithm without DTW algorithm. This is because our DTW algorithm was capable enough to identify some of the undefined paths that were actually predicted by the PF based TPD algorithm and compare them against the possible predefined paths to determine the actual path used by the tag bearer.

However, the DTW algorithm did not provide a significant improvement in accuracy and provide results comparable to experiments conducted with a single person. This is a result of the RFID system failing to read the tags worn by the participants in the experiments, especially for the $patient_2$. These missed reads are caused due to human interference in the state space which seriously affects the received signal strength as a result of fading, absorbing and scattering as well as instances where the body worn tag is completely occluded from the RFID infrastructure. In fact, one of the biggest challenges we faced while evaluating this data was missed reads. For example, the second person involved in the experiment often had on few tag detections in most traversal paths when $patient_1$ was walking closely before or after $patient_2$. The RF waves were completely absorbed and blocked by the $patient_1$ who was standing in between $patient_2$ and the antennas. Nevertheless, our algorithm was still able to identify the traversing direction used by the tag bearer with 100% accuracy in all the discussed paths.

The *No-traversal* paths were rarely identified in paths 1, 2, 5 and 6. As explained before, due to the significantly large number of missed reads our TPD algorithm was often unable to estimate the exact path used by the tag bearer, for example, *Left-in* to *Right-in*. Even though



(a) Example for path 1

(b) TPD evaluation of the example

Fig. 6.5 Performance Discussion of our Heading Out Accuracy in the Path 1

the algorithm failed to predict the whole path used by the tag bearer due to the missed reads and noisy RSSI data, in most of the circumstances, partial paths were correctly identified as shown in Fig 6.4. Consequently, *No-traversal*, i.e. the person is staying in the care area, was correctly identified by the TD algorithm but the path used was either partially identified or completely missed and subsequently evaluated as being incorrectly identified.

Therefore, we have investigated the accurate estimation of heading out direction or eloping direction as in practice that is the most important information to be provided to a caregiver. These results are presented in Table 6.1. Here, our intention is to evaluate whether the algorithm is able to identify the heading out direction used by the tag bearer i.e. *Left-out* or *Right-out* or *Straight-out*. Correctly predicting the heading out direction can be helpful in narrowing down the search space in the event of searching for a eloped patient. The last column in the Table 6.1 discusses the heading out direction accuracy for all the traversing out paths. On comparing the accuracy of the multi-people traversal paths, evaluating the heading out direction considerably improves the accuracy of the TPD algorithm by since we now allow partial paths to be counted as correct path estimations.

The obtained heading out direction prediction accuracy was $\leq 72\%$. However, the heading out accuracy is significantly less than the accuracy of our previous results, which were 95.3% for the 6 segmented supervised scenario with KL divergence discussed in Chapter 5 and 91% for the PF based technique discussed in Chapter 4.

Taking a detailed look at the experiments we can see that, in path 1, $patient_1$ is moving in the *Straight-in* to *Straight-out* path whereas $patient_2$ was using the *No-traversal Left-in* to *Right-in* path. Once $patient_1$ has passed the central region there is no interference from $patient_2$ to the $patient_1$ tag bearer. However, the accuracy of the heading out direction is

60%. Next, path 7 and path 8 hardly have human interference in tag readability, and their accuracy is only slightly higher when compared to rest of the heading out accuracy. There might be two reasons for this issue addressed below.

Firstly, the initial RSSI readings obtained for $patient_1$ are noisy because of $patient_2$'s interference in the radio wave propagation environment. In this circumstance, our PF algorithm starts predicting the path with the noisy readings and can lead to wrongly predicting the initial path of the tag bearer as shown in Fig. 6.5. In Fig. 6.5a, the real initial path the person started walking was in the *Straight-in* path, but due to the interference this path was wrongly identified as *Left-in* by our prediction algorithm. At the later prediction stages, the PF algorithm is unable to rectify the error because of the huge difference between the continuous prediction and the real path used as shown in Fig. 6.5a which also resulted in the wrong heading out direction as shown in Fig. 6.5b (ii). Secondly, for path 7 and path 8, even though the tag bearers are walking parallel to each other, there is some impact on the tag readability due to the thermal noise [55], phase noise [9] and occlusion of the tag. Also, the number of reads per reader for a tag decreases with the increase in the number of tags which leads to fewer tag readings and lower accuracy in finding the heading out direction.

