Indoor Localisation System and Methods using Passive UHF RFID with A Mobile Platform

Zheng Liu

Department of Engineering
University of Cambridge

This dissertation is submitted for the degree of

Doctor of Philosophy

Girton College

December 2022
I would like to dedicate this thesis to my loving parents ...
Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

Zheng Liu
December 2022
Indoor Localisation System and Methods using Passive UHF RFID with A Mobile Platform

Zheng Liu

Abstract

High accuracy localisation in a complicated and varied indoor environment such as a warehouse or a factory is one of the most important requirement and it is still challenging. In this dissertation, this problem is solved by designing a system which combines radio frequency identification (RFID) technology with a mobile platform and development of localisation methods.

The system designed in this dissertation is composed of ultra-high frequency (UHF) RFID passive tags, a mobile platform and a computer. UHF RFID passive tags are either placed as reference tags or attached to objects as targets to locate. The mobile platform is comprised of a UHF RFID reader, a Raspberry Pi board, multiple antennas, a robot, and batteries. The computer is used to control the mobile platform remotely to collect information of tags. Both the low-cost of passive tags and the mobility of the mobile platform make the system suitable for indoor localisation in a warehouse or a factory.

After designing the system, a novel inverse synthetic aperture radar (ISAR)-synthetic aperture radar (SAR) localisation method is proposed and experimentally tested. In order to reduce the cost of devices for trajectory measurement, reference tags with known locations are used to estimate the trajectory of the mobile platform by the ISAR algorithm. A novel ISAR-SAR loop is introduced to find out the optimal estimated trajectory, which will be used to perform SAR algorithm and locate target tags. Experimental results of 2D localisation show that the ISAR-SAR method using a straight-line trajectory can achieve a mean absolute localisation error of 15 cm, which is similar to that using a traditional SAR algorithm and by the ISAR-SAR method using an L-shape trajectory, the error can be reduced to 8 cm, which is slightly smaller than light detection and ranging (LiDAR)-SAR method.
The SAR-based algorithms can achieve high localisation accuracy but require the calculation of the probability function over a fine grid and this results in a high computational load particularly for 3D localisation, which is one of the main drawbacks of the SAR-based algorithms. This thesis also proposes and demonstrates a high accuracy localisation method with reduced computational burden based on the received signal strength indicator (RSSI) and the unwrapped phase profile. After measuring the phase and RSSI, a valid dataset can be obtained by analysing the received RSSI, the strength of which can indicate whether the signal is stable or not. The stationary point of the unwrapped phase profile combined with the known trajectory of the moving platform is used to estimate the distance along the trajectory, which is termed as cross-range. The distance perpendicular to the trajectory, which is termed as down-range, can be estimated by estimating the integer number (k-parameter) of wavelengths which fits the cross-range location and phase profile. For 2D localisation, only a single straight-line trajectory is required while in 3D space, multiple antennas at various heights are used and after obtaining x- and y-coordinate of the tag by cross-range estimation with a L-shape trajectory, a possible range for the height of the tag will be estimated by received RSSI values and the accurate height can be calculated by the k-parameter estimation method. Experimental results demonstrates that the mean 2D localization error is around 12 cm and mean 3D localization error is around 14 cm.

SAR-based methods typically require LiDAR sensors or high quality optical cameras to measure the trajectory so the localisation accuracy by these methods is affected by the accuracy of the measurement for trajectory while fingerprint methods require deployment of reference tags so the accuracy depends on the density of reference tags, which requires a lot of reference tags. This dissertation also propose a method that aims to reduce the number of required reference tags and reduce the requirement for devices to measure the trajectory by further exploiting the phase profile and analysing the relationship between tags and the trajectory of the mobile platform. To achieve 2D localisation, three reference tags with known locations and two non-collinear straight-line trajectories are required. The main idea of the proposed method is analysing the geometric relationship between the trajectory and tags using the minima of the unwrapped received phase profile. The direction of the trajectory relative to the reference tags is firstly determined and direction of two trajectories is used to calculate the location of target tags. Experiments show the mean 2D localization error is around 12 cm.
Acknowledgements

Firstly, I would like to offer my deepest gratitude to my supervisors Dr Michael Crisp and advisor Prof. Richard Penty, for their continuous support and insightful advice throughout my PhD.

My sincerest thanks to Dr Zhe Fu. He has been a great help with my research.

In addition, I would like to thank Dr. Tongyun Li, Dr. Shuai Yang, Dr. Rui Chen and other group colleagues for communication and discussion of my research work.

Last but not least, I would like to thank my parents and my friends for their constant encouragement, love and support throughout my life.
Publications


## Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>List of Figures</td>
<td>xiii</td>
</tr>
<tr>
<td>List of Tables</td>
<td>xv</td>
</tr>
<tr>
<td>Nomenclature</td>
<td>xvii</td>
</tr>
<tr>
<td>1 Introduction</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Overview and Motivation</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Aims and Objectives</td>
<td>7</td>
</tr>
<tr>
<td>1.3 Outline and Original Contributions</td>
<td>7</td>
</tr>
<tr>
<td>2 RFID systems and Localisation Methods</td>
<td>11</td>
</tr>
<tr>
<td>2.1 RFID Systems</td>
<td>11</td>
</tr>
<tr>
<td>2.1.1 History</td>
<td>11</td>
</tr>
<tr>
<td>2.1.2 Overview of an RFID system</td>
<td>14</td>
</tr>
<tr>
<td>2.2 Localisation Methods</td>
<td>21</td>
</tr>
<tr>
<td>2.2.1 Geometry-based</td>
<td>21</td>
</tr>
<tr>
<td>2.2.2 Non-Geometry-based</td>
<td>30</td>
</tr>
<tr>
<td>2.2.3 Summary</td>
<td>39</td>
</tr>
<tr>
<td>2.3 Literature Review</td>
<td>40</td>
</tr>
<tr>
<td>2.3.1 Methods based on SAR</td>
<td>40</td>
</tr>
<tr>
<td>2.3.2 Methods for spatial ordering</td>
<td>42</td>
</tr>
<tr>
<td>2.3.3 Methods with reference tags</td>
<td>43</td>
</tr>
<tr>
<td>3 Localisation Method Based on ISAR-SAR</td>
<td>45</td>
</tr>
<tr>
<td>3.1 System Design and Setup</td>
<td>45</td>
</tr>
<tr>
<td>3.1.1 Aims</td>
<td>45</td>
</tr>
<tr>
<td>3.1.2 System Design</td>
<td>46</td>
</tr>
<tr>
<td>3.1.3 Environment and Setup</td>
<td>49</td>
</tr>
<tr>
<td>Section</td>
<td>Title</td>
</tr>
<tr>
<td>---------</td>
<td>-------</td>
</tr>
<tr>
<td>3.2</td>
<td>Introduction</td>
</tr>
<tr>
<td>3.3</td>
<td>Algorithm</td>
</tr>
<tr>
<td>3.3.1</td>
<td>ISAR</td>
</tr>
<tr>
<td>3.3.2</td>
<td>ISAR-SAR</td>
</tr>
<tr>
<td>3.4</td>
<td>Results</td>
</tr>
<tr>
<td>3.4.1</td>
<td>Results with a straight-line trajectory</td>
</tr>
<tr>
<td>3.4.2</td>
<td>Results with an L-shape trajectory</td>
</tr>
<tr>
<td>3.5</td>
<td>Conclusion</td>
</tr>
<tr>
<td>4</td>
<td>Localisation Method Based on k-parameter Estimation</td>
</tr>
<tr>
<td>4.1</td>
<td>Introduction</td>
</tr>
<tr>
<td>4.2</td>
<td>Algorithm</td>
</tr>
<tr>
<td>4.2.1</td>
<td>Cross-range Estimation</td>
</tr>
<tr>
<td>4.2.2</td>
<td>Down-range Estimation For 2D Localisation</td>
</tr>
<tr>
<td>4.2.3</td>
<td>Estimation For 3D Localisation</td>
</tr>
<tr>
<td>4.3</td>
<td>Results</td>
</tr>
<tr>
<td>4.3.1</td>
<td>2D Localisation Results</td>
</tr>
<tr>
<td>4.3.2</td>
<td>3D Localisation Results</td>
</tr>
<tr>
<td>4.4</td>
<td>Conclusion</td>
</tr>
<tr>
<td>5</td>
<td>Localisation Method Based on Geometrical Relationship</td>
</tr>
<tr>
<td>5.1</td>
<td>Introduction</td>
</tr>
<tr>
<td>5.2</td>
<td>Algorithm</td>
</tr>
<tr>
<td>5.2.1</td>
<td>The minima of the unwrapped phase</td>
</tr>
<tr>
<td>5.2.2</td>
<td>Geometric relationship</td>
</tr>
<tr>
<td>5.3</td>
<td>Results</td>
</tr>
<tr>
<td>5.4</td>
<td>Conclusion</td>
</tr>
<tr>
<td>6</td>
<td>Conclusion and Future Work</td>
</tr>
<tr>
<td>6.1</td>
<td>Overall Conclusion</td>
</tr>
<tr>
<td>6.2</td>
<td>Future Work</td>
</tr>
<tr>
<td></td>
<td>Bibliography</td>
</tr>
</tbody>
</table>
## List of Figures

1.1 RFID technology market revenue worldwide from 2014 to 2019 ........................................ 2  
1.2 Trend of RFID technology from 2001 to 2014 ................................................................. 3  
2.1 The structure of an RFID system ................................................................. 15  
2.2 Frequency Bands for RFID ................................................................. 16  
2.3 Bi-static and mono-static configurations ................................................................. 17  
2.4 Linearly-polarised antenna ................................................................. 18  
2.5 Circularly-polarised antenna ................................................................. 19  
2.6 Different type of tags ................................................................. 20  
2.7 The trilateration algorithm ................................................................. 22  
2.8 The elliptical model ................................................................. 23  
2.9 The hyperbolic model ................................................................. 24  
2.10 The approach of AoA ................................................................. 29  
2.11 Improved AoA technique ................................................................. 31  
2.12 An example of LANDMARC system ................................................................. 33  
2.13 The diagram of SAR algorithm ................................................................. 36  
3.1 The diagram of the system ................................................................. 46  
3.2 Components of the system ................................................................. 48  
3.3 Environment of the lab ................................................................. 50  
3.4 The steps of ISAR-SAR method ................................................................. 53  
3.5 The diagram for variables \( l \) and \( \theta \) of the hypothetical step ................................................................. 54  
3.6 The flow chart of ISAR-SAR method ................................................................. 57  
3.7 Experiment setup with a straight-line trajectory ................................................................. 60  
3.8 Trajectory results of one of the tests ................................................................. 62  
3.9 Comparison of points between LiDAR trajectory and ISAR trajectory ................................................................. 62  
3.10 Localisation results of target tags of one of tests ................................................................. 64  
3.11 Picture of the controlled environment with a straight-line trajectory ................................................................. 64
3.12 Experiment setup with an L-shape trajectory ........................................ 67
3.13 Trajectory results of one of the tests ...................................................... 68
3.14 Errors between ISAR trajectory and LiDAR trajectory along x-direction
(samples are taken every centimetre) ......................................................... 69
3.15 Errors between ISAR trajectory and LiDAR trajectory along y-direction
(samples are taken every centimetre) ......................................................... 69
3.16 Probability heatmap with a straight-line trajectory ............................... 71
3.17 Probability heatmap with an L-shape trajectory .................................... 72
3.18 Localisation results of target tags of Test 5 ........................................ 73
3.19 The straight-line trajectory for Test1 and Test3 ................................. 74

4.1 Estimation of the minima of the unwrapped phase ............................... 79
4.2 Coordinate for the setup ........................................................................... 81
4.3 Received phase values after unwrapping and the fitting curve .............. 82
4.4 Received RSSI and unwrapped phase values ........................................ 84
4.5 Phasor diagram of worst cases ............................................................... 84
4.6 Simulated results of y-coordinate estimation with different k ............... 86
4.7 Estimation of y location with wrong k-parameter ............................... 87
4.8 The received RSSI by four antennas for the tag with the height of 1.15 m 91
4.9 Flowchart for 3D localisation ................................................................. 93
4.10 Experiment setup for 2D localisation .................................................... 95
4.11 y-coordinate estimation results with different k .................................... 96
4.12 Localisation results of target tags of Test 2 ....................................... 97
4.13 Experiment setup for 3D localisation .................................................... 98
4.14 The CDF of the 3D localisation error along each axis and the total
  error magnitude ......................................................................................... 99
4.15 Localisation results for all tags ............................................................. 100
4.16 The received RSSI by four antennas for the tag with the height of 0.75 m .... 101

5.1 Estimation of the minima of the unwrapped phase ............................... 106
5.2 Estimation of the direction of the trajectory ....................................... 107
5.3 Estimation of the target tag location .................................................... 107
5.4 Experiment setup and the picture of the environment ....................... 110
5.5 Localisation results ............................................................................. 111
5.6 CDF of the localisation error ............................................................... 112
List of Tables

2.1 A summary of major events in RFID development .................. 14

3.1 Effect of parameters on ISAR process showing the error between the true and estimated location of the reference tag ......................... 61

3.2 Difference between trajectory measured by LiDAR and estimated by ISAR ................................................... 63

3.3 Mean localisation error value of 10 tests by SAR with a straight line trajectories ......................................................... 65

3.4 Error in the trajectory estimation by the ISAR process ............... 70

3.5 Mean localisation error value of five tests by SAR with two trajectories ................................................................. 74

3.6 The std of the error between the received phase and theoretical phase ............................................................ 75

4.1 Mean localisation error of five tests ................................. 99
Nomenclature

Symbols

\( \eta \)  power transfer efficiency

\( \lambda \)  signal wavelength

\( \pi \)  the ratio of a circle’s circumference to its diameter

\( G \)  gain

\( P \)  power

Acronyms/Abbreviations

AIDC  Automatic Identification and Data Capture

AoA  Angle of Arrival

Auto-ID  Automatic Identification

BkNN  Bayesian probability and k-Nearest Neighbour

CPS  Cyber-Physical Systems

CW  Continuous Wave

DBSCAN  Density-Based Spatial Clustering of Applications with Noise

EAS  Electronic Article Surveillance

ELM  Extreme Learning Machine

EM  ElectroMagnetic

EPC  Electronic Product Code
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>FD</td>
<td>Frequency Domain</td>
</tr>
<tr>
<td>FDX</td>
<td>Full Duplex</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>HDX</td>
<td>Half Duplex</td>
</tr>
<tr>
<td>HF</td>
<td>High Frequency</td>
</tr>
<tr>
<td>IC</td>
<td>Integrated Circuit</td>
</tr>
<tr>
<td>IFF</td>
<td>Identification of Friends or Foes</td>
</tr>
<tr>
<td>ISAR</td>
<td>Inverse Synthetic Aperture Radar</td>
</tr>
<tr>
<td>kNN</td>
<td>k-Nearest Neighbour</td>
</tr>
<tr>
<td>LANDMARC</td>
<td>LocAtioN iDentification based on dynaMic Active Rfid Calibration</td>
</tr>
<tr>
<td>LF</td>
<td>Low Frequency</td>
</tr>
<tr>
<td>LiDAR</td>
<td>Light Detection And Ranging</td>
</tr>
<tr>
<td>LoS</td>
<td>Line-of-Sight</td>
</tr>
<tr>
<td>LSVRT</td>
<td>Least Square Variance-based Radio Tomography</td>
</tr>
<tr>
<td>MAE</td>
<td>Mean Absolute Error</td>
</tr>
<tr>
<td>NLoS</td>
<td>Non-Line of Sight</td>
</tr>
<tr>
<td>PDoA</td>
<td>Phase Difference of Arrival</td>
</tr>
<tr>
<td>RFID</td>
<td>Radio Frequency Identification</td>
</tr>
<tr>
<td>ROS</td>
<td>Robot Operating System</td>
</tr>
<tr>
<td>RSSI</td>
<td>Received Signal Strength Indicator</td>
</tr>
<tr>
<td>RTI</td>
<td>Radio Tomographic Imaging</td>
</tr>
<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
</tr>
<tr>
<td>SLAM</td>
<td>Simultaneous Localisation And Mapping</td>
</tr>
<tr>
<td>TDoA</td>
<td>Time Difference of Arrival</td>
</tr>
</tbody>
</table>
ToA  Time of Arrival
ToF  Time of Flight
UAV  Unmanned Aerial Vehicle
UGV  Unmanned Ground Vehicle
UHF  Ultra High Frequency
UPC  Universal Product Code
UWB  Ultra-wideband
VIRE Virtual Reference Elimination
Chapter 1

Introduction

1.1 Overview and Motivation

Since the first Industrial Revolution in 18th century, the first three industrial revolutions have brought comprehensive changes in manufacturing, from steam engines to automated digital mass production, making manufacturing processes increasingly complicated and automatic [1–3]. The first industrial revolution saw many important inventions including the steam engine, which changed the means available for production, canal and later railway networks, which increased communication ability, and the stock exchange, which led to the rise of banks, financiers, and private investment, and so on [3, 4]. The second industrial revolution saw major technological developments in various fields such as steel, chemicals, electricity, which was a crucial development and was used to power various types of machines for many industries to operate and expand their businesses, and so on [3, 5]. The third industrial revolution saw many advances in information and communications technologies, which have played a critical role in facilitating cross-border flows of information and data, such as the advancement of the electronics, metadata, Internet, which is the infrastructure powering the third revolution, and so on [3, 4, 6]. Nowadays, the fourth Industrial Revolution, driven by advanced technologies such as gene sequencing, nanotechnology, quantum computing, artificial intelligence (AI), robotics and the Internet of things (IoT) [7–9], is expanding current production systems into cyber-physical systems (CPS) by adding network connections and digital twins on the Internet [10, 11]. A CPS is formed by three levels: the physical objects such as smart factories or warehouses, data models of the physical objects in a network infrastructure, and services based on the data obtained from the physical objects [10, 12].
In a smart factory or warehouse, where components, products and people are connected via a network leading to autonomous production [10], authentication of identification for objects such as materials and products is vital for manufacturing procedure and logistics management [13]. In order to fulfil this requirement, automatic identification (Auto-ID) or automatic identification and data capture (AIDC) technologies have been widely adopted [14–16]. Radio frequency identification (RFID) technology is one of the most widespread methods and has been employed in many areas such as purchasing and distribution logistics, supply chain management, manufacturing industries, and so on [15–18].

The history of RFID technology can be traced back to the World War II when the British army developed a prototype identification of friends or foes (IFF) system to remotely identify aeroplanes [19]. With advancement in technology and growing interests in related areas, RFID is playing an increasingly important role in both commercial and academic areas. According to Avery Dennison Corporation [20], the global market revenue of RFID technology reached $15 billion in 2019, which is about four times the revenue in 2014. Although the market of RFID technology is dominated by the apparel sector, the non-apparel sector has seen its market share rise by 50% from around 20% in 2014 to 30% in 2019 as shown in Fig. 1.1. Meanwhile, the global RFID technology market revenue is forecast to keep growing rapidly. In total, 23.8 billion passive RFID tags were sold in 2020 and a double-digit growth rate is expected to continue over the next few years [21].

![Figure 1.1 RFID technology market revenue worldwide from 2014 to 2019](image)

Apart from rapid growth in commercial sector, RFID technology has also attracted increasing attention in academic area. As shown in Fig.1.2a, based on the SCI...
1.1 Overview and Motivation

Figure 1.2 Trend of RFID technology from 2001 to 2014 [22]
and SSCI databases, there has been a sharp increase in the number of publications each year since the new millennium [22] and around 700 papers were published each year from 2011 to 2014 which is about 54 times the number in 2001. The number of citations each year also witnesses a dramatic increase since 2001 as shown in Fig.1.2b. RFID papers were cited only a few times in 2002 while in 2014 the number of citations jumped to over 9000 which indicates RFID has become a hot research area during the past decade. Although a slowdown is expected in the growth and RFID technology has been widely applied in apparel sector for inventory checking (each passive tag is only a few pence), applications of RFID in various fields such as indoor localisation are still challenging and research on RFID topics will continue to increase and evolve in the future [22].

The reason why RFID technology is being widely used in many areas and being a heated research topic is that it has several advantages compared with other AIDC technologies such as barcodes, magnetic stripe or QR codes. The advantages can be briefly explained as follows [14, 23]:

- RFID does not require direct contact or a line of sight to communicate with RFID tags
- RFID is capable of identifying a large number of items simultaneously from a distance by radio waves
- RFID can work in various environments for over years which significantly reduces maintenance costs
- RFID has the capacity to remotely locate and track tagged items
- RFID can achieve a relative high read rate of hundreds of tags per second
- RFID enables a large amount of data for items such as serial number, lot number, location, status, etc.
- RFID can provide offer unique identification for individual objects when using the Electronic Product Code (EPC) while the barcode with the Universal Product Code (UPC) can only identify categories of product
- RFID with EPC uses a 96-bit numbering scheme which is divided into a header part with 8 bits, a manufacturer part with 24 bits or over 16 million unique IDs, a product part with 24 bits or over 16 million unique IDs, and a serial number part with 40 bits or over 1 trillion unique IDs, while a barcode with UPC-A
uses a 12-digit system which is divided into a manufacturer part with 6 digits or 1 million unique IDs, a product part with 5 digits or 100 thousand unique IDs, and 1 check digit.

All these advantages created the economic and academic boom in RFID technology. Nowadays, RFID technology continues to play an important role in the fourth Industrial Revolution, which focuses heavily on automation, interconnectivity and real-time data [7]. In order to achieve the goal of full automation, an autonomous and collaborative robot has become one of essential components in a factory or warehouse and has been considered as one of the nine pillars sustaining the current "Manufacturing Renaissance" [10, 24]. In the field of mobile robotics, localisation has been referred to as the most fundamental requirement providing autonomous abilities for a mobile robot [25–30].

In contrast to industrials robots, autonomous robots, which are built on mobile platforms, move around in a highly complicated and unstructured environment [25]. In an outdoor environment, traditional satellite positioning technologies such as global positioning systems (GPS) or techniques based on a cellular network can provide location information. However, these technologies can’t provide stable and reliable service in indoor scenarios [31]. So indoor localisation or positioning methods are required to measure the position of robots, materials, and products so that robots can determine where they are and whether they are going in the correct direction.

In a factory or a warehouse, there is also a growing demand for accurate location information (of the order of tens of centimetres) about materials and products to improve decision making and increase manufacturing efficiency and automation [32, 33]. For example, where automated robots are used to fetch desired materials and products, they must know the accurate location of items, not just whether they exist within the inventory. By using automated robots, the time and cost spent searching for items which is generally performed by humans can be significantly reduced [34, 35]. Moreover, supply chains suffer from disruptions caused by human-related disasters such as the Covid-19 pandemic, which has brought a global tragedy not only for human lives, but also for economic activities such as operations in manufacturing, supply chain and logistics [36–39]. Fully automated factories and warehouses can prevent spread of infections and hence avoid consequent economic losses.

