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 supervisor Dr. Damith C Ranasinghe for the support to pursue research in RFID, all the time he has given, his 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 supervisor A/Prof. Michael Sheng for the kind advice 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 would 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 mum 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, we have concentrated on two applications: i) asset tracking; and ii) tracking people. Our 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.


# Statement of Authorship

<table>
<thead>
<tr>
<th>Title of Paper</th>
<th>A Highly Accurate Method for Managing Missing Reads in RFID Enabled Asset Tracking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Publication Status</td>
<td>📅 Published, 📅 Accepted for Publication, 📅 Submitted for Publication, 📅 Publication style</td>
</tr>
</tbody>
</table>

## 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.

<table>
<thead>
<tr>
<th>Name of Principal Author (Candidate)</th>
<th>Renganathi Sankarkumar</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td>Performed simulation, gathered and interpreted data, wrote manuscript and acted as corresponding author.</td>
</tr>
<tr>
<td>Signature</td>
<td>Date 09/07/2015</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Name of Co-Author</th>
<th>Thuraliappah Sathyan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td>Helped to evaluate and edit the manuscript.</td>
</tr>
<tr>
<td>Signature</td>
<td>Date 03/07/2015</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name of Co-Author</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td></td>
</tr>
<tr>
<td>Signature</td>
<td>Date</td>
</tr>
</tbody>
</table>
**Statement of Authorship**

<table>
<thead>
<tr>
<th>Title of Paper</th>
<th>A Highly Accurate and Scalable Approach for Addressing Location Uncertainty in Asset Tracking Applications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Publication Status</td>
<td>Θ Published, ○ Accepted for Publication, ○ Submitted for Publication, ○ Publication style</td>
</tr>
</tbody>
</table>

**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.

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

<table>
<thead>
<tr>
<th>Name of Co-Author</th>
<th>Damith Ranasinghe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td>Supervised development of work, helped in data interpretation, manuscript evaluation and edit the manuscript.</td>
</tr>
<tr>
<td>Signature</td>
<td>Date 10/07/2015</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name of Co-Author</th>
<th>Thuraiappah Sathyyan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td>Helped to develop the algorithm, evaluate and edit the manuscript.</td>
</tr>
<tr>
<td>Signature</td>
<td>Date 03/07/2015</td>
</tr>
</tbody>
</table>

| Name of Co-Author | |
|--------------------||
| Contribution to the Paper | |
| Signature | Date |
### Statement of Authorship

<table>
<thead>
<tr>
<th>Title of Paper</th>
<th>Watchdog: A Novel, Accurate and Reliable Method for Addressing Wandering-off using Passive RFID Tags</th>
</tr>
</thead>
<tbody>
<tr>
<td>Publication Status</td>
<td>〇 Published, 〇 Accepted for Publication, 〇 Submitted for Publication, 〇 Publication style</td>
</tr>
</tbody>
</table>

### 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.

<table>
<thead>
<tr>
<th>Name of Principal Author (Candidate)</th>
<th>Rengamathi Sankarkumar</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td>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.</td>
</tr>
<tr>
<td>Signature</td>
<td>[Signature]</td>
</tr>
<tr>
<td>Date</td>
<td>09/07/2015</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name of Co-Author</th>
<th>Damith C Ranasinghe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td>Conceptualization of the study, supervised development of work, helped in data interpretation, manuscript evaluation and edit the manuscript.</td>
</tr>
<tr>
<td>Signature</td>
<td>[Signature]</td>
</tr>
<tr>
<td>Date</td>
<td>10/07/2015</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name of Co-Author</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td></td>
</tr>
<tr>
<td>Signature</td>
<td></td>
</tr>
<tr>
<td>Date</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name of Co-Author</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td></td>
</tr>
<tr>
<td>Signature</td>
<td></td>
</tr>
<tr>
<td>Date</td>
<td></td>
</tr>
</tbody>
</table>
# Statement of Authorship

<table>
<thead>
<tr>
<th>Title of Paper</th>
<th>Watchdog: Practicable and Unobtrusive Monitoring Technology for Addressing Wandering-off with Low Cost Passive RFID</th>
</tr>
</thead>
<tbody>
<tr>
<td>Publication Status</td>
<td>○ Published, ○ Accepted for Publication, ○ Submitted for Publication, ○ Publication style</td>
</tr>
</tbody>
</table>

## 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.

<table>
<thead>
<tr>
<th>Name of Principal Author (Candidate)</th>
<th>Rengamathi Sankarkumar</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td>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.</td>
</tr>
<tr>
<td>Signature</td>
<td>[Signature]</td>
</tr>
<tr>
<td>Date</td>
<td>09/07/2015</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name of Co-Author</th>
<th>Damith C Ranasinghe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td>Supervised development of work and in data interpretation, manuscript evaluation and edit the manuscript.</td>
</tr>
<tr>
<td>Signature</td>
<td>[Signature]</td>
</tr>
<tr>
<td>Date</td>
<td>10/07/2015</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name of Co-Author</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td></td>
</tr>
<tr>
<td>Signature</td>
<td>Date</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name of Co-Author</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Contribution to the Paper</td>
<td></td>
</tr>
<tr>
<td>Signature</td>
<td>Date</td>
</tr>
</tbody>
</table>
Table of contents

Table of contents xvii
List of figures xix
List of tables xxi
Nomenclature xxi

1 Introduction 1
  1.1 Motivation .................................................. 2
  1.2 Challenges .................................................. 4
  1.3 Author’s Main Contributions ................................. 8
     1.3.1 Addressing Location Uncertainty in Asset Tracking ........ 8
     1.3.2 Addressing Location Uncertainty in Tracking People .......... 8
  1.4 Document Overview .......................................... 9

2 Literature Review 11
  2.1 General Overview of Particle Filters .......................... 11
  2.2 Asset Tracking in Supply Chain Applications ................. 14
     2.2.1 Data Cleaning Techniques ................................ 14
     2.2.2 Managing Location Uncertainty ............................ 15
  2.3 Tracking People in Indoor Environments ...................... 16
     2.3.1 Identifying Traversing Direction and Traversal Path Used in an Indoor Environment ........................................ 17
     2.3.2 Localisation Methods ...................................... 17
<table>
<thead>
<tr>
<th>Chapter</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td><strong>Addressing Location Uncertainty in Asset Tracking</strong></td>
<td>21</td>
</tr>
<tr>
<td>3.1</td>
<td>An Accurate Method for Managing Missing Reads in RFID Enabled Asset</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tracking</td>
<td>21</td>
</tr>
<tr>
<td>3.2</td>
<td>An Accurate and Scalable Approach for Addressing Location Uncertainty</td>
<td></td>
</tr>
<tr>
<td></td>
<td>in RFID Enabled Asset Tracking</td>
<td>27</td>
</tr>
<tr>
<td>4</td>
<td><strong>Addressing Location Uncertainty in Tracking People</strong></td>
<td>37</td>
</tr>
<tr>
<td>5</td>
<td><strong>Development of a Generic Sensor Model</strong></td>
<td>49</td>
</tr>
<tr>
<td>6</td>
<td><strong>Tracking in a Complex Multiple People Environment</strong></td>
<td>75</td>
</tr>
<tr>
<td>6.1</td>
<td>Introduction</td>
<td>75</td>
</tr>
<tr>
<td>6.2</td>
<td>Dynamic Time Warping</td>
<td>76</td>
</tr>
<tr>
<td>6.3</td>
<td>Generalizable PF based Monitoring with DTW</td>
<td>77</td>
</tr>
<tr>
<td>6.3.1</td>
<td>DTW Algorithm</td>
<td>78</td>
</tr>
<tr>
<td>6.3.2</td>
<td>Multi People Tracking Algorithm</td>
<td>78</td>
</tr>
<tr>
<td>6.4</td>
<td>Experiments and Results</td>
<td>79</td>
</tr>
<tr>
<td>6.4.1</td>
<td>Settings</td>
<td>81</td>
</tr>
<tr>
<td>6.4.2</td>
<td>Statistical Analysis</td>
<td>83</td>
</tr>
<tr>
<td>6.4.3</td>
<td>Results</td>
<td>83</td>
</tr>
<tr>
<td>6.5</td>
<td>Conclusion</td>
<td>85</td>
</tr>
<tr>
<td>7</td>
<td><strong>Conclusion and Future Work</strong></td>
<td>87</td>
</tr>
<tr>
<td>7.1</td>
<td>Conclusion</td>
<td>87</td>
</tr>
<tr>
<td>7.2</td>
<td>Future Work</td>
<td>89</td>
</tr>
<tr>
<td>References</td>
<td></td>
<td>91</td>
</tr>
</tbody>
</table>
List of figures

1.1 Applications that Utilise Tracking ........................................ 1
1.2 A Simple RFID System: 1) An RFID Tag; 2) An RFID Reader Antenna; and 3) An RFID Reader .................................................. 2
1.3 An Example Supply Chain Routine ........................................ 4
1.4 Missed Reads in the Distribution Centre ................................. 5
1.5 Environmental effects on received RFID data .......................... 7
2.1 PF Process and an Example for the PF Steps .......................... 12
6.1 Motivation for DTW (Dynamic Time Warping) ....................... 76
6.2 Warping Cost Matrix ......................................................... 77
6.3 Path Used by the Tag Bearers ............................................. 80
6.4 Performance of our TPD Algorithm in the Detection of Path 1 & 5 81
6.5 Performance Discussion of our Heading Out Accuracy in the Path 1 84
List of tables

1.1 Types of RFID tags .................................................. 3
6.1 Multi-People Tracking Results with and without DTW .............. 82
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 [32]. 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](image)
Introduction

Table 1.1 Types of RFID tags

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

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 [42]. 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 [13].

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 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
Introduction

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 [37].

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 in
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 [42, 43]. 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 [11]. 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.

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

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 [11] 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

<table>
<thead>
<tr>
<th>Position</th>
<th>Read rate %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before the bottle</td>
<td>100</td>
</tr>
<tr>
<td>Behind the bottle</td>
<td>0</td>
</tr>
<tr>
<td>Behind the bottle with 3 cm of the tag unblocked</td>
<td>89</td>
</tr>
<tr>
<td>Side of the bottle</td>
<td>99</td>
</tr>
</tbody>
</table>

(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 co-ordinates 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 [17]. 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 [34] 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, 20, 31]. 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 [50]. 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 [44, 48, 54]. Particle filtering is a sequential Monte Carlo method that uses a set of particles for state estimation, where the state space model can be non-linear/non-Gaussian. PF operates in a recursive fashion to estimate the unknown state of the object as shown 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
(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
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 [14, 17, 30, 49] such as those associated with inventory control. According to [26], one of the most important benefits of such improved information visibility is realized in inventory management and asset utilization. According to the results in [26], 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 [12].

Uncertainty in RFID based asset tracking is particularly prone to false negatives, which is also known as missed reads. Missed reads make RFID data incomplete [34] 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 [21–23] 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 [51], 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 [15, 27, 46, 54] have used Bayesian techniques to manage the location uncertainty problem in tracking applications. In [15] authors have only addressed uncertainty caused by false positives. In [54] 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 [27], 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 [46] 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 [34], 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 [27], 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 [54], 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 [46], 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 [34].

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 [54]. Existing outdoor location based tracking technologies [29, 41] 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 [45] 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 [24], 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 [36], 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 [55], 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 [57], 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 [18, 25] 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 [25] 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 [37] 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 [10]:

1. **Distance based estimation:** This kind of estimation depends upon the use of properties of triangles such as triangulation and trilateration [10, 28]. The range measurement parameters are obtained from Received Signal Strength Indicator (RSSI) [16], Time of Arrival (ToA) [24], Angle of Arrival (AoA) [47], Time Difference of Arrival (TDoA) [36] and Received Signal Phase (RSP) [57].

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 [28].

3. **Scene analysis:** Scene analysis consists of two distinct steps [16, 33, 39, 56]. 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 [47]. 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 [33] 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 [39, 52, 56]. In [56], the authors localise the desired tag’s location by utilising a 2D grid of reference tags and proximity, while in [39], the kalman filter based technique is used in locating the desired tag and in [52] 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 [19, 38], the authors have proposed a device-free tracking method using passive reference RFID tags. In Twins [19], 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 [38], 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, [19] and [38] 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 [54] 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 [54] serve as a basis for our work, which also does not rely on reference tags. In contrast to [54] we are interested in continuous and accurate monitoring of temporal and spatial coordinates of a tag bearer.