6.5 Conclusion

Our approach can efficiently address wandering-off behavior by recognizing the direction and path used by multiple tag bearers simultaneously. In particular, our approach identified the tag bearer's traversal direction with an accuracy of 100%. Even though our TPD algorithm partially or completely failed in some path detections, the heading out direction of the in to out path's accuracy was $\geq 60\%$.

Even though our heading out accuracy was considerably lesser than our previous results, due to the inability to recover from the initial wrong predictions and thermal noise, our algorithm was able to predict the final exit partition as shown in Fig. 6.5. In Fig. 6.5a, the last prediction of our algorithm was in the *Straight-out* path. On having a look on the Fig. 6.5a, there is a high chance of estimating that $patient_1$ should have taken the *Straight-out* path. However, due to the nature of our TPD evaluation with relies strictly on the prediction count on each partition our algorithm predicted the actual path as *Left-out*.

For future works, the complexity of natural environments and users of these technologies will need to be taken into account in the evaluation through clinical trials. Also, the reported improvement in Table 6.1 due to using DTW in all cases is about 4%, which is overall only a slight improvement. This might be because the backscatter signal from an RFID tag is orientation sensitive i.e., the reader antenna's power reflected by the tag is not always the same and it is highly dependent on the orientation of the tag. This leads to RSSI value fluctuation. As discussed in [49] such sensitivity might degrade the performance of the DTW algorithm. This is because, the DTW algorithm fails to find obvious and natural alignment in two profiles caused by RSSI values fluctuation [49]. It is expected that by computing the derivatives of each paths before comparison might considerably increase the performance of our system and this is left as future work.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

This thesis presents a generalizable approach to manage location uncertainty in RFID based object or person tracking, and explores two specific application areas; returnable asset tracking; and automatic monitoring of wandering-off in aged care and hospital settings. The problem context is described in Chapter 1 where we have explained the two application areas and the challenges faced by passive RFID tag based tracking systems. Chapter 2 gives an overview of the current technology for both of the applications and reviews the state-of-the art in RFID based tracking approaches in the context of other technologies.

In Chapter 3, we have discussed our initial results while tracking assets in a coarse-grained, simple 1-Dimensional state space using a PF based tracking algorithm in Section 3.1. Our algorithm exclusively deals with missed reads in the asset tracking problem. Later in Section 3.2, we have analysed the problem more in depth and provided an improved solution for the problem considered in Section 3.1 with the following new contributions: i) introduced an object flow graph to model the possible moving path of objects in a 2D space and support the creation of a dynamic motion model; ii) provided, in detail, the particle filtering algorithm used in our approach to predict the location of objects under uncertainty caused by missing reads; iii) investigated a new motion model (dynamic motion model) and evaluated its ability to attain the same accuracy as that of the previously discussed static motion model; iv) improved the optimization technique by exploiting business related contextual information to aggregate objects that travel together instead of aggregating objects that travel together within a fixed time window as done in the previous paper; v) investigated the performance of our approach with respect to a growing business with an increasing number of customer locations; vi) presented results and extensively discuss: 1) the effect of number of particles used in the PF; 2) accuracy at locations where missing reads are highest in practice (loading docks and back entrance); 3) overall accuracy; 4) overall accuracy with increasing nodes in the object flow graph (i.e. increasing client base); 5) processing time (scalability); 6) memory usage (scalability); and vii) we also investigated the proposed the dynamic motion model and its accuracy.

In Chapter 4, we discuss a related but different problem which requires fine grained location tracking accuracy using noisy raw RFID data in the context of tracking people in an aged care environment. Our newly developed real-time system was able to accurately identify the traversal path and the traversal direction used by a tag bearer. Our approach was a significant enhancement when compared to existing approaches. Our approach can also be generalized to solve other problems like tracking goods that need fine-grain localization, for example, in a warehouse context.

In Chapter 5, we provide a more generalizable, practicable and unobtrusive monitoring technology to overcome the need for collecting training data while deploying our people tracking approach in a new environment. To achieve this, we proposed a generic sensor model for the PF based algorithm by utilising kernel density estimation. Furthermore, we integrate KL divergence into our sensor model to overcome problems posed by information loss when the RSSI distribution in the training data set is used to generate a generic sensor model based on an approximate RSSI distribution over the monitoring region.

