Accuracy Improvement of RFID based 2D Tracking and Localisation

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To my dear parents, beloved wife and daughter

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ABSTRACT

The purpose of localization and tracking technology in indoor application is to extract moving object parameters accurately and precisely. This thesis investigates the problem of how to utilize RFID technique for the accurate and precise extraction of indoor 2D moving object position parameters. Firstly, a framework named *RFID-Loc* with three modules: RFID-Loc Infrastructure, RFID-Loc Data Filter and RFID-Loc Localisation Algorithm, is established from a theoretical perspective. This framework can guide the research and design of methods used in an RFID based object localisation system with enhanced localisation accuracy and precision. Secondly, from practical perspective, few methods are proposed in RFID-Loc framework to improve the localisation accuracy and precision. A sparse RFID Tag Arrangement strategy is proposed in this RFID-Loc framework, aiming at reducing the impacts of *regular false reading error* from RFID infrastructure level on localisation precision. The efficiency of this methods and the assumptions upon which it relies, are investigated empirically. A rectangle-based feature selection method is justified as the major RFID Data Filter algorithm, with the capability of maximally reducing *regular false reading errors*. The possibility to resist *unexpected false reading error* in an RFID-Loc system is investigated by discussing and comparing several RFID-based localisation algorithms. A dynamic localisation algorithm for RFID-Loc system is proposed to accurately and precisely extract moving object position parameters overtime in an RFID-Loc system. This algorithm is shown to have a better capability of resisting *unexpected false reading error* than conventional localisation algorithms used in RFID-based localisation systems, while having a higher computational complexity. By following the theoretical guidelines in RFID-Loc framework and implementing the proposed methods, the experimental results demonstrate that the localisation accuracy and precision can be significantly improved, up to 10 centimetres and 3 centimetres under current RFID devices.

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NOMENCLATURE

Moving Object Localisation System: The system is to establish the spatial and temporal relationships between moving objects and stationary objects.

RFID-Loc: RFID object Localisation Framework.

RFID-Loc System: the localisation system based on RFID-Loc framework.

Accuracy: the accuracy of an object localisation or tracking system is to measure how correct the object localisation or tracking system is.

Precision: the precision of an object localisation or tracking system is to show how consistently close the further measurements to the ideally accurate result over a period of time.

RFID (Radio Frequency identification): is an automatic identification technology that relies on remotely storing and retrieving data using tags and readers.

SLAM: Simultaneous Localisation and Mapping.

EKF : Extended Kalman Filter

False Reading: a phenomenon is that many RFID based systems have to generate incorrect or uncompleted RFID tag detections due to the tags or readers collision problem.

False Reading Error: errors made from false reading in an RFID based system.

Regular False Reading Error: refers to some error regularly occurring in a RFID system, which is mainly from characteristic limitations of RFID devices.

Unexpected False Reading Error: refers to some causal error causing by accident event, which is from changeable environment or erratic movement motion.

False Negative Readings: refers the case that RFID tags within an effective RFID reader detection area may not be detected due to RF collision occurring or signal interfering with each other RFID tags.

False Positive Readings: refers to the case that unexpected RFID tags detections are generated.

Repeated Readings: refers to repeated detection of RFID tags by a RFID reader in a short time.

System Reading Efficiency: the ratio of the number of successful reads of RFID Tags to the total number of read attempts of RFID Tags in a RFID system.

Global Tag Density: refers to the whole number of RFID tags placing in an efficient detection area of RFID antenna.

Directional Tag Density: refers to the number of RFID tags placing on individual row or column directions in an efficient detection area of RFID antenna.

Chapter 1:

Introduction

Localisation and tracking technology is one of the most important aspects in many applications, from mobile computing to robotics, particularly on the application of indoor mobile object localisation and tracking area. In indoor moving object localisation and tracking applications, the purpose of localisation and tracking technology is to accurately and precisely establish the spatial relationships between the moving object and its corresponding sensors. In order to reach this goal, there are various sensor based localisation and tracking technologies being delivered, such as optical sensor, radar and laser range finders, electromechanical sensors. However, for indoor moving object applications, they all suffer from various demerits resulting in the loss on accuracy and robustness, such as high-dependence on feature visibility, uncertain measurements, time-consuming calibration procedures or drift. Therefore, it is worthwhile to explore new localisation and tracking technologies to substitute those conventional ones for indoor moving object localisation applications. RFID (Radio Frequency Identification) is recently a popular technique, which has been widely deployed on a large-scale of industrial applications, particularly on object tracking and localisation (Weinstein, 2005). This thesis aims to investigate the possibility of optimally utilizing RFID technique to achieve accurate and precise moving object localisation and tracking in an indoor environment. This chapter briefly gives an introduction of the research work outline, including the background, motivation, research issues, aim and objectives, and knowledge contributions.

1.1 Background

Indoor location awareness technology has become a popular research topic during the last several decades. In the field of mobile computing, by providing the location information of a user, it can be applied to build a context-aware application, e.g. a wearable computer providing in-door localisation incorporating other reactive technology. In such systems, localisation has been of central importance, as it provides the information that the mobile robots or moving objects need for navigation or location. In a typical indoor moving objects or mobile robots application, localisation is the process of establishing the spatial relationships between the robot and stationary objects, which aims to solve a static problem: "where am I ?"; the tracking is the process of establishing the spatial and temporal relationships between moving objects and the robot or between moving objects and stationary objects, which involves the use of a model and history of measurement for mobility problem: "what is my trajectory ?". As for different applications, the location information can be classified into different types, such as physical location, symbolic location, absolute location, and relative location. For most of indoor moving object location applications, the localisation information mainly considers the absolute location of targeted moving objects. Liu et al has provided us with a description of the performance benchmarking of localisation and tracking techniques in mobile robots or moving objects applications, as below (Liu et al, 2007):

Accuracy: The accuracy of a localisation and tracking system is to measure how correct the localisation and tracking system is. Usually, mean distance error is adopted as the performance metric, which is the average Euclidean distance between the estimated location and the true location. Accuracy is the fundamental requirement in most localisation and tracking systems. The higher the accuracy is, the better the localisation and tracking system is.

Precision: The precision of a localisation and tracking system is to show how consistently close the further measurements to the ideally accurate result over a period of time. Accuracy only considers the value of mean distance errors. However, location precision considers how consistently the localisation and tracking system works, i.e., it is a measure of the robustness of the positioning technique as it reveals the variation in its performance over many trials.

Complexity: Complexity of a localisation and tracking system can be attributed to hardware, software, and operation factors. If the computation of the localisation algorithm is performed on a centralized server side, the localisation could be calculated quickly due to the powerful processing capability and the sufficient power supply. Usually, it is difficult to derive the analytic complexity formula of different positioning techniques; thus, the computing time is considered.

Robustness: The robustness of a localisation and tracking system reflects the ability of coping with errors during the tracking process and operating in an abnormal input data. In an indoor sensing environment, there are some uncertainty issues; sometimes, the signal from a transmitter unit is totally blocked; or sometimes, some measuring units could be out of function or damaged in a harsh environment. The localisation and tracking system should be resistant to these error sources.

Scalability: The scalability of a localisation and tracking system refers to whether the localisation and tracking system can be easily deployed and configured in an indoor environment. An indoor location and tracking system may need to scale on two axes: geography and density. Geographic scale means that the area or volume is covered. Density means the number of units located per unit geographic area/space per time period.

Cost: The cost of a localisation and tracking system may depend on many factors. Important factors include money, time, space, weight, and energy. The time factor is related to installation and maintenance. Mobile units may have tight space and weight constraints. Measuring unit density is considered to be a space cost.

1.2 Motivation

The existing indoor localisation and tracking techniques can be mainly classified into two categories, which are the sensor-based tracking techniques and the wireless indoor localisation techniques (Liu et al, 2007). The sensor-based tracking techniques reply on one or more than one particular sensor to track the movement of objects. The typical sensors include mechanical sensor (Sutherland et al, 1968), inertial sensor (Song et al 2011), magnetic sensor (Chao et al, 2010) and optical sensor (Rolland et al, 2001). Also, some hybrid tracking technologies which combine two or more types of sensor tracking technologies, have been developed for indoor moving object localisation. Nevertheless, these hybrid tracking or localisation technologies are still expensive and require complicated calibration and setup procedure (Auer et al, 1999). The advantage of sensor based tracking techniques is that they normally can track either the position or the orientation of targeted moving objects with a higher accuracy than the wireless indoor localisation techniques, but with a lower flexibility and scalability. The wireless indoor localisation techniques localize or position the indoor moving object by using some wireless technologies (Liu et al, 2007), such as GPS-basd (Engee, 1994), Cellular-based (Caffery et al, 1998), UWB-based (Gezici et al, 2005), WLAN-based (Bahl, 2000) and Bluetooth-based (Kotanen et al, 2003). The wireless indoor localisation techniques are usually highly flexible and scalable, but have lower localisation accuracy than sensor-based tracking techniques since the wireless transmission signal is easily interfered. Moreover, the wireless indoor localisation technologies usually need more intelligent algorithms to compensate for the low accuracy of the measured metrics, which would increase the complexity of localisation systems.

While the above localisation and tracking technologies have been practically used into indoor moving object localisation applications, each one of them has its specific limitations. It is necessary to explore the new possible localisation and tracking techniques to replace the conventional ones in indoor moving objects localisation applications. The increasing widely application of RFID (Radio Frequency Identification) technique (Foster et al, 2007) attracts many researcher’s attentions.

Some of them (Lim et al, 2006) have attempted to utilize RFID technology for objects tracking in supply chain applications. Compared with the existing identification technologies such as barcode technology (Gao et al, 2007), RFID technique owns a longer working distance and faster reading ability. Also, due to the cost effectiveness and scalability of RFID technique, its applications are normally implemented with highly flexibility and practicality. As for the localisation and tracking applications, RFID based localisation and tracking technology has no problems of drift on inertial sensors tracking technology and high-dependence on feature visibility of optical sensor tracking technology. Considering the above potential benefits, it is valuable to investigate the possibility of using RFID technique instead of the conventional localisation and tracking technologies to achieve a feasible solution in indoor moving object applications.

However, as reviewed the performance benchmarking of localisation and tracking techniques in mobile robots or moving objects applications in the last section, the utilization of RFID technology as a new localisation and tracking solution also faces many challenges. Firstly, the fundamental requirements of indoor localisation or tracking technologies require a high accuracy, for instance: the optical sensor tracking technology and the inertial sensor tracking technology both have a very high accuracy, up to 1 millimetre. But the currently available RFID based localisation technologies cannot reach this accuracy. Most of RFID based localisation system with higher accuracy would distribute RFID tags as landmarks in the tracking environment; so the localisation accuracy is directly determined by the distance between adjacent RFID tags. To improve the physical size and shape of RFID tags to millimetres level is a challenging task in terms of the nowadays start-of-the-art of RFID devices manufacturer. Secondly, the high precision is needed for indoor localisation and tracking technologies, but is hardly achieved by current RFID based localisation technology. The main reason is that the radio signal can be easily affected by various factors such as absorption, attenuation, diffraction, space loss and interference; therefore over a period of time, the RFID reader might miss the detection of desired RFID tags or detect the unexpected RFID tags, so that the precision of RFID based localisation system is influenced. Additionally, normally there is a trade-off between accuracy and precision in RFID based localisation and tracking technologies, thus it is hard to get a both highly accurate and precise localisation performance for RFID based localisation systems. It is because the high accuracy of RFID based localisation system needs a high density of RFID tags distribution, but this would seriously increase the influence of RFID tag and reader collisions on localisation precision. Thirdly, the conventional tracking techniques can accurately localise and track the moving objects in 3 dimensions, but it is a hard task for RFID based localisation technologies. Using RFID technologies to localise moving object, the moving object is normally attached to a RFID reader so that the height of moving object is fixed in order to keep the effective detection area of RFID reader's antenna unchanged. The accuracy and precision of RFID based localisation technologies here actually refers to a 2 dimensions localisation application. If it expects to extend RFID based localisation technologies into a 3 dimensions localisation application, the number of RFID readers and RFID tags both have to be increased, then the accuracy and precision of 2 dimensions localisation can be influenced due to a increasing collision problem. Finally, the requirement of low complexity and strong robustness in indoor localisation or tracking technologies might be a difficulty for RFID based localisation technology. In order to enhance the tracking accuracy and keep the scalability of object movement, the number of RFID tags and RFID readers might increase; it makes the deployment and configuration of a RFID based localisation system difficult. Meanwhile, more RFID tags mean more raw data to process, more shading effect for tag collision, and more time for communication, with potentially leading to either longer latency of system response or high complexity of algorithms.

Consequently, the motivation of this research work is to investigate the possibility of using RFID technique instead of the conventional localisation and tracking technologies to achieve a feasible solution in indoor moving object applications. Typically, the idea localisation and tracking techniques in mobile robots or moving objects applications requires high accuracy and precision, low complexity, cost-effective and good scalability. While RFID technology has been widely recognized as cost-effective and good scalability, the current state-of-the-art of RFID technology is difficult to achieve both highly accuracy and precision in indoor moving object localisation applications with 3 dimensions. So this work would primly consider the problem on how to use RFID technique to accurately and precisely extract the 2 dimensional position parameters of moving object in an indoor environment. Figure 1.1 illustrates the conceptual mode of RFID localisation.

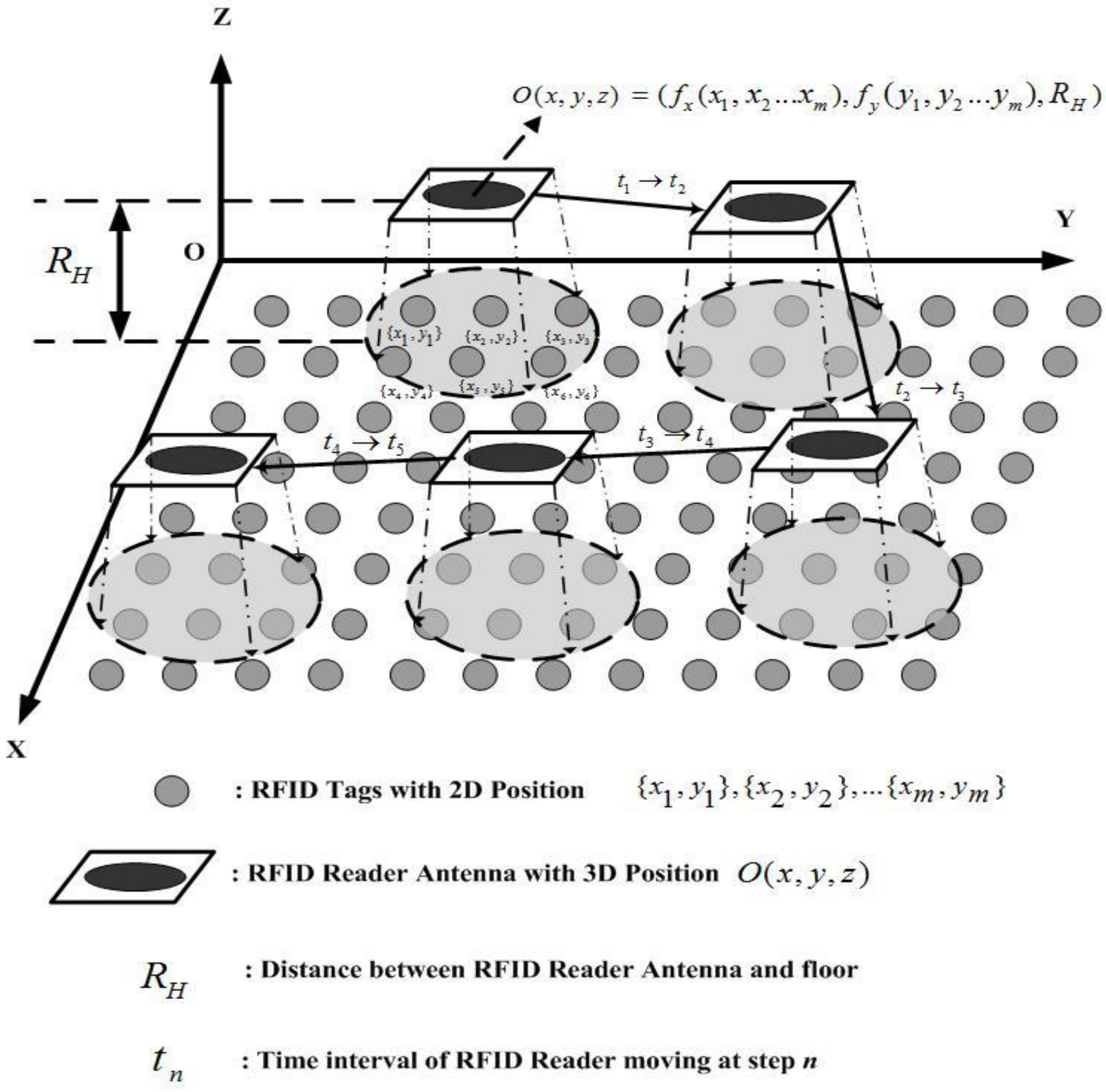


Figure 1. 1 The conceptual illustration of a RFID based 2D moving object localisation system in an indoor environment.

In Figure 1.1, many RFID tags spread on the floor under a predefined rectangular grid pattern. The RFID reader attached with the moving object to observe RFID tags over time. The moving object localisation system can calculate the position of moving object by processing the captured RFID data on some prior knowledge such as where the tags are located.

1.3 Aim and Objectives of Research

The aim in this thesis is to investigate the possibility of using RFID technique to achieve a feasible solution in indoor moving object applications. In order to reach this goal, the research will focus on the accurate and precise extraction of 2D position parameters of moving object in an indoor environment by using RFID technique. This involves research into RFID hardware infrastructure design and configuration, RFID data filter and processing, tracking and localisation technology.

The objectives of this research are:

- To review the literature of localisation and tracking techniques for indoor moving object applications, and investigate RFID techniques and its applications.
- To study the theoretical framework of RFID based localisation system from hardware to software level, and propose a work flow of the RFID based localisation system.
- To investigate the RFID hardware devices, and choose the suitable RFID infrastructure and configuration to improve the localisation accuracy and precision.
- To analyse the captured RFID data, and propose some solution to filter the raw data with more reliable features.
- To examine the localisation algorithms and use them to process the RFID data to estimate the position of moving object, analyse and compare the localisation accuracy and precision.
- To propose a localisation algorithm to improve the accuracy and precision of an RFID localisation system.
- To validate the RFID localisation system in an indoor moving object application.

1.4 Contribution to Knowledge

To summarize, the main knowledge contributions are:

1. A formal framework is proposed for investigating the problem of use of RFID technique to accurately and precisely localize the moving object in an indoor environment. The framework provides a coherent and consistent solution with three modules, which are RFID infrastructure module, RFID data filter module and RFID localisation algorithm module; to study the factors impacting the performance of an RFID based 2D localisation technology in a indoor moving object application. Also, this framework can guide the research and design of the optimization methods used in an RFID based 2D localisation technology with enhanced accuracy and precision.

2. There is an investigation into the factors of an RFID infrastructure component influencing the localisation accuracy and precision of moving object 2D position. A sparse RFID Tag Distribution is proposed for the RFID infrastructure module, with the capability of enhancing the system reading efficiency from RFID infrastructure level, so as to improve the accuracy and precision of the 2D RFID based moving object localisation.

3. A comparison is given of the date filter methods to remove the regular false reading errors from RFID infrastructure level. A rectangle-based feature selection method is selected and justified as the major algorithm in RFID data filter module, with the capability of maximally reducing the regular false reading errors from RFID infrastructure level.

4. A discussion and comparison of localisation algorithms is addressed to evaluate their performance in precisely and accurately localising moving object position. A dynamic localisation algorithm for an RFID localisation algorithm module is proposed, which can accurately and precisely extract 2D position parameters of a moving object over time, also with the resilience to unexpected false reading error in indoor environments.

1.5 Organization of the thesis

This thesis is divided into eight major chapters. The first chapter is the introduction to this research work, motivation and knowledge contribution. Chapter two begins with an introduction to moving object tracking techniques in the indoor, and reviews various types of sensor tracking techniques, as well as RFID-based localisation techniques. Then it introduces the state-of-the-art nature of localisation algorithms, which can potentially be used in this work. Chapter three proposes a formal theoretical framework RFID-Loc for investigating the optimal use of RFID techniques in moving object position localisation systems for indoor applications. Chapter four represents the experimental configuration and procedure which are required by each module in RFID-Loc framework. Chapter five investigates the relationship between RFID tag arrangement and localisation accuracy or precision. An optimal RFID Tag Distribution design strategy is suggested in this chapter under this framework with the capability of enhancing the system reading efficiency, so as to improve the moving object localisation precision. Chapter six investigates the research issues in feature selection and localisation algorithms, which contains the selection of features from RFID raw data and the comparison of localisation algorithms. Chapter seven illustrates the experimental results and compare the performance of proposed solutions on accuracy and precision with current RFID based localisation solutions. The final chapter gives a conclusion to the research work. Possible future development work and enhancements are also discussed in this chapter.

Chapter 2:

Literature Review

The purpose of this chapter is threefold: first, it tries to give an outline of the areas of research influencing this thesis. These include the survey of various localisation and tracking techniques for indoor moving object or mobile robots application, the review of RFID technique and RFID-based localisation applications. It discusses what the limitations of conventional localisation and tracking techniques in indoor applications are, and why an RFID technique can potentially be of use for localising the moving object position. The second part of this chapter gives a survey of current start-of-the-art of RFID-based localisation techniques and their performance. Also, the issues of hardware choices and configurations in an RFID-based localisation system are analyzed. The final part of this chapter reviews the probabilistic localisation and relevant techniques, which includes SLAM, particle filter and kalman filter.

2.1 State of the Art in Indoor Localization and Tracking

The theory and techniques of localization in the early literature are mostly concerning about robotics. In a typical indoor moving objects or mobile robots application, localisation is the process of establishing the spatial relationships between the robot and stationary objects, which aims to solve a static problem: “where am I ?”; the tracking is the process of establishing the spatial and temporal relationships between moving objects and the robot or between moving objects and stationary objects, which involves the use of a model and history of measurement for mobility problem: “what is my trajectory ?”. As for different applications, the location information can be classified into different types, such as physical location, symbolic location, absolute location, and relative location. For most of indoor moving object location applications, the localisation information mainly considers the absolute location of targeted moving objects. Localization and tracking have been under active development during the past several decades, whose design paradigm has been dramatically changed. The sensor-based tracking techniques and the wireless indoor localisation techniques are two major categories of approaches used in indoor localisation applications. Considering that the accuracy and precision is the essential requirement of indoor localisation and tracking technique, the sensor based tracking techniques would be mainly reviewed and discussed.

2.1.1 Mechanical Tracking Technique

The mechanical sensor based tracking technique relies on electromechanical sensors, which are capable of detecting and recording 3D motion of a moving object. Mechanical tracking technology is based on the physical connection between the objects to be tracked and a reference point. The inertial sensor typically used in mechanical based moving object tracking methods, makes this method suitable for indoor camera tracking for augmented reality applications. Typically, it consists of accelerometers recording lateral accelerations and gyroscopes recording rotational accelerations; inertial tracking systems do not record the moving object position and orientation directly, but record acceleration and deceleration in all six degrees of freedom. EI-Sheimy (EI-Sheimy et al, 2008) has analysed the properties of inertial sensor based navigation system, which can provide high-accuracy position, velocity and attitude information. However, the accuracy of inertial sensor based navigation system degrades rapidly with time, which named as drift error. Zainab (Zainab et al, 2008) also has proposed an inertial sensor based microelectromechanical tracking system which consists of three gyros and three accelerometers. This system keeps a high tracking accuracy as conventional inertial sensor based tracking system, but also is capable of resisting the effect of misalignment errors by using the partial IMU with nonholonomic constraint.

To sum up, the key advantage of mechanical sensor based tracking techniques is its high accuracy, which can be up to 1,000,000 divisions per 360 degrees of movement. Also, mechanical sensor based tracking technique can reasonably be used only in very special circumstances, and are simple to build, provide high accuracy and update rates. However, there are some disadvantages. Firstly, mechanical sensors suffer from drift with time, and thus become imprecise and imprecise. Secondly mechanical sensors need a relatively complicated calibration and set-up procedure, and also are very expensive. This would restrict the moving object's movement massively.

2.1.2 Magnetic Tracking Technique

The magnetic tracking technique is actually based on an electromagnetic sensor. A transmitter is mounted at a fixed location and is emitting a magnetic field. Mobile receivers are moved within this magnetic field and measurements are used to determine both position and orientations. Hashi (Hasi et al, 2007) has implemented a wireless magnetic motion capture system using an LC resonant magnetic marker. This system use a compensatory process in consideration of the mutual inductance has been employed for positional calculation in order to improve the positional accuracy. The absolute positional accuracy of this system is less than 2 mm within 140 mm of the pickup coil array. Fang and Son (Fang & Song, 2011) also presents an optimized method of measuring magnetic fields to estimate orientation and position of a moving object including a magnet in 3D space. This method can effectively characterize the magnetic fields and computer position or orientation, which offers a number of advantages in real-time measurement and control applications. But it has some difficulties in designing and optimizing sensor configurations. Additionally, Ma (Ma et al, 2) has proposed a magnetic hand motion tracking system for human-machine interaction. The advantage of this system is that it does not require wire connections and can be used conveniently and unobstructively. However, it is hardly to track the moving object in a large or wide area. To sum up, the magnetic tracking technique can track the 6DOF position and orientation of a moving object in its magnetic field, but it suffers from the magnetic field being distorted in the vicinity of metallic objects (Chao et al, 2010). Also, the disadvantages of magnetic field sensing tracking system are that calibration procedures are extensive and time-consuming, and it is expensive.

2.1.3 Optical Tracking Technique

The optical sensor based tracking technique is based on image information; to track the 3D pose of a moving object actually is equivalent to track the 3D pose of a moving camera by using the information contained in images sequences, such as fiducial markers or feature points. Nonetheless, the process of tracking the 3D position and orientation of a camera by using image sequence information is challenging; the difficulty is that small errors in the calculation of 2D motion in image sequences have a tremendous influence on the estimated camera position and orientation parameters.

In the early stage, the optical sensor based tracking techniques (Cornelis et al, 2001) (Prince et al, 2002) were mainly designed for off-line use on pre-recorded image sequences. This kind of approaches can approximately estimate the camera pose in terms of a large amount of image information, but it is computationally demanding, so is not appropriate for use in real-time, time-critical applications. So, many researchers have considered the possibility of tracking camera in a continuous mode, in which the camera tracking system must run in parallel with the image acquisition. It is referred to as the real-time optical tracking mode. The approaches in a real-time optical tracking mode are to process the image sequences in a continuous way, estimating the camera 3D motion on the current image frame by the past image frames. Beardsley & Zisserman were among the first to attempt to extract camera 3D motion in a continuous way (Beardsley et al, 1997), estimating the camera position and orientation parameters from the recovered 3D structure. This kind of approach can successfully calculate the matrix containing the camera position and orientation parameters by recovering the 3D scene, however the computational efficiency is challenging because the task of recovering 3D scene from continuous 2D image sequences is highly time-consuming. In order to enhance the computational efficiency, some researchers have thought of methods to avoid 3D scene recovery procedure or limit the camera motion in simple way. For instance, Avidan and Shashua (Avidan & Shashua, 2001) have proposed a method to calculate the consistent projective camera matrices, but without the need to reconstruct the 3D scene. Prince (Prince, Ke, & Cheok, 2002) also proposed a robust real time camera rotation tracking algorithm for augmented reality applications. While those sets of approaches have enhanced the efficiency of camera tracking algorithms in real-time mode, they just simplify the process of estimating camera position and orientation parameters, without solving the fundamental problems that influence the robustness and accuracy of optical based camera tracking, such as the visibility of features.

The key problem of the optical tracking technique is how to observe enough persistent and reliable features from 2D image sequences while the camera is moving. Depending on the types of features, real-time optical tracking methods can be generally classified into marker-based tracking approaches (Azuma, 1999) or Marker-less tracking approaches (Comport et al, 2006). Marker-less tracking approaches are generally used to perform tracking and recognition task of the real environment without using any special placed markers. They do not require particular fiducial markers or other special infrastructure in the environment, to estimate the camera moving (Davison, 2007) (Davison & Murray, 2002). Their features of image are casual and of unlimited viewpoint-invariance, so that the task of robust and accurate optical tracking becomes challenging. Marker-based tracking approaches (Madritsch & Gervautz, 1996) utilize the fiducial markers to track the camera 3D pose. The various geometric markers can be considered as the image features, such as points (Dementhon & Davis, 1995) segments (Dhome et al, 1990), and straight lines (Kumar & Hanson, 1994). For instance, typical camera tracking software packages such as ARToolkit (Fiala, 2005a) and ARTag (Fiala, 2005b) are both based on the fiducial markers, which have been particularly developed for augmented reality applications.

To sum up, the main advantage of optical tracking techniques for indoor moving object applications is relatively high accuracy. Given an indoor environment with well-visible marker or features, optical sensor tracking technology can deliver a highly accurate and precise localisation performance for moving object. However, optical sensor tracking technology fails when the referenced features of the image sequences in some environments are out of focus, occluded or even out of view. Also, the price of implementing an optical tracking system is high computational cost.

2.1.4 Hybrid Tracking Technique

Researchers have also looked into the hybrid tracking technique for achieving better object pose estimation (Danette et al, 2001) (Schwann, 2001). Hybrid tracking technique combines the strengths of at least two tracking technologies. Many combinations (Lobo & Dias, 2003) (Lee et al, 2002) (Roetenberg et al, 2007) are possible; examples are inertial and optical tracking, or magnetic and vision-based tracking. Auer and Pinz (Auer & Pinz, 1999) present a hybrid tracking system that combines a standard magnetic tracker and an optical tracking system; data from the magnetic tracker is used to predict feature locations for the optical tracking system. You et al. (You et al, 1999a) (You et al, 1999b) have developed a hybrid tracking system which combines inertial and optical tracking technologies. In this system, optical tracking technology is used solely for image stabilization and thus for correcting the inertial tracking system. Roetenberg (Roetenberg et al, 2007) attempted to design a porTable magnetic system combined with miniature inertial sensors, for ambulatory 6 degrees of freedom human motion tracking. With a suitable sensor fusion filter, the hybrid tracking system can solve some of the problems of the individual tracker and get more accurate and robust results. Nevertheless, each individual tracker has different characteristics**;** the hybrid tracking technique might increase the complexity and redundancy of the tracking system and lead to the problem of asynchrony. Additionally, the hybrid tracking systems for indoor moving object tracking applications are normally expensive and involve a complicated calibration and setup procedure.

2.1.5 Wireless Indoor Localization Technique

The wireless indoor localization technologies can be mainly classified into two basis approaches. The first one is based on the location positioning algorithm, which makes use of various types of measurement of the signal, such as Time of Flight, signal strength or angle. The second one is based on the physical layer of sensor networking infrastructure, which localize the moving objects by communicating information with stationary server. Lin (Lin et al, 2006) has reviewed the current available wireless indoor localisation techniques in terms of the type of wireless signal, which can be classified into GPS-Based, Radio Frequency-based, Cellular-Based, UWB based, WLAN and Bluetooth. GPS-based localisation system is mostly famous as the successful positing systems in outdoor systems. The poor coverage of satellite signal for indoor environment makes a difficulty on maintaining accuracy in an indoor application. However, some companies such as SnapTrack (SnapTrack, 2010), Atmel (Atmel, 2010), U-Blox (U-Blox, 2010), have already considered to overcome this limitations by using some wireless assisted technology to support the indoor GPS localisation. The achieved accuracy of these systems is up to 5-50m. Radio Frequency based localisation system is actually the pioneer of RFID based localisation technology, so it would be reviewed in next section. Celluar-Based localisation system uses global system of mobile/code/division multiple access mobile cellular network to estimate the location of outdoor mobile clients. This localisation technique is also originally designed for outdoor tracking usage, but extended by some researchers to indoor localisation system. Otsaen et al. (Otsaen, 2005) presented a GSM based indoor localisation system, which can achieve accuracy as low as 2.5 meter. UWB based localisation system is based on sending ultrashort pulses (typically < 1ns) with a low duty cycle. So far, several UWB based localisation systems (Fontana et al, 2003) have been developed, such as Ubisense system. This system is a unidirectional UWB location platform with a conventional bidirectional time division multiple access control channel. The achieved accuracy of UWB localisation system can be up to 20 cm. The WLAN (wireless local area network) based localisation system is to use an existing WLAN infrastructure for indoor location. The well-known WLAN based indoor localisation system is RADAR, which proposed by Bahl (Bahl, 2000) for in-building user location and tracking system. This system adopts the nearest neighbours in signal space technique, with accuracy up to 2-3m. The blue tooth based localisation system has a similar basis of WLAN localisation system, just with a lower gross bit rate (1Mbps) and the shorter range (10-15m). Tadlys (Tadlys, 2010) has developed a local position solution based on Tadly's Bluetooth infrastructure and accessory products. The system can provide localisation accuracy up to 2 meters with 95% reliability. However, it usually has a positing delay about 15-30s. Apart from these, ultrasonic sensors also can be used for indoor localisation application. The famous time of flight localisation technique for indoor localisation and tracking application is ultrasonic sensor based localisation system (Lin et al, 2008) (Bank, 2002). Ultrasonic sensor based localisation system is flexible and cost-effective, but the localisation accuracy is easily to be influenced by ambient noise, multipath reflections and variations in the speed of sound. In terms of Lin's review (Lin et al, 2006), Table 2.1 summarized the performance of current wireless indoor position system and solution.

Table 2. 1 Comparison of wireless indoor localisation techniques (Lin et al, 2006).

	Accuracy	**Precision**	**Scalability**	**Robustness**	**Complexity**
GPS-based	5-50m	50%	Good/2D,3D	Poor	High
Cellular-based	7-7.5m	50%	Good/2D	Good	Medium
UWB-based	0.3m	50%	Good/2D,3D	Poor	Real-Time
WLAN-based	3-5m	50% - 90%	Good/2D, 3D	Good	Moderate
Bluetooth-based	2 m	95%	Nodes placed every 2-15m	Poor	Delay 15-30s
Ultrasonic	2-15cm	50%	Good/2D,3D	Good	Medium
RFID	10cm – 2m	50% - 70%	Good/2D,3D	Poor	Medium

2.2 RFID Technology and Applications

None of the above-mentioned conventional localisation and tracking techniques is a completed solution with high standard performance for indoor moving object applications. The sensor based tracking techniques can track either the position or the orientation of targeted moving objects with a higher accuracy than the wireless indoor localisation techniques, but with a lower flexibility and scalability. The wireless indoor localisation techniques are usually highly flexible and scalable, but have lower localisation accuracy than sensor-based tracking techniques since the wireless transmission signal is easily interfered. Recently, within the various wireless indoor localisation techniques, due to the low-cost, RFID technology (Glover & Bhatt, 2006) is a hot topic in industry, stimulating the desire for RFID-supported applications such as product tracking, supply chain optimization, asset and tool management. This section will review the history of RFID technology development and its typical applications, especially RFID technology for localisation.

2.2.1 Introduction of RFID Technology

RFID (Radio Frequency identification) is an automatic identification technology that relies on remotely storing and retrieving data using tags and readers. The first application of RFID (radio frequency identification) technology can be traced back to World War II. The foundation of this technology is that radio waves with a spectrum of frequencies are used to transfer the identification information between two communication devices. In 1973, Cardullo received the first patent for a passive, read-write RFID tag, and Walton received a patent for a passive transponder used to unlock a door without a key. After that, a group of scientists began to investigate its application in facilities security (Ding, Li, & Feng, 2008) (Tadayoshi, 2008) (Juels, 2006). Today, RFID techniques are used to replace existing identification technologies such as the barcode (Gao, Prakash, & Jagatesan, 2007). Compared with barcode technology, the advantages of RFID technology are that there is no need for a direct line of sight, it has much greater working distances, a much faster reading ability, and a read and write capability. Meanwhile, due to the rapid development of integrated circuit design, the gradually enhanced functionality of RFID readers and tags could make RFID technology support a wide spectrum of applications, from tracking cattle to tracking trillions of consumer products worldwide.

2.2.2 Typical RFID Technology Applications

The typical applications of RFID technology are listed as:

Asset tracking: This includes tracking of assets everywhere, such as in offices, labs, warehouses, and libraries. For instance, Bhanage et al. (Bhanage et al, 2007) proposed an RFID-based inventory tracking system to support low-cost, long-lived and continual tracking of assets.

Automated toll collection system: The RFID reader on the highway toll booth and a tag attached to the vehicle's windshield facilitate automatic charging to the car owner's account and eliminate the need for the driver to stop and manually pay the toll. Ren & Gao (Ren & Gao, 2009) have developed an electronic toll collection system with a new RFID authentication and authorization protocol model, which has the advantages of lower cost, small size and high reliability.

Supply chain tracking: This includes tracking items through the supply chain and managing inventory. The supply chain filed is the key early adopter of RFID technology. Many researchers have studied how to utilize RFID technologies efficiently in supply chain areas. Lin and Bin (Lin & Bin, 2009) developed a methodology for exploring and mapping supply chain networks by the methods of RFID-enabled capturing and sharing of the information throughout supply networks.

Health care applications: This includes positively identifying and tracking patients in a health care facility or a hospital, linking a patient with the right medicine and doctor. Many industrial companies provide RFID healthcare solutions, such as PDC's RFID Wristband System (PDC, 2007).

Tracking in warehouse: This includes real-time inventory tracking and management in a warehouse or storeroom by tracking items inside, coming in and going out. For instance, Zhen et al. (Zhen et al, 2009) developed an RFID-based logistics resources management system for formulating and suggesting the appropriate material handling solutions in a warehouse environment.

These typical RFID-based applications show that RFID technology can localize or track any object or people in a particular area. Moreover, owing to the gradually reduced cost of RFID tags and readers, it becomes possible to employ a large number of RFID devices in a dense environment. As a result, RFID technology has recently become more widely used in object identification, mobile robots tracking and navigation, and wearable computing. These successful applications illustrate that RFID has been recognized as a new popular tracking technology by researchers and engineers.

2.3 RFID for Indoor Localisation

2.3.1 State of the Art in RFID Indoor Localisation

Aimed at different goals, the design and implementation of an RFID system are dissimilar. RFID techniques are suitable for localisation because of their cost-effective and scalability. In this section, it might be useful to review the RFID technology for localisation tasks, for instance, using RFID for localisation of indoor mobile objects.

The first task of the RFID-based object localisation approach was to analyze the radio-frequency signal strength to estimate the distance so that moving objects could be localized. A radio-frequency system based on RADAR (Bahl & Padmanabhan, 2000) was firstly proposed to locate and track users in an indoor environment. Radar operates by reading and processing radio frequency signal strength information at multiple based stations to estimate user location with accuracy of up to 2 meters. Later on, Hightower et al. (Hightower et al, 2000) proposed a 3D location-sensing technology based on RF signal strength analysis, called SpotON. The SpotOn system can operate standalone SpotOn tags with location-sensing technology, achieving a localisation accuracy of up to 1 metre. Similarly, there are other methods (Priyantha et al, 2001) (Harder et al, 2005) (Fukujiet et al, 2003) developed on the same basis. Although the above RF signal based systems may achieve the task of localisation by analyzing the strength of the radio frequency signals to estimate the distance, they do not strictly use the concept of RFID techniques. Moreover, due to scattering and reflection of the transition signal, radio-frequency signals are easily interfered with, so accuracy of these systems is imprecise, usually limited to meter level.

In order to enhance the accuracy of the RFID-based localisation system, some methods attempt to study the localisation of a mobile robot using RFID tags with unique ID as landmarks in the environment (Hahnel et al, 2004) (Tuttle, 1997) (Roy et al, 1999). Due to the long effective sensing distance, active RFID tags are firstly used as landmarks for localisation. A typical example is the LANDMARC system (Ni et al, 2003), which is a location-sensing prototype system that uses RFID technology for locating objects inside buildings. The researchers installed a number of RFID readers in the building. Each reader has a pre-determined power level, thus defining a certain range in which it can detect RFID tags. By properly placing the readers in known locations, the whole region can be divided into a number of sub-regions, where each sub-region can be uniquely identified by the subset of RFID readers that cover that sub-region. Given an RFID tag, based on the subset of readers that can detect it, it should be able to associate that tag with a known sub-region. The major advantage of LANDMARC is that it improves the overall accuracy of object location by utilizing the concept of reference tags. Additionally, Yamano (Yamano et al, 2004) proposed a new method of self-localising mobile robots with an RFID system by using a Support Vector Machine (SVM) algorithm. Chae and Han (Chae & Han, 2005) presented an algorithm for mobile robots, which is to divide the space into separate and individual regions, and weight active tags by their distance. Although methods using RFID active tags could achieve better accuracy than the earlier methods using signal analysis, the key drawback is that RFID active tags would continuously send radio signals so that the RFID reader might detect some unexpected RFID tags. On the other hand, the long latency and variation of the behavior of tags limits the increased accuracy and localisation range. Consequently, passive RFID technology has been utilized to recognize and localize the position of the moving object (Tsukiyama, 2002) (Tsukiyama, 2005). Zhang et al. (Zhang et al, 2007) firstly examined the applicability of direction-of-arrival estimation methods to the localisation and localising problems of passive RFID tags. Later on, Park & Hashimoto (Park & Hashimoto, 2009) presented an efficient localisation algorithm for mobile robots based on RFID; the system reads the RFID tags and computes the absolute position of tags on the floor to localize the mobile robot. Similarly, by distributing RFID passive tags on the floor, an absolute location scheme (Lim et al, 2006) was designed to localize the mobile robot's position and orientation. Beyond that, Han et al (Han et al, 2007) proposed a new RFID passive tag arrangement pattern for a driving mobile robot, with precision up to 6 centimetres. The utilization of high density RFID passive tags distribution could possibly enhance the localising accuracy, but it would also increase the tag collisions due to the long latency and variation of the behaviour of tags. Higher tag collisions would lead to the failure of some passive tags being detected. Compared to active tags, passive RFID tag-based localising technology would result in increased accuracy of the RFID-based object localisation system, but also reduced precision.

While the RFID technique is widely applied in object localisation, the achievable accuracy and precision in indoor moving object localisation are still very low and instable. In order to improve the accuracy and precision, it is necessary to review some literature on the different layers of a typical RFID localisation system, which includes RFID infrastructure, data processing and some localisation algorithms. Table 2.2 summarized the performance of current state of art in RFID indoor localisation solutions.

Table 2. 2 Comparison of RFID indoor localisation solutions

	Accuracy	**Precision**	**Robustness**	**Complexity**
RF Signal Analysis	1-2m	50%-100%	Poor	High
Active RFID based	0.5-1m	50%	Good	Medium
Passive RFID based	0.1-0.3m	50%	Poor	Simple

2.3.2 RFID Infrastructure

This section briefly presents some issues in RFID infrastructure that need to be considered. Due to the rapid development of RFID manufacture, review does not emphasis current physical limitation of RFID hardware devices, but focus on the analysis of a theoretical basis.

RFID systems can generate and radiate electromagnetic waves that fall along the radio frequency spectrum. The requirements of an RFID system's application significantly restrict the suitable operating frequency ranges for RFID systems, because interference and noise vary between different application environments. It is important to ensure that these environments are not disrupted or impaired by RFID systems. According to the common RFID ISO standards (Sanghera, 2007), the operating frequency of an RFID system can be classified into four ranges: low frequency (30-300KHZ), high frequency (3-30 MHz), ultra-high frequency (300MHz – 3GHz), and microwave frequency (1-300 GHz). The effective reading distance of the RFID system varies according to the frequency range, as shown in Table 2.2 (Sanghera, 2007).

Table 2. 3 Radio Frequency Ranges in RFID systems

Name	**Frequency Range**	**Effective Read Range for Passive Tags**
Low Frequency	30-300KHZ	<50cm
High Frequency	3-30MHZ	<3m
Ultrahigh Frequency	300MHZ-3GHZ	<9m
Microwave Frequency	3GHZ- 300GHZ	>10m

Table 2.3 shows the effective reading range of passive tags corresponding to each frequency range. Active tags can have a read range of up to 100 meters. For example, active tags used on large assets such as cargo containers, rail cars, and large reusable containers, which usually operate at 455 MHz, 2.45GHz, or 5.8GHz, typically have a read range of 20 meters to 100 meters.

Designing an RFID-based moving object localisation system with highly accuracy and precision, it is mandatory to consider at which frequencies RFID devices will operate in an indoor environment. The LF (low frequency) range is more robust to external influences, and is generally used in access control, animal and personnel tracking. Benelli et al. (Benelli et al, 2009) developed an LF RFID-based system for the underwater tracking of pebbles on artificial coarse beaches. Due to the low level of interference from the surrounding environment, the LF RFID-based system could work in abominable environmental conditions. The HF range provides greater options for data transfer speed, compared to LF, and is usually used in building access control, item-level tracking, including baggage handling. Jain et al. (Jain et al, 2009) presented a custom low-cost HF RFID system for hand washing compliance monitoring. The UHF range has a higher reading speed and longer read distance, which makes it suitable for automated toll collection and warehouse management. For instance, Lehto et al. (Lehto et al, 2009) discuss the application of passive UHF RFID systems in the paper industry. The microwave range offers a high data transfer rate, and is suitable for use in long-range vehicle identification (Kaleja et al, 1999) and supply chain.

The selection of feasible RFID tags and RFID reader in a RFID based localization system is also an important issue. There are two major types of RFID tag, which are passive tag and active tag (Sanghera, 2007). The passive tag does not have its own battery, so cannot initiate communication. The active tag has its own battery and can initiate communication by sending its own signal. In terms of this characteristic, passive tags are usually physically small in size and have a longer lifespan, but lower read range and smaller memory. Regarding the RFID reader (Sanghera, 2007), it is an interrogator which collects the information from tags and sends it to a host system. Types of RFID reader are generally categorized into read-only and read-write, which is the operation ability to deal with RFID data. Meanwhile, some RFID readers have the ability to read multiple tags at the same time, which is named as anti-collision ability. Having mentioned anti-collision ability, it is necessary now to explain the collision problem (Engels & Sarma, 2002) in RFID systems. In an RFID system, there are two main communication techniques that the RFID readers and tags use to communicate with one other, which are coupling and backscattering. The coupling process is to transfer energy from one circuit to another through a shared magnetic field. The backscattering process is to collect the RF signal, change the signal with carried data, and reflect it back to readers. Both of these two communication techniques in an RFID system use a physical medium to transfer signals, so there is a high likelihood of a collision problem. RFID reader collision (Kin et al, 2005) means that when the interrogation zone of one reader overlaps with the interrogation zone of another reader, the problem of multiple reads and signal interference occurs. RFID tag collision (Sanghera, 2007) means that when two or more tags try to respond to one RFID reader at the same time, the RFID reader misses or ignores some tags. The collision problem is a challenging issue in any RFID system, particularly in a highly dense environment. Many researchers (Myung et al, 2006) (Choi et al, 2007) (Shin & Kim, 2009) have studied the possibility of reducing the collision problem from both RFID infrastructure level and RFID software level. Due to the collision problem, many RFID based systems have to generate incorrect or uncompleted RFID tag detections; this phenomenon is usually called *false reading* in an RFID based system. The errors made from *false reading* in an RFID based system is called *false reading error*.