Other than [19, 38, 54], 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.

A Highly Accurate Method for Managing Missing Reads in RFID Enabled Asset Tracking

Rengamathi Sankarkumar\(^{(2)}\), Damith Ranasinghe, and Thuraiappah Sathyan

Auto-ID Lab, The School of Computer Science, University of Adelaide, Adelaide, Australia
{rengamathi.sankarkumar,damith.ranasinghe,thuraiappah.sathyan}@adelaide.edu.au

Abstract. RFID based tracking systems have to overcome some significant challenges such as uncertainty to improve accuracy. We describe a highly accurate and scalable location tracking algorithm achieved by integrating an object compression technique with particle filtering.

Keywords: RFID · Tracking · Particle filter · Optimization · Supply-chain

1 Introduction

Radio Frequency Identification (RFID) is a promising unique identification technology widely adopted for tracking applications such as the location of goods in supply chains where the motivation behind using RFID based tracking is to improve the visibility of objects travelling though a supply chain [1]. But, RFID technology cannot be directly utilized because to obtain an accurate location tracking system, first, we must overcome uncertainty in RFID based tracking networks [2]. Uncertainty in RFID data is mainly caused by missed reads, where tagged objects exist in a readable zone but the RFID readers fail to read the tags due to factors such as interference, noise, distance between the reader and the tag [4]. The missed reads make RFID data incomplete [2] and when such noisy data is used in tracking applications the location of objects can become ambiguous.

Recent research such as [3] applied smoothing techniques to clean individual tag streams and estimate tag counts in a given location. However, these techniques are not suitable to identify anomalies such as missed reads. In [2] authors used a time varying graph model to capture packaging level information (containment relationships) and the location of an object is estimated using data inferred from the graphical model. But, this technique can only be applied for objects having a containment relationship such as cases on a pallet.

In this paper, we present a technique that addresses location uncertainty caused by missed reads in an RFID enabled returnable asset tracking application [1]. We propose a highly accurate method for real time tracking capable of estimating the most likely location of assets under uncertainty (missed reads) based
on a sampling-based inference technique known as particle filters. Furthermore, we develop a real-time object compression technique by exploiting objects that travel together to optimize the tracking algorithm. Finally, we conduct extensive experiments and evaluate the performance of the proposed tracking algorithm. The rest of the paper is organized as follows: Sect. 2 describes the problem we have considered; Sects. 3 and 4 explain the main contribution of the paper; and Sect. 5 concludes the paper.

2 Problem Statement

Before defining the problem, we define the notations used in this paper: (i) \( L = \{l_p | p = 1, \ldots, s\} \) denotes a set of locations where RFID tag reading capability is deployed; (ii) \( T = \{t_i | i = 1, \ldots, m\} \) gives a set of discrete time stamps; (iii) \( O = \{o_j | j = 1, \ldots, q\} \) is a set of tagged objects; and (iv) \( \text{transit} = \{\text{transit}\_l_p | p = 1, \ldots, s\} \) denotes transit times between fixed locations. Then raw RFID reads from a reader can be represented by the schema \{time\( (t_i)\), objectID\( (o_j)\), location\( (l_p)\)\}.

Returnable asset management requirements are derived from a linen services company in South Australia. In this scenario, trolleys (objects) are the returnable assets which are attached with RFID tags to increase their visibility. The company’s linen distribution scenario is depicted in Fig. 1, where RFID readers are installed in the trolley allocation area, loading docks, premises of customer locations and the back entrance of the company’s warehouse. If there is a missed read in any of these locations then the location of the object is ambiguous. The particle filtering (PF) based tracking algorithm attempts to resolve this ambiguity by predicting the most likely location.

3 PF Based Tracking Algorithm with Object Compression

A particle filter can be applied to any non-linear recursive Bayesian filtering problem [4]. To define the problem of tracking, we consider the evolution of the state sequence from: (i) the Motion Model \( x_t = f_t(x_{t-1}, v_{k-1}) \), where \( f_t \) is a possible non-linear function, and \( v_{k-1} \) is i.i.d. process noise; and (ii) the Measurement Model \( y_t = h_t(x_t, u_k) \), where \( h_t \) is a possible non-linear function,
Algorithm 1. PF-based tracking with object compression

Require: raw_reads^r = (T, O, L) where r = 1,2,... // (time, object ID, location) where T = {t_i | i = 1,..., m}, O = {o_j | j = 1,..., q}, L = {l_p | p = 1,..., 25}

Require: transit = {transit_k | k = 1,..., 25}, δt

1: t ← r.t_1 // get the initial time from raw_reads
2: while ∀ r ∈ raw_reads do
3:  if r.t_i >= t and r.t_i <= t + δt then
4:       if new_object_found then
5:         object_list.add(r.t_i, r.o_j, r.l_p, probability ← 1, new_object ← true)
6:       else
7:         object_list.update(r, probability, new_object ← false)
8:     end if
9:   else
10:      while ∀ o_j ∈ object_list do
11:         group_object ← grouped objects by location for time window [t and t + δt]
12:     end while
13:   for k = 1 to n do
14:      hashtable.put(ID^k, group_object^k)
15:      group ← (t, ID^k, location of k^th group_object)
16:     if group_object^k contains new_object(true) then
17:         initialize group
18:     end if
19:     predict, update, normalize and resample group
20:     object^d ← hashtable.get(ID^k) //get back the compressed objects
21:      object_list.update(∀ d ∈ object, probability)
22:   end for
23:   t ← r.t_i // next t from r
24: end if
25: end while
26: current_time ← current time from the system
27: while not_end_of(object_list) do
28:  obj ← object_list.get_next
29:  max_time ← obj.t_i + transit_{obj,l_p}
30:  if current_time > max_time then
31:     pred_loc ← the most likely location; pred_time ← obj.t_i + (transit_{obj,l_p})/2
32:     probability ← estimated probability of o_j
33:     obj.t_i ← pred_time, obj.l_p ← pred_loc
34:     object_list.update(obj)
35: end if
36: end while

and u_k is i.i.d. measurement noise. The PF consist of five steps: initialization, prediction, update, normalization and resampling [4].

The PF based tracking algorithm gives the most probable location l_p of the object o_j with N state particles, at every timestep t_i, as a probability distribution over l_p possible locations. The state space is defined along the x-axis. Every reader involved is represented as a sensor location along the x-axis.
The motion model is constructed with a transition matrix $M$. **Transition Matrix:** The transition probability is defined with a conditional probability, $p(L_{t_i}|L_{t_{i-1}})$ between locations $L_{t_i}$ and $L_{t_{i-1}}$, where the current time step is $t_i$ and previous time step is $t_{i-1}$. If $L$ has $p$ locations, then $M$ can be represented by a $p \times p$ matrix. **Measurement Model:** The measurement model used to update particles is drawn from a Gaussian distribution, because it models the decreasing probability of a tag being read as tags moves further from a reader.

Even though PF can improve location tracking accuracy, it suffers from high computational cost when implemented in large scale tracking applications involving large number of objects. To overcome the computational cost, we optimize the particle filtering based tracking algorithm by compressing the object stream reported by readers. The real-time object compression technique exploits objects that travel together from one location to another (not containment relationships [3]). Our approach is based on compressing a group of trolleys (objects) that are travelling together within a time window to a single aggregated object as shown in Algorithm 1. This compression can be achieved in three steps: (i) create a dynamic time window $\delta t$ and collect objects within that time window; (ii) group collected objects based on their location; and (iii) compress the group of trolleys to a single aggregated object. A hash table data structure is used to maintain a mapping between a grouped object and the trolleys contained within a group. A hash table also supports maintaining aggregation changes and disaggregation of trolleys from grouped objects. Then PF based tracking algorithm is applied to the aggregated object. The benefit of compressing the object stream is to minimize the need for using the PF based tracking algorithm for individual objects and to, consequently, achieve both greater scalability and accuracy.

In Algorithm 1, line 3–15 explains the object compression, resulting in one compressed trolley for each group. Line 16–24 explains the PF applied to the compressed trolley. Then, the location $l_p$ with the highest probability is estimated as the most likely location. Line 27–36 checks for possible missed reads for objects currently being tracked by comparing the current time with the max_time ($t_i + \text{transit~time}$).

### 4 Experiments and Results

We implemented the linen company’s business process in Matlab (Fig. 1) and conducted extensive experiments to evaluate the performance of our tracking algorithm. In the simulation, the time duration from trolley allocation to its return to the back entrance is 2–6 h, read rate is defined as the probability that a tag is read successfully by a reader and the error rate is specified as the percentage of incorrect location predictions. The results reported were generated by averaging 10 repeated experimental runs using randomly generated trolley movement data.

Figure 2 concretely depicts that the object compression technique based PF outperforms the simple PF based tracking algorithm in terms of both accuracy and scalability. When the read rate is above 0.8, the error rate in object compression technique is below 5%, which is a considerable improvement in accuracy.
Fig. 2. Experimental results: (a) accuracy; (b) execution time; (c) memory usage compared to PF based tracking algorithm. Figures 2(b) and (c) show the execution time and memory usage of the proposed algorithm, which clearly shows that the object compression technique significantly reduces the time taken and memory usage of the system.

5 Conclusion

In this paper, we presented an object location tracking algorithm that is robust under uncertainty and demonstrated its performance in an RFID enabled returnable asset management scenario. In practical deployments, the miss rate (1-read rate) is around 5% and at this miss rate our system reduces the overall error rate to less than 2% which is a significant improvement in performance. Comparing our algorithm with [2], where data compression is based on containment relationships, when read rate is 80% and containment is 100% their accuracy is around 94% but with 0% containment (similar to our scenario) the system accuracy falls to below 87%. In contrast our tracking algorithm yields 96% accuracy with a read rate of 80% and outperforms the method in [2]. Furthermore, our technique can also be applied to contained objects, as in [2].

Acknowledgement. This work has been supported by ARC-Linkage grant LP100200114.

References

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.

A Highly Accurate and Scalable Approach for Addressing Location Uncertainty in Asset Tracking Applications

Rengamathi Sankarkumar, Damith C. Ranasinghe
Auto-ID Labs, The University of Adelaide, Adelaide SA 5005, Australia
{rengamathi.sankarkumar,damith.ranasinghe}@adelaide.edu.au

Thuraiappah Sathyan
The School of Computer Science, The University of Adelaide, Adelaide SA 5005, Australia
thuraiappah.sathyan@adelaide.edu.au

Abstract—Tracking systems that use RFID are increasingly being used for monitoring the movement of goods in supply chains. While these systems are effective, they still have to overcome significant challenges, such as missing reads, to improve their performance further. In this paper, we describe an optimised 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 characterises 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. The results of a detailed simulation study shows that our object compression technique yields high location accuracy (above 98% at 0.95 read rate) with significant reductions in execution time and memory usage.

I. INTRODUCTION

RFID enabled tracking of objects, such as their condition and location, improves the visibility of objects travelling through a supply chain. Improving the visibility of objects is the key to resolving several problems that arise in supply chains such as counterfeiting, cold chain monitoring, and inventory management [1]–[3]. According to [4] one of the most important benefits of improved information visibility is realized in inventory management and asset utilization. However, RFID technology cannot be directly utilized, because to obtain an accurate location tracking system, first, we must overcome uncertainty in RFID based tracking networks [5].

Uncertainty in RFID data can be caused by false negatives and false positives [6]. Among them RFID based asset tracking is particularly prone to false negatives, which is also known as missed reads. Missed reads refer to objects that exist in a readable area, but may not have their tag detected by readers due to environmental factors such as interference, noise, malfunction of RFID components and distance between a reader and a tag. Missed reads make RFID data incomplete [7] and using such RFID data in object tracking lead to ambiguity in the locations of objects. Hence, managing missed reads in raw RFID data is important for developing effective tracking applications.