Many indoor solutions have been proposed based on various techniques including infrared, ultrasonic, Wi-Fi, Bluetooth, RFID and so on [31, 40–52]. In a
infrared-based system [44, 45], infrared sensors deployed in a building are receiving the modulated infrared signal emitted from a tag equipped with an infrared LED emitting infrared beacons periodically. Based on the received signal, the location server can obtain the position of the target tag. The ultrasonic system measures the distance by emitting ultrasonic sound waves and measuring the time of flight (ToF) or time of arrival (ToA) [46–48]. As many indoor environment such as a university or an office has already distributed Wi-Fi hotspots, localisation system based on Wi-Fi, which is based on fingerprinting method using received signal strength indicator (RSSI), has been employed in many indoor scenarios [49, 50]. As Bluetooth, which is a technical standard enabling short-range wireless communication between devices, is widely equipped in mobile phones and computers, the Bluetooth system based on RSSI is a popular solution for indoor localisation [51, 52].

RFID is another popular technology for indoor localisation systems. Similar to Wi-Fi and Bluetooth, it is hard to measure ToA due to limited bandwidth and it is able to exploit RSSI information for localisation methods. RFID technology can also provide phase information which is comparatively stable in a complicated environment compared with RSSI. RFID technology can operate in various frequency bands while Bluetooth operates in 2400-2480 MHz and Wi-Fi operates in 2.4 GHz and 5 GHz bands [53]. Passive RFID tags can be deployed without requirement of batteries and maintenance so it is cheaper than Bluetooth or Wi-Fi which require communications between two Bluetooth or Wi-Fi compatible devices requiring batteries.

Among all these technologies, RFID technology has become one of the most popular technologies and has been widely adopted in object localisation [54–57] because it has many advantages such as contactless communication which is essential in a complicated indoor environment containing many obstacles including shelves and products [58], multi-object recognition providing the ability to track a large number of items which is crucial in a warehouse [30, 54], and low-cost leading to higher profitability and enabling large-scale applications which is important in a factory or a warehouse [40, 54, 59–61]. The challenges to be solved using RFID technology for localisation include the $2\pi$-periodicity, the phase offset term, the orientation between the tag and the reader antenna, and multipath effects, especially for passive RFID devices [62, 63].
1.2 Aims and Objectives

As described in the previous section, many solutions have been proposed aiming to meet the requirement for localisation of assets and could provide comparatively effective location services in their respective application scenarios. However, they have drawbacks and limitations. The infrared-based system requires line-of-sight (LoS) communication between the infrared sensor and LED and suffers from fluorescent light and sunlight interference, which limits the applications of infrared-based systems [64]. Disadvantages of conventional ultrasonic systems include the transmission attenuation which means limited ranging distance and high construction cost, which means it cannot be applied widely for indoor localisation [65, 66]. In a system based on Wi-Fi, the target can only be a device with wireless capacity so Wi-Fi tags are usually less power-efficient and more expensive than other alternatives [66, 67]. Bluetooth-based localisation system suffers from comparatively low localisation accuracy and poor real-time performance [67, 68].

In a scenario like a factory or a warehouse where the environment is complicated and varied, RFID technology is more suitable for locating and tracking a great number of items due to its advantages like multi-object recognition and low-cost. Thus, the main aim of the work in this dissertation is to design a localisation system based on RFID technology, propose localisation methods in order to achieve higher localisation accuracy in an indoor environment such as a warehouse, and experimentally demonstrate and verify the localisation algorithm using the designed system.

1.3 Outline and Original Contributions

The dissertation is organized as follows:

Chapter 2 presents an overview of RFID systems including the history and components of RFID systems. An introduction of localisation and positioning theory is given to discuss details of different localisation methods with a focus on methods applicable to passive ultra high frequency (UHF) RFID. The final section gives a literature review of indoor localisation methods, which are related to this dissertation, based on passive RFID systems.

Chapter 3 firstly gives the requirements of the problem to be solved in this dissertation. The detail for the design of the system used in this dissertation and the environment as well as the setup for the experimental evaluation are also given. This chapter proposes a novel inverse synthetic aperture radar (ISAR)-synthetic
aperture radar (SAR) localisation method using Passive UHF RFID. The proposed method uses reference tags with known locations to estimate the trajectory of the mobile platform and locate target tags with unknown locations using the estimated trajectory. After obtaining the estimated trajectory of the moving antenna by the ISAR algorithm, a novel ISAR-SAR loop is proposed to adjust the estimated trajectory. The ISAR-SAR loop exploits the known locations of reference tags and determines whether the estimated trajectory is the optimal estimated trajectory or not by using localisation error of reference tags. The optimal estimated trajectory, combined with phase measurements of target tags, is used to determine location of targets via the SAR algorithm. With a straight-line trajectory, the ISAR-SAR method can achieve a mean absolute localisation error of 15 cm, which is similar to that using a traditional SAR algorithm, the trajectory of which is based on light detection and ranging (LiDAR). Using an L-shaped trajectory, the error can be reduced to 8 cm for the ISAR-SAR method, which is slightly smaller than LiDAR-SAR method.

Chapter 4 proposes a phase and RSSI-based method for indoor localisation of UHF RFID tags. This method requires a known trajectory but the computational burden is comparatively small compared with SAR-based methods since it does not need to traverse the area which is divided into a fine grid. The phase and RSSI are measured by a moving RFID reader carried by a mobile robot. After obtaining a valid dataset by analysing the received RSSI, where its strength can indicate whether the signal is stable or not, the cross-range location of the target is calculated by the stationary point of the phase curve combined with the corresponding location of the moving antennas. A novel algorithm for estimating down-range distance is proposed. The down-range distance is estimated by estimating the integer number (k-parameter) of wavelengths which fits the cross-range location and phase profile. 2D localisation requires only one straight-line trajectory while 3D localisation requires an L-shaped trajectory. In the case of 3D localisation, after estimating the x- and y-coordinate using the cross-range estimation method, a possible range of height for target tags is determined by the strength of RSSI received by multiple antennas and the final height is obtained by down-range estimation method. 2D localisation accuracy can reach 12 cm while 3D localisation accuracy is around 14 cm (mean absolute error). This method further exploits the stationary point of the unwrapped phase curve, which is only used to determine spatial ordering of tags in previous methods, to calculate absolute location of tags with a small computational burden and achieve comparatively high localisation accuracy.
Chapter 5 proposes a novel phase-based relative localisation method. The proposed method requires a minimum of three reference tags with known locations to achieve a 2D localisation. After deploying three reference tags with known locations and collecting phase information along two non-collinear straight-line trajectories, the direction of trajectories will be estimated using the minima of the unwrapped phase profile and the relative geometric relationship between reference tags and target tags will be determined using the received phase and the estimated direction of trajectories. Experiments show a 2D mean localisation error is around 12 cm. Based on this demonstration, this new method provides a novel solution without requirement for knowledge of the precise trajectory. Compared with other methods, this new method requires fewer reference tags and reduces the cost in terms of other sensing devices calibration in different localization scenarios.

Chapter 6 concludes the dissertation and provides ideas for future work.
Chapter 2

RFID systems and Localisation Methods

2.1 RFID Systems

RFID technology is a technology using electromagnetic (EM) waves as communication medium that enables related information to be stored, read and updated remotely and enables objects with tags attached to them to be automatically identified and tracked. An RFID system mainly consists of two components: an interrogator or a reader and a transponder or a tag. Due to the fact that RFID has many great advantages, it has been widely employed by indoor localisation systems.

In order to help understand the rest of this dissertation, this chapter provides an overview of the RFID technology and the localisation methods. The rest of this chapter is organised as follows: Section 2.1 gives an overview of the RFID system including the history, frequency bands, and components of the RFID system. A review of localisation methods is give in Section 2.2 to introduce and explain different localisation methods and applications.

2.1.1 History

During World War II, identifying hostile aircraft was one of the most challenging problems for all countries. As the radar technology during that time could only detect the presence of an aircraft and was unable to identify the identity, German pilots solved this problem by rotating their planes to change the backscattered signal reflected from the aircraft allowing German radar operators to mark them as friendly targets [15]. This method has a problem of security which means that any aircraft can
be rolled. Hence, simple IFF systems, which employ backscattered signals to achieve communications, were developed and widely used by many countries during the war [19]. These systems provide various functions including identification of a target by a radio signal without requirement of visual contact and an ID space big enough to provide unique identification. However, wider application of these backscattered communications systems was limited by the cost and size of the equipment.

Due to the economic requirement that the method of identifying targets must cost less than the value of the targets, several possible technologies to reduce the cost and complexity of the circuit have been proposed such as skipping the transmitter, which is usually large and complex, by varying property of the signal backscattered from an object, and using passive systems without using batteries, which require maintenance and are expensive. In 1948, Harry Stockman proposed a mathematical model of backscattered communication in his paper *Communication by Means of Reflected Power*, which encouraged further investigation of solving the remaining problems and has been considered as the fundamental model and theory of RFID communication technology [69].

The idea of the integrated circuit (IC) was invented in 1950’s by the German physicist and engineer Werner Jocobi, who developed and patented the first known integrated transistor amplifier in 1949 [70] and the British radio engineer Geoffrey Dummer, who proposed the idea to integrate various standard electronic components in a semiconductor crystal in 1952 [71]. The idea was implemented to invent prototype of ICs by Jack Kilby of Texas Instruments [72] and Robert Noyce of Fairchild Semiconductor [73] independently in late 1950’s. Since the invention of ICs, according to Gordon Moore’s law, the number of transistors in an IC doubles about every two years. This trend not only has impacted almost every aspect of modern life but also enables low-cost fabrication and mass production of modern RFID which leads to broader application [19].

In the 1960’s, electronic article surveillance (EAS) systems, where the transmitter and receiver are inductively coupled, were developed to prevent theft of retail goods and books. The EAS uses a simple tag with 1-bit space for marking the state of payment so if the tag is marked as unpaid an alarm will be raised when the tagged item leaves the store. EAS systems were the first commercial application of RFID technology and are still widely employed in stores and libraries.

In the 1970’s there was a continuous effort in further development of RFID systems. A compact and inexpensive transponder with no need for a battery can be achieved by using a resonant circuit. Several types of transponders were patented
by Charles Walton in the early 1970’s. Tags of this type were used by the Schlage Lock Company and several million electronic keys using the frequency of 3-32 MHz were produced. Although the frequency used in this period was comparatively low, studies related to ultra high frequency (UHF) band were carried out by various companies, academic institutions and national laboratories. For example, Koelle and co-workers described a system with a read range of a few meters using a 1 GHz signal in 1975 [74]. This system had many similar features to a modern passive UHF RFID system such as a transponder powered by the incident signal and the reflected signal is modified by the impedance of the transponder.

Since the 1980’s, the RFID technology has witnessed a growing interest in many fields such as the rail industry, traffic management, automated tolling, livestock management, and so on. By the late 1980’s, a standard for railcar identification (AAR S-918), which uses the US industrial, scientific, and medical (ISM) band at 902-928 MHz, was established and all rail cars were equipped with S-918 compliant RFID devices to identify and track their locations by 1994 [19]. In the 1990’s, extending the effective detection range by using much higher frequencies was one of main topics. A typical application of this topic was the traffic management system. Philips Electronics and Mitsubishi Heavy Industries, in cooperation with the government of Singapore, developed a traffic management system operating at 2.45 GHz for automated tracking and tolling [16]. In the early 1990’s, although various UHF RFID systems were developed by companies such as IBM and Intermec [75], these systems were never adopted due to the high costs and the lack of open and international standards. A broader vision for the implementation of RFID was triggered by the activities of the Auto-ID Centre founded at the Massachusetts Institute of Technology (MIT) by the Uniform Code Council (UCC), European Article Number (EAN) International, Procter & Gamble and Gillette [76]. The main result of this centre was the Electronic Product Code (EPC) numbering scheme, which is designed as a universal identifier providing a unique identity for physical objects and ensures the wide applications of the technology in supply chain [77].

RFID continued to evolve in the new millennium. In 2003, the EPCglobal Inc. was founded to facilitate the standardisation and commercialization of RFID [16, 75]. In 2005, Wal-Mart, the world’s largest retailer, announced it was mandating its top 100 suppliers to put RFID tags on all cases and pallets delivered to Wal-Mart by January of 2005 [78]. This announcement was followed by other large retailers such as Tesco and Metro. All these activities brought RFID technology to the attention of the world especially in the area of supply chain and logistics.
management. The RA dio frequency IdentificatioN (RAIN) alliance, which was founded by four leading companies in 2014 and has become one of the major alliances in the RFID industry, is a global collection of companies and organizations promoting the universal applications of UHF RFID technology and developing solutions with UHF RFID technology [79]. Today, from tags for apparel in stores to inventory management systems in warehouses, RFID technology has been broadly used in our daily life and manufacturing process. A summary of major events of RFID technology development is shown in Table 2.1.

<table>
<thead>
<tr>
<th>Date</th>
<th>Events</th>
</tr>
</thead>
<tbody>
<tr>
<td>1940-1950</td>
<td>Development during World War II</td>
</tr>
<tr>
<td>1950-1960</td>
<td>Early prototypes of RFID in laboratories</td>
</tr>
<tr>
<td></td>
<td>Fundamental theory</td>
</tr>
<tr>
<td>1960-1970</td>
<td>Theoretical developments of RFID</td>
</tr>
<tr>
<td></td>
<td>First commercial application EAS system</td>
</tr>
<tr>
<td>1970-1980</td>
<td>First passive RFID patent</td>
</tr>
<tr>
<td></td>
<td>Development of UHF RFID</td>
</tr>
<tr>
<td>1980-1990</td>
<td>Commercial applications for RFID entered the mainstream</td>
</tr>
<tr>
<td></td>
<td>Implementation of wide-range RFID in traffic control</td>
</tr>
<tr>
<td>1990-2000</td>
<td>RFID applications widely adopted</td>
</tr>
<tr>
<td></td>
<td>Establishment of the Auto-ID Center</td>
</tr>
<tr>
<td>2000-present</td>
<td>Development of EPCglobal</td>
</tr>
<tr>
<td></td>
<td>RAIN alliance founded</td>
</tr>
<tr>
<td></td>
<td>Continuation of RFID innovations</td>
</tr>
</tbody>
</table>

2.1.2 Overview of an RFID system

As shown in Fig. 2.1, an RFID system mainly consists of two components including an interrogator, more often known as a reader and a transponder or a tag [15, 19]. The downlink represents the process of providing energy and transmitting data from the interrogator to the transponder while uplink represents transmitting data from the tag and receiving data by the reader. The antenna of the reader could be an individual unit, which is connected to the reader with a cable, or it could be integrated with the reader whereas the antenna of the tag is typically integrated within the tag [19].
2.1 RFID Systems

A reader typically consists of several modules including a RF module or a transmitter and a receiver, a control unit, amplifiers and sometimes a coupling element [15]. The reader is usually connected with another system like a host computer, by which users are able to control the reader, store and process received data.

A transponder, often known as a tag is usually made up of a coupling element, at least one microchip or IC, and, for some types of transponders, a power supply and a transmitter. The tag is the actual data-carrying device and stores the unique ID and the logic in its IC so that the object could be identified and tracked with a tag attached to it [19]. More details of types of tags will be discussed later.

Figure 2.1 The structure of an RFID system [19]

Frequency Band

RFID systems can be operating at various frequencies ranging from 100 kHz to over 5 GHz as shown in Fig. 2.2 [80]. The common frequency bands for RFID include the low-frequency (LF) band operating at 125/134 kHz, commonly used in short-range scenarios such as access control through showing a card to the reader and livestock tracking by attaching tags to animal ears [81, 82]; the high-frequency (HF) band at 13.56 MHz, which is often used in contactless payments and physical access control systems [82]; the UHF band at 860-960 MHz, which will be used in this dissertation, and 2.4 GHz, which is used in long-range applications such as logistics and supply chain management [82].

RFID systems operating at LF and HF bands are usually inductively coupled using magnetic fields where the wavelength is much larger than the antenna [19, 83]. The antenna of an inductive-coupled system is much smaller than the wavelength
and the power density drops very rapidly in the near-field. The antenna of a tag often uses multiple-turn coils to collect the energy [19, 84]. Tags can send data to the reader by changing the load on its coil and the reader coil detects the change in current flow due to opposing magnetic field caused by the tag coil [16]. Because the magnetic field decreases rapidly in the near field region as a factor of $1/r^3$, where $r$ is the distance between the reader and the tag, the read range of an inductive-coupled system is comparatively short (up to 1 m). Since the range is very short, it is difficult to speak of a separate transmitted and backscattered wave due to the delay is less than a few nanoseconds (4 ns at the distance of 1.5 m) and is very short compared with the RF cycle at 13.56 MHz, which is about 74 ns so the communications between tag and reader is effectively instantaneous. As a result, changes in the tag antenna can be seen as inducing changes in the electrical impedance of the reader antenna.

A UHF RFID system is coupled using electromagnetic waves where the wavelength is comparable in size to the antenna [15, 19]. In a UHF RFID system, because RFID tags are placed outside the reader’s near field region, instead of using load modulation, backscattering is used for far-field RFID tags, where tags can send information by reflecting back the signal, which is modulated by changing its impedance. The reader antenna firstly launches a EM wave and the delay before the EM wave interacts with the tag (about 10 ns at the distance of 3 m) is much longer than the RF cycle (about 1.2 ns at 865 MHz). After the tag modulates the signal, a distinct scattered wave will return to the reader antenna. In contrast to LF and HF RFID systems, UHF RFID systems have a longer read range up to tens of metres, so it is widely applied in many fields such as asset tracking. Different countries allocate different frequency bands for UHF RFID systems. For example, the frequency band
for USA, China and EU are 902-928 MHz, 917-922 MHz, and 865-868 MHz (EU lower band) and 915-921 MHz (EU upper band) respectively.

**RFID Readers**

An RFID reader is a radio transceiver and is a vital component of a RFID system since it deals with most of steps of signal processing such as filtering, amplification, transmitting, receiving, and so on. In the case of a passive RFID system, where tags have no internal power supply, the reader is much more important as it also provides power for passive tags remotely. In general, RFID readers communicate with tags via air interface communication protocol such as the EPC standard [85].

An RFID reader can operate in either full-duplex (FDX) or half-duplex (HDX) mode depending on whether it is capable of bi-directional data transmissions over one channel at the same time. In FDX mode, the reader is able to transmit and receive signals simultaneously while in HDX mode, the data transfer of the uplink alternates with that of the downlink [15, 19]. In the case of a passive RFID system, which is the system used in this dissertation, an RFID reader must operate in FDX mode because the reader is required to transmit continuous-wave (CW) powering up passive tags and to listen for their responses at the same time [19].

![Figure 2.3 Bi-static and mono-static configurations](image)

**Figure 2.3 Bi-static and mono-static configurations [19]**

As shown in Fig. 2.3, antenna configurations of RFID readers can be divided into two types, mono-static and bi-static configurations [15, 19]. In mono-static configuration, which is the antenna configuration for the system used in this dissertation, the same antenna is used for both transmitting and receiving purposes.
As tags and the reader normally use the same frequency band, the received signal backscattered from tags can be significantly affected by the signal leakage from the transmitter of the reader, which limits the sensitivity of the receiver. The other type of configuration can be used to reduce the effect of leakage from the transmitter. In a bi-static configuration, separated antennas are used for transmitting reader commands and receiving tag signals, which could minimize signal leakages from transmitter antenna to receiver antenna [83]. Although the bi-static configuration could ensure minimal signal leakages, separating antennas increase the size and cost of the system. Therefore, compared with the bi-static configuration, the mono-static configuration would be more suitable for size and cost sensitive applications such as handheld RFID readers [86].

**Antennas**

The antenna can be either linearly polarized, which is the type of the antenna used in this dissertation, or circularly polarized. The current of a simple antenna like a dipole flows only in one direction which creates a linearly-polarized radiated wave. If a linearly-polarized antenna is used by the reader, as shown in Fig. 2.4, a dipole antenna, which is typically used for passive tags, has to be matched in polarization to the reader antenna so that it can receive the maximum possible signal. Otherwise, if a dipole is placed perpendicular to the field, it will receive no signal at all.

![Figure 2.4 Linearly-polarised antenna](19)
2.1 RFID Systems

The limitation of a linearly-polarized antenna is that a tag with a dipole antenna oriented perpendicular to the electric field will receive no voltage and cannot be read. A circularly-polarized antenna could be used to solve this problem, which can vary the direction of the electric field with time and create a circularly-polarized wave as shown in Fig. 2.5. As long as the tag with a dipole antenna is aligned perpendicular to the direction of propagation, it can always receive signals regardless of its direction.

Using a linearly-polarized or a circularly-polarized antenna will bring different effects of multipath especially in terms of ground reflections. A linearly-polarized antenna will not receive multipath signals perpendicular to its direction while a circularly-polarized antenna will receive multipath signals from all directions.

RFID Tags

There are many different formats of tags such as disks and coins, glass housing, plastic housing, keyring, smart labels, and so on [15]. According to whether there is a power supply and a radio transmitter, RFID tags can be roughly classified into three categories which are passive, semi-passive and active tags as shown in Fig. 2.6.

Passive tags, which are used in the system designed by this dissertation, have no independent battery and have no transmitter [15, 19]. The energy required for passive tags is fully provided by the reader. The incoming electromagnetic field is converted into high-frequency voltage by the antenna of the passive tag. After
rectifying by a diode and smoothing by a capacitor, a roughly constant voltage is obtained to power the IC and generate a modulated backscatter signal. Due to the absence of the power supply, passive tags have many disadvantages such as comparatively low backscatter power, limited read range [19]. Because complexity of strong cryptographic algorithms is very high and energy consumption is increased when the complexity rises, the security of passive tags would be compromised due to the limited power available to implement complex cryptographic algorithms [19, 87]. In contrast, it also brings various benefits, for example, the simple circuit, no need for maintenance, and the low cost.

Semi-passive or battery-assisted passive tags have its own battery to provide energy for operation [19]. Since the power supply does not contribute to data transmission in the uplink, the semi-passive transponder is only able to modulate and backscatter the signal from the reader rather than generating signals by itself [15]. As a result, the procedure in the uplink is similar to passive transponders where the data is transmitted through backscatter signals. However, with the help of the battery, standard commercial ICs with comparatively higher complexity could be adopted in a semi-passive transponder. At the same time, the battery enables the utilization of high-frequency amplification and other RF functions [19].
It also extends the read range to tens of metres and makes the tags more robust to reader interrogation. Nevertheless, a local power supply means requirement for maintenance, increased size, and higher cost.