Once RFID readers and tags have been selected, the next task is to work out how to deploy them as a feasible RFID infrastructure to satisfy the requirements of an indoor moving object application. In a dense environment, tag collision would easily lead to false reading errors of RFID readers, further impacting on the precision of the RFID-based localisation system. While it is impossible to eliminate completely the impacts of false reading from the RFID infrastructure, it is possible to utilize the optimal design and configuration of RFID hardware devices to reduce the impact of false reading on the precision of the RFID-based localisation system. For instance, Mo et al. (Mo et al, 2009) use the EPCglobal Network to design and implement a large-scale RFID infrastructure for two Australian national RFID projects with improved performance.

2.3.3 RFID Data Processing

RFID data processing technology is discussed in this section, which is related to the methods of processing the RFID data for generating the moving object position. The first goal of RFID data processing in an RFID-based localisation system is to remove noise and false reading errors from a continuous high volume set of RFID raw data captured by RFID readers, called RFID Data Filter. Secondly, it aims to use some localisation algorithms to process the RFID data for extracting the targeted parameters, such as moving object position. The first goal has been achieved by some RFID data filtering techniques. For instance, in a number of RFID middleware systems (Hoag & Thompson, 2006), RFID data filtering is supported to process a large volume of real-time RFID data streams, in order to provide accurate data used for RFID-based applications. Additionally, conventional data stream processing and continuous query optimization (Chawathe et al, 2004) (Jeffery et al, 2006) are adopted to filter the RFID raw data for achieving accurate stream sources. In this research work, the first goal is to select the reliable features from RFID raw data, and to reduce the impacts of noise and false reading interference.

The second goal mainly refers to the tracking and localisation algorithms, which deal with the selected features to extract the moving object position. Localisation deals with the problem of trying to locate the moving object, given a map and some sensor reading data. The theory and techniques of localisation have been under active development during the past several decades, and their design paradigm has been dramatically changed. In the 1970s, it was focused on path planning and control problems (Thrun, 2002). Normally this paradigm is called model-based. Seeing the drawbacks of the model-based paradigm, researchers sought to find some other way; one in particular that became popular in the 1980s was Brooks' behaviour-based architecture (Brooks, 1989). In addition to the above two paradigms, another paradigm which has emerged since the mid 1990s, and is still developing, is usually termed probabilistic based localisation (Thrun, Fox, Burgard, & Dellaert, 2001) (Degroot & Schervish, 2002) (Doucet, Freitas, Murphy, & Russell, 2000). Since the world model is not perfect, the sensor measurement can be unreliable, control input can be full of noise, and even the environment can be highly dynamic. The probabilistic method describes all the information in a probabilistic way, unlike the above methods which are deterministic.

Since then, the localisation algorithms most commonly used in RFID-based location systems are the ones which use the RFID data collected at some time interval to calculate the output position parameters. For instance, an absolute localisation scheme (Lim et al, 2006) is proposed by using RFID passive tags arranged on the floor to obtain robustly the position of a moving object. Han (Han et al, 2007) proposed an efficient localisation scheme by using a triangular tag pattern, which is based on the average mean method, for enhancing the tracking accuracy and precision. However, these methods are all using a static process to deal with the RFID data, which means the data is only processed from the current time interval. It may be unable to avoid occasional sudden unexpected false reading errors. Therefore, rather than trying to use 'static' solutions, by integrating some probabilistic processes, the dynamic algorithm attempts to 'estimate' the moving object position by using data from previous time intervals in a dynamic process. Consequently this has a potentially stronger ability to resist sudden errors.

The probabilistic localisation method aims to estimate the state of the mobile object and its environment from some sensor measurements. Since all the states are uncertain, Bayes filtering (Degroot & Schervish, 2002) is a classical mathematical representation which can help to represent and calculate the estimations. Currently, the most popular form of probabilistic localisation is SLAM (Simultaneous Localisation and Mapping).

2.4 Probabilistic Localisation Algorithm and SLAM

The theory and techniques of localisation and SLAM are both original from the field of robotics. Localisation deals with the problem of trying to find the location of the robot, given a map and some sensor reading data. A robust localisation system is arguably the most fundamental component for autonomous systems (Williams 2001), and is the basis for navigation and mission planning. Mapping is the process of building and maintaining a model of the surrounded environments. Although in some circumstances, the creation of an accurate map of the environment may be a goal in itself, most of the time it is served as an input to the localisation component.

2.4.1 Bayes Filtering

Most of the localisation and mapping techniques have gone probabilistic since then, almost all the state-of-the-art robotic system are based on probabilistic techniques, not only on the level of motion modelling and observation modelling, but also on decision making (Thrun 2002). A probabilistic tracking or localisation system can cope with both “Position tracking” problem and “Global localisation” (where the initial states is not given) problem, or even “Robot kidnapping”. In a probabilistic tracking system, the aim of localisation is to estimate the state of the mobile object and its environment, from some sensor measurement. Since all the states are uncertain, Bayes filtering (Degroot & Schervish, 2002) is a mathematical representation which can help to represent and calculate the estimations. The key idea of Bayes filtering is to estimate a probability density (by a posterior density function, or *pdf*) over the *state* space conditioned on the given sensor data. It is often called the *belief*. In our research work, let us denote the state of the moving object at time *t* by s_t, and the RFID observed data from time *0* to *t* by $d_{0:t}$. The *belief* of state *S* at time *t* can be written as:

$$Bel(s_t) = \Pr(s_t \mid d_{0:t}) \tag{2.1}$$

The state s_t typically consists of the location information of the moving object, which are the coordinates in a two dimensional Cartesian space. While d is the measurement, it depends on the RFID sensors equip on the moving object. Here, the RFID sensors have some difference from the other typical sensors. Usually in typical mobile robots application, the sensors are some relative range and bearing measurer, e.g., laser range finder, ultrasonic transmitter or even moving objects, etc. However, the RFID sensors would only recognize the RFID tag ID, but possibly matching with position or range information.

Before go into the details of Bayes Filtering, it first needs to revise the Bayes Theorem, as shown in Appendix A, which is the fundamental theory for probabilistic estimation problem. Bayes Theorem can calculate the probability of event B_i, when A is observed. In probabilistic localisation area, it helps to determine when given the measured data, what is the current state of the mobile object and its environment. Additionally, there is another important assumption, called *Markov Assumption*. It refers that in a stochastic process, the Markov assumption means that the future states of the process, given the present state, depends on only upon the current state. Backing to Bayesian filtering, it assumes that the initial *belief* of the state $Bel(s_t)$ is given as the *prior* distribution. In the case of *global localisation*, the *initial belief* is unknown and is normally initialized as a *uniform distribution* over all allowable positions (Dellaert et al, 1998). Then the estimation of $Bel(s_t)$ can be obtained in two steps: the prediction step and the update step. Firstly, it applies Bayes Theorem onto Equation 2.1:

$$\begin{aligned} Bel(s_t) &= \Pr(s_t \mid d_t, d_{o:t-1}) \\ &= \frac{\Pr(d_t \mid s_t, d_{0:t-1}) \Pr(s_t \mid d_{0:t-1})}{\Pr(d_t \mid d_{0:t-1})} \\ &= \eta \Pr(d_t \mid s_t, d_{0:t-1}) \Pr(s_t \mid d_{0:t-1}) \end{aligned} \tag{2.2}$$

Where $\eta = \Pr(d_t \mid d_{0:t-1})^{-1}$ is a normalizing constant relative to S_t, which is determined by the observation model and system noise.

Here it assumes the evolution process of the states is a Markov process. In practice, this assumption implies that the current state of the mobile object is the only element in the environment that will affect sensor reading, or in other words we do not need to take into account the past data but only the most current data. After applying Markov assumption, i.e. $\Pr(d_t \mid s_t, d_{0:t-1}) = \Pr(d_t \mid s_t)$, Equation 2.2 becomes :

$$\begin{aligned} Bel(s_t) &= \eta \Pr(d_t \mid s_t) \Pr(s_t \mid d_{0:t-1}) \\ &= \eta \Pr(d_t \mid s_t) \int \Pr(s_t \mid s_{t-1}, d_{0:t-1}) \Pr(s_{t-1} \mid d_{0:t-1}) ds_{t-1} \\ &= \eta \Pr(d_t \mid s_t) \int \Pr(s_t \mid s_{t-1}) \Pr(s_{t-1} \mid d_{0:t-1}) ds_{t-1} \\ &= \eta \Pr(d_t \mid s_t) \int \Pr(s_t \mid s_{t-1}) Bel(s_{t-1}) ds_{t-1} \end{aligned} \tag{2.3}$$

In order to calculate the Equation 2.3, it needs to specify $\Pr(s_t \mid s_{t-1})$ and $\Pr(d_t \mid s_t)$. The former is the system's motion model, which represents how likely a state of the moving object will be, given the previous state. The later one is the observation model, which tells the possibility of obtaining a particular sensor reading given a particular state. Also the Equation 2.3 reveals the recursive nature of Bayes Filters, *belief* $Bel(s_t)$ at time t is calculated based on the *belief* $Bel(s_{t-1})$ at the time t-1. At each time interval, the calculation of Equation 2.4 involves two stages: first by incorporating the motion model and previous belief, it obtains $\int \Pr(s_t \mid s_{t-1}) Bel(s_{t-1}) ds_{t-1}$. This stage is often referred to as the prediction step, where the current state is predicted. When the most recent sensor reading becomes available, $\Pr(d_t \mid s_t)$ is calculated and multiplied by the product of $\int \Pr(s_t \mid s_{t-1}) Bel(s_{t-1}) ds_{t-1}$. And this is called the update step, where the current belief is updated according to the sensor reading to refine the prediction. Using the recursive approach, and together with the initial belief, Bayes Filter iteratively estimates every state of the mobile object along its trajectory.

Bayes filter is the basic Equation for most probabilistic localisation system. It is, however, only a theoretical framework to this estimation problem. The integration in Equation 2.3 is a vital problem. If the state space is continuous, the implementation of Equation 2.3 requires memory storage for the representation of the whole posterior distribution, which is an infinite dimensional vector. In cases where the state space is discrete and high dimensional, the integration is still extremely complicated and not practical to implement. Only in some cases where strong assumptions and constraints are applied can this implantation be computationally feasible. There are two major solutions to the Bayesian filtering, which are Kalman Filter and Particle Filter.

2.4.2 Kalman Filter Localisation

Kalman filter is the most common and well-known approach for implementing the Bayesian filters in continuous state space, which assumes that the initial state is given as a Gaussian distribution, and both the motion and the observation model are also linear with Gaussian noise. By exploiting the linear relationship, system models in the Bayesian Filter can then be written as a Kalman Filter's way as shown in Appendix B.

Kalman filter recursively computes the covariance and mean which fully describes the posterior Gaussian distribution $Bel(s_t)$, whose *mode* yields the current state of the mobile object, and the state covariance represents the object's uncertainty. If, in addition, the noise variables are drawn from normal distributions, then the Kalman Filter produces the optimal minimum-variance Bayesian estimate, which is equal to the mean of the a posterior conditional density function of state s_t, given the prior statistics of s_{t-1} and the statistics of the measurement z_t. No non-linear estimator can produce estimates with smaller mean-square errors. If the noise does not have a normal distribution, then the Kalman Filter is not optimal, but produces the optimal linear estimate (Smith et al. 1990). However, localisation approaches using Kalman filters require that the initial position of the mobile object is given or within certain error range, and that features in the environment can be uniquely identified (the observation model is unimodal). Therefore they are not able to solve the "Global localisation" and "Robot kidnapping" problems where the *pdf* might be bimodal or multimodal.

2.4.3 Particle Filter Localisation

Another important family that implements Bayesian filters is based on sampling techniques. It approximates the posterior distribution by a (random) set of samples. Besides, the observation and motion model can also be represented by a set of random samples. This method is particularly suitable for nonlinear estimation problems. More specifically the sample technique is often called Particle Filter. But in different field Particle filter have some other names, e.g. SIR (Sampling Importance Resampling) in statistics, Sequential Monte Carlo (SMC), Bootstrap Filtering (Gordon et al. 1993), Monte Carlo Localisation (MCL) in robotics, and Condensation Algorithm in computer graphics (Isard & Blake 1998). Doucet (1998) presents a comprehensive review of Particle Filter and includes them into a unified framework. In fact, they are all based on the theory of SIS (Sequential Importance Sampling) which was first introduced by statisticians dating back to 1950s. Most likely the reason that it was not being actively researched in the field of robotics and mobile computing is the limited computational speed at that time. To solve the integration in Equation 2.3, the basis of Particle filters is to perform a Monte Carlo simulation, i.e. the desired posterior distributions is represented by a set of randomly chosen samples (particles) with importance sampling (weighting), and then compute the required estimation based on these samples with regard to associated weights. As the number of the particles becomes large enough, these particles will become an equivalent representation of the posterior distribution.

After applying the sampling, the *belief* of the moving object at time interval *t* becomes:

$$Bel(s_t) \cong S_t = s_t^i \;\; w_t^i \;\; i = 1, \ldots, m \qquad (2.4)$$

Here *m* is the number of the particles, w_t^i is the importance factor and s_t^i is the state of the moving objects. In terms of the "global localisation" problem, the initial belief can be represented by a uniformly distributed particle set of size m (the particles are "spread" uniformly in the whole state space) and each particle has a weights of 1/*m*. If the initial state of the robot is given, the initial belief can then be initialized by samples drawn from a narrow Gaussian centered on the correct pose (Thrun et al. 2001b). In both cases, each particle s_t^i stands for a possible state of the moving object (i.e. a possible location in a room), while the associated importance factor w_t^i indicates the probability that the robot is in this state. The importance factor w_t^i should be non-negative and sum up to 1.

The principal algorithm of Particle Filter can be described as Figure 2.1

> $S_{t+1} = 0$ and S_t is a set of particles of previous belief
>
> For i = 1 to m
>
> Generate a random particle s_t^i from particle set S_t according to $w_t^1, ..., w_t^m$
>
> Generate a particle s_{t+1}^i form s_t^i based on $\Pr(s_{t+1} | s_t)$
>
> Generate a weight $w_{t+1}^i = \Pr(d_{t+1} | s_{t+1})$
>
> Add $\{s_{t+1}^i, w_{t+1}^i\}$ to S_{t+1}
>
> Normalize all importance factors w_{t+1} in S_{t+1}
>
> Return S_{t+1} as the new belief

Figure 2. 1 Algorithm of a standard particle filter

There are two steps in this algorithm, the first one is the sampling step, given the previous belief S_t, particles are generated randomly from particle set S_t, based on their weights (Hence a particle with high weight may be picked multiple times whilst those with low weight might never be picked). Then for each picked particles, new particles are generated based on the motion model $\Pr(s_{t+1} | s_t)$, which gives a *proposal distribution* (from Thrun et al. 2001b) denoted as $q_{t+1} = \Pr(s_{t+1} | s_t) Bel(S_t)$, we can see that this step implements the prediction step of basic Bayesian filter. Figure 2.2 illustrates an example of this propagation process: the solid line indicates the motion of the robot, the particle "cloud" is the *proposal distribution*. We can see that as the mobile object keeps moving, the particles become "spreading out", which is a sign of the uncertainties of the motion model due to imperfect motion control. The proposal distribution is not the desired posterior distribution since it does not take into account the sensor measurement. This can be done by assigning the importance factor $w_{t+1}^{i} = \Pr(d_{t+1} \mid s_{t+1})$ to the i particle s_{t+1}^{i}, using the observation model. This step is called the weighting step, which implements the update step in basic Bayesian filters.

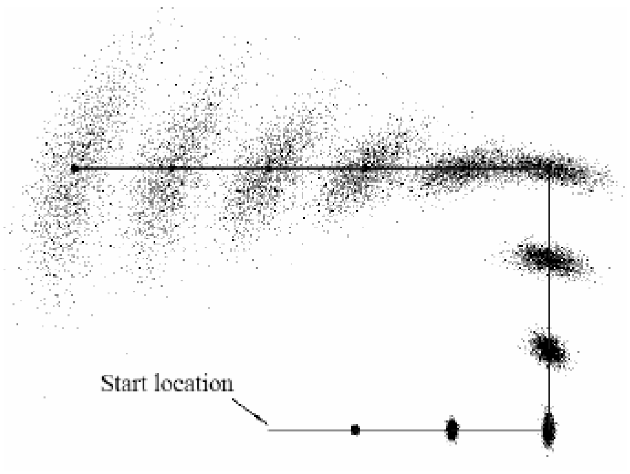


Figure 2. 2 The proposed distribution of particle filter (Fox et al. 1999)

Moreover, Figure 2.3 (Delaert et al. 1998) shows the basic working process of particle filters. Here we assume the initial position is roughly known (represented by the picture in row 1, column A, denoted A1), and the state space is two dimensional. A2 is the initia particle set. Firstly the mobile object (moving object or human carrying a mobile computer) moves, for example, one meter away from the initial position. Therefore B1 is the motion model which gives the *proposal distribution* in B2. When the sensor reading becomes available (assume we are using range finder, e.g. ultrasonic transmitter), C1 is the observation model, say the likelihood of observing the sensor at a certain position. After incorporating the sensor reading we then update the weights of the particles. And this gives the new particle set, shown by C2, where the particles with darker grey level indicated a highly possible state.

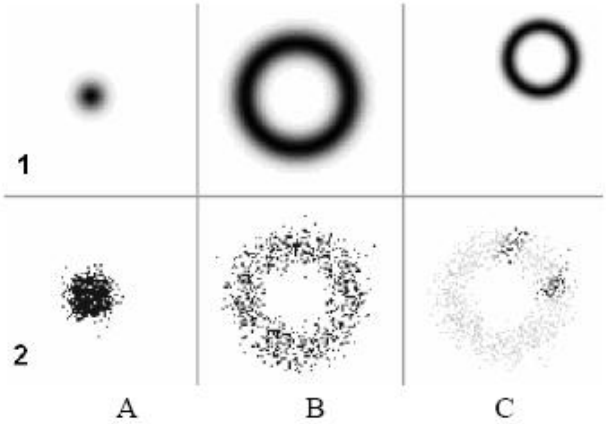


Figure 2. 3 A working process of particle filter (Delaert et al. 1998)

The above algorithm is identical to the SIS algorithm, which, however, has a common problem that significantly affects its accuracy on approximating the true posterior: usually after some recursive steps, some weights will become very large and concentrate on only a few particles, while the other particles' weight decrease or even become negligible. This is called the *degeneracy* problem. Kong et al. (1994) present a way to measure the degeneracy, as follows:

$$Deg_t = \frac{1}{\sum_{i=1}^{m} w_t^i} \quad \text{(t is the time interval, m is number of particles)} \quad (2.5)$$

The feature of Equation 2.5 is that if all weights concentrate, say, to one particle, then Deg = 1. If the weights are distributed uniformly, then $Deg_t = m$. Therefore this Equation can be used to measure how serious the *degeneracy* is. There have been several approaches in the literature dedicated to solve this problem, based on the idea of *resampling*, which according to Bolic (Bolic, 2004), was first introduced by Rubin et al (Rubin, 1988). Its basic idea is to eliminate those particles with low weights and multiply those with high heights, while at the same time maintain the sum of all weights unchanged), see the following Figure 2.4 (Merwe et al. 2000).

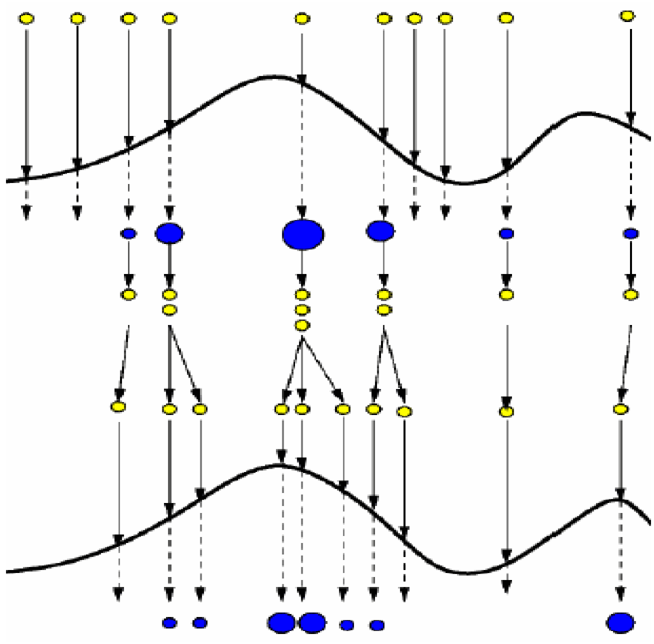


Figure 2. 4 Resampling process (Merwe et al. 2000)

After applying resampling, the recursive step of particle filter becomes:

1, sampling step (same as above)

2, weighting step (same as above)

3, resampling step

In fact most state-of-the-art implementations of particle filter algorithm involve the resampling step. They differ mainly on how to implement the motion model and the resampling algorithm. In the context of localisation, there is another problem of particle filters. Although in theory the Particle Filter can handle the "robot kidnapping" problem, in practice when the robot is moved to a random position, it might happen that there are no particles near that position, hence it will take a long time for the robot to re-localize itself (if the number of particles is too small this process can be very long). Possible solution to this problem includes sensor resetting (Lenser & Veloso 2000), Mixture Monte Carlo localisation (Thrun et al. 2001b), and another simple approach by Fox (Fox, 1999) where they add a small number of uniformly distributed, random samples after each iteration.

The last issue about particle filter, concerns about its computational load. As the number of particles increased, in general the performance will decrease dramatically. Also, the particle number cannot be too small since it also influences the accuracy (depends on true problem). To avoid such a trade-off, there is solution called adaptive sampling scheme (Koller & Fratkina 1998), which determines the number of particles during the localisation process: when the robot is sure where it is, it reduce the particle numbers to save computational load; while uncertainties arises, it increase the particle numbers.

2.5 Summary

To summarize, this section has reviewed various conventional moving object tracking techniques in indoor productions and discussed their limitations in section 2.1. The review in section 2.2 shows that the RFID technique has recently been a hot topic for various industrial applications, particularly in the areas of object tracking and localisation. However, so far there are no research works successfully delivering an accurate and precise RFID based localisation solution for indoor use. The first difficulty is that wireless indoor localisation technique (RFID is one of wireless indoor localisation technique) is not widely recognized by most researchers as a sufficiently accurate and precise tracking technology in section 2.2. Secondly, the high precision of moving object position localisation in an indoor production is not really achievable by using RFID technology in section 2.4. Many factors can easily make the RFID reader incorrectly detect or fail to detect RFID tags, so that it is difficult to remove or manage *false reading error* in an indoor environment. In order to investigate the possibility of using RFID techniques for accurate and precise moving object localisation in indoor applications, the next chapter will give a detailed analysis of the optimal usage of RFID techniques for moving object localisation by designing a formal framework.

Chapter 3:

RFID-Loc Framework and Investigation Procedure

In order to find how to accurately and precisely localize moving object in an indoor environment by using RFID technique, the prime task is to design a theoretical framework for clearly understanding the process of RFID based localisation system. In a concise manner, this framework is named as RFID-Loc. In this chapter, it firstly presents the components and work flow of RFID-Loc framework. The framework consists of three components, which are RFID-Loc infrastructure module, RFID-Loc data filter module, RFID-Loc localisation algorithm module. Secondly, the issues and investigation procedure of each module in RFID-Loc framework are defined and classified in this chapter. Following the investigation procedures, each module in RFID-Loc framework can potentially deliver a solution to improve accuracy and precision of a RFID based indoor moving object localisation application.

3.1 Design Goals

Considering the performance benchmarking of indoor moving object localisation listed in Chapter one, a discussion of the goals that lead the design of RFID-Loc framework is presented in this section.

Ability of delivering a practicable solution: The primary goal of this framework is to be capable of delivering a practicable RFID based moving object localisation solution for indoor use.

Ability of enhancing localisation accuracy and precision: The accuracy and precision are two critical issues to evaluate the performance of a localisation solution or system. The practicable solution proposed from an RFID-Loc framework has to provide a higher accuracy and precision than traditional RFID based localisation solutions.

Analyticity and Guidance: The analyticity and guidance of RFID-Loc framework refers that the framework can not only offer a practically optimal use of RFID technique solution with enhanced localisation accuracy and precision, but also provide the investigation procedure to guide how to achieve this solution. Through investigation procedures, users can flexibly conduct their required RFID-Loc based system.

Feasibility and Generic: The feasibility and generic of RFID-Loc framework means that the framework cannot be limited on a particular type of RFID device or RFID infrastructure. It would avoid particular constraints of RFID hardware devices under current state-of-the-art of manufacture. The dissimilar requirements of applications would utilize it wholly.

3.2 Fundamentals

As reviewed in section 2.3.1, passive RFID localisation solutions can reach the highest accuracy within the current start-of-the-art in RFID localisation techniques. So the fundamental of RFID based 2D moving object localisation in an indoor environment in this thesis is from typical passive RFID object localisation solutions. In a typical passive RFID object localisation solution, RFID tag is used to mark a preliminary defined position point; RFID reader is usually attached to a mobile object, such as vehicles, humans and animals. Localisation technique is expected to enable the RFID reader to efficiently gather information and understand the context of the environment by using RFID tag's location as well as stored information. As RFID reader moving, its position value can be calculated by using a number of stored RFID passive tags' information with a localisation algorithm.

In an indoor environment, the targeted moving object position is denoted as $C(x, y, z)$, which is equal to the position $R(x, y, z)$ of a mobile RFID reader. A set of passive RFID tags with predefined position X and Y are defined as $T_N(x, y) = \{T_1, T_2, ...T_n\}$. Z represents the height of RFID reader, which is equal to the distance R_H from antenna plane of a RFID reader to RFID tags plane. A set of number N of passive RFID tags with predefined position X and Y is defined as $T_N = \{T_1, T_2, ...T_n\}$. M represents the number of passive RFID tags $T_M = \{T_1, T_2, ...T_m\}$ having been detected by RFID reader at each time interval t. $\{x_1, y_1\}, \{x_2, y_2\}, ...\{x_m, y_m\}$ represents the coordinates of passive RFID tags being detected. At each time interval t, there is a spatial relationship between them as shown in Equation 3.1, where f_x and f_y respectively represent localisation algorithms to calculate the position of the targeted object $C(x, y, z)$ from captured RFID data.

$$C(x, y, z) = C(f_x(x_1, x_2, \ldots x_m), f_y(y_1, y_2, \ldots y_m), R_H) \quad (3.1)$$

Figure 3.1 illustrates that the indoor object moves in a passive RFID localization system. RFID reader in Figure 3.1 is assumed to read one passive tag at each moving step, in terms of Equation 3.1, the moving object trajectory in Figure 3.1 could be from t1 to t5.

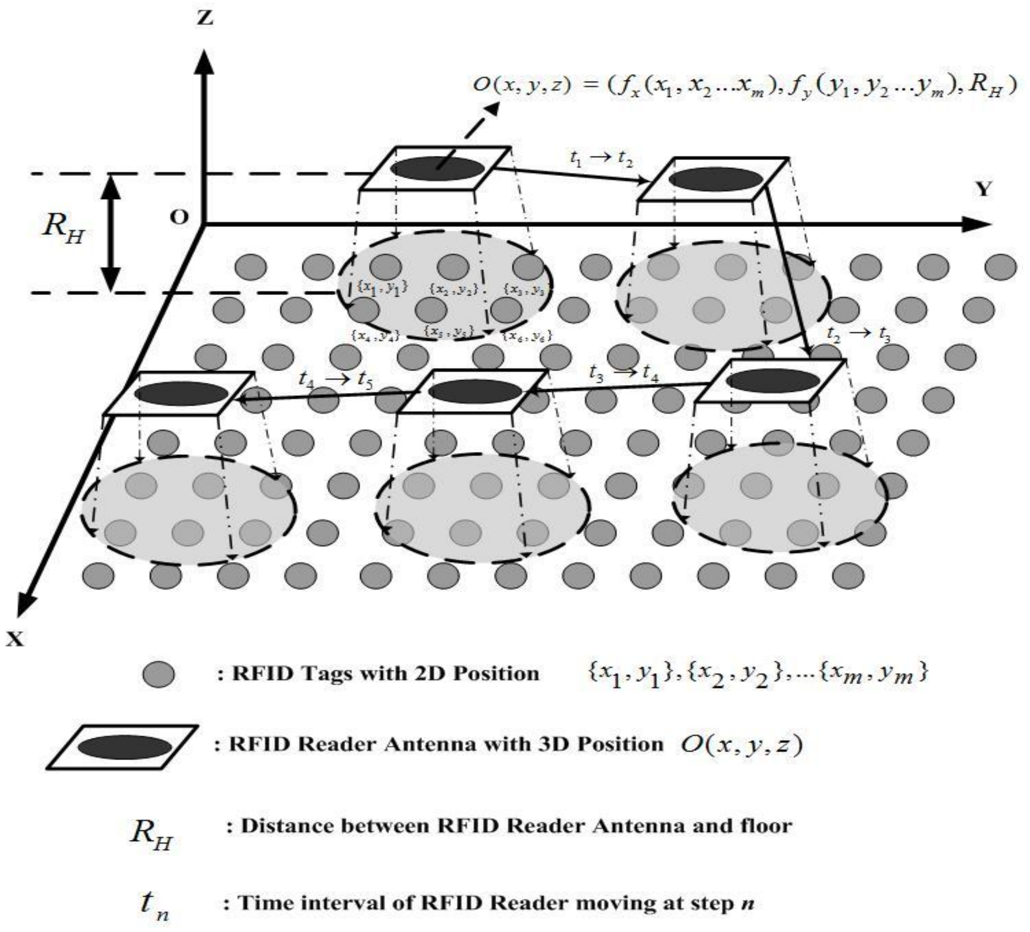


Figure 3. 1 The fundamentals of a passive RFID localisation system

3.3 RFID-Loc Framework

RFID-Loc framework is built to describe the whole work flow of passive RFID localisation system in Figure 3.1. The framework consists of three modules, which are RFID-Loc Infrastructure, RFID-Loc Data Filter, and RFID-Loc Localisation Algorithm. As shown in Figure 3.2, as the indoor object moving, a sequence of raw RFID tag IDs is firstly observed from a RFID-Loc Infrastructure module; and then RFID-Loc Data Filter module would match the sequence of raw RFID tag IDs with corresponding position information; also select the reliable features from these raw data; finally RFID-Loc Localisation Algorithm module would process selected features to generate a sequence of moving object position.

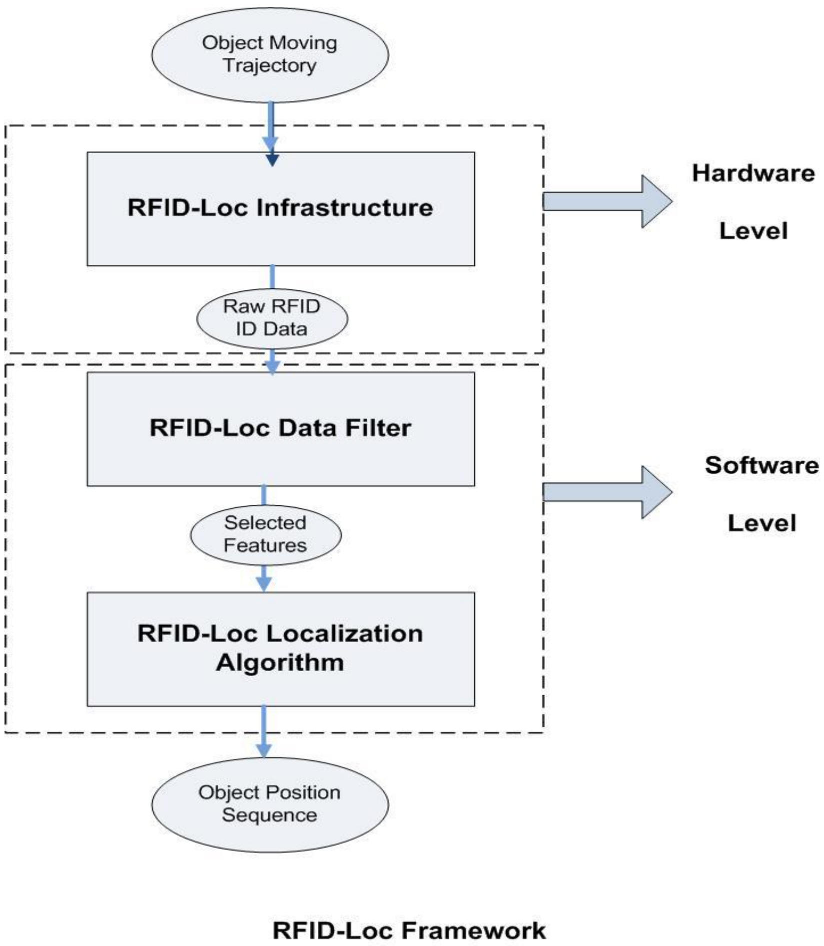


Figure 3. 2 Work flow diagram of RFID-Loc Framework

3.3.1 RFID-Loc Infrastructure

RFID-Loc Infrastructure module contains the selection of RFID hardware devices and the configuration of RFID hardware devices, such as specification of RFID readers and tags, number and type of RFID readers and tags, RFID tags distribution pattern. This information can be represented as some fundamental parameters in an RFID-Loc Infrastructure module. The choice of these parameters would influence the whole performance of an RFID-Loc system. A benchmark naming ***system reading efficiency*** (***SRE***) is defined in an RFID-Loc framework to measure the performance of an RFID-Loc infrastructure module, which is the ratio of the number of successful reads to the total number of read attempts, as follows:

$$\text{System Reading Efficiency (SRE)} = \frac{\text{Practical number of success reading tags}}{\text{Ideal number of expected reading tags}} \qquad (3.2)$$

Where: $0 < SRE < 1$

Theoretically, the value of *system reading efficiency* in an RFID-Loc Infrastructure module is expected to be one, which explores that practical number of success reading RFID tags is equal to ideal number of reading RFID tags. However, practically, due to unavoidable environment noise and interference, it is impossible to achieve such a perfect value of *system reading efficiency*. The practical value of *system reading efficiency* is usually below 1. High value of *system reading efficiency* in an RFID-Loc system explores its strong ability on successfully detecting RFID passive tags. Thus, *System Reading Efficiency* is a very important bench marker to evaluate the efficiency of selecting and configuring RFID hardware components in an RFID-Loc Infrastructure module. RFID-Loc Infrastructure module aims to study how fundamental parameters in an RFID-Loc infrastructure module impacting on the value of *system reading efficiency*, and propose some approaches to enhance the value of *system reading efficiency*.

3.3.2 RFID-Loc Data Filter

RFID-Loc data filter module is to choose useful and reliable features from a set of practically captured RFID raw data. While optimal design of RFID-Loc infrastructure can possibly enhance the reliability of practical RFID output data by improving the value of *system reading efficiency*, the practically captured RFID raw data is still vague since the value of *system reading efficiency* is impossible to be perfect. Therefore, we call those regular noises and interferences leading to imperfect *system reading efficiency* of an RFID-Loc system as *regular false reading errors*. Due to these *regular false reading errors*, the practically captured RFID data is usually inaccurate and uncertain. Most of current passive RFID based localisation systems directly process RFID raw data to generate a target position, instead of using the filtered RFID data or the selected features. It is because they believe the completeness and large-volume of RFID data can contain more useful and reliable information. However, there is an ignored issue that the completeness and large-volume of RFID raw data would also contain more false reading information, which can enlarge its impacts on the accuracy and precision of localisation results. The goal of RFID Data Filter module is to explore the problem on how to select useful and reliable features from the set of RFID raw data.

3.3.3 RFID-Loc Localisation Algorithm

RFID-Loc Localisation Algorithm module would process the selected features from RFID-Loc Data Filter module, for generating moving object position over time. Typical RFID-based localisation algorithm is to process RFID data from current time interval, for calculating the position value of moving object. This type of algorithms can be named as *static* localisation algorithm. Average mean method and weight average mean method are simply adapted into static localisation algorithms. While static localisation algorithm can successfully generate the moving object position most of time, it has a weak ability to resist some unexpected false readings errors. For instance at some time interval, if the value of selected features from RFID data filter module is zero, or equal with the value of selected features at the latest previous time interval; since the outcome of static algorithm merely relies on the data of the current time interval; static localisation algorithm would output the incorrect moving object position. In order to solve this problem, the possibility of other possible localisation algorithms has to be examined in this work. Dynamic localisation algorithm based on the probabilistic localisation, is possibly a potential candidate. The original idea of dynamic localisation algorithm in this research work takes its source at SLAM (Simultaneous localisation and mapping) techniques. The chapter 2 reviewed that there are two major dynamic localisation algorithms to solve the SLAM problem, which are Extended Kalman Filter and Particle Filter. The RFID-Loc localisation algorithm module would evaluate and justify the performance of those two techniques in RFID-Loc framework and attempt to propose a new dynamic localisation algorithm for improving the accuracy and precision of indoor moving object localisation.

3.4 Localisation Accuracy and Precision in RFID-Loc framework

Typically as defined in section 1.1, accuracy refers to the ability of a measurement to match the actual value of the quantity being measured; precision refers to the ability of a measurement to be consistently reproduced. In a RFID-Loc framework, accuracy and precision are clearly defined in the following:

Accuracy: The accuracy is the ability of the solution or system being able to measure the minimum moving distance of an object. In a RFID-Loc framework, accuracy is normally limited to the minimum distance between two adjacent tags of a passive RFID tag distribution pattern. For instance, if the distance between each two adjacent tags is 5 centimetre, the maximum achievable accuracy of this passive RFID localisation solution can be 5 centimetres.

Precision: The precision is the ability of the solution or system being able to reach how closely and consistently the further measurements can be performed to obtain the ideal accurate result. Accuracy only considers the value of mean distance errors. However, location precision considers how consistently the localisation solution or system works, i.e., it is a measure of the robustness of the positioning technique as it reveals the variation in its performance over many trials. In a RFID-Loc framework, precision would be influenced by many factors in RFID infrastructure, such as environment noise, signal strength, tag collision etc.

Thus, the measurements of a RFID-Loc based system can include the value, an error term and the units in Equation 3.3, for example 10 centimeters + /- 2.56 centimeters. Here, accuracy is up to 10 centimeters, precision is within 2.56 centimeters.

$$\boldsymbol{Measurement} = \boldsymbol{Value} \times \boldsymbol{Units} + \boldsymbol{Error} \qquad (3.3)$$

Where: **Units** refer to Accuracy, **Error** refers to Precision.

In order to analyse the issues affecting accuracy and precision in a RFID-Loc framework, Figure 3.3 illustrates a diagram to explore the major potential issues affecting localisation accuracy and precision in three defined modules of a RFID-Loc framework. The evaluation of localisation accuracy and precision in a RFID-Loc system is based on a comparison between real object moving trajectory and estimated moving object position sequence. The difference between real object trajectory and estimated moving object position sequence reflects how accurate RFID-Loc system can be. However, there are some issues potentially leading to a difference between real object moving trajectory and estimated moving object position sequence. The first issue is *false reading* comes from RFID-Loc infrastructure module. The concept of *false reading* has been reviewed and defined in section 2.3. Due to the limitations of radio frequency signal, *false reading* is a typical reason leading to some errors in most of RFID based system, especially on multiple passive RFID tags detection situations. In a RFID-Loc framework, *false reading error* directly comes from RFID-Loc infrastructure module, which has been classified into two categories: regular and unexpected. *Regular false reading error* refers to some error regularly occurring at every time interval of indoor object moving in a RFID-Loc based localisation system, which is mainly from characteristic limitations of RFID-Loc infrastructure. *Unexpected false reading error* refers to some causal error causing by accident event, which is usually from changeable environment or erratic motion of moving object. *Regular false reading error* and *unexpected false reading error* are fundamental issues affecting accuracy and precision in an RFID-Loc based system, because they are directly from system hardware level and environment, which are unavoidable and unpredicTable. The second and third issues are *Feature Selection Method* and *Localisation Algorithm*. These two issues are separately delivered from RFID-Loc Data Filter module and RFID-Loc Localisation Algorithm module. Actually, for many RFID-based localisation systems, these two issues are considered together as a localisation algorithm in a calculation process. The impractical choice of them might affect some accuracy and precision of an RFID-Loc system, but they are not the fundamental issues causing error to localisation accuracy and precision.

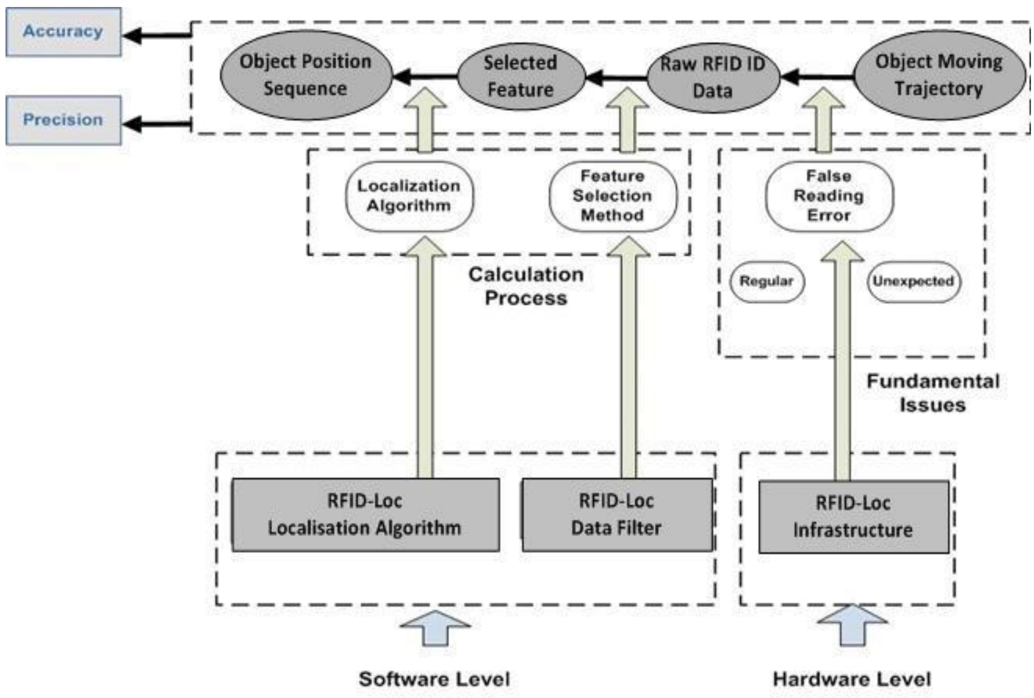


Figure 3. 3 Issues affecting Accuracy and Precision in RFID-Loc Framework

Figure 3.3 show that all three modules of a RFID-Loc framework have some impacts on localisation accuracy and precision. Some benchmarks in each individual module has to be conducted to measure their impacts on accuracy and precision of an RFID-Loc system. In a RFID-Loc Infrastructure module, Tag Distance and *System Reading efficiency* can used to be benchmarks, as discussed in last section. *System reading efficiency* can reflect the ability of RFID-Loc infrastructure module on reducing *regular false reading error*. In RFID-Loc Data Filter and RFID-Loc Localisation Algorithm modules, methods they delivered are mainly used in calculation process, which probably cannot reduce *regular false reading error* directly; but the suitable use of them probably can indirectly reduce the impact of regular false reading error on localisation accuracy and precision in a RFID-Loc based localisation system, also potentially resist *unexpected false reading error*. While it is hard to give a benchmark to measure their performance, moving object position sequences can be directly used to measure how well the performance of RFID-Loc Data Filter module and RFID-Loc Localisation Algorithm are. Table 3.1 illustrates the benchmarks on how to measure the impacts of each module in a RFID-Loc framework on localisation accuracy and precision.

Table 3.1 Benchmarks for measuring the impact of modules in a RFID-Loc framework on accuracy and precision.

	Hardware Level	Software Level	
	RFID-Loc Infrastructure	**RFID-Loc Data Filter**	**RFID-Loc Localisation Algorithm**
Accuracy	*Tag Distance*	*Moving object position sequence*	*Moving object position sequence*
Precision	*System Reading Efficiency*	*Moving object position sequence*	*Moving object position sequence*

The noticeable thing here is that while the performance of RFID-Loc infrastructure on accuracy and precision can be measured directly by *Tag Distance* and *System reading efficiency*, it is better to also evaluate accuracy and precision on an given localisation algorithm. Regarding as measuring the performance of RFID-Loc Data Filter and Localisation Algorithm modules, a known RFID-Loc infrastructure must be known.

3.5 Investigation Procedures

In this section, various impacted issues of each module under RFID-Loc framework have to be discussed and classified. It defines and analyses the issues and investigation procedure of each module in terms of Table 3.1. Considering that RFID-Loc Data Filter and Localisation Algorithm both have to be measured by moving object position sequence, this thesis would put them together in one chapter to discuss.

3.5.1 RFID-Loc Infrastructure Module

The key point of this module is to study how to get a high *system reading efficiency*, with some strategies on selecting and configuring RFID hardware. RFID hardware device selection is to select the suitable specification of RFID tags or readers, such as operating frequency, tag size and types. RFID hardware configuration is to determine how to setup those devices, such as RFID tags distribution, RFID reader sensing range. The investigation work in this module is summarized into several stages in Figure 3.4.