In this paper, we present an approach to address location uncertainty caused by missed reads. Here, we model objects travelling through a supply chain using an object flow graph to capture possible movements of objects in a two dimensional state space. Our approach overcome location uncertainty in a continuous state space, even though raw RFID data are incomplete. Finally, we evaluate the performance of our approach to demonstrate its accuracy and scalability in an RFID enabled returnable asset tracking application. This paper is an extension of the work presented in [8]. The summary of our contributions are:

- We introduce an object flow graph, which models the possible moving paths of objects and supports the creation of a dynamic motion model that is capable of adapting to changes in object flow as a result of evolving Business to Business (B2B) and Business to Client (B2C) relationships.
- We propose an approach that exploits business related contextual information to aggregate objects that are travelling together to develop an optimised Particle Filter (PF) based tracking algorithm. This algorithm is highly scalable and capable of improving the accuracy of estimating the most likely location of assets under uncertainty.
- Finally, we implement the algorithm in a returnable asset management scenario and conduct extensive simulated experiments to evaluate: i) the accuracy at locations where missing reads are high in practice as well as the overall accuracy; ii) the accuracy with increasing number of customers; iii) the effectiveness of the proposed motion model; and iv) scalability (processing time and memory usage) of our algorithm.

The rest of the paper is organised as follows. Section II discusses related work and Section III presents the problem statement. Sections IV, V and VI explain the main contributions of the paper and Section VII concludes the paper.

II. RELATED WORK

Previous research on managing uncertainty in RFID systems [9], [10] proposed an adaptive temporal smoothing filter for cleaning raw RFID data. To address uncertainty, this approach decides whether a tag is still within the read range or moved away from the read range of a given reader. However, these techniques are not applicable to estimate the location of
objects in a supply chain because they cannot predict a missed object’s likely location.

A number of existing publications [6], [8], [11]–[13] have used Bayesian techniques to address the location uncertainty problem. In [6] authors have only addressed uncertainty caused by false positives. In [11] 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 for a period of time.

In [8] and [12], the authors designed a transition model that depicts the probable flow of objects and serves as a base for their prediction 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 the approach in [12] cannot be used for continuous object tracking. The work in [13] 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 the 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 [7], 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 find missed reads is highly dependent on the inter-object containment relationship such as cases on a pallet.

We propose a tracking algorithm that is capable of estimating an object’s location in the case of missed reads. In contrast to [12], 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 [11], 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 all other readers. In contrast to [13], 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, as in [7].

III. PROBLEM STATEMENT

In returnable asset management, objects such as trolleys and pallets are attached with RFID tags and not the individual entities inside these objects. Increasing the visibility of the returnable assets is of significant interest to effectively manage inventories, prevent shrinkage and to ensure timely delivery. If the asset tags are not read by readers (missed reads) then the location of the asset in the supply network is ambiguous. In this paper, we focus on developing a real-time tracking algorithm, which is capable of estimating the most likely location of assets in RFID enabled returnable asset tracking.

We have derived our returnable asset management scenario requirements from the International Linen Services company (ILS), where trolleys (assets) are reusable containers for linens and they are attached with RFID tags. The company’s business scenario is depicted in Fig. 1(a), where RFID readers are installed in the trolley allocation area, the loading docks, the customer locations and the receiving dock. On the exit of the trolleys from the allocation area, the reader in the allocation area reports all the RFID tags in read successfully. Then, the trolleys are scanned in one of three loading docks through which the linen is loaded into trucks that depart the warehouse and deliver the linen to various customer locations. Trolleys are scanned next, after reaching the customer location, to acknowledge the delivery of the linens. Finally, the trolleys are collected from the customer locations and they are attached with RFID tags. In returnable asset management, objects such as trolleys and pallets are attached with RFID tags and not the individual entities inside these objects. Increasing the visibility of the returnable assets is of significant interest to effectively manage inventories, prevent shrinkage and to ensure timely delivery. If the asset tags are not read by readers (missed reads) then the location of the asset in the supply network is ambiguous. In this paper, we focus on developing a real-time tracking algorithm, which is capable of estimating the most likely location of assets in RFID enabled returnable asset tracking.

We have derived our returnable asset management scenario requirements from the International Linen Services company (ILS), where trolleys (assets) are reusable containers for linens and they are attached with RFID tags. The company’s business scenario is depicted in Fig. 1(a), where RFID readers are installed in the trolley allocation area, the loading docks, the customer locations and the receiving dock. On the exit of the trolleys from the allocation area, the reader in the allocation area reports all the RFID tags in read successfully. Then, the trolleys are scanned in one of three loading docks through which the linen is loaded into trucks that depart the warehouse and deliver the linen to various customer locations. Trolleys are scanned next, after reaching the customer location, to acknowledge the delivery of the linens. Finally, the trolleys are collected from the customer locations and they are attached with RFID tags. In returnable asset management, objects such as trolleys and pallets are attached with RFID tags and not the individual entities inside these objects. Increasing the visibility of the returnable assets is of significant interest to effectively manage inventories, prevent shrinkage and to ensure timely delivery. If the asset tags are not read by readers (missed reads) then the location of the asset in the supply network is ambiguous. In this paper, we focus on developing a real-time tracking algorithm, which is capable of estimating the most likely location of assets in RFID enabled returnable asset tracking.

We have derived our returnable asset management scenario requirements from the International Linen Services company (ILS), where trolleys (assets) are reusable containers for linens and they are attached with RFID tags. The company’s business scenario is depicted in Fig. 1(a), where RFID readers are installed in the trolley allocation area, the loading docks, the customer locations and the receiving dock. On the exit of the trolleys from the allocation area, the reader in the allocation area reports all the RFID tags in read successfully. Then, the trolleys are scanned in one of three loading docks through which the linen is loaded into trucks that depart the warehouse and deliver the linen to various customer locations. Trolleys are scanned next, after reaching the customer location, to acknowledge the delivery of the linens. Finally, the trolleys are collected from the customer
locations with or without soiled linens and are delivered and read at the receiving dock. If a trolley is missed (not detected by a reader) at any of these locations, then the location of the trolley is unknown until it is seen again, possibly at the next location.

We now define the notations that are used in this paper: i) \( L = \{t_p | p = 1, \ldots, s\} \) denotes a set of locations where the RFID readers are deployed; ii) \( T = \{t_i | i = 1, \ldots, m\} \) denotes a set of discrete timestamps; iii) \( O = \{o_j | j = 1, \ldots, q\} \) is a set of tagged objects; and iv) \( transit = \{transit_p | p \in L\} \) denotes the maximum transit time from a given location \( l_p \) to the next possible set of locations.

Raw RFID reads from RFID readers can be represented by the schema \{time \((t_i)\), objectID \((o_j)\), location \((l_p)\)\}. When an object \( o_j \) exists at location \( l_p \) (say in allocation area), it is next expected to be at a defined set of possible locations (in loading docks 1, 2 or 3) within a transit time period \( transit_p \). If an object \( o_j \) is not seen in any of the predefined locations within the specified time period \( transit_p \) (due to various reasons such as a missed read, the object is still in transit between two locations or the object is misplaced/miss directed or stolen), then the location of that object is unknown. We construct a PF based tracking algorithm to predict the most likely location of an object when the state of the object is unknown, using the observations obtained so far. Here we assume that the most likely reason for an unknown state is a missed read.

IV. PARTICLE FILTERING BASED TRACKING ALGORITHM

In this section, first, we present the object flow graph, which serves as a state space for applying PF based tracking algorithms. Then, we briefly review the bootstrap particle filter [14], which is used in the proposed algorithm. Finally, we present the proposed tracking algorithm that utilises the object flow graph.

A. Object Flow Graph

In PF, a workspace under investigation is modelled as a state space. Here, we model the state space with a graphical model called the object flow graph, which also helps define the motion model of the objects to be tracked. The object flow graph \( G(L,E) \) is derived from considering all the possible movement paths of the objects. The graph \( G \) has a set of nodes \( L \) and a set of edges \( E \). Each RFID reader deployed in the business process is represented as a node. We use the \((x,y)\) co-ordinates to represent a reader location in the graph. Edges are the possible moving path between locations (nodes). Then, we restrict the movement of the particles to be along the edges of the graph to reduce the complexity of the state space and to constrain the tracking region since object movement is possible over a large geographical zone and is not limited to a warehouse.

Fig. 1(b) depicts the object flow graph of the linen services business process. Each reader is denoted by a node in the object flow graph: i) one node in the allocation area; ii) three nodes at the loading docks; iii) 20 nodes for the twenty customer locations (the most important 20 customer locations); and iv) one node at the receiving dock. The possible moving paths are denoted by the edges represented by blue arrows connecting the nodes. The trolley travels in and out of the warehouse as depicted in the object flow graph in Fig. 1(b).

**Algorithm 1: particle_filtering_based_tracking_algorithm**

**Require:** raw_reads \(= (T,O,L) \) where \( r = 1,2,\ldots \) (time, object ID, location) where \( T = \{t_i | i = 1,\ldots,m\} \), \( O = \{o_j | j = 1,\ldots,q\} \), \( L = \{l_p | p = 1,\ldots,s\} \)

**Require:** \( N = \) state particles, where \( N = \{p_i | n = 1, 2,\ldots\} \)

1. while \( \forall r \in \) raw_reads do
   2. if new_object_found then
      3. initialize the state particles \( N \)
      4. object_list.add(r, t, o, r.o_p, probability ← 1)
   5. else
      6. object_list.update(r) //update \( t \) and \( l_o_p \) of \( r.o_j \)
   7. end if
   8. for every particle \( p_n \) of \( o_j \) do
      9. let \( p_n \) move along the edges at a constant speed
   10. number of particles and direction is determined by
      11. motion model
   12. predict, update, normalize and resample
   13. \( r.o_p \) ← estimate the most likely location of \( o_j \)
   14. probability ← estimated probability of \( o_j \) being in the location \( l_p \)
   15. object_list.update(r, probability)
   16. end while
   17. managing_missing_objects(object_list)

B. Particle Filters

PF is sequential Monte Carlo method that is an effective technique for state estimation in nonlinear/non-Gaussian state space models [14]. The state space model is defined using a motion model \( f_t \) and measurement model \( h_t \) and the PF operates on the state space model in a recursive fashion to estimate the unknown state.

**Motion model:** It describes how the system evolves (system dynamics) from one time step \( t - 1 \) to another \( t \). \( x_t = f_t(x_{t-1}, u_{t-1}) \), where \( f_t \) is a possible non-linear function, \( x_t \) and \( x_{t-1} \) is the state of the object at current and previous time steps and \( u_{t-1} \) is independent and identically distributed (i.i.d.) process noise.

**Measurement model:** The measurement model describes how an observation \( y_t \) relates to the true state \( x_t \) of the system. \( y_t = h_t(x_t, u_t) \), where \( h_t \) is a possible non-linear function, \( y_t \) is the observation, and \( u_t \) is i.i.d. measurement noise. We now describe the steps involved in one iteration of the PF.

**Initialise:** Particles corresponding to the state of an object are initialised according to \( x_0^i \sim p(x_0) \), \( i = 1,\ldots,N \), 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 particles \( x \) are predicted to be in a location considering the state at \( t - 1 \) and the observations (raw_reads) obtained so far. For \( i = 1,\ldots,N \), predict particles \( x_{t-1}^i \sim q(x_t|x_{t-1}^i, raw_reads_{1:t}) \), where \( q(.) \) is an importance function [14].

**Update:** On receiving an observation the location of predicted particles are updated by weighting the particles using the measurement model to obtain importance weights \( w_i \).
Algorithm 2 managing_missing_objects

Require: object_list

Require: transit = \{\text{transit}_t, |p \in L\} //mean time of an object to move from the given location to the next location

1: current_time ← current time from the system
2: while not end of(object_list) do
3: obj ← object_list.get_next
4: max_time ← obj.t + transit(obj.t)
5: if current_time > max_time then
6: predict
7: pred_loc ← estimate the most likely location of \(o_j\)
8: probability ← estimated probability of \(o_j\) being in the location \(L_p\)
9: pred_time ← current_time
10: obj.t ← pred_time, obj.Lp ← pred_loc
11: object_list.update(obj)
12: end if
13: end while

\[ w^*_i = p(y|\hat{x}^*_i) \], where high weights are given to the particles nearer to the measurement.

Normalize: The weights are normalised according to \( w_i = w_i / \sum_{j=1}^{N} w^*_i \).

Resample: Increasing number of prediction and update iterations leads to a situation where the weights of only a few of the particles are non-negligible. This is referred to as sample degeneracy [14]. Resampling step eliminates the particles that have lower weights and replicates the particles that have higher weight within a probabilistic framework. This results in a new set of i.i.d. particles [11].