Active tags are more sophisticated than passive and semi-passive transponders and have its own power source and transmitters. This means that active transponders are bidirectional radio communications devices and they can communicate with the reader using a specified frequency band, which may be different from the frequency channel of the reader, and generate signals by its local oscillator [15, 19]. Since the power of the chip is provided by a local power source, active tags no longer depend on the magnetic or electromagnetic field emitted by the reader. As a result, active tags can transmit more complex modulated signals. The independent battery enables active tags to employ more advanced modulation schemes such as phase-shift keying (PSK), quadrature amplitude modulation (QAM), which is more efficient in available spectrum, and code-division multiple access (CDMA), which is more robust to noise. Active tags usually have high sensitivity and the read range could be substantially extended to even a few kilometres. However, compared with passive tags, they suffer from much higher cost, larger size, and higher maintenance requirement.

2.2 Localisation Methods

Localisation methods could be classified into different groups according to which characteristic of the RF signal is used in the method such as RSSI-based, phase-based, time-based, angle of arrival (AoA) and so on. However, many methods have used not only one physical metric but two of them and it is hard to classify these methods in this way. In term of the localisation algorithm, localisation methods could be divided into two categories geometry-based methods and non-geometry methods.

2.2.1 Geometry-based

Geometry-based localisation methods, which are the most common localisation methods, utilise the relationship between the characteristics of the RF signal like RSSI and the distance or angle to locate targets by geometrical relationship such as trilateration. These methods have been broadly employed in traditional positioning applications. These methods could also be categorized into two groups. The first group, which is using trilateration, is based on distance measurement which esti-
mates the range between the reader and the tag by different characteristics of the RF signal like RSSI, phase or time. The second group using triangulation, which is based on angle measurement, estimates the location of targets by calculating the angle instead of distance between the reader and the tag. After obtaining the range or angle between the reader and the tag, the location of the target can be calculated by the geometrical relationship. These methods have the advantage of simple principle, but suffer from many drawbacks such as low accuracy in complex environment.

Methods Based on Distance Measurement

Methods based on distance measurement use the range between the reader and the tag to calculate the location of the target. Once the range or the distance is estimated, the target tag could be located by the trilateration method [88], which is also known as the triangular positioning algorithm [89], or multilateration [90]. The trilateration method, which is the fundamental algorithm, is shown in Fig. 2.7. \( P_1, P_2 \) and \( P_3 \) are three points with known locations. \((x_1, y_1), (x_2, y_2)\) and \((x_3, y_3)\) represent the location of the three points. \( r_1, r_2 \) and \( r_3 \) are estimated ranges between the target and three known points. After obtaining ranges, the position of the target could be calculated by solving the equation group 2.1. The multilateration methods use the similar algorithm but the equation group consists of more equations.
2.2 Localisation Methods

\[
\begin{align*}
(x - x_1)^2 + (y - y_1)^2 &= r_1^2 \\
(x - x_2)^2 + (y - y_2)^2 &= r_2^2 \\
(x - x_3)^2 + (y - y_3)^2 &= r_3^2
\end{align*}
\]

Figure 2.8 The elliptical model [91]

In order to improve the accuracy of the classic trilateration localisation technique, Fortin-Simard et al. proposed an improved trilateration model using RFID technology [91]. In this work, directional antennas are used and since the loss of signal is higher when the object moves away from the side of the antenna than when it moves perpendicularly. When the received power is similar, the distance along the direction perpendicular to the antenna is longer than that along the direction parallel to the antenna and this would give an ellipse. As a result, an elliptical model instead of the circular model is proposed to achieve better accuracy as it is able to estimate the range more accurately than the traditional circular trilateration model as shown in Fig. 2.8. In Fig. 2.8, A1, A2, A3, A4 represent antennas and ellipses show the estimated possible locations for a target tag. Each pair of ellipses gives an estimated location and this method also calculate weight for each estimated location by using
RSSI. The final estimated location can be obtained by using these estimated locations and their weights. The accuracy can be further improved by assigning a weight to the antenna according to strength of received RSSI. However, higher accuracy is achieved by this improved model at cost of higher complexity and longer processing time. This method could obtain an average accuracy of \(\pm 14.12\) cm over an area of 6 m\(^2\).

![Figure 2.9 The hyperbolic model [66]](image)

Fig. 2.9 shows another algorithm which is called hyperbolic localisation method [66, 92, 93]. As shown in Fig. 2.9, for example, a fundamental hyperbolic system consists of three antennas and one target tag. Two reader antennas can be seen as two focuses of a hyperbolic curve where the target tag locates. The location of the target tag can be calculated by the intersection of two hyperbolic curves using following equations

\[
\begin{align*}
|\sqrt{(x_1 - x)^2 + (y_1 - y)^2} - \sqrt{(x_2 - x)^2 + (y_2 - y)^2}| &= |d_1 - d_2| \\
|\sqrt{(x_1 - x)^2 + (y_1 - y)^2} - \sqrt{(x_3 - x)^2 + (y_3 - y)^2}| &= |d_1 - d_3|
\end{align*}
\]  

(2.2)

Where \((x, y)\) is the location of the target tag, \((x_1, y_1)\), \((x_2, y_2)\) and \((x_3, y_3)\) are positions of three antennas, \(d_1\), \(d_2\) and \(d_3\) are ranges, which is generally estimated by information of tags such as RSSI, between the target and three known points.
This method is using the distance difference rather than the absolute distance to build the relationship between tags. The evaluation results of the work by Liu et al. [94], which proposed a phase-based hyperbolic localisation algorithm, show that the mean position error could be reduced to around 12.8 cm over an area of 500 × 800 cm². The initial phase offset caused by RFID readers or wires usually needs to be processed and cancelled otherwise the estimated distance will not be accurate, which is one of limitations for this method. Meanwhile, the accuracy of such method depends on the number of antennas employed, which will lead to increased cost and requirement for maintenance.

As mentioned above, distance between the reader and the target could be estimated by different physical characteristics of the received RF signal. The first way is calculating distance by using received RSSI values. RSSI-based localisation method exploits the relationship between the received power and the distance. Typically, a passive tag uses the same antenna as transmission and receiving antenna and a mono-static antenna configuration uses the same antenna to transmit and receive the signal. In free space, the power received by the reader could be expressed as

\[
P_{Rx,r} = \eta P_{Tx,r} G_r^2 G_t^2 (\frac{\lambda}{4\pi d})^4
\]

where \(P_{Rx,r}\) is the power received by the reader, \(\eta\) is the modulation efficiency of the tag, \(P_{Tx,r}\) is the power transmitted by the reader, \(G_r\) is the gain of the antenna of the reader, \(G_t\) is the gain of the antenna of the tag, \(\lambda\) is the wavelength of the signal, and \(d\) is the distance between the antenna of the reader and the tag.

In practice, buildings have a wide variety of partitions and obstacles made of different types of materials [95]. For example, houses typically have concrete between floors and use a wood frame partition with plaster board to form internal walls within the same floor. On the other hand, office buildings usually use metal reinforced concrete between floors and have large open areas which are divided into small areas by moveable plastic partitions within the same floor. As a result, in real indoor environment, the path loss varies greatly due to various attenuation rate and the RF signal strength depends not only on the range between the reader and the tag but also on the structure and materials of the buildings. Hence, a more accurate modified mode of the relationship between the power and the range can be expressed as

\[
P_{Rx,r} = \eta P_{Tx,r} G_r^2 G_t^2 (\frac{\lambda}{4\pi d})^{2n}
\]
Where $n$ is path loss exponent and this exponent could vary significantly under different environment ($n$ could be between 1.6 and 6 [95]). If the link budget of the RFID is taken into consideration, under a comparatively ideal condition, the received power is around -55 dBm when the distance between the reader and the tag is 3 m, which is about 20 dB in excess of the sensitivity of the reader (the sensitivity of the reader is assumed to be -75 dBm). Since the margin is limited, it is assumed that the indoor environment is not too complicated so the situation where obstacles such as walls within the same floor will be considered and under this condition, $n$ would vary between 1.6 and 3.3 [95]. After receiving RSSI information and estimating the range, the position of the target tag can be calculated by trilateration, elliptical, or hyperbolic methods.

Another parameter that can be provided by readers is the phase information of the backscattered signal, which is exploitable only for passive or semi-passive RFID tags since they communicate with readers by modulating and backscattering the signal without using an internal local oscillator [96]. The distance measurement method can also be based on phases of received signals. Nikitin et al. [97] and Povalac et al. [98] have analysed a frequency domain (FD) method based on the phase difference of arrival (PDOA). The method proposed by Povalac et al. has achieved a 1D localisation error of around 14 cm [98]. In a FD-PDOA system, a reader sends two CW signals with different carrier frequencies. Two signals backscattered by tags, which propagate over the same distance, are received by the reader and have different phase delays due to different carrier frequencies [66, 88]. Ideally, the relationship between the phase delay $\phi$ and the LoS range $d$ can be expressed as follows

$$\phi_i = \frac{4\pi f_i d}{c}, \quad i = 1, 2 \tag{2.5}$$

where $\phi_i$ is the phase value, $f_i$ is the operation frequency, $c$ is the velocity of light. The range could be calculated based on the observed phase difference by the following equation

$$d = \frac{c\Delta \phi}{4\pi \Delta f} \tag{2.6}$$

where $\Delta \phi = \phi_1 - \phi_2$ is the phase differences of the two signals, $\Delta f = f_1 - f_2$ is the frequency difference of the two signals [99].

The maximum unambiguous range is determined by the frequency difference. When the object distance exceeds the maximum unambiguous range range, the
measured phase difference will be larger than $2\pi$ and wrapped into range of 0 to $2\pi$. Hence the measured distance will be incorrectly calculated. The maximum unambiguous range can be expressed as [88]

$$d_{\text{max}} = \frac{c}{2|\Delta f|}$$

(2.7)

For a frequency difference of 30 MHz as an example where the maximum unambiguous range is 5 m, objects located at 2.5 m and 7.5 m both have a phase value $\phi$ of $\pi$. As a result, the estimated range for both objects will be 2.5 m by equation 2.6. To correct this error, this equation can be modified as [100]

$$d = \frac{c\Delta\phi}{4\pi\Delta f} + \frac{cm}{2\Delta f}$$

(2.8)

where $0 < \Delta\phi = \phi_1 - \phi_2 < 2\pi$ is the wrapped phase differences of the two signals, $m$ is an unknown integer due to phase ambiguity as received phase is wrapped within $[0,2\pi]$ range.

According to the equation 2.7, a simple method to avoid the ambiguity problem is to reduce the frequency separation as a smaller frequency separation leads to a larger maximum unambiguous range [100]. However, due to the presence of noise, decreasing the frequency separation increases measurement uncertainty and hence degraded range estimation accuracy [100], which means a trade-off has to be made between the maximum unambiguous range and noise sensitivity [101]. In order to overcome this problem, the dual-frequency PDoA approach can be extended to multiple frequency approach with three or more carrier frequencies through data fusion over different frequency pairs [101]. With equal frequency separation within each pair, the accuracy for estimation of tag range can be improved [88]. The simulation results by Zhang et al., which places four readers at the corner of the 10 m $\times$ 10 m area and uses 10 frequencies, shows that multiple frequency PDoA approach could achieve a mean 2D localisation error of 1 m [102]. Maximum unambiguous range can also be extended by using multiple frequency PDoA approach with unequal frequency separation [101]. Furthermore, PDoA approach can also be fused with additional signal processing techniques such as non-linear Kalman filtering to achieve higher accuracy in a complicated environment [103].

Another method to estimate the distance between target tags and antennas is based on ToA [88, 92, 104, 105]. The relationship between the range and the round-trip time-of-arrival of the signal can be written as
RFID systems and Localisation Methods

\[ d = \frac{c \cdot \text{ToA} - T_p}{2} \]  

(2.9)

where ToA is round-trip time of arrival of the received signal, \( T_p \) is the signal processing time of the tag. Problems of such methods include the difficulty of synchronization between sensors, which can be resolved by time-difference-of-arrival (TDoA) [106], and the requirement of bandwidth. For example, if a signal is sampled at 1MHz, the time resolution would be poor which is \( 1/1\text{MHz} = 1\mu s \), which corresponds to a poor spatial resolution of \( 3 \times 10^8 \text{m/s} \times 1\mu s = 300\text{m} \). In order to obtain a higher spatial resolution, a higher sample rate or a wider bandwidth is required. This means that this method is not possible for a system using passive RFID tags, the bandwidth of with is limited, so this method will not be discussed in detail in this dissertation.

Methods Based on Angle Measurement

Another popular localisation method is based on the angle measurement. The localisation method based on angle measurement is usually achieved by AoA, which is also called direction of arrival (DoA). This method typically estimates the incident angle of a backscattered signal by using phased array antennas [107–109]. Fig. 2.10a shows a simple phased array antenna with only three antenna elements \( A_1, A_2 \) and \( A_3 \). The distance between two adjacent antennas, for example \( A_1 \) and \( A_2 \), is denoted as \( d \) where \( d < \lambda/2 \) [40].

If the range between the antenna \( A_2 \) and the target tag is denoted \( R \), the one-way phase delay of the signal received by the antenna \( A_2 \) is

\[ \phi_2 = \frac{2\pi R}{\lambda} \]  

(2.10)

The distance between the antenna \( A_1 \) and the target tag is \( R + d \sin \Theta \) and the phase delay of the signal received by the antenna \( A_1 \) is

\[ \phi_1 = \frac{2\pi (R + d \sin \Theta)}{\lambda} \]  

(2.11)

The phase difference between two adjacent elements can be calculated by

\[ \Delta \phi = \phi_1 - \phi_2 = \frac{2\pi}{\lambda} d \sin \Theta \]  

(2.12)
2.2 Localisation Methods

(a) Phased array antenna [107]

(b) Triangulation approach [107]

Figure 2.10 The approach of AoA
Hence the incident angle could be estimated by the average of phase difference $\hat{\phi}$

$$\Theta = \arcsin \frac{\lambda \Delta \hat{\phi}}{2\pi d} \quad (2.13)$$

After three incident angles of the backscattered tag signal with respect to known positions of three antennas have been estimated, as shown in the Fig. 2.10b, the location of the target tag can be determined by triangulation approach. Ideally, only one intercept point will be obtained which is the location of the target tag. However, in a real indoor environment, the imperfect estimated angles due to noise or multipath influence lead to deviations between estimated direction and the correct direction and this results in an intersection area [107]. Since the target tag could be located anywhere within the intersection area, there are two basic approaches to determine the location of the target tag [107]. The first approach is to choose the centroid of the triangle intersection area defined by the three intercept points. The other approach is to choose a subset of two out of three antennas to calculate the estimated angle of arrival and estimate the position of the target. The experimental results in an area of $3 \times 3 \text{m}^2$ show that the first approach achieves a localisation error of around 0.26m and the second approach performs slightly better with 0.21m accuracy [107].

An improved AoA method is proposed in cooperation with RSSI information [109]. The RSSI information can be seen as the indicator for distance between the reader antenna and the tag and it is assumed that the antenna with the highest received RSSI, which means the smallest distance, can provide a more accurate signal and hence more accurate AoA. As a result, the improved AoA method uses more than three antennas as shown in Fig. 2.11a. The subset of antennas with the highest RSSI, which means that they are closer to the target tag, is chosen to estimate the location of the target tag [109]. As shown in Fig. 2.11b, tests are conducted in a $3 \times 3 \text{m}^2$ area without any obstacles and five antenna arrays are deployed. By this improved AoA method, the localisation error can be reduced to around 0.14 m [109].

### 2.2.2 Non-Geometry-based

Methods described above are based on the geometric relationship between the reader antenna and the tag. These methods convert the physical characteristics such as RSSI, phase, etc to the range or angle between the reader antenna and the target and analyse the geometric relationship using the estimated range or angle. The other group of methods such as the method based on fingerprinting, which is widely
2.2 Localisation Methods

(a) Antenna configuration [109]

(b) Experimental environment used in [109]

Figure 2.11 Improved AoA technique
used in fields such as Wi-Fi and Bluetooth, is not based on geometric relationship and has attracted increasing attention [110–112]. Non-Geometry-based methods include fingerprinting methods [113–115], synthetic aperture radar (SAR) methods [116–119], and radio tomographic imaging methods [120–124].

Fingerprinting

The basic assumption of fingerprint methods is that physical metrics of RF signals including RSSI and phase are reasonably stable in a static environment, which is due to the fact that signals are affected by multipath effect and in a static environment multipath effect is also stable. This makes them suitable for being used as an indicator of the electromagnetic field distribution in the environment. Therefore, the RSSI and phase information can be regarded as the fingerprints of a certain environment. Fingerprinting-based localisation mainly consists of two steps: offline (training) and online (test). The offline step of fingerprinting is designed for collecting the information of the environment at each reference point where usually a reference tag is deployed. The position of reference tags and the RSSI and phase information are collected and stored to establish a fingerprint database. The database can be processed and trained to build a model for the current environment using a machine learning approach. After having a database or a localisation model, the online step estimates the location of the target tag by comparing the received signal with the database or the trained model.

A representative technique based on fingerprinting and reference tags is the LocAtioN iDentification based on dynaMic Active Rfid Calibration (LANDMARC) system proposed by Ni et al. [113]. LANDMARC locates active target RFID tags by using several readers and reference tags as shown in Fig. 2.12. The system consists of $m$ readers and $n$ reference tags which are placed in a grid array.

Fig. 2.12 shows a simple example of LANDMARC where four readers ($m = 4$), 16 reference tags ($n = 16$) and one target tag are deployed. To estimate location of the target tag by this system, firstly, the RSSI of the $j$-th reference tag could be written in the form of a vector as $\vec{R}_j = (R_{j1}, R_{j2}, \ldots, R_{jm})$ where $R_{ji}$ is the RSSI of the $j$-th reference tag received by the reader $i$ and the RSSI of the target tag is denoted as $\vec{T} = (T_1, T_2, \ldots, T_m)$ where $T_i$ is the RSSI received by the reader $i$. Secondly, Euclidean distance is calculated as the distance between the target tag and the $j$-th reference tag by the equation follows
2.2 Localisation Methods

After obtaining the distance vector between the target and \( n \) reference tags \( \vec{E} = (E_1, E_2, \ldots, E_n) \), \( k \) nearest reference tags would be chosen by sorting the Euclidean distance vector, which means that the tag with the smallest Euclidean distance is the nearest reference tag. Finally, the location of the target tag can be estimated by these reference tags as follows

\[
(x, y) = \sum_{i=1}^{k} w_i (x_i, y_i)
\]  

(2.15)

Where \( (x_i, y_i) \) is the coordinate of the \( i \)-th of \( k \) nearest reference tags, \( w_i \) is the weight of the \( i \)-th reference tag which could be expressed as

\[
w_i = \frac{1}{\sum_{i=1}^{k} \frac{1}{E_i^2}}
\]  

(2.16)

A higher localisation accuracy can be achieved by increasing the density of reference tags which requires a large number of reference tags. At the same time, deploying too many reference tags would increase interference between tags and deteriorate localisation accuracy. In order to improve localisation accuracy without placing additional reference tags and avoiding severe interference between tags, Virtual Reference Elimination (VIRE) has been proposed. The main concept of
VIRE is inserting virtual reference tags, the RSSI of which can be calculated by interpolation techniques, to provide high density of reference tags with a relatively small number of actual tags [61].

As mentioned above, machine learning approach can also be used in fingerprinting-based methods. Berz et al. trained a machine learning model based on support vector regression (SVR) to learn the relationship between the RSSI fingerprint database and the locations of reference tags and this model will be used to predict locations of target tags [125]. In order to improve the accuracy, a k-means approach is also applied to determine the location of the target. This method can reduce the localisation error to 17.6 cm in $2.25m^2$ area coverage.

Machine learning using a neural network has also been applied in some literature such as the extreme learning machine (ELM) for trajectory tracking, which is combined with Kalman filter by Ma and Wang [114] and the 3D-LANDMARC system by Wu et al. [115].

**Synthetic Aperture Radar**

The accuracy of fingerprinting localisation is related to the density of reference tags, which means that high accuracy requires a large number of reference tags leading to high cost. Therefore, non-fingerprinting localisation methods have been investigated and are attracting a lot of attention. The synthetic aperture radar (SAR) method, which is one of the most popular non-fingerprinting localisation methods, has been introduced to estimate the location of the target tag by generating a spatial likelihood distribution [116–119].

The idea of SAR in RFID originated from the field of imaging radar. SAR exploits the motion of a moving platform such as an aircraft or a spacecraft to create high-resolution images of target objects or area and compared with conventional radars, it can provide higher spatial resolution with relatively small antennas [126]. The distance the moving platform travels during the period when the target is illuminated creates a synthetic aperture and larger synthetic aperture leads to higher resolution of images. It was first applied in the late 1950s and now plays an important role in both the civil and military fields because it is able to effectively identify camouflaged vehicles and to provide high quality images [127].

Recently, mobile platforms such as unmanned ground vehicles (UGV) or unmanned aerial vehicles (UAV) have been applied in more and more fields. The concept of SAR has been introduced in the field of RFID to utilise the mobility of the mobile platform in the indoor environment for industrial inspection, logistic
management, and accurate localisation. In all these scenarios, the mobile platform equipped with a RFID reader or antenna is able to locate and track products and materials with RFID tags attached to them [128, 129]. The SAR localisation method can be divided into two main steps. Firstly, physical characteristics of backscattered signals will be received by a moving reader or a moving reader antenna with a known trajectory. Secondly, a probability heat map or a holograph will be calculated by a spatial probability density function based on received RSSI and phase values. The position of the target will be the location with the largest probability.

In order to simplify equations, a SAR-based holographic algorithm will be discussed in a 2D space as shown in Fig. 2.13. The antenna, which is carried by a mobile platform such as a robot moves along a trajectory and this generates a virtual antenna array. The total length of the antenna movement is called the synthetic aperture. The localisation area where target tags are located is divided into a grid as shown by dashed lines. At time $t$, the location of the reader is expressed as

$$q_t = [x_t, y_t]$$ (2.17)

The potential locations of the target tags can be expressed as a vector by applying a grid to the area or pixelating the potential area. The $k$-th potential position of the $n$-th tag can be written as

$$b'_nk = [x'_nk, y'_nk]$$ (2.18)

The distance between each potential position and the location of the reader antenna can be calculated by

$$d_{t,nk} = \|q_t - b'_nk\|_2$$ (2.19)

where $\| \cdot \|_2$ is the L2 norm. The expected phase for a tag at each potential location can be calculated by the following equation

$$\phi'_t, nk = (\phi_0 + \frac{4\pi d_{t,nk}}{\lambda}) \ mod \ 2\pi$$ (2.20)

where $\phi_0$ represents the fixed phase shift caused by the measurement equipment such as the antenna and cable.