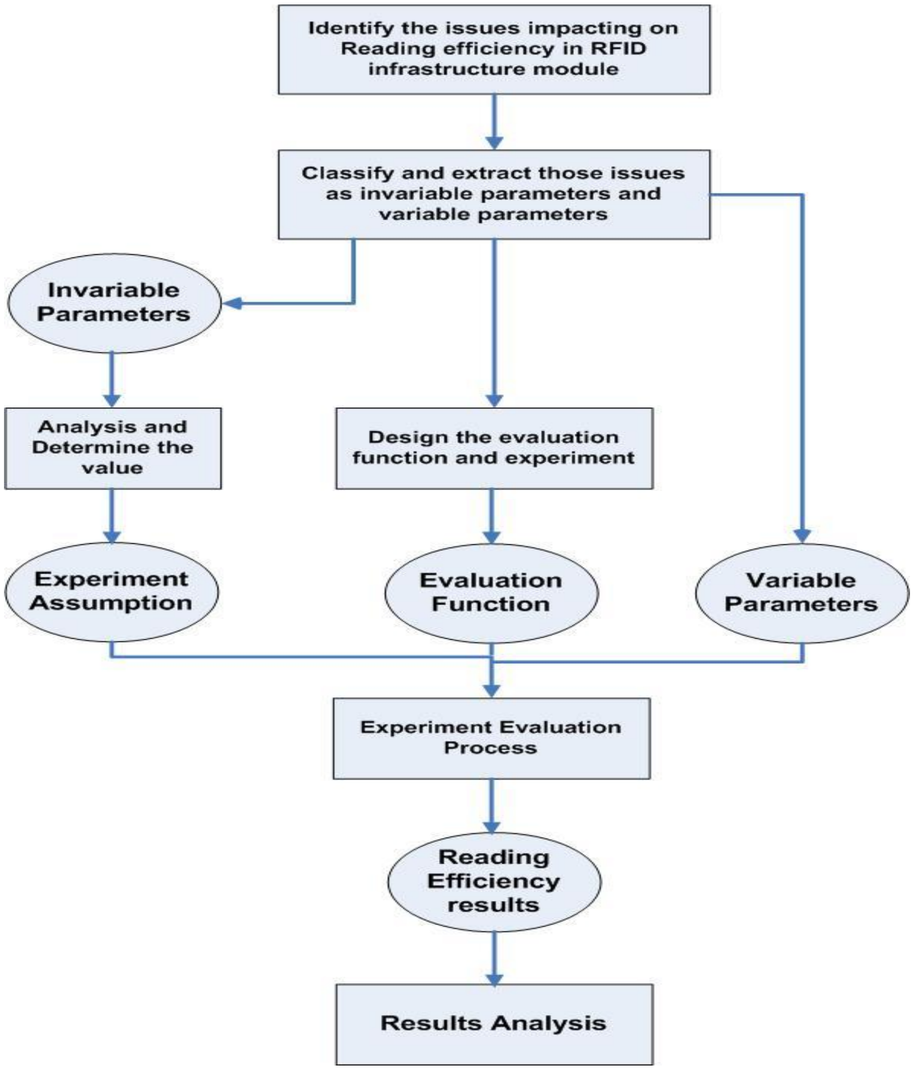


Figure 3. 4 Investigation Procedure of RFID-Loc Infrastructure Module

The issues impacting on *system reading efficiency*, is related to many basic RFID parameters in the selection of RFID devices and the configuration of RFID devices. The selection of RFID hardware devices includes Operating Frequency, Tag type, Tag read rang, Tag form and size, Tag quantity, Reader type, Reader sensing range, Reader quantity. The type of tag is generally classified into passive and active. The utility of placing passive RFID tags can potentially reach a higher accuracy than active RFID tags. RFID reader is to collect data from tags and send it to an RFID system application. Theoretically, it is possible to install multiple RFID readers in an indoor environment to collect the moving object moving data. However, as considering the reader mobility and the collision of multiple readers, single RFID reader with anti-collision ability is selected to attach with the moving object, ideally using wireless technology to communication the captured Data. RFID hardware devices configuration is particularly on the arrangement of RFID passive tags. The fundamental of RFID-Loc system illustrates that the density of a RFID Tag Arrangement would determine the accuracy of RFID-Loc system, which is directly related to the distance between two adjacent tags. So an assumption of RFID Tag Arrangement as a well-proportioned grid pattern was setup, in the later chapter; other possible RFID Tag Arrangements would be discussed. As for the variable parameters, the first one is RFID tag distance of a well-proportioned grid pattern; the second one is the number of RFID tags placing in a well-proportioned grid pattern. Both of those two variable parameters can be evaluated by some experimental methods. Relying on the experimental findings and results analysis, a strategy can be proposed as a guideline on how to select and conFigure the RFID hardware devices under an unknown specification, with a high *system reading efficiency*. The explicit investigating tasks in this module are shown in Table 3.2.

Table 3. 2 Explicit investigating tasks in a RFID-Loc Infrastructure Module

Tasks	***Contents***
1	Analyse and identify the considerable issues in RFID-Loc infrastructure module
2	Determine the controllable items and uncontrollable items in those issues
3	Design the experimental approach to explore the relationship between those uncontrollable items and system reading efficiency
4	Evaluation of RFID devices characteristics and Tag arrangement in terms of experimental approach
5	Analyse and discuss the experimental findings and results
6	Propose a strategy to design the RFID infrastructure.

3.5.2 RFID-Loc Data Filter Module

Many RFID localisation solutions consider RFID data filter process as a feature selection stage in a particular localisation algorithm. However, RFID-Loc framework would consider RFID data filter as an individual module for deep investigation; the investigation work in this module can be summarized in Figure 3.5.

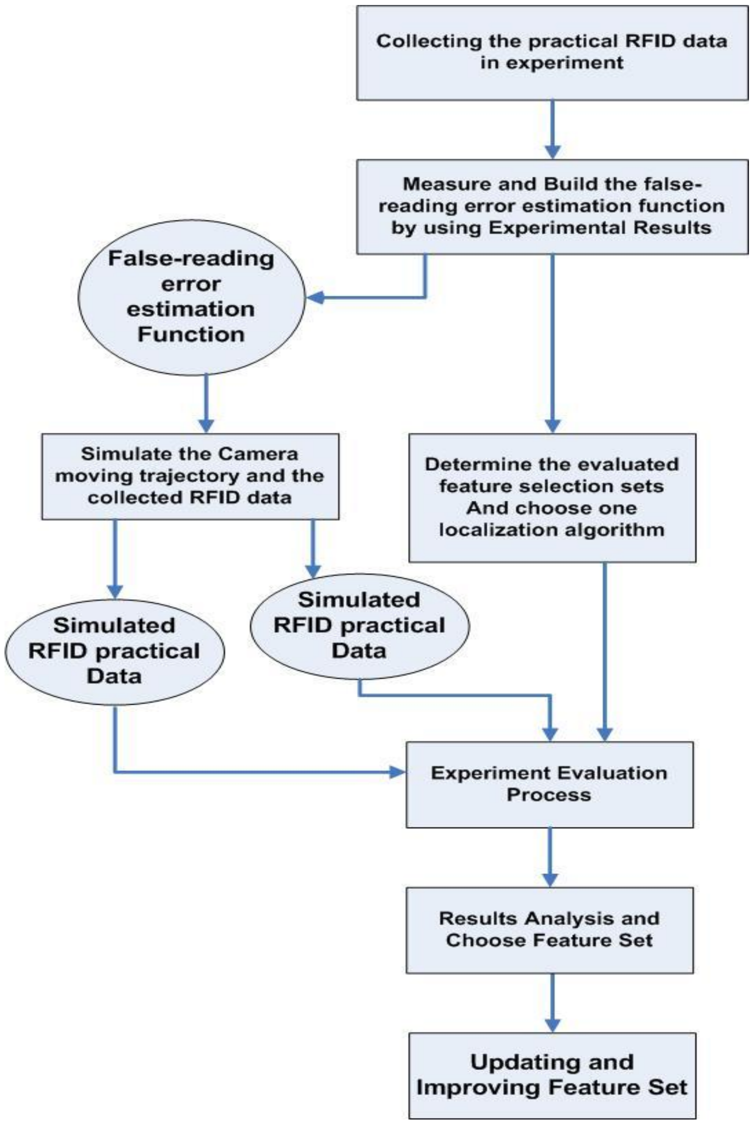


Figure 3. 5 Investigation Procedure of RFID-Loc Data Filter Module

The practically captured RFID data contains some incorrect and incomplete information due to *regular false reading error* from an RFID-Loc infrastructure.

However, if the fundamental infrastructure of an RFID-Loc based system is determined, the influence of noise and interference from external indoor environment would be regular and stable in a period time. While *regular false reading error* is possibly variable in single time frame, it would follow some principles to occur in a continuous time period. Thus, the trail-and-error experiment approach can be used to build a false reading error estimation function. Based on false reading error estimation function, the different feature subsets can be evaluated and compared. In terms of the evaluation results, the justified feature selection method can be used to generate the reliable features in an RFID-Loc data filter module. The explicit investigating tasks in this module are shown in Table 3.3.

Table 3. 3 Explicit investigating tasks in a RFID-Loc Data Filter Module

Tasks	***Contents***
1	Analyze and identify the considerable issues in RFID-Loc Data Filter module
2	Design the experimental approach to explore the false reading error distribution
3	Capture the experimental dataset
4	Evaluate several feature selection methods on the above dataset
5	Analyze and discuss the experimental findings and results
6	Propose a feature selection method

3.5.3 RFID-Loc Localisation Algorithm Module

RFID-Loc Localisation module is to generate moving object position by using a localisation algorithm to process features from an RFID-Loc data filter module. The goal of this module is to look for a feasible localisation approach achieving high accuracy and precision of an RFID-Loc system. In most RFID based localisation approaches, static algorithms are widely used. This research work would investigate dynamic localisation algorithm on processing the reliable features, and compare its performance to static algorithms. The investigation work in this module is summarized in Figure 3.6.

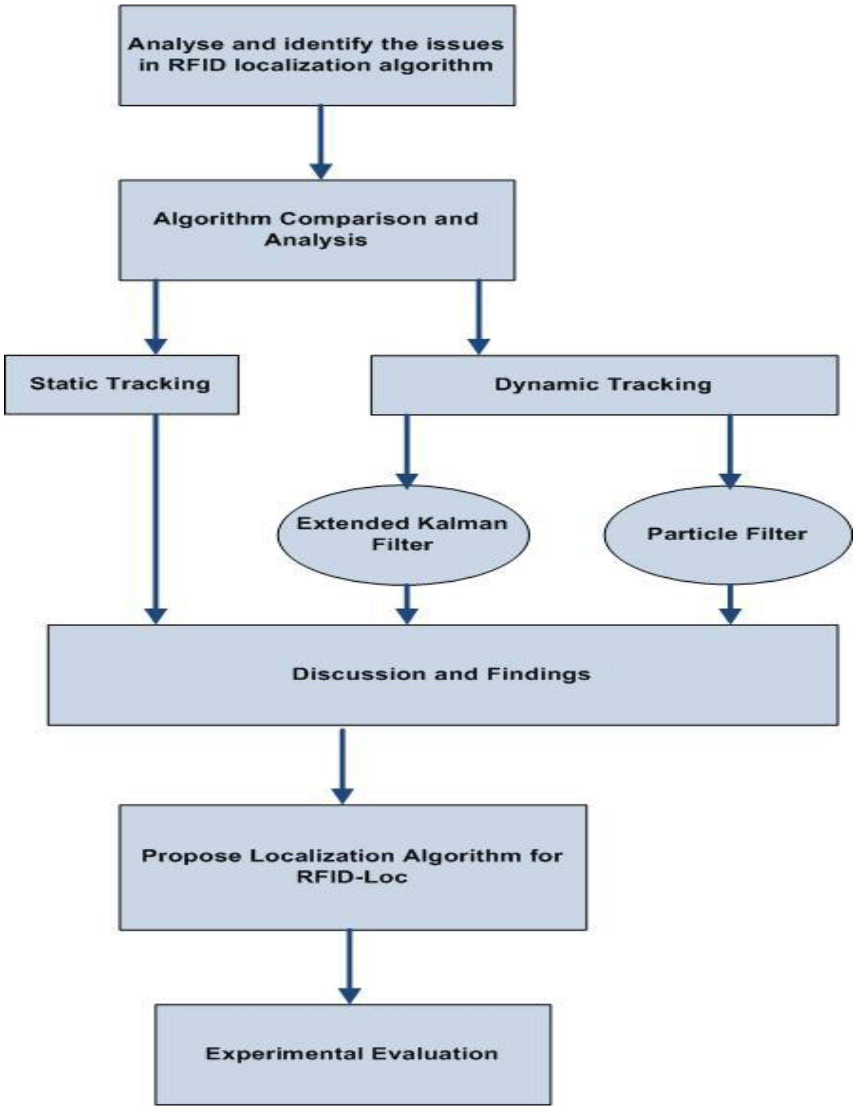


Figure 3. 6 Investigation Procedure of RFID-Loc Localisation Algorithm Module

Static localisation algorithm has been proved by many researchers that it is capable of locating object in a RFID based localisation system, but it has a weak ability on resisting *unexpected false reading error*. The crucial point in RFID-Loc Localisation Algorithm module would be the examination of dynamic localisation algorithm, whether being capable of delivering a better accurate and precise localisation algorithm in an RFID-Loc based system. Literature review in Chapter 2 appears that particle filter technique is highly recommended as a solution to deal with dynamic localisation problem. Hence, the investigation of dynamic localisation approaches would focus on particle filters based localisation approaches. The explicit investigating tasks in this module are shown in Table 3.4.

Table 3. 4 Explicit investigating tasks in a RFID-Loc Localisation Algorithm Module

Tasks	***Contents***
1	Analyse and identify the considerable issues in RFID-Loc localisation algorithm module
2	Analyse and compare the static tracking algorithm and dynamic tracking algorithm
3	Simulate those algorithms and discuss the findings
4	Propose a novel localisation algorithm for RFID-Loc use
5	Analyse and discuss the experimental findings and results
6	Address the limitations

3.6 Summary

In this chapter, a formal RFID-Loc framework has been built to describe the procedure of extracting moving object position in an indoor environment by using RFID technique. The design goal of this framework is to identify and analyse the factors impacting on the accuracy and precision of passive RFID based moving object position localisation system in indoor applications, further to offer some solutions to improve localisation accuracy and precision. The framework is addressed in details from three modules, which are RFID-Loc infrastructure, RFID-Loc Data Filtering, and RFID-Loc Localisation Algorithm. The investigation procedure and purpose of each module with diagram and Table has been illustrated and discussed in section 3.4 and 3.5. Due to the requirement of experimental platform in the investigation procedures, chapter 4 would address the setup and configuration of experimental platform. Then, chapter 5 would follow the investigation procedure of RFID-Loc Infrastructure module, aiming to provide a design strategy of RFID Tag Distribution to enhance localisation accuracy and precision from RFID hardware level; chapter 6 would follow the investigation procedure of RFID-Loc Data Filter module and RFID-Loc Localisation Algorithm module, aiming to propose a localisation algorithm to enhance localisation accuracy and precision from RFID software level.

Chapter 4:

Experimental Configuration and Procedure In RFID-Loc Infrastructure

4.1 Introduction

This chapter represents the experimental configuration and procedure which are required by each module in RFID-Loc framework. Section 4.2 firstly examines the characteristics of RFID devices widely being used in passive RFID localisation systems. Section 4.3 would conduct the experimental platform used in this research work, which is based on the examination results from section 4.2. Section 4.4 outlines the experimental procedures which include the design of experimental approaches in both RFID-Loc infrastructure module and RFID-Loc data filtering module, and the experimental verification of proposed solutions.

4.2 Characteristic Examination of RFID Device

4.2.1 Impacted Factors in RFID-Loc Infrastructure

The characteristic examination of RFID devices is actually one investigation procedure of RFID-Loc infrastructure module. The performance of an RFID-Loc based system is relevant to many influencing issues, i.e. the type, position, and direction of tags; the moving speed of moving object; the type, position and angle of antenna; the power, type, gain, frequency range, and number of antenna; the work environment. Of those issues, some are controllable factors which can be adjusted or selected in the process of RFID hardware configuration; while some are uncontrollable factors which are already determined by RFID hardware manufactures. The impacted factors in RFID-Loc infrastructure module have been summarized in Table.3.2 and Fig.3.4. Here, a completely considerate version of Table 3.2 is extended in Table.4.1. The issues in Table 4.1 are classified as controllable factors and uncontrollable factors.

Table 4. 1 Impacted Factors in RFID-Loc Infrastructure Module

Factors	Items	Available Choices
Operating Frequency (UC)	Frequency Band and Typical RFID Applications	LF, HF, UHF, Microwave
Tag Selection (UC)	Kinds of Tag (Type and Class), Form and Size of Tag,	Passive and Active; RO and WORM, Card and Button Tag;
Reader Selection (UC)	Type of Reader, Detection Ability, Effective Detection Area.	Single or Multiple Detection; Fixed or Mobile.
Tags Arrangement (C)	Number of Tags, Tag Distance, Tag Pattern.	Grid Pattern, Triangle Pattern, Hybrid Pattern.
Reader Arrangement (C)	Number of Readers, Position of Reader, Angle of Antenna	Single or Multiple; Parallel to Ground.
Environment Condition (C)	Object Moving Speed, Compatibility and Interoperability.	Slow Speed, Compatible with other Components in VR

Notice: C is Controllable; UC is Uncontrollable.

Operating Frequency: There are four major available used radio frequency ranges: Low Frequency (30-300KHz), High Frequency (3-30MHz), Ultra-high Frequency (300Mhz-3GHz), and Microwave Frequencies (1-300GHz) (Foster, Jaeger, 2007). Low Frequency RFID systems have a short read range (less than half a meter) and lower reading speed. Due to the less absorption, LF systems are more robust to external influences; but the bandwidth available at low frequency is limited, which leads to very slow data transfer rate (5kbits/second in the case ISO18000). So the Low Frequency RFID system is not suitable for indoor applications because it would impact on the RFID data transfer speed of a RFID-Loc system. Oppositely, Ultra High Frequency RFID systems possess a smaller wavelength, and have a higher reading speed and longer read distance (up to 8 meters). The high reading speed would increase the probability of error detection; as a result that RFID reader would detect some unexpected RFID tags placed in the indoor environment from any directions. In this case, the object position is hardly to be identified by a unique set of RFID Ids. So the Ultra High Frequency RFID system is not suitable for indoor applications. Similarly, Microwave range RFID system is also not suitable for indoor applications due to its even much higher operating frequency. Consequently, High Frequency range can only be selected as an operating frequency for indoor applications, since it has a reasonable accuracy and read speed, feasible reading distance, and data transfer speed comparing to others frequency range.

RFID Tag: Regarding the selection of RFID Tags, as reviewed in Chapter 2, due to the smaller sensing range, the utility of placing a high density of passive tags would potentially reach higher localisation accuracy than the utility of placing active tags in RFID-based localisation system. So RFID passive tags can be chosen as a major hardware component in RFID-Loc infrastructure. As for the class of RFID tag class, RFID-Loc system merely needs RFID tags to store a unique identifier of position; so RO (read only) or WORM (write once and read many) tags can be used (Sanghera, 2007). The form and size of RFID tag must be compatible with the indoor environment. The card and button shape passive tags are most commonly available in industry application. Considering the availability of space in a indoor environment, the size of a RFID tag is expected as small as possible; so that RFID tag distribution can be as dense as possible.

RFID Reader: The selection of RFID reader concerns some characteristics of RFID reader. RFID reader could typically support one, four or eight antenna ports (Sanghera, 2007). In an indoor moving object localisation application, moving object is the only target aiming to be localized; so the position of moving object, the position of RFID reader and its antenna must be consistent. RFID reader in this case should be chosen as a single RFID reader containing one plane antenna, attached to a moving object. RFID reader must be anti-collision and mobile so that it can observe a large volume of RFID data over time as object is moving.

The uncontrollable factors in a RFID-Loc infrastructure module can follow guidance in Table 4.2:

Table 4. 2 Uncontrollable Factors Guidance in a RFID-Loc Infrastructure

Factors	***Suggested Choices***
Operating Frequency (UC)	High Frequency
Tag Selection (UC)	Passive, Read only, Button or Card Tag
Reader Selection (UC)	One Plane Antenna, Multiple Detection, Mobile.

Thus, in terms of Table 4.2, the current widely used RFID devices are examined, which are normal passive Button and Card tags, and an anti-collision RFID reader with one plane antenna.

4.2.1 Characteristic of Single Tag Operating

In this experiment, the characteristic of single tag operating is examined. An RFID reader was provided for each RFID tag. Tags were attached to the front or sides of a moving object. The antenna of RFID reader sent the power and signal to an RFID tag, and the tag returned a response signal to the RFID reader. The assumption is that Ratio of the number of RFID reader to the number of RFID tag: 1:1; Effect of tag's orientation is ignored; Effects from metallic substances are eliminated.

a) Effect of tag size on operating range

A tag was attached to a wheel, and the effective operating range was measured while a researcher pushed the wheel in front of the RFID reader at a natural speed. The testing results are shown in Table 4.3:

Table 4. 3 Effect of RFID tag size on efficient sensing range

	Button Tags	***Card Tags***
Tag dimensions	3 cm (R)	5.5 (w) × 8.5 (d) cm
Tag surface area	7.065 cm^2	46.75 cm^2
Operating range	1-3 cm	0 – 18 cm

b) Effect of tag orientation

The orientation of RFID tag would also affect the efficient operating range. The operating range varied as the angle of the RFID reader antenna coil relative to the tag antenna coil changed. This effect is referred to as the tag's orientation characteristic. When the angle of inclination from the Y-axis (parallel to the plane of the RFID reader antenna coil) is θ ,

θ = 0 (parallel) : Maximum operating range

θ = 90 (parallel) : Minimum operating range

RFID tags were attached to the front (0) and sides (90) of a cube, and the operating range was tested. The operating characteristic was also checked with θ values of 0, 30, 60 and 90 degrees. The test was conducted with the cube at various angles, and the effect of the tag angle on the operating range was measured in Table 4.4. It can be seem that when the card tag angle was 90, the operating range decreased by 30%.

Table 4. 4 Effect of RFID tag orientation

	Button Tags				***Card Tags***			
Tag angle	0	30	60	90	0	30	60	90
Operating range	1cm	1cm	1cm	1cm	18cm	14cm	14cm	12cm

4.2.2 Characteristic of Single Reader Operating

The antenna of RFID reader is a plane with 31 × 62 cm^2, which can be calibrated approximately as a number of gird (3cm × 4cm). RFID tags were located into different positions in Figure 4.1.

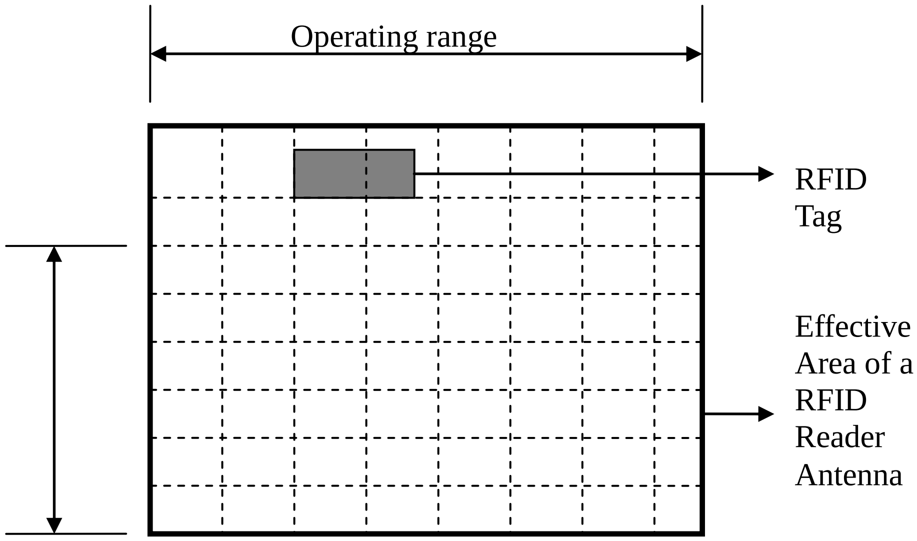


Figure 4. 1 Testing a effective detection area of RFID reader antenna

The test was conducted with attached tags of various sizes, and the effect of the tag size on the range was measured. The results are shown in Figure 4.2 and Table 4.5.

Table 4. 5 Effect of RFID Reader Operating Range

	Button Tags	***Card Tags***
Antenna dimensions	31 × 62 cm^2	31 × 62 cm^2
Antenna effective area	470 cm^2	1800 cm^2
Operating range	1cm	14cm

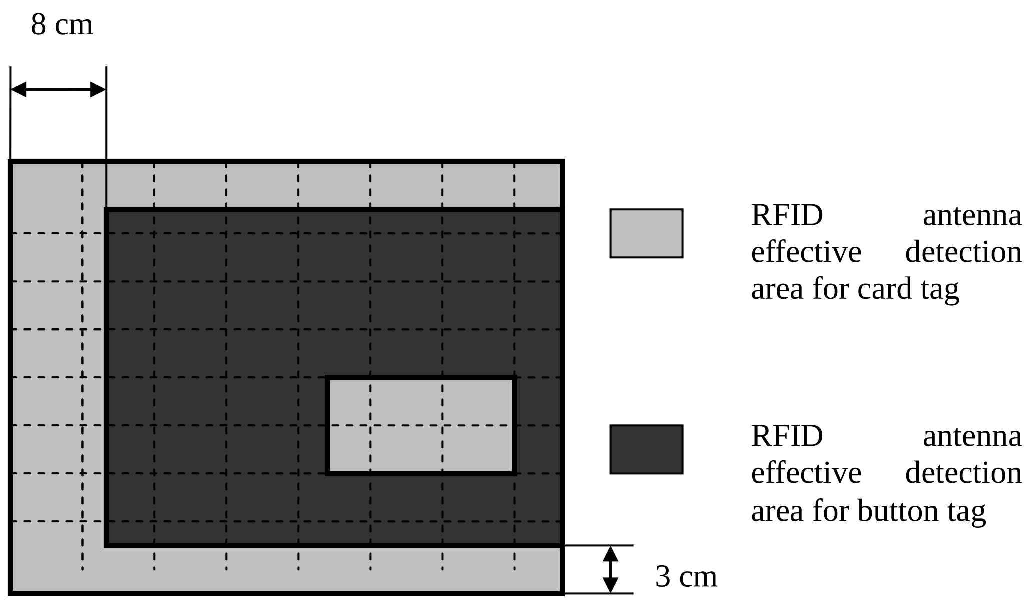


Figure 4. 2 Effective detection area of a RFID reader antenna for button and card tags.

4.2.3 Characteristics of Multiple Tags Operating

The multiple passive tags are distributed on the floor in different numbers, and then testing the success detection rates for different numbers of tags. For this test, the movement velocity of RFID reader was relative low, and communication data volume was also low. The results are shown in Table 4.6, when the number of RFID tags was 10 or more, operating failures occurred. If the movement velocity or data volume were increased, the operating success rate would decrease further. Meanwhile, the card tags perform a higher success detection rate than the button tags in multiple tags operating condition.

Table 4. 6 Characteristics of Multiple Tags Operating

	Button Tags				***Card Tags***			
Number of Tags	5	10	15	20	5	8	10	15
Operating successful rate	60%	50%	40%	30%	100%	100%	100%	93%

4.3 Experimental Configuration

By examining the characteristics of RFID devices, passive RFID card tags have a longer effective sensing distance than passive RFID button tag; it may because RFID card tag has a larger area to reflect the radio frequency signal. However, due to a smaller size of button tags, the density of passive RFID button tags distributing in an assumed grid pattern can be higher than the card tags, which potentially lead to smaller tag distance and higher object localisation accuracy. Considering this issue, passive RFID button tags are more feasible to be used in RFID-Loc infrastructure with providing potential higher localisation accuracy. Also, the results show that the orientation of RFID tags has a slight influence on the successful detection of RFID reader within an effective sensing range. The reason is that passive RFID tags cannot send signals continuously and RFID reader communicates with passive RFID tags by coupling techniques; so if passive RFID tags within an effective sensing zone of RFID reader, the distance between RFID tags and RFID readers has stronger impacts on the successful detection than the angle of RFID tags. As for the characteristics of multiple tags operating, RF wave travels from the transmitter to the receiver, it can be affected by various factors, i.e. absorption, attenuation, dielectric effect, diffraction, free space loss, interference, reflection, refraction, scattering. Both passive RFID card tags and button tags cannot be detected completely in practical, which means that the collision of passive RFID tags occurs and cannot be removed. The experiment of multiple tags operating is based on a dense RFID tags environment; the collision between passive RFID tags is sensitive and uncertain. False reading error in an RFID-Loc infrastructure is an indefensible issue.

Therefore, the parameters of RFID devices configuration in the experiment platform of this thesis are as follow:

Operating frequency: 13.56 MHz

Antenna: directional rectangle panel of size 66 × 30 cm^2

Number of RFID reader: One

Type of RFID tag: Passive

RFID reader: mobile and anti-collision

RFID Tag Arrangement pattern: A non-overlap grid pattern

RFID Tag form and size: Card Tag, 8.5×5.5cm^2

Button Tag, 3cm

Height of RFID reader : Card Tag Pattern, 10cm

Button Tag Pattern, 1cm

Effective reading area of an RFID reader's antenna : Card Tag, 35 × 65 cm^2

Button Tag, 31 × 58 cm^2

4.4 Experimental Procedure

4.4.1 RFID-Loc Infrastructure Module

As mentioned in Chapter 3, *system reading efficiency* can be used as a benchmark to evaluate the design of an RFID-Loc infrastructure. The successful design of an RFID-Loc infrastructure can deliver a stably high *system reading efficiency* over time, resulting in a precise indoor object localisation. An experimental approach is designed in this section to explore the influence of the controllable factors on *system reading efficiency* in an RFID-Loc infrastructure. The proposed experimental approach would focus on a comprehensive study of RFID Tag Arrangement. A qualitative study on the relationship between Global Tag Density and *System Reading Efficiency* is firstly carried out in this part. Secondly, a qualitative study on the relationship between Directional Tag Density and *System Reading Efficiency* is done. The specific content of this experimental approach is listed in the Table 4.7

Table 4. 7 Experimental procedure in an RFID-Loc Infrastructure module

Parts	**Contents**	**Items**
Study on RFID Tag Distribution	Global Tag Density and System Reading Efficiency	Reduced Tag number
	Directional Tag Density and System Reading Efficiency	Reduced Columns of Tag Pattern
		Reduced Rows of Tag Pattern
		Reduced Both Rows and Columns of Tag Pattern

4.4.2 RFID-Loc Data Filter Module

In this module, the experimental approach is designed to explore how *regular false reading errors* influencing on RFID raw data under a given RFID-Loc infrastructure. The experimental approach is designed into two parts. The first part is to collect the required RFID data; the second part is the analysis of RFID data and discussion. Data collection aims to observe RFID raw data from varied situations in order to analyse a distribution of regular false reading error. Most of RFID devices in the RFID-Loc infrastructure are fixed and unchangeable; so the moving trajectory of indoor object is an issue to be considered in this experiment. Indoor object moving trajectory in this experiment is assumed to be three types: moving along X axis; moving along Y axis; randomly moving in the area. Another concerned issue is time period of each time interval. RFID reader requires a time period to collect a sufficient RFID raw data; if time period is too short, RFID reader cannot observe a fulfilled data; if time period is too long, time gap between two steps of localising a moving object is not satisfied with indoor requirements. By testing some time intervals (2 minutes, 1 minute, 40 seconds, 20 seconds and 10 seconds), 40 seconds at each time interval is an acceptable time period to observe a sufficient RFID data. The number of time interval sequence is given as 25. As for the RFID data analysis, the first step is to investigate the occurring possibility of the type's *regular false-error reading* in terms of collected RFID data. The second step is to conduct an evaluation function by distribution of these occurring possibilities of *regular false-error reading.* The conducted evaluation function can be used to justify feature selection methods.

4.4.3 Experimental Verification of RFID-Loc Framework

The experimental verification of RFID-Loc mainly includes three parts, which are:

a): verification of new strategies of RFID Tag Arrangement delivered from RFID-Loc infrastructure module on improving accuracy and precision.

b): verification of new localisation algorithms from RFID-Loc localisation algorithm module on improving accuracy and precision.

c): verification of the whole solution from RFID-Loc framework on improving accuracy and precision

The experimental data would be from three moving object trajectories, which are X (vertical direction) axis moving, Y (horizontal direction) axis moving and both X axis and Y axis moving.

4.5 Summary

This chapter represents the experimental configuration and procedure which are required by the investigation procedure of each module in RFID-Loc framework. The characteristics of RFID devices widely used in passive RFID localisation systems are examined in section 4.2, passive RFID card and button tag, HF based anti-collision RFID reader are selected as the major experimental devices in this thesis. Section 4.3 conducts the experimental platform used in this research work. The relevant experimental procedures which are used in RFID-Loc framework are explained and outlined in section 4.4 including the design of experimental approaches in both RFID-Loc infrastructure module and RFID-Loc data filtering module, and the experimental verification of potentially proposed solutions. The next chapter focuses on how to design an RFID Tag Arrangement strategy to improve the localisation accuracy and precision.

Chapter 5:

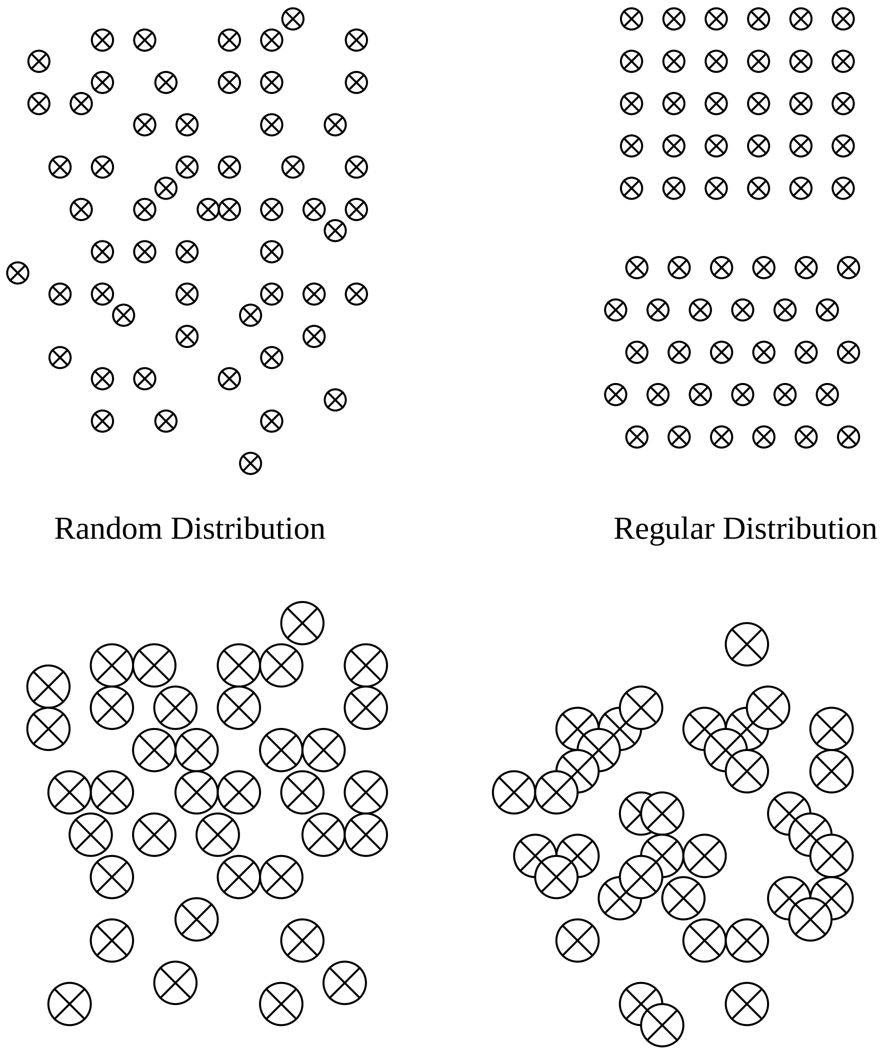
RFID Tag Arrangement

5.1 Introduction

Section 4.2 has addressed that RFID-Loc infrastructure module includes the uncontrollable factors of selecting RFID hardware devices and the controllable factors of their deployment. Under a given experimental configuration with known uncontrollable factors in Chapter 4, this chapter would focus on how to arrange RFID tags distribution for improving localisation accuracy and precision in a RFID-Loc framework. Section 5.3 defines a model of measuring accuracy and precision from RFID-Loc infrastructure level for indoor object localisation system. Then, by carrying on the experimental procedures defined in last chapter, section 5.4 conducts a function to reflect the relationship between RFID Tag Distribution and localisation precision. A sparse RFID Tag Distribution is proposed for an RFID-Loc solution in section 5.5, with the capability of enhancing *system reading efficiency* from RFID infrastructure level, so as to improve precision of RFID-Loc solution.

5.2 Fundamental Concept

RFID tags arrangement is to study how to distribute RFID passive tags as a pattern. Typically, RFID Tag Arrangements can be classified into four types by two criterions in Figure 5.1, i.e. *Random Distribution* and *Regular Distribution, Overlap distribution* and *Non-overlap Distribution.*



Random Distribution Regular Distribution

Non-Overlap Distribution Overlap Distribution

Figure 5. 1 Typical classification of Tag Arrangement patterns

RFID tag pattern can be also consisted of multiple types' tags, which are named as *Uniform Distribution* and *Hybrid Distribution* in Figure 5.2. The pattern of *Uniform Tag Distribution* refers that the distributed passive tags are uniformly made from the same type. The pattern of *Hybrid Tag Distribution* means that the distributed passive tags are mixed by various types.

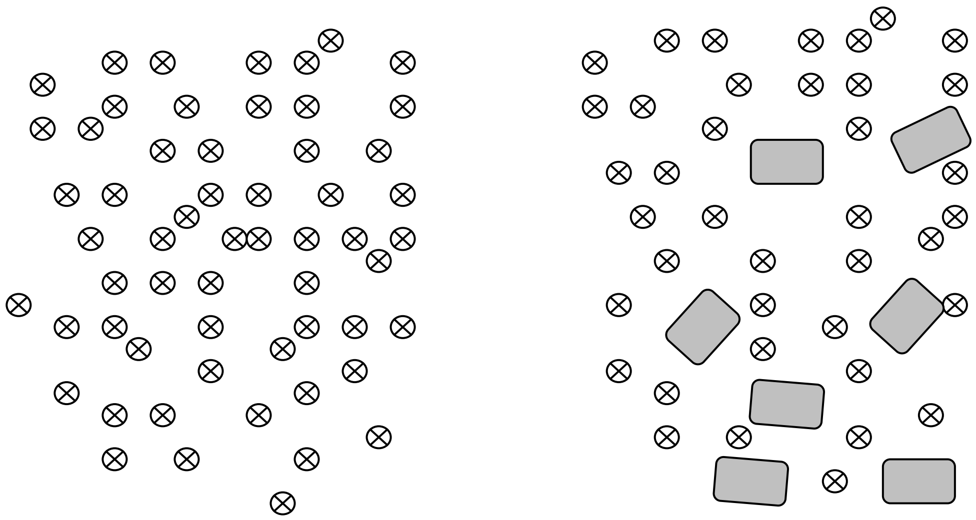


Figure 5. 2 Complemented classification of Tag Arrangement patterns

As mentioned in Chapter 1, 2D localisation system for an indoor moving object application demands a precise and homogeneous accuracy. Random tag distribution cannot ensure a homogeneous accuracy in a 2D space, because tags in this pattern are placed in a random and inhomogeneous manner. Overlap tag distribution would enhance the tag collision due to the shadowing affect between adjacent tags. So the RFID passive tag pattern in an RFID-Loc infrastructure can be initially assumed as a regular, non-overlap and well-proportioned grid pattern. As illustrated in Figure.5.3, a well-proportioned Grid Pattern can be presented by denoting four parameters C_p, R_p, D_x and D_y in an effective detection area of RFID reader antenna**,** where C_p is the number of grid point placing on each column of the Grid pattern; R_p is the number of grid point placing on each row of the Grid pattern; D_x is the distance between each two neighbouring grid points along the row direction of the Grid pattern; D_y is the distance between each two neighbouring gird points along the column direction of the Grid pattern. Regarding to this Grid pattern, most of passive RFID based object localisation system would make RFID Tag Distribution fully cover each grid point of the Grid pattern, where C_g and R_g represent the number of passive RFID tag placing on column and row direction of the Grid pattern respectively.

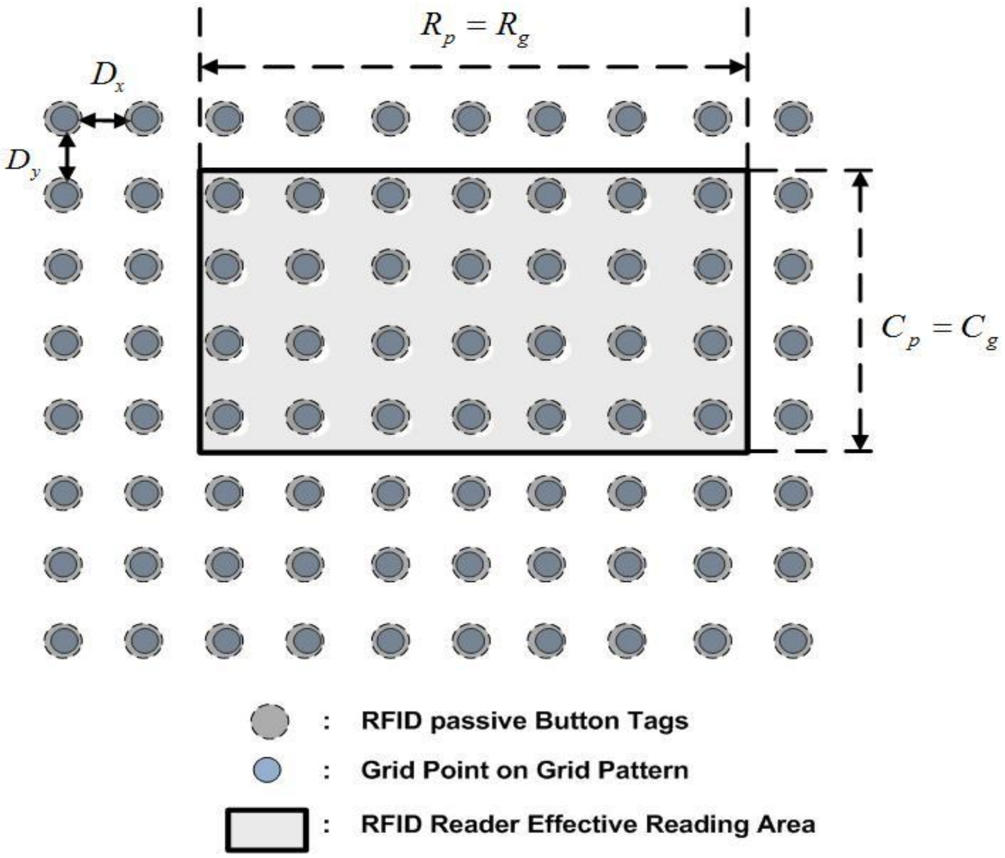


Figure 5. 3 Typical Grid Pattern fully covered by passive RFID Tag Distribution

And then the relationship between C_p, R_p and C_g, R_g can be written as:

$$\begin{cases} C_p = C_g \\ R_p = R_g \end{cases} \qquad 5.1$$

Given the above assumption, the firstly controllable factors in an RFID-Loc infrastructure include that tags distance and size, tags density, the column and row of the pattern. The secondly controllable factors in an RFID infrastructure involve the effective reading area of RFID reader, the size of Antenna, the height of RFID reader and the angle of antenna. These controllable factors are highly sensitive and relevant to the state-of-the-art of current RFID manufactures. Table 5.1 shows a list of parameters relevant to the controllable factors in an RFID-Loc Infrastructure and mathematical symbolization in this thesis.

Table 5. 1 Mathematical Symbolization of parameters

Factors	***Mathematical Symbolization of Parameters***
Tag Arrangement (C)	**N:** Number of grid points placing in an effective detection area of RFID reader Antenna,
	C_p : Number of grid point placing on each column of the Grid pattern.
	R_p : Number of grid point placing on each row of the Grid pattern.
	D_x **:** Distance of tags on X axis in the RFID reader detection area.
	D_y **:** Distance of tags on Y axis in the RFID reader detection area.
	M: Number of passive RFID tags distributing in an effective detection area of RFID reader antenna
	C_g : Number of RFID Tags placing on each column of the Grid pattern.
	R_g : Number of RFID Tags placing on each row of the Grid pattern.
Reader Arrangement (C)	**H :** Height of RFID reader effective detection
	W_R : Width of the RFID reader effective detected elliptical area.
	L_R : Length of the RFID reader effective detected elliptical area.
	θ **:** Angle of Antenna to the tag pattern.

5.3 Measure for Localisation Accuracy and Precision

This section defines a model of measuring accuracy and precision from RFID-Loc infrastructure level for indoor object localisation system. This model contains two Equations, which are used to separately measure the accuracy and precision in a RFID-Loc based system. With a given RFID tag distribution based on Grid pattern shown in Figure. 5.3, the number of grid points placing in an effective detection area of RFID reader antenna has been denoted as N, the number of passive RFID tags distributing in an effective detection area of RFID reader antenna has been denoted as M , where N and M satisfy Equation 5.2.

$$\begin{cases} N = C_p \times R_p \\ M = C_g \times R_g \end{cases} \quad 5.2$$

Typically, the accuracy and precision are relevant to many influencing issues, i.e. the type, position, and direction of tags; the moving speed of object; the type, position and angle of antenna; the power, type, gain, frequency range, and number of antenna; the work environment; localisation algorithm. This chapter merely focuses on the impacted factors of RFID Tag Arrangement on localisation accuracy and precision in a passive RFID object localisation system. But, the localisation algorithm used in our verification is initially assumed as an effective and simple localisation method proposed by Han (Han, 2007), as follows:

$$\begin{cases} f_x = \dfrac{Min(x_1, x_2, \ldots x_m) + Max(x_1, x_2, \ldots x_m)}{2} \\ f_y = \dfrac{Min(y_1, y_2, \ldots y_m) + Max(y_1, y_2, \ldots y_m)}{2} \end{cases} \quad 5.3$$

Here, $\{x_1, y_1\}, \{x_2, y_2\}, \ldots \{x_m, y_m\}$ represents the coordinates of passive RFID tags being detected at each time interval t; f_x and f_y respectively represent localisation algorithms to calculate the position of the targeted position of object from captured RFID data. Regarding to the description of Grid pattern in Figure.5.3 and Table 5.1, the parameters C_p and R_p has determined a density of Grid pattern, so the localisation accuracy would be decided by the parameters D_x and D_y. Then the first Equation of this model to measure the localisation accuracy can be written as:

$$\text{Accurracy}: \begin{cases} A_x = D_x \\ A_y = D_y \end{cases} \quad 5.4$$

In order to quantitively evaluate the impacts of RFID Tag Distribution on localisation precision, a benchmark named as *system reading efficiency* (defined in Chapter 3) is used to reflect the successful detection ability from RFID-Loc infrastructure level in a RFID-Loc based system.