Chapter 6 provides a fusion of all the discussed methods for fine grained tracking in the context of tracking people in an aged care environment consider the problem of tracking multiple people. Furthermore, we have utilized the DTW approach in our PF based tracking algorithm to identify the actual path used by the tag bearer.

Our thesis provides an approach for addressing location uncertainty, a significant challenge that would potentially degrade the performance of passive RFID systems in tracking applications. We particularly concentrated on two applications (i.e. asset tracking and tracking people) to identify generalizable solutions for the tracking problems. On having an option of either cleaning or managing uncertain data, we opt to manage the uncertain data. This is because cleaning data may identify missed reads but fail to identify the probable location of the moving object in case of missed reads. We successfully managed the uncertain RFID data by utilizing an effective PF based approach as a base and developed solutions for both the applications to overcome the location uncertainty caused by the uncertain RFID data. Our PF based asset tracking algorithm can be generalized to for use in any goods tracking application with minor or no changes in the algorithm. Similarly, our *watchdog* system can be used in any indoor based spatial monitoring system that needs fine grained details of a person's or object's position in an indoor space. Therefore, our algorithms can be generalized to solve location uncertainty problems in other tracking applications, such as baggage tracking in airports monitoring the location of goods in large warehouses, with few or no changes in the algorithm according to the application context and needs.

7.2 Future Work

Even though, our algorithm can be generalized to solve RFID based location tracking problems, it is not without limitations.

In the asset tracking application, although the dynamic model based tracking algorithm can quickly adapt to the changing nature of a business, the adaptability highly depends on the number of transactions made in a day. Also, the efficiency of the optimization of the tracking algorithm relies on the contextual information and the system is scalable because the objects that travel together are grouped and compressed as one object. If the objects travel independently then it is expected that the scalability of the system will reduce. Further, the results shown and discussed in Chapter 3 are from a simulation experiment, as practical implementation of the project was not possible due to the time constraints of the project. However, data requirements are derived from ILS company and the simulation was designed to closely match the actual data flows. At last, our approach works on the assumption that the object is not stolen. If an object is stolen at the first expected reading area, the object is assumed to have been missed by the RFID system, only when the object is continuously missed in the consecutive reading areas will our approach give an indication of the possibility of the object being stolen. Thus future work should focus on not only addressing missed reads but also differentiating insertions into the supply chain and as well as shrinkage (goods stolen) from the supply chain.

In tracking people, even though our algorithm performed well throughout the study, certain path results such as *No-Traversal*, discussed in Chapter 6 under the multiple people tracking scenario, frequently performed poorly due to the higher occurrences of missed reads caused by the interference of people present in the tracking space. As discussed in the chapter, since there were no reads for the tag at the beginning or the end of the path, it lead to the algorithm predicting an incorrect path. Positioning multiple tags such as one tag on both the shoulders i.e., replacing the single tag on the right shoulder with a tag on both shoulders may lead to better visibility of the tag. Similarly other combinations will also be trialed, for example, placing the tags on the front and back, only front and only back. Validating the multiple tag approach to improve the accurate identification of traversal paths is left as future work. We have not conducted experiments to evaluate the performance of our algorithm with more than two patients being tracked at the same time. We expect the accuracy of the direction and path estimation to reduce as we increase the number of people to be tracked. However increasing the number of particles used for prediction might mitigate this issue. On the other hand increasing the particles count will lead to high computational cost.

PF can perform better state estimation in non-linear/non-Gaussian models, albeit at additional computational effort. The number of particles used for prediction and the estimation accuracy of the hidden state are directly propositional. Lower number of particles will eventually lead to poor predictions about the hidden state. On the other hand large number of particles will lead to related high computational cost. In both of our applications, we have conducted experiments to evaluate the compromise between the number of particles (computational complexity) and state estimation accuracy.