C. PF based Tracking Algorithm

The PF algorithm estimates the location of an object with \(N\) state particles, at every timestep \(t_i\), as a probability distribution over \(L\) possible locations at \(t_i\).

Motion Model: We explore two kinds of motion models in this paper: i) a static model; and ii) a dynamic model. Both models assume objects are moving with a nearly constant velocity and we use a transition matrix to represent transition probabilities of objects from one location to the other. Hence, the transition probability matrix defines the possible moving paths of an object [12]. The matrix is built using conditional probabilities, \(p(L_i,|L_{i-1})\) between locations \(L_{i-1}\) and \(L_{i-1}\), at current and previous time steps \(t_{i-1}\) and \(t_{i-1}\), respectively. Assume that set \(L\) has \(p\) locations, then \(M\) can be represented by a \(p \times p\) matrix.

\[ M = \begin{bmatrix}
    p(l_1|l_1) & \ldots & p(l_1|l_f) \\
    \vdots & \ddots & \vdots \\
    p(l_p|l_1) & \ldots & p(l_p|l_f)
\end{bmatrix} \]

However, the static model can only be constructed after studying the transaction history of a business to derive the full set of transition probabilities because obtaining an accurate prediction requires having a motion model that captures the underlying movements of objects accurately. Therefore, this model can only be used in a well-structured business process with access to the complete transaction history.

Algorithm 3 object_compression_based_tracking_algorithm

Require: raw_reads = \{(T, O, L)\} where \(r = 1,2,... \// (time, object ID, Location)

Require: \(\delta t\)

1: \(t ← r.t_1\), //get the initial time from raw_reads
2: while \(\forall r \in raw_reads\) do
3: if \(r.t_1 > t\) and \(r.t_1 <= t + \delta t\) then
4: if new_object_found then
5: object_list.add(r.t, r.o, r.L, probability ← 1, new_object ← true)
6: else
7: object_list.update(r, probability, new_object ← false)
8: end if
9: end else
10: while \(\forall o \in object_list\) do
11: collect_object ← collect objects within the time window \([t + \delta t\]
12: group_object* ← grouped objects by their delivery location obtained from the contextual information
13: end while
14: for \(k = 1\) to \(n\) do
15: hashtable.put(\(ID^k, group_object^k\))
16: group ← \((ID^k, location\, of\, k^{th}\, group_object)\)
17: if group_object^k contains new_object(true) then
18: initialize group
19: end if
20: predict, update, normalize and resample group
21: object^k ← hashtable.get(\(ID^k\)) //get back the compressed objects
22: object_list.update(\(vd \in object\, probability)\)
23: end for
24: \(t ← r.t_2\), //next t from r
25: end if
26: end while
27: managing_missing_objects(object_list)

In contrast, the dynamic model is based only on the object flow graph and initially we assume every transition is equally likely. After each step of a transaction, the model gains some knowledge of the object flow and updates the model. The dynamic model is more suitable for large scale businesses where it is hard to analyse large volumes of complex transaction records, often distributed across third parties.

Measurement Model: The measurement model is defined such that the particles that are in the vicinity (i.e., within the active range) of a reader antenna are assigned a higher weight compared to particles that are farther from the reader antenna. The default sensor model used in this paper to assign weights is a Gaussian distribution, as it models the decreasing probability of the tag being read as it moves farther from the reader. Here, we consider the reader antenna to be at the centre of a node and the active range to be the radius of a node.

We designed a PF based tracking algorithm with prior knowledge of the object flow graph. In Algorithm 1, lines 1 to 7 examine raw_reads to identify if objects are seen for the first time to initialize the state particles for new objects. The new
objects are added to the object_list, while the existing objects are updated. In lines 8 to 15, the algorithm predicts and updates the locations of objects based on their most recent readings.

A missed reading event is identified if there is no read for an object in the object_list within the expected transit time. In Algorithm 2 we explicitly manage possible missed readings of objects. First line of Algorithm 2, retrieves the current_time from the system and evaluates if the transit time of all the objects are within their maximum thresholds. If the current time is greater than the maximum transit time threshold for a given object, then, only the prediction step of the PF is carried out to estimate the approximate location of the object. Next, we estimate the probability of each missed object being in the active range of every location. The probability of an object \( o_j \) being at each possible location \( l_p \) is \( p(o_j) = n/N \) where \( n \) is the number of particles that is present within the active range of that reader and \( N \) is the total number of particles. Thus, the location \( l_p \) having the maximum probability \( p(o_j) \) is assumed as the location of the missed object.

In spite of PFs effectiveness in improving location tracking accuracy, high computational cost is an important drawback when implementing PFs in large scale tracking applications. For example, as the object flow graph becomes more complex, more particles are required to achieve greater accuracy. Further, tracking a large number of objects also increases the memory requirement. In the following section we show how the scalability of the PF based tracking algorithm can be improved.

V. OPTIMIZATION OF THE TRACKING ALGORITHM

We propose an object compression technique for things travelling together to the same location to reduce the computational complexity of the proposed algorithm. Our approach exploits contextual information (customer order information) to aggregate objects that are travelling together from one location to another into a single aggregated object. This compression can be achieved in three steps:

Collect objects: The first step is to create a time window of small duration \( b_l \) and collect all the objects that are observed within this time duration. A time window is used to segment the incoming data from RFID readers and limit delays because all the objects related to a single order may not be loaded onto a truck immediately after orders are processed. Group objects: Collected objects are grouped, according to the delivery location obtained from customer orders and objects allocated during order processing (contextual information). Compressing objects: Finally, compress the grouped objects travelling to the same location to a single aggregated object. A hash table maintains the mapping between a grouped object and the objects contained within a group.

VI. SIMULATIONS AND RESULTS

A. Simulation Scenario

We implemented a prototype of the linen company’s business process (see Fig. 1) in Matlab and conducted an extensive simulation study to evaluate the performance of the proposed algorithm. The simulated trolleys’ operational period (time spent in the supply chain) was 2 - 6 hours. The number of trolleys per transaction (order) was randomly selected to be either 5 or 10. Approximate time between customer requests (transactions) was randomly selected to be within 2 - 15 minutes. The transit times between the allocation area to loading dock, loading dock to customer locations and customer locations to the receiving dock were also randomly selected to be between 20 - 40, 60 - 120 and 180 - 240 minutes, respectively. Number of orders sent to each loading dock and the number of orders generated for each customer, was based on the probabilities generated from historical transactions captured from the company and presented in the static model given in Fig. 3.

We have defined read rate as the probability that a tag is read successfully by the reader and error rate as the percentage of incorrect location predictions. For simulating the trolley movements, we set the speed of the particles to be a Gaussian distribution with \( \mu = 0.42 \) m/s and \( \sigma = 0.01 \). The readable range is set as 10 m in the object flow graph.

B. Illustration of the Tracking Algorithm

Fig. 4 illustrates the implementation of the PF based tracking algorithm using the business process of the linen company. In Fig. 4, we tracked a trolley with ID 356 from the allocation area to its return at the receiving dock. Trolley 356, had missed a read at the loading dock at 10:42. The PF-based tracking algorithm initialised the object particles at the first time step, i.e., at 10:32, in the allocation area. Then, the particles started moving according to our static motion model until the transit time expired. After the transit time expired our tracking algorithm identified a missed reading in the loading dock. Then, the object location is predicted using the particle filter based tracking algorithm to manage the missed read. Our algorithm managed to correctly predict the location of the object.
trolley to be in \( l_3 \) as shown in the Fig. 4(c)(2). Later, at 11:02, the trolley was located at the customer location and at 13:25, at the receiving dock. Fig. 4(c) shows the probability distribution over the state space and the most likely location identified by our tracking algorithm. In Fig. 4(c)(2), the probability of the trolley being at \( l_3 \) is lower because of the uncertainty caused by the missed read.

C. Simulation Study

In this section, we discuss the experiments conducted to evaluate the accuracy and scalability of the proposed tracking algorithm and the utility of the static and dynamic motion models. First we investigate the effect of the number of particles on the performance of the tracking algorithm. Then, in order to determine the effectiveness of our algorithms in the ILS scenario, compared to not employing them, we conducted three simulations to evaluate the accuracy of location estimates at: a) the loading dock; b) receiving dock; and c) over all locations. This is because in practice, handheld RFID readers are used to scan the trolley at the allocation area (where trolleys are checked manually) and at customer locations. Therefore, we assume that the probability of missing reads is higher at the loading and receiving docks, and negligible at the other locations. The results reported for accuracy were generated by averaging 10 repeated simulation runs using randomly generated trolley movement data. Next, to study the effects of an increase in the number of locations and the corresponding location accuracy, we expand the business process by increasing the number of customer locations as shown in Fig 7. The new business process has \( i \) customer locations, where \( i = 40, 60, 80 \) and 100, instead of 20 (considered before). We also evaluate the processing time and memory requirement of our tracking algorithm with up to 10,000 trolleys to investigate its scalability. Finally, we investigate the dynamic motion model’s ability to adapt to changes in the object flow. As already discussed, object compression with the dynamic model is an adaptive tracking algorithm. Therefore we considered 5 different business transaction scenarios where 100, 200, 300, 400 and 500 trolleys per day, respectively, were processed and investigated the agility of the proposed tracking algorithm.

D. Results

In this section, we discuss the results of our approach in terms of accuracy and scalability. We first discuss the effects...
of the number of particles used for tracking each object in the PF based tracking algorithm. In order to avoid the degeneracy problem, we need a sufficient number of particles. On the other hand, keeping a large number of particles will significantly increase computational costs. We perform simulations to explore the effects of the number of particles on location estimation accuracy to determine the appropriate size of particles. As shown in the Fig. 5, the accuracy of the algorithm increases with higher numbers of particles. Another observation is that the accuracy changes slowly when the number of particles is above 100. Therefore, we conclude that 100 particles are adequate for our algorithm to guarantee good enough accuracy without a high computational cost.

Accuracy is measured by error rate with respect to the read rate of the simulated readers. In Fig. 6(a), object compression with the static model outperformed the other two techniques, because the PF based tracking algorithm tracks the individual object and does not have any knowledge of other trolleys travelling with the trolley whose tag reading is missed. The dynamic model requires time to learn the flow of trolleys from executed transactions. Any missed reads occurring during the learning period have a higher chance of an incorrect location estimation. Therefore tracking algorithm with dynamic model did not outperform the tracking algorithm with the static motion model.

Fig. 6(b) shows the accuracy in case of missed reads at the receiving dock. The error rates in all three techniques are significantly less than at the loading dock (Fig. 6(a)) because even with missed reads the possible location estimations are limited to a single active range as opposed to three at the loading dock. Fig. 6(c) shows the overall accuracy at all locations obtained after having varied read rates at all 25 locations. At 90% read rate, the accuracy of all three algorithms was above 95%. Therefore using a particle filter has halved the error rate from 10% to 5%. Again, object compression with dynamic model has slightly lower accuracy than the static model.

Fig. 6(d) shows the overall accuracy (where the read rate is set to 95%) with increasing number of customer locations. It can be seen that increasing the number of locations has an adverse effect on the accuracy of the system. Object compression with the static model achieved the highest accuracy when compared to others. When the number of nodes reaches 100, even the accuracy of the static model falls to 95.8%. Consequently, the PF based tracking algorithm cannot provide a performance improvement in relation to read rate (set at 95%) beyond 60 customer locations. This is because the probable set of locations for the missed object increases as the number of customer locations increase.

We have only considered the algorithms with the static model to investigate execution time and memory consumption because the motion model does not have an impact on the execution time and memory used. Fig. 6(e) shows the total execution times taken by the returnable asset management

![Fig. 7: Object flow graph with increased nodes](image-url)
error rate (%)
3 4 5 6 7

Table 8: Investigate the accuracy of the dynamic motion model scenario simulated. In Fig. 6(e) it is clear that the object compression technique with the static model outperformed the PF based tracking technique because the PF based tracking had to track individual trolleys as opposed to groups.

Memory usage is dominated by the number of trolleys and particles used in the algorithm. Particle count is constant, i.e., 100 for all techniques, therefore the number of trolleys tracked drives the amount of memory consumed. Object compression technique compressed a group of trolleys to a single object and thus, around 50% of the memory storage is saved compared to PF based tracking. The object compression technique considerably reduces memory usage as shown in Fig. 6(f).