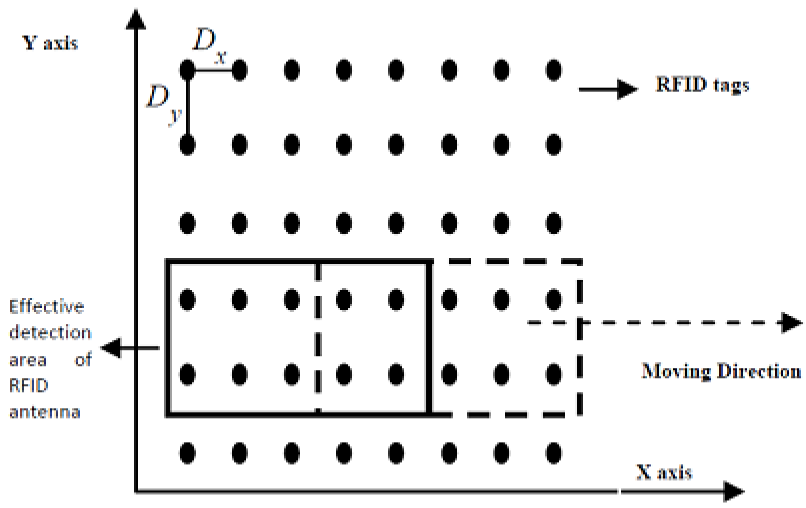
If RFID reader can successfully detect any passive tags within its effective detection area, the value of *SRE* would be “1”, which means all readings have been successfully attempted. Practically, it is impossible to consistently get all attempted RFID tag detections, the practical value of *SRE* can be a value between “0” and “1”. As for RFID Tag Distribution, the value of *SRE* would be relevant to the number of passive RFID tags distributing in an effective detection area of RFID reader antenna M . Then the impacts of RFID Tag Distribution on *system reading efficiency* can be initially conducted into a function, which is relevant to the parameters M ; this function can be written as:

$$F_{SRE} = f(M) = f(C_g, R_g) \qquad 5.5$$

Expect *system reading efficiency*, considering the localisation algorithm in Equation 5.3, localisation precision is also determined by two factors of RFID Tag Distribution, which are C_g and R_g. Practically, the value of *system reading efficiency* in a dense RFID tag environment is not high due to tag collision. Considering that passive RFID tags producing from one manufacturer, here the detection ability of individual passive RFID tag within an effective reading area of RFID reader can be approximately assumed as equivalent, so the value of SRE can be recognized as the probability of an individual passive RFID tag being detected within an effective reading area of RFID reader. The successful process of localisation algorithm in Equation 5.3 has to guarantee a condition that at each time interval, RFID reader is capable of detecting at least one RFID tag along each border of the effective reading area of RFID reader, with respectively representing the feature value of $Min(x_1, x_2, ...x_m)$, $Max(x_1, x_2, ...x_m)$ and $Min(y_1, y_2, ...y_m)$, $Max(y_1, y_2, ...y_m)$. Consequently, localisation precision here can be recognized as the possible number of RFID tag being detected along each border of effective reading area of RFID reader. If the value of possible number is higher, it means that localisation precision is smaller. Then the second Equation of this model to measure localisation precision can be written as:

$$\text{Precision}: \begin{cases} P_x = R_g \times F_{SRE} = R_g \times f(M) \\ P_y = C_g \times F_{SRE} = C_g \times f(M) \end{cases} \qquad 5.6$$

In order to measure the practical value of *system reading efficiency*, an evaluation function is defined to measure it in the experiments. Theoretically, if an indoor environment was not interfered, the value of *system reading efficiency* in an RFID-Loc infrastructure can be approximately stable as object is moving. Practically, there are some uncertain issues potentially influencing the value of *system reading efficiency* at individual measurement, i.e. the changeable moving speed, variable environment interference. Therefore, an average mean method is used to calculate the value of *system reading efficiency* over a number of time intervals as the practical value of *system reading efficiency*. An evaluation function for *system reading efficiency* in this experiment is defined to measure the practical value of *system reading efficiency*.



$$N = M = 10 \qquad R_p = R_E = 5 \quad C_p = C_E = 2$$

Figure 5. 4 Practical Setup for measuring SRE by Equation 5.7

Figure 5.4 illustrate s a diagram of a RFID-Loc infrastructure setup with a given experiment platform. From Figure 5.4, it can be seen that a grid pattern of RFID tags is placed on the floor with tag distance of D_x on X axis and D_y on Y axis. The number of RFID tags placing in an effective detection area is 10; the number of Column and Row in an effective detection area of RFID antenna is separately 5 and 2. RFID reader can only move along the X direction in a time intervals of T. At each individual time interval, e.g. T_m, RFID reader is assumed to practically detect a certain number of passive RFID tags M_t. Practical value of *System Reading Efficiency (SRE)* can be calculated by using Equation 5.7.

$$SRE = \frac{\sum_{1}^{T} m_t}{M \times T} = \frac{\sum_{1}^{T} m_t}{C_g \times R_g \times T} \quad 5.7$$

Where :

SRE : Value of *System Reading Efficiency*

T : Number of time steps

M : Number of passive RFID tags distributing in an effective detection area of RFID reader antenna

m_t : Number of RFID tags being practically detected at time step t.

C_g **:** Number of passive RFID tag placing on column direction of the Grid pattern

R_g **:** Number of passive RFID tag placing on row direction of the Grid pattern

Additionally, considering the parameters of experiments configuration in Chapter 4.3, RFID reader has to wait a sufficient time period until as many as RFID tags within a effective detection area of RFID antenna are scanned and their data being processed. Regarding as the experimental testing, the feasible period is tested by 20 seconds, 40 seconds, 60 seconds and 120 seconds. The testing results show that the period of 40 seconds can approximately get a *system reading efficiency* up to 50%, and the period of 60 seconds and 120 seconds cannot obviously improve a value of *system reading efficiency*, which is about 52% and 55%. So in this experiment, the period of every time interval is given as 40 seconds.

5.4 Investigation of RFID Tag Distribution

This section would mainly consider Global tags density and RFID tags arrangement in a RFID infrastructure as the key influencing factors. RFID tags density is normally a value relating to the size of an effective detection area of RFID reader and the number of passive RFID tags in this area. Considering that the size of an effective detection area of RFID reader is already fixed once the uncontrollable factors in Section 4.2 have been determined, global tag density directly depends on the number of tags in the effective RFID reading area: M . If RFID tags are placing on the floor, the effective operating range of RFID tag would be the height of RFID antenna, and the effective reading area of RFID antenna is normally affected by the height of RFID antenna. So the investigation in this section would use the number of RFID tags in an effective RFID reading area to instead of the representation of tag density. The angle of RFID reader antenna is parallel to the plane placing passive RFID tags. Ideally, RFID reader would be expected to detect sufficient RFID tags within an effective sensing area at each time interval, which is 40 seconds.

5.4.1 Global Tag Density and System Reading Efficiency

Global Tag Density refers to the whole number of RFID tags placing M in an efficient detection area of RFID antenna. Under the given experimental platform, if RFID tags are chosen as button tag or card tag, height of RFID reader would be determined by an effective sensing range of RFID tags, so that an effective detection area of RFID antenna would be known as a constant value. The investigation of relationship between Global Tag Density and *System Reading Efficiency* is actually to study the impact of total number of RFID tags in an efficient detection area M on *system reading efficiency*. Therefore, in this experiment, it carries out a procedure of regularly reducing M in a given constant effective reading area, and analyzes its impacts on *system reading efficiency*. The procedure of reducing M in this section is to regularly make a reduction in both columns and rows of different RFID tags pattern.

The first tested pattern is based on RFID button tags. RFID Button tags are placed in a highly dense grid pattern, with 11×4 number of RFID tags. Then C_g and R_g in this grid pattern would be reduced regularly in 5 steps, with the number of RFID card tags as: 6×4, 6×2, 4×2, 3×2, 3×1, as shown in Figure 5.5. The explicit information of RFID button tag patterns in Figure 5.5 is shown in Table 5.2.

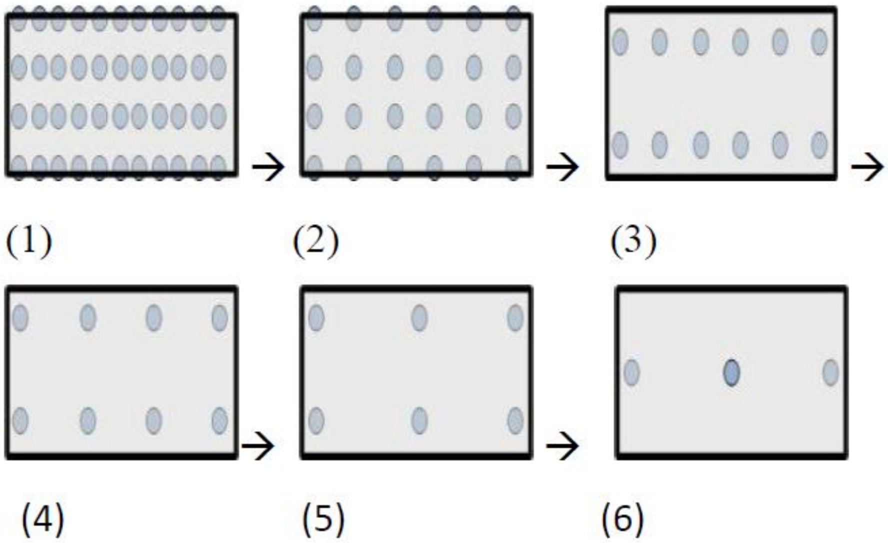


Figure 5. 5 Experiment process of reducing Global Tag Density of RFID Button Tags from Step 1 to Step 6

Table 5. 2 Explicit Value of RFID Button Patterns in Figure 4.6

	Step 1	***Step2***	***Step 3***	***Step 4***	***Step 5***	***Step 6***
M	**44**	**24**	**12**	**8**	**6**	**3**
R_g	**11**	**6**	**6**	**4**	**3**	**3**
C_g	**4**	**4**	**2**	**2**	**2**	**1**
D_x **(cm)**	**5**	**10**	**10**	**15**	**30**	**30**
D_y **(cm)**	**8**	**8**	**16**	**16**	**16**	**32**

From Table 5.2, it appears that **M** has reduced from 44 to 3. And the value of *system reading efficiency* at different value of ***M*** is measured and drawn in Figure 5.6.

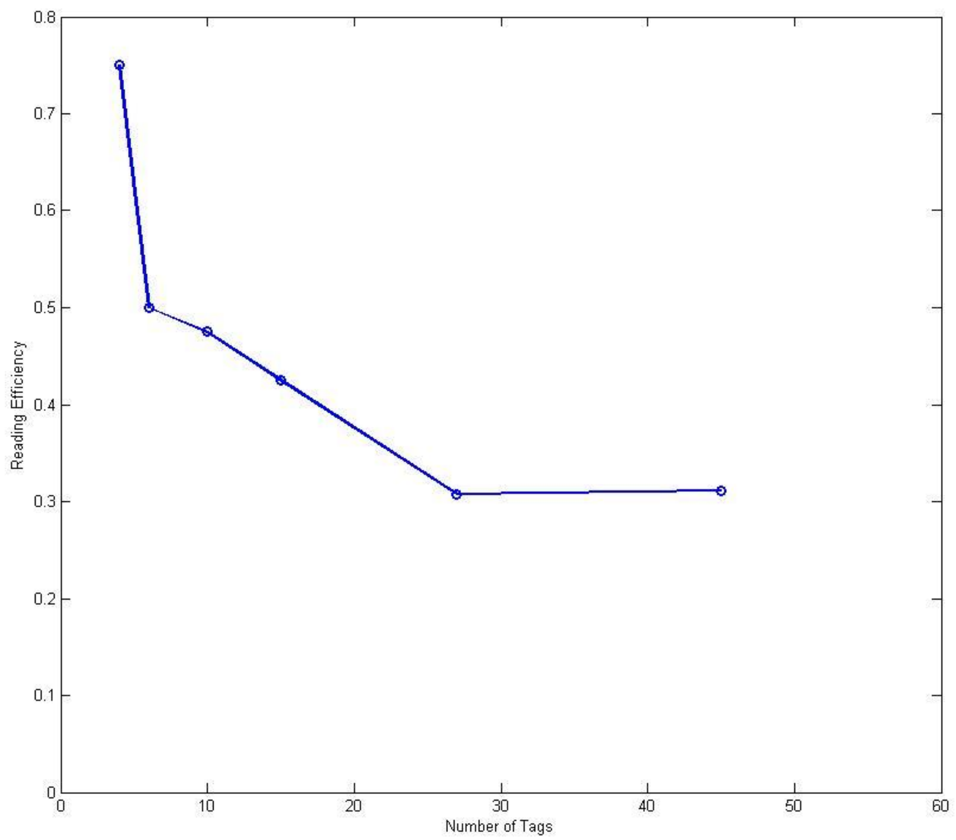


Figure 5. 6 *SRE* evaluation on reducing M on RFID Button tag patterns

Figure 5.6 illustrates that as the reduction of ***M***, the value of *system reading efficiency* would gradually increase. However, the increasing speed of this line in Figure 4.8 is not consistently constant. On the condition that RFID Button tag pattern is under a low-level tag density, the value of *system reading efficiency* would sharply increase; oppositely, on the condition that RFID Button tag pattern is under a high-level tag density, the value of *system reading efficiency* would not dramatically increase.

The second tested pattern is based on RFID Card tags. RFID Card tags are placed in a seamless non-overlap grid pattern, with 12×5 number of RFID tags. Then C_g and R_g in this seamless non-overlap grid pattern would be reduced regularly in 7 steps, with the number of RFID card tags as: 9×3, 6×3, 3×3, 3×2, 2×2, 2×1, as shown in Figure 5.7. The explicit information of RFID card tag patterns in Figure 5.7 is shown in Table 5.3.

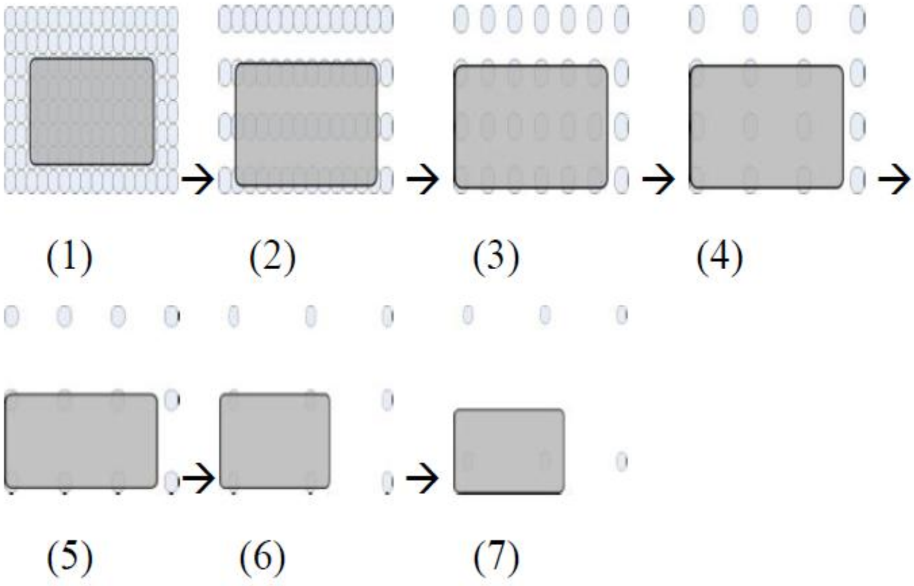


Figure 5. 7 Experiment process of reducing Global Tag Density of Card Tags from Step 1 to Step 7

Table 5. 3 Explicit Value of RFID Card Tag Patterns in Figure 5.7

	Step 1	*Step 2*	*Step 3*	*Step 4*	*Step 5*	*Step 6*	*Step 7*
M	60	36	18	9	6	4	2
R_g	12	12	6	3	3	2	2
C_g	5	3	3	3	2	2	1
D_x (cm)	5.5	5.5	11	22	22	32	32
D_y (cm)	8	16	16	16	32	32	64

From Table 5.3, it appears that **M** has reduced from 60 to 2. And the value of *system reading efficiency* at each ***M*** is measured and drawn in Figure 5.8.

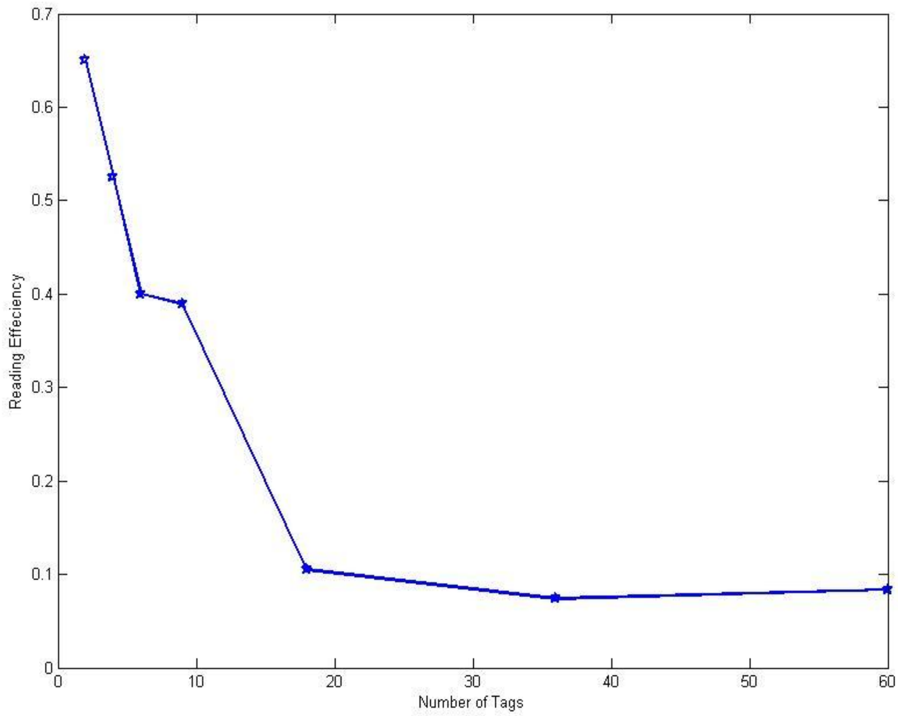


Figure 5. 8 *SRE* evaluation on reducing M on RFID Card tag patterns.

Figure 5.8 indicates that as the reduction of ***M***, the value of *system reading efficiency* would also gradually increase. The increasing speed of this line in Figure 5.8 is not consistently constant, as similar as the phenomenon in RFID button tags pattern in Figure 5.6.

The experimental results in Figure 5.6 and 5.8 explore that on both passive RFID button and card tag pattern conditions, *System Reading Efficiency* can be reduced as **M** increasing. The results also reflect that the value of *SRE* can be continuously enhanced by global tag density in a grid RFID tag pattern, which means that the precision of RFID object localisation system can be improved. However, as the reduction of global tag density in a grid RFID tag pattern, Tag distance D_x and D_y would be increased, which leads to the loss of accuracy in an RFID object localisation system. Oppositely, in order to achieve a high accuracy of RFID based object localisation system, RFID tag pattern has to be highly dense with a small Tag distance, but this action would reduce the value of *system reading efficiency* and lead to a lower localisation precision. Additionally, Figure 5.6 and 5.8 also shows that given a similar tag distance, RFID button tags can offer a higher *system reading efficiency* than RFID card tags. Consequently, the recommended RFID tag pattern in a passive RFID object localisation system has to be based on a balance of global tag density, *system reading efficiency* and tag distance.

5.4.2 Directional Tag Density and System Reading Efficiency

Experiments in last section are under an assumption that the reduction of global tag density is regular. While passive RFID tags are manufactured from the uniform industrial standard, behaviour of each individual RFID tag in this grid pattern is usually not equivalent. This section gives a qualitative research on exploring the relationship between directional tag density and *system reading efficiency (SRE)*. Directional tag density refers to the number of RFID tags placing on individual row or column directions in an efficient detection area. The effect of *system reading efficiency* can be examined by merely reducing C_g in a RFID tag pattern, or merely reducing R_g in a RFID tag pattern.

Impact of merely reducing Column's number on SRE

In this experiment, it evaluates the impact of merely reducing R_g in a given grid tag pattern on *system reading efficiency*. As for RFID card tags, it starts from a seamless grid tag pattern of Step 1 in Figure 5.5. Then it gradually reduces R_g in this pattern from 12 to 6, 3,2, , with a unchangeable C_g = 5 and D_y = 8cm. As for RFID button tags, Figure 5.9 reflects that under a pattern with highly-dense global tag density, *system reading efficiency* of RFID button tags does not change dramatically, it begins from a grid based button tag pattern with R_g = 4 and D_x = 5cm, C_g = 4 and D_y = 8cm. Then it gradually reduces R_g in this pattern from 4 to 3, 2,1, with a unchangeable C_g = 4 and D_y = 8cm. The explicit value of experiments Pattern is shown in Table 5.4. The experiment results are illustrated in Figure 5.9.

Table 5. 4 Explicit Value of RFID Pattern in merely reducing R_g

	Pattern Information	Step 1	Step2	Step3	Step4
Card Tag	M	60	30	20	10
	R_g	12	6	4	2
	C_g	5	5	5	5
	D_x (cm)	5.5	11	16	32
	D_y (cm)	8	8	8	8
Button Tag	M	16	12	8	4
	R_g	4	3	2	1
	C_g	4	4	4	4
	D_x (cm)	5	10	10	15
	D_y (cm)	8	8	8	8

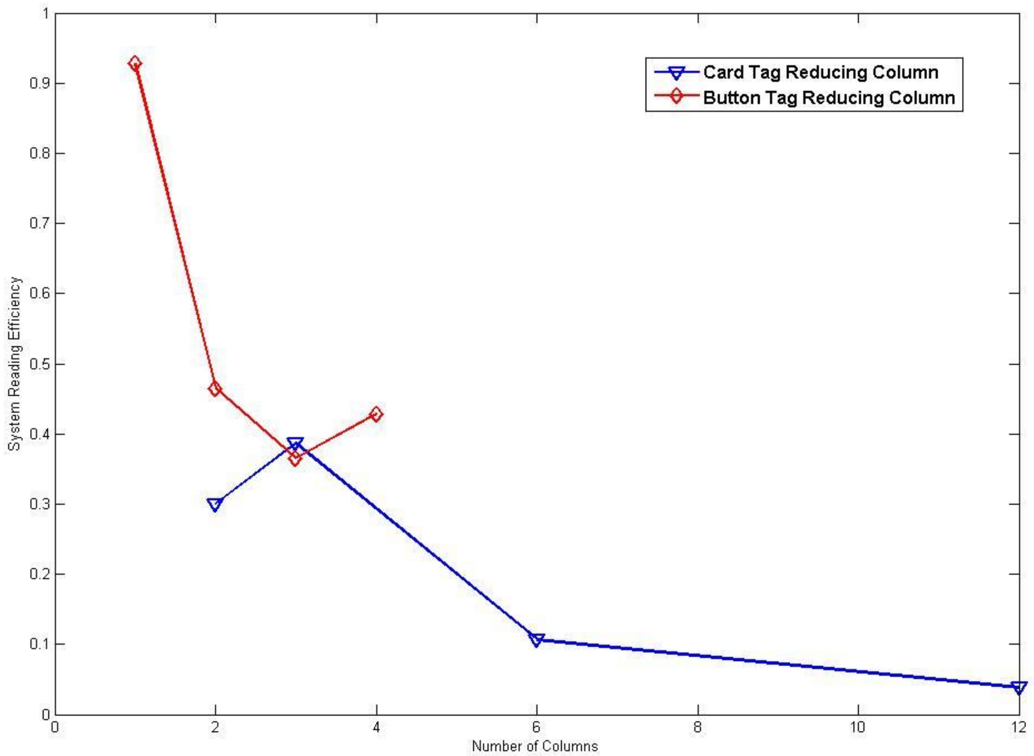


Figure 5. 9 *SRE* evaluation on merely reducing R_g on grid tag pattern

From Figure 5.9, it appears that as the reduction of R_g, the general trend of *SRE* is increasing. The reason is that the total number of RFID tags in an effective detection area **M** is reduced so that the impact of RFID passive tag collision is less. On card tags situations, with the reduction of column's number, the value of *SRE* initially increases to a maximum peak, and then reduces bit. On button tag situations, with the reduction of column's number, the value of *SRE* firstly decreases to a peak, and then increases rapidly.

Impact of merely reducing Row's number on SRE

In this experiment, it evaluates the impact of merely reducing C_g in a given grid tag pattern on *system reading efficiency*. As for RFID card tags, it starts from a seamless tag pattern of Step 1 in Figure 5.7. Then it gradually reduces C_g in this pattern from 5 to 4, 3,2,1, with a unchangeable R_g = 12 and D_x= 5.5 cm. As for RFID button tags, it has a smaller size with 3 centimeters radius so this time it begins from a grid tag pattern with smaller tag distance D_y = 5cm, then it gives a higher value of C_g = 7, also with R_g = 6 and D_x= 10cm.In the following steps, it gradually reduces C_g in this pattern from 7 to 4, 3, 2,1, with a unchangeable R_g = 6 and D_x= 10cm. The explicit value of experiments Pattern is shown in Table 5.5. The experiment results are illustrated in Figure 5.10.

Table 5. 5 Explicit Value of RFID Pattern in Merely reducing C_g

	Pattern Information	*Step 1*	*Step 2*	*Step 3*	*Step 4*	*Step 5*
Card Tag	**M**	**60**	**48**	**36**	**24**	**12**
	R_g	**12**	**12**	**12**	**12**	**12**
	C_g	**5**	**4**	**3**	**2**	**1**
	D_x **(cm)**	**5.5**	**5.5**	**5.5**	**5.5**	**5.5**
	D_y **(cm)**	**8**	**15**	**20**	**30**	**50**
Button Tag	**M**	**42**	**24**	**18**	**12**	**6**
	R_g	**6**	**6**	**6**	**6**	**6**
	C_g	**7**	**4**	**3**	**2**	**1**
	D_x **(cm)**	**10**	**10**	**10**	**10**	**10**
	D_y **(cm)**	**5**	**8**	**10**	**15**	**20**

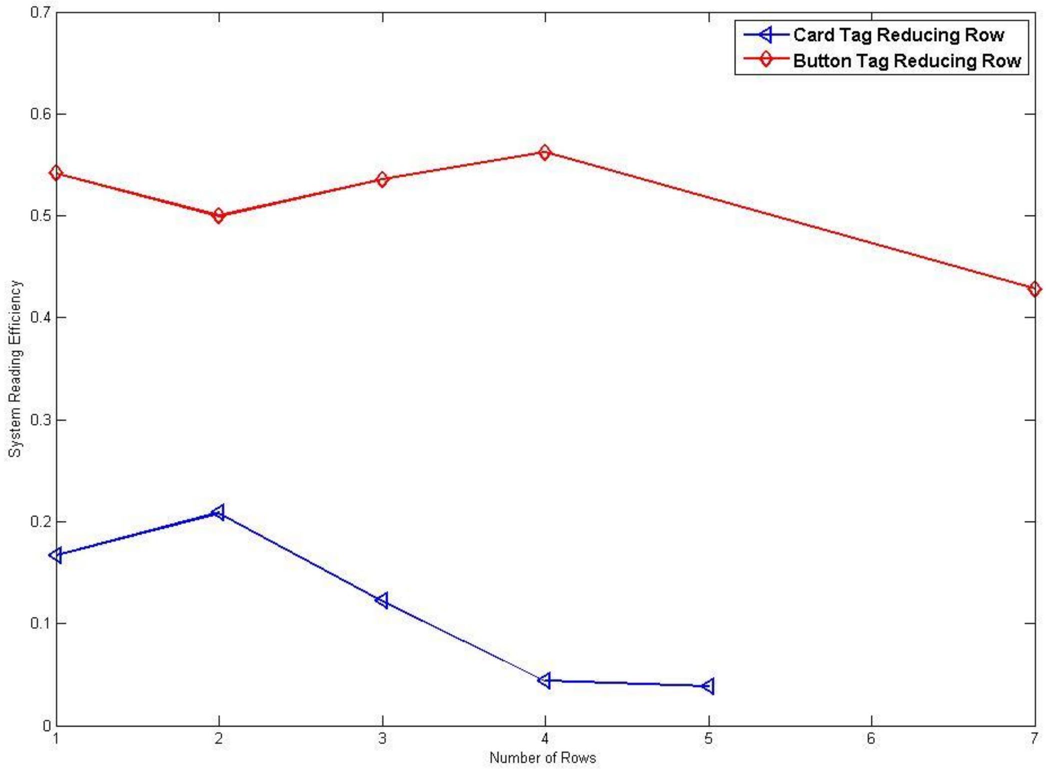


Figure 5. 10 *SRE* evaluation on reducing Rows' number C_g on grid tag pattern.

Figure 5.10 illustrates the impact of reducing C_g in a grid tag pattern on SRE is similar as the reduction of R_g in last section. As the reduction of row's number, the trend of *SRE* is also increasing. However, the growth of *SRE* in Figure 5.10 is not monotone, even with some points out of the expectation.

Actually, the value of *SRE* is a ratio related to both the practical number of success reading tags and desired number of reading tags. As the reduction of column's number or the reduction of row's number in a grid tag pattern, both the desired number of reading tags and practical number of success reading tags are actually reduced. The value of *SRE* is merely to reflect their ratio of change, so the ratio of change is not always monotone. Additionally, comparing to button tag, the circuit area of card tag is larger, so the *SRE* of card tags pattern are less impacted by the reduction of rows or columns than the *SRE* of button tags pattern.

Comparison of Directional and Global tag density's Impact on SRE

The impact of directional and global tag density on *SRE* are compared by respectively reduce both the columns' number and rows' number on card tags pattern in this section. Card tag curve of reducing rows' number in Figure 5.10 is selected as a case, if on this case, the value of given C_g is reducing from 12 to 6 and 4, the Card tag curve of reducing rows' number in Figure 5.11 is drawn by the same experimental procedure in Table 5.5, Figure 5.11 shows their performance on C_g = 12, 6 and 3.

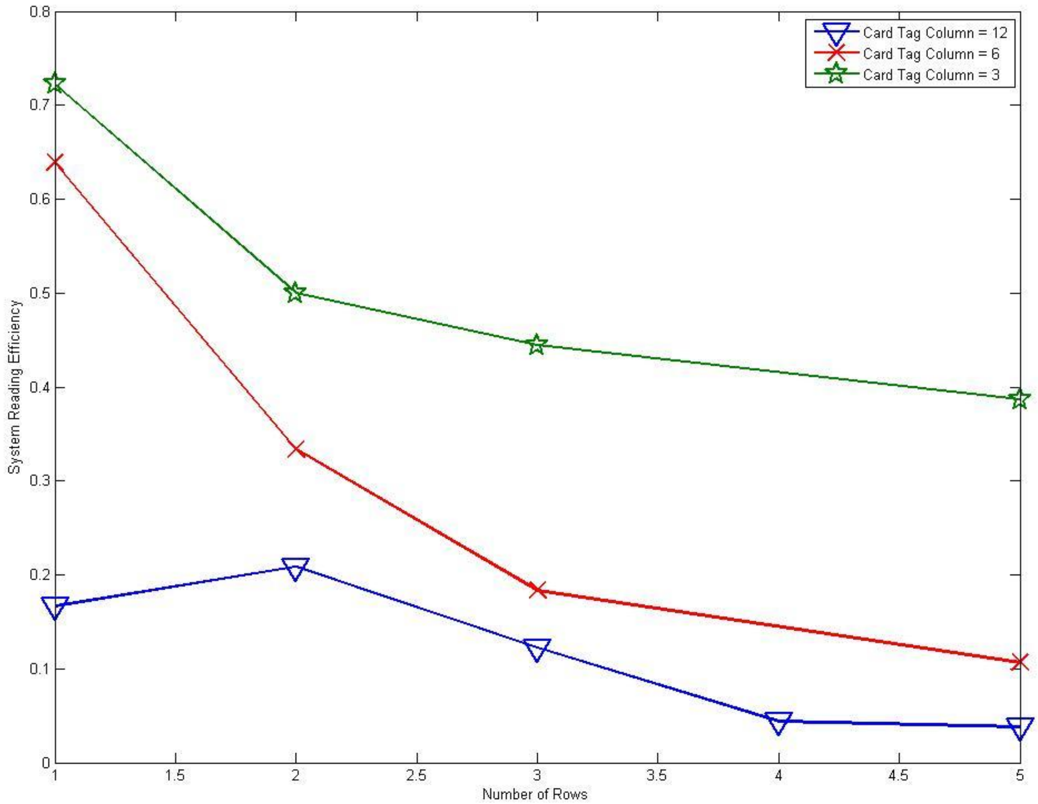


Figure 5. 11 *SRE* on reducing both Row and Column's number of Card Tag Pattern

Figure 5.11 indicates that as the reduction of columns 'number in a RFID card tag grid pattern, the curve describing *SRE with the reduction of row's number* would clearly move upward, without any collisions. It implies that the major issue impacting on *SRE* is the total number of tags placing in RFID reader effective detection area, not directional tag density of a RFID grid pattern. The number of rows and columns on grid tag pattern also are some issues influencing on *SRE*, but they are not the key issues. Regarding to the assumption in part A, the influence of global tag density in this experiment can be equal to the influence of the number of tags ***M*** in an effective RFID antenna reading area. In other words, global tag density on a grid tag pattern is the key issue influencing the value of *SRE*. The directional tag density on tag pattern is the secondary issue influencing the value of *SRE*.

5.4.3 RFID Reader Moving Direction and System Reading Efficiency

The impact of moving direction of RFID reader on *System Reading Efficiency* (SRE) is investigated in this section. Typically, a RFID reader can move along either its antenna's width or length directions, as shown in Figure 5.12.

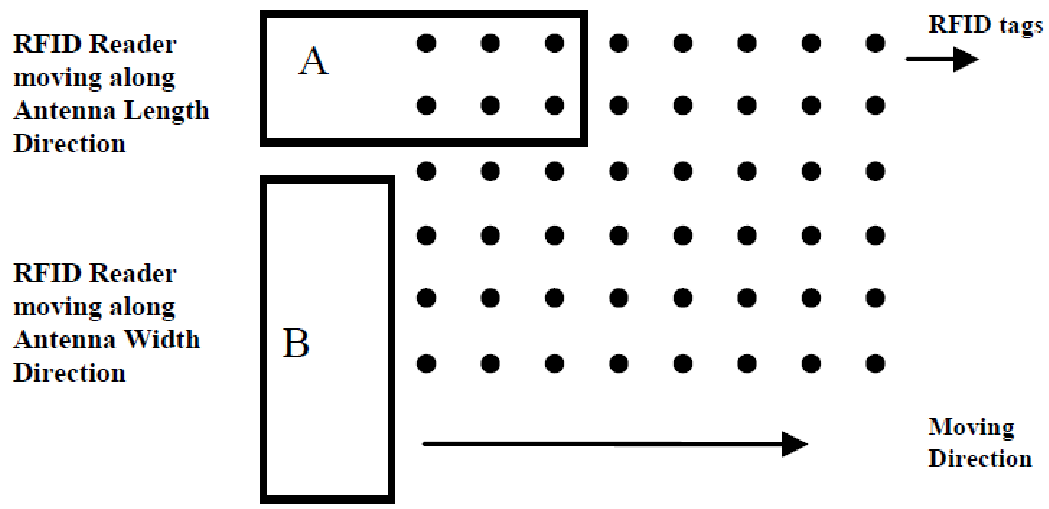


Figure 5. 12 Two typical RFID reader's moving directions

The antenna of RFID reader used in the experiment is rectangle. Theoretically, RFID reader can move forward from any degree, but for the sake of simplicity, it initially considers RFID reader moves along the direction of its length axis **A** or its width axis **B**. From Figure 5.12, it illustrates two directions of RFID reader's moving, one is moving along the length direction of antenna of RFID reader, the other is moving along the width direction of antenna of RFID reader.

Firstly, RFID card tag pattern is used to test the impact of RFID reader's moving directions on *system reading efficiency*. Under given experimental platform, if five card tag patterns are initially used with D_x = D_y = 8cm, 10cm, 20cm, 30cm, 40cm; the corresponding number of row and columns on RFID reader moving direction A and B can be shown in Table 5.6.

Table 5. 6 Explicit Value of Card Tag Pattern on Testing impacts of RFID moving directions A and B.

	Pattern Information	***Step 1***	***Step 2***	***Step 3***	***Step 4***	***Step 5***
	Num	**40**	**24**	**12**	**6**	**1**
Directions	D_x **(cm)**	**8**	**10**	**20**	**30**	**40**
	D_y **(cm)**	**8**	**10**	**20**	**30**	**40**
A	R_g	**8**	**6**	**4**	**3**	**1**
	C_g	**5**	**4**	**3**	**2**	**1**
B	R_g	**5**	**4**	**3**	**2**	**1**
	C_g	**8**	**6**	**4**	**3**	**1**

The previous sections have conducted that global tag density is the major issue affecting the value of *system reading efficiency*, so while two directions give different value of R_g and C_g on the same RFID grid pattern, **M** has not changed yet. So **M** is used as the index of X axis for evaluation. The evaluation results of *system reading efficiency* on above five RFID card tag rectangle patterns are shown in Figure 5.13.

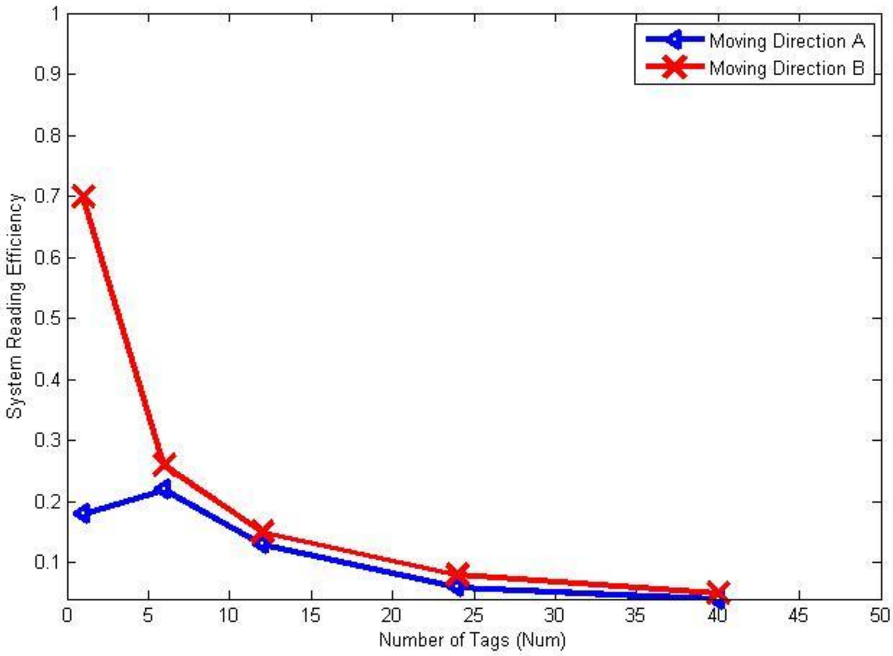


Figure 5. 13 *SRE* evaluation with different RFID reader moving directions on RFID Card Tag Pattern.

Figure 5.13 firstly has proved the argument in previous section that global tag density on a grid tag pattern is the key issue influencing the value of *SRE*. Also, under an identical RFID card tag grid pattern, RFID reader moving directions A and B can give an approximately identical value of *system reading efficiency* on a middle-level or high-level global tag density conditions. However, on a low-level global tag density conditions, RFID reader moving direction B get a much higher value of *system reading efficiency* than RFID reader moving direction A.

Secondly, RFID Button tag pattern is used to test the impact of RFID reader's moving directions on *system reading efficiency*. Under given experimental platform, if four button tag patterns are initially used with $D_x = D_y$ = 5cm, 10cm, 20cm, 30cm; the corresponding number of row and columns on RFID reader moving direction A and B can be shown in Table 5.7.

Table 5. 7 Explicit Value of Button Tag Pattern on Testing impacts of RFID moving directions A and B.

	Pattern Information	***Step 1***	***Step 2***	***Step 3***	***Step 4***
Directions	**Num**	**84**	**24**	**6**	**2**
	D_x **(cm)**	**5**	**10**	**20**	**30**
	D_y **(cm)**	**5**	**10**	**20**	**30**
A	R_g	**12**	**6**	**3**	**2**
	C_g	**7**	**4**	**2**	**1**
B	R_g	**7**	**4**	**2**	**1**
	C_g	**12**	**6**	**3**	**2**

The evaluation results of *system reading efficiency* on above four RFID button tag rectangle patterns are shown in Figure 5.14.

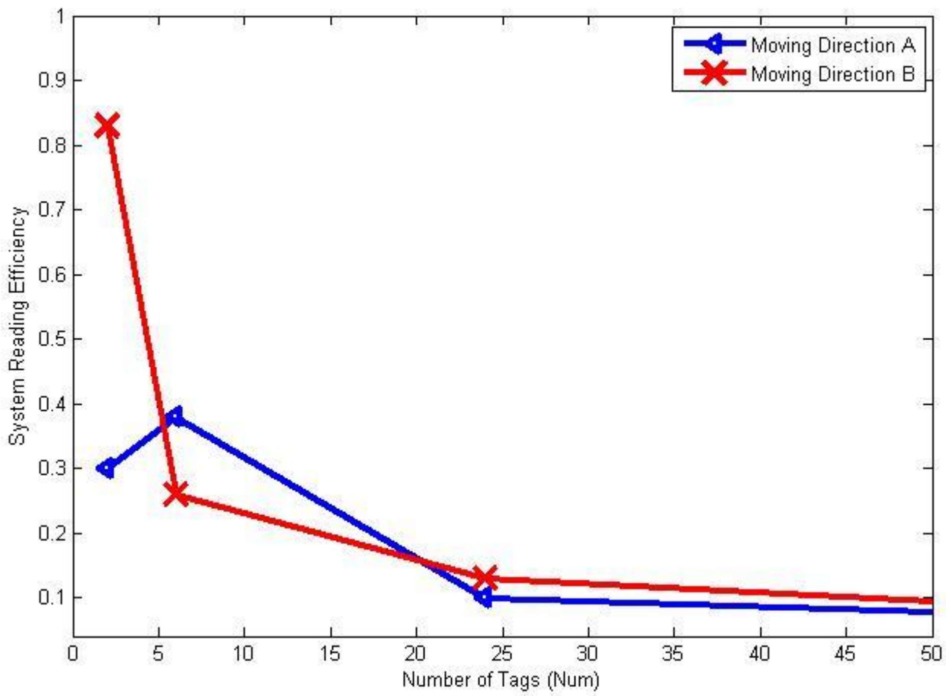


Figure 5. 14 *SRE* evaluation with different RFID reader moving directions on Button Tag Pattern.

Figure 5.14 illustrates a similar affect as Figure 5.12. On an identical RFID Button tag grid pattern, RFID reader moving directions A and B can give an approximately identical value of *system reading efficiency* on a middle-level or high-level global tag density conditions. However, on a low-level global tag density conditions, RFID reader moving direction B get a much higher value of *system reading efficiency* than RFID reader moving direction A.

The results in Figure 5.14 and 5.12 explore that the moving direction of RFID reader is definitely influencing on the value of *SRE* on both RFID card tag and button tag grid pattern. Regarding as most of RFID reader's antenna, power gains are not equal along the four edges of antenna, so that the measured value of *SRE* would be different when RFID reader moves along different directions. However, on the condition that global tag density of a grid RFID pattern is in a middle or high level, this influence is slight to affect the value of *system reading efficiency* of a passive RFID localisation system. It is probably because on a middle or high global tag density, the topology of RFID distribution in a pattern does not change the effect of tag collision too much. On the other hand, Figure 5.14 and 5.12 also prove the argument of previous sections that global tag density on a grid tag pattern is the key issue influencing the value of *SRE*. Additionally, Figure 5.14 and 5.12 shows that given a similar tag distance, RFID button tags can offer a higher *system reading efficiency* than RFID card tags.

5.4.4 Findings and Discussion

The experimental findings of above sections can be concluded as follow:

(1) Global tag density is a major factor impacting on *system reading efficiency* in a passive RFID objective localisation system. Directional tag density is the secondary issue influencing *system reading efficiency*. The effect of directional tag density is merely obvious on the condition with a low global tag density.

(2) The impact of an increasing number of RFID tags in an effective reading area **M** on the value of *system reading efficiency* approximately follows a decreasing trend. It means that with the reduction of global tag density in a RFID grid pattern, *system reading efficiency* of a passive RFID localisation system would be enhanced.

(3) The direction of RFID reader moving has some impacts on *system reading efficiency* in a passive RFID objective localisation system. But this impact only obviously appears in a RFID tag pattern with low-level global tag density. On a middle or high level global tag density, the effect of RFID moving directions on *system reading efficiency* can be ignored.

(4) On a similar experimental platform and given a similar tag distance, RFID button tag has a higher *system reading efficiency* than RFID card tag.

Based on above experimental findings, it implies that there is a difficulty to get both high accuracy and precision of a passive RFID object localisation system. High accuracy in a passive RFID object localisation system requires a high global density of tag pattern, which would increase the number of tags in an effective reading area so that the value of *system reading efficiency* would be reduced. The low value of *system reading efficiency* would lead to a loss of localisation precision in a RFID based localisation system. The possible solution to get both feasible accuracy and precision in a passive RFID localisation system is to achieve a balance choice on global tag density of a RFID tag pattern and *system reading efficiency* in a RFID localisation system.

In order to explore solution, we would primarily attempt to construct a mathematical function to describe the impacts of **M** on *system reading efficiency***.** The experimental finding 2 summarizes that the relationship between *system reading efficiency* and **M** can approximately follow a decreasing trend. Curving fitting techniques can be used to find the best fit to their data. Regarding to the results shown in Figure.5.6 and 5.8, a mathematical function can be conducted to describe the impacts of M on SRE by Curve Fitting techniques**.** Power function fitting and polynomial fitting and exponential function fitting can be all used to fit a non-linear monotonic decreasing function. However, considering the less utilization of estimated parameters and the fact that the value of SRE is within a range from 0 to 1, the exponential function with one estimated parameter is conducted to describe Equation 5.8, as below:

$$F_{SRE} = f(M) = e^{a \times M} = e^{a \times C_g \times R_g} \qquad 5.8$$

In this experimental platform, the times of measurement is not sufficiently large so the less number of parameters of Equation can give a better fitting. Additionally, the value of *System Reading Efficiency* is a ratio, which has to be below the value “1”. If **M** is assumed as unlimited massive, the value of *System Reading Efficiency* should be nearly equal to the value “0”. Oppositely, if **M** is as small as one, the value of *System Reading Efficiency* has to be nearly equal to the value “1”. Thus Equation 5.8 can be formally represented as in Equation 5.9.

$$F_{SRE} = f(M) = e^{a \times M} = e^{a \times C_g \times R_g} \qquad 5.9$$

Where:

SRE : Value of *System Reading Efficiency*

M : Number of passive RFID tags distributing in an effective detection area of RFID reader antenna

C_g **:** Number of passive RFID tag placing on column direction of the Grid pattern

R_g : Number of passive RFID tag placing on row direction of the Grid pattern

a: Estimated parameter.