After measuring a sequence of signals, the phase of the first received signal is selected as the reference to eliminate the effect of $\phi_0$. The relative received phase which is measured by the reader for the $n$-th target tag is

$$\Delta\phi_t, n = \phi_t, n - \phi_1, n$$ (2.21)
The trajectory of the moving antenna

Figure 2.13 The diagram of SAR algorithm
2.2 Localisation Methods

The sequence of relative received phases over time $t_N$ could be expressed as

$$\Delta \Phi_n = [0, \Delta \phi_{2,n}, ..., \Delta \phi_{t,N,n}, \Delta \phi_{t_N,n}]^T$$

(2.22)

All phase values of $N$ target tags measured can be written as

$$\Phi_{tar} = [\Delta \phi_1, ..., \Delta \phi_{n}, ..., \Delta \phi_{N}]^T$$

(2.23)

The expected relative phase of each potential tag position could also be written as

$$\Delta \phi_{t, nk}' = \phi_{t, nk}' - \phi_{1, nk}'$$

(2.24)

The matching function, which is a measure of the difference between the expected and measured phase for each time step, is defined as

$$C_{t, nk} = A_{t, n} \exp(-j(\Delta \phi_{t, nk}' - \Delta \phi_{t, n}))$$

(2.25)

where $A_{t, n}$ is the amplitude of the received signal of $n$-th tag at time $t$ and if the received signal is not stable, including the amplitude could lead to increased localisation error so the amplitude can be replaced by 1 which means that only phase value is used. The use of the complex field resolves the wrapping problem with the phase angles recognizing that the phase shift between $\Delta \phi$ and $2\pi - \Delta \phi$, is $2\Delta \phi$ rather than $2\pi - 2\Delta \phi$.

The probability that the tag is at a particular location can be calculated as the sum of the matching function over a number of phase measurements taken at different antenna locations

$$P_{n,k} = \left| \sum_{t=1}^{t_N} C_{t, nk} \right|$$

(2.26)

where $t_N$ is the total number of received phase and RSSI values during the time when the robot is moving and collecting the information of the target tag.

If the reader is moved along multiple trajectories and uses multiple antennas, the probability of the $n$-th tag by $i$-th antenna along $j$-th trajectory can be marked as $P_{n,k,i,j}$. The final probability with multiple antennas along multiple trajectories will be

$$P_{fin,n,k} = \prod_{j=1}^{N_{tra}} \prod_{i=1}^{N_{ant}} P_{n,k,i,j}$$

(2.27)
where \( M_{tra} \) is the number of trajectories and \( N_{ant} \) is the number of antennas.

The estimated position of the \( n \)-th tag would be the location with the largest probability

\[
b_n = \arg \max_{b'_{nk}} P_{f'in,n,k}
\]  

(2.28)

The estimated locations of all target tags can be expressed as

\[
B = [b_1, \ldots, b_n, \ldots, b_N]^T
\]

(2.29)

Radio Tomographic Imaging

Another non-fingerprint method for localisation is called Radio Tomographic Imaging (RTI), the idea of which originated from radar systems and computed tomography. When an object occurs in an area, signals passing through the object suffer from shadowing losses and the shadowing losses of the signal can be used to construct an image within the area for tracking the object. Wilson and Patwari proposed a linear model for obtaining images of moving objects using received RSSI [120]. Another model of RTI using passive RFID tags based on RSSI is proposed by Wagner et al., of which the mean 2D localisation error could reach 0.3 m in an indoor environment [121].

Some works have been proposed to improve the performance of RTI [122–124]. In [122], the influence of moving objects on RSSI have been discussed. Since variance of RSSI is related to the location of moving objects relative to the reference node, the paper provides a method to estimate a motion image based on variance measurements. Experiments show that a moving object can be located with a mean error of around 46 cm. In [123], a new shadowing model, which is the inverse area elliptical mode, has been introduced. Rather than using equal weights, some pixels have a greater contribution and as a result, have a greater weight. Experimental results show the proposed model can image structures more accurately. Zhao and Patwari proposed a new estimator, which is called least square variance-based radio tomography (LSVRT), for tracking a moving object [124]. LSVRT reduces the impact of the variance caused by intrinsic motion and does not require manual tuning of additional parameters providing a mean error of around 0.6 m.
2.2 Localisation Methods

2.2.3 Summary

The existing methods have been categorized into two groups according to whether or not they are using the geometric relationship to localise the target tag. Geometry-based methods measure physical metrics of signal such as RSSI, phase, ToA, AoA and convert these physical metrics to distance or angle. The location of the target tag is calculated by algorithms including trilateration, multilateration, elliptical model, hyperbolic model, and triangulation. RSSI-based and AoA-based methods require several antennas in order to use trilateration or triangulation. Although they are relatively easy to employ, they are sensitive to multipath which will affect localisation accuracy. In addition, longer range will also reduce the localisation accuracy. In contrast, time-based techniques are robust to longer range, which is one of main advantages of time-base methods. However, it requires comparatively expensive devices and suffers from NLoS condition, which limits the application of time-based methods and are not suitable for passive RFID systems. Phase-based methods are more robust to the multipath propagation and could provide a better localisation accuracy compared with RSSI-based methods, but have the problem of phase wrapping and distortion which deteriorates the performance of the system.

The other group refers to non-geometry methods which either create a fingerprint database, which could be processed by machine learning or neural network, with reference tags or generate a holograph of probability using SAR or an image using RTI to track the target. Localisation methods based on reference tags provide a cost-effective way to deal with effects of the real environment. By using reference tags, it is important to make a trade-off between getting a good pattern of the environment with a large number of tags and avoiding using too many reference tags to limit cost and reduce interference between tags. SAR utilises a moving reader antenna to locate the target tag. The reader can either follows a sophisticated designed trajectory or moves manually to avoid objects or human. Because it is based on phase of backscattered signals, compared with methods using RSSI, SAR is robust to multipath propagation and can provide a comparatively high localisation accuracy as it uses multiple measurements along the trajectory, but it suffers from phase wrapping and distortion. In addition, it requires accurate positions of the moving reader or reader antenna which is one of the main limitations of the SAR algorithm.
2.3 Literature Review

As this dissertation is focusing on SAR-based RFID localisation methods, this chapter will give a literature review of SAR-based systems and methods. Meanwhile, since some other methods are also related to this dissertation, a review of methods for inferring relative location and methods using reference tags is also presented. Because other methods such as AoA, RTI, and so on are not related to this dissertation, the review will not include these methods.

2.3.1 Methods based on SAR

SAR-based methods can provide high localisation accuracy and have attracted increasing attention. Many companies, for example, Jovix, Flybase, EXPONENT, inventAIRy, and Clearpath [130–134], have already applied mobile platforms such as a drone or a robot to inventory management. However, rather than an RFID system, some of them utilise an optical system, which includes barcodes or QR codes attached to goods or materials and scanners to scan the barcodes or the QR codes, because the optical system is more mature and easier to implement than the RFID system. However, an optical system has many disadvantages such as scanners need a direct line of sight to the barcodes or QR codes to be able to read them, and barcodes and QR codes are easily damaged. As a result, some companies utilise an RFID system and integrate the RFID reader and antennas with the mobile platform to collect information from RFID tags attached to items. However, details including configuration and performance are not provided due to commercial considerations.

Apart from companies, many researchers have proposed various systems. Some approaches use a UAV as their mobile platforms. The system designed by Buffi et al. is based on a Colibri I3-A drone to perform a typical SAR method to locate target tags [129]. An Impinj R420 reader, operating at a frequency of 865.7 MHz, is equipped with the Wi-Fi module Vonets VAP11G-300 so that the reader is able to communicate with a laptop wirelessly. 25 tags have been put on the ground in an outdoor area with size $5 \times 5$ m, and the inter-tag distance is 2 m. As it is an outdoor scenario, the location of the drone is provided by GPS and the error of the trajectory of the drone is less than 2 cm. The mean 2D localisation error along x-axis is 3.9 cm while that along y-axis reaches 27 cm. Other research by Buffi et al. has a similar set up and test environment [135] with a more complicated signal model. In this paper, it points out the speed of the drone is between 0.17 m/s and 0.67 m/s.
and that 263 readings are obtained. The mean error along x-axis is 2.3 cm and that along y-axis is -4.4 cm.

Another drone-based system is RFly and it enables a comparatively long range of communication with RFID at over 50 m [136]. The localisation accuracy with RFly could achieve a median accuracy of 19 cm. The key innovation of RFly is introducing a full-duplex relay for a passive network. The drone is used as a relay to preserve and forward physical characteristics such as phase information so that the range is extended.

Other researchers design their systems based on UGVs. MobiTagbot [137], which is another research using the typical SAR method, has mounted the antenna to an iRobot-Create 2 robot. A reader hops over up to 16 channels in the frequency band of 920.625-924.375 MHz. The speed of the robot is set to 5 cm/s. The median accuracy of localisation is around 3.4 cm with 16 frequency channels and the error rises to approximately 7 cm when 4 channels are used.

3DinSAR achieved a 3D localisation with a moving antenna [138]. The phase measurement is collected by a moving antenna at different heights to generate SAR images. After creating several 2D holographic images at different heights, the phase difference between the phase measurement at different heights is used to estimate the height of the tag which is inspired by the phase-based Interferometric Synthetic Aperture Radar (InSAR) height estimation theory. A group of candidate location can be obtained and the final position is determined by the density-based spatial clustering of applications with noise (DBSCAN) clustering method. 6 tags are put in a 3 m $\times$ 3 m $\times$ 2 m area and the median localisation error is 0.24 m. E3DinSAR [139] proposed an optimized scheme based on 3DinSAR. The proposed method extends the linear aperture of the moving robot to an arbitrary trajectory by dividing the arbitrary trajectory into multiple linear apertures. At the same time, the computational time is reduced by using an aperture beam prediction (ABP) method. E3DinSAR could achieve a mean localisation accuracy of 18.4 cm in 3D space.

In [140], another SAR-based localisation method, which is an extension of Phase ReLock, is presented in 3D space. In Phase ReLock, the least square method is used and this method suffers from local minima due to wrapped phase so they unwrap the phase to avoid local minima. After measuring phase by multiple antennas and unwrapping the received phase measurements, a confidence metric is introduced to identify measured data and remove faulty data which deteriorates the accuracy of the localisation accuracy. The filtered data is used to create a multi-antenna synthetic aperture to locate target tags. This method can achieve a mean 3D localisation
error less than 20 cm using four antennas on top of a simultaneous localisation and mapping (SLAM)-enabled robot.

In [141], the effect of trajectories on localisation accuracy by the SAR-based method is investigated. As the localisation performance by the SAR-based algorithm is related to the length of synthetic aperture, the accuracy may be improved by combining the phase data measured by various trajectories which enlarges the synthetic aperture. This method improves the localisation accuracy by investigating different combination of dataset and choosing the best combination of trajectories. This method can achieve a mean localisation error of centimetre order in 2D space.

In [142], a SAR-based method is proposed for 3D localisation of tags. In contrast to conventional SAR methods which traverse grids in 3D space to search the maximum point, the particle swarm optimization approach is employed to reduce the computational burden and processing time. This method could obtain a centimetre-order 3D localisation error in the considered scenario and it suggests that a decimetre-order localisation error could be achieved regardless of the application scenario.

The idea of SAR can also be used to track a moving object. Tagoram locates a moving target with a fixed antenna [116]. It is not a typical SAR method, but the concept is similar, which exploits the movement to construct a virtual antenna array. A Speedway R420 is programmed to hop between 16 channels in the band of 920-926 MHz. The key innovation is using received phase to build a differential augmented hologram which improve the accuracy significantly. It is able to locate a mobile tag with error of only a few centimetres and with error to the level of millimetre in the lab.

SAR methods can accurately locate targets but it suffers from many limitations such as the computational burden which is typically very large, especially for 3D localisation in a large area and it requires the trajectory of the mobile platform to be accurately known, which is usually measured by additional sensors like LiDAR sensors or cameras.

2.3.2 Methods for spatial ordering

Some phase-based methods focus on spatial ordering of tagged objects instead of their absolute locations. For example, in the scenario like a library, it is required to obtain the current order of the books on shelves rather than their absolute coordinate values so any misplaced book can be found. Many methods have been proposed to meet such requirement such as STPP [143], RFScanner [144] and RLLL [30].
The method proposed by Shangguan et al. is a typical method for estimating the 1D spatial order of target tags [143] and the approach is called spatial-temporal phase profiling (STPP). The basic idea of STPP is using the phase profile of the tag which is a sequence of phase values. By analysing the spatial-temporal dynamics in the phase profile of the target tag, STPP can infer the spatial ordering of tags without requiring dedicated infrastructure or special hardware. The method was tested in a library for determining the order of books and in an airport for calculating the order of baggage. Results show about 84% ordering accuracy in a library and 95% ordering accuracy in an airport, where the ordering accuracy is defined as the percentage of tags ordered correctly in all tags (if the order of 1-2-3-4-5 is estimated as 1-2-4-3-5, the accuracy would be 3/5 = 60%).

In [144], a system called RFScanner is proposed to perform the method for calculating the order of books. This method also exploits the phase profile of a tag. In order to improve the accuracy, the method removes the periodic patterns in the received phase so a longer curve and more data can be used for this method. Curve-fitting is also used in this method to reduce the effect of noise. The method can also be used to detect the lying-down books by analysing metrics including the duration and the number of reads of a tag to be read and the curve of RSSI.

Another method for relative localization is called RLLL [30]. This method also utilizes the phase profile, but it only uses the core part of the received phase, which is determined by the change of the slope of the fitted lines. By this method, the negative effects of low-quality data when the tag is far from the antenna can be avoided. As a result, the latency can be reduced and the accuracy can be improved. Experimental results show that RLLL can achieve an ordering accuracy of higher than 0.986 with latency less than 0.8 seconds.

Although all these methods can provide high ordering accuracy, they are not suitable for calculating absolute locations since they are designed for finding the order of the object with respect to other objects rather than the absolute coordinate of the object.

### 2.3.3 Methods with reference tags

LANDMARC estimates locations of targets by comparing similarity between reference tags and target tags. In order to improve the performance of the LANDMARC system, many methods have been proposed [145–148].

Kalman filtering and a probabilistic map has been used to reduce the localisation error in [145]. This method calculates a probabilistic map of the localisation error for
each reference tag and the probabilistic map can be used to correct the estimation of the target tag. The measurement noise parameters measured from the nearest landmark can also be applied to that of the target tag. So the estimation of the location for targets can be predicted and corrected using the measurement noise parameters by the Kalman filter steps. The 2D location root mean square error (RMSE) is around 0.6 m.

Since different $k$ values show various results in diverse environment, Han and Cho introduced an adaptive k-nearest neighbour algorithm to estimate the best $k$ value [146]. The proposed method firstly finds the nearest reference tag which is called the Key reference tag by using the Euclidean distance between reference tags and the target tag. LANDMARC is applied to the Key reference tag using different $k$ values and the best $k$ value, which leads to the lowest localisation error, is obtained. By using this method, the mean 2D localisation error can be reduced from around 0.8 m to 0.7 m.

Xu et al. use a Gaussian filter to reduce the fluctuations of RSSI caused by the environment and filter abnormal RSSI values [147]. Because the measurement can be repeated multiple times and supposing that the measurements are independent, Bayesian estimation together with the kNN algorithm can be used to improve positioning accuracy for target tags. This method can achieve a mean 2D localisation error of 15 cm.

In [148], an improvement on localisation accuracy is achieved by redefining the formulas of weights. Both equations of the correlation degree and the weight are modified to express the relationship between the signal strength and the distance more accurately. Simulation results indicate the mean 2D localisation error can be reduced from 0.62 m to 0.4 m using the modified weight equation.

The main disadvantages of these methods is that they typically utilise the RSSI value which is easily affected by the environment such as multipath propagation so the localisation accuracy is compromised. These methods usually require many reference tags which lead to comparatively high cost and the number of reference tags also limits the localisation accuracy.
Chapter 3

Localisation Method Based on ISAR-SAR

In this chapter, the system used in the following chapters will be introduced firstly and the environment and setup for the following chapters will also be shown in Section 3.1. Then, details of a novel ISAR-SAR method will be shown in the following sections.

3.1 System Design and Setup

3.1.1 Aims

The main aim of the work in this dissertation is to design a localisation system, propose localisation methods to accurately locate objects in an indoor environment such as a warehouse, and experimentally demonstrate and verify the localisation algorithm using the designed system. The requirements of the task include:

- The system needs to cover a large area (e.g., the size of a large warehouse can reach 15 m × 40 m or larger)
- The number of items to track can reach hundreds
- The system should be cost-effective as the cost should not be more expensive than the value of the item to track
- The localisation accuracy should be of the order of decimetres since the length of large items is around 1 m such as a chair and the size of small objects such as mobile phones is only tens of centimetres in a warehouse
In order to meet these requirements, a mobile platform is required to carry the RFID devices and move in a large warehouse so a large area can be covered without deploying many devices and the cost of infrastructure can be reduced. Passive RFID tags, which are more cost-effective than active tags and require no maintenance as they have no battery, are used and attached to items. It is also required to use a reader which has a high read rate to ensure that hundreds of items attached with passive RFID tags can be tracked.

### 3.1.2 System Design

![Diagram of the system](image)

Fig. 3.1 shows the structure of the system. The system consists of tags, a mobile platform and a computer. UHF RFID passive tags are placed in the localisation area as either reference tags or target tags. The mobile platform is comprised of an RFID reader (the type is Impinj R420), a Raspberry Pi board, multiple antennas, a Turtlebot3 Waffle Pi robot, and batteries.

The Turtlebot3 Waffle Pi robot [149], as shown in Fig. 3.2c, is selected as our mobile platform and it is controlled by Raspberry Pi modules. It is a small, programmable, Robot Operating System (ROS)-based mobile robot which is designed for education, research, and product prototyping. The small size (281 mm × 306 mm × 141 mm) makes it suitable for research in a small indoor area (4 m × 3 m × 3 m). The robot can also be customized in various ways by adding more scalable structure...
and reconstructing the mechanical parts so RFID devices such as the reader and the antenna can be integrated with the robot. In addition, it can be controlled remotely from a laptop and it is based on ROS. ROS is a set of open-source software libraries and tools to build robot applications and it can be deployed by MATLAB through the ROS Toolbox, which includes MATLAB functions to import and analyse ROS data.

The robot is driven by two motors in the front and two wheels are placed in the front with only one steel bearing ball at the back. This platform provides four plates for mounting other components such as LiDAR, UHF RFID Reader, batteries, and antenna pole. In this design, up to four antennas are used and mounted to the antenna pole. In order to reduce the effect of multipath from ground reflection, linearly polarised antennas are used. The antenna is placed vertically and the directions of maximum radiation will be horizontal so the effect from the ground reflection will be reduced. The antenna, as shown in Fig. 3.2b, is a linearly polarised antenna (linear vertical polarization) and the type is MT-242021/NV/K [150], the operating frequency range of which is 865-870 MHz. The maximum speed of the robot is 0.26 m/s [149] and the speed for experiment is set to 5 cm/s. The LiDAR sensor in the robot can measure the distance between the robot and obstacles around the robot to provide the position of the robot. The accuracy of the LiDAR is ±15 mm within 500 mm and ±5.0% when the distance is 500-3500 mm [151].

The reader, as shown in Fig. 3.2a, is an Impinj R420 reader [154] providing four ports and its operating frequency is 865-869 MHz. It operates in FDX mode since it is require to provide power for passive tags while listen for the responses from the tags as mentioned in Section 2.1.2. Mono-static configuration is used so the robot can carry less antennas as both transmitting and receiving purposes can be fulfilled by the same antenna. By adding antenna hubs, it can support up to 32 antennas and it has a high read rate (up to 1100 tags per second). It is controlled by the Raspberry Pi board. The control boards of the reader and the robot are remotely controlled by the computer. Since both boards are connected to a local network rather than the Internet, their timestamps will not be synchronised to the real time. As a result, synchronisation is required to ensure the data collected by the robot and the reader have the same timestamp. Their timestamps are synchronised through a WLAN to allow alignment of the tag reads with the robot LiDAR. The synchronisation between the reader and the robot is achieved by Network Time Protocol (NTP). They are connected to the same local network. The board controlling the reader is used as the server and the robot is synchronized to the server.
Figure 3.2 Components of the system

(a) The reader [152]  
(b) The antenna [150]  
(c) The robot [153]
3.1.3 Environment and Setup

Fig. 3.3 shows the environment of the indoor scenario for this dissertation. The size of the localisation area is approximately $4 \text{ m} \times 3 \text{ m} \times 3 \text{ m}$. Anechoic materials are used in order to partially reduce the influence of metal objects, equipment and unused tags in the lab as shown Fig. 3.3a. The position of the mobile platform is obtained by LiDAR of the robot which is measuring the distance between the mobile platform and some boards placed at the edges of the area as references. Tags are hold by either cotton strings as shown in Fig. 3.3a or plastics boxes as shown in Fig. 3.3b. For the scenario of 2D localisation, only one antenna is used (although more than one antennas are placed in the robot as shown in the figures) and tags are placed in the same plane at the same height of the moving antenna. For the scenario of 3D localisation, four antennas are used as shown in Fig. 3.3b and tags are placed at various heights. The distance between two adjacent tags is around 40 cm.

3.2 Introduction

As discussed in previous sections, over the last decade, UHF RFID technology has received increasing attention and has been widely applied in many scenarios including inventory checking in stores and warehouses, and manufacturing management in factories [59, 155] since it has various important advantages such as cost-effective, contactless communication, and multi-object detection [59, 60]. Recently, one of its most promising applications is providing accurate locations for materials and products in such indoor environment where the GPS is too expensive and is not stable or reliable [33, 156]. In order to reduce the cost of infrastructure such as wires and antennas, RFID reader and antennas are integrated with an indoor UGV so that it can cover a large area and provide high accurate positional information at a low cost [34, 35, 157].

There are many indoor localisation methods using RFID technology, which have been discussed in Section 2.2, e.g., phase-based, RSSI-based, and AoA-based [158]. Among these methods, phase-based localisation has attracted increasing interest due to the fact that it is more robust and stable in complex indoor environments. Various phase-based localisation methods have been proposed [118, 129, 135, 138, 159–168] and the SAR method, which utilises the mobility of a moving platform, is one of the most promising and popular localisation algorithms since it could achieve high
Localisation Method Based on ISAR-SAR

(a) Setup with strings to hold tags

(b) Setup using boxes attached with tags

Figure 3.3 Environment of the lab
localisation accuracy with minimal radio hardware [160, 161], the detail of which can be found in Section 2.2.2.

Different mobile platforms carrying the RFID reader and antennas have been used including a robotic arm [118], a UGV [159–162, 168, 169] or a UAV [129, 135, 164]. In the scenario such as a warehouse, a UGV is typically deployed as it has larger battery life so it is more stable and it can cover a larger area.

The trajectory of the moving antenna is an essential prerequisite to most of algorithms such as the SAR algorithm. In order to obtain the robot trajectory, previous studies have applied various systems such as the GPS [129, 135, 164], an optical motion capture system [160, 161], and a hybrid system which is based on cameras and LiDAR [162, 168–170]. Instead of using these systems, some methods focus on estimation of the trajectory using reference tags. For example, DiGiampaolo and Martinelli proposed a tracking method exploiting reference tags with known locations on the ceiling to estimate the trajectory of a moving robot, which is based on Kalman filtering and the SAR algorithm [171, 172].