From the discussion in the Chapter 6, it is clear that the TPD algorithm evaluation fails to identify the heading out path in some cases, such as, where the initial path was wrongly estimated as shown in Fig. 6.5. This shows that our PF based TPD algorithm needs a more sophisticated sensor model. In addition to the RSSI values, modern RFID readers can also provide phase angle measurements which can be utilised in estimating the distance between the tag bearer and the reader. As described in [36], by measuring the phase of the tag signal at two different frequencies the distance between the tag and the reader can be estimated using this formula.

$$d = -\frac{c}{4\pi}.\frac{\partial \varphi}{\partial f}$$

At present, the likelihood function we use relies only in the obtained RSSI values. Instead, joint likelihood function that can analyse obtained RSSI and change in phase measurements, might improve the location estimation accuracy. In future, utilisation of the phase angle measurements is expected to be one of the potential enhancement to the current system.

Furthermore, the complexity of natural environments and users of these technologies should be taken into account in an evaluation performed in clinical trials in the future. It is expected that deploying the system in an aged care environment might raise issues such as the appropriate positioning of sensors in nursing home buildings due to constraints imposed by the building. It should also be noted that we have not considered the extreme scenario in which the patients might completely remove their attire (attached with tags) from the body and still wander-off from a care area. Developing a solution to such a scenario may require investigating implantanble RFID tags.

References

[1] About health: Dementia. http://alzheimers.about.com/od/whattoexpect , 30/06/2014.

[2] Ageing population: http://www.pc.gov.au/research/completed/ageing-australia, 25/06/2015.

[3] Alzheimer's facts and figures. www.alz.org, 10/06/2014.

[4] The department of health: Dementia. www.health.gov.au/dementia, 10/06/2014.

[5] Fujitsu laundry tags. www.atlasrfidstore.com/rfid_laundry_tags_s, 17/10/2014.

[6] The history of RFID technology, http://www.rfidjournal.com/articles/view?1338/2, 11/05/2015.

[7] Azheimer's association and others. 2013 alzheimer's disease facts and figures. *Alzheimer's & Dementia: the Journal of the Alzheimer's Association*, 9(2):208, 2013.

[8] M. A. Aud. Dangerous wandering: elopements of older adults with dementia from long-term care facilities. *American Journal of Alzheimer's Disease and Other Dementias*, 19(6):361–368, 2004.

[9] J.-H. Bae, J.-C. Kim, B.-W. Jeon, J.-W. Jung, J.-S. Park, B.-J. Jang, H.-R. Oh, Y.-J. Moon, and Y.-R. Seong. Analysis of phase noise requirements on local oscillator for rfid system considering range correlation. In *Microwave Conference, 2007. European*, pages 1664–1667. IEEE, 2007.

[10] D. J. Berndt and J. Clifford. Using dynamic time warping to find patterns in time series. In *KDD workshop*, volume 10, pages 359–370. Seattle, WA, 1994.

[11] M. Bouet and A. L. Dos Santos. RFID tags: Positioning principles and localization techniques. In *Wireless Days, 2008. 1st IFIP*, pages 1–5, 2008.

[12] J. M. Chuah. *Managing Uncertainty in RFID Traceability Networks*. Undergraduate honors thesis, The University of Adelaide, November 2011.

[13] Y. Diao, B. Li, A. Liu, L. Peng, C. Sutton, T. Tran, and M. Zink. Capturing data uncertainty in high-volume stream processing. *The Biennial Conf. on Innovative Data Systems Research*, 2009.

[14] F. Doshi-Velez, W. Li, Y. Battat, B. Charrow, D. Curthis, J.-g. Park, S. Hemachandra, J. Velez, C. Walsh, D. Fredette, et al. Improving safety and operational efficiency in residential care settings with WiFi-based localization. *Journal of the American Medical Directors Association*, 13(6):558–563, 2012.

[15] M. J. Franklin, S. R. Jeffery, S. Krishnamurthy, F. Reiss, S. Rizvi, E. Wu, O. Cooper, A. Edakkunni, and W. Hong. Design considerations for high fan-in systems: The HiFi approach. In *CIDR*, pages 290–304, 2005.

[16] M. Goller and M. Brandner. Probabilistic modeling of rfid business processes. In *IEEE Int. Conf. on RFID-Tech. and Applications (RFID-TA)*, pages 432–436, 2011.

[17] M. Goller, C. Feichtenhofer, and A. Pinz. Fusing RFID and computer vision for probabilistic tag localization. In *IEEE Int. Conf. on RFID*, Orlando, USA, 2014.

[18] H. Gonzalez, J. Han, X. Li, and D. Klabjan. Warehousing and analyzing massive RFID data sets. In *22nd ICDE*, pages 83–83, 2006.