Considering the experimental findings 3, RFID button tag is more feasible to be applied into our case than RFID card tag. Thus we would focus on conducting an explicit function for RFID button tag to describe a qualitative relationship between localisation precision and its relevant parameters C_g and R_g. In order to reach this aim, it has to estimate the value of parameter *a* in Equation 5.9 by using Least Squares Fitting of observed data. The sample data are measured by 25 pairs of the value of SRE and its corresponding parameters C_g and R_g of RFID Tag Distribution, which includes the data in Figure.5.6, 5.8 and 5.10, and also some data being observed randomly. Therefore, *SRE* Curve of RFID button tag distribution can be estimated in Equation 5.10.

Button Tag Case :

$$F_{SRE} = f(M) = e^{-0.0543 \times M} = e^{-0.0543 \times C_g \times R_g} \qquad 5.10$$

The Equation 5.4 and 5.6 of proposed model to measure localisation accuracy and precision in an passive RFID button tag based localisation system can be written as below :

$$\text{Accurracy}:\begin{cases}A_x = D_x\\ A_y = D_y\end{cases} \tag{5.11}$$

$$\text{Precision}:\begin{cases}P_x = R_g \times e^{-0.0543\times C_g\times R_g}\\ P_y = C_g \times e^{-0.0543\times C_g\times R_g}\end{cases} \tag{5.12}$$

5.5 Sparse RFID Tag Arrangement

Experiment finding in last section indicates that with a passive RFID grid tag pattern, it is hard to achieve both high accuracy and precision in a passive RFID based object localisation system. Yet, experimental finding also implies that the reduction of **M** can enhance *system reading efficiency of* an RFID localisation system. Consequently, the basic idea of sparse RFID Tag Arrangement strategy is to study the possibility of using an sparse RFID tag distribution pattern to reach a higher *system reading efficiency*, but not leading to loss of localisation accuracy in an RFID localisation system.

For a passive RFID based localisation system, if RFID Tag Distribution fully fills Grid Pattern in Figure 5.2, as the number of RFID tags M increases, localisation accuracy can be improved as the distance D_x and D_y are reduced; but localisation precision would loss as the system reading efficiency are reduced in terms of Equation 5.6. It implies that there is a difficulty to get both high accuracy and precision of a passive RFID object localisation system with a full RFID Tag Distribution. Actually, the distance D_x and D_y merely depends on the parameters C_p and R_p of Grid pattern, not determined by the parameters C_g and R_g of RFID Tag Distribution. Thus, if RFID Tags Distribution covers Grid Pattern with a sparse covering way not fully covering way, the distance D_x and D_y is not changed so that localisation accuracy can be kept as unchangeable, but localisation precision has a potent to increase due to a higher system reading efficiency. Figure 5.15 illustrates a comparison of localisation accuracy and precision with M between full RFID Tag Distribution and Sparse RFID Tag Distribution.

$C_p = C_g, R_p = R_g$ $\quad\quad$ $C_p \neq C_g, R_p \neq R_g$

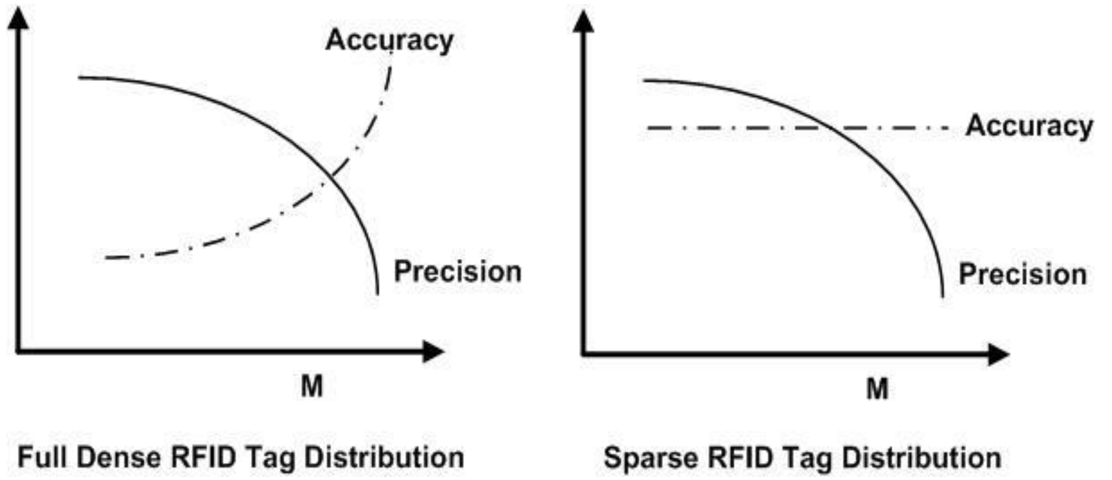


Figure 5. 15 Comparison between Two Types RFID Tag Distribution

There is another noticeable issue in sparse RFID Tag Distribution, which is to consider Equation 5.6 of proposed model to measure localisation precision. In terms of Equation 5.6, the best choice of sparse RFID tag distribution can make the precision in Equation 4.6 get the maximum value. This section would use our given experimental platform to seek out one sparse RFID Tag Distribution with improved localisation precision. Regarding as the experimental findings, RFID button tags have a better performance than RFID card button, so if we give localisation accuracy as 10 centimeters, then $D_x = D_y = 10$ cm, $C_g = C_p = 4$ and $R_g = R_p = 6$, a full RFID Button Tag Distribution over grid pattern is shown in Figure 5.16.

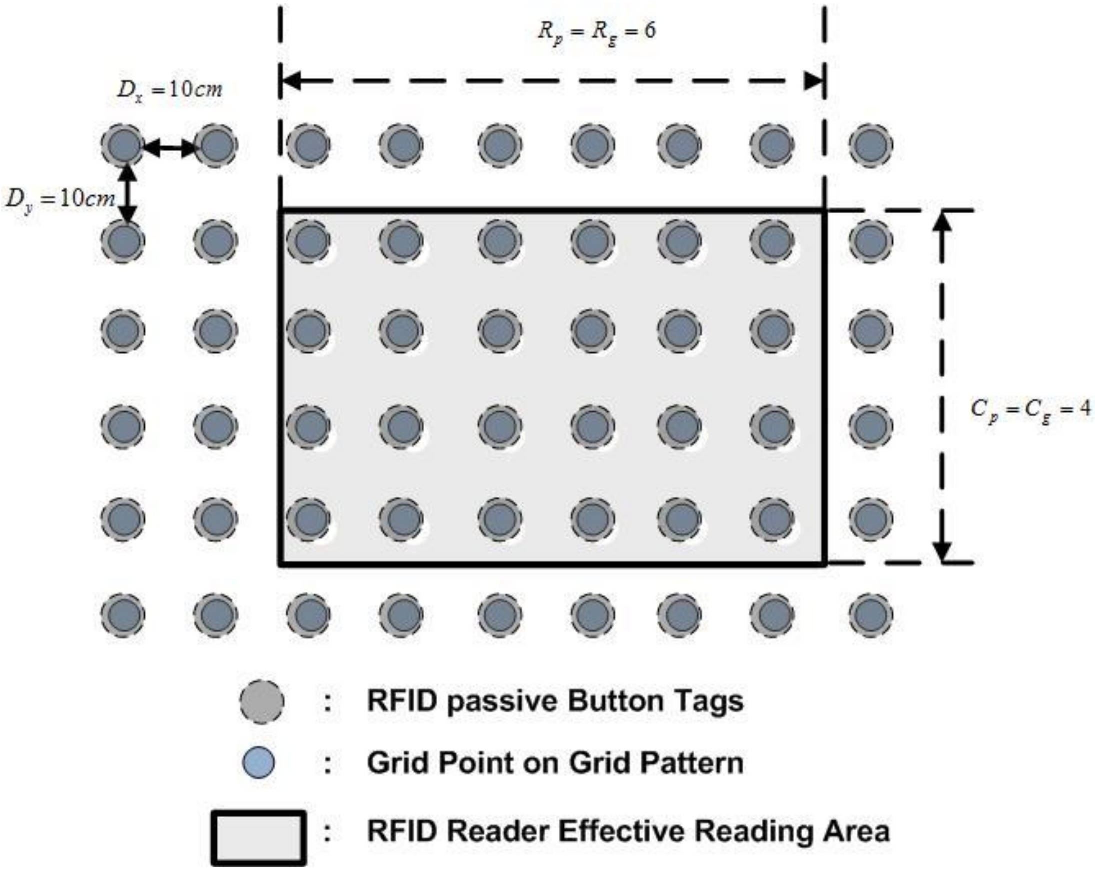


Figure 5. 16 Fully Covered RFID Button Tags Distribution

Here, the accuracy Equation 5.11 can be written as:

$$\text{Accurracy}: \begin{cases} A_x = 10\text{cm} \\ A_y = 10\text{cm} \end{cases} \qquad 5.11$$

With a given unchangeable parameters D_x and D_y of a Grid Pattern, the localisation accuracy can be not influenced by the changeable parameters C_g and R_g in RFID Tag Distribution. As for the localisation precision, it has to evaluate the value of parameters C_g and R_g with the largest value of precision by Equation 5.11. Considering that the parameters C_g and R_g cannot be changed independently, it would use M, which is the practical number of passive RFID tags distributing in an effective detection area of RFID reader antenna, to take replace of some parts in the Equation 5.12, as below:

$$\text{Precision}: \begin{cases} P_x = R_g \times e^{-0.0543\times C_g \times R_g} = R_g \times e^{-0.0543\times M} \\ P_y = C_g \times e^{-0.0543\times C_g \times R_g} = C_g \times e^{-0.0543\times M} \end{cases} \qquad 5.13$$

Then, we separately measure the precision X with the value of R_g given 6,5,4,3,2, the value of M would be respectively 24, 20, 16, 12, 8; the precision Y with the value of C_g given 4,3,2,1, the value of M would be respectively 24, 18, 12, 6. Figure 5.17 illustrates the Precision Value of Equation 5.13 with different value of parameters C_g and R_g in RFID Tag Distribution

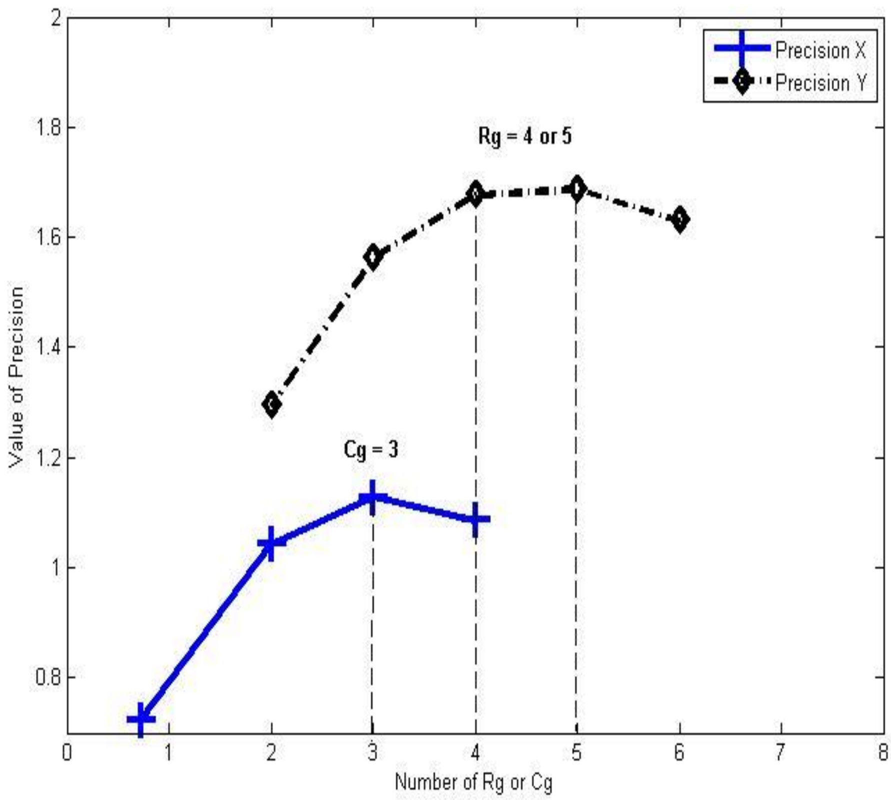


Figure 5. 17 Comparison of different C_g and R_g in RFID Tag Distribution

Figure 5.17 illustrates that when $C_g = 3$, the Precision X curve marked by solid line can reach a largest value; when $R_g = 4 \text{ or } 5$, the Precision Y curve marked by dash line can reach the largest value. Therefore, it means that in Figure 5.17, we can reduce one RFID button tag on each column of grid pattern, so that the parameter $C_g = 3$ and the parameter $M = 18$. Additionally, in order to ensure the accuracy, it has to guarantee that there are no rows of Grid pattern with non RFID Tag being placed. Therefore, the sparse RFID Tag Arrangement strategy can be summarized below:

(1) To check the possibility of sparse RFID Tag Arrangement: If the extracted value of C_g and R_g can satisfy the condition $C_g < C_p, R_g < R_p$, the possibility exists.

(2) To determine the direction of reducing tags: if $(C_p - C_g) <= (R_p - R_g)$, reducing tags from column direction of tag pattern, the reduced number of tags on each column is $(C_p - C_g)$; otherwise, reducing tags from row direction, the reduced number of tags on each row is $(R_p - R_g)$

(3) To produce the sparse RFID Tag Arrangement: start from original grid pattern, if $(C_p - C_g) <= (R_p - R_g)$, from the first column, reduce $(C_p - C_g)$ tags; however, the reduction of each column has to avoid the same row position of tag with its neighbour

(4) To recheck the sparse RFID Tag Pattern to ensure there is at least one tag on each row or column direction.

We would use a simple V-shape reduction method to produce a kind of improved RFID button Tag Distribution, shown in Figure 5.18.

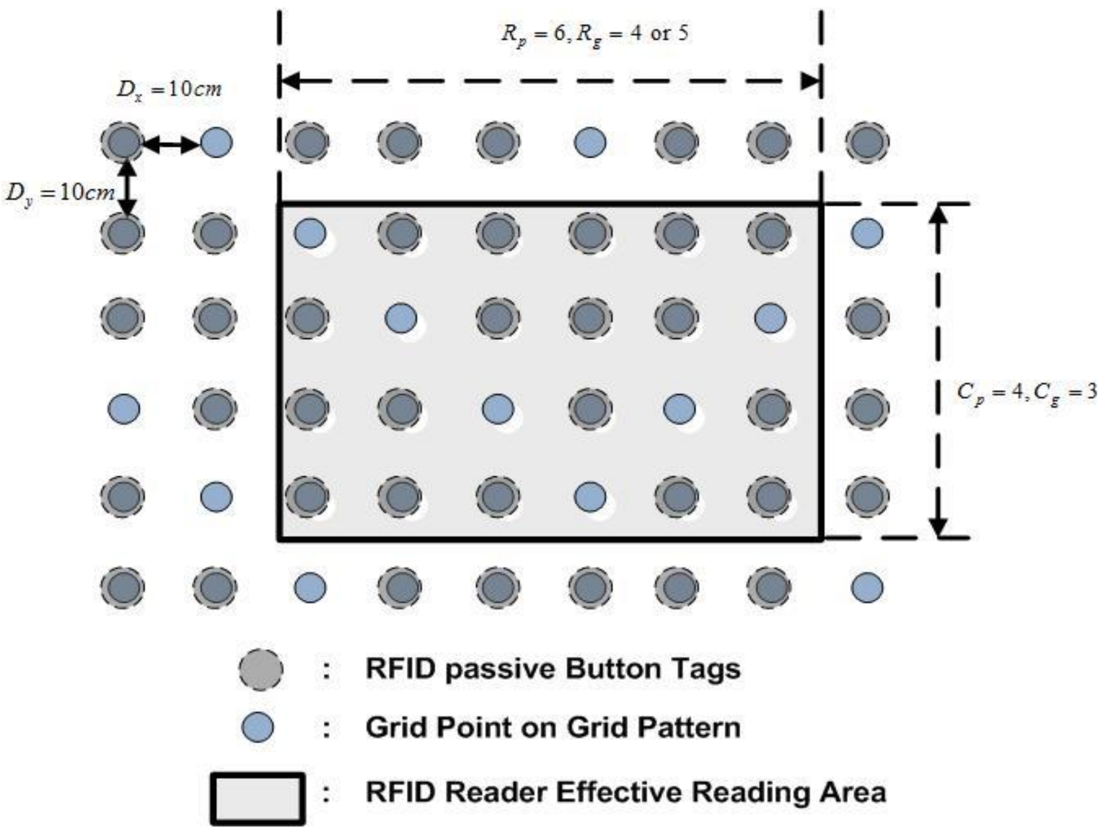


Figure 5. 18 Sparse RFID Button Tags Distribution

5.6 Summary

In this chapter, the major impacted issues in RFID Tag Arrangement of RFID-Loc with high accuracy and precision have been investigated. A model to evaluate the localisation accuracy and precision of a RFID-Loc solution, particularly on the use of RFID tag distribution pattern is proposed in section 5.3. By identifying the influencing factors of RFID Tag Distribution, an experimental solution is designed to explore the relationship between global tag density, tag distance and system reading efficiency. The experimental results in section 5.4 show that it is challenging task to get both high accuracy and precision in a passive RFID localisation solution; and there is a balance between distributing a suitable density of RFID tags so that the localisation solution can achieve a reasonable object localization accuracy and precision. The impact of RFID tag distribution and pattern design on accuracy and precision in a passive RFID localisation solution is defined and verified as an exponential based function. A spare RFID tag distribution pattern is proposed in section 5.5 for RFID-Loc infrastructure, which can enhance *system reading efficiency* with better localisation precision, but not reduce localisation accuracy of an RFID-Loc solution.

Chapter 6:

Feature Selection and Localisation Algorithm

6.1 Introduction

Chapter 5 mainly concerns the problem of how to design an effective RFID Tag Arrangement for an RFID-Loc system to enhance *system reading efficiency* for reducing *regular false reading error* from RFID hardware level. However, experimental results in Chapter 5 proves that *system reading efficiency* of an RFID infrastructure is impossible to be one in practical environment, which means that *regular false reading error* of an RFID-Loc system can be merely reduced but not completely removed by an optimal designed RFID Tag Arrangement. In this chapter, it focuses on exploring the possibility of reducing the impacts of *false reading error* on localisation accuracy and precision by using some approaches from RFID software level. Section 6.2 addresses the possibility of selecting features from RFID-Loc Data Filter module to remove the *regular false reading error*, so that improve the localisation accuracy and precision. Section 6.3 studies the possibility of improving localisation algorithm from RFID-Loc localisation algorithm module to improve the localisation accuracy and precision.

6.2 Feature Selection

6.2.1 Classification of False-Reading in RFID-Loc Data

Investigation in Chapter 5 illustrates that under current experimental platform, the practical value of *system reading efficiency* in an optimized RFID-Loc infrastructure is usually in a range from 40% to 60%. For the reason that *system reading efficiency* is impossible to be 100%, RFID data being observed at each time frame are raw and unornamented. These data are a set of RFID tag identifiers over time, and do not carry much information. While these identifiers can be corresponding to some position, they are still inaccurate and uncertain. Additionally, the observation process of RFID data is spatial and temporal, which can be dynamically variable over time. On this condition, RFID data at each time interval cannot be completely equivalent. The usage of RFID-Loc data filter module is to filter some useless information from RFID raw data, and select reliable features to feed localisation algorithm.

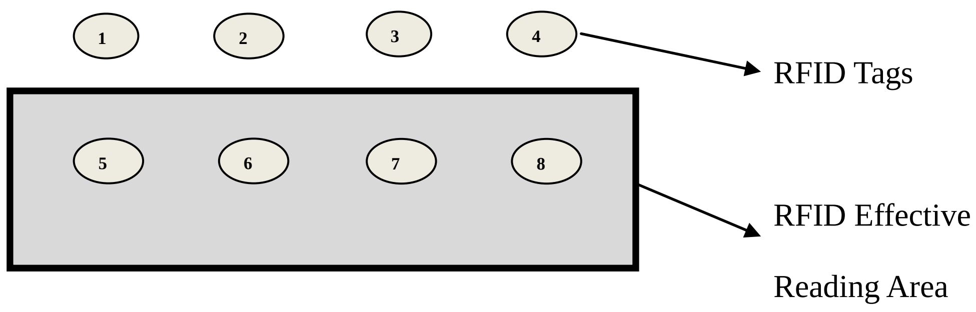
Inaccuracy and uncertainty of RFID raw data are two major challenging characteristics in a RFID-Loc system. *Regular false readings* in RFID raw data can be classified into three types: *false negative readings*, *false positive readings*, and *repeated readings*.

False negative readings: It mainly refers the case that RFID tags within an effective RFID reader detection area may not be detected due to RF collision occurring or signal interfering with each other RFID tags. These problems are common in most RFID applications and usually happen in a situation of low-cost and low-power hardware, which result in frequently dropped reading.

False positive readings: It mainly refers to the case that unexpected RFID tags detections are generated. The reasons leading to this problem are that RFID tags outside a normal reading scope of a RFID reader are captured by the RFID reader. For instance, while reading items from a case, a RFID reader may read items from an adjacent case.

Repeated readings: It mainly refers to repeated detection of RFID tags by a RFID reader in a short time. This problem is typically recognized as redundant reading issue in some RFID and sensor networks. Redundancy can happen at two different levels, redundancy at reader level and redundancy at data level. Repeated reading is a phenomenon that redundancy at data level occurred as data streams.

Of the above three type's *regular false reading*, effect of repeated reading can be ignored in a RFID-Loc system. It is because RFID raw data does not have any meaningful information before RFID raw data being stored in a database. Repeated data can be automatically eliminated in a corresponding process of position information. The definition of an effective RFID reading area here refers to a robustly stable detection area, which is a limited zone surround RFID antenna. It is not similar to some impression that once RFID tags can be detected in a certain area; this area would be considered as an effective RFID reading area. Figure 6.1 illustrates some difference of false-negative readings, false-positive readings and repeated readings.



a) False-negative reading Sample ID : {1,5,6,7,8} {2,3,5,6,7,8}….

b) False-positive reading Sample ID : {5,6,7} {6,7,8} {5,7}…..

c) Repeated readings Sample ID : {5,5,5,5,6} {6,6,6,7,7,7,8}…

Figure 6. 1 Difference of *false-negative readings, false-positive readings* and *repeated readings*.

6.2.2 Experimental Analysis

Given the classifications, experimental approach is designed to explore how *regular false reading errors* influencing on RFID raw data under an optimal RFID-Loc infrastructure. The experimental approach is designed into two parts. The first part is to collect the required RFID data; the second part is the analysis of RFID data and discussion.

6.2.2.1 Data Collection

RFID data is observed on a recommended optimal RFID-Loc infrastructure from chapter 4, which consists by a single RFID reader: anti-collision, antenna dimensions 65×31 cm^2; multiple RFID passive button tags: radius 3 cm; effective sensing height of RFID reader: 1-2cm; operating frequency: 13.56 MHz. The distance between tags is 10 centimetres; and the total number of tag in an effective RFID detection area is 18; RFID passive tag pattern is shown in Figure 6.2, which reflects that the practically desired number of RFID tags in an effective RFID detection area is 18.

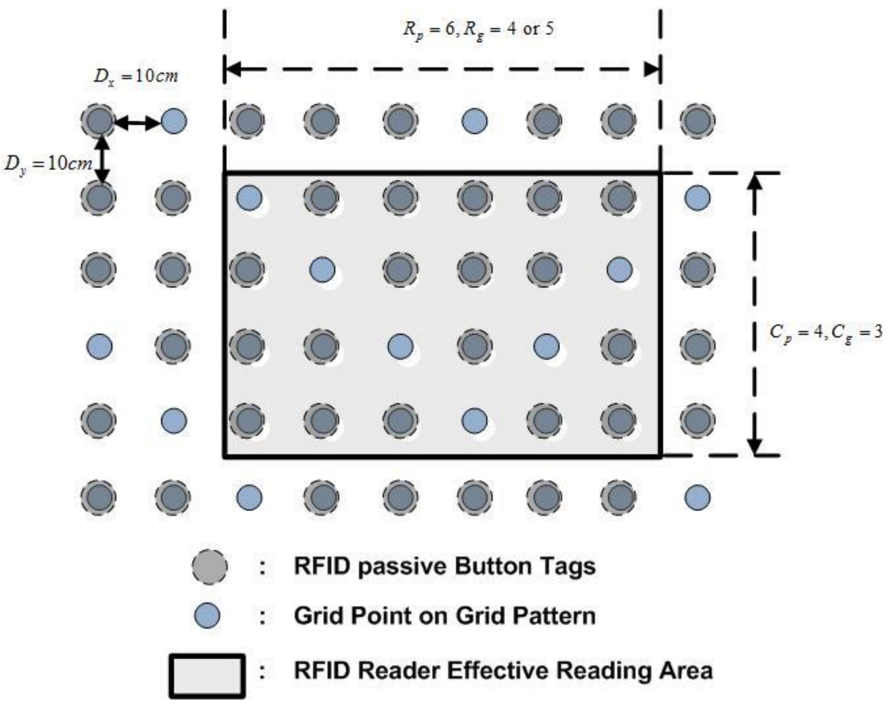


Figure 6. 2 Experimental Platform for Data Collection

Data collection aims to observe RFID raw data from varied situations in order to analyse a distribution of regular false reading error. Most of RFID devices in the RFID-Loc infrastructure are fixed and unchangeable; so object moving trajectory is an issue to be considered in this experiment. Object moving trajectory in this experiment is assumed to be three types: moving along X axis; moving along Y axis; randomly moving in the area. Another concerned issue is time period of each time interval. RFID reader requires a time period to collect a sufficient RFID raw data; if time period is too short, RFID reader cannot observe a fulfilled data; if time period is too long, time gap between two steps of localising a object is not satisfied with indoor requirements. By testing some time intervals (2 minutes, 1 minute, 40 seconds, 20 seconds and 10 seconds), 40 seconds at each time interval is an acceptable time period to observe a sufficient RFID data. The number of time interval sequence is given as 25.

6.2.2.2 Experimental Results

The first step is to investigate the occurring possibility of three type's *regular false-error* reading. The occurring times of each kind of false-error reading are recorded, so a qualitative result on which type of *false reading error* occurs mostly can be displayed in Table 6.1.

Table 6. 1 *Regular false reading error* occurring results in an RFID-Loc infrastructure

Times	***X axis***	***Y axis***	***Randomly***
False Positive Reading	**1**	***1***	***0***
False Negative Reading	***25***	***25***	***25***
Repeated Reading	***22***	***23***	***23***
Overall Times	**25**	***25***	***25***

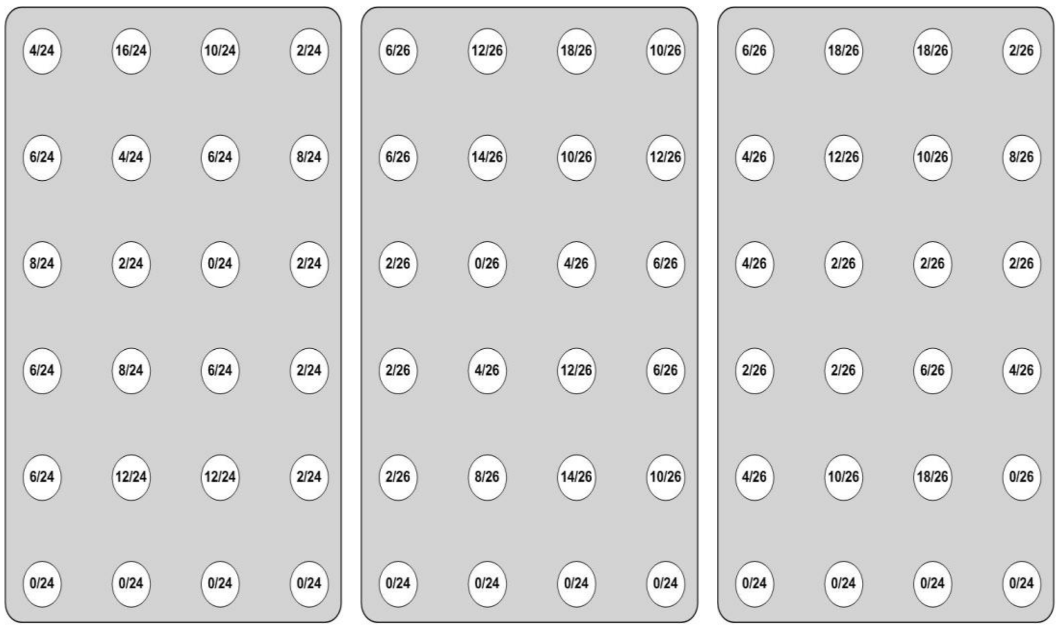
In Table 6.1, *false-negative reading* and *repeated reading* both have a high occurring probability; oppositely, *false-positive reading* has a very low occurring probability.

The results obey the discussion of choosing operating frequency on Chapter 4, which reflects that High Frequency radio signal has a short sensing range so false-negative reading more probably occurs than false-positive reading in this case. A frequent occurrence of *repeated reading* may be because that slow speed of object moving makes some RFID tags being frequently detected. Consequently, the key challenging of *regular false reading error* in an RFID-Loc system is *false-negative reading*. Regarding Equation 5.8 in Chapter 5, if the total number of RFID tags in an efficient RFID reader detection area is 18, the estimated *system reading efficiency* would be approximately 38%. Considering environment noise and experimental operational errors, *system reading efficiency* can be within a reasonable range from 30% to 40%. Table 6.2 shows that practical measurements of *system reading efficiency* from those three trajectories roughly fall into the range.

Table 6. 2 Evaluation of *System Reading Efficiency*

System Reading Efficiency	***X axis***	***Y axis***	***Randomly***
Estimated Range	*30%-40%*	*30%-40%*	*30%-40%*
Practical Measurement	*28.2%*	*33.76%*	*28.6%*

In the above three trajectories, *system reading efficiency* can reflect a general continuous detectable ability of RFID-Loc system. However, it does not illustrate the sensing ability of different position in effective RFID reader detection area. Theoretically, the sensing ability in effective RFID reader detection area is related to the design of RFID antenna and signal strength over distance. In this case, the sensing range between RFID tags and RFID antenna is very short to 1 centimetre. Within this range, the signal strength of RFID reader could be considered as a well distribution over antenna area so that it is not the primary issue leading to the false-negative reading. The more possible reason is the collision between tags, due to the high dense tag distribution. While for each individual time interval, the regular false reading error occurs on the varied position of an effective RFID detection area. Nevertheless, for a sequence of time intervals, the regular false reading error should obey some rules since the physical environment and RFID infrastructure are fixed and unchanged. Consequently, if the effective RFID reading area is divided into some small parts by the tag pattern in Figure 6.2, and accumulate the times of tags successfully detected in each small part, a rough distribution of false reading occurring probability could be concluded, as shown in Figure 6.3.



(a) X axis **(b) Y axis** **(c) Random**

Where: 4/24 at some position means that RFID Tag at this position can be successfully detected 4 times in a total 24 times of Tag detection.

Figure 6. 3 Distribution of *regular false negative reading* occurring probability through experiments.

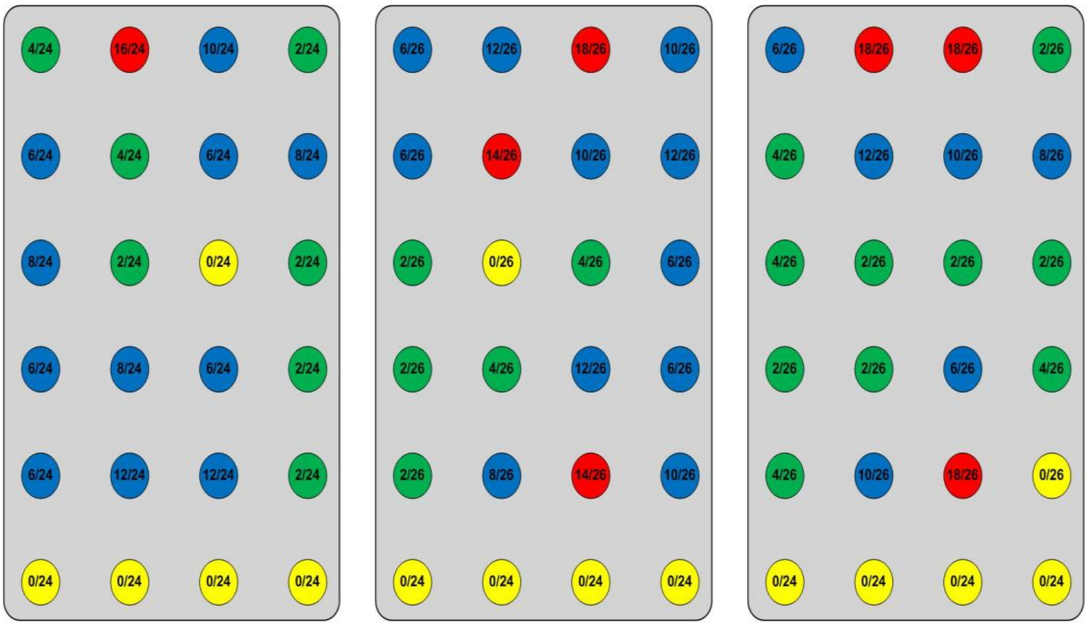
6.2.2.3 Analysis and Findings

Figure 6.3 shows that the probability of each RFID passive tag being detected on the pattern varied as its location. Additionally, the trajectory of object moving could have some impacts on the distribution of regular false reading occurring. While there are so many variations here, the distribution of regular false reading occurring probability indeed obeys some disciplines. For instance, each bottom-line of the pattern has not detected any tags over time; the middle part of top-line of the pattern has a higher detection probability. In terms of the varied range of those probabilities, we can define a simple Equation to classify the tag detection ability over different regions of an effective RFID detection area, as shown in Equation 6.1. The occurring probability of *regular false reading* is averagely divided into zero, low, middle and high. With this Equation, the effective RFID reading area could be divided into different zone with zero, low, mid, high probability detecting tags. Meanwhile, if we separately use Yellow, Green, Blue, Red colour to identify them, the Figure 6.3 could be replaced by Figure 6.4.

$$f(p)=\begin{cases} Zero & (if\ \ P=0) \\ Low & (if\ \ P\in(0,4/24)) \\ Mid & (if\ \ P\in(5/24,12/24)) \\ High & (if\ \ P\in(13/24,1)) \end{cases} \tag{6.1}$$

Where:

P : the probability of RFID tags being detected at some position



(a) X axis **(b) Y axis** **(c) Random**

Figure 6. 4 Distribution of *regular false negative reading* occurring probability with evaluation Function.

Figure 6.4 clearly shows that the majority of effective RFID reader area is within the low and middle range of detection probability, with blue and green colour. The bottom line of RFID effective reader area has very weak detection abilities so that it could be avoided consideration as selected features. There are few high range detection probability points on each trajectory, whose position is nearly similar. Meanwhile, by using this Equation 6.1, it explores that the regular false reading error distribution is not closely influenced by the object moving trajectory. While the regular false reading error distribution is varied from individual RFID tag samples' behaviour, it continuously follows some disciplines about low, middle, high range of detection probability. Thus, a simple distribution of regular false reading occurring probability diagram is concluded in Figure 6.5. This diagram is based on the Equation 6.1, but has some slight adjustment on some points with some rules as follow:

(a) If the points on the same position of these three distributions have the same colours, the generic distribution would make the same position point as this colour.

(b) If the points on the same position of these three distributions have different colours; but two of them have the same colours, the generic distribution would make the same position point as the colour of those two.

(c) If the points on the same position of these three distributions have different colours; and none of them have the same colours, the generic distribution would make the same position point as the colour of the middle range one.

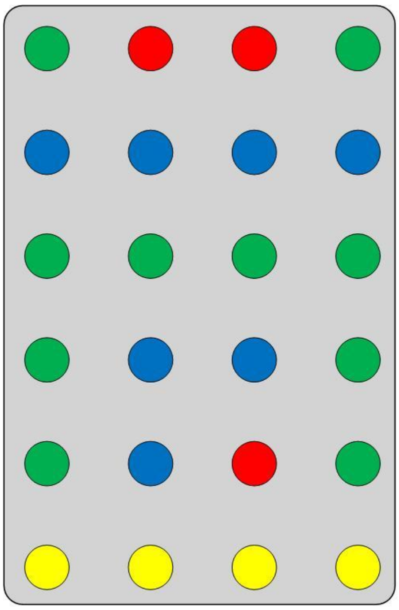


Figure 6. 5 Generic Estimated Distribution of *regular false negative reading* occurring probability for particular RFID reader in this experiment platform.

In Figure 6.5, the generic distribution of *regular false negative reading* occurring probability is nearly symmetrical along the length side of RFID antenna. In terms of this diagram, it should roughly estimate that the regular false reading occurring probability of different positions on RFID effective detection area.

6.2.3 Feature Selection Method

Feature selection method is to choose reliable features from RFID raw data for a localisation algorithm. The reliable features are some data, which can reduce the impact of *regular false reading error* on accuracy and precision of an RFID-Loc localisation algorithm. Experimental findings in section 6.2.2 show that some regions in an effective RFID detection area have a high range of detection probability. The straightforward feature selection method can directly select RFID data in these regions as points based features. However, the features selected by this method may be not the most reliable ones for an RFID-Loc system. The primary reason is that points based features are not fixed over time and symmetric distributed, so direct utilization of these features would probably generate some errors on localisation accuracy. Secondly, the concept of features in RFID-Loc data filter does not merely refer to points. Lines, edges or graphs in a passive RFID tag pattern can also be recognized as features in RFID-Loc data filter. This section attempts to evaluate methods of selecting different types of features, and justify them. Localisation algorithm of generating object position would use a simple centroid method here; other possible localisation algorithms would be discussed in section 6.3.

6.2.3.1 Set of Points Method

The set of point's based feature selection method relies on choosing points as the features. The centroid of a finite set of points $x_1, x_2, ..., x_k$ in R^n is :

$$C = \frac{x_1 + x_2 + ... + x_k}{k} \tag{6.2}$$

The challenge of this method is which kinds of points can be chosen for use. Conventionally, on a hypothesis that each point owning the equivalent probability of being detected, whole set of points at each time interval can be averaged to get the centroid as target position. In this case, points are located into regions of different levels of false reading occurring probability. Regarding to Equation 6.1, points based features can be selected from RFID data by using four types of way, which are Set A (Zero, Low, Mid, High), Set B (Low, Mid, High), Set C (Mid, High), Set D (High). At each time interval, features can be abstracted regardless of the colour zone in Figure 6.5. Nevertheless, there is an important issue in a points based feature selection method, which is that the number of chosen features has to guarantee sufficiency for localisation algorithm to process at each time interval. For instance, given that points in Set D being chosen as features; but on some time intervals, there are no RFID data in Red zone of Figure 6.5; then localisation algorithm would calculate a incorrect value of position. Considering the sufficiency of number of features, it would mainly evaluate Set A, Set B and Set C in X axis, Y axis and Random trajectories. Localisation results of using these three set of points based feature selection methods are shown in Figure 6.6, 6.8 and 6.10. The localisation errors on X and Y axis in each trajectory are shown in Figure 6.7, 6.9 and 6.11.

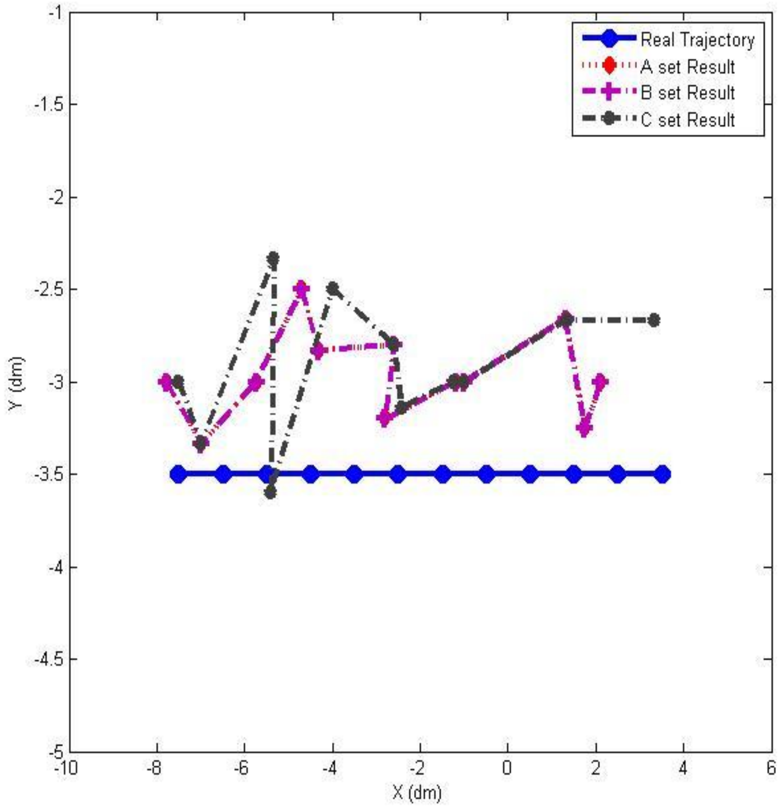
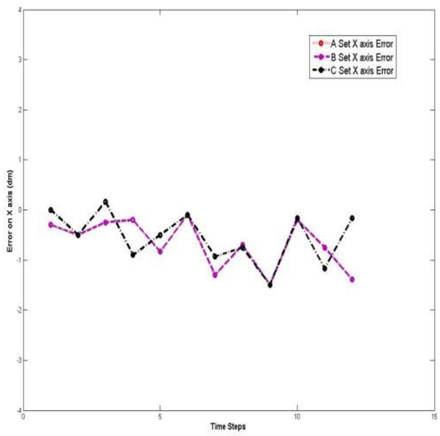
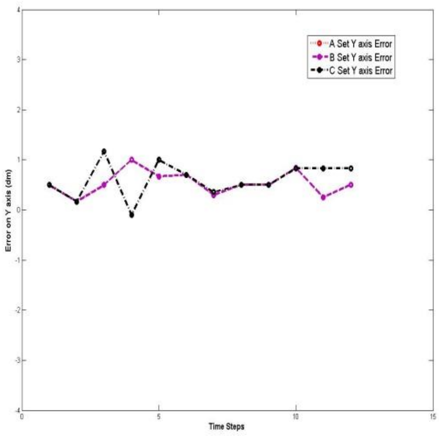


Figure 6. 6 Localisation Results on X Trajectory by using Different Set of Points based feature selection methods





(a) Error on X axis (b) Error on Y axis

Figure 6. 7 Accuracy Errors on X Trajectory by using Different Set of Points based feature selection methods

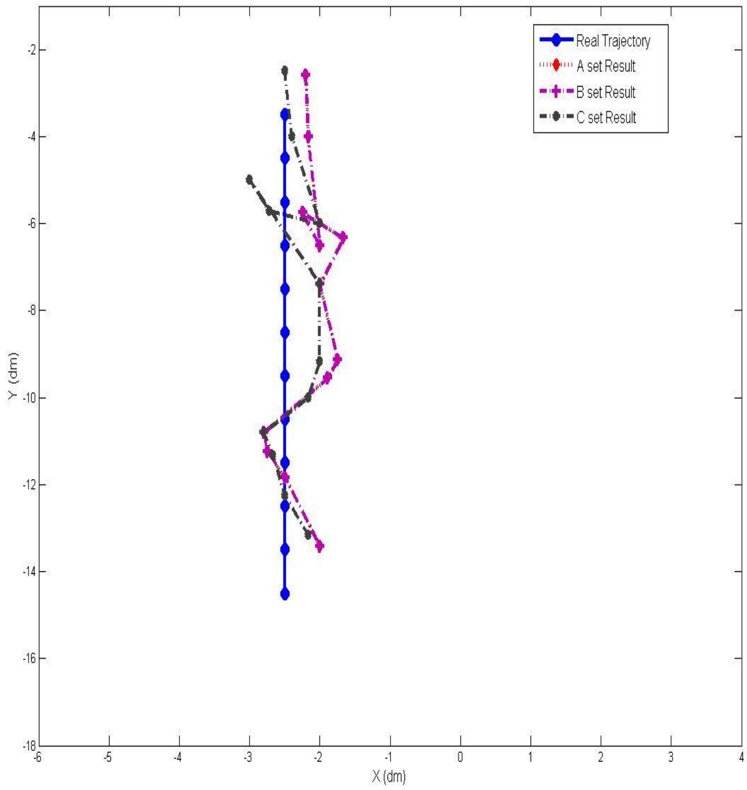
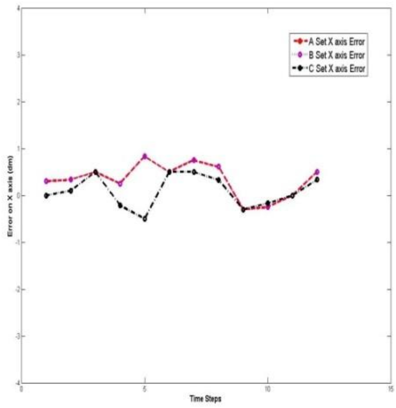
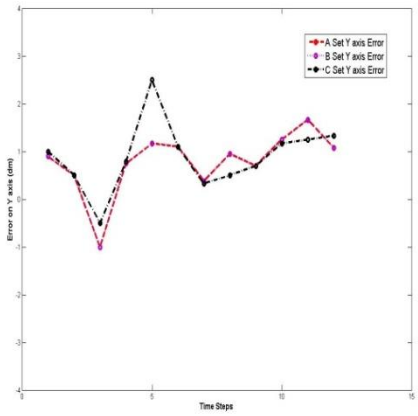


Figure 6. 8 Localisation Results on Y Trajectory by using Different Set of Points based feature selection methods



(a) Error on X axis



(b) Error on Y axis

Figure 6. 9 Accuracy Errors on Y Trajectory by using Different Set of Points based feature selection method

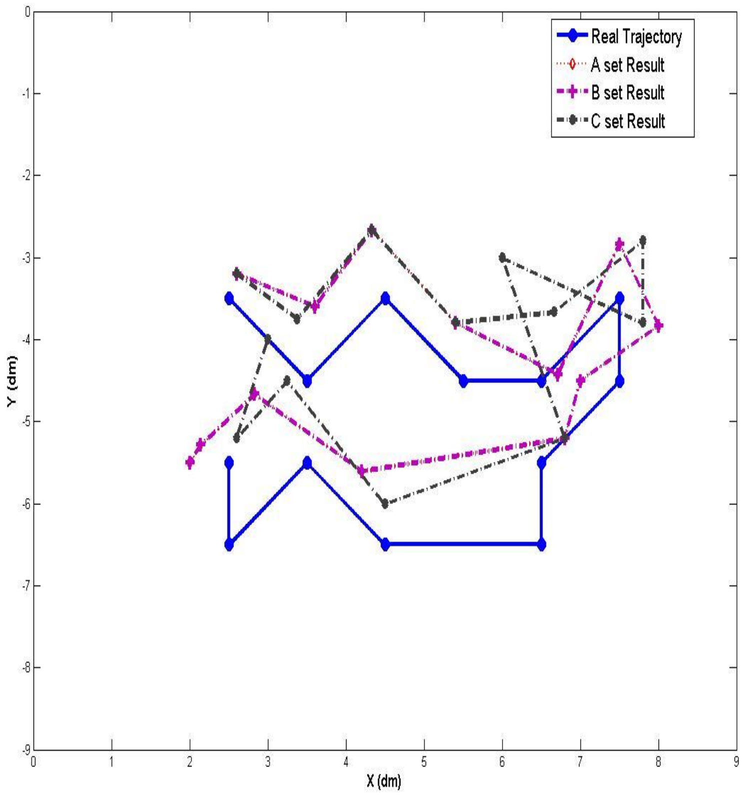
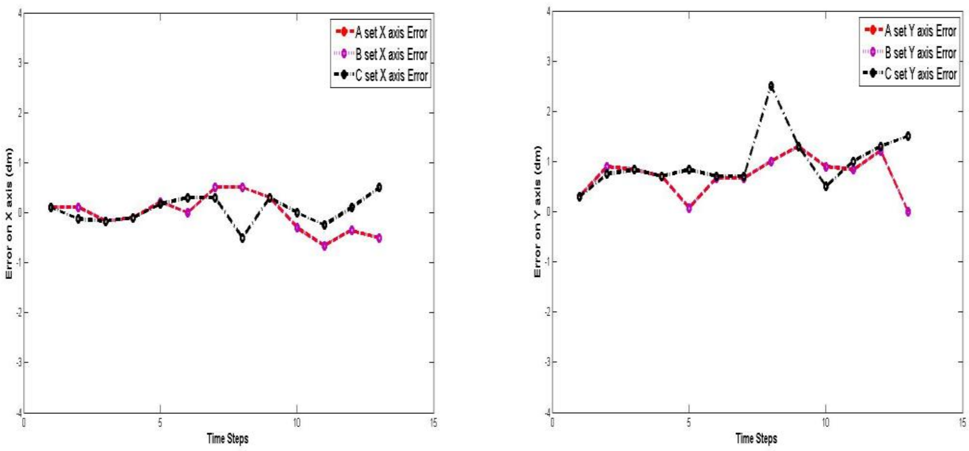


Figure 6. 10 Localisation Results on Random Trajectory by using Different Set of Points based feature selection methods



(a) Error on X axis (b) Error on Y axis

Figure 6. 11 Accuracy Errors on Random Trajectory by using Different Set of Points based feature selection methods

The results illustrate that feature selection method by choosing Set A points can achieve a smaller absolute accuracy error than feature selection method by choosing Set C points. While Set C owns more number of stable points being detected than Set A, Set A has more number of available points being used than Set C. Object position is a average mean of the position data of those features. Thus, localisation accuracy of object position does not merely rely on the selected features from RFID data with a high detection probability, but also depends on the number of selected features being used over time. Figures also reflects that features in a zero level region actually are none, so feature selection method by choosing Set A is absolutely identical to feature selection method by choosing Set B. Feature selection method by choosing Set A points can reach an approximately equal accuracy as feature selection method by choosing Set B. Consequently, among those three points based feature selection methods, feature selection method by choosing Set A is a method with the best localisation accuracy.