Over a period of time we can expect the dynamic model based tracking algorithm to achieve the same accuracy as that of the static model based algorithm. So, we set our target to the highest accuracy (98.2%) reached by the static model at 95% read rate (typically good read rate obtained from practical deployments) in the ILS scenario. This target is represented in Fig. 8 with a red horizontal line. On day one, the simulation ran with the designated number of trolleys and as a result the dynamic model is updated based on the transaction data and the error rate gradually decreased at different rates for different trolley volumes. Fig. 8 shows that as the number of trolleys increases, the target is reached more rapidly. This is because the model adapts and updates quickly when the number of transactions is high. Therefore, if 500 or more transactions are carried out in a day, the dynamic model attains the same accuracy as that of the static model within a day. Hence, as long as business conditions do not change dramatically from day to day the dynamic model will be able to deliver high accuracy while still being able to adapt to respond to change relatively quickly.

VII. CONCLUSION AND DISCUSSION

In this paper, we proposed and evaluated an optimised object tracking algorithm that is capable of addressing missed reads in a returnable asset management scenario. We proposed and evaluated an optimized PF based tracking algorithm that is both scalable and capable of accurately estimating the most likely location of objects. The algorithm with the static motion model was able to minimize the error rate to 1.8% at 95% read rate with considerable improvement in the scalability.

Compared to our previous work in [8] based on using a static motion model for tracking objects, the algorithm that we proposed utilises the dynamic motion model and business context information. By using this dynamic model and contextual information our method can even work in widely distributed supply chains where it is hard to analyse huge volumes of complex transaction data. Furthermore, in contrast to [8], the dynamic motion model based approach is adaptive to changing business conditions requiring only around 500 transactions a day to completely learn the motion model. Next we compared our approach to [7]. Although we have not implemented their algorithm in our business process, we compared their accuracy results with ours, because both papers discussed tracking objects in a supply chain scenario. At 80% read rate, with 0% (as in our scenario) and 100% containment relationship their accuracy was approximately 87% and 94%, respectively. In contrast, with a larger supply chain model than in [7] (5 in [7] vs. 25 locations in ours) our algorithm achieved 95% accuracy with the same read rate.

VIII. ACKNOWLEDGEMENT

This work was supported by an Australian Research Council Linkage grant (LP100200114) and was partially funded by the International Linen Services (ILS), South Australia.

REFERENCES
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.

Watchdog: A Novel, Accurate and Reliable Method for Addressing Wandering-off using Passive RFID Tags

Rengamathi Sankarkumar, Damith C Ranasinghe
Auto ID Lab
The University of Adelaide
North Adelaide, Australia
rengamathi.sankarkumar,damith.ranasinghe@adelaide.edu.au

ABSTRACT
Hospitals and residential homes have a significant need for monitoring and recognising wandering-off (e.g. elopement) 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. Due to increasing ageing populations across the globe we can expect wandering-off to become a significant problem of scale affecting all of us. Existing technologies used to address wandering-off are inadequate for providing close supervision as they use proximity based sensing that often lead to false alarms. In this study, for the first time, we try to mitigate false alarms by identifying the traversal direction and traversal path used by people instrumented with a single low cost batteryless UHF RFID tag. 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 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. Our extensive experiments with 14 young adult volunteers show that: i) our TD algorithm can identify the moving direction of a person with 100% accuracy; ii) our TPD algorithm reduces the false alarms to < 9%, when detecting the traversal path used while eloping; and iii) our algorithms can be implemented in a different environment without further scene analysis.

Categories and Subject Descriptors
L.4 [Image Processing and Computer Vision]: Scene Analysis—Tracking; C.3 [Special-Purpose and Application - Based Systems]: Real-time and embedded systems

Keywords
wandering-off, RFID, tag traversing direction, traversing path detection, particle filter

1. INTRODUCTION
Wandering-off (e.g. elopement) [6] among older people with dementia, Alzheimer’s disease (AD) and other cognitive impairments are common [2, 12, 18, 4]. Wandering-off may result in serious consequences such as getting lost, collision with vehicles or even death and the responsible aged care service providers are liable for such actions [2]. Therefore, continuous monitoring among wandering-off patients is essential. Due to ageing populations around the globe, occurrences of wandering-off incidences are expected to increase. It is estimated that, by 2050 the number of people with AD is expected to be around 900,000 in Australia [2] and about 16 million in U.S. [2]. Monitoring and recognising these patients when they are exiting cared areas with a reliable system can minimise the occurrence and associated risks of wandering.

Current technologies [6, 25, 27], that address wandering-off are mostly boundary alarms that use simple proximity based sensing. As a result, false alarm rates (i.e. incorrectly detecting that the person has walked through the doorway when they are still in the cared area) are high in these systems [6]; also, information about the traversal path used by the older person is non-existent. Using such technologies to provide continuous care to prevent wandering-off can be challenging, stressful and frustrating for caregivers [6].

RFID (Radio Frequency Identification) is an enabling technology in tracking applications. RFID is capable of automatically and uniquely identify individuals [9]. In this study, for the first time to the best of our knowledge, we introduce Watchdog, a system to mitigate false alarms by accurately and reliably identifying the traversal direction and traversal path used by people instrumented with a single passive RFID tag. Watchdog recognises the tag traversal direction and traversal path by utilising a Particle Filter (PF) with Received Signal Strength Indicator (RSSI) maps obtained from the interrogation between an RFID reader and a passive tag. Detecting tag traversal direction and traversal path is vital among wandering-off older people because, the undesirable traversal direction of a person can be known by a caregiver, for example, if a caregiver is aware that a patient is moving out of their room, then the caregiver can stop them from elopement or go in search of them immediately after elopement. Furthermore, knowing the traversal
path can be helpful to reduce the search space and to estimate the level of risk associated while eloping. For example, as shown in Fig. 1, knowing the traversing path used by a patient is towards the right corridor, reduces the search space in the event of an elopement. Knowing the traversing path allows estimating the level of risk associated with an elopement and help prioritise the searching process. For instance in Fig. 1, if the patient has used a path forwards to the main entrance then the associated risk with this path is higher when compared to other paths.

We summarise the main contributions of our paper as follows:

- We propose an accurate and reliable system, Watchdog, to determine wandering-off among older people wearing a low cost passive RFID tag attached over their attire to alert the caregivers with identified traversal direction and traversal path when the tag bearer approaches or exits a doorway.
- We develop two algorithms, namely, traversing direction (TD) detection algorithm and traversing path detection (TPD) algorithm to accurately identify the tag traversing direction and tag traversing path, respectively, used by the tag bearer from the spatial and temporal data obtained from a real-time PF based technique.
- Finally, we implement the algorithms in two environments (a supervised environment and an unsupervised but similar environment) and conduct extensive experiments with 10 volunteers to evaluate the performance and accuracy of our proposed algorithms. We also compare the performance of our approach with traversing direction (TD) detection and traversing path detection with scene analysis and demonstrate the superior performance of Watchdog.

2. RELATED WORK

For a clearer overview we divide our discussion into three parts. Firstly, we discuss some of the existing methods employed to prevent wandering-off. Secondly, we discuss literature that identify tag traversing direction, thirdly, we discuss the traversal path detection techniques used with networked RFID and finally, we discuss existing localisation methods.

### 2.1 Overview of Existing Alarm Methods

Uses of alarms on door exits is one of the well known technologies in monitoring older people. There are two types of alarm systems [6]: i) alarms that sounds 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 immediately identify the location of the alarm, older people removing the bracelet or battery of the worn device being flat [6, 21]. Some of the recent researchers have used android powered phones [25] and battery powered WiFi tags [27] to address wandering. However, a common drawback for all the above mentioned technologies is the need to carry bulky battery powered devices. Furthermore, in systems that sound an alarm when doors are opened, automatically and uniquely identifying an individual is still a challenging task because door alarms sound when a person enters its readable range and are not capable of differentiating caregivers from patients. Therefore, even in case of hearing an alarm, there is negligence among caregivers as alarms are assumed to be triggered by a caretaker [6]. In contrast to existing methods our PF based algorithms for continuous monitoring of older people are robust and accurate and thus capable of drastically reducing false alarms.

### 2.2 Traversing Direction and Traversal Path Detection

Number of works that utilise passive tags for determining tag traversal direction are limited. In [13], 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 [20], 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 [30], 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 [32], 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, 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 [14, 11] 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 [14] 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 [21] instead of low cost, lightweight and batteryless 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 Localisation Methods

Nevertheless, a number of localisation methods exists that can be used to infer the tag bearer’s location. These RFID based localisation techniques can be broadly classified into three main categories [8]:

1. Distance based estimation: This kind of estimation depends upon the use of properties of triangles such as triangulation and trilateration [8, 16]. The range measurement parameters are obtained from Received Signal Strength Indicator (RSSI) [10], Time of Arrival (ToA) [13], Angle of Arrival (AoA) [28], Time Difference of Arrival (TDoA) [20] and Received Signal Phase (RSP) [32].

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 [16].

3. Scene analysis: Scene analysis consists of two distinct steps [10, 19, 31, 22]. 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.

In [28], authors introduce a robust, fine grained RFID tag positioning system that utilises AoA and proximity based localisation. In addition to these techniques, $k$-NN algorithm is used to infer the desired tag location from the nearest reference tag. Passive RFID tags are used for both the desired and reference tags. Landmarc [19] utilises scene analysis technique to identify the spatial position of a desired tag from reference tags with known locations. They first locate the reference tags that are near to the desired tag and then using the RSSI values and $k$-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 [31, 22, 7]. In [31], the authors localise the desired tag’s location by utilising a 2D grid of reference tags and a proximity map, while in [22], kalman filter based technique is used in locating the desired tag and in [7] weighted centroid localisation and PF are employed to track the objects. However, all the above discussed methods, regardless of the technique they use, rely on reference tags to localise the position of the desired tag.

In [29] 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 localisation. Also, the discontinuity in their antenna setup does not allow continuous tracking of objects, instead, objects missing over a period is assumed to be in one of the rooms that is nearest to the last seen location. Although such methods can be beneficial in estimating spatial queries, it cannot be directly implemented in determining the traversal direction and path. However, the research methods used in [29] serves as a basis for our work which also does not rely on reference tags. In contrast to [29], we are interesting in continuous and accurate monitoring of temporal and spatial coordinates of a tag bearer. In particular, our Watchdog system is capable of identifying 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 [29], 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 re-
Figure 3: (a) State Space for scene analysis (b) rssi_map for Antenna 1 (c) rssi_map for Antenna 2 (d) Scene Analysis

3. AN OVERVIEW OF WATCHDOG

We introduce Watchdog, a real-time algorithm 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 hazards. Also their keen sense of smell is capable of identifying the traversing path used by a particular person. Fig. 2(a) depicts an overview of our system and Fig. 2(b) shows an experimental setup of our system. 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 algorithms: detecting the tag traversal direction and the traversing path used while eloping.

When a passive RFID tag enters the monitoring zone, the 4 mounted RFID antennas power and interrogate the tag in order to obtain time of the read, EPC (Electronic Product Code) assigned for each person, antenna ID that identified the the antenna reading the tag and the RSSI value. Thus, raw RFID reads r obtained here can be represented by the schema: \(t, \text{patientID}, \text{ant}, \text{rssi}\). In contrast to the existing RFID localisation systems, Watchdog accurately identify the traversal path used by a tag bearer without any reference tags deployed in the state space. Instead, Watchdog employs an rssi_map that depicts the state space features through a scene analysis technique [10]. Further, Watchdog enhances the system by utilising the spatial and temporal data obtained from the PF because scene analysis is prone to noise in RSSI measurements that can lead to location uncertainty.

The following sections of the paper are summarised as follows: Section 4, describes scene analysis to acquire rssi_map individually, for each antenna deployed in the state space and provides an overview of a baseline method using scene analysis to determine TD and TPD; Section 5 describes the PF based algorithms employed by Watchdog to determine TD and TPD; Section 6 presents the experimental evidence to demonstrating the performance of our Watchdog system; and we conclude our article in Section 7.

4. SCENE ANALYSIS

Before explaining the techniques involved in Watchdog we perform scene analysis in the monitoring zone. First, we partition the 2-D state space equally where the dimensions of a partition is approximately equal to a walking step. We denote the intersection of each partition with their x and y axis as \((x, y)\).