After obtaining the trajectory, different processes can be used to calculate the location of target tags. In [135], a SAR-based outdoor localisation method using GPS is demonstrated, in which the localisation error along the x-axis and y-axis is 2.3 cm and -4.4 cm respectively. In addition to SAR-based methods, Tzitzis et al. introduce their Phase ReLock method, which is based on a phase-unwrapping process eliminating the local minima [173]. A SLAM procedure is applied in their method to measure the trajectory of the mobile platform and a SAR-based method is compared with their Phase ReLock method. Results show that both methods can achieve around 17 cm accuracy in 2D space and they suggest that one source of the error comes from the measurement of the trajectory by SLAM and the accuracy could be improved by deploying reference tags with known locations to mitigate the effect of the trajectory measurement. In [140], the Phase ReLock method is extended to localise tags in 3D space. After measuring the phase information of tags using multiple antennas and unwrapping the received phase measurements by the phase-unwrapping process, faulty data, which degrade the perform of the method, are removed using a confidence metric. The filtered data is used to calculate locations of target tags by creating a multi-antenna synthetic aperture. A mean 3D localisation error of less than 20 cm can be achieved using four antennas by the proposed method. Another phase-based fingerprinting localisation method is proposed in [170], which estimates the trajectory by SLAM with multiple sensors, and achieves a mean 2D localisation error of 15-22 cm. Most localisation solutions require complex
sensors such as cameras or LiDAR to provide position information about the moving platform. Although the optical camera, which requires LoS operation, or the LiDAR sensor, which could estimate the relative position of the robot from a reference plane, is able to provide the position of the moving robot, the accuracy is limited by several factors such as obstructions, lighting, and discontinuity of the reference plane and LiDAR systems are not suitable for a scenarios such as a big warehouse since it is a bit difficult to construct a map in a warehouse. Other sensors such as accelerometers can also be used to determine the trajectory but the accuracy is comparatively low so they are used with multiple sensors and with complex algorithms. Meanwhile, high performance cameras or LiDAR systems, which can provide high measurement accuracy, are also expensive. As a result, alternative or complementary solutions are required to estimate the trajectory of the robot and calculate the location of targets in a complicated and dynamic environment with a comparatively low cost.

This chapter proposes and demonstrates a novel cost-effective ISAR-SAR localisation method. The ISAR in this chapter is a bit different from traditional meaning of ISAR. In this chapter, ISAR means that fixed reference tags are used to track a mobile platform. Passive UHF RFID tags with known locations, which can be placed on physically meaningful positions such as shelf bays in loading areas, where now many barcodes are placed in these positions for recording the positions of objects and these barcodes could be replaced with passive RFID tags, to allow simple registration of the coordinate system with the physical world, are used as reference tags to help estimate the trajectory of the mobile platform. After obtaining the optimal estimated trajectory via the ISAR-SAR loop, unknown locations of target tags can be calculated by the SAR algorithm using the estimated trajectory. Details of the novel ISAR-SAR loop, which is the core step of the ISAR-SAR localisation method, will be presented in the following algorithm section. In order to analyse the performance of the proposed method, results of the proposed ISAR-SAR-based method are compared with a LiDAR-SAR-based method which estimates the trajectory by a LiDAR sensor and calculates the location of the target tag by a SAR process.

The rest of this chapter is organized as follows. The ISAR-SAR localisation algorithm is explained in Section 3.3 which is followed by the experimental setup and results in Section 3.4. Section 3.4.1 shows localisation results of a straight-line trajectory and Section 3.4.2 shows results when the mobile platform is moving along an L-shape trajectory. Finally, the conclusion of this chapter is given in Section 3.5.
3.3 Algorithm

Fig. 3.4 shows the main steps of the proposed ISAR-SAR-based localisation method. Phase information of both reference and target tags is collected by a moving RFID reader. The ISAR step is applied using phase measurements of the reference tags to estimate the best-fitting trajectory of the moving platform. After estimating the best-fitting trajectory, the SAR step is used to compute the locations of target tags using received phase values and the optimal estimated trajectory. The SAR algorithm has been discussed in Section 2.2.2 and Section 3.3.1 describes details of the ISAR algorithm for estimation of the trajectory. The novel ISAR-SAR loop is presented in Section 3.3.2, which is the core part of this proposed ISAR-SAR method. The ISAR-SAR loop consists of two main steps. Firstly, an estimated trajectory is calculated by the ISAR algorithm using received phase values of reference tags. The second step is to carry out an evaluation of this estimated trajectory. The SAR algorithm is applied to compute the locations of the reference tags based on the trajectory estimated from the previous ISAR step. The mean absolute localisation error between the actual locations and estimated locations of reference tags is used to evaluate the quality of the estimated trajectory. According to the localisation error, the loop can adjust the setting and parameters of the ISAR step and compute a new trajectory of the moving platform in order to find a better fitting estimated trajectory. By using this loop, any unintended variation in speed and any unintended displacement caused by bearing of the mobile platform can also be partially eliminated.

![Figure 3.4 The steps of ISAR-SAR method](image)

3.3.1 ISAR

Since the mobile platform is more stable and less affected by the uneven floor and castor bearing when it moves along a straight-line trajectory than along an arbitrary trajectory, when the trajectory extends to an L-shape trajectory, the L-shape trajectory is divided into two straight-line trajectories. The mobile platform is firstly moving along the first straight-line trajectory and turning in place followed by moving along
the second straight-line trajectory of which the direction is almost perpendicular to the first trajectory. The ISAR algorithm is initially designed for a straight-line trajectory so the turning point would lead to a larger error in the direction estimated by the ISAR step due to limitations of the dynamic model in the ISAR process. As a result, the data collected when the mobile platform is turning is removed and only the data collected when the mobile platform is moving along a straight-line trajectory will be used.

The ISAR algorithm originates from the SAR method which exploits a moving platform with a known trajectory to compute the locations of static tags with unknown locations. During the ISAR process, a number of passive UHF RFID tags with known locations are placed and used to estimate trajectory of the moving platform where the initial location of the antenna is assumed to be known and accurate. At time $t-1$, the position of the moving platform can be expressed as

$$a_{t-1} = [x_{t-1}, y_{t-1}]$$  \hspace{1cm} (3.1)

![Figure 3.5](image.png)

Figure 3.5 The diagram for variables $l$ and $\theta$ of the hypothetical step

The platform then moves according to the $j$-th hypothetical step

$$v_{t,j} = [l\cos\theta, l\sin\theta]$$  \hspace{1cm} (3.2)

Where $l$ is the displacement of the platform which belongs to the range $[l_{\text{min}}, l_{\text{max}}]$ hence $l \in [l_{\text{min}}, l_{\text{max}}]$, $\theta$ is the angle of direction for each step relative to the direction of the trajectory which belongs to the range $[\theta_{\text{min}}, \theta_{\text{max}}]$ hence $\theta \in [\theta_{\text{min}}, \theta_{\text{max}}]$ as shown in Fig. 3.5. The parameter range for the displacement and the angle is defined at the beginning of the ISAR process. A matrix of possible $l, \theta$ combination will be evaluated by the process and the best one will be chosen. The hypothetical location at time $t$ can be calculated by

$$a'_{t,j} = a_{t-1} + v_{t,j}$$  \hspace{1cm} (3.3)
The known location of \( m \)-th reference tag can be written as
\[
h_m = [x_m, y_m]
\] (3.4)

All locations of \( M \) reference tags can be expressed as
\[
H = [h_1, \ldots, h_m, \ldots, h_M]^T
\] (3.5)

The distance between the hypothetical position of the platform and the known location of the reference tag at time \( t \) is
\[
d_{t,i,m} = ||a'_{t,i} - h_m||
\] (3.6)

Where \( || \cdot || \) is the norm operator of the distance vector.

At time \( t \), the relative received phase which is measured by the reader from the \( m \)-th reference tag is
\[
\Delta \phi_{t,i,m} = \phi_{t,i,m} - \phi_{1,m}
\] (3.7)

The relative received phase of \( M \) reference tags can be written as
\[
\Delta \Phi_{t} = [\Delta \phi_{1,t}, \ldots, \Delta \phi_{t,m}, \ldots, \Delta \phi_{t,M}]^T
\] (3.8)

All phase values of reference tags measured by the reader over \( K \) seconds can be written as
\[
\Phi_{ref} = [\Delta \Phi_1, \ldots, \Delta \Phi_t, \ldots, \Delta \Phi_K]^T
\] (3.9)

For each hypothetical position of the moving platform, the expected calculated phase of each tag can be obtained by
\[
\phi'_{t,i,m} = (\phi_0 + \frac{4\pi d_{t,i,m}}{\lambda}) \mod 2\pi
\] (3.10)

The relative expected phase can be expressed as
\[
\Delta \phi'_{t,i,m} = \phi'_{t,i,m} - \phi'_{1,i,m}
\] (3.11)

The sequence of relative expected phase can be expressed in vector form as
\[
\Delta \Phi'_{t,i} = [\Delta \phi'_{t,i,1}, \ldots, \Delta \phi'_{t,i,m}, \ldots, \Delta \phi'_{t,i,M}]^T
\] (3.12)
The matching function defined as
\[ C_{t,j} = [C_{t,j,1},...,C_{t,j,m},...,C_{t,j,M}]^T = \exp(-j(\Delta \Phi'_t - \Delta \Phi_t)) \] (3.13)
is a measure of the difference between the expected and measured phase for each hypothetical position of the moving platform.

The probability for each hypothetical position of the moving platform can be expressed as the sum of the result of the matching function across all reference tags being read
\[ P_{t,j} = |\sum_{m=1}^{M} C_{t,j,m}| \] (3.14)
The estimated position of the moving platform at time \( t \) would be the position with the largest probability
\[ a_t = \arg \max_{a'_{t,j}} P_{t,j} \] (3.15)
After obtaining the estimated position at time \( t \), the process described above will repeat to estimate the position at time \( t+1 \). And finally, an estimated trajectory of the moving platform can be written as
\[ A = [a_1,...,a_t,...,a_T] \] (3.16)

### 3.3.2 ISAR-SAR

After calculating the estimated trajectory of the moving platform using the initial parameter, the SAR process is applied using the estimated trajectory and the recorded phase values of the reference tags to calculate locations of the reference tags. The mean localisation error between the actual locations and the estimated locations of all reference tags can be used to check the accuracy of the estimated trajectory. The mean localisation error for reference tags is compared with the expected localisation error \( E \). If it is larger than \( E \), the estimated trajectory will not be regarded as an optimal estimated trajectory and will be abandoned and a new trajectory will be calculated using different parameters. By changing the parameters of the ISAR algorithm including the range of the length of the displacement and the range of the angle of direction, a new trajectory can be calculated and the localisation error using this new estimated trajectory will be used to check the fitness of the estimated trajectory again as described above. This process, which will be repeated several
3.3 Algorithm

Figure 3.6 The flow chart of ISAR-SAR method
Algorithm 1 ISAR-SAR method

Input: Phase data $\Phi_{\text{tar}}, \Phi_{\text{ref}}$, Locations of reference tags $H$

Output: Estimated locations of target tags $B$

Set $E, l, \theta$

$e \leftarrow \infty$ \hfill \triangleright \text{This is a comment}

while $e > E$ do

$A \leftarrow \text{F-ISAR}(\Phi_{\text{ref}}, H, l, \theta)$

for $m \leftarrow 1$ to length($\Phi_{\text{ref}}$) do

$H'(m) \leftarrow \text{F-SAR}(\Phi_{\text{ref}}(m), A)$

end for

$e \leftarrow H', H$

if $e > E$ then

Reset $l, \theta$

else

return $A$

end if

end while

for $m \leftarrow 1$ to length($\Phi_{\text{tar}}$) do

$B(m) \leftarrow \text{F-SAR}(\Phi_{\text{tar}}(m), A)$

end for

\begin{function}
\text{F-SAR}(\Phi, Tra)
\begin{align*}
&\text{for } i \leftarrow 1 \text{ to length}(\Phi) \text{ do} \hfill \triangleright \text{for each time step} \\
&C(i) \leftarrow \Phi(i), Tra(i) \hfill \triangleright \text{eq. 2.25}
\end{align*}
\end{function}

$P \leftarrow C$ \hfill \triangleright \text{eq. 2.26}

$Loc \leftarrow P$

return $Loc$ \hfill \triangleright \text{eq. 2.28}

\end{function}

function $\text{F-ISAR}(\Phi, Loc, l, \theta)$ \hfill \triangleright \text{for each time step}

$A' \leftarrow l, \theta$

\begin{function}
\text{F-SAR}(\Phi, \text{Loc}, A')
\begin{align*}
&\text{for } m \leftarrow 1 \text{ to length}(\Phi) \text{ do} \hfill \triangleright \text{for each tag} \\
&C(m) \leftarrow \Phi(t, m), \text{Loc}, A' \hfill \triangleright \text{eq. 3.13}
\end{align*}
\end{function}

$P \leftarrow C$ \hfill \triangleright \text{eq. 3.14}

$A(t) \leftarrow P$ \hfill \triangleright \text{eq. 3.15}

end for

return $A$

end function
3.4 Results

3.4.1 Results with a straight-line trajectory

The experiment where the mobile platform is moving along a straight-line trajectory was carried out in an indoor scenario as shown in Fig. 3.7b. As shown in Fig. 3.7a, reference tags were placed in two rows, at locations marked by black circles, and one row of tags was placed as targets to locate, at locations marked by blue crosses. A linearly polarised antenna was used and placed at the same height as the plane of tags. The platform carrying the reader and the antenna is moved along a straight-line trajectory which is shown by the blue line and the moving direction is shown by the arrow in Fig. 3.7a. Fixed boards were placed at the edges of the area at a known location to allow the LiDAR sensor to estimate the trajectory of the mobile platform for comparison with the ISAR derived trajectory. The initial position of the mobile platform is measured before tests to be (0.09 m, 0.17 m). The first row of the reference tags was placed 1.2 m away from the intended trajectory of the mobile platform while the second row of the reference tags was placed 2 m away. One row of target tags was placed in between the two rows of reference tags. Both the distance between the rows and the distance between tags within rows are 0.4 m (in a warehouse, each shelf for small objects has two positions per metre and each position has one barcode to record the position information). As shown in Fig. 3.7a, the first tag of the first row was placed at (0.2 m, 1.2 m) and the first tag of the third row was placed at (0.4 m, 2.0 m) while the first tag of the target tags was at (0.3 m, 1.6 m).

Table 3.1 shows the results of the mean absolute error (MAE) between the true and estimated location for reference tags during the ISAR process with various parameters. Since the actual speed of the robot is affected by many factors including the surface of the floor, the weight of the mobile platform and so on, the displacement
Figure 3.7 Experiment setup with a straight-line trajectory
3.4 Results

of the platform is varied slightly so in order to better estimate the trajectory, the range of the length of the displacement is also varied. For example, the expected value of $l$ is around 5 cm but due to the imperfect condition, the mean of the true values is around 4.5 cm. As a result the $l_{\text{max}}$ should also be smaller rather than using the initial value of 6 cm. When $l_{\text{min}}/l_{\text{max}}$ is varied, a new trajectory is estimated. As a result, the localisation error of reference tags also varies. Table 3.1 shows that when the parameter is 3.5/5.0 cm (the mean of true values of $l$ is around 4.5 cm), the MAE of reference tags reaches a minimum (17.49 cm).

Table 3.1 Effect of parameters on ISAR process showing the error between the true and estimated location of the reference tag

<table>
<thead>
<tr>
<th>$l_{\text{min}}$</th>
<th>$l_{\text{max}}$</th>
<th>MAE</th>
<th>$l_{\text{min}}$</th>
<th>$l_{\text{max}}$</th>
<th>MAE</th>
<th>$l_{\text{min}}$</th>
<th>$l_{\text{max}}$</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.5</td>
<td>5.0</td>
<td>45.17</td>
<td>1.5</td>
<td>5.5</td>
<td>26.07</td>
<td>1.5</td>
<td>6.0</td>
<td>38.22</td>
</tr>
<tr>
<td>2.0</td>
<td>5.0</td>
<td>38.03</td>
<td>2.0</td>
<td>5.5</td>
<td>19.94</td>
<td>2.0</td>
<td>6.0</td>
<td>53.17</td>
</tr>
<tr>
<td>2.5</td>
<td>5.0</td>
<td>27.36</td>
<td>2.5</td>
<td>5.5</td>
<td>24.56</td>
<td>2.5</td>
<td>6.0</td>
<td>71.23</td>
</tr>
<tr>
<td>3.0</td>
<td>5.0</td>
<td>22.48</td>
<td>3.0</td>
<td>5.5</td>
<td>33.92</td>
<td>3.0</td>
<td>6.0</td>
<td>86.17</td>
</tr>
<tr>
<td>3.5</td>
<td>5.0</td>
<td>17.49</td>
<td>3.5</td>
<td>5.5</td>
<td>48.04</td>
<td>3.5</td>
<td>6.0</td>
<td>97.49</td>
</tr>
<tr>
<td>4.0</td>
<td>5.0</td>
<td>23.06</td>
<td>4.0</td>
<td>5.5</td>
<td>63.17</td>
<td>4.0</td>
<td>6.0</td>
<td>107.78</td>
</tr>
</tbody>
</table>

Fig. 3.8 shows that the measured trajectory by the LiDAR sensor is very close to the calculated trajectory by using the ISAR process. Although the expected trajectory is a straight-line parallel to the X-axis, the actual trajectory is not perfectly parallel to the X-axis due to the imperfect condition of the floor and the limitation of the robot where there is one bearing ball at the back of the robot so any small objects on the floor may result in the trajectory not perfectly parallel to the X-axis. Fig. 3.9 is a zoomed-in view of Fig. 3.8 and shows more details of measured and estimated trajectories. The black lines represent the error vectors and show the corresponding relationship between two trajectories lining points corresponding to the same time step. The error increases as the length of the trajectory increases due to the cumulative error and the mean difference between the trajectories is of the order of a centimetre.

The results of error between the measured trajectory and estimated trajectory along the x-axis and y-axis of ten tests are summarised in Table 3.2. The mean of MAE of ten tests along the x-axis and y-axis is around 3 cm and 2 cm respectively. As shown in Table 3.2, except for Test 2, the MAE along the x-axis of other tests are
Figure 3.8 Trajectory results of one of the tests

Figure 3.9 Comparison of sample points between LiDAR trajectory and ISAR trajectory
smaller than 5 cm and the MAE along the y-axis of ten tests as well as the MAE of total error is within 5 cm which is similar to the accuracy of the LiDAR sensor according to the data sheet (±15 mm within 500 mm and ±5.0% when the distance is 500-3500 mm [151]), so the recorded differences are within the error bounds of the LiDAR itself.

Table 3.2 Difference between trajectory measured by LiDAR and estimated by ISAR

<table>
<thead>
<tr>
<th>Test</th>
<th>x-axis</th>
<th>y-axis</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.21</td>
<td>4.85</td>
<td>5.83</td>
</tr>
<tr>
<td>2</td>
<td>10.67</td>
<td>2.90</td>
<td>10.88</td>
</tr>
<tr>
<td>3</td>
<td>2.44</td>
<td>1.18</td>
<td>3.33</td>
</tr>
<tr>
<td>4</td>
<td>3.00</td>
<td>0.81</td>
<td>3.77</td>
</tr>
<tr>
<td>5</td>
<td>1.11</td>
<td>4.01</td>
<td>4.63</td>
</tr>
<tr>
<td>6</td>
<td>3.56</td>
<td>1.36</td>
<td>3.66</td>
</tr>
<tr>
<td>7</td>
<td>2.14</td>
<td>1.26</td>
<td>3.03</td>
</tr>
<tr>
<td>8</td>
<td>1.14</td>
<td>3.67</td>
<td>4.03</td>
</tr>
<tr>
<td>9</td>
<td>1.67</td>
<td>0.62</td>
<td>3.08</td>
</tr>
<tr>
<td>10</td>
<td>4.60</td>
<td>0.93</td>
<td>5.09</td>
</tr>
<tr>
<td>Mean</td>
<td>3.35</td>
<td>2.16</td>
<td>4.73</td>
</tr>
</tbody>
</table>

After obtaining the best-fitting trajectory estimated by the ISAR-SAR loop, the SAR algorithm is performed to calculate the location of target tags. Both the trajectory measured by LiDAR and the trajectory estimated by ISAR are used to perform the SAR algorithm to locate target tags. The results are shown in Fig. 3.10.

The actual locations of target tags are marked by black circles and blue crosses show the estimated locations using the LiDAR trajectory while red stars show the estimated locations using the best-fitting trajectory estimated by the ISAR method. The blue lines and red lines, which are similar to each other, show the error vectors between the actual locations and estimated locations. This shows that two trajectories estimated by two different methods can achieve similar localisation accuracy of the target tags. The mean localisation error obtained from the LiDAR trajectory is around 16 cm while the mean localisation error using the ISAR trajectory is about 13 cm. 10 tests have been carried out and mean localisation error value as well as the mean localisation error in percentage with respect to the minimum reader to
Localisation Method Based on ISAR-SAR

Figure 3.10 Localisation results of target tags of one of tests

Figure 3.11 Picture of the controlled environment with a straight-line trajectory
Table 3.3 Mean localisation error value of 10 tests by SAR with a straight line trajectories

<table>
<thead>
<tr>
<th>Environment</th>
<th>Uncontrolled (Fig. 3.7)</th>
<th>Semi-anechoic (Fig. 3.11)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test</td>
<td>LiDAR (cm)</td>
<td>ISAR (cm)</td>
</tr>
<tr>
<td>1</td>
<td>16.83</td>
<td>19.05</td>
</tr>
<tr>
<td>2</td>
<td>14.21</td>
<td>13.24</td>
</tr>
<tr>
<td>3</td>
<td>14.63</td>
<td>15.89</td>
</tr>
<tr>
<td>4</td>
<td>15.69</td>
<td>15.02</td>
</tr>
<tr>
<td>5</td>
<td>13.96</td>
<td>14.46</td>
</tr>
<tr>
<td>6</td>
<td>16.57</td>
<td>21.41</td>
</tr>
<tr>
<td>7</td>
<td>12.72</td>
<td>12.70</td>
</tr>
<tr>
<td>8</td>
<td>13.39</td>
<td>11.42</td>
</tr>
<tr>
<td>9</td>
<td>16.30</td>
<td>13.34</td>
</tr>
<tr>
<td>10</td>
<td>16.57</td>
<td>14.59</td>
</tr>
<tr>
<td>Mean</td>
<td>15.09</td>
<td>15.11</td>
</tr>
</tbody>
</table>

tag range (1.6 m) have been summarized in Table 3.3. The mean localisation error of 10 tests by using LiDAR and ISAR methods is similar to each other (around 15 cm). It is worth noting that the error vectors are generally consistent between the results obtained by LiDAR-SAR and ISAR-SAR, this may indicate that multipath propagation, which is the same in both cases, is one of the main sources of the localisation error. Many other factors, such as non-ideal phase offset [174], errors on locations of reference tags, the error of the trajectory estimation, may also affect the accuracy of localisation.