[19] D. Hahnel, W. Burgard, D. Fox, K. Fishkin, and M. Philipose. Mapping and localization with RFID technology. In *Proc. of IEEE Int. Conf. on Robotics and Automation, 2004. ICRA'04.*, volume 1, pages 1015–1020. IEEE, 2004.

[20] J. Han, C. Qian, X. Wang, D. Ma, J. Zhao, P. Zhang, W. Xi, and Z. Jiang. Twins: Device-free object tracking using passive tags. In *2014 Proceedings IEEE INFOCOM*, pages 469–476. IEEE, 2014.

[21] R. Hope and C. G. Fairburn. The nature of wandering in dementia: A community-based study. *Int. Journal of Geriatric Psychiatry*, 5(4):239–245, 1990.

[22] S. R. Jeffery, G. Alonso, M. J. Franklin, W. Hong, and J. Widom. *A pipelined framework for online cleaning of sensor data streams*. Citeseer, 2005.

[23] S. R. Jeffery, G. Alonso, M. J. Franklin, W. Hong, and J. Widom. Declarative support for sensor data cleaning. In *Pervasive Computing*, pages 83–100. Springer, 2006.

[24] S. R. Jeffery, M. Garofalakis, and M. J. Franklin. Adaptive cleaning for RFID data streams. In *Proceedings of the 32nd international conference on Very large data bases*, pages 163–174. VLDB Endowment, 2006.

[25] Y. Jian, Y. Wei, and Y. Zhang. Estimating the direction of motion based on active RFID. In *5th Int. Conf. on New Trends in Information Science and Service Science (NISS)*, volume 2, pages 286–290. IEEE, 2011.

[26] D. Joho, C. Plagemann, and W. Burgard. Modeling RFID signal strength and tag detection for localization and mapping. In *IEEE Int. Conf. on Robotics and Automation, 2009. ICRA'09.*, pages 3160–3165. IEEE, 2009.

[27] Y. V. Joshi. *Information visibility and its effect on supply chain dynamics*. PhD thesis, MIT, 2000.

[28] T. Kelepouris, M. Harrison, and D. McFarlane. Bayesian supply chain tracking using serial-level information. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews,*, 41(5):733–742, 2011.

[29] S. C. Kim, Y. S. Jeong, and S.-O. Park. RFID-based indoor location tracking to ensure the safety of the elderly in smart home environments. *Personal and ubiquitous computing*, 17(8):1699–1707, 2013.

[30] K. C. Lee, W.-C. Lee, B. Zheng, and Y. Tian. Road: a new spatial object search framework for road networks. *IEEE Transactions on Knowledge and Data Engineering*, 24(3):547–560, 2012.

[31] M. Lehtonen, D. Ostojic, A. Ilic, and F. Michahelles. Securing rfid systems by detecting tag cloning. In *Pervasive Computing*, pages 291–308. Springer, 2009.

[32] F. Miskelly. A novel system of electronic tagging in patients with dementia and wandering. *Age and Ageing*, 33(3):304–306, 2004.

[33] B. Nath, F. Reynolds, and R. Want. RFID technology and applications. *IEEE Pervasive Computing*, 5(1):22–24, 2006.

[34] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil. Landmarc: indoor location sensing using active RFID. *Wireless Networks*, 10(6):701–710, 2004.

[35] Y. Nie, R. Cocci, Z. Cao, Y. Diao, and P. Shenoy. Spire: Efficient data inference and compression over RFID streams. *IEEE TKDE*, 24(1):141–155, 2012.

[36] P. V. Nikitin, R. Martinez, S. Ramamurthy, H. Leland, G. Spiess, and K. Rao. Phase based spatial identification of uhf rfid tags. In *RFID, 2010 IEEE International Conference on*, pages 102–109. IEEE, 2010.

[37] Y. Oikawa. Evaluation of tag moving direction detection in a UHF RFID gate system. *Journal of Circuits, Systems, and Computers*, 21(06), 2012.

[38] 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 *34th Int. IEEE EMBS Conference*, San Diego, USA., 2012.

[39] W. Ruan, L. Yao, Q. Z. Sheng, N. J. Falkner, and X. Li. Tagtrack: device-free localization and tracking using passive RFID tags. In *Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*, pages 80–89. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2014.