6.2.3.2 Polygon Method

Polygon method relies on choosing some certain area or region in a RFID tag pattern as features. The advantage of this method is that it can include a finite set of points. The centroid of a non-overlapping closed polygon defined by n vertices (x_i, y_i) can be calculated as follows. The area of the polygon is :

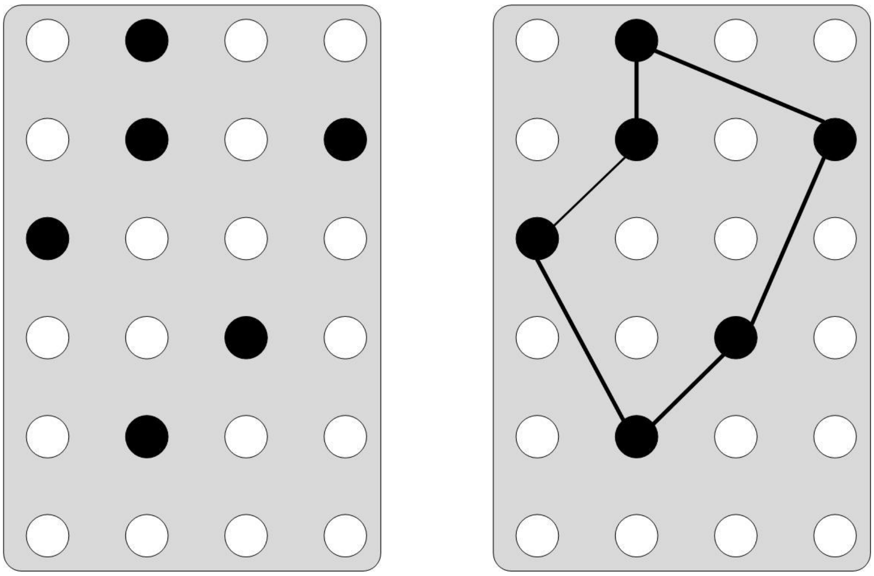
$$A = \frac{1}{2}\sum_{i=0}^{n-1}(x_i y_{i+1} - x_{i+1} y_i) \qquad (6.3)$$

And its centroid is C = (C_x, C_y) where:

$$C_x = \frac{1}{6A}\sum_{i=0}^{n-1}(x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i)$$

$$C_y = \frac{1}{6A}\sum_{i=0}^{n-1}(y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \qquad (6.4)$$

In our case, feature in a polygon based feature selection method can be a special graph; edge of this special graph is important to the calculation of centroid of this polygon. Figure 5.12 shows that difference between points based feature and polygon area based feature.



(a) Points Set Feature (b) Polygon Area Feature

Figure 6. 12 Difference between points based feature and polygon area based feature

In order to evaluate the performance of polygon based feature selection method, points based feature selection method by choosing Set A method is choose as a comparable solution. Localisation results of using these two methods in X axis, Y axis and Random trajectory are shown in Figure 6.13, 6.15 and 6.17. The localisation errors on X and Y axis in each trajectory are shown in Figure 6.14, 6.16 and 6.18.

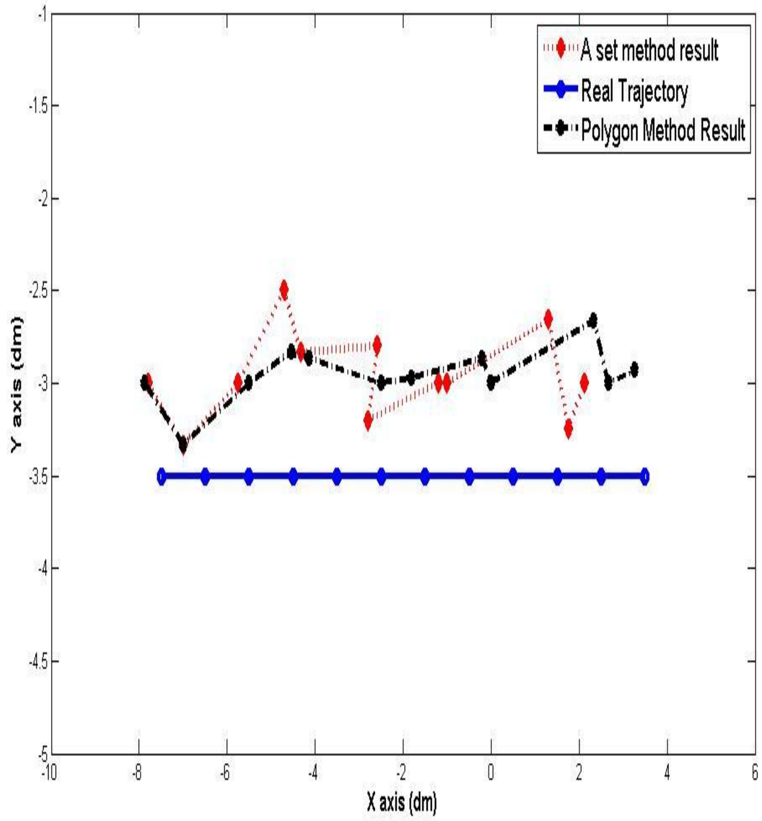
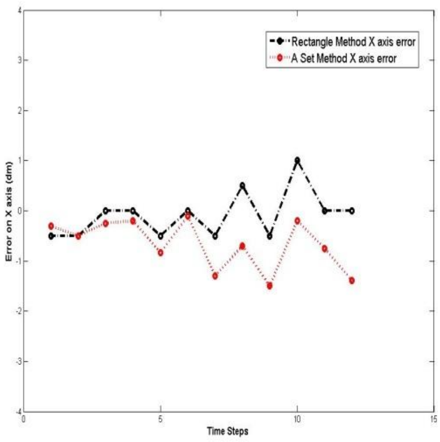
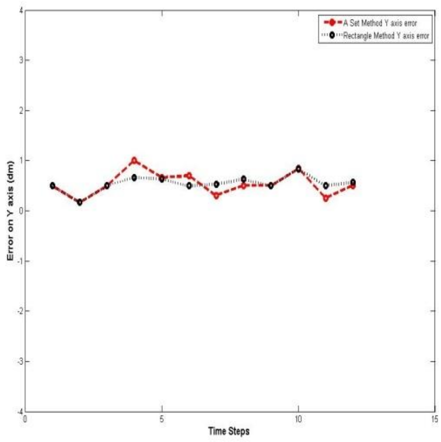


Figure 6. 13 Localisation Results on X Trajectory by using Polygon Method



(a) Error on X axis



(b) Error on Y axis

Figure 6. 14 Accuracy Errors on X axis Trajectory by using Polygon Method

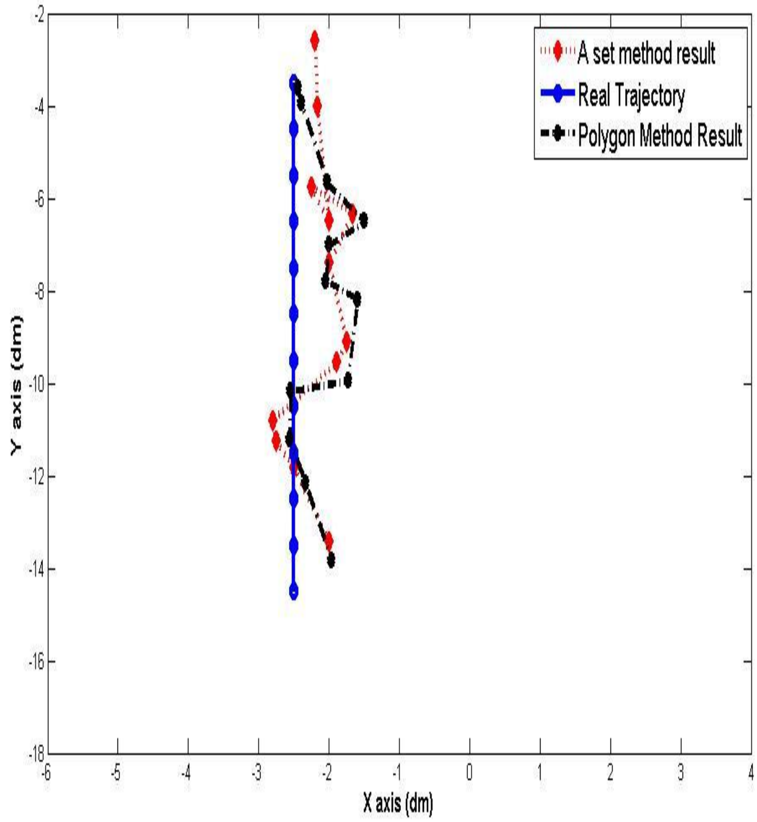
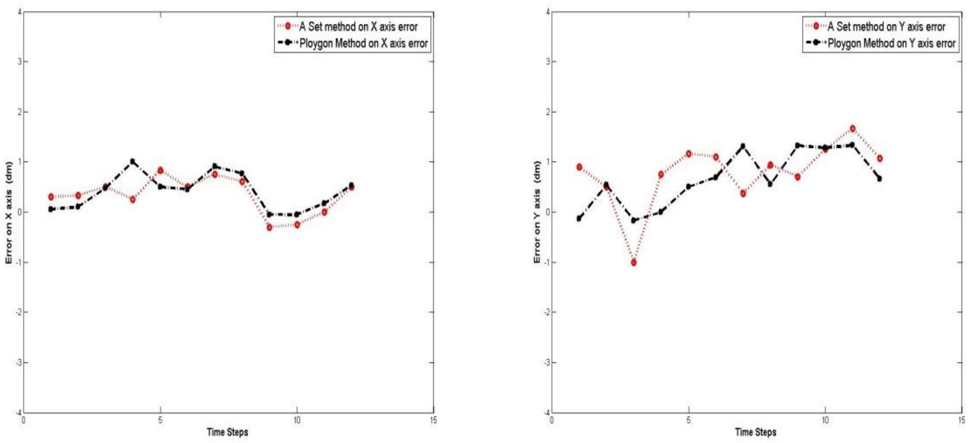


Figure 6. 15 Localisation Results on Y Trajectory by using Polygon Method



(a) Error on X axis (b) Error on Y axis

Figure 6. 16 Accuracy Errors on Y axis Trajectory by using Polygon Method

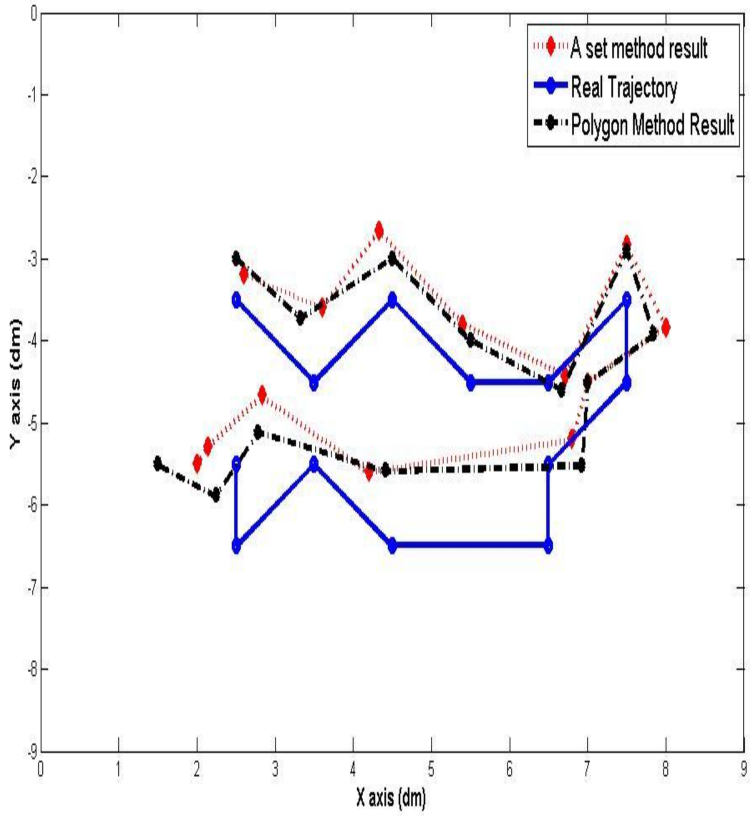
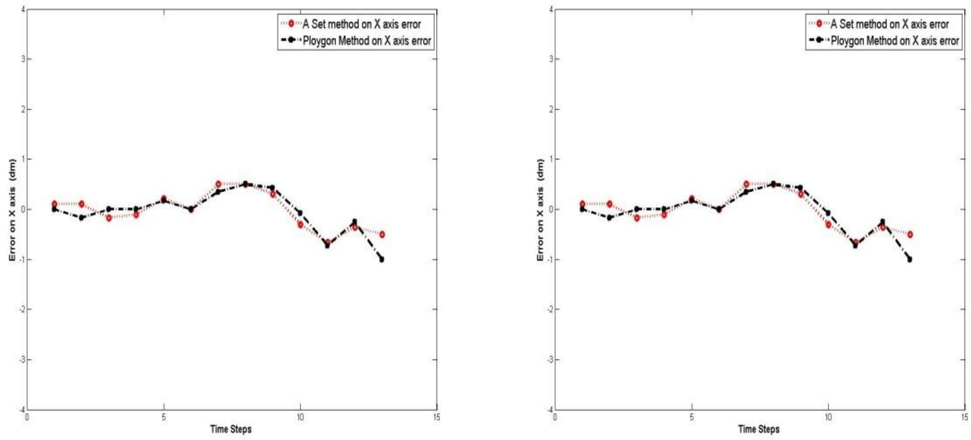


Figure 6. 17 Localisation Results on Random Trajectory by using Polygon Method



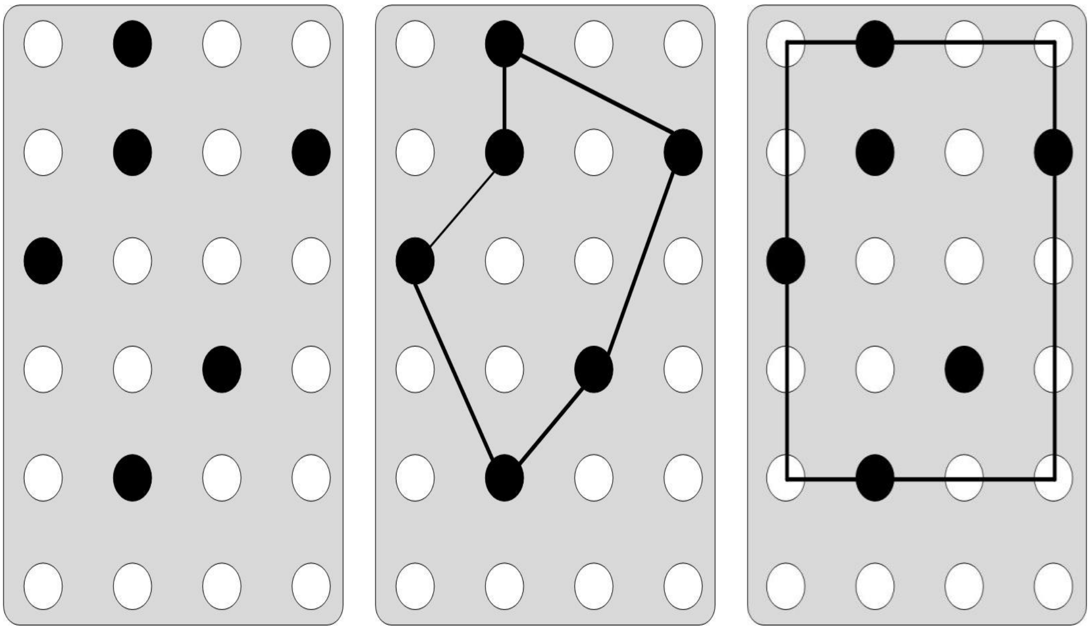
(a) Error on X axis (b) Error on Y axis

Figure 6. 18 Accuracy Errors on Random Trajectory by using Polygon Method

The comparison shows that either polygon based feature selection method or pointed based feature selection method by using Set A can be effective on some trajectory. On X axis trajectory, polygon based feature selection method has a better localisation performance than feature selection method by choosing Set A method, with a smaller accuracy error on object position. On Y axis trajectory, polygon based feature selection method has an equivalent localisation performance as feature selection method by choosing Set A method, causally on some point with larger accuracy error. On Random trajectory, polygon based feature selection method has an essentially equivalent localisation performance as feature selection method by choosing Set A method on each time interval. The reason causing to differences may be an unsymmetrical distribution of false reading error due to the RFID antenna design on width and length. The set of points in a polygon feature is straightforward determined by Equation 6.1. In some cases, it may overuse or underuse edge points of a polygon. These unsymmetrical issues would affect calculating the centriod of a polygon. However, generally speaking, polygon based feature selection method has a similar localisation results as feature selection method by choosing Set A points based method.

6.2.3.3 Rectangle Method

The discussion in previous section reflects that polygon area is not a symmetric graph so localisation algorithm of calculating its centroid usually can generate some errors. This section would use a rectangle area substitutes a polygon area for balancing the problem of asymmetry of features. To choosing a rectangle area can enhance the symmetry of features, since its shape is only decided by some maximum or minimum value of point’s position. Figure 6.19 shows difference of choosing features by using Polygon and Rectangle method.



(a) Points Set Feature (b) Polygon Area Feature (c) Rectangle Area Feature

Figure 6. 19 Comparison between three different features

By using rectangle area, four edge features $F_{xp}, F_{xn}, F_{yp}, F_{yn}$ are used, which are the minimum and maximum values on X and Y axis among the position value of all detected RFID tag at a time interval t, as shown in Equation 6.1. Assuming at current time interval *t*, object position (X_t^c, Y_t^c) can be obtained through a set of position information from RFID data (X_T^N, Y_T^N), where *N* represents Number of RFID tags being detected by RFID reader, and (X_T^N, Y_T^N) represents position information of those RFID data; edge features can be represented in Equation 6.5.

$$F_{xp} = Max(x_T^1, x_T^2, ...x_T^N), \qquad F_{xn} = Min(x_T^1, x_T^2, ...x_T^N),$$

$$F_{yp} = Max(y_T^1, y_T^2, ...y_T^N), \qquad F_{yp} = Min(y_T^1, y_T^2, ...y_T^N), \qquad (6.5)$$

Localisation results of using rectangle and polygon based feature selection methods are compared in Figure 6.20, 6.22 and 6.24. The localisation errors on X and Y axis in each trajectory are shown in Figure 6.21, 6.22 and 6.23.

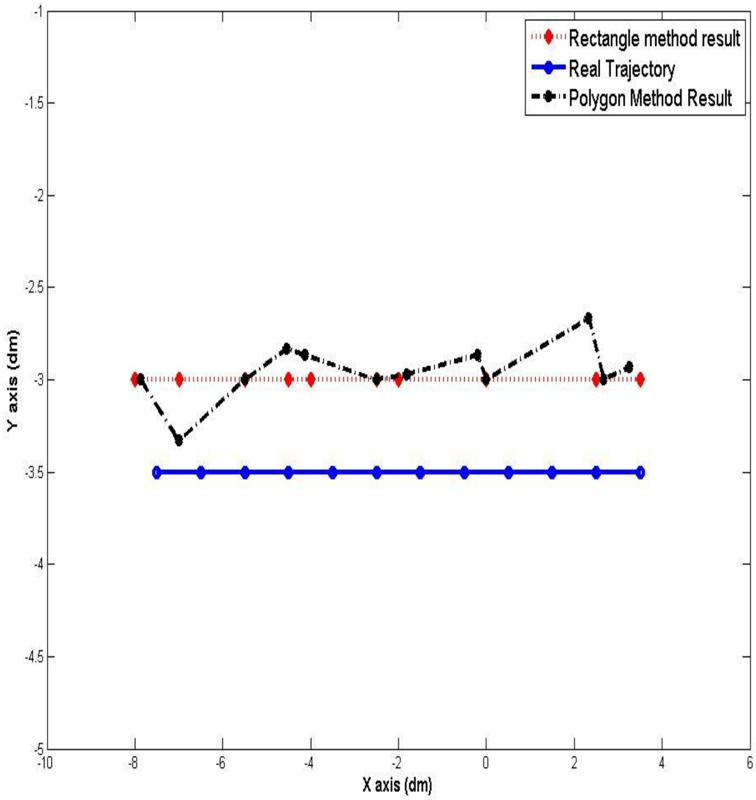
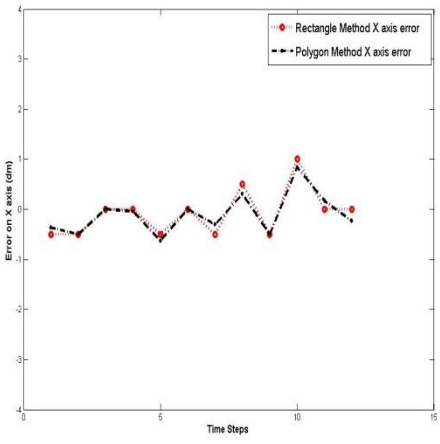
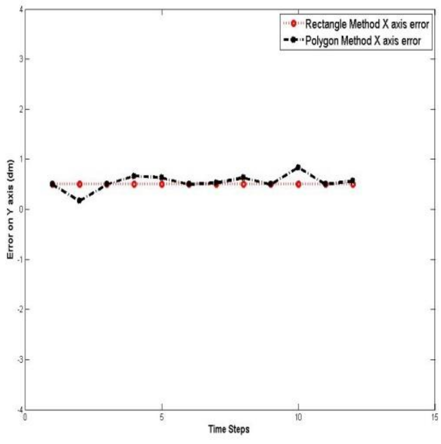


Figure 6. 20 Localisation Results on X Trajectory by using Rectangle based Method



(a) Error on X axis



(b) Error on Y axis

Figure 6. 21 Accuracy Error on X Trajectory by using Rectangle based Method

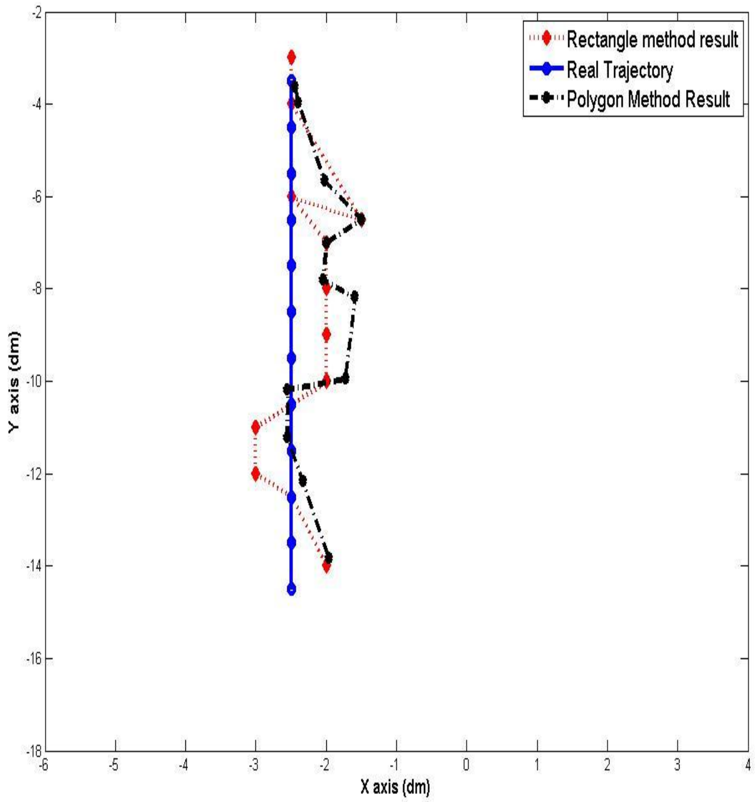
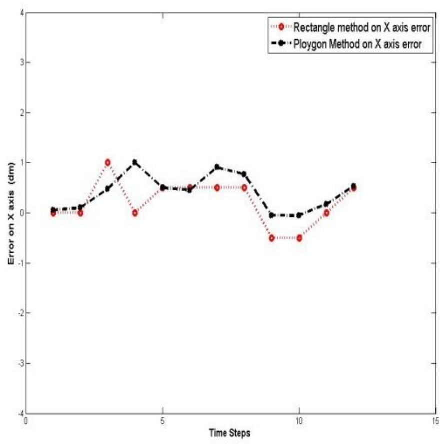
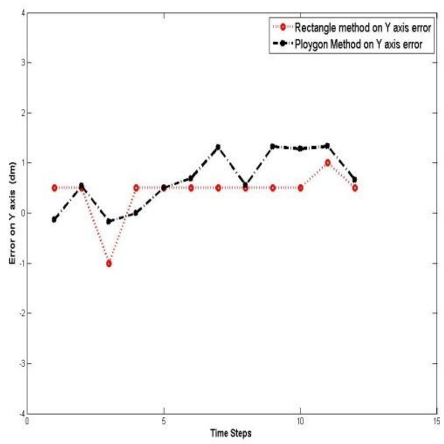


Figure 6. 22 Localisation Results on Y Trajectory by using Rectangle based Method





(a) Error on X axis (b) Error on Y axis

Figure 6. 23 Accuracy Errors on Y Trajectory by using Rectangle based Method

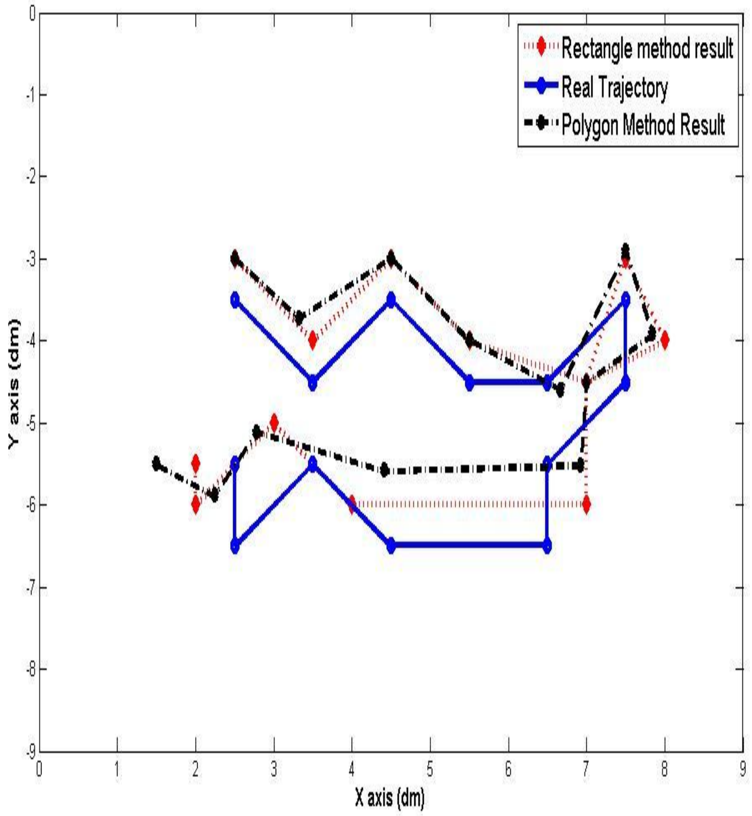
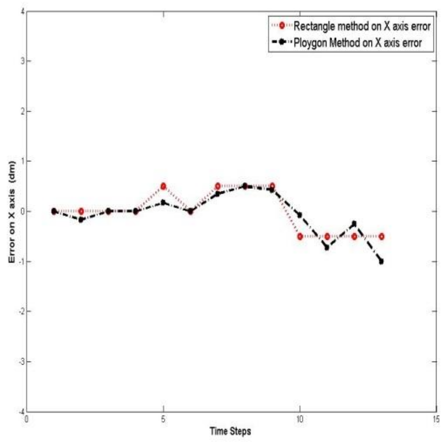
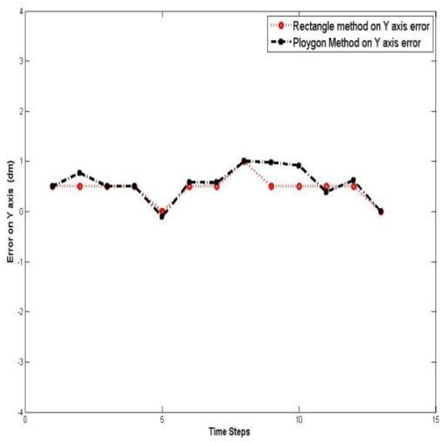


Figure 6. 24 Localisation Results on Random Trajectory by using Rectangle based Method



(b) Error on X axis



(b) Error on Y axis

Figure 6. 25 Accuracy Errors on Random Trajectory by using Rectangle based method

Based on the experiments, the comparison between Rectangle based feature selection method and Polygon based feature selection method reflects that Rectangle feature selection method apparently has a lower localisation accuracy error than Polygon based feature selection method. On X axis trajectory, Rectangle based feature selection method has a better localisation performance than Polygon based feature selection method, with nearly no error on Y value of object position. On Y axis trajectory, Rectangle based feature selection method has a smaller localisation accuracy error on both X value and Y value of object position than Polygon based feature selection method. On Random trajectory, while it is not obvious as the previous X and Y trajectory, the sequence of object position producing by Rectangle based feature selection method is more close to the original real trajectory than the sequence of object position producing by polygon based feature selection method. Consequently, Rectangle method is more suitable as a feature selection method than polygon method in a RFID-Loc Data Filter module.

6.2.4 Comparison of Feature Selection methods

In order to compare the performance of above feature selection methods in a RFID-Loc Data Filter module, section 3.4 has pointed out that it has to directly evaluate localisation accuracy and precision with a given RFID-Loc infrastructure. Section 5.3 has proved that experiments in this section are based on an spares RFID Tag Arrangement in RFID-Loc infrastructure from last chapter. Moreover, localisation accuracy of these above three feature selection has been given as 10 centimetres, since Tag distance is already given as :

$$D_x = D_y = 10 \quad \text{cm}$$

Localisation precision can be compared by mean of precision in Table 6.3 and range of precision in Table 6.4. The mean of precision can be calculated by Standard Deviation in Equation 6.6.

Standard Deviation Equation:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{6.6}$$

Table 6. 3 Comparison of Feature Selection Methods by mean of precision

Methods	*X Trajectory*		*Y Trajectory*		*Random Trajectory*	
	X value	*Y value*	*X value*	*Y value*	*X value*	*Y value*
A set Method	**6.686 cm**	**5.353 cm**	**3. 356 cm**	**7. 854 cm**	**0. 289 cm**	**7. 220 cm**
C set Method	**5.427 cm**	**6. 075 cm**	**0. 905 cm**	**8. 891 cm**	**0. 481 cm**	**9. 936 cm**
Polygon Method	**1.066 cm**	**5. 441 cm**	**4. 052 cm**	**6. 594 cm**	**0. 611 cm**	**5. 566 cm**
Rectangle Method	**0.833 cm**	**5. 000 cm**	**2. 083 cm**	**2. 500 cm**	**0.0000 cm**	**4. 615 cm**

Table 6. 4 Comparison of Feature Selection Methods by range of precision

Methods	*X Trajectory*		*Y Trajectory*		*Random Trajectory*	
	X value	*Y value*	*X value*	*Y value*	*X value*	*Y value*
A set Method	**(-2.8, 9) cm**	**(-13, 1) cm**	**(-3, 8.3) cm**	**(-10, 16.7) cm**	**(-6.7, 5) cm**	**(0, 13) cm**
C set Method	**(-5, 4.5) cm**	**(-5, 1.5) cm**	**(-5, 5) cm**	**(-5, 25) cm**	**(-5, 5) cm**	**(3, 25) cm**
Polygon Method	**(-5.5, 9.1) cm**	**(1, 9) cm**	**(-0.5, 9.1) cm**	**(1.6, 13.3) cm**	**(-10, 5) cm**	**(-1, 10) cm**
Rectangle Method	**(-5, 10) cm**	**(5, 5) cm**	**(-5, 10) cm**	**(-10, 5) cm**	**(-5, 5) cm**	**(0, 10) cm**

From Table 6.3 and 6.4, it appears that rectangle based feature selection method can give a better precision than other feature selection methods, particularly on X axis value of moving object position. On X trajectory situation, average precision of rectangle based feature selection method can reduce to 0.8 centimetres on X axis value of moving object position, 5 centimetres on Y value of moving object position. While there are no apparent enhancements on Y axis value of moving object position by choosing rectangle based feature selection method.

6.3 Localisation Algorithm

6.3.1 Algorithms Comparison and Analysis

Chapter 2 has reviewed many RFID-based localisation algorithms. Some of them are designed for RFID reader localisation, some of them are proposed for RFID tag localisation. Table 6.5 lists some major algorithms' performance. (Sanpechuda, 2008).

Table 6. 5 Comparison of RFID-based localisation algorithms (Sanpechuda, 2008)

Solution	***Accuracy &Precision***	***RFID infrastructure***	***Merits***	***Demerits***	***Algorithms***
Lee& Lee	0.026m	Reader Localisation	Both Position and Orientation, Reduce the error by the boundary tag of read range	Requires a large number of tags	Weighted Average& Hough Transform
Han&Lim	0.016m	Reader Localisation	Both Position and Orientation, Reduce the number of tags with the same accuracy as Lee&Lee	More computation at the server	Triangular tag arrangement instead of grid tag pattern
Yamano &Tanaka	80%	Reader Localisation	Self-localisation, no tag pattern need. Propagation environment independent, optimal number of tags	Requires the reader with signal intensity output No orientation	Support Vector Machine
Xu& Gang	1.5m	Reader Localisation	Fewer sample number Insensitive to NLOS	Depend on movement probabilistic model	Bayesian Technique
SpotON	Depend on Cluster Size	Tag Localisation	3D localisation No fixed infrastructure Low cost	Attenuation less accurate than time of Flight Need special tag	Ad hoc lateration
LANDMARC	1-18m	Tag Localisation	Use off the self active tag Accuracy with less Reader and low cost	Dense configuration of references tags Require the reader with signal intensity output	K nearest neighboring + weighting

RFID-Loc system is similar to RFID reader localisation by using passive RFID tags, since they both target on localising position of a single mobile RFID reader. The available localisation algorithms can be classified into two types. The first type can be named as *static* localisation algorithms, which produce position of a RFID reader by using RFID data merely from current time interval. During the process of *static* localisation algorithm, computation of target's position at each time interval is independent to other time frames, so that there is no drift error on target's position. However, *static* localisation algorithm has weak resilience ability to error motion of target. The second type can be named as *dynamic* localisation algorithms, which produce the target position by not merely using RFID data from current time frame, but also employing RFID data from previous time frames as a supplement. In a dynamic localisation process, algorithm usually includes prediction and update processes, so as to computation of a target's position at each time frame can be highly relevant to other time frames. The merit of this algorithm is that it is more robust and resilience to error motion than *static* localisation algorithms, since *dynamic* localisation process is usually a probabilistic basis. However, *dynamic* localisation algorithms might suffer with drift errors due to the dependence of current target's position on previous target's positions. In order to explore the feasibility of those two types of solutions in an RFID-Loc system, a typical *static* localisation algorithm and some *dynamic* localisation algorithms are selected to do a theoretical comparison. The chosen *static* localisation algorithm is Arithmetic Average Mean method. The chosen dynamic localisation algorithms are based on EKF (Extended Kalman Filter) (Welch & Bishop, 1995) and Particle Filter (Doucet, Freitas, Murphy, & Russell, 2000).

Those two types of algorithms can be evaluated in terms of accuracy, robustness and computational efficiency. High accuracy requirement of a object position tracking system in indoor application is the fundamental principle for a RFID-Loc localisation algorithm module. It would determine the degree of compositing for high realism, and exact mixing results in indoor applications. Accuracy is the primary assessment index of comparison among these two types of localisation algorithms. Secondly, the robustness of localisation algorithm is a considerable issue, since localisation algorithm has to process a large amount of feature with uncertain errors. How well a localisation algorithm can robustly against with unexpected false reading errors and noise in a RFID-Loc system is important. Robustness may also have to consider convergence rate, which measures the speed of localisation algorithms arrives at a stable localisation status. Thirdly, computational efficiency is a benchmark to judge the performance of localisation algorithms. RFID-Loc system deserved to extract object position parameters with a low latency. The efficiency of localisation algorithms have to support this demand. Advanced computational efficiency and low algorithm complexity can ensure localisation algorithm in an RFID-Loc system to achieve low latency.

6.3.1.1 Static Localisation

Typical *static* localisation algorithms are arithmetic mean and weighted mean. In an RFID-Loc system, arithmetic mean based localisation algorithm is to average the value of selected features on X axis and Y axis from RFID-Loc data filter for producing moving object position over time. Weighted mean based localisation algorithm is similar to arithmetic mean, where instead of each of features points contributing by different weights to moving object position. If weights of features points are equal, weighted mean based localisation algorithm is equal to arithmetic mean localisation algorithm. If object position is denoted as (x_c, y_c); at each time frame, RFID reader can obtain

position data of RFID tags (x_t^1, y_t^1), (x_t^2, y_t^2), (x_t^3, y_t^3) ,……, (x_t^N, y_t^N); and N represents number of RFID tags detected by RFID reader at some time interval, t represents current time interval; (x_t^N, y_t^N) represents position information of RFID tag n; then we can get the values of selected features by using rectangle based feature selection method from section 6.2.

$$F(xp, xn, yp, yn) = \begin{cases} F_{xp} = Max(x_t^1, x_t^2, ...x_t^N) \\ \\ F_{xn} = Min(x_t^1, x_t^2, ...x_t^N) \\ \\ F_{yp} = Max(y_t^1, y_t^2, ...y_t^N) \\ \\ F_{yn} = Min(y_t^1, y_t^2, ...y_t^N) \end{cases} \quad \textit{Rectangle feature selection} \text{ (6.2)}$$

Where:

F_{xp} is features' value along X positive axis of RFID reader antenna

F_{xn} is features' value along X negative axis of RFID reader antenna

F_{yp} is features' value along Y positive axis of RFID reader antenna

F_{yn} is features' value along Y negative axis of RFID reader antenna

(x_t^N, y_t^N) represents the coordinate's information of RFID tags.

N represents number of RFID tags detected by RFID reader at some time interval

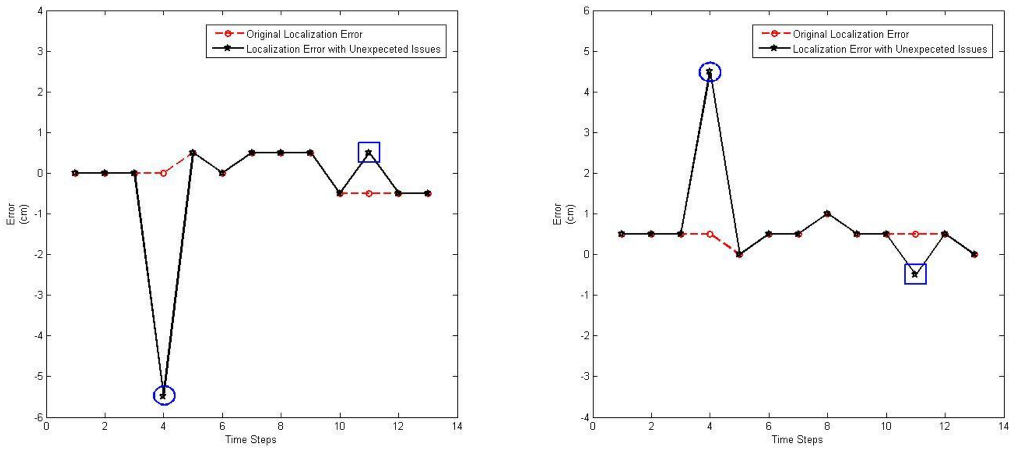
t represents current time interval.

The position of moving object can be calculated by using arithmetic mean in Equation 6.7:

$$\begin{cases} x_c = \dfrac{F_{xp}+F_{x}}{2} \\ y_c = \dfrac{F_{yp}+F_{y}}{2} \end{cases} \qquad (6.7)$$

Results of Chapter 5 illustrate that, under recommended RFID-Loc infrastructure design and rectangle based feature selection method, arithmetic mean based localisation method can reach 10 centimetres accuracy with up to 4.6 centimetres precision. The key barriers on enhancing the accuracy of an RFID-Loc system are from the limitations of current RFID hardware devices; these limitations are extremely likely to be overcome in future as rapid development of high quality materials and manufactures; so it is highly possible for an RFID-Loc system to satisfy accuracy requirement of a indoor application in future with advanced RFID hardware devices.

Robustness of localisation algorithm is also of concern. Due to the constraints of RFID hardware limitations, RFID data captured over time would contain some *regular false reading* information. While *regular false reading error* can be impossible to completely remove, they are controlled and filtered regularly by optimizing RFID-Loc infrastructure and RFID-Loc data filter as so to manage localisation precision into an acceptable level. However, except *regular false reading error*, there are some *unexpected false reading errors* possibly affecting accuracy and precision of an RFID-Loc system, as discussed in section 3.4. There are two typical poor localisation results resulting by *unexpected false reading error*. The first one refers to a phenomenon that RFID reader fails detection any RFID tag on some time intervals, called *dead reading error*. The occurrence of *dead reading* is usually due to fast speed of object moving, erratic moving motion of object or some sudden environmental changes. The second one is a phenomenon that RFID reader detects the same amount of RFID tags in continuous time intervals, called *repeated reading error*. It happens when object moving too slow or keeping stable. Taking an example of random moving trajectory in Chapter 5, if it assumes that above two type of *unexpected false reading error* occur at some time intervals in this trajectory, accuracy and precision of localisation would be influenced, as shown in Figure.6.26.



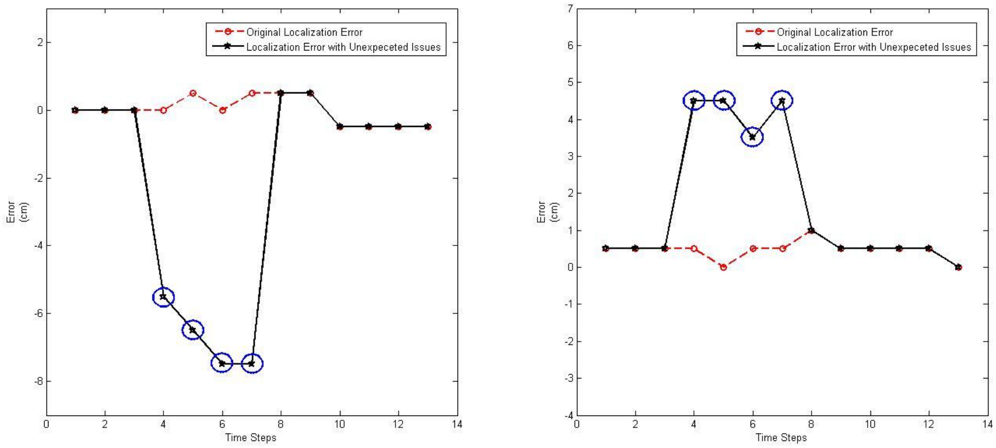
(a) Error on X axis (b) Error on Y axis

Figure 6. 26 *Unexpected false reading errors* occurring on Random Trajectory

In Figure 6.26, circle marker highlights a point on the occurrence of *dead reading error*. Rectangle marker points out a point on the occurrence of *repeated reading error*.