As shown in Fig. 3(a) the state space used in our experiment is 6m in length and 2m in width, where we considered the width of the state space along the x axis and the length along the y axis. We divided the space in such a way that each partition measures 25 cm in length and 25 cm in width. We ask a tag bearer to stand static in each of these intersections for approximately 4 seconds. Then, we calculate the mean of the obtained RSSI values and generate an rssi_map for each individual antenna deployed in the state space. For example, Fig. 3(b) and (c) show the rssi_map for the two antennas deployed in the inner side in our experiment scenario shown in Fig. 2(b). The combined collected rssi_map obtained from all the antennas deployed reveals the RSSI features over the state space.

4.1 TD and TPD with Scene Analysis

We employed scene analysis based approaches described in [10, 19, 31, 22] to serve as a baseline for evaluating Watchdog. We utilise the scene analysis technique to detect the tag traversal direction and tag traversal path. We partition a sequence of tag reading \(r_{1:m} = \{(t_i, \text{rssi}_i, \text{ant}_i)\}_{i=1}^m\) in a non-overlapping fixed time segment \(\delta t\) for a given patientID where \(t\) is the time stamp of a tag read, rssi is the Recertify Signal Strength Indicator 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 RSSI value \(\text{rssi}_{\text{ant}}\) for each antenna \text{ant} that obtained a tag read.

\[z_t = \frac{\sum_{\text{ant}=1}^{\text{w}} \text{rssi}_{\text{ant}}}{\text{w}}\]

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 \(r_{1:m}\).
obtained mean RSSI value \( \text{rssi}_{\text{ant}} \) is compared with the previously developed \( \text{rssi}_{\text{map}} \) to infer the tag bearer’s location and then subsequently determine TD and TPD.

Fig. 3(d) shows the result of directly comparing the \( \text{rssi}_{\text{ant}} \) with the acquired \( \text{rssi}_{\text{map}} \) to identify the tag traversal path from the left corner of the state space to right corner. From Fig. 3(d) it is clear that readings from the passive RFID tags are highly noisy and no exact inference about the tag traversal path can be made with just scene analysis. Therefore in the next section we introduce a PF based TD and TPD algorithms to overcome this location uncertainty.

5. PF BASED TD AND TPD ALGORITHM

A particle filter (also known as sequential monte carlo) works in a recursive 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 measurement process [5]. Our approach is capable of continuously tracking the tag location with information about the tag traversing direction. Our approach is also capable of overcoming missed reads (false negatives) in the real time RFID data, which are usually quite common in raw RFID data [23, 24].

Next, we explain the two critical models that are used to infer the location of an object (e.g. tag) in a dynamic system. They are: i) motion model; and ii) sensor model.

Motion model: Motion model or system dynamics describes how the system evolves from the time step \( t \) to \( t - 1 \)

\[
l_t = f_t(l_{t-1}, v_{t-1})
\]

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

\[
p(l_t|l_{t-1}) = p(l_t|s, \theta, l_{t-1})
\]

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, \( \theta \). 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 [7] for people aged 40 and above and the probability of moving in any of the given direction \( \theta \) to be equiprobable where \( \theta = \{0^\circ, 45^\circ, 90^\circ, 135^\circ\} \). 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 \( \theta \) is updated by multiplicative increases of the probability in the direction of traversal in the previous time \( t-1 \) and decreases in the probability of moving in all other directions.

Sensor model: Once there is an observation the measurement model describes how the observation \( z_t \) relates to the true state \( l_t \) of the system.

\[
z_t = h_t(l_t, u_t)
\]

where \( h_t \) is a possible non-linear function, and \( u_t \) is i.i.d. measurement noise.

\[
p(z_t|l_t) = p(\text{rssi}_{\text{ant}}|l_t, \text{ant}, \text{rssi}_{\text{map}})
\]

The sensor model \( p(z_t|l_t) \) used in our system specifies the likelihood of obtaining a measurement \( z \) given the true state of the tag \( l_t \). The probability of having a mean RSSI \( \text{rssi}_{\text{ant}} \) for a given predicted location \( l_t \), antenna ID \( \text{ant} \) and the corresponding map \( \text{rssi}_{\text{map}} \) for \( \text{ant} \) is determined in our sensor model. Below we discuss briefly the steps involved in one iteration of the PF.

**Initialize:** The given particles are first initialised for the state \( l \). At time step \( t = 0 \), for \( N = 1,...,n \) sample the state particles, \( l^o_0 \sim p(l_0) \)

**Predict:** Using the motion model predict the location of
Algorithm 1 PF based traversing path detection algorithm

Require: $z_t$ // $rssi_{ant}$, $t$
Require: $N = $ state particles, where $N = 1,2,...n$
Require: $rssi_{map}$ // state space features from scene analysis
1: initialize the state particles $N$ used in estimating the traversing path to cover the whole state space in the first time step
2: for $\forall$ particles in $N$ do
3: at prediction, the motion model is used to predict $l_t$ from $N$
4: if $rssi_{ant} != [ ]$ then
5: update $N$ using the sensor model
6: normalize and resample
7: end if
8: end for
9: estimate the most likely coordinates $l_t$
10: traversing_path.add($l_t$)
11: traversing_direction_algorithm ($l_t$, traversing_path)

the object at each time step. At $t$ the state $l_t$’s particles are predicted to be in a location considering the state at $(t-1)$ and the observations ($z$) obtained so far. For $N = 1,...,n$, predict particles, $l_t^N \sim q(l_t|l_{t-1}, z, t)$, where $q(.)$ is an importance function [5].

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 particle’s weight 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 [5]. The resampling step eliminates the lower weighted particles and replicates higher weight particles to generate a new set of particles with equal weights [29]. The new set of particles thus obtained is equal to the original number of particles. For $N = 1,...,n$, set, $w_t^N = 1/n.$

5.1 Traversing Path Detection Algorithm

We detect the traversing path used by the tag bearer using a PF based TPD algorithm with prior knowledge of the state space features. Algorithm 1 is called with the observation $z$ with mean RSSI $rssi_{ant}$ at $t$. In line 1, we initialise the $N$ particles used in estimating the traversing path. In line 3, we predict the possible current locations from the motion model. Line 4, checks whether the $rssi_{ant}$ is empty, in order to identify missed reads.

If there is a missed read in the real-time data, i.e., no reading was obtained in time $\delta t$, then our TPD algorithm simply predicts the current location and conclude the estimation without updating and resampling. This is because update and resample steps are only necessary when there is an observation (see lines 5 to 8). In line 9, we finally estimate the $(x,y)$ coordinates.

Algorithm 2 traversing_direction_algorithm

Require: $l_t$
Require: traversing_path
Require: get boundaries of zone_A, zone_B, zone_C
1: if $l_t$ falls within zone_A then
2: $status = \text{‘In’}$
3: end if
4: if $l_t$ falls within zone_B then
5: $status = \text{‘Near door’}$
6: send an alert message to the caregiver with status
7: end if
8: if $l_t$ falls within zone_C then
9: $status = \text{‘Out’}$
10: send an alert message to the caregiver with status and traversing_path
11: end if

5.2 Traversing Direction Algorithm

In this section we explain the traversing direction algorithm. From the estimated $(x,y)$ coordinates from $l_t$ obtained from the PF based TPD algorithm we find the tag traversing direction. We classify the state space into three categories to implement the TD algorithm: i) zone_A is the space that is covered uniquely by the antennas that are deployed in the inside region of the state space; ii) zone_B is the space where the reading zone of antennas deployed inside and outside overlap; and iii) zone_C is the space that is covered uniquely by the antennas that are deployed in the outside region of the state space. Our Algorithm 2, classifies the estimated location $l_t$ of the tag bearer to a corresponding zone. If the tag bearer is found approaching or entered the disallowed zones an alert is given to a caregiver with the direction $status$ and the traversal path used by the tag bearer traversing_path (see Algorithm 2).

6. EXPERIMENTS AND RESULTS

We conducted extensive experiments in two laboratory environments (supervised and unsupervised) to evaluate the ability of our algorithms to accurately identify the traversing path and the traversal direction used by the tag bearer. We further compare the results of our PF based TD and TPD algorithm with the scene analysis technique described in Section 4 as a baseline.

6.1 Settings and Data Collection

An overview of our system is shown in Fig. 3(a) and the experimental setup is shown in Fig. 4. 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 wooden frame (shown in Fig. 4) 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.
Figure 5: (a) Initialisation (b) At first observation (c) Eloped from the secured caregiving area but still in the reader detectable area (d) After complete elopement in the Right out direction

Figure 6: (a) Effects of number of particles used in PF (b) Accuracy in terms of speed (c) Comparison of our algorithm results with the supervised environment and an unsupervised environment

We considered 12 paths as shown 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 in two environments, namely, supervised (where scene analysis was conducted) and unsupervised (a new and different environment without where scene analysis was not performed) as shown in Fig. 4(a) and (b), in order to evaluate the robustness of our algorithms in a different environment and to assess the ability to use the noise model developed through scene analysis in the supervised environment in a completely new environment. 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 trials (25 randomly selected from moving out paths) and 20 non-traversing path trials.

Fourteen healthy, young adults aged between 25 to 35 participated in the laboratory experiments. The mean ± SD height of our participants was 169 ± 5 cm. However, only the first 6 participants were involved in both the experiments the last 4 participants were different in the supervised and unsupervised environment experiments. The passive RFID tag was attached over each participant’s attire using a double sided adhesive tape over the right shoulder as shown in Fig. 4(a). All the participants were asked to walk at their normal speed and were not instructed to walk at any specified speed.

6.2 Illustration of the PF based TPD Algorithm
Fig. 5(a-d) shows an step by step example of the TPD algorithm’s prediction and final estimation for the path starting from Left-in to Right-out. At the initialisation step particles are distributed over the state space as shown in Fig. 5(a) since the location of the tag bearer is completely uncertain. Then, after an observation our algorithm predicted the tag bearer’s location as shown in Fig. 5(b). Red circles in the figures denote the predictions of TPD in the current time step and blue asterisks denote the estimation of TPD. Fig. 5(c) shows the estimated traversing path of the tag bearer in further iterations. Fig. 5(d) shows the detected traversing path used after eloping. Considering our TPD algorithm’s results in Fig. 5(d) with scene analysis results obtained in Fig. 3(d) which utilised the same path (Left-in to Right-out) and RSSI measurements to detect the traversing path clearly illustrates the robustness of approach even under highly uncertain RSSI measurements.

6.3 Method for Evaluating the TPD Algorithm
In order to evaluate the performance of our TPD algorithm we partition our state space 2 m × 6 m into 9 equal partitions as shown in Fig. 6(a). We evaluated accuracy by counting the number of final estimation in each of these partitions. For example, in Fig. 6(a) we evaluate the Straight-in to Straight-out path. Here counting the number of location estimations in each partition is as indicated Fig. 6(b)(i). From this result we determine the maximum occurrence in each
row and flag that partition as shown in Fig. 6(b)(ii). Finally, we compare this result with the ground truth to evaluate the accuracy of our TPD algorithm. In this example the ground truth for Straight-in to Straight-out is given in Fig. 6(b)(iii).

6.4 Statistical Analysis

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 Positives + False Negatives + False Positives + False Negatives).

Since we are interested in determining if the supervised environment is similar to the unsupervised environment, we evaluated the if the results in supervised environment is statistically significantly different from the unsupervised environment. We used a two-tailed t-test where statistical significance was at p-values < 0.05.

6.4.1 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 Not-traversal out); and False positives (FPs) are other movements that were identified as a moving direction of interest.

6.4.2 Traversing Direction Algorithm

Here, we define the terms used in TD algorithm. 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 is not being reported). FPs are other movements that were identified as a moving direction of interest (e.g. No-traversal in is being identified as Moving out).

6.5 Results

The results from Table 1 and Table 2 show that our TD algorithm was able to identify the tag traversal direction with 100% recall, precision and accuracy in both, supervised and unsupervised environments.

Although the mean performance values for TPD were higher in the supervised environment compared to the unsupervised environment, the difference is performance is not significantly different (p<0.01). Evaluating our TPD algorithms in both environments show that precision is ≥ 86% and is noticeably higher than recall and accuracy which is ≥ 68% and ≥ 90%, respectively, for both moving in and moving out paths. This is because the number of FPs are comparatively lower than the number of FNs and hence the algorithms miss identifying complete paths. This is mostly due to missing readings in as a result of the tag over the shoulder being shadowed by a persons head.