[40] S. S. Saad and Z. S. Nakad. A standalone RFID indoor positioning system using passive tags. *IEEE Trans. on Industrial Electronics,*, 58(5):1961–1970, 2011.

[41] S. Salvador and P. Chan. Toward accurate dynamic time warping in linear time and space. *Intelligent Data Analysis*, 11(5):561–580, 2007.

[42] H. Samet, J. Sankaranarayanan, and H. Alborzi. Scalable network distance browsing in spatial databases. In *Proceedings of the 2008 ACM SIGMOD international conference on Management of data*, pages 43–54. ACM, 2008.

[43] R. Sankarkumar, D. C. Ranasinghe, and T. Sathyan. A highly accurate method for managing missing reads in RFID enabled asset tracking. In *10th Int. Conf. on Mobile and Ubiquitous Systems*, Tokyo, Japan, 12/2013 2013.

[44] R. Sankarkumar, D. C. Ranasinghe, and T. Sathyan. A highly accurate and scalable approach for addressing location uncertainty in asset tracking applications. In *IEEE Int. Conf. on RFID*, Orlando, USA, 2014.

[45] S. Sen and A. Nehorai. Sparsity-based multi-target tracking using OFDM radar. *IEEE Transactions on Signal Processing*, 59(4):1902–1906, 2011.

[46] D. Simon. *Optimal state estimation: Kalman, H infinity, and nonlinear approaches*. John Wiley & Sons, 2006.

[47] L. Sullivan. RFID implementation challenges persist, all this time later. *Information Week*, 1059:34–40, 2005.

[48] T. Tran, C. Sutton, R. Cocci, Y. Nie, Y. Diao, and P. Shenoy. Probabilistic inference over RFID streams in mobile environments, 2009.

[49] J. Wang and D. Katabi. Dude, where's my card?: RFID positioning that works with multipath and non-line of sight. In *Proc. of the Conf. on SIGCOMM 2013*, pages 51–62. ACM, 2013.

[50] E. Welbourne, N. Khoussainova, J. Letchner, Y. Li, M. Balazinska, G. Borriello, and D. Suciu. Cascadia: a system for specifying, detecting, and managing RFID events. In *6th Int. Conf. on Mobile systems, Applications, and Services*, pages 281–294, 2008.

[51] Y. Wu, D. C. Ranasinghe, Q. Z. Sheng, S. Zeadally, and J. Yu. RFID enabled traceability networks: a survey. *Distributed and Parallel Databases*, 29(5-6):397–443, 2011.

[52] D. Xie, Y. Qin, Q. Z. Sheng, and Y. Xu. Managing uncertainties in RFID applications-a survey. In *2014 IEEE 11th International Conference on e-Business Engineering (ICEBE)*, pages 220–225. IEEE, 2014.

[53] D. Xie, J. Xiao, G. Guo, and T. Jiang. Processing uncertain RFID data in traceability supply chains. *The Scientific World Journal*, 2014, 2014.

[54] L. Yang, J. Cao, W. Zhu, and S. Tang. A hybrid method for achieving high accuracy and efficiency in object tracking using passive RFID. In *IEEE Int. Conf. on PerCom*, pages 109–115. IEEE, 2012.

[55] L. Yang, Y. Qi, J. Fang, X. Ding, T. Liu, and M. Li. Frogeye: Perception of the slightest tag motion. In *Proc. of IEEE INFOCOM*, 2014.

[56] J. Yu, W.-S. Ku, M.-T. Sun, and H. Lu. An RFID and particle filter-based indoor spatial query evaluation system. In *Proc. of the 16th Int.Conf. on Extending Database Technology*, pages 263–274. ACM, 2013.

[57] Y. Zhang, M. G. Amin, and S. Kaushik. Localization and tracking of passive RFID tags based on direction estimation. *Int. Journal of Antennas and Propagation*, 2007.

[58] Y. Zhao, Y. Liu, and L. M. Ni. Vire: Active RFID-based localization using virtual reference elimination. In *Int. Conf. on Parallel Processing, ICPP 2007.*, pages 56–56. IEEE, 2007.

[59] M. Zhou and D. C. Ranasinghe. A novel approach for addressing wandering off elderly using low cost passive RFID tags. In *Int. Conf. on Mobile and Ubiquitous Systems*, Tokyo, Japan, 2013.