The results appear that *static* localisation algorithm has a weak ability to robustly localize object and recover object position from *unexpected false reading errors*. The first reason is that unexpected false reading error in an RFID-Loc system is irregular and hardly controlled, which is different with *regular false reading errors*. *Regular false reading error* in an RFID-Loc system is mainly from the constraints of RFID hardware devices. The characteristic of RFID hardware devices would be not changed as indoor object moves, so that it can follow some principles to manage *regular false reading errors*. On dealing with *regular false reading errors*, *static* localisation algorithm can localize moving object position efficiently. However, *unexpected false reading error* in an RFID-Loc system comes from changeable environment, or sudden erratic motion. Those issues are hardly controlled and managed, which can significantly influence the accuracy and precision of an RFID-Loc system. Secondly, regarding characteristics of *static* localisation algorithm, object position at each time interval is dependently calculated by features at current time interval. There are no connections with known features at pervious time intervals. Once some sudden error reading occurs at certain step, *static* localisation algorithm cannot utilize previous relevant features to correct them. The major limitation of *static* localisation algorithm is no capacity to resist unexpected false reading error in an RFID-Loc system.

Response time of RFID reader sensing RFID passive tags is varied and irregular, possibly recognizing multiple RFID tags in some time frame, or possibly sensing no tags in some time frame. *Unexpected false reading error* can possibly frequently occur in an RFID-Loc system. These *unexpected false reading error* might continuously come about in continuous time frames, as shown in Figure 6.2. *Static* localisation algorithm is unable to overcome those errors.



(a) Error on X axis (b) Error on Y axis

Figure 6. 27 Continuous occurrence of unexpected false reading errors on Random Trajectory

As for computational efficiency, arithmetic average based localisation algorithm does not require a long time to generate the value of object position since it is a simple mathematical computation for current available computer. So the impact of its computational efficiency on latency of an RFID-Loc system does not need to be concerned.

6.3.1.2 Dynamic Localisation

The idea of dynamic localisation comes from probabilistic localisation algorithm. During a probabilistic localisation process, it contains the prediction and updating processes, which is potentially benefited for overcoming some problem on resisting unexpected regular false reading error in *static* localisation algorithm. Currently, SLAM (Simultaneous Localisation and Mapping) technique is one of the most popular solutions for probabilistic localisation algorithm. As reviewed in Chapter 2, there are two major approaches to implement SLAM, which are Extended Kalman Filter and Particle Filter. In this section, the possibility of those two approaches applying into an RFID-Loc framework is discussed.

Extended Kalman Filter:

Before looking into the details of EKF, it firstly needs to specify some mathematical terms. Unlike localisation problem which aims to estimate *location state*, the objective of SLAM is to estimate the *system state* which includes the *location state and feature state*, as shown in Equation 6.3:

$$x_t = \begin{cases} s_t \\ m_{1,t} \\ m_{2,t} \\ \cdots \\ m_{n,t} \end{cases} \qquad (6.3)$$

Where : x_t is the *system state* at time *t*,

s_t is the *location state*

$m_{n,t}$ is the *feature state*

n is the number of features

t is the time interval.

Here, a feature is a specific object of surrounding environment, e.g. a door or a window in a room. In literature, this kind of SLAM is often called feature-based SLAM. If object is assumed to move on a 2D Cartesian map, then *location state* of object can be denoted as position (x, y) and orientation of object θ relative to a global reference frame, as shown in Equation 6.4.

$$s_t = \begin{cases} x \\ y \\ \theta \end{cases} \qquad (6.4)$$

Each feature's state is commonly represented by a point in map by Equation 6.5.

$$m_{n,t} = \begin{bmatrix} r \\ \theta \end{bmatrix} \qquad (6.5)$$

The mathematical framework of EKF approach includes two models that operate on the above *system state*. The first model is the system transition model that describes the relationships of system states at different time *t*:

$$x_{t+1} = f(x_t) + v \qquad (6.6)$$

Here v is a mutually independent zero-mean white Gaussian noises with noise covariance Q, and $f()$ is a non-linear function.

If the map is assumed to be static, i.e. the position of features will stay constant over time. This gives:

$$m_{n,t+1} = m_{n,t} \qquad (6.7)$$

After applying Equation 6.7 into Equation 6.1, the *system state* is simplified into only the *location state*, hence the system transition model becomes:

$$x_{t+1} = f(x_t) + v \quad ==> \quad s_{t+1} = f(s_t) + v \qquad (6.8)$$

Hence, it is obvious the system transition model only operates on the location state.

The other model is the *observation model*:

$$z_{k+1} = h(x_{k+1}) + w \qquad (6.9)$$

Where : w is a mutually independent zero-mean white Gaussian noises with noise covariance R, and $h(.)$ is a non-linear function that gives the relationship between the moving object and a certain feature. Given the above two models, following the notation of Kalman Filter Localisation, the each iteration of EKF (Welch & Bishop, 1995) is given by Appendix B:

In accordance with above EKF Equations, Newman (Newman, 2006)'s code is used to simulate EKF based localisation. Figure 6.28 shows the trajectory of an assumed moving object though a field of random point features. There are 30 random point features distributed as landmarks in an object moving area. At the each time frame, object would observe a point feature with its distance and angle. However, when no observations are made, object would move with increasing error; when features are re-observed, error would be reduced.

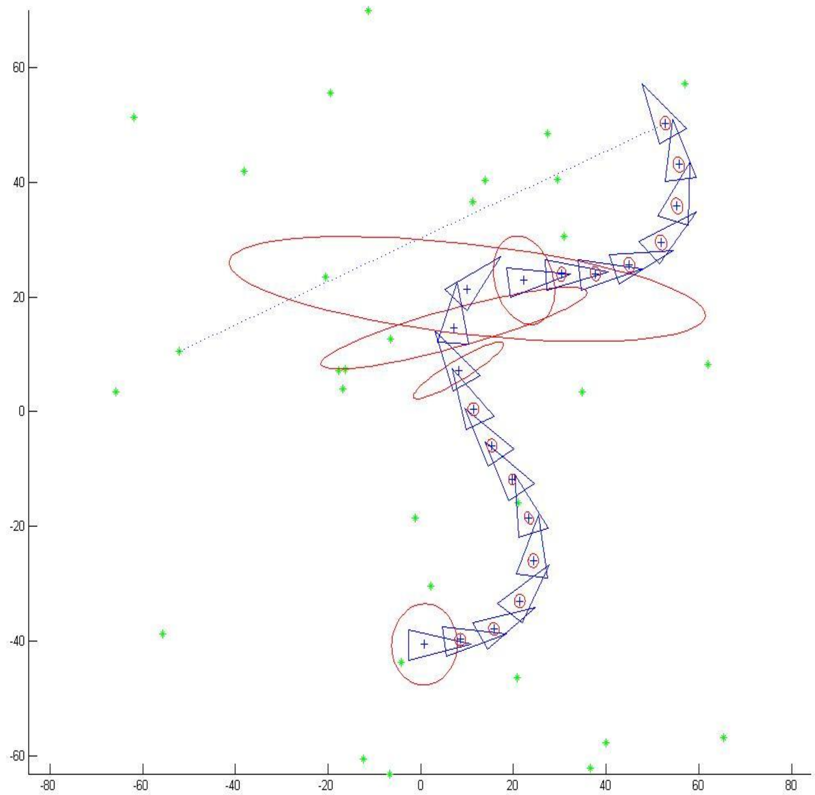


Figure 6. 28 EKF Feature Based Localisation (Newman, 2006)

From the above discussion, EKF is a popular dynamic localisation algorithm in wide applications. The major reason is that it is easy to implement, and is capable of providing accurate non-linear estimation in some practical problems. However, EKF localisation algorithm is not a feasible solution in an RFID-Loc system. The first one is difference of features' type on EKF based localisation algorithm and RFID-Loc localisation algorithm. In a typical EKF based localisation algorithm, features are measured by polar coordinates, distributing with a large number in moving area.

However, in an RFID-Loc system, features are selected as four rectangle coordinate values through an RFID-Loc data filter. The transformation between polar coordinates and rectangle coordinates is hardly to handle, and the reduction on number of features might impact accuracy and precision of EKF based localisation algorithm. Therefore, if we simulated EKF based localisation algorithm with reduced number of features, on a same moving trajectory, localisation results would show in Figure 6.29.

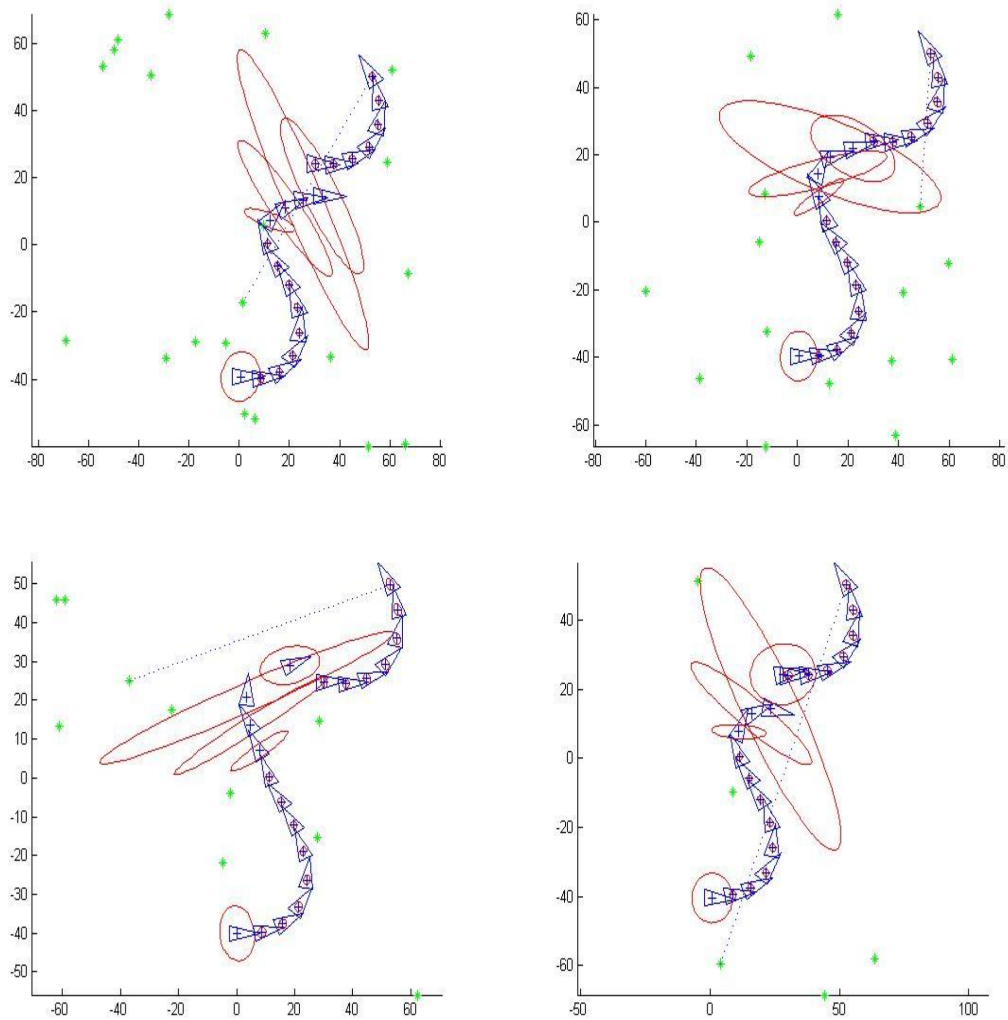


Figure 6. 29: EKF Feature Based Localisation with reduced number of features by using Newman Code (Newman, 2006).

Figure 6.29 shows that EKF feature based localisation algorithm requires a sufficient number of feature points, with appropriate distribution. If the number of feature points is not sufficient, or the positions of feature are not distributed appropriately, EKF based localisation algorithm would have a low accuracy and precision. This is a widely-recognized problem called Data Association Problem (or Correspondence problem, see Cox, 1993). EKF based localisation algorithm is based on an assumption that the moving object can identify each feature. For example, if the equipped sensor is a range detector, we assume at each observation, the moving object knows its distance to a unique feature. This is impossible to achieve in an RFID-Loc system, since RFID reader is impossible to ensure the correct identification of each feature every time. Especially when RFID tag pattern is highly dense, it is extremely difficult to properly identify each feature. Another issue of EKF is the linear approximation of motion and observation model. The errors produced by the linear approximation can affect the map consistency. In an indoor environment, object moving trajectory is highly non-linear and random, which is not suitable to use EKF based localisation algorithm.

Particle Filter:

Particle Filter has been shown to be more robust than Kalman Filter for Localisation. The robustness is a key demerit of *static* localisation algorithm in an RFID-Loc tracker. In light of this point, Particle Filter is more appropriate to be investigated in RFID-Loc localisation algorithm module than EKF. Meanwhile, particle filter has no limitations on linear approximation of motion model of EKF, which is more suitable in a indoor environment. In this section, it explores the possibility of particle filter method for an RFID-Loc system.

Recently, a typical particle filter algorithm is proposed for SLAM by Montemerlo (Montemerlo.etal, 2003), called FastSLAM. It is typically used for ranged based sensor localisation. The observed features at that each time frame is distance or angle. Like Particle Filter Localisation techniques reviewed in Chapter 2, FastSLAM is based on the probabilistic framework. Recall that in localisation the goal is to estimate the system states belief representing the posterior probability of the location state s_t, conditioned on the sensor distance measurement $d_{0:t}$:

$$Bel(s_t) = \Pr(s_t \mid d_{0:t}) \qquad (6.10)$$

In the context of SLAM, it requires to estimate both *location state* and *feature state*. If we denote the whole map containing N *features* as M, and each features as m_n then the belief of system states becomes:

$$Bel(s_t, M) = \Pr(s_t, M \mid d_{0:t}) \qquad (6.11)$$

Where:

$$m_{n,t} = \begin{bmatrix} d \\ \theta \end{bmatrix}$$

In FastSLAM, it is not momentary *location states*, but the entire path is estimated. Based on the fact that each feature can be estimated independently given the path, the belief is then:

$$\begin{aligned} Bel(s_{0:t}, M) &= \Pr(s_{0:t}, M \mid d_{0:t}) \\ &= \Pr(s_{0:t} \mid d_{0:t}) \Pr(M \mid s_{0:t}, d_{0:t}) \\ &= \Pr(s_{0:t} \mid d_{0:t}) \prod_{n=1}^{N} \Pr(m_n \mid s_{0:t}, d_{0:t}) \end{aligned} \qquad (6.12)$$

Equation 6.12 is the basic math for FastSLAM. It divides the SLAM problem into a *location path estimation* problem along with *N feature estimation problem* (Montemerlo 2002). We use FastSLAM to carry out a simulation, which has four assumed features in the map, with the following states: A(10,10), B(21.92, -0.65), C(-11.95,-16.6), D(-5,15). In particular, a Gaussian with zero mean and a standard deviation of 0.6 is used as the noise in the observation model. Figure 6.30 shows the simulation result from the dataset. At the beginning the *path* estimation is not correct, and neither do the *feature* estimations. This is due to the fact that there are a lot of ambiguities about each *feature*. For instance, at time interval 3, there are several estimations to *feature C*, which are distributed quite depressively (the grey circles). These ambiguities cause the *path* estimation to be 'twisted' (the blue line). However as the object keeps moving, at time interval 60, both the *feature* estimations and *path* estimation converge to the real ones.

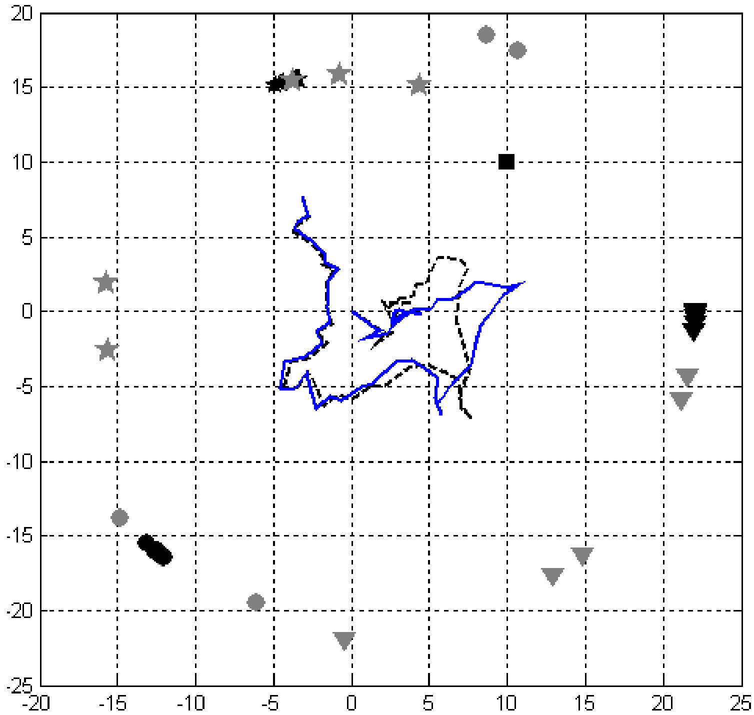


Figure 6. 30: An simulation result by using FastSLAM with 150 particles:

The black dashed line is the *real path* (begins from the origin) while the blue line is the *estimated path* from the particle filter SLAM algorithm. The square, triangle, circle and star represent the estimation to feature A, B, C and D respectively. In these feature estimations the grey ones are the results at time interval 3 while the black ones are the results at time interval 60. The initialization method for the first observed feature (here it is feature A) is to pick a random point as its *state*, hence the estimation to feature A will remain constant. Also in this experiment feature A is initialized to be overlapped with its *real feature state* so that the estimated path will have the same orientation with the real one.

The above Figure appears that particular filter can potentially be a dynamic localisation algorithm in an RFID-Loc localisation algorithm. However, there are still some key barriers on this attempt, which would be discussed and solved in next section.

6.3.2.3 Discussion

The first key barrier of typical Particle Filter localisation algorithms is the high computational complexity of Particle Filter. Since in localisation, the state space usually has just 3 or 4 dimensions (e.g. three Cartesian coordinates and possibly one orientation), while in SLAM the number of features can easily be an order of hundreds. In order to get a satisfactory result with Particle Filter, the number of particles needs to rise rapidly with the dimension of the state space (Gordon et.al. 1993). Actually, In FastSLAM, the posterior over *location path* is estimated by particle filter, and each particle maintains its own map with *N features.* These *features* are estimated by Extended Kalman Filter (each EKF for one *feature*) using the same techniques. Thus if there are *M* particles, then there will be $N \times M$ EKFs in total. Compared with standard particle filter, far fewer particles are required. And because each EKF only estimate one single *feature*, a high-dimensional SLAM problem is then factorized into a product of low-dimensional estimation problems, which yields a much improved efficiency. The algorithm used by FastSLAM is actually an instantiation of the *Rao-Blackwellised Particle Filter* (Murphy 1999), which uses a combination of particle representation and parametric representation for a high-dimensional Bayes estimation problem. For a complete derivation and proof of this factorization, refer to (Thrun et al 2004). FastSLAM absorbs the advantage of both Kalman Filter and Particle Filter. As a result it can be applied into highly non-linear SLAM problems while at the same time maintains efficiency and accuracy. For the sake of clarity, we carried out some more simulations in Figure 6.31 with different number of particles, to examine the programming running time and error of estimation. Figure 6.6 demonstrates the relationship between the number of particles and the running time of simulation program and the error of estimation. From the Figure 6.6, it shows that the more number of particles would have a higher accurate estimation, but with a longer running time. Oppositely, if the number of particles reduced, it is possible to reduce the running time, but with some loss on accuracy. In an RFID-Loc system, long running time of localisation algorithm would lead to a time delay, thus it is necessary to balance running time and error of estimation of Particular Filter based localisation algorithm.

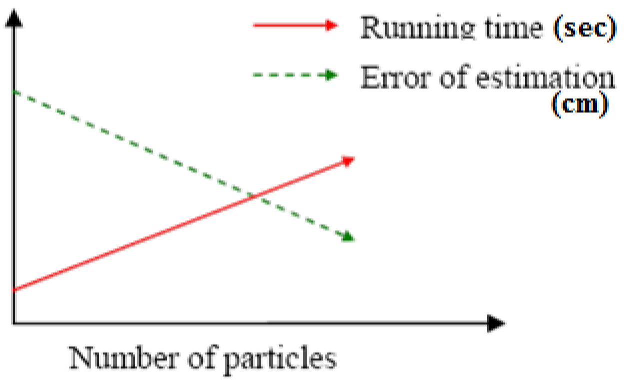


Figure 6. 31: The influence of the number of particles

Secondly, the sensor environment and features of an RFID-Loc system are different with the typical FastSLAM applications. It is critical to identify their differences so that we can adopt particular filter technique in an RFID-Loc system. The conventional FastSLAM particle filters algorithm is to deal with several fixed or unfixed feature points, which in practical presents the range-measurement sensors, to measure the distance information at each time intervals. The observation is distance information. However, in an RFID-Loc system, features are extracted by RFID-Loc data filter, which are position information. The impacts of features on object position are not equal. In a conventional FastSLAM algorithm, features would impact on localisation of both X axis and Y axis of moving object. In an RFID-Loc system, two features on X axis impacts on X value of object position, another two features on Y axis impacts on Y value of object position. Considering those differences on sensor environment and features, FastSLAM particle filter algorithm cannot be directly applied into an RFID-Loc system. The aim of FastSLAM is to accurately localize the mobile object by using range sensor with the environment of unknown start position and feature position. It contains the feature based estimation for mapping and localisation. But in an RFID-Loc system, although the features extracted by RFID-Loc data filter have some uncertainty and errors, the mapping between features and object position is clear and explicit. Strictly speaking, dynamic localisation process for an RFID-Loc system is solely a localisation process without mapping process. In light of those differences between RFID-Loc environment and typical FastSLAM applications, it is necessary to propose a new particle filter based localisation algorithm for an RFID-Loc system. In a typical FastSLAM algorithm, by using the observation model and motion model, it would estimate the position information of moving object. The whole localisation process contains initializing, applying model, weighting, and resampling. It can use some range-only measurement sensors in that for mobile objects localisation, and most sensors are easily to observe the distance information rather than position information. As for an RFID-Loc application, dynamic localisation process can also contain initializing, applying model, weighting and resampling process. However, since RFID reader observes position value of RFID tags instead of distance value, the proposed dynamic localisation algorithm would rebuild different observation model, motion model, and define feature points, weighting process, resampling process. The comparison of a proposed dynamical localisation approach and conventional FastSLAM approach is shown in Table 6.6.

Table 6. 6 Comparison of RFID-Loc Dynamic Localisation and SLAM

	RFID-Loc Dynamic Localisation	**FASTSLAM**
Feature points	Position information, Mobile.	Distance information, Nearly fixed.
Initialization	Known start position, Known start features.	Unknown start position, Unknown start features position.
Sensor Data	Position information	Distance information
Applying motion model	Gaussian model, but the radius is determined by known accuracy (tag distance)	Gaussian model, the radius could be any value.
Observation model and weighting	Observation model is based on the position difference between predicted value and observed value.	Observation model is based on the distance difference between predicted value and observed value.
Feature Impacts	Two features on X axis impacts on output X value, another two features on Y axis impacts on output Y value.	Four features impacts on both output X and Y value.
Resampling	Directly use the particles with largest weight.	Those particles with large weight will be duplicated while those with small weight will be deleted.
Aim	Accurately localize the object by using position sensor with the environment of known start position and feature position.	Accurately localize the mobile object by using range sensor with the environment of unknown start position and feature position.
Performance	No strict convergence, the accuracy at each time interval is only determined by the closeness of predicted features to observation features.	With increasing time intervals, the position has a convergence with high accuracy.

6.3.3 System State and Model Definitions

In this section, it proposes a new particle filter based dynamic localisation algorithm for an RFID-Loc system. This section provides a comprehensive description of the implementation of system states, system models and the particle filter in this algorithm.

6.3.3.1 System state

Hence all features as well as the location of the object can be represented by Cartesian coordinates. The chosen four feature points $F_{xp}, F_{xn}, F_{yp}, F_{yn}$ are the minimum and maximum values on X and Y axis among all the detected RFID tag position value at time interval *t*, as shown in Equation 5.1 in Chapter 5. If current time interval is denoted as *t*, object position (X_t^c, Y_t^c) can be obtained through the position data of RFID tags (X_T^N, Y_T^N), where *N* represents the number of tags detected by the reader, and (X_T^N, Y_T^N) represents the coordination information of the tags. Then the chosen feature points are represented in the following Equation 6.13

$$F(xp, xn, yp, yn) = \begin{cases} F_{xp} = Max(x_t^1, x_t^2, ...x_t^N) \\ F_{xn} = Min(x_t^1, x_t^2, ...x_t^N) \\ F_{yp} = Max(y_t^1, y_t^2, ...y_t^N) \\ F_{yn} = Min(y_t^1, y_t^2, ...y_t^N) \end{cases} \qquad \textit{Feature State} \qquad (6.13)$$

After defining the state of four feature points, it requires to define a system state to represent the localisation process. The location state represents the position of object, is defined as S in Equation 6.14, where *n* is index of feature points, *t* is the time interval.

$$S_t = (\ x_t,\ y_t \qquad \textit{Location state} \qquad (6.14)$$

Having defined the feature states and location states, the system state, at time *t*, the system state ST_t is shown as Equation 6.15:

$$ST_t = \begin{bmatrix} s_t \\ F_t^{xp} \\ F_t^{xn} \\ F_t^{yp} \\ F_t^{yn} \end{bmatrix} \qquad \textit{System State} \qquad (6.15)$$

Given the above overview of system state, the specific objective of this dynamic localisation algorithm is : the object starts moving from an initial position s_0 with prior knowledge of the feature points: $F_0^{xp}, F_0^{xn}, F_0^{yp}, F_0^{yn}$. As the object keeps moving it receives different features' data from the RFID readers. The value of feature points would change as the object moving.

6.3.3.2 System models

Besides system states, there are two models that need to be defined, namely the observation model and motion model. Their specific implementation is characterized by the nature of the RFID sensor system and the motion of object moving.

The observation model tells the probability of obtaining a object position at a certain location state. Recalling the theory of Bayes Filter, this is defined as a probabilistic distribution:

$$\Pr(F_t(xn, xp, yn, yp) \mid S_t)$$

Where: $F_t(xn, xp, yn, yp)$ and S_t are the RFID reading and location state, respectively.

Unlike most other SLAM problems in literature that uses range-bearing sensors. The characteristic of RFID reader is that it can only provide relative position information, but not distance or bearing information. This will bring a lot of differences on the initialization and observation process in the proposed dynamic localisation. Also RFID tag position information will contain some noise which is caused by environment. Therefore, the *straight observation model* would be in Equation 6.16:

$$\begin{cases} d_t^{xp} = F_t^{xp} + \delta \\ d_t^{xn} = F_t^{xn} + \delta \\ d_t^{yp} = F_t^{yp} + \delta \\ d_t^{yn} = F_t^{yn} + \delta \end{cases} \tag{6.16}$$

Where: $d_t^{xp}, d_t^{xn}, d_t^{yp}, d_t^{yn}$ are the observations of features at time interval *t*.

δ is the noise of measurement each time interval.

At each time interval, RFID reader will receive observation information from all features. Figure 6.32 is an example showing an RFID-Loc system measuring the position information from four features at the same time. While in practice, RFID reader may receive observation of each RFID tag one by one, a time gap is given to collect enough RFID raw data, etc, 20 seconds in Chapter 4 case. And then the four features can be treated as simultaneously extracting from RFID raw data.

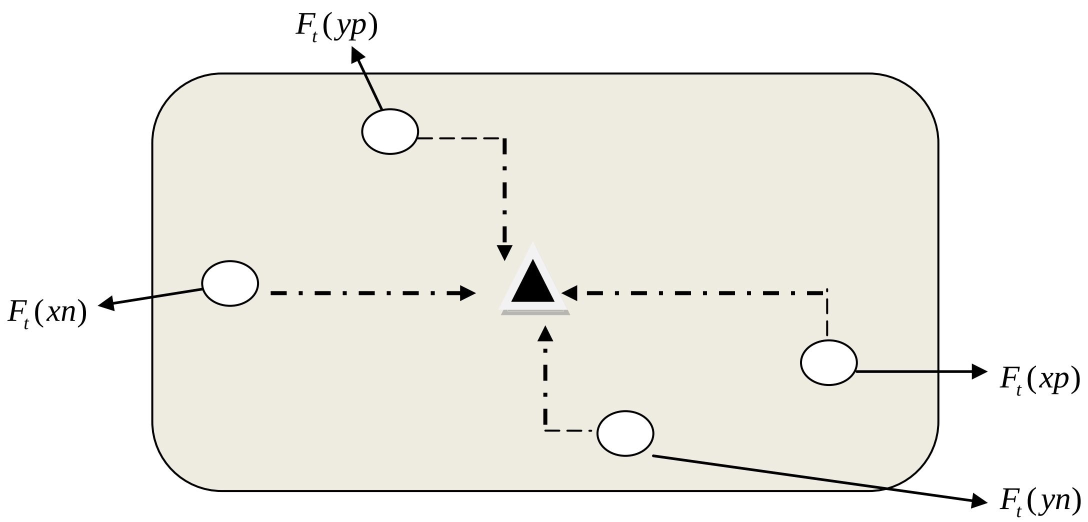


Figure 6. 32: The Observation Model

The straight observation model gives the relationship between the object position and the features value. But it is not enough as we need another model which can provide the feature states given the location state of the object and the observation information. The *inverse observation model* offers such functionality.

The motion model is used to characterize the moving object location states over time. It helps to predict the next moving object location state given the most current one. In a real indoor environment, moving object is possibly human carrying or wheel driving. Moving object might change its direction or speed of the movement randomly. So the targeted moving object trajectory is assumed to be associated with direction or speed of the movement that is random. To cope with the randomness of the motion moving, a 2D Gaussian model is used to approximate the motion. More specifically, when given the location state s_t at the time interval *t*, to predict the location state S_{t+1} at the time *t+1*, a number of particles are drawn randomly from a 2D Gaussian distribution with zero-mean. These particles will be distributed in a circle with origin at s_t and its radius is determined by the standard deviation of the 2D Gaussian distribution. For instance, if moving object position start from position (0, 0), and localisation accuracy in a RFID-Loc system would reach 5 centimeters, so the next step of position possibly is on the circle which is on the centre (0,0), with the radius $5*\sqrt{2}$, and draw 200 particles, the diagram is shown in Fig 6.33

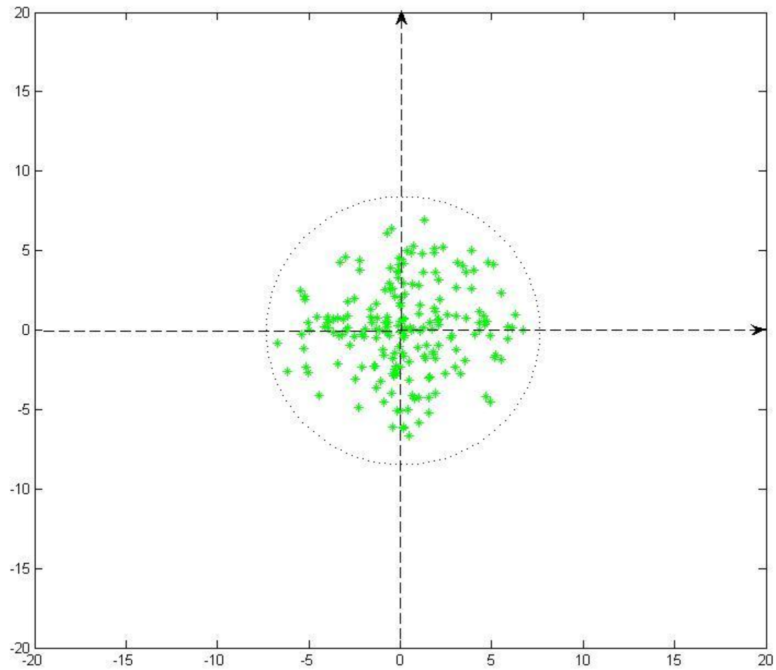


Figure 6. 33: The Motion Model

Figure 6.33 shows an example of the motion model using 200 particles. Notice that in practice it is not necessary to use so many particles. Usually around 100 particles are enough to obtain satisfactory results. But using more particles can improve the accuracy for the estimation of location states.

The main advantage of using a 2D Gaussian to approximate the motion model is its ability to cover all possible motion directions. In order to predict location state accurately, the standard deviation of this 2D Gaussian has to be carefully specified. However, this motion model also has two limitations which may significantly affect the efficiency of the dynamic localisation algorithm in certain circumstances. The first problem arises because it simply draws particles from a 2D Gaussian randomly and consequently there will be some particles being "wasted" since they may be placed at positions with low observation likelihood. The other drawback is a direct consequence of the particle-wasting problem. If the total number of the particle is not big enough then there will be too few particles placed at the high observation likelihood area and therefore the prediction accuracy will be significantly affected. There two problems are from the nature of the resampling process of standard particle filter and have been broadly recognized by researchers. In order to overcome this problem, we would employ a simple method, which only select the biggest weight particle for generating the location states.

6.3.4 Dynamic Localisation Algorithm for RFID-Loc

After defining the system state and observation model, it requires clearing the structure of each particle. The conventional particle filter structure only contains the localisation state and feature states without including weight issues. But in this algorithm, we would put the weight state into particle state. Each particle has a mathematical way in Equation 6.17.

$$ST_t^M = \{ S_t^M , F_{xp,t}^M , F_{xn,t}^M , F_{yp,t}^M , F_{yn,t}^M , W_{xp,t}^M , W_{xn,t}^M , W_{yp,t}^M \} \tag{6.17}$$

Where:

M is the index of the particle,

t is the time interval.

s_t^m is the location of the object

$f_{n,t}^m$ represents feature points.

$w_{n,t}^M$ represents the weight of each feature.

U_t^M is the updated location of object.

The particle filter algorithm is then operating on a set of particles. Each iteration of the algorithm can be divided into the following stages:

(a) Initialization:

(b) Applying motion model:

(c) Apply observation model and weight all the particles

(d) Resampling

Note that the initialization stage is required only one in the first iteration.

6.3.4.1 Initialization

Initialization is an important stage in all conventional SLAM algorithms. In EFK based SLAM, its task is to initialize the mean and covariance matrix for the state vector. In the typical particle filter algorithm, it is to initialize the location state and feature states in each particle. Most of times, the start position of target and features are unknown, so that the errors at the beginning stage is big. However, in RFID-Loc case, the RFID sensor could provide the position information initially; it could start at a known position and feature points. Hence, according to the theoretical model, the start position is zero, radius as the accuracy of localisation required, feature points position are calculated as the RFID reader detection area. (Length as Y axis, Width as X axis).

$$S_0 = (0,0) \quad , \quad r = \text{Accuracy} \quad , \quad W_{n,0}^M = 1$$

$$f_{1,0}^m = near(L)\,, \quad f_{2,0}^m = near(W)\,, \quad f_{3,0}^m = near(-L)\,, \quad f_{4,0}^m = near(-W)$$

$$Initialization \qquad (6.18)$$

Where : Near () : the nearest tag in the RFID reader detection edge area

6.3.4.2 Applying Model and Weighting

After the initialization, the motion model is applied to all particles. More specifically, the *location state* of each particle will be replaced with a new predicted one generated from the motion model, and the predicted feature state of each particle will be updated as well. The process is as followed:

At the time intervals t : Once applying motion model to Equation 6.9, the M particles get M numbers of different predicted position state S_{t+1}^M, which are allocated in the circle of centre point S_t^M , radius as Accuracy

$$Predict\ S_{t+1}^M = Motion\ S_t^M \qquad (6.19)$$

Then due to the known RFID reader detection area, it could estimate the position of predicted features:

$$\begin{aligned}
PredictF^{M}_{xp,t+1} &= PredictS^{M}_{t+1} + near_W \\
PredictF^{M}_{xn,t+1} &= PredictS^{M}_{t+1} - near_W \\
PredictF^{M}_{yp,t+1} &= PredictS^{M}_{t+1} + near_L \\
PredictF^{M}_{yn,t+1} &= PredictS^{M}_{t+1} - near_L
\end{aligned} \tag{6.20}$$

Here, each particle has its estimation to the location state and feature states. Then we define predicted location state as the location state after being applied the motion model. And define predicted observation as the features' value. Then the weight of each particle should be determine by the difference of the predicted observation and real observation. If the predicted location state and feature state is very close to the real states. Then the predicted observation will be very close to the real observation. Hence this particle will have a high weight. In a probabilistic math form, the weight of each particle is given by:

$$W^{m} = \int \Pr(d_t \mid f_n, s_t^{m}) \Pr(f_n, s^{m}_{0:t-1} \mid d_{0:t-1}) \tag{6.21}$$

Where the superscript m is the index of the particle, subscript t is time interval,

Equation 6.21 is implemented by calculating the real observation under a Gaussian with mean and standard deviation determined by the observation noise. More specifically, the weight of each particle is calculated using the following Equation 6.22. Meanwhile, it already got the four predicted feature points value at time intervals $t+1$, it could apply the observation model by using the observed feature points date to calculate the weight of each particles.

$$
\begin{cases}
W^M_{xp,t+1} = (2\pi\sigma^2)^{1/2} e^{-\frac{(\mathrm{Predict}\_F^M_{xp,t+1} - d^{xp}_{t+1})^2}{2\sigma^2}} \\
W^M_{xn,t+1} = (2\pi\sigma^2)^{1/2} e^{-\frac{(\mathrm{Predict}\_F^M_{xn,t+1} - d^{xn}_{t+1})^2}{2\sigma^2}} \\
W^M_{yp,t+1} = (2\pi\sigma^2)^{1/2} e^{-\frac{(\mathrm{Predict}\_F^M_{yp,t+1} - d^{yp}_{t+1})^2}{2\sigma^2}} \\
W^M_{yn,t+1} = (2\pi\sigma^2)^{1/2} e^{-\frac{(\mathrm{Predict}\_F^M_{yn,t+1} - d^{yn}_{t+1})^2}{2\sigma^2}}
\end{cases}
\tag{6.22}
$$

Currently, it already got all the weights, the next stage is to use these weights and get the update object position.

6.3.4.3 Resampling

This step is similar as the one in particle filter localisation. In a conventional particle filter localisation process, those particles with large weight will be duplicated while those with small weight will be deleted. And all the weight would accumulate to impact on the position value. However, in this dynamic algorithm, the situation varies the traditional one in that the four features weight would separately influence the X and Y axis value by two parts, which is that $W^M_{xp,t+1}$ and $W^M_{xn,t+1}$ would determine the X position value, $W^M_{yp,t+1}$ and $W^M_{yn,t+1}$ would determine the Y position value. Consequently, it would pick up the largest weight to calculate the updated object position, since it means that the possibility of object position at that predicted location is the largest. If it is denoted the particle number of largest weight on X positive, X negative, Y positive and Y negative directions are i_xp, i_xn, i_yp, i_yn, then

$$\begin{cases} i\_xp = Max\_index(W^1_{xp,t+1}, W^2_{xp,t+1}, ..., W^M_{xp,t+1}) \\ i\_xn = Max\_index(W^1_{xn,t+1}, W^2_{xn,t+1}, ..., W^M_{xn,t+1}) \\ i\_yp = Max\_index(W^1_{yp,t+1}, W^2_{yp,t+1}, ..., W^M_{yp,t+1}) \\ i\_yn = Max\_index(W^1_{yn,t+1}, W^2_{yn,t+1}, ..., W^M_{yn,t+1}) \end{cases} \tag{6.23}$$

The updated moving object position U^M_{t+1} could be the next step moving object position state s^M_{t+2}, and the algorithm would continue running to estimate the moving object position.

$$U^M_{t+1} = \left(\frac{\text{Predict}\_S^{i\_xp}_{t+1} + \text{Predict}\_S^{i\_xn}_{t+1}}{2}, \frac{\text{Predict}\_S^{i\_yp}_{t+1} + \text{Predict}\_S^{i\_yn}_{t+1}}{2} \right) \tag{6.24}$$

6.3.5 Algorithm Summary

This section will provide a summary of the whole dynamic localisation algorithm for RFID-Loc, as shown in Figure 6.34:

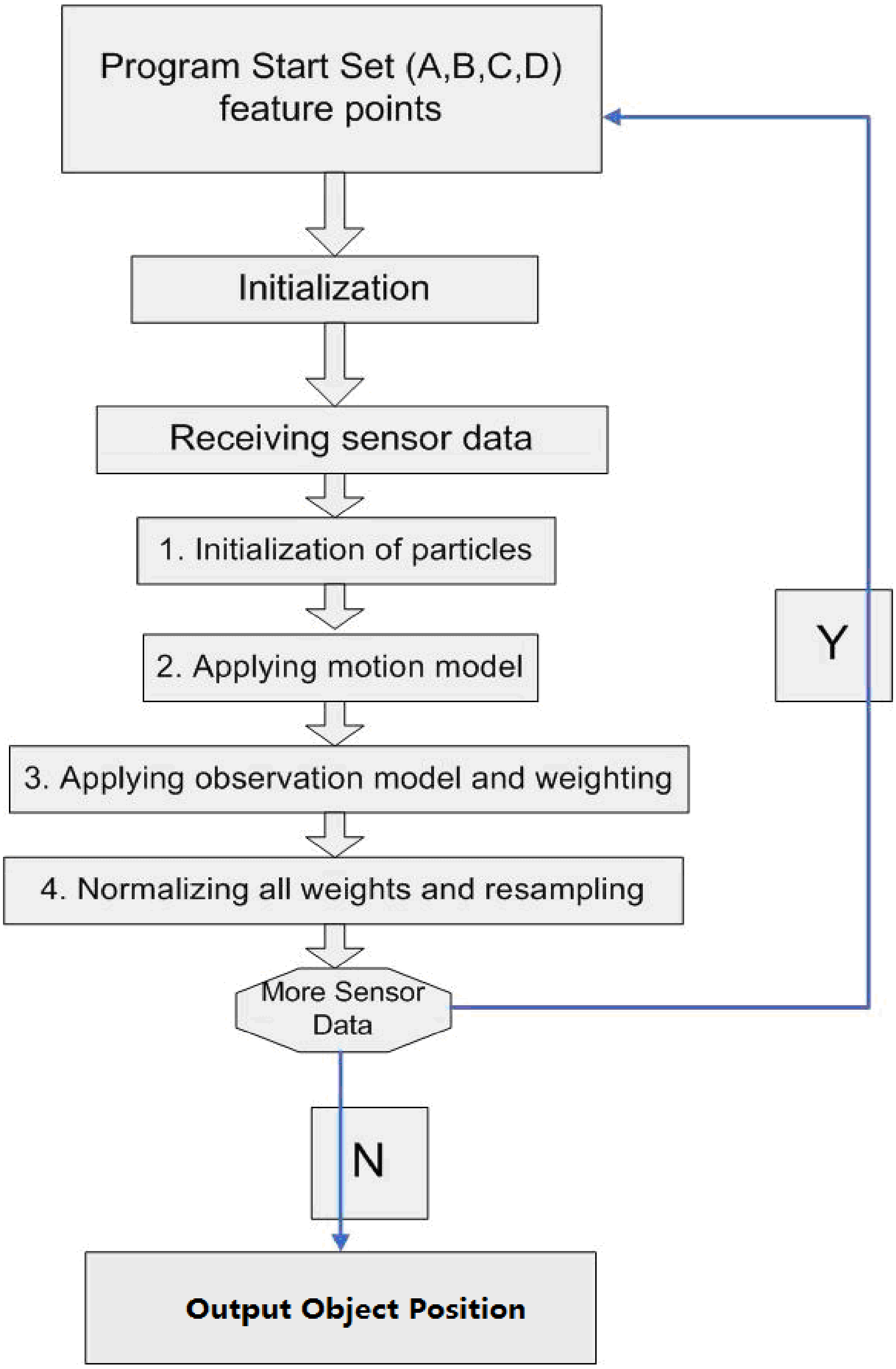


Figure 6. 34: Dynamic Localisation Algorithm Flow Chart

6.4 Summary

In this chapter, how to filter RFID raw data and select reliable features and process these features to localize object position in RFID-Loc are discussed. Under a given RFID-Loc infrastructure platform, experiment results showed that *regular false negative reading* is the most frequently occurring factor affecting to inaccuracy and uncertainty of RFID raw data. Points based, polygon based and rectangle based feature selection methods are compared by evaluating accuracy and precision of an RFID-Loc system in three different trajectories. The comparison explores that by using centroid localisation algorithm, rectangle based feature selection method can give higher localisation precision than points and polygon based feature selection method, particularly on X axis value of object position. It means that rectangle based feature selection method can maximum reduce the impacts of *regular false reading error* on localisation precision from software level, because rectangle area substituting a polygon area in a feature selection method can solve the problem of asymmetry of features in RFID raw data. While under proposed RFID-Loc infrastructure and feature selection method, *static* localisation algorithm in an RFID-Loc system can localize the object position with a good accuracy. But static localisation algorithm has a weak ability to resist *unexpected false reading error* in an RFID-Loc system. Analysis shows that RFID-Loc is a simpler case than typical SLAM problem, but with much difference. A dynamic localisation algorithm based on particle filter technique is proposed and implemented to solve the problem of resisting *unexpected false reading error* in an RFID-Loc system, particularly on *dead reading error* and *repeated reading error*. Experiments showed that dynamic localisation algorithm has a similar accuracy and precision to static localisation algorithm in *regular false reading error* occurring situation, and a better precision than static localisation algorithm in *unexpected false reading error* occurring situation. The robustness of proposed dynamic localisation algorithm has to depend on the chosen number of particles and initial distributed radius.

Chapter 7:

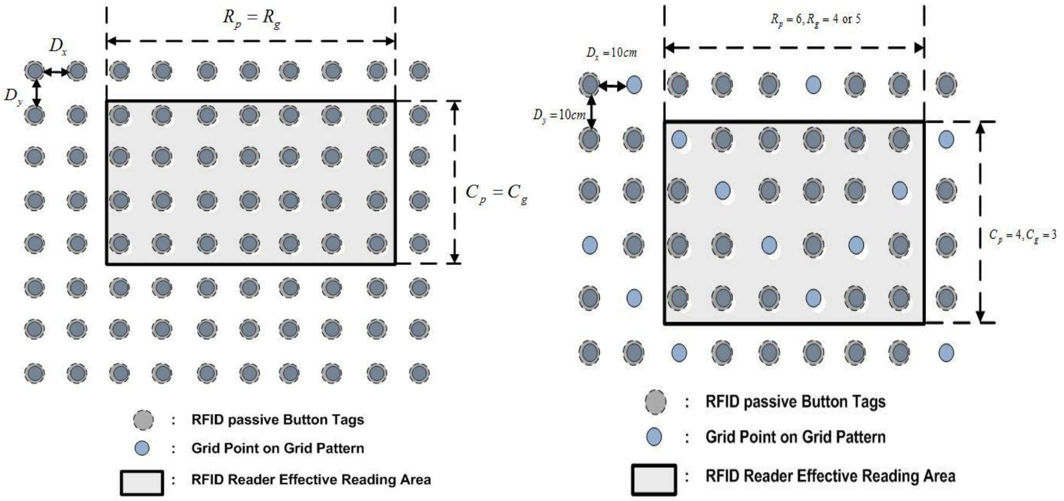
Results Analysis and Discussion

7.1 Introduction

In this Chapter, the application of RFID-Loc framework is discussed, verifying its potential use for indoor application, and providing examples of how it can be used in different scenarios. In order to verify the framework, several experiments with different object moving trajectories are carried out. Section 7.2 focuses on the validation of proposed spare RFID Tag Arrangement Strategy on improving localisation precision by comparing with conventional grid RFID Tag Arrangement. Section 7.3 verifies the performance of proposed dynamic localisation algorithm on resisting *false-reading error*. Section 7.4 illustrates the whole performance of an RFID-Loc based system by using proposed RFID infrastructure and algorithms on localisation accuracy and precision, with comparison to some traditional RFID based localisation systems.