In order to evaluate the effect of multipath, as shown in Fig. 3.11, 10 tests have been carried out in a controlled environment with anechoic materials placed to partially reduce the reflections from surrounding objects. Both the arrangement of tags and intended trajectory of the mobile platform are the same as shown in Fig. 3.7 to allow the effect of the environment to be evaluated. The localisation accuracy is comparatively higher than that achieved without placing anechoic materials. Under a controlled environment, the mean localisation error achieved by LiDAR-SAR method is 13.71 cm while the mean error obtained by ISAR-SAR method is 14.76 cm. These results may indicate that anechoic materials slightly reduce the multipath effect and leads to higher localisation accuracy. However, the improvement in
localisation accuracy is not significant compared with the results achieved in the uncontrolled environment as shown in Table 3.3. Because anechoic materials only partially reduce reflections from surrounding objects and the ground reflection remains unaffected as previous tests in a uncontrolled environment, the effect of the multipath from ground reflection might be the main source of error for localisation of target tags. For ISAR-SAR-based method, which the trajectory is estimated using reference tags, many other factors, such as errors on locations of reference tags, configuration of reference tags, the error of the trajectory estimation, may also affect the accuracy of localisation.

3.4.2 Results with an L-shape trajectory

It can be seen in Fig. 3.10 that the localisation error is mainly along the y-axis which is perpendicular to the straight-line trajectory of the moving platform. When the mobile platform is moving along a straight-line trajectory, the SAR algorithm lacks depth information perpendicular to the trajectory of the mobile platform, as there will be little change in the received phase difference. As a result, the localisation error is mainly from the error along the direction perpendicular to the straight-line trajectory. In order to address this problem and further improve the accuracy, an L-shape trajectory can be used.

The experiment setup with an L-shape trajectory is shown in Fig. 3.12a. Some boards with known locations are placed at the edges of the area as references for the LiDAR sensor to calculate the location of the mobile platform and the initial position of the mobile platform is measured at the beginning of tests to be (0.1 m, 2.08 m). The L-shape trajectory, which is shown by the black line in Fig. 3.12a, can be divided into two straight-line trajectories and the arrow shows the moving direction of the trajectory. The first straight-line trajectory, which is parallel to the x-axis, is 3 m followed by a 2 m long trajectory parallel to the y-axis (limited by the size of the experimental area). Eight target tags shown by the green crosses are placed in the middle of reference tags shown by the blue circles and the distance between tags is 0.4 m. Because there are many objects such as equipment and metal shelves in the lab, anechoic materials, which partially reduce the influence of the objects in the lab, were used to reduce reading other unused tags in the environment which could increase the reading rate of the desired tags.

Fig. 3.13 shows the results of the trajectory estimation by ISAR-SAR loop. The trajectory measured by the LiDAR sensor is shown by the blue line while the red line represents the trajectory calculated by the ISAR method. As with the straight
Figure 3.12 Experiment setup with an L-shape trajectory
trajectory, as the trajectory gets longer, the error between the measured trajectory by the LiDAR sensor and the estimated trajectory by the ISAR method also increases due to the cumulative error.

![Figure 3.13 Trajectory results of one of the tests](image)

Fig. 3.14 shows components of the error in the straight-line trajectory estimated by the ISAR method along the x-axis and y-axis for the portion of the track parallel to the x-axis. The length of the trajectory is around 3 m and total 300 samples are taken so samples are taken every centimetre. The MAE of the component along the x-axis is 3.07 cm and the MAE of the component along the y-axis is 1.43 cm. As shown in Fig. 3.14a, a clear trend can be seen that the error rises and reaches around 8 cm which is due to the cumulative error and will have a negative effect on the estimation for the straight-line trajectory along the y-direction.

The components of the error for the portion of the estimated trajectory parallel to the y-axis are shown in Fig. 3.15. Fig. 3.15a shows the error component in the x-direction while Fig. 3.15b shows the error component in the y-direction. The MAE along the x-axis is 1.59 cm and the MAE along the y-axis is 7.77 cm and one reason for the error is the cumulative error since each estimated step of the mobile platform is based on previous estimated step so the error of each step may be cumulative. The error along y-axis could reach around 16 cm and the main reason for larger error in the trajectory estimation along y-axis is that fewer reference tags locations (four)
are used along the y-direction leading to a smaller effective aperture compared with larger effective aperture using six different locations along the x-direction.

Figure 3.14 Errors between ISAR trajectory and LiDAR trajectory along x-direction (samples are taken every centimetre)

Figure 3.15 Errors between ISAR trajectory and LiDAR trajectory along y-direction (samples are taken every centimetre)

Five tests were carried out and the results of the trajectory estimation are summarized in Table 3.4. The MAE along the x-direction is 6.62 cm and the MAE along the y-direction is 8.36 cm. The error in trajectory estimation is slightly larger which may be due to the longer trajectory.

Fig. 3.16 shows an example for the result of the probability function in order to show the difference between using the straight-line and L-shape trajectory. For the L
Table 3.4 Error in the trajectory estimation by the ISAR process

<table>
<thead>
<tr>
<th>Trajectory</th>
<th>along x-direction</th>
<th>along y-direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test</td>
<td>x-axis</td>
<td>y-axis</td>
</tr>
<tr>
<td>1</td>
<td>1.53</td>
<td>8.30</td>
</tr>
<tr>
<td>2</td>
<td>8.00</td>
<td>6.23</td>
</tr>
<tr>
<td>3</td>
<td>7.05</td>
<td>2.00</td>
</tr>
<tr>
<td>4</td>
<td>3.07</td>
<td>1.43</td>
</tr>
<tr>
<td>5</td>
<td>4.16</td>
<td>2.43</td>
</tr>
<tr>
<td>Mean</td>
<td>5.76</td>
<td>4.08</td>
</tr>
</tbody>
</table>

shape trajectory, the trajectory is decomposed into 2 straight segments to produce two probability heat maps as shown in Fig. 3.16 where the yellow area represents the positions with high probability while the area with low probability is shown by the blue area. Fig. 3.16a shows the probability heat map obtained using the straight-line trajectory along x-direction while Fig. 3.16b is the heat map when the trajectory is along the y-direction. The SAR-based method using RFID is different from radar SAR in that the frequency range used in RFID SAR is very narrow (in this dissertation only one frequency is used) so there is very little range information. Therefore, the high probability area, which is shown by the yellow area in Fig. 3.16a, is extended along the y-axis while in Fig. 3.16b it is more extended along the x-axis. If only a straight-line trajectory is used as shown in Fig. 3.16b, for example, the lack of depth information along with influences from the environment such as multipath results in a relatively large error in the estimated y position as shown by the red cross.

Fig. 3.17 shows the probability heat map of localisation using an L-shape trajectory. By combining results obtained using the straight-line trajectories along x-direction and y-direction (the product of Fig. 3.16a and Fig. 3.16b), the localisation accuracy can be improved as shown by the red cross which is much closer to the actual location shown by the green circle.

Fig. 3.18 shows the localisation results for all target tags when the mobile platform is moving along an L-shape trajectory. Black circles are the actual locations of target tags. Locations estimated by the LiDAR-SAR method are shown by blue crosses.
3.4 Results

(a) Probability heatmap with the trajectory along x-direction

(b) Probability heatmap with the trajectory along y-direction

Figure 3.16 Probability heatmap with a straight-line trajectory
while red crosses represent locations estimated by the proposed ISAR-SAR method. The mean localisation error for LiDAR-SAR is 7.95 cm and for ISAR-SAR is 4.38 cm.

Figure 3.17 Probability heatmap with an L-shape trajectory

The localisation error of five tests using either a straight-line trajectory along the x-axis or an L-shape trajectory by two different methods are summarized in Table 3.5. The localisation error achieved by the ISAR-SAR method with a straight-line trajectory is much smaller than that by the LiDAR-SAR method which may indicate the proposed ISAR-SAR method provide good localisation accuracy when the trajectory is straight-line as the ISAR-SAR loop uses the reference tags to estimate a best-fitting trajectory and this could reduce the effect of multipath. By using an L-shape trajectory, the LiDAR-SAR method can reduce the localisation error to 7.83 cm compared with the localisation error of 12.36 cm with a straight-line trajectory. In some cases, the ISAR-SAR method with an L-shape trajectory leads to a slightly larger localisation error than that with a straight-line trajectory. Since the straight-line trajectory is a subset of the L-shaped data, it can be concluded that in these cases the second half of the L-shaped trajectory, which is shorter than the first half, is contributing to increase the error. This may be due to the different aperture of the reference tags in the y direction leading to larger error in the estimation of the
3.4 Results

Figure 3.18 Localisation results of target tags of Test 5

trajectory. As shown in Fig. 3.12a, there are only four different locations of reference tags, the length of spread of reference tags is only 1.2 m, along the y-direction while reference tags are placed in six different locations, the length of spread of reference tags is 2 m, along the x-direction leading to lower resolution along the y-axis than along the x-axis. This will reduce the accuracy of trajectory estimation along the y-direction and, as a result, reduce the accuracy for localisation using the L-shape trajectory. The initial location of the second half of the trajectory is also dependent on the error at the end of the first half of the trajectory, which results in larger trajectory estimation error in the second trajectory. The results may also indicate that the localisation accuracy by the ISAR-SAR method is influenced by both number and configuration of reference tags. In some tests, the ISAR-SAR method can achieve higher localisation accuracy than the LiDAR-SAR method. The process of estimating the best-fitting trajectory involves the step of trajectory estimation and the step of checking the estimated trajectory by localisation of reference tags. As a result, the trajectory estimated by the ISAR process might not match the physical trajectory accurately but it could compensate the influence of multipath so the localisation accuracy could be improved using the best-fitting trajectory.

There are two possible reasons for the variability between experimental tests. Fig. 3.19 plots the straight-line trajectory along the x-axis for Test1 and Test3, the blue line
Table 3.5 Mean localisation error value of five tests by SAR with two trajectories

<table>
<thead>
<tr>
<th>Test</th>
<th>LiDAR-SAR</th>
<th>ISAR-SAR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Straight-line</td>
<td>L shape</td>
</tr>
<tr>
<td>1</td>
<td>17.86</td>
<td>10.15</td>
</tr>
<tr>
<td>2</td>
<td>11.91</td>
<td>7.95</td>
</tr>
<tr>
<td>3</td>
<td>8.09</td>
<td>7.18</td>
</tr>
<tr>
<td>4</td>
<td>8.61</td>
<td>7.58</td>
</tr>
<tr>
<td>5</td>
<td>15.33</td>
<td>6.29</td>
</tr>
<tr>
<td>Mean</td>
<td>12.36</td>
<td>7.83</td>
</tr>
</tbody>
</table>

Figure 3.19 The straight-line trajectory for Test1 and Test3 shows the trajectory of the Test1 and it can be seen that when the mobile platform reach 2 m along the x-axis it suddenly slightly turns right, which could be caused by small obstacles on the floor, as shown by the black arrow. This leads to errors in trajectory measurement as marked by black circle and results in larger localisation error. Other tests do not have the problem of the trajectory and another possible reason is the received phase as presented in Table 3.6. Table 3.6 shows the std of the
3.5 Conclusion

The error between the received phase and theoretical phase for 5 tests. The smaller std indicates error are clustered around the the mean and larger std shows the phase errors are more spread out which leads to larger localisation error. Test1 and Test5 have largest std than other tests while Test2 has larger std than Test3 and Test4 and this could explain the variability between tests. The difference of phase error between tests could be caused by the environment such as the noise and multipath, which could be the result of the movement of the people in the lab during the test.

Table 3.6 The std of the error between the received phase and theoretical phase

<table>
<thead>
<tr>
<th>Test</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>std of the error</td>
<td>2.4773</td>
<td>0.9139</td>
<td>0.9943</td>
<td>0.9371</td>
<td>1.5206</td>
</tr>
<tr>
<td></td>
<td>2.1983</td>
<td>0.9363</td>
<td>0.9624</td>
<td>2.4777</td>
<td>0.9727</td>
</tr>
<tr>
<td></td>
<td>1.9393</td>
<td>1.6052</td>
<td>0.7781</td>
<td>0.8055</td>
<td>1.8034</td>
</tr>
<tr>
<td></td>
<td>1.9517</td>
<td>2.0904</td>
<td>0.9945</td>
<td>0.9819</td>
<td>2.2834</td>
</tr>
<tr>
<td></td>
<td>2.5436</td>
<td>1.6735</td>
<td>0.8952</td>
<td>1.2202</td>
<td>1.0726</td>
</tr>
<tr>
<td></td>
<td>0.8575</td>
<td>0.9942</td>
<td>0.5931</td>
<td>0.7159</td>
<td>2.5885</td>
</tr>
<tr>
<td></td>
<td>2.303</td>
<td>1.3487</td>
<td>0.6012</td>
<td>1.1826</td>
<td>2.2258</td>
</tr>
<tr>
<td></td>
<td>0.7207</td>
<td>1.5168</td>
<td>0.6748</td>
<td>0.5668</td>
<td>0.7407</td>
</tr>
<tr>
<td>mean</td>
<td>1.8739</td>
<td>1.3849</td>
<td>0.8117</td>
<td>1.1110</td>
<td>1.6510</td>
</tr>
</tbody>
</table>

3.5 Conclusion

In this chapter, a novel ISAR-SAR 2D localisation method with an ISAR-based trajectory estimation algorithm by deploying reference tags and an ISAR-SAR loop for trajectory checking is proposed and tested. The method is reliant on phase values and known locations of reference tags, which are placed at the same plane with the height same as the antenna, and the phase of target tags to estimate locations of targets.

The proposed method exploits low-cost passive UHF RFID tags with known locations as reference tags to estimate the trajectory of the mobile platform. The known locations of reference tags are used in an ISAR-SAR loop to evaluate and adjust the estimated trajectory in order to find the best fitting trajectory and improve the localisation accuracy.
Experimental results with a straight-line trajectory in an uncontrolled environment show that the MAE between the trajectory estimated by the ISAR method and the trajectory measured by the LiDAR sensor is smaller than 5 cm. The ISAR-SAR localisation method can achieve a localisation error of 15 cm, which is similar to the accuracy achieved by using the trajectory measured by the LiDAR sensor.

Although the error in the estimation of the trajectory is slightly larger due to the longer trajectory and cumulative error, the localisation accuracy can be improved by using an L-shape trajectory. In a controlled environment where anechoic materials are placed to reduce the effect of multipath, the LiDAR-SAR method using the straight-line segment along the x-axis of the L-shape trajectory can reduce the localisation error to 12 cm while the full L-shape trajectory can reach the localisation accuracy of 8 cm. The proposed ISAR-SAR method performs better and both the straight-line segment and the L-shape trajectory can provide the localisation accuracy of around 6 cm. This demonstrates the capability of the ISAR-SAR approach to eliminate the need for the LiDAR sensor, however the initial position of the mobile platform needs to be known.
Chapter 4

Localisation Method Based on k-parameter Estimation

4.1 Introduction

Although the SAR-based algorithms can achieve high localisation accuracy, the resolution highly depends on the density of points in the grid used by the algorithm. A high resolution requires the calculation of the probability function over a fine grid in order to achieve high localisation accuracy and this leads to a high computational load particularly for 3D localisation. Many works focus on more efficient algorithms to overcome this drawback.

In [142], the 3D localisation of target tags is achieved by a SAR-based method. The conventional SAR-based methods traverse points in the grid in 3D space to find the maxima, which leads to a high computational burden. In order to reduce the computational burden, a particle swarm optimization (PSO) approach is employed in the proposed method. The accuracy of 3D localisation by this method is in the order of centimetres in the considered scenario and it suggests that the accuracy is in the order of decimetres by the proposed method regardless of application scenarios.

E3DinSAR [139] proposed an optimized interference SAR-based method to achieve 3D localisation of target tags. The approach firstly extends the aperture of the mobile platform, which is usually linear, to an arbitrary trajectory by dividing the trajectory into multiple linear apertures. After obtaining information of target tags, instead of generation of a 3D holographic image using the traditional grid-based approach, several 2D holographic images are generated at different heights and accordingly, a group of candidate locations can be obtained. The final position is
Localisation Method Based on k-parameter Estimation

Experimental results show that E3DinSAR can achieve a mean localisation accuracy of 18.4 cm in 3D space.

Rather than calculating the absolute locations of target tags, some phase-based methods focus on estimating spatial ordering of tags, which are designed for the scenario like a library. In a library environment, the reader antenna moves along the passageway between shelves of tagged books to collect information of RFID tags. After obtaining information of RFID tags, different methods are proposed such as STPP [143], RFScanner [144] and RLLL [30]. The method called Spatial-Temporal Phase Profiling (STPP) is a typical method for inferring the 1D spatial order of target tags [143] and it exploits the concept of the "V-zone" in the phase profile. Fig. 4.1a shows the shape of the received phase, which changes periodically between $[0, 2\pi]$. During the period when the mobile platform moves from the position Loc1 to Loc2, the change in distance between the tag and the antenna will be smaller than half a wavelength so a "V" shape will be observed for the received phase during this period, which is referred as the V-zone of the phase profile. By analysing the V-zone in the phase profile of each tag and the spatial relationship between tags, the order of tags can be determined. However, these methods only estimate ordering information between tags and don't provide the absolute position of tags.

Apart from phase information, some localisation methods using reference tags also use RSSI information, which is also commonly used for indoor localisation. The similarity between recorded RSSI of target tags and reference tags is used to compute the location of target tags under the assumption that tags close to one another will have similar RSSI. 64 reference tags are used by the method proposed by Mo and Li and both the received phase and RSSI information are collected for 2D localisation [175]. Since the accuracy by the method using similarity is affected by the number of reference tags, in order to further improve the accuracy without deploying too many reference tags, virtual reference tags have been created by natural neighbour interpolation, which is a method of spatial interpolation to interpolate a point and create a cell for this inserted point using weights of surrounding points and cells. Moreover, the method also introduces the Laiyite criterion to mitigate the effect of multipath. The Laiyite criterion is used to remove outliers from measured data and the basic idea is that when measured data follow a normal distribution the data which falls outside of the $3\sigma$ (3 standard deviations from a mean) range will be considered as outliers and will be removed. The 2D localisation accuracy by this method can reach around 10 cm.
In this chapter, the author proposes and demonstrates a high accuracy localisation method with reduced computational complexity based on the received RSSI and the unwrapped phase profile. The distance along the trajectory, which is termed as cross-range, can be calculated from the inflection point of the V-zone of the unwrapped phase profile combined with the known trajectory of the moving platform. The distance perpendicular to the track, which is termed as down-range, can be estimated from the shape of the profile by adjusting the k-parameter. For 2D localisation, only a single straight-line trajectory is required to calculate the location of the target tag while in 3D space, after obtaining x- and y-coordinate of the tag by cross-range estimation with a L-shape trajectory, a possible range for the height of the tag will be estimated using the RSSI values received by multiple antennas at various heights and the accurate height can be calculated by the k-parameter estimation method.

The remainder of this chapter is organized as follows. Section 4.2 presents the localisation algorithm which is divided into three parts. The cross-range estimation is explained in Section 4.2.1. The down-range estimation for 2D localisation is shown in Section 4.2.2. Section 4.2.3 shows the steps for 3D localisation. The experimental setup and results are presented in Section 4.3 which is followed by the conclusion in Section 4.4.
4.2 Algorithm

The diagram shown in Fig. 4.2 defines the coordinate system for the localisation algorithm. 2D localisation requires only a straight-line trajectory while an L-shape trajectory is required for 3D localisation. For 2D localisation, the green arrows represent the cross-range, which is the distance along Trajectory1, and the down-range, which is the distance perpendicular to Trajectory1. The 3D localisation approach estimates the x- and y-coordinate of the target tag by cross-range estimation on each trajectory and the height of the target is estimated by solving the intersection of the down-range estimation. Although Trajectory2 is shown to be perpendicular to Trajectory1, this is not a requirement of the algorithm, which requires only two non-collinear straight-line trajectories. However, the L-shape trajectory will provide the best localisation accuracy.

4.2.1 Cross-range Estimation

As the platform moves past a tag along a straight-line trajectory the distance between the tag and the moving antenna firstly decreases and then increases. As a result, a V-zone will be observed in the received phase profile as shown by the blue line in Fig. 4.1a. The corresponding location of the bottom of the V-zone in the phase profile is the location along the trajectory where the distance between the antenna and the tag reaches the minimum. The known trajectory of the mobile platform combined with this approach can be used to calculate the cross-range of the tag.

As shown in Fig. 4.1a, the received phase will change periodically between $[0, 2\pi]$ when the mobile platform is moving along the straight-line trajectory. In order to ensure correct identification of the minima by unwrapping the received phase, the phase must be sampled at least every half wavelength. After collecting the phase information, the received phase is required to unwrap firstly so that the cross-range can be better estimated. It is assumed that the received phase is not severely affected by the multipath effect which means that the the shape of the V-zone will not be totally distorted.

Fig. 4.3 shows the received phase profile by the blue line and the fitting curve by the red line. The real samples of received phase are discrete so it is possible that the V-zone does not cover the minima, the probability will be much higher when the speed of the mobile platform is very fast [144] (which is not a big problem here since the speed is comparatively slow). And the received phase values are influenced by the noise and multipath effect [116, 144]. It is clear that the received phase profile
4.2 Algorithm

Figure 4.2 Coordinate for the setup
Figure 4.3 Received phase values after unwrapping and the fitting curve
is not a perfectly smooth curve, which would occur in free space. The quadratic fitting, which is done offline after receiving the phase information and unwrapping the phase curve, can be used as an approximate way to calculate a fitting curve for the unwrapped phase to better estimate the location of the real minima and to take full use of all data [143, 144]. The distance can be expressed as

\[ d = \sqrt{(x - m)^2 + (y - n)^2} \]  
(4.1)

where \((x, y)\) represents the location of the mobile platform and \((m, n)\) is the location of the tag. And the phase can be written as

\[ \phi = \frac{4\pi}{\lambda} \sqrt{(x - m)^2 + (y - n)^2} \]  
(4.2)

As the mobile platform is moving along a straight-line trajectory, it can be assumed that the \(y\)-coordinate of the mobile platform remains unchanged and the distance can be rewritten as

\[ \phi = B \sqrt{(x - m)^2 + C^2} \]  
(4.3)

where \(B = \frac{4\pi}{\lambda}\) and \(C^2 = (y - n)^2\) are constant. The phase could be expressed by Taylor series.

\[ \phi = A_0 + A_2(x - m)^2 + A_4(x - m)^4 + ... \]  
(4.4)

where \(A_0 = B|C|\), \(A_2 = \frac{B}{2|C|}\), and \(A_4 = -\frac{B}{8|C|^3}\). And the fourth and higher orders of the Taylor series can be ignored which makes the distance approximately a quadratic so that the quadratic fitting can be used to calculate the fitting curve. When a simple least mean squares (LMS) fit is used to calculate the fitting curve, an implicit assumption is that the variance of the error in the phase at all locations is the same.