Detecting the path used while eloping had < 9% false alarm rate (chance of having incorrect path estimation such as Right-in to Left-out as Left-in to Right-out) in the supervised environment and ≤ 14% false alarm rate in the unsupervised environment. Consequently, as expected, there are less false alarms in the supervised environment compared to the unsupervised environment. Also, from Fig. 6(d) it is clear that the overall performance (mean recall, precision and accuracy) of the unsupervised environment is lower than the results of the supervised environment, because we used the same rss_map for both the environments. The actual rss_map was generated from the supervised environment and therefore the map was able to model measurement noise more accurately for the supervised environment than for the unsupervised environment.
Next, we compare the results of scene analysis from Table 1 and Table 2. As expected, our TPD algorithm outperformed the baseline approach formulated using scene analysis to identify the traversal path used by a tag bearer. This is because, our PF based TPD algorithm is capable of continuously estimating the location of the tag bearer in a non-linear and dynamic system using noisy RSSI measurements, in contrast, scene analysis technique simply compares the real-time rssi value with the collected rssi_map to infer the person’s current location.

Comparing results for TD using scene analysis in the supervised environment with that of PF based TD shows that both approaches perform equally well. However, comparing the algorithms in the unsupervised environment show that the recall (87%) and accuracy (91%) results for scene analysis technique are lower in the moving out path. This is due to the missed read occurrences in the Right-in to Right-out path caused by the head obstructing the tag which is attached to the right shoulder from being interrogated by any of the deployed four antennas that are to the left of the person. The supervised environment has a wall located approximately 1.5 m from the setup and reflections from the wall contributed to illuminating the tag on the right shoulder while participants were in zone_C. Hence the scene analysis technique was able to predict the direction of the tag bearer in the supervised environment. However, in the unsupervised environment with a wall located from the right side of the setup and therefore, due to the obstruction caused by the head, there were only a few readings beyond zone_B in the Right-in to Right-out path. These missing readings resulted in FN in the evaluation of TD. In contrast, our TD algorithm is capable of predicting a person’s future location in the presence of missing reads based on the motion model that describe how the state evolves over time and thus able to achieve better performance.

In particular, comparing the data presented in Table 1 and Table 2 we can also observe that the results for Person 4, Person 5, Person 8, Person 9 and Person 10 in the Table 2 have the lowest TPs compared to other participants. A possible reason for the increased occurrences of FNs is the tag shifting position over the shoulder as a consequence of loosely worn clothing during the trial resulting in RSSI measurements that cannot be correctly filtered using the sensor model based on our measured rssi_map. On further investigation of the cause for the lowest number of TPs recorded for Person 9, we observed that measured RSSI values for Person 9 was lower compared to other participants. Person 9 was in fact the shortest participant (height: 153cm) among the 14 persons that participated in the trial. A possible reason for the increased number of FNs is the limitation of the measured sensor model (rssi_map) to adequately relate the location of the person to the measure RSSI values since the rssi_map was generated using a much more taller person with height of 170cm.

We also evaluated the effect of a tag bearer’s traversing speed on the accuracy of our algorithms. We varied the walking speed from 0.18 km/h (0.05 m/s) to 9 km/h (2.5 m/s). As shown in Fig. 6(c) walking speed had some impact on the accuracy. When the speed was too slow such as from 0.18 km/h to 0.9 km/h there is a small reduction (down to 78%), in the accuracy of the TPD algorithm. This is because our motion model is initialised 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, with 100% accuracy, determine 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 [7] for people aged 40 and above.

7. CONCLUSIONS
We developed a novel, robust, real-time system that can accurately detected the traversal path used by the tag bearer and the tag bearer’s moving direction such as moving out and moving in. In our study we used minimum number of instruments i.e a single, low cost passive RFID tag and four RFID antennas to achieve a 100% accuracy while detecting tag traversal direction, ≤ 9% false alarm on traversal path detection and ≤20% misses.

Our approach is a significant enhancement when compared to the existing approaches and the elimination of false alarms and misses (i.e. for TD) and the relatively accurate estimations of paths travelled is likely to results in higher levels of acceptance among caregivers since we are able to comprehensively address frustrations from false alarms while reliably identifying the eloping direction. Our algorithm can also be generalised to solve other problems such as detect goods that are travelling in and out of a warehouse however, there may be limitations in the performance depending on the speed at which goods are in transit.

Even though, our algorithm performed well throughout the study, certain paths results such as Right-in to Right-out frequently performed poorly due to the higher occurrences of missed reads. TD performance in the unsupervised environment suggests that it is possible to use apply a sensor model developed in a similar context in a different environment. However, the performance of the algorithm with respect of heights of people still needs to be investigated. Also, we did not investigate the accuracy of our algorithms with multiple participants and we have left this as future work. We are currently looking at developing a generic sensor model instead of scene analysis, so that it can be directly implemented in new environments to achieve similar performance to that possible in a supervised environment.

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

9. REFERENCES


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.

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’ [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 monitoring problems using batteryless transponders that are often 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 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 generic 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. 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 generic sensor model based on an 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 generic 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 approach 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 the 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, 7]. 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 [8], 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 [9], the time interval between tag detection 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 [10], 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 site specific scene analysis technique by developing a generic sensor model integrated with KL divergence to develop a generalisable RF based algorithm.

A related research problem can also be found in research works in the area investigating Mobile robots’ trajectories [11, 12] 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 inventorrying stocks in supermarkets [11] 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 [7] 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.

**Distance based estimation:** This kind of estimation depends upon the use of the properties of triangles such as triangulation and trilateration [13, 14].
The range measurement parameters are obtained from Received Signal Strength Indicator (RSSI) [15], Time of Arrival (TOA) [8], Angle of Arrival (AOA) [16], Time Difference of Arrival (TDOA) [9] and Received Signal Phase (RSP) [5]. For instance, in [9] 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 [15, 17, 18, 19]. 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. Landmark [17] 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 [18, 19, 20]. In [18], the authors localise the desired tag’s location by utilising a 2D grid of reference tags and a proximity map, while in [19], a Kalman filter based technique is used in locating the desired tag and in [20] weighted centroid localisation together with a PF is 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.

In [21] 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 to continuously track the 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 [21] 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 [21], 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 and therefore 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 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, the 4 mounted RFID antennas power and interrogate the tag in order to obtain the time of the read,
EPC (Electronic Product Code) assigned for each person, antenna ID that identifies the antenna reading the tag and the RSSI value. Thus, raw RFID reads $r$ obtained here can be represented by the schema: $[t, \text{patient}_{ID}, \text{ant}, \text{rssi}]$. 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 [22]. 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 [23, 24]. 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 \( t \).

\[
l_t = f_t(l_{t-1}, v_{t-1})
\]  

(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.

\[
p(l_t | l_{t-1}) = p(l_t | s, \theta, l_{t-1})
\]  

(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, \( \theta \). 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 [25] for people aged 40 and above and the probability of moving in any of the given direction \( \theta \) to be equiprobable where \( \theta = \{0^\circ, 45^\circ, 90^\circ, ..., 315^\circ\} \). 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 \( \theta \) is updated by multiplicative increases of 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 generic 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 \( \delta t \) 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

\[
\overline{z}_t = \{\{\overline{rssi}_{ant}\}_{ant=1}^{ant=w}\}
\]

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. Then, we calculate a mean RSSI map \( rssi_{\text{map mean}} \) and a RSSI standard deviation map \( rssi_{\text{map std}} \) from the collected RSSI values.

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 previously developed mean RSSI map, \( rssi_{\text{map mean}} \), 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 particle filter [6]. However, this approach is limited by the need to conduct a laborious scene analysis to develop the mean RSSI map \( rssi_{\text{map mean}} \) for each deployment setting; therefore such an approach is not suitable for practical deployments which ideally require a generic model that is agnostic to the deployment environment. We describe how we derived an effective generic sensor.
4.2.1. Generic Model

Kernel density estimation (KDE) is a method used to estimate the probability density function of a random variable [26] given a finite data sample. Our generic model is derived with the help of multi variant KDE by utilising the rssi\_map\_mean and rssi\_map\_std.

\[ \hat{f}_h(x) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{h_1 \ldots h_d} \mathcal{K} \left( \frac{x_1 - X_{i1}}{h_1}, \ldots, \frac{x_d - X_{id}}{h_d} \right) \]  

where \( \mathcal{K} \) denotes a multivariate kernel function operating on rssi\_map\_mean argument, \((h_1, \ldots, h_d)\) is a vector of bandwidths obtained from rssi\_map\_std, \(X_1, \ldots, X_d\) are the \( y \) dimensions of our state space having \( n \) observations for each of the \( d \) variables. Overall, from equation 3 we estimate the probability density of \((X_1, \ldots, X_d)\), which is just the joint pdf \( f \) of the state space \( X_1, \ldots, X_d \). The measured sensor model of antenna 1 and its corresponding generic model are shown in Fig. 1 (b) and (c), respectively. The rest of this section discusses how we utilise the generic model we have developed for the sensor model used in our tracking algorithm.

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.

\[ z_t = h_t(l_t, u_t) \]  

where \( h_t \) is a possible non-linear function, and \( u_t \) is i.i.d. measurement noise. The sensor model that we used in our system is shown below.

\[ p(z_t|l_t) = p(rssi\_map\_area, rssi\_ant|l_t, ant, \hat{f}_h(x)) = p(rssi\_ant|rssi\_map\_area) \cdot p(rssi\_map\_area|l_t, ant, \hat{f}_h(x)) \]  

where \( p(z_t|l_t) \) specifies the likelihood of obtaining a measurement \( z_t \) given the true state of the tag \( l_t \). The probability of having a measurement \( z_t \) is determined by two variables: i) rssi\_map\_area, the area of interest in the \( \hat{f}_h(x) \)
acquired generic model; and ii) $\overline{\text{rssi}}_{\text{ant}}$, the real-time segmented mean and standard deviation RSSI value. The conditional probability $p(\text{rssi}_\text{map,area}|l_t, \text{ant,}\hat{f}_h(x))$ specifies the area of interest in the RSSI map for every possible combination of ant and $l_t$. Furthermore, $p(\text{rssi}_\text{ant}|\text{rssi}_\text{map,area})$ specifies the likelihood of the obtained real-time segmented mean RSSI value $\overline{\text{rssi}}_\text{map,area}$ given the RSSI map and all possible combination of $a_j$ and $l_t$. Since $\overline{\text{rssi}}_\text{ant}$ and $\overline{\text{rssi}}_\text{map,area}$ are two different probability distributions and we are interested in measuring the accuracy of the predicted location, 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 [21]. For two probability distributions $P$ and $Q$, KL divergence is defined to be,

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

where $D_{KL}(P||Q)$, measures the information lost when the probability distribution $Q$ is given to approximate the probability distribution $P$ [21]. Therefore, in our sensor model KL divergence is used to find the maximum-likelihood location by replacing $p(\text{rssi}_\text{ant}|\text{rssi}_\text{map,area})$ in Eqn. (5) as shown below.

$$p(z_t|l_t) = D_{KL}(\overline{\text{rssi}}_\text{ant}||\overline{\text{rssi}}_\text{map,area}) \cdot p(\text{rssi}_\text{map,area}|l_t, \text{ant,}\hat{f}_h(x))$$

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.

**Initialize:** The state particles $x$ are first initialised. At time step $t = 0$, for $i = 1, \ldots, N$ sample state particles, $l_{0i} \sim p(l_0)$.

![Particle filtering algorithm](image)
Predict: Using the motion model, predict the location of the object at each time step. At $t$ the state of the particles $l$ are predicted to be in a location considering the state at $t - 1$ and the observations ($raw\_reads$) obtained so far. For $i = 1, \ldots, N$, predict particles, $l_i^t \sim q(l_i^t | l_{i-1}^t, raw\_reads_{1:t})$, where $q(.)$ is an importance function [22].