7.2 Validation of Sparse RFID Tag Arrangement Strategy

To evaluate the validity of proposed sparse RFID Tag Arrangement strategy for an RFID-Loc system, the direct way is to check how much improvement on *system reading efficiency* of RFID-Loc Infrastructure module. Comparing RFID tag pattern in Figure 5.18 and 5.3, **M** has reduced from 28 to 18, as shown in Figure 7.1.



Conventional Grid Tag Pattern Spare Tag Arrangement Pattern

Figure 7. 1 Comparison of two RFID Tag Arrangement patterns

In terms of Equation 4.6, under given experimental platform, *system reading efficiency* of RFID-Loc infrastructure has increased from 30% to 40%, which means that proposed sparse RFID Tag Arrangement strategy can reduce *regular false reading error* in an RFID-Loc system.

Apart from evaluating *system reading efficiency*, as mentioned in section 4.4, it would also focus on evaluating localisation accuracy and precision with the proposed sparse RFID Tag Arrangement on some object moving trajectories. In both two patterns of Figure 7.1, accuracy is given as up to 10 centimetres, then:

$$D_x = D_y = 10 \quad \text{cm}$$

So in practical experiment process, the distance of object moving between two time intervals is equal to this accuracy, which is 10 centimetres. The testing trajectories are to move along X axis, move along Y axis and move along both X and Y axis. Time interval of localisation sequence is measured by 12. Localisation algorithm for calculating object position is to use Equation 4.3. The experimental results of object moving along X axis, Y axis, both X and Y axis, are shown in Figure 7.2, 7.3 and 7.4.

These three Figures illustrate that sparse RFID Tag Arrangement can give a better localisation performance than original RFID grid Tag Arrangement. This phenomenon occurs apparently on object moving along X axis. While on object moving along Y axis, new sparse RFID pattern cannot give an apparently improved localisation performance than original RFID grid pattern, it reduced localisation precision on some time interval in original RFID grid pattern. As for object moving along both X and Y axis, original RFID grid pattern produces some significant errors on some time intervals, but new sparse RFID pattern gives a roughly better performance than grid one.

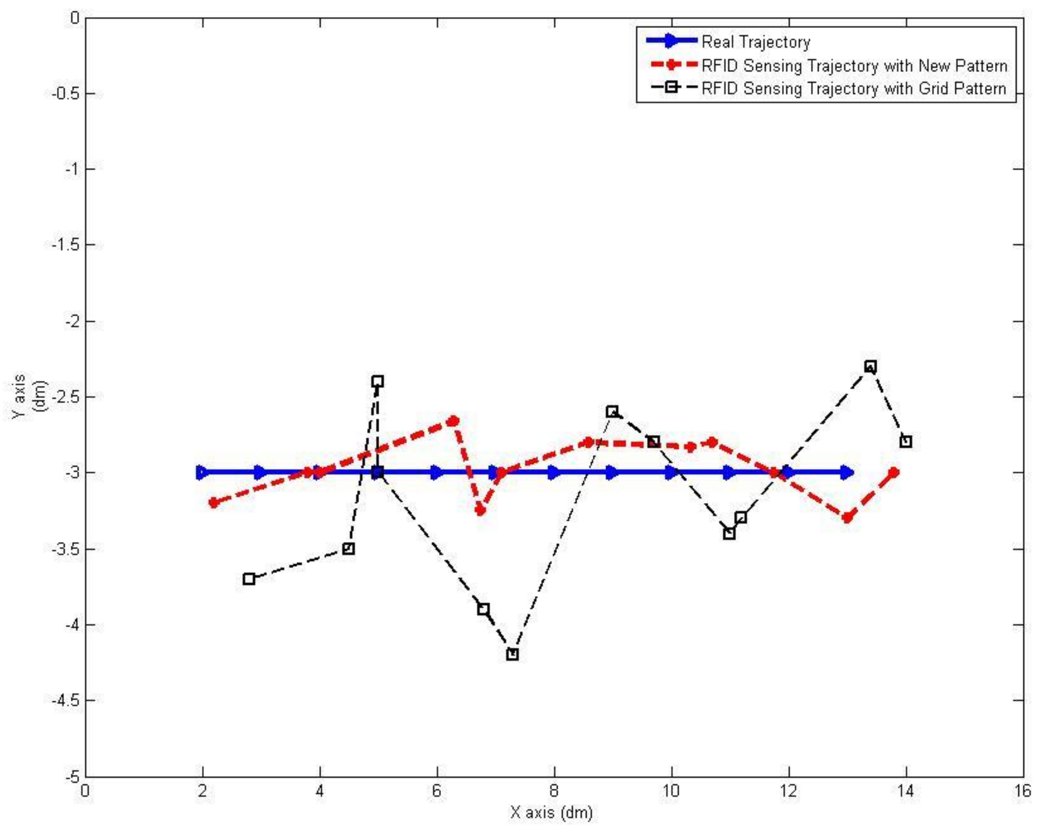


Figure 7. 2 RFID sensing trajectory along X axis.

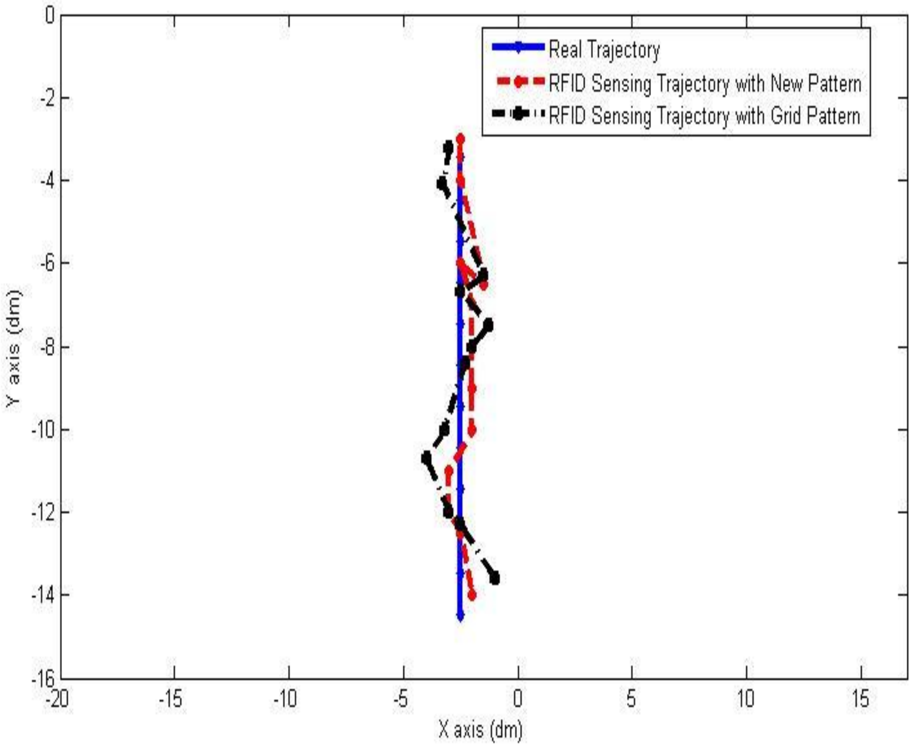


Figure 7. 3 RFID sensing trajectory along Y axis.

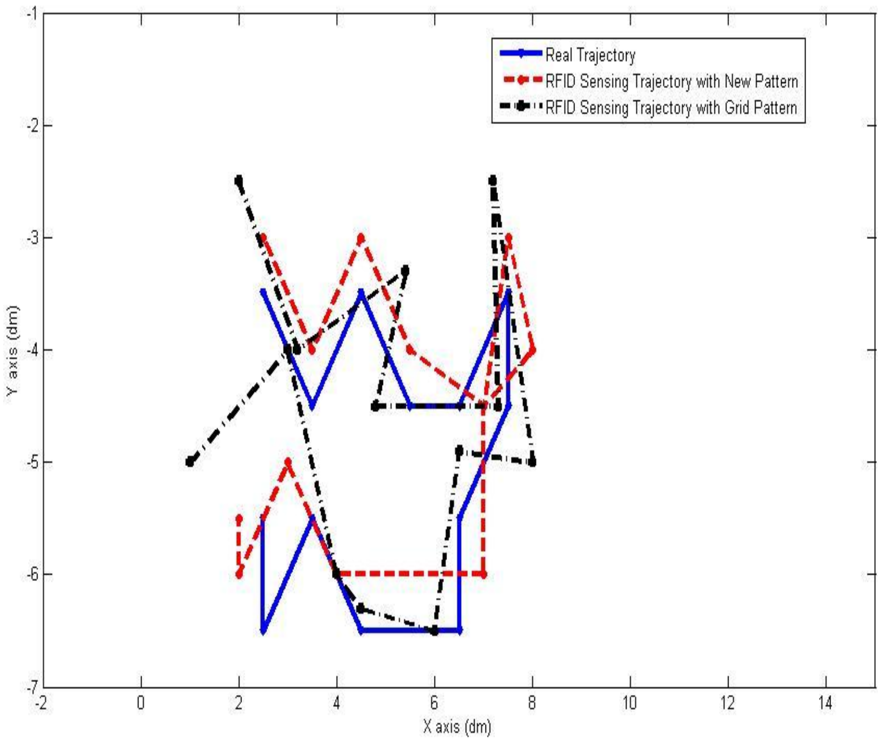


Figure 7. 4 RFID sensing trajectory along both X axis and Y axis.

In terms of the above three trajectories, localisation accuracy and precision of new sparse RFID pattern and traditional RFID grid pattern are compared in Table 7.1. Also, value of localisation precision over 12 time intervals is averaged into Figure 7.5. By using new sparse RFID pattern, the range of localisation precision has been reduced from 10 centimetres level to 5 centimetres level.

Table 7. 1 Comparison of Accuracy and Precision Range on two RFID tag patterns

			X Axis Trajectory	*Y Axis Trajectory*	*X and Y Trajectory*
Accuracy	**Grid Pattern**	**X and Y value of position**	10cm	10cm	10cm
	New Pattern	**X and Y value of position**	10cm	10cm	10cm
Precision	**Grid Pattern**	**X value of position**	(-8,10) cm	(-10,12)cm	(-11,10) cm
		Y value of position	(-5,7) cm	(-6,11) cm	(-8,12) cm
	New Pattern	**X value of position**	(-5,5) cm	(-4,4.5) cm	(-5,4) cm
		Y value of Position	(-3,2) cm	(-5,4) cm	(-4.5,5) cm

Figure 7.5 shows that average localisation precision in continues time intervals has also reduced from 10 centimetres to 3 centimetres. So it indicates that compared to original RFID grid tag pattern, sparse RFID tag pattern can significantly improve the performance of RFID-Loc based object localisation system. While the improvement on objective position X and Y is with different degree, comparing to the localisation performance of original grid tag pattern, localisation precision of object moving along three different trajectories can enhance nearly 50% with the proposed sparse RFID pattern. As for localisation accuracy, tag distance between those two patterns is equivalent to 10 centimetres, so it means that localisation accuracy is unchanged. To the end, the proposed new sparse RFID Tag Arrangement strategy is superior to the current RFID Tag Arrangement method in terms of precision.

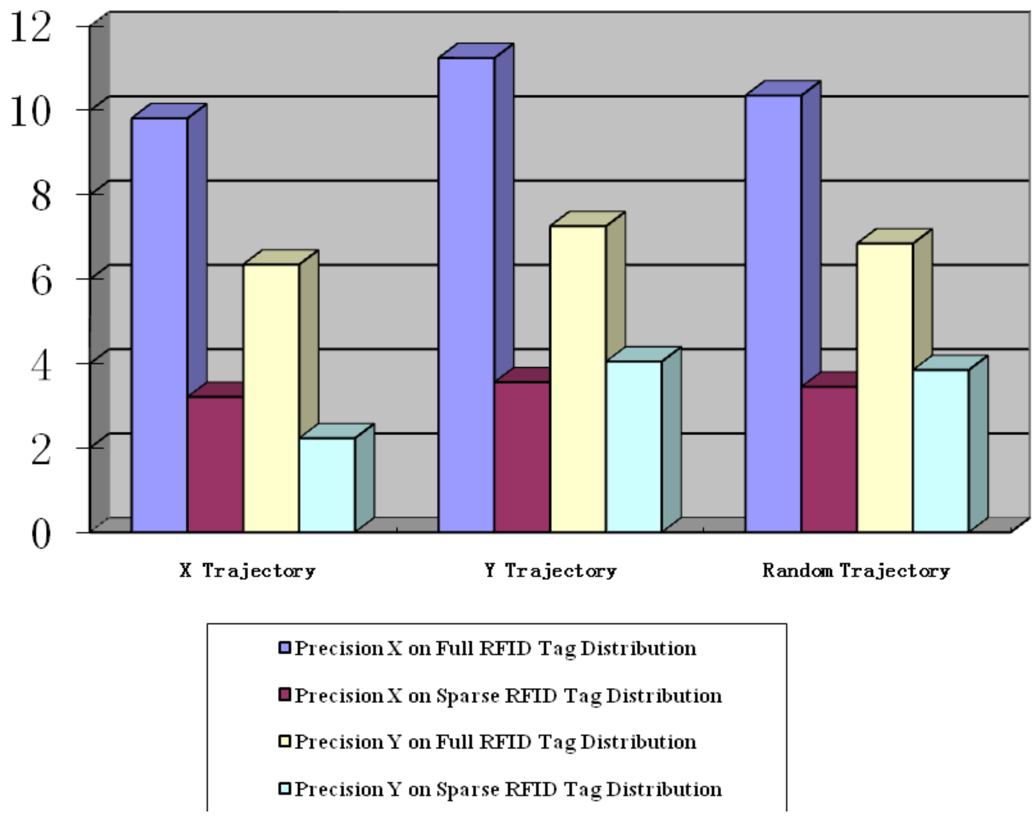


Figure 7. 5 Comparison of Average Precision on two RFID Tag Patterns

7.3 Validation of Dynamic Localisation Algorithm

A number of experiments have been carried out, using different datasets, different numbers of particles and other various settings. These experiments are to evaluate the performance of particle filter based dynamic localisation algorithm on resisting to false reading error, and to investigate if this algorithm has been successfully implemented for 2D position estimation and localisation in a RFID-Loc system in terms of accuracy, precision and robustness. The datasets in these experiments are similarly collected from last section, which includes three object moving trajectories along X axis, Y axis and Random motion. Hence, the parameters in these experiments are the same as previous chapters.

7.3.1 Regular False Reading Error

To begin with, it compares localisation performance of proposed dynamic localisation algorithm with *static* localisation algorithm on accuracy and precision, with the same extracted features. Moving distance of object at each time interval is 10 centimetres, which is equal to the assumed localisation accuracy. The radius of circle for distributing particles is initialized as 20 centimetres, so that it can potentially cover all possible moving directions and positions. As for start position, since every dataset started from different position, different ones are selected as start position. The number of particles would be assumed as 100 at the beginning.

Figure 7.6 and Figure 7.7 shows that the performance of static and dynamic localisation algorithm on the situation that object only moving along X axis. The start position is (0,-2).

Figure 7.8 and Figure 7.9 shows that the performance of static and dynamic localisation algorithm on the situation that object only moving along Y axis. The start position is (0,-2).

Figure 7.10 and Figure 7.11 shows that the performance of static and dynamic localisation algorithm on the situation that object only moving along a random trajectory. The start position is (0,-2).

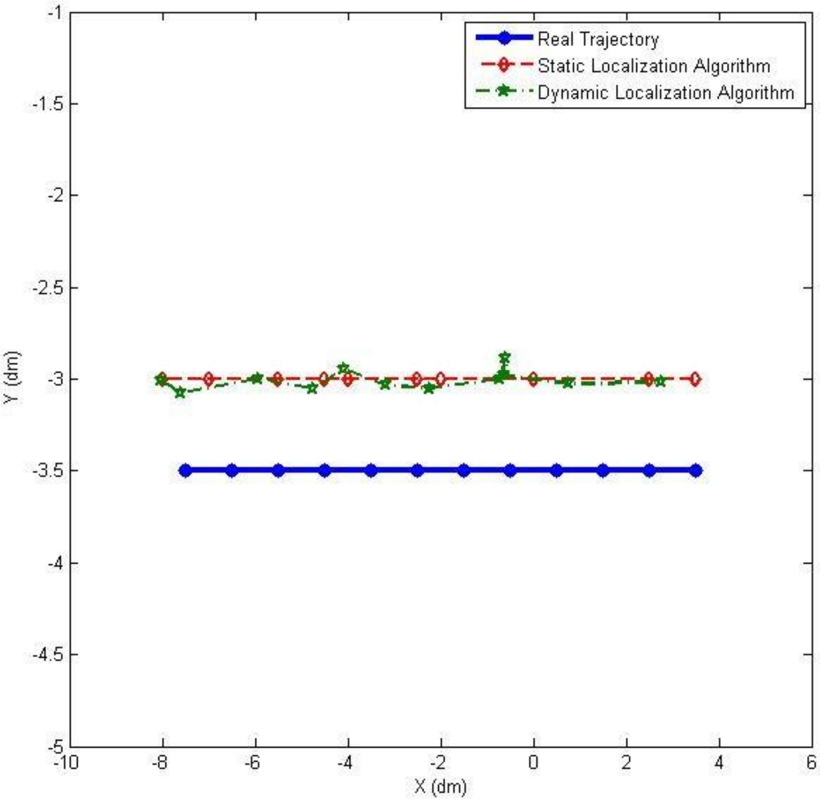
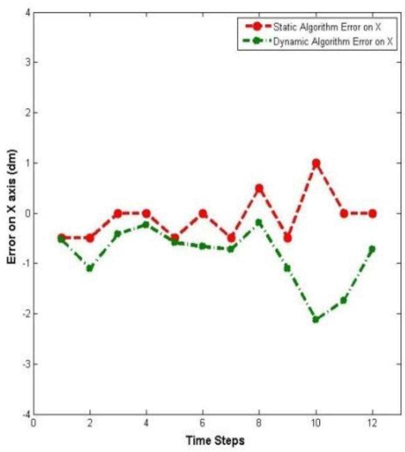
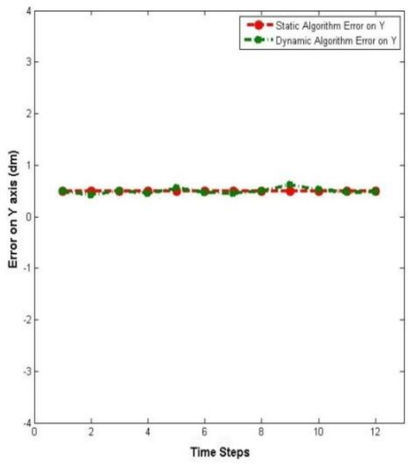


Figure 7. 6 Comparison on X Trajectory



(b) Error on X axis



(b) Error on Y axis

Figure 7. 7 Errors Comparison on X Trajectory

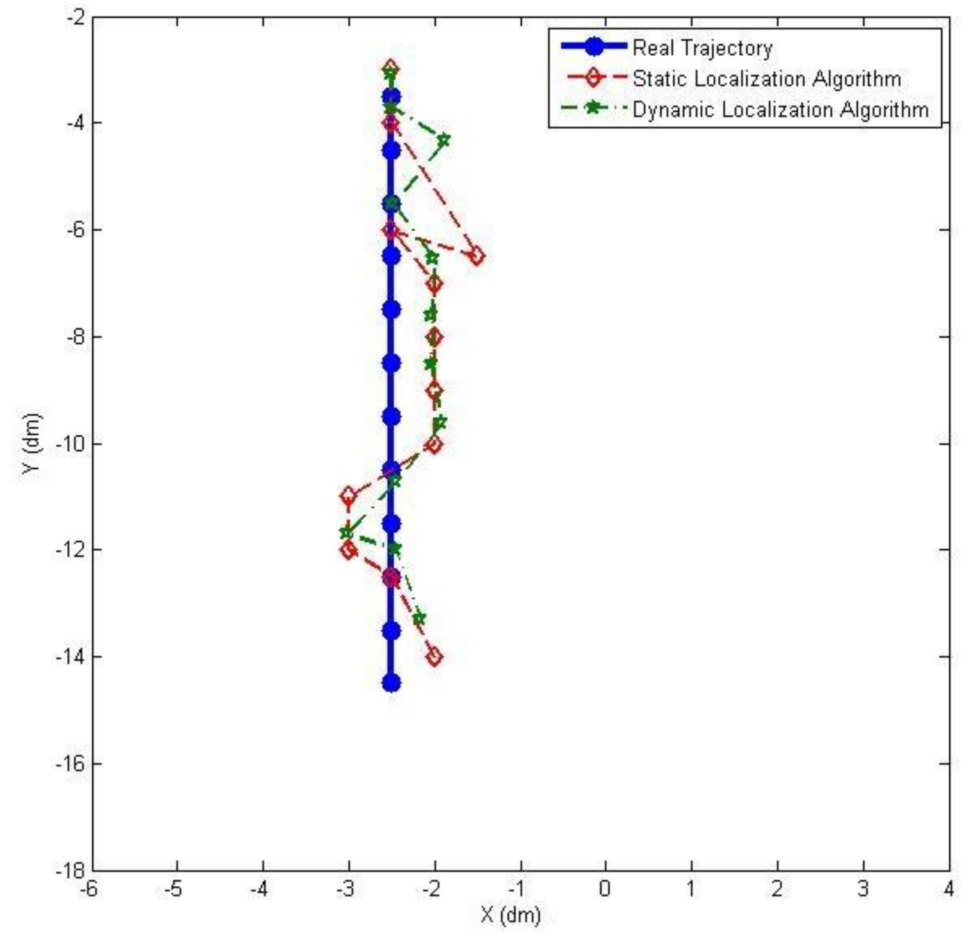
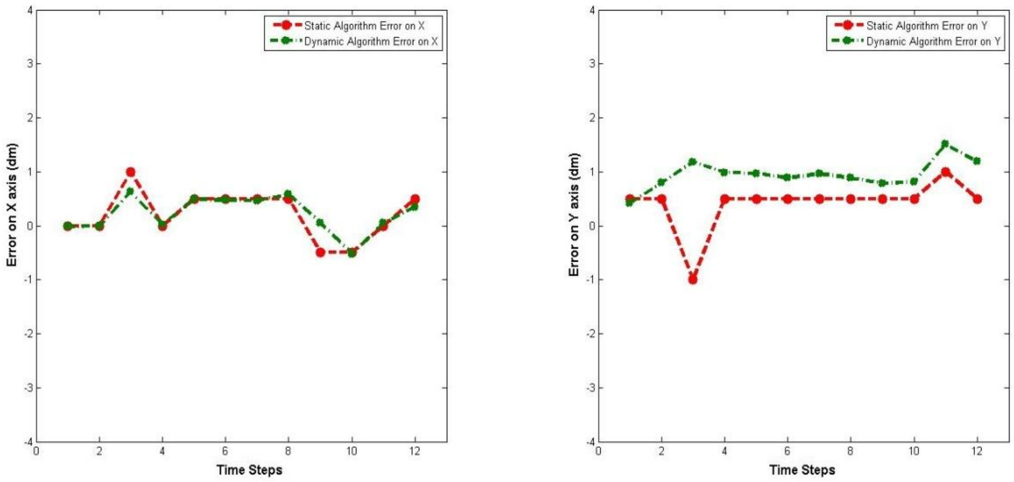


Figure 7. 8 Comparison on Y Trajectory



(a) Error on X axis (b) Error on Y axis

Figure 7. 9 Errors Comparison on Y Trajectory

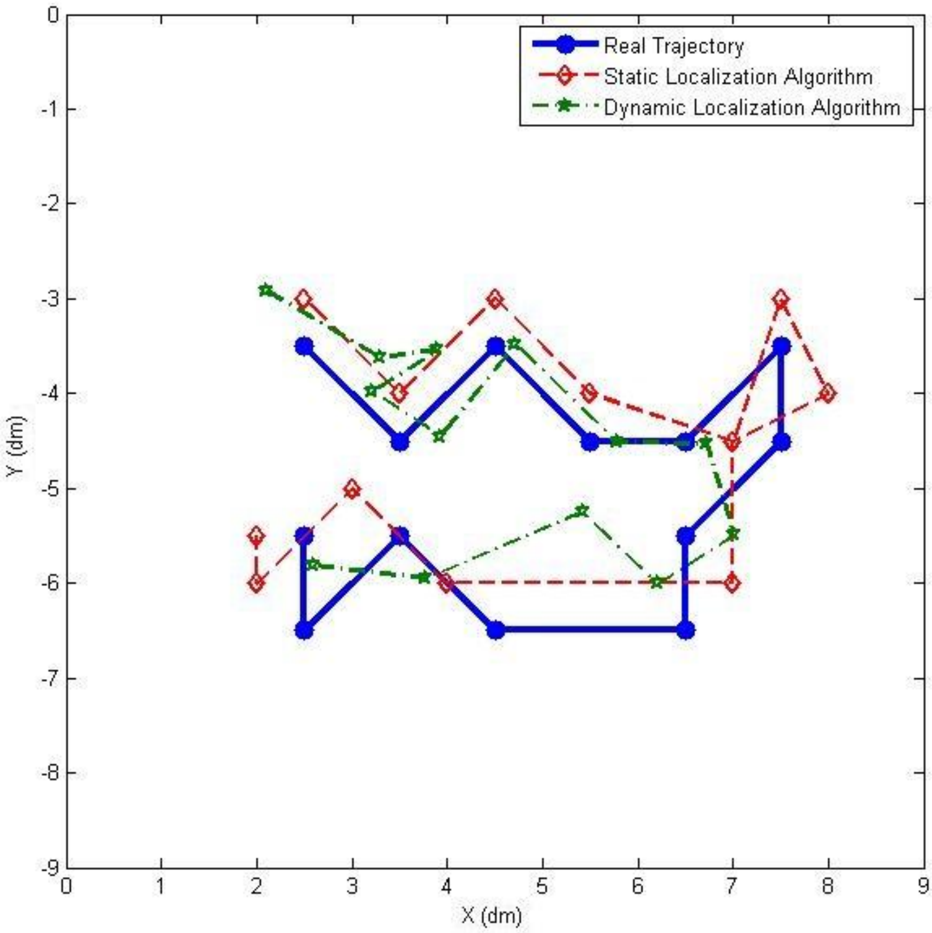
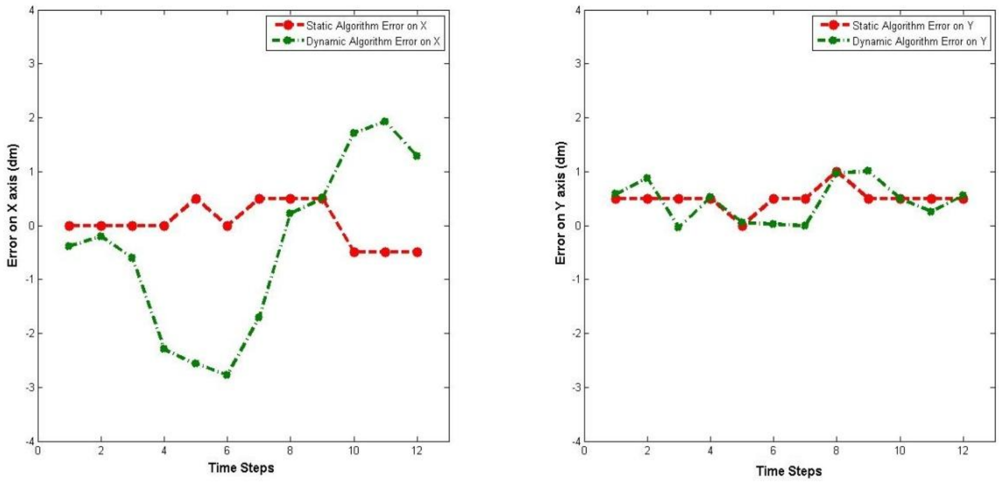


Figure 7. 10 Comparison on Random Trajectory



(a) Error on X axis

(b) Error on Y axis

Figure 7. 11 Errors Comparison on Random Trajectory

From the above Figures, X and Y trajectory represent that dynamic localisation algorithm can get a roughly identical accuracy as *static* localisation algorithm on those two cases. However, in this situation of random trajectory, dynamic localisation algorithm generates a bigger error than *static* localisation algorithm. Theoretically, random trajectory can be viewed as a combination of many small moving segments on X axis or Y axis. Consequently, if dynamic localisation algorithm can be effective on those two cases, it would be also effective on random moving trajectory. The possible reason leading to bigger error of dynamic localisation algorithm is the length of radius to distribute the particles. If length of radius is not long enough, the particles in the circle would be impossible to cover all possible moving directions and positions at next step. In order to explore the impact of the length of radius on the performance of dynamic localisation algorithm, the length of radius is selected and evaluated by 30 centimetres, Figure 7.12 and 7.13 shows algorithm performance on random trajectory.

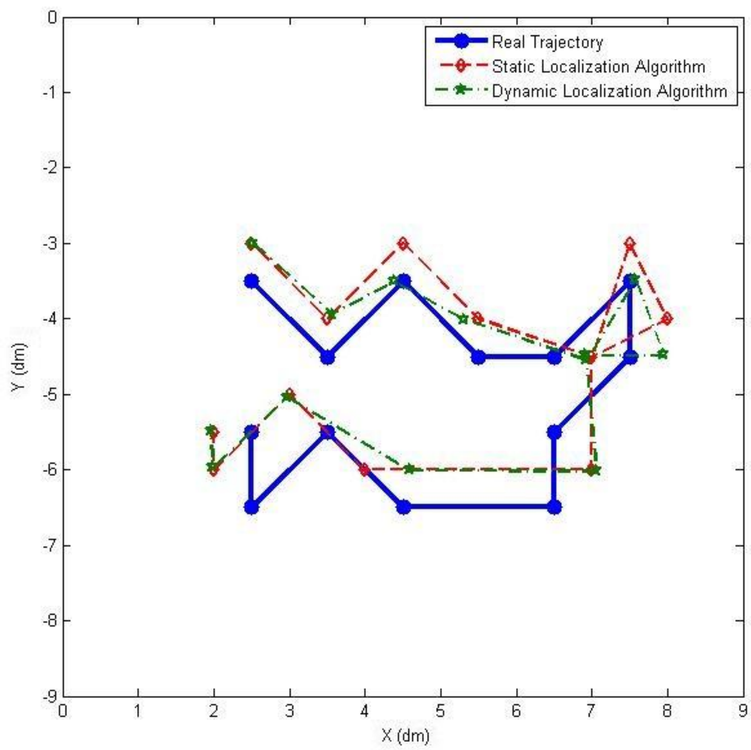
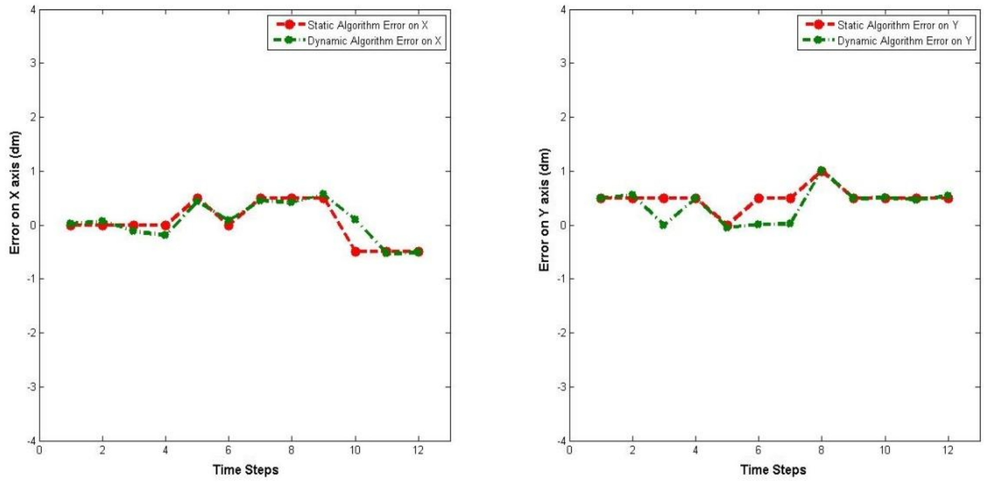


Figure 7. 12 Radius at 30 centimetres on Random Trajectory



(b) Error on X axis (b) Error on Y axis

Figure 7. 13 Comparison Errors on Random Trajectory (Radius 30 centimetres)

To summary above localisation precision by using similar criteria in section 5.4.4, accuracy has already given as 10 centimetres; precision can be compared by mean of precision in Table 7.2 and range of precision in Table 7.3. The mean of precision can be calculated by Standard Deviation.

Table 7. 2 Comparison of Feature Selection Methods by mean of precision

Methods	*X Trajectory*		*Y Trajectory*		*Random Trajectory*	
	X value	*Y value*	*X value*	*Y value*	*X value*	*Y value*
Static	**6.686 cm**	**5.353 cm**	**3. 356 cm**	**7. 854 cm**	**0. 289 cm**	**7. 220 cm**
Dynamic	**5.427 cm**	**6. 075 cm**	**0. 905 cm**	**8. 891 cm**	**0. 481 cm**	**9. 936 cm**

Table 7. 3 Comparison of Feature Selection Methods by range of precision

Methods	*X Trajectory*		*Y Trajectory*		*Random Trajectory*	
	X value	*Y value*	*X value*	*Y value*	*X value*	*Y value*
Static	**(-2.8, 9) cm**	**(-13, 1) cm**	**(-3, 8.3) cm**	**(-10, 16.7) cm**	**(-6.7, 5) cm**	**(0, 13) cm**
Dynamic	**(-5, 4.5) cm**	**(-5, 1.5) cm**	**(-5, 5) cm**	**(-5, 25) cm**	**(-5, 5) cm**	**(3, 25) cm**

It appears that as the increased length of radius, dynamic localisation algorithm can work effectively on a random trajectory. Also it can reach approximately same localisation accuracy as *static* localisation algorithm. Therefore, it shows that with the selected suitable radius and start position, the proposed dynamic localisation algorithm can have a similar localisation performance with *static* localisation algorithm.

7.3.2 Unexpected False Reading Error

This section compares the performance of proposed dynamic localisation algorithm with *static* localisation algorithm on dealing with *unexpected false reading error* situations. *Dead reading error* and *repeated reading error* are mainly tested since they are serious and typical in unexpected false reading error. Those two kinds of *unexpected false reading error* can possible occur *discretely* and *continuously*. Therefore, it would evaluate the proposed dynamic localisation algorithm performance on those four situations. The results of the proposed dynamic localisation algorithm with the conventional static localisation algorithm are compared. The dataset is from a object moving trajectory including moving along X axis, moving along Y axis and moving random directions.

a) Discrete dead reading error

On this condition, it assumed that *dead reading error* discretely occurs at the time interval 10, 20, 30; start position (-8.5, -3.5), radius length 30 centimeters. Figure 7.14 and 6.19 shows the error of estimated value along X axis and Y axis between dynamic and static algorithm and real simulated object moving path.

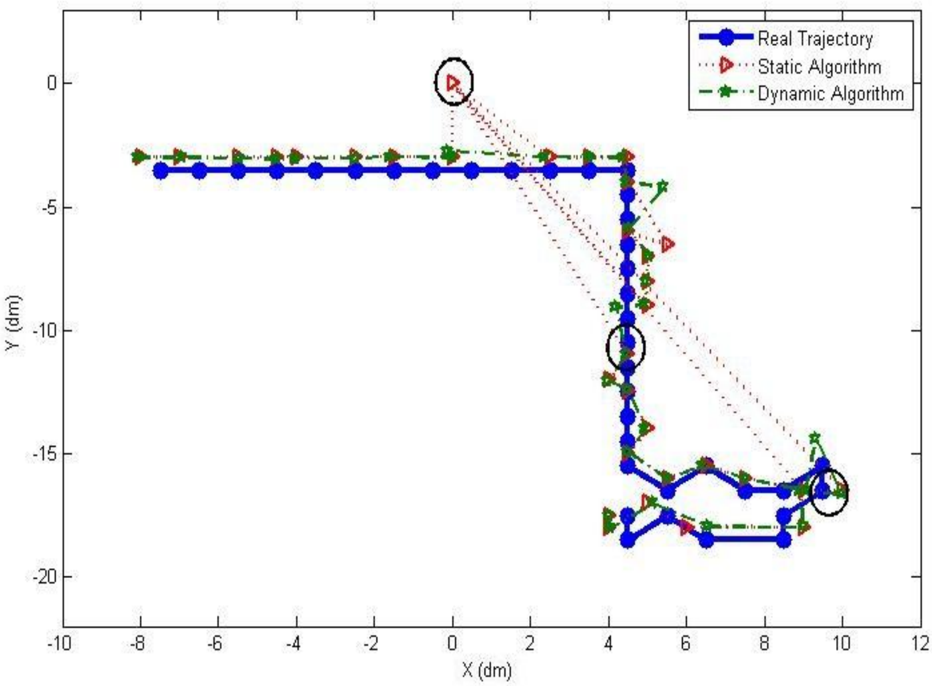
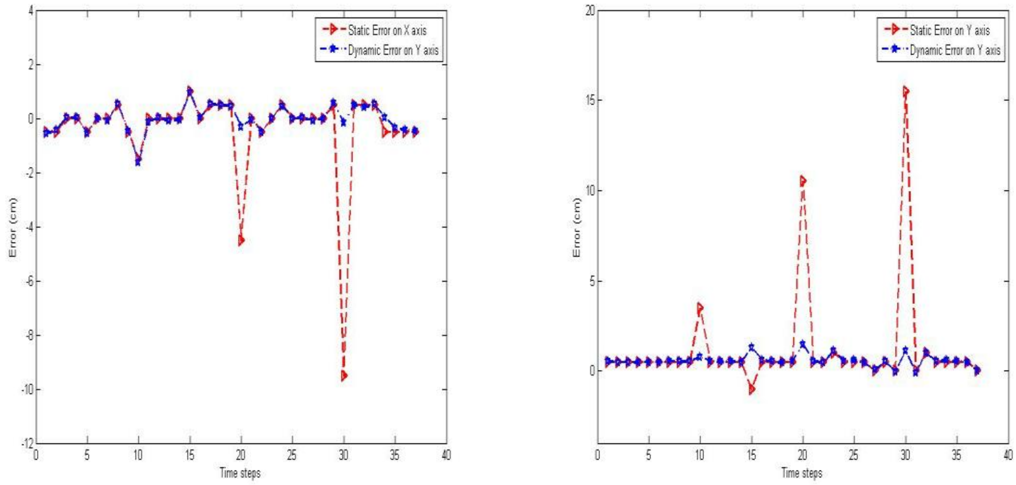


Figure 7. 14: Dynamic algorithm localisation performance on discrete dead-reading



(a) Error on X axis (b) Error on Y axis

Figure 7. 15 Errors Comparison on *discrete dead reading error*

In comparison to conventional *static* localisation algorithm, dynamic localisation algorithm can effectively improve localisation precision on discrete dead reading error situations. It is because particle filter based dynamic localisation algorithm has limited the possible object position in a circle with radius 30 centimetres, so that the possible localisation errors would also be limited in this range. Once RFID reader observes the new features, dynamic localisation algorithm can recover object position immediately.

b) Continuous dead reading error

On this condition, it assumed that the *dead reading error* continuously occurs at the three time interval 5,6,7; 15,16,17; 25,26,27; start position (-8.5, -3.5), radius length 30 centimetres. Fig 7.16 and 7.17 shows the error of estimated value along X axis and Y axis between dynamic and static algorithm and real simulated object moving path.

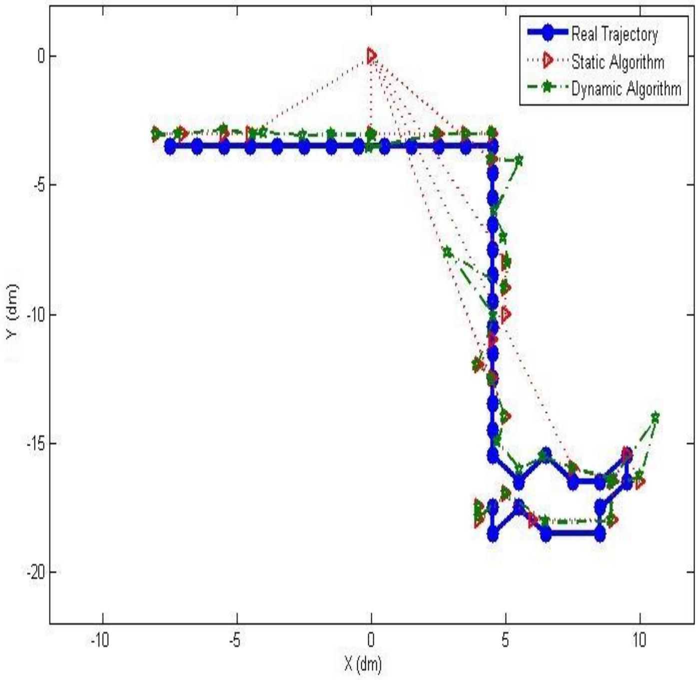
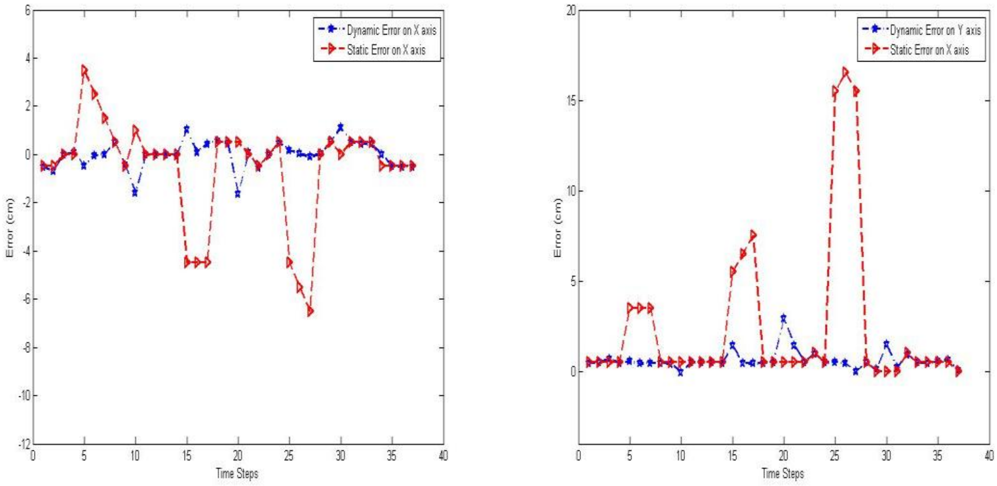


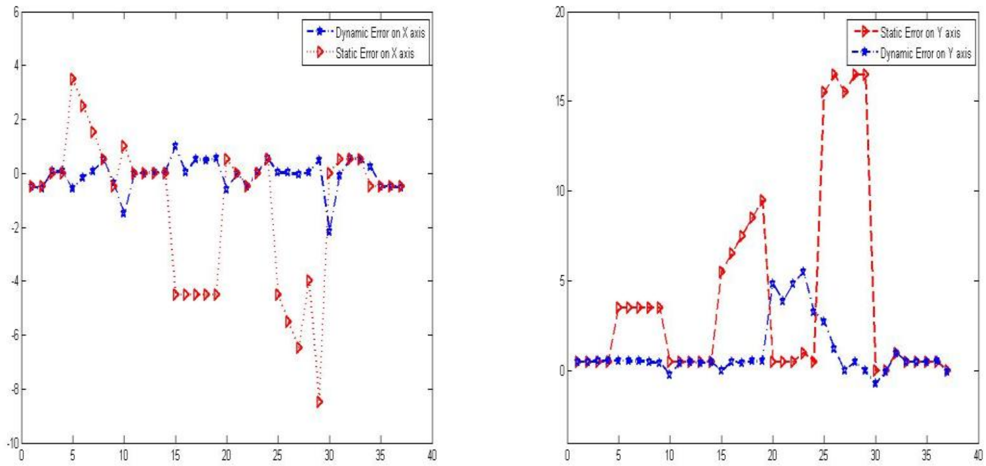
Figure 7. 16 Dynamic algorithm localisation performance on *continuous dead reading error*



(a) Error on X axis (b) Error on Y axis

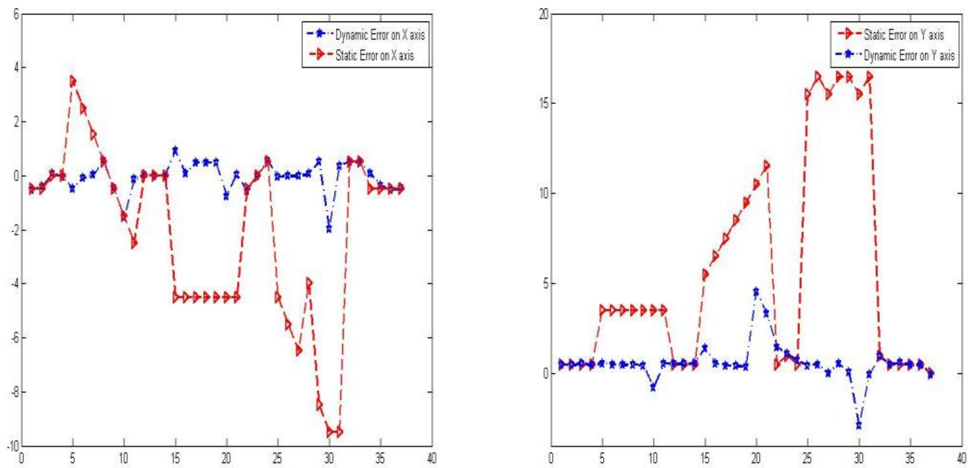
Figure 7. 17 Errors Comparison on *continuous dead reading error* in three time intervals

During the three time intervals, it appears that in comparison to the conventional static localisation algorithm for RFID-Loc, dynamic localisation algorithm can effectively improve localisation accuracy on *continuous dead reading error* situations. However, the period of three continuous time intervals can not represent all the possible situations of *continuous dead reading error*, thus the time intervals are extended to 5 and 7, then to see their performance, as shown in Figure 7.18 and Figure 7.19. The results show that dynamic localisation algorithm can still effectively recover the object position from *continuous dead reading error* situation