Fig. 4.4 shows an example profile of the received phase and corresponding RSSI against the distance between the tag and the antenna. When the corresponding RSSI is low the received phase values are less reliable, which is probably due to two effects. The effect of random noise in the receiver will be greater as the SNR decreases. At the same time, as the paths get longer, which leads to lower RSSI, the effect of multipath will also increase leading to unreliable phase measurements. When the distance increases, there is a greater chance that the amplitude of the LoS and multipath signals will be similar which results in unreliable phase measurements. Since RSSI tends to decrease over increasing path length, removing data with low RSSIs will tend to eliminate data over longer path lengths which is severely affected. When the LoS and multipath signals are nearly in phase, the RSSI will be enhanced by
multipath and only a small phase error is introduced in this situation while anti-phase between the LoS and multipath signals will reduce the RSSI, which can result in large phase errors for similar magnitude signals as shown in Fig. 4.5. Therefore, phase data needs to be pre-processed and valid phase data can be determined according to the received RSSI. Phase data with RSSI higher than the average of RSSI (in dB) would be considered as valid dataset, and only this valid dataset will be used for curve fitting.

Figure 4.4 Received RSSI and unwrapped phase values

(a) When the phase error is small
(b) When the phase error is large

Figure 4.5 Phasor diagram of worst cases
4.2 Algorithm

4.2.2 Down-range Estimation For 2D Localisation

When the mobile platform traverses the trajectory, the distance variation between the tag and the interrogating antenna is typically larger than half wavelength. As a result, at each location the received phase $\phi_{rec}$ is related to the actual phase $\phi_{act}$ by

$$\phi_{rec} = \phi_{act} + 2(n + k)\pi$$  \hspace{1cm} (4.5)

where $n$ and $k$ are the integer number of $2\pi$ phase required such at $\phi_{rec} \in (0,2\pi)$. In the unwrapping process, $n$ increases or decreases by 1 each time the received phase is wrapped into the range of $(0,2\pi)$ such that $n$ varies along the trajectory. However, $k$ is the residual number of $2\pi$ required at the point when the distance between the tag and the interrogating antenna reaches a minima which is termed as the k-parameter. After the unwrapping process $n$ is eliminated and $k$ remains. The k-parameter will be constant over the whole trajectory and the unwrapped received phase plus a $2k\pi$ is equal to the true phase delay ($\phi_{unwrapped} + 2k\pi = \phi_{act}$). The residual k-parameter can therefore be used to calculate the range at the point when the distance between the tag and the reader antenna reaches its minima.

The trajectory can be expressed as a vector of $N$ locations

$$Q = [q_1, ..., q_i, ..., q_N]^T$$  \hspace{1cm} (4.6)

where $q_i = [m, n_i]$ are the coordinates of the antenna at each observation point where the phase is recorded. The actual location of the target tag can be written as

$$A = [x, y]$$  \hspace{1cm} (4.7)

The distance between the location of the target tag and the location of the reader antenna at point $i$ can be calculated by

$$d_i^2 = (x - m_i)^2 + (y - n_i)^2$$  \hspace{1cm} (4.8)

So the $y$-coordinate of the tag is

$$y = \sqrt{d_i^2 - (x - m_i)^2} + n_i$$  \hspace{1cm} (4.9)
The relationship between the unwrapped phase $\phi_i$ and the distance at each observation point can be expressed by the following equation

$$\phi_i + 2k\pi = \phi_0 + \frac{4\pi d_i}{\lambda}$$

(4.10)

where $k$ is an unknown integer and $\phi_0 \in [0, 2\pi]$ is offset caused by equipment and cable length which can be calibrated. Equation 4.10 can be rewritten as

$$d_i = \frac{\lambda}{4\pi} (\phi_i - \phi_0) + k\frac{\lambda}{2}$$

(4.11)

As a result, the relationship between y-coordinate and phase is

$$y = \sqrt{\left(\frac{\lambda}{4\pi} (\phi_i - \phi_0) + k\frac{\lambda}{2}\right)^2 - (x - m_i)^2} + n_i$$

(4.12)

The phase offset $\phi_0$ can be calibrated and eliminated, leaving the integer number $k$ as the only unknown variable in equation 4.12.

![Figure 4.6 Simulated results of y-coordinate estimation with different k](image)

As mentioned above, after the unwrapping process, the k-parameter will be constant over the whole trajectory. Therefore correct value of $k$ can be found by using multiple phase measurements along the trajectory with the correct value of $k$ resulting in a constant $y$ for a particular tag. If $k$ is not correct, the resulting $y$ would be a curve as shown in Fig. 4.6a. The correct $k$ can be evaluated by calculating the standard deviation of y-estimations along the trajectory and selecting the smallest standard deviation as shown in Fig. 4.6b.
Figure 4.7 Estimation of y location with wrong k-parameter
Before further explaining the reason why different $k$ results in different shape of the results, some assumptions need to be made to simplify the calculation. Firstly, it is assumed that the tag is located at the origin of the coordinate system and the phase offset is 0. The equation 4.12 can be rewritten as

$$y = \sqrt{(d_i + \Delta d)^2 - x^2}$$

(4.13)

where $d_i = \frac{\lambda}{4\pi} \phi_i$ and $\Delta d = k\frac{\lambda}{2}$. Secondly, it can be assumed that the correct k-parameter is 0 hence $\Delta d = 0$ and at the observation point $i = 0, x = 0$ while when $i = 1, x = A$. Based on these assumption, when the k-parameter is correct ($k = 0$ hence $\Delta d = 0$), the y location calculated at different sample time has to be the same and relations can be derived as follow

$$i = 0, \quad y = d_0$$

(4.14)

$$i = 1, \quad y = \sqrt{d_1^2 - A^2} = d_0 \Rightarrow A^2 = d_1^2 - d_0^2$$

(4.15)

The previous relations are derived under the condition that the k-parameter is correct. When the k-parameter is wrong, for example, $k = 1$ hence $\Delta d > 0$, the y location at different sample time can be calculated

$$i = 0, \quad y = d_0 + \Delta d$$

(4.16)

$$i = 1, \quad y = \sqrt{(d_1 + \Delta d)^2 - A^2}$$

(4.17)

$$= \sqrt{(d_0 + \Delta d)^2 + 2\Delta d(d_1 - d_0)} > d_0 + \Delta d$$

(4.18)

which means that if k-parameter is wrong, the calculated y-location at different time is not the same, which can be shown be the Fig. 4.7, and this results in a curve shape.

After finding the correct k-parameter, a straight line will be obtained which can be used to calculate the y location of the target tag. In practical cases, the real shape will not be a perfect straight line due to errors in the phase measurement and the effects of multipath. The final estimated location would be the average of calculated results.

### 4.2.3 Estimation For 3D Localisation

Multiple antennas at different heights moving along an L-shape trajectory are required to estimate the 3D locations of target tags. Fig. 4.2 shows the setup when
Algorithm 2 Method based on k-parameter estimation for 2D localisation

Input: $\Phi_{all}, Tra, RSSI$

Output: $x, y$

1. $indx \leftarrow \text{find}(RSSI > C \ast \text{mean}(RSSI))$
2. $\Phi \leftarrow \Phi_{all}(indx)$
3. for $i \leftarrow 2$ to length($\Phi$) do
   4. $\Delta \phi = \Phi(i) - \Phi(i - 1)$
   5. if $\Delta \phi > \text{Threshold}_P$ then
      6. $\Phi(1:i-1) \leftarrow \Phi(1:i-1) + 2\pi$
   7. else if $\Delta \phi < \text{Threshold}_N$ then
      8. $\Phi(1:i-1) \leftarrow \Phi(1:i-1) - 2\pi$
   9. end if
10. end for
11. $\Phi_{\text{fit}} \leftarrow \Phi$ \hfill $\triangleright$ calculating a fitting curve
12. $T_{\text{min}} \leftarrow \text{Min}(\Phi_{\text{fit}})$ \hfill $\triangleright$ finding the corresponding time of the bottom
13. $x \leftarrow T_{\text{min}}, Tra$
14. $y_{\text{std}} \leftarrow \infty$
15. for $k \leftarrow 1$ to $N$ do \hfill $\triangleright$ $N$ can be estimated according to maximum read range
   16. $Y \leftarrow k,x, \Phi, Tra$
   17. if $y_{\text{std}} > \text{std}(Y)$ then
      18. $y_{\text{std}} \leftarrow \text{std}(Y)$
      19. $y \leftarrow \text{mean}(Y)$
   20. end if
21. end for
the mobile platform is moving along an L-shape trajectory. Both the x-coordinate
and y-coordinate of the target tag can be estimated by the cross-range estimation
method using the highest antenna combined with two known straight-line trajecto-
ries. The highest antenna is used since it can be observed that the signal received by
the highest antenna is comparatively stable so the phase measured by the highest
antenna will be comparatively more reliable which is likely due to that the lower
antennas are affected by both the antenna pattern and the larger multipath from the
floor than the highest antenna.

In order to improve the accuracy of the estimation for the height of the target
tag, the approximate range for the height of the target tag is determined firstly
by comparing the RSSI received by multiple antennas. The range of heights is
estimated by calculating the largest and second largest received RSSI measured by
the four antennas. Fig. 4.8 shows received RSSI values of one target tag with x-
and y-coordinates of 1.615 m and 1.2 m and height of 1.15 m by four antennas with
heights of 1.3 m, 1.0 m, 0.7 m, and 0.4 m respectively. Since the RSSI received by
antenna 1 and antenna 2 are similar to each other and larger than the RSSI received
by the other two antennas, it can be deduced that the target tag is located between
the height of antenna 1 and antenna 2.

After obtaining the approximate range of the height, the span of which is 0.3 m,
the z-coordinate can be estimated by finding the integer number of wavelengths
which fits the x, y location and phase profile.

The relationship between the received phase and the distance can be written as

\[
\phi_i + 2k\pi = \phi_0 + \frac{4\pi}{\lambda} \sqrt{(x - m_i)^2 + (y - n_i)^2 + (z - h_i)^2} \tag{4.19}
\]

where \(k\) is an unknown integer number, \(\phi_0 \in [0, 2\pi]\) is offset caused by equipment
and cable length, \((m_i, n_i)\) is the location of the mobile platform at time \(i\) which is
measured by LiDAR, \(h_i\) is the height of the antenna, \((x, y, z)\) represents the location
of the target tag and \(x\) and \(y\) are estimated by cross-range estimation.

The z-coordinate is expressed as

\[
z = h_i \pm \sqrt{\left(\frac{\lambda}{4\pi}(\phi_i - \phi_0) + k\frac{\lambda}{2}\right)^2 - (x - m_i)^2 - (y - n_i)^2} \tag{4.20}
\]

And the height can be calculated by adjusting k-parameter to obtain a straight
line with smallest standard deviation. However, as shown in equation 4.20, there
would be two ambiguous results if only a single antenna is used to calculate the
Figure 4.8 The received RSSI by four antennas for the tag with the height of 1.15 m
height. This problem can be solved by deploying more than one antenna in a vertical arrangement to determine the range of the height as described above so that only one solution, which is within the estimated range, is left. After obtaining a straight line of estimated heights, the final estimated z-coordinate of the target would be the average of the straight-line estimated by k-parameter estimation method using four antennas.

Although two antennas are sufficient to solve the problem of ambiguity, in practice, both the multipath effect and the error of x- and y-coordinate estimation will results in large errors in the estimation of the height. Using RSSI received by four antennas to determine the approximate range of z-coordinate can reduce the occurrence of large errors. For example, consider a target tag where the real z-coordinate is 1.15 m and the RSSI received by antenna 1 and antenna 4, the difference between the heights of which is large and the RSSI received by antenna 4 is affected by multipath more severely than antenna 1 so it could show the difference between estimated heights more clearly. Without setting the range for the height of the tag, the two ambiguous heights estimated by antenna 1 are 1.39 m and 1.21 m while the estimated heights by antenna 4 are 0.69 m and 0.11 m. The difference between estimated heights is larger than half meter. The reason for this large error is the selection of the wrong k-parameter, due to the geometry this results in a large error in estimation of z-coordinate.

Fig. 4.9 shows the flowchart for 3D localisation. After collecting and unwrapping received phase values, cross-range estimation is used to compute x- and y-coordinate while RSSI is used to determine the range of the height and the final height of the target tag is calculated by down-range estimation.

4.3 Results

4.3.1 2D Localisation Results

Fig. 4.10a shows the setup of the experiment locating eight target tags. The position of the moving platform is obtained by using the LiDAR sensor to measure the distance between the mobile platform and some boards placed at the edges of the area as references. Anechoic materials were placed at the edges of the area to partially reduce the influence of the equipment, metal objects and unused tags as shown in Fig. 4.10b.
4.3 Results

Figure 4.9 Flowchart for 3D localisation

- Collecting phase values
- Phase unwrapping
- Calculating x and y coordinate by cross-range estimation
- Estimating the range of the height by RSSI
- Estimating the height by k-parameter method
Algorithm 3 Method based on k-parameter estimation for 3D localisation

**Input:** $\Phi_1, Tra_1, RSSI_1, \Phi_2, Tra_2, RSSI_2, H$

**Output:** $x, y, z$

```plaintext
indx ← find($RSSI_1 > C \cdot \text{mean}(RSSI_1)$)
Φ_1valid ← Φ_1(indx)
Φ_unwrap_1 ← F_UNWRAP(Φ_1valid)
x ← F_DOWN_RANGE_EST(Φ_unwrap_1, Tra_1)
indx ← find($RSSI_2 > C \cdot \text{mean}(RSSI_2)$)
Φ_2valid ← Φ_2(indx)
Φ_unwrap_2 ← F_UNWRAP(Φ_2valid)
y ← F_DOWN_RANGE_EST(Φ_unwrap_2, Tra_2)
```

if mean($RSSI_1$) > mean($RSSI_2$)
  ```plaintext
  indx ← find($RSSI_1 > C \cdot \text{mean}(RSSI_1)$)
  RSSI ← RSSI_1(indx)
  ```
else
  ```plaintext
  indx ← find($RSSI_1 > C \cdot \text{mean}(RSSI_1)$)
  RSSI ← RSSI_2(indx)
  ```
end if

$h_{\text{max}}, h_{\text{min}} ← RSSI, H$

for $k ← 1$ to $N$
  ```plaintext
  Z ← $k, x, y, \Phi_z, Tra_z$
  if $z_{\text{std}} > \text{std}(Z)$ then
    $z_{\text{std}} ← \text{std}(Z)$
    $z ← \text{mean}(Z)$
  end if
end for

function F_UNWRAP($\Phi$)
  ```plaintext
  for $i ← 2$ to length($\Phi$) do
    $\Delta \phi = \Phi(i) - \Phi(i - 1)$
    if $\Delta \phi > \text{Threshold}_P$ then
      $\Phi(1:i-1) ← \Phi(1:i-1) + 2\pi$
    else if $\Delta \phi < \text{Threshold}_N$ then
      $\Phi(1:i-1) ← \Phi(1:i-1) - 2\pi$
    end if
  end for
  return $\Phi$
end function

function F_DOWN_RANGE_EST($\Phi, Tra$)
  ```plaintext
  $\Phi_{\text{fit}} ← \Phi$  \> calculating a fitting curve
  $T_{\text{min}} ← \text{Min}(\Phi_{\text{fit}})$  \> finding the corresponding time of the bottom
  $p ← T_{\text{min}}, Tra$
  return $p$
end function
```
Figure 4.10 Experiment setup for 2D localisation
After the cross-range estimation by estimating the minimum of the V-zone combined with the corresponding position of the moving platform, the down-range estimation algorithm is applied. One example of results with the value of $k$ ranging from 0 to 4 is shown in Fig. 4.11 where samples are taken every centimetre and totally there are more than 60 valid samples. By adjusting the value of $k$, the shape of the curve for y-coordinate of the target tag gets straighter and reaches optimal, which means that the standard deviation reaches the minimal, when $k$ is three in this example, which is shown by the purple line. The average value of this optimal line is the final estimate y-coordinate.

![Figure 4.11 y-coordinate estimation results with different $k$](image)

Table 4.1 summarizes the results of five tests. The mean localisation error of five tests by the proposed method is smaller than 15 cm and the average value of the mean localisation errors for five tests is around 12 cm which is smaller than the results obtained using traditional phase-based SAR processing as mentioned in Chapter 2 Section 2.2.2 and Phase Relock [173] but slightly larger than some other phase-based methods [161, 162, 175] (although variation in experimental setup makes direct comparison difficult). Since the known trajectory is required by the proposed method, one source of error in cross-range estimation is the error introduced by the trajectory measurement. The trajectory is obtained by measuring the distance provided by the LiDAR sensor and the accuracy is of the order of
4.3 Results

centimetres (±15 mm within 500 mm and ±5.0% when the distance is 500-3500 mm [151]). By employing a higher accuracy system for trajectory estimation, the accuracy of the cross-range estimation could be further improved. Moreover, other factors from the environment such as multipath effects, which results in inaccurate received phase values, will also affect the accuracy of both cross-range and down-range estimation.

4.3.2 3D Localisation Results

The setup of the experiment for 3D localisation is shown in Fig. 4.13. Four antennas are deployed and the height of the four antennas is 1.3 m, 1.0 m, 0.7 m and 0.4 m respectively. The trajectories of the four antennas are shown by black dashed lines. 32 passive UHF tags are attached to plastic boxes as targets to locate and they are placed in two layers with heights of 1.15 m and 0.75 m as shown in Fig. 4.13a. Anechoic materials are placed at the edges of the area to partially reduce the effect of the metal objects and other unused tags in the lab as shown in Fig. 4.13b.

The CDF of the localisation error using four antennas for all tags along each axis and the total error magnitude is shown in Fig. 4.14. The purple line shows the mean value of the total localisation error magnitude, which is around 14 cm. The blue line
Figure 4.13 Experiment setup for 3D localisation
4.3 Results

Table 4.1 Mean localisation error of five tests

<table>
<thead>
<tr>
<th>Test</th>
<th>SAR</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>17.86</td>
<td>13.75</td>
</tr>
<tr>
<td>2</td>
<td>11.91</td>
<td>10.12</td>
</tr>
<tr>
<td>3</td>
<td>8.09</td>
<td>13.11</td>
</tr>
<tr>
<td>4</td>
<td>8.61</td>
<td>12.23</td>
</tr>
<tr>
<td>5</td>
<td>15.33</td>
<td>9.219</td>
</tr>
<tr>
<td><strong>Mean</strong></td>
<td><strong>12.36</strong></td>
<td><strong>11.68</strong></td>
</tr>
</tbody>
</table>

represents the localisation error in the x-axis and the mean value is around 5 cm while the localisation error in the y-axis is shown by the red line and the mean value is around 7 cm. The majority of the localisation error is from the vertical, z-axis, of which the mean value is around 10 cm as shown by the yellow line.

![Figure 4.14 The CDF of the 3D localisation error along each axis and the total error magnitude](image)

Fig. 4.15 plots the estimated and the actual location, which is shown by the red cross and the black circle respectively and the error vectors are shown by lines. The
tags placed in the upper layer have a smaller localisation error than the tags in the bottom layer. And most of the tags placed in the bottom layer are predicted to be lower than their actual locations.

Either wrong estimation of the \( k \) or the wrong estimation for the range of the height by the RSSI, which is influenced by multipath, can result in localisation error. Fig. 4.8a shows the RSSI values of one of tags in the upper layer and Fig. 4.16a shows the RSSI values of one of tags in the bottom layer. The height of tags placed in the upper layer is between the heights of two higher antennas (antenna 1 and 2), the RSSI received by which is similar to each other and the two higher antennas also have larger RSSI than the other two antennas (antenna 3 and 4) as shown in Fig. 4.8 so the range of height can be estimated accurately using the RSSI received by four antennas. The height of the bottom layer is close to antenna 3 rather than in the middle of two antennas as shown in Fig. 4.16b and consider the tag, for example, at the location of \((1.615 \text{ m}, 0.4 \text{ m}, 0.75 \text{ m})\). Ideally, the RSSI received by antenna 3 should be the largest and the RSSI received by antenna 2 should be the second largest. This can be used to determine the range of the height for the tag at the bottom layer. However, in practice, many factors will affect the received RSSI such as imperfect antenna pattern and stronger multipath effect from the ground reflection. As a result, the RSSI received by antenna 4 can be as large as that received by antenna 3 as shown...
Figure 4.16 The received RSSI by four antennas for the tag with the height of 0.75 m
in Fig. 4.16a which leads to wrong estimated range of the height for the tag. The estimated range of the height for the tag as shown in Fig. 4.16b, for example, will be between 0.4 m and 0.7 m according to received RSSI as shown in Fig. 4.16a rather than the actual range, which is between 0.7 m and 1.0 m. Therefore, tags placed at the bottom layer have larger localisation error. Moreover, tags located further from the trajectory of the moving platform have larger localisation error on the z-axis which could be the result of the lower LoS signals and the larger multipath effect from the ground reflection.

4.4 Conclusion

In this chapter, a phase and RSSI-based localisation method is proposed. The proposed method exploits the V-zone of the received phase profile and the relationship between the shape of the results and the k-parameter to calculate locations of tags with known trajectory of the mobile platform.

In 2D space, the location of the target tag can be calculated using only a straight-line trajectory. After unwrapping the received phase profile, a fitting curve is obtained to reduce the effect of multipath. The cross range of the target tag can be calculated by finding the minimum point of the unwrapped phase profile and corresponding position of the mobile platform. The k-parameter estimation method can be used to estimated the down range of the target tag. In 3D space, both the x- and y-coordinate of the target tag can be estimated by using the minimum point of the unwrapped phase curve with an L-shape trajectory. Before calculating the height of the target tag, received RSSI values by multiple antennas are used to estimate a possible range of the height for the target tag. The final height can be estimated by k-parameter estimation method.

Experimental results with a straight-line trajectory show that the mean 2D localisation error is around 12 cm. Different from the method proposed in Chapter 3, the computational burden of this method is comparatively low but this method requires measurement of the trajectory. Compared with the results in Chapter 3, the 2D localisation error obtained by this method is smaller than the result with a straight-line trajectory under an uncontrolled environment (15 cm) and similar to that with a straight-line trajectory under a controlled environment (12 cm) but larger than that using a L-shape trajectory (8 cm). Using four antennas and an L-shape trajectory, the mean 3D localisation error can be reduced to around 14 cm by this proposed method.
Chapter 5

Localisation Method Based on Geometrical Relationship

5.1 Introduction

This chapter aims to further exploit the phase profile to fulfil the absolute localisation of the target tag. The method proposed in this chapter also aims to reduce the number of required reference tags and reduce the requirement for devices to measure the trajectory and estimate the trajectory by analysing the relationship between tags and the trajectory of the mobile platform.