Update: Update involves three steps: i) On receiving an observation ($z_t$) the predicted particles’ locations are updated by weighting the particles using the measurement model to obtain importance weights $w_t$, $w_i^t = p(z_t | l_i^t)$, where high weights are given to the particles nearer to the measurement; ii) The particle’s weight is normalised. For $i = 1, \ldots, N$, normalize the importance weight, $w_i^t = w_i^t / \sum_{j=1}^N w_j^t$; and iii) Increasing numbers of PF iterations lead to sample degeneracy, which means only few particles would have non-negligible weights while the remaining would have near-zero weights [22]. Thus the resampling step eliminates the lower weighted particles and replicates higher weight particles to generate a new set of particles with equal weights [21]. The new set of particles thus obtained is equal to the original number of particles. For $i = 1, \ldots, N$, set, $w_i^t = 1/N$. 

Figure 3: (a) Four antenna setup (b) Two antenna setup (c) Traversal path
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 that works with measured sensor models. Instead, our algorithm utilizes the $rssi_{map_{mean}}$ and $rssi_{map_{std}}$ to develop a generic 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 generic 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 generic 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 length = 6 m, width = 2 m and height = 2.65 m 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 $45^\circ$ 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 generic 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 generic 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 used two approaches to evaluated 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 while the remaining 8 participants were divided equally into the supervised and
Table 1: Performance of our proposed TPD algorithm in the 2 antenna setting

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>TPD Algorithm</th>
<th>TP</th>
<th>FN</th>
<th>TN</th>
<th>FP</th>
<th>Recall ±%</th>
<th>Precision ±%</th>
<th>Accuracy ±%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two ant. with 9 segments</td>
<td>Without KL</td>
<td>108</td>
<td>392</td>
<td>47</td>
<td>153</td>
<td>21.6 ± 3%</td>
<td>41.5 ± 3%</td>
<td>22.3 ± 2%</td>
</tr>
<tr>
<td>Two ant. with 9 segments</td>
<td>With KL</td>
<td>113</td>
<td>387</td>
<td>51</td>
<td>149</td>
<td>23.0 ± 3%</td>
<td>43.7 ± 3%</td>
<td>23.9 ± 2%</td>
</tr>
<tr>
<td>Two ant. with 6 segments</td>
<td>Without KL</td>
<td>130</td>
<td>370</td>
<td>60</td>
<td>140</td>
<td>26.6 ± 3%</td>
<td>48.5 ± 2%</td>
<td>27.7 ± 3%</td>
</tr>
<tr>
<td>Two ant. with 6 segments</td>
<td>With KL</td>
<td>138</td>
<td>362</td>
<td>65</td>
<td>135</td>
<td>28.4 ± 2%</td>
<td>51.2 ± 3%</td>
<td>29.2 ± 2%</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>TPD Algorithm</th>
<th>TP</th>
<th>FN</th>
<th>TN</th>
<th>FP</th>
<th>Recall ±%</th>
<th>Precision ±%</th>
<th>Accuracy ±%</th>
</tr>
</thead>
<tbody>
<tr>
<td>In a supervised envi.</td>
<td>Without KL</td>
<td>366</td>
<td>134</td>
<td>141</td>
<td>59</td>
<td>73.2 ± 6%</td>
<td>86.0 ± 3%</td>
<td>72.4 ± 5%</td>
</tr>
<tr>
<td>In an unsupervised envi.</td>
<td>Without KL</td>
<td>313</td>
<td>187</td>
<td>125</td>
<td>76</td>
<td>62.6 ± 4%</td>
<td>80.5 ± 2%</td>
<td>62.5 ± 3%</td>
</tr>
<tr>
<td>In a supervised envi.</td>
<td>With KL</td>
<td>371</td>
<td>129</td>
<td>146</td>
<td>50</td>
<td>74.2 ± 5%</td>
<td>88.2 ± 3%</td>
<td>74.3 ± 4%</td>
</tr>
<tr>
<td>In an unsupervised envi.</td>
<td>With KL</td>
<td>325</td>
<td>175</td>
<td>129</td>
<td>71</td>
<td>65.0 ± 3%</td>
<td>82.1 ± 2%</td>
<td>66.9 ± 3%</td>
</tr>
<tr>
<td>6 segmented supervised envi.</td>
<td>Without KL</td>
<td>393</td>
<td>167</td>
<td>161</td>
<td>39</td>
<td>78.6 ± 3%</td>
<td>91.0 ± 2%</td>
<td>79.1 ± 2%</td>
</tr>
<tr>
<td>6 segmented unsupervised envi.</td>
<td>Without KL</td>
<td>350</td>
<td>150</td>
<td>157</td>
<td>43</td>
<td>70.0 ± 3%</td>
<td>89.1 ± 2%</td>
<td>72.4 ± 3%</td>
</tr>
<tr>
<td>6 segmented supervised envi.</td>
<td>With KL</td>
<td>398</td>
<td>162</td>
<td>163</td>
<td>37</td>
<td>79.6 ± 2%</td>
<td>91.6 ± 2%</td>
<td>80.1 ± 2%</td>
</tr>
<tr>
<td>6 segmented unsupervised envi.</td>
<td>With KL</td>
<td>363</td>
<td>137</td>
<td>161</td>
<td>39</td>
<td>72.6 ± 5%</td>
<td>90.4 ± 3%</td>
<td>74.9 ± 4%</td>
</tr>
</tbody>
</table>

unsupervised environment 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 trials (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 simi-
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

lar 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 $2 \times 6$ into 9 equal partitions as explained in [6]. We evaluated accuracy by counting the number of final 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. Non-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 generic 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 generic model because measured models are concise formulation whereas generic 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),
Table 3: Performance of our Proposed TPD Algorithm using Measured Model in the Four Antenna Settings

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>TPD Algorithm</th>
<th>TP</th>
<th>FN</th>
<th>TN</th>
<th>FP</th>
<th>Recall</th>
<th>Precision</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>In a supervised envi.</td>
<td>Without KL</td>
<td>397</td>
<td>103</td>
<td>161</td>
<td>39</td>
<td>79.4 ± 5%</td>
<td>91.1 ± 3%</td>
<td>79.7 ± 4%</td>
</tr>
<tr>
<td>In an unsupervised envi.</td>
<td>Without KL</td>
<td>343</td>
<td>157</td>
<td>143</td>
<td>57</td>
<td>68.6 ± 4%</td>
<td>85.8 ± 3%</td>
<td>69.4 ± 4%</td>
</tr>
<tr>
<td>In a supervised envi.</td>
<td>With KL</td>
<td>404</td>
<td>96</td>
<td>167</td>
<td>33</td>
<td>80.8 ± 5%</td>
<td>92.5 ± 2%</td>
<td>81.6 ± 4%</td>
</tr>
<tr>
<td>In an unsupervised envi.</td>
<td>With KL</td>
<td>367</td>
<td>133</td>
<td>150</td>
<td>50</td>
<td>73.4 ± 5%</td>
<td>88.0 ± 3%</td>
<td>73.9 ± 4%</td>
</tr>
<tr>
<td>6 segmented supervised envi.</td>
<td>Without KL</td>
<td>417</td>
<td>83</td>
<td>175</td>
<td>25</td>
<td>83.4 ± 3%</td>
<td>94.4 ± 2%</td>
<td>84.6 ± 3%</td>
</tr>
<tr>
<td>6 segmented unsupervised envi.</td>
<td>Without KL</td>
<td>385</td>
<td>114</td>
<td>159</td>
<td>41</td>
<td>77.2 ± 3%</td>
<td>90.4 ± 2%</td>
<td>77.8 ± 3%</td>
</tr>
<tr>
<td>6 segmented supervised envi.</td>
<td>With KL</td>
<td>424</td>
<td>76</td>
<td>179</td>
<td>21</td>
<td>84.8 ± 3%</td>
<td>95.3 ± 2%</td>
<td>86.14 ± 3%</td>
</tr>
<tr>
<td>6 segmented unsupervised envi.</td>
<td>With KL</td>
<td>392</td>
<td>108</td>
<td>160</td>
<td>34</td>
<td>78.4 ± 2%</td>
<td>92.2 ± 3%</td>
<td>79.7 ± 2%</td>
</tr>
</tbody>
</table>

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 in the training data set is used to generate a generic 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: Performance of our proposed TD algorithm

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>TD Algorithm</th>
<th>TP</th>
<th>FN</th>
<th>TN</th>
<th>FP</th>
<th>Recall</th>
<th>Precision</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Four ant. with 9 &amp; 6 segments With &amp; without KL</td>
<td>500</td>
<td>0</td>
<td>200</td>
<td>0</td>
<td>100%</td>
<td>100%</td>
<td></td>
<td>100%</td>
</tr>
<tr>
<td>Two ant. with 9 &amp; 6 segments With &amp; without KL</td>
<td>453</td>
<td>47</td>
<td>200</td>
<td>0</td>
<td>90%</td>
<td>100%</td>
<td>93.9%</td>
<td></td>
</tr>
</tbody>
</table>

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 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 [25] 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 generic model using KDE performed well by providing 100% accuracy in terms of detecting eloping incidents and virtually eliminating all false alarms. In particular, there was no change in performance when employing the measure sensor model and the generic model in either supervised or unsupervised environments. In terms of detecting the eloping path, our generic 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


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) [40, 47].
Multiple People Tracking

(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 [9]. 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 partitions 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: www.psb.ugent.be/cbd/papers/gentxwarper/DTWAlgorithm.ppt.
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,

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

$$B_u = b_1, b_2, b_3, ..., b_j, ..., b_n \text{ where } B_u \in B$$

DTW searches for the best alignment that minimizes the total cost $C$ [40] 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

$$Cost_u = \sum C \text{ where } Cost_u \in Cost$$

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\textsubscript{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 $\delta t$ observation for that patient ID patient\textsubscript{1}. Later, at time 9.03, we observe a reading for person 2 with a tag ID patient\textsubscript{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\textsubscript{1}. The TPD and TD algorithm is now initiated to track the path and direction of patient\textsubscript{2}. The tag reading partition in Chapter 4, Section 4.1 works as below.

We partition a sequence of tag reading $r_{1:m} = \{(\text{patientID}, t_i, \text{rssi}_i, \text{ant}_i)\}_{i=1}^{m}$ in a non-overlapping fixed time segment $\delta t$ for a given patientID where patientID 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 $t$. From the sequence $r_{1:m}$, we obtain the observation $z_t$ for each patientID, by calculating the mean RSSI value $\overline{\text{rssi}}_{\text{ant}}$ for each antenna ant that obtained a tag read.

$$z_t(\text{patientID}) = \{\overline{\text{rssi}}_{\text{ant}}\}_{\text{ant}=1}^{w}$$

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 $\overline{\text{rssi}}_{\text{ant}}$ 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.
Multiple People Tracking

Fig. 6.3 Path 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
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$\text{$_1$}$ and patient$\text{$_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$\text{$_1$}$ (blue path) moving inside the cared path and the patient is the patient$\text{$_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

<table>
<thead>
<tr>
<th>Path</th>
<th>Person 1</th>
<th>Person 2</th>
<th>TD</th>
<th>TPD Accuracy (without DTW)</th>
<th>TPD Accuracy (with DTW)</th>
<th>Heading Out Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Path 1</td>
<td>patient 1</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>patient 2</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Path 2</td>
<td>patient 1</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>patient 2</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Path 3</td>
<td>patient 1</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>patient 2</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Path 4</td>
<td>patient 1</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>patient 2</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Path 5</td>
<td>patient 1</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>patient 2</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Path 6</td>
<td>patient 1</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>patient 2</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Path 7</td>
<td>patient 1</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>patient 2</td>
<td>100%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Path 8</td>
<td>patient 1</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>
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\textsubscript{1} and patient\textsubscript{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\textsubscript{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\textsubscript{1} was walking closely before or after patient\textsubscript{2}. The RF waves were completely absorbed and blocked by the patient\textsubscript{1} who was standing in between patient\textsubscript{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
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 care-giver. 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, \textit{patient}_1 is moving in the \textit{Straight-in} to \textit{Straight-out} path whereas \textit{patient}_2 was using the \textit{No-traversal Left-in} to \textit{Right-in} path. Once \textit{patient}_1 has passed the central region there is no interference from \textit{patient}_2 to the \textit{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 [53] 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.
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
Conclusion and Future Work

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-Traversals, 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. Having tags 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. Validating the multiple tag approach to improve the accurate identification of traversal paths is left as future work.

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 [35], 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.

\[
d = \frac{c}{4\pi} \frac{\partial \phi}{\partial f}
\]

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 implantable RFID tags.
References


Conclusion and Future Work