The previous chapter mentions that some methods are proposed to determine the order of tagged books in a bookshelf such as RFScanner [144], RLLL [30], and STPP [143]. These methods are applied in a library environment where the antenna of the reader is moving between bookshelves to collect the phase information. The shape of the phase profile is used to estimated the order of tagged books but not provide more information about their absolute location.

Other methods have been proposed to provide absolute location of target tags such as the method proposed by Buffi et al. [129] and Tzitzis et al. [140]. A typical SAR-based method is proposed by Buffi et al. using a drone-based system which is carrying an RFID reader and an antenna. The mean 2D localisation error achieved by this method is of the order of 10 cm. The SAR-based localisation method proposed by Tzitzis et al. is an extension of Phase ReLock and this method can perform 3D localisation with the mean localisation error of less than 20 cm using four antennas. The SAR-based methods can provide comparatively high localisation accuracy but the accuracy is affected by the accuracy of the measurement for trajectory which
is provided by sensors such as LiDAR sensors and cameras. Another problem of SAR-based methods is that the processing burden to derive the location of target tags is relatively high.

Apart from phase measurements, RSSI has also been used in localisation methods which is based on reference tags. LANDMARC calculates a weight for each reference tag by comparing the similarity between the received RSSI of the target tag and the reference tag [113]. The location of target tag is estimated by using weighted mean of coordinates of k-nearest neighbour (kNN) reference tags. Details have been discussed in Chapter 2 Section 2.2.2. LANDMARC is widely applied to calculate location of the target tag by many indoor RSSI-based localisation methods. In the method proposed by Zhang et al. [176], virtual tags are used to reduce the number of reference tags. The LANDMARC with kNN is combined with the extreme learning machine (ELM) for better classification of the similarity between target and reference tags and the mean 2D localisation error by this kNN-ELM method is around 0.3 m. In [147], a Bayesian probability and kNN (BkNN) indoor localisation method is proposed. Since the measurement can be repeated several times and each time the measurement is independent, a Bayesian probability model can be applied to determine the location of the target tag using data obtained from multiple measurements. The error in estimation of 2D location by this BkNN method is around 15 cm. The accuracy of these fingerprint methods highly depends on the density of reference tags [175, 177] which requires deployment of a large number of reference tags to cover a large area (the number of required reference tags per square meter to obtain decimetre level localisation accuracy is varied according to different methods and it is approximately between 1 and 10 [145–147, 178, 179]). As fingerprint methods use RSSI information to determine the similarity, these methods are susceptible to factors such as multipath and antenna orientation. Moreover, since the estimated location is determined by a weighted mean of selected reference tags, selection of wrong reference tags will lead to large localisation errors.

The localisation accuracy achieved by SAR-based methods is affected by the measurement accuracy of the trajectory, which typically requires LiDAR sensors or high quality optical cameras, while the accuracy of fingerprint methods depends on the density of reference tags, which requires a lot of reference tags. In order to reduce the requirement of sensors for measuring trajectory and the number of reference tags, this chapter proposes a localisation method requiring only three reference tags with known locations and basic odometry information along with phase information from a moving platform. To achieve 2D localisation, three reference
tags with known locations must be deployed and two non-collinear straight-line trajectories are used. It is not required for reference tags to surround the target tag unlike the fingerprint methods. The main idea of the proposed method is analysing the geometric relationship between the trajectory and tags using the unwrapped received phase information. The direction of the trajectory relative to the reference tags is firstly determined and direction of two trajectories is used to calculate the location of target tags.

The remainder of this chapter is organized as follows. Section 5.2 describes steps for the localisation algorithm based on geometric relationship. The estimation of the minima of the unwrapped phase is shown in Section 5.2.1 and the step for computing the locations of tags is discussed in Section 5.2.2. Section 5.3 shows the experimental setup and results which is followed by the conclusion in Section 5.4.

5.2 Algorithm

5.2.1 The minima of the unwrapped phase

This method requires the minima of the unwrapped phase which is based on the V-zone of the phase profile as described in Chapter 4, Section 4.1. The V-zone can be observed during the period when the change in distance between the tag and the moving platform is less than half a wavelength. This corresponds to the time when the mobile platform is moving from the position Loc1 to Loc2 along the trajectory as shown by the black line in Fig. 5.1a. The phase changes periodically between \([0, 2\pi]\) when the mobile platform moves along the trajectory as shown by the blue line in Fig. 5.1a. Since the proposed method is based on the minima of the V-zone in the phase profile, it is assumed that the V-zone will not be distorted, severely affected by the multipath, and there is a dominant LoS signal. In order to better estimate the minima of the V-zone, multiple measurements and curve fitting can be applied and the received phase profile is required to unwrap firstly for curve fitting. The phase must be sampled at least every half wavelength to ensure the unwrapping step can be applied.

Since the phase is affected by multipath effect, the blue line in Fig. 5.1b, which represents the unwrapped phase, is not a perfectly smooth curve and this will lead to errors in the calculation of the minima of the V-zone. A fitting curve, which is shown by the red line, can be used to mitigate the multipath effect so the accuracy in estimation of the minima can be improved. Details of curve fitting is discussed in
Chapter 4 Section 4.2.1. After finding the minima of the V-zone, the corresponding time when the distance between the tag and the moving platform reaches a minimum can be obtained.

(a) The received phase profile

(b) The unwrapped phase and the fitting line

Figure 5.1 Estimation of the minima of the unwrapped phase

5.2.2 Geometric relationship

At least three reference tags are required in this proposed method for 2D localisation. For ease of calculation, a coordinate system is defined as shown in Fig. 5.2 where one of the reference tags is at the origin and another reference tag is located along the x-axis. The first step of the proposed method is to calculate the direction of the straight-line trajectory relative to the coordinate system defined by the reference tags. As shown in Fig. 5.2, three reference tags with known locations are represented by A, B and C respectively. The distance $|AC|$ between the reference tag A and C can be calculated using the known locations. By finding the minima of the unwrapped phase profile as described in previous section, the time when the mobile platform is closest to A and C can be estimated and the time spent by the mobile platform moving from D to E can be obtained. Since the mobile platform is moving with a constant speed (5 cm/s), the approximate distance $|DE|$ between point D and E can be obtained. Using $|AC|$ and $|DE|$, the angle between the straight-line trajectory and the x-axis can be calculated by

$$\phi = \arccos \frac{|DE|}{|AC|}$$

(5.1)
Because there are two possible solutions corresponding to $\phi_1 = \pm \phi$, the wrong direction, which is shown by the blue dashed line in Fig. 5.2, can be rejected by using a third reference tag $B$. By repeating the step for estimation of the angle using reference tags $A$ and $B$, the angle $\alpha$ between the trajectory and the line $AB$ can be calculated, which also has two possible solutions. The angle $\beta$ between the x-axis and the line $AB$ can be obtained from the known reference tag locations. As a result,
the angle of the trajectory relative to the x-axis can be calculated $\phi_2 = \beta \pm \alpha$. Only one combination of $\phi_1, \phi_2$ will overlap (provided $A, B, C$ are not collinear) hence the ambiguity has been resolved

\[
\begin{cases}
\theta = \phi_1 = \pm \phi \\
\theta = \phi_2 = \beta \pm \alpha
\end{cases}
\] (5.2)

In practice, there may not be perfect agreement so an averaging approach is adopted to get the best estimates. In order to calculate the location of the target tag, a second trajectory is required which should be almost orthogonal to the first trajectory for best accuracy. The direction of a second trajectory relative to the x-axis can be estimated by repeating the steps described above. Note that the method only needs to calculate the directions of the trajectories relative to the arrangement of reference tags and does not need any range estimation.

After calculating the direction of trajectories relative to the arrangement of the reference tags, the location of the target tag with respect to the reference tags can be calculated as shown in Fig. 5.3. The point $F$ where the distance between the target tag and the mobile platform trajectory reaches the minimum can be estimated by analysis of the minima of the unwrapped phase profile as described in Section 5.2.1. After calculating the length $|DF|$, a straight line locus of possible tag positions with respect to the reference tags can be obtained. In order to improve the accuracy, this process can be repeated three times using different reference tags to obtain three lengths and the average is taken since in practical cases the direction is always orthogonal to the trajectory but the distances along the track vary. As a result, the straight line locus of possible tag positions can be estimated which is marked as Estimated direction 1 in Fig. 5.3. Using the second trajectory, a second locus of possible target tag locations can be calculated marked as Estimated direction 2. By combining these two results, a point of intersection can be obtained which is the final estimated location of the target tag as shown in Fig. 5.3.

5.3 Results

The setup of the experiment is shown in Fig. 5.4a which is similar to the setup in Chapter 3 where tags are placed by using a metal support and cotton strings and anechoic materials are placed at the edge of the area to partially mitigate the influence of multipath from equipment, metal objects, and unused tags in the lab as
Algorithm 4 An algorithm with caption

Input: $\Phi_1, $RSSI_1$, $\Phi_2, $RSSI_2$, $v, $P$

Output: $\text{Loc}$

$$indx \leftarrow \text{find}(\text{RSSI}_1 > C \ast \text{mean}(\text{RSSI}_1))$$

$$\Phi_{1\text{valid}} \leftarrow \Phi_1(indx)$$

$$\Phi_{\text{unwrap}}_1 \leftarrow \text{F_UNWRAP}(\Phi_{1\text{valid}})$$

$$\theta_1, T_1 \leftarrow \text{F_TRA_EST}(\Phi_{\text{unwrap}}_1, P)$$

$$indx \leftarrow \text{find}(\text{RSSI}_2 > C \ast \text{mean}(\text{RSSI}_2))$$

$$\Phi_{2\text{valid}} \leftarrow \Phi_2(indx)$$

$$\Phi_{\text{unwrap}}_2 \leftarrow \text{F_UNWRAP}(\Phi_{2\text{valid}})$$

$$\theta_2, T_2 \leftarrow \text{F_TRA_EST}(\Phi_{\text{unwrap}}_2, P)$$

for $i \leftarrow 1$ to $N$ do

$$\theta_{\text{tar}1}(i) \leftarrow \text{F_DIR_EST}(\Phi_1(i), P, v, \theta_1, T_1)$$

$$\theta_{\text{tar}2}(i) \leftarrow \text{F_DIR_EST}(\Phi_2(i), P, v, \theta_2, T_2)$$

$$\text{Loc}(i) \leftarrow \theta_{\text{tar}1}(i), \theta_{\text{tar}2}(i)$$

end for

function $\text{F_UNWRAP}(\Phi)$

for $i \leftarrow 2$ to $\text{length}(\Phi)$ do

$$\Delta \phi = \Phi(i) - \Phi(i - 1)$$

if $\Delta \phi > \text{Threshold}_P$ then

$$\Phi(1:i-1) \leftarrow \Phi(1:i-1) + 2\pi$$

else if $\Delta \phi < \text{Threshold}_N$ then

$$\Phi(1:i-1) \leftarrow \Phi(1:i-1) - 2\pi$$

end if

end for

return $\Phi$

end function

function $\text{F_TRA_EST}(\Phi, P)$

for $i \leftarrow 1$ to $3$ do

$$T(i) \leftarrow \Phi(i)$$

end for

$$d_{\text{est}1} \leftarrow T(1), T(2), v$$

$$d_{\text{ref}1} \leftarrow P(1), P(2)$$

$$\theta_{\text{est}1} \leftarrow d_{\text{est}1}, d_{\text{ref}1} \quad \triangleright \text{eq. 5.1}$$

$$d_{\text{est}2} \leftarrow T(1), T(3), v$$

$$d_{\text{ref}2} \leftarrow P(1), P(3)$$

$$\theta_{\text{est}2} \leftarrow d_{\text{est}2}, d_{\text{ref}2} \quad \triangleright \text{eq. 5.1}$$

$$\theta \leftarrow \theta_{\text{est}1}, \theta_{\text{est}2} \quad \triangleright \text{eq. 5.2}$$

return $\theta, T$

end function

function $\text{F_DIR_EST}(\Phi, P, v, \theta, T)$

$$T_{\text{tar}} \leftarrow \Phi$$

$$d_{\text{tar}} \leftarrow T_{\text{tar}}, T, v$$

$$\theta_{\text{dir}} \leftarrow d_{\text{tar}}, \theta$$

return $\theta_{\text{dir}}$

end function
Figure 5.4 Experiment setup and the picture of the environment
shown in Fig. 5.4b. Green crosses represent three reference tags and black circles show 17 target tags to locate. Both reference and target tags are placed to lie in the same plane at the height of around 1.2 m and they have the same polarisation and antenna pattern. Two straight-line trajectories are shown by black lines for clarity but are assumed to be unknown. The mobile platform is moving with a constant speed of around 5 cm/s.

Fig. 5.5 shows the localisation results where the estimated location of target tags is shown by the red crosses. It is worth noting that tags placed at the bottom right of the area have larger localisation errors and they have larger errors parallel to the Trajectory-2. A possible explanation for this is that these tags are placed at the end of the trajectory and the distance between the Trajectory-2 and tags is comparatively longer. These factors lead to an incomplete and unstable phase profile, which result in larger error in the estimation of the relative position parallel to the Trajectory-2. It is also apparent that tags which are not surrounded by reference tags can be accurately located.

![Figure 5.5 Localisation results](image)

Fig. 5.6 plots the CDF of localisation error and the total localisation error is decomposed into two distance error along two straight-line trajectories. The blue line and red line show the relative distance error along the Trajectory-1 and Trajectory-2 respectively. The error along the Trajectory-2 is slightly larger than that along the
Localisation Method Based on Geometrical Relationship

Trajectory-1 for the majority of tags. Many factors may contribute to larger errors such as the shorter length of the Trajectory-2, which results in larger error for tags placing near the edge of the trajectory, and the longer mean distance between the target tags and the Trajectory-2, which leads to larger effect of multipath. The yellow line shows the total localisation error and the mean value is around 12 cm.

Figure 5.6 CDF of the localisation error

5.4 Conclusion

In this chapter, a 2D localisation method using only three reference tags without a requirement of measurement of trajectories has been proposed and demonstrated. The method is based on the minima of the unwrapped phase profile to estimate the locations of target tags by analysing the relationship between reference and target tags.

Three reference tags with known locations have been deployed and the mobile platform is moving along two non-collinear trajectories to collect phase information of tags. The direction of trajectories relative to arrange of reference tags can be estimated by calculating the minima of the unwrapped phase profile. With two non-collinear trajectories, two loci for possible locations of target tag can be calculated.
by analysing the relationship between the target tag and reference tags and the intersection point of two loci will be the final estimated location.

Experimental tests demonstrate that the mean localisation error is around 12 cm. Compared with the results of ISAR-SAR method in Chapter 3, it is smaller than the result using a straight-line trajectory under an uncontrolled environment (15 cm) and similar to the result using a straight-line trajectory under a controlled environment (12 cm) but larger than that using a L-shape trajectory (8 cm). And the result is similar to the result using a straight-line trajectory in Chapter 4 (12 cm). This method provides a novel solution to reduce the effect from the error in the measurement of the trajectory. It also increases the flexibility in terms of reference tag deployment and does not require deployment of lots of reference tags. Moreover, it reduces the cost in terms of other sensing devices calibration in various localisation scenarios as it does not need measurement of the trajectory.
Chapter 6

Conclusion and Future Work

6.1 Overall Conclusion

This dissertation has presented methods for the indoor localisation of passive UHF RFID tags. In general localisation with RFID is challenging due to the need for multiple spatial measurements, weak signal strength and multipath. A mobile platform with RFID devices is used to reduce the installed infrastructure and exploit measurements along a trajectory to improve accuracy.

For the system design part, the system for indoor localisation, which consists of a mobile robot, a RFID reader, RFID antennas, and passive UHF RFID tags, is proposed. Three localisation methods have been proposed and experimentally tested. The ISAR-SAR method exploits the reference tags with known locations and introduces the ISAR-SAR loop to estimate the trajectory of the mobile platform and locates target tags using SAR algorithm. The method based on k-parameter utilises the V-zone of the received phase profile and locates target tags by adjusting k-parameter using a known trajectory. The method based on geometric relationship deploys three reference tags and uses the minima of the received phase profile to calculate target tags by analysing the geometric relationship between trajectories and tags without requiring measurement of trajectories.

Specifically the conclusion of this dissertation can be summarised as follows:

• An ISAR-SAR-based method is proposed and tested in Chapter 3. Instead of using a LiDAR sensor, reference tags with known locations are used to estimate the trajectory. A novel ISAR-SAR loop is introduced to calculate an optimal estimated trajectory. Experiments with a straight-line trajectory in an uncontrolled environment have been performed. In this uncontrolled envi-
Conclusion and Future Work

In the environment, the 2D mean localisation accuracy achieved by ISAR-SAR method is around 15 cm, which is similar to the accuracy by using the trajectory measured by a LiDAR sensor. Experiments have also been performed in a controlled environment. The proposed ISAR-SAR method can achieve better 2D mean localisation accuracy (at around 6 cm) than the LiDAR-SAR method. This demonstrates the capability of the ISAR-SAR method to reduce the cost of devices by eliminating the requirement of the LiDAR sensor. Meanwhile, the proposed ISAR-SAR method can provide better accuracy than the LiDAR-SAR method by using the ISAR-SAR loop, which reduces the effect of multipath by calculating an optimal estimated trajectory. Although the ISAR-SAR method performs better than LiDAR-SAR methods, it is difficult to apply the proposed method in real-time. This method is suitable for a scenario such as in a warehouse where there are shelves where many barcodes are placed to record the positional information, which can be replaced by RFID tags.

Chapter 4 proposes a phase and RSSI-based method for indoor localisation of UHF RFID tags with a comparatively low computational load. After obtaining phase and RSSI information, a valid dataset will be firstly determined according to the strength of the received RSSI, which can indicate whether the received signal is stable or not. The valid dataset is then used to calculate the location of target tags. The cross-range location of the target tag is estimated by analysing the stationary point of the unwrapped phase curve and finding out the corresponding location of the trajectory, which is known and provided by the LiDAR sensor, of the mobile platform. The down range distance is calculated by adjusting the k-parameter which fits the cross-range location and the unwrapped phase profile. This method can also apply for 3D localisation which calculates x and y coordinate using the cross-range estimation method and estimates the height by using the down-range estimation method within the estimated range of height which is determined by the strength of RSSI received by multiple antennas. Experiments with a straight-line trajectory in a controlled environment have been performed and 2D mean localisation accuracy of around 12 cm can be achieved. Experiments for 3D mean localisation have also been performed and 3D localisation accuracy is around 14 cm using an L-shape trajectory. One of the main sources of error is the multipath effect, especially the ground reflection, which leads to larger localisation error for tags closer to the ground. Although the localisation error is larger than that achieved by the ISAR-SAR method, the computational burden is com-
paratively low and the time required for localisation is comparatively short and this method is suitable for a scenario such as a store and an archive room where objects are placed at various fixed heights on shelves and there is an aisle between shelves.

- Chapter 5 proposes a phase-based relative localisation method which reduces the number of reference tags. A minimum of three reference tags is required without requiring measurement of the trajectory. After deploying three reference tags with known locations and collecting phase information along two non-collinear trajectories, the direction of the trajectories will be estimated using the minima of the unwrapped phase profile and the relative geometric relationship between reference tags and target tags will be determined using the received phase and the estimated direction of the trajectories. Experiments for 2D localisation have been performed in a controlled environment and the mean accuracy is around 12 cm. Although the error is slightly larger than that achieved by the ISAR-SAR method, the computational burden for this method is also comparatively low and this method requires no precise measurement of the trajectory, which reduces the effect of the error from trajectory measurement. Meanwhile, this method only requires a few reference tags which can reduce the cost and time required for deploying reference tags.

6.2 Future Work

Although great gains have been made in localisation accuracy, more research is required in this area to reach the ultimate potential of RFID systems:

- Reference tags - Since the ISAR-SAR method exploits reference tags to estimate the optimal trajectory and the geometric method requires reference tags to determine the geometrical relationship, further investigation will focus on the relationship between the accuracy and the number of reference tags to find out the optimal required number. The arrangement of reference tags is another topic. Because only three reference tags are used in the geometric method while the reference tags used in the ISAR-SAR method are placed every 40 cm, if the number of reference tags varies, the arrangement is required to change to obtain the best result. As a result, future research includes both the number and arrangement of reference tags and the impact on speed and accuracy of localisation.
• Hybrid methods - The performance of LiDAR sensor may degrade in a complicated environment due to obstacles or out of the maximum range of the sensor, future research can also focus on sensor fusion algorithm which uses multiple sensors such as the LiDAR sensor and an inertial measurement unit (IMU) and combines these sensors with ISAR-SAR method, which can be used as a complementary method, to further improve the performance in both tracking of the mobile platform and localisation of targets.

• Optimised antennas - In order to achieve 3D localisation, multiple antennas will need to be used. However, the performance of antennas is affected by the locations of antennas such as the heights, which may result in different multipath effect. The future investigation will include selecting the optimal antennas or assigning weights to different antennas to reduce the effect of variation in received signals by different antennas.

• Speed - The required number of reads of tags to provide accurate location is also a topic for future research. Since in environments such as a warehouse, there will be a very large number of tags, which might lead to a smaller number of reads for each tag. Currently, the speed of the robot is only 5 cm/s and if the speed of the robot increases, the number of reads of tags would be reduced. If the minimal required number is determined, the speed of the robot can increase and the time spent for collecting information and inventorying can be reduced. As a result, the required number of reads of tags for localisation needs further investigation to allow fast and stable operation in such environment.

• Real time - Current methods are not real-time and this means that information has to be collected and processed before calculating locations of target tags. In the future, a real-time model such as particle filter, for example, which is a common model for real-time application could be applied to achieve a real-time system and provide real-time position information.

• Range - The range is also a big problem. The range for receiving stable signals is only a few metres and this limits the application of RFID. Although RFID devices are installed in a mobile platform to utilise the mobility and compensate the limited read range, the limited range increases the time spent for collecting information and results in fewer valid data. Future work may also include extending the range to reduce the time required for collecting information and provide more valid data for localisation.
Bibliography


[152] “Speedway R420 4-port (ETSI).” https://www.logiscenter.co.uk/ipj-rev-r420-eu12m1-impinj-speedway-revolution?gclid=Cj0KCQjwhLKUBhDiARIsAMaTLnFwPy-WtNhYq7UFsHKj1_GuNOQndHobKx8XVbEBLV5GV95WC2XQY0aAqR4EALw_wcB. Accessed: 2022-05-24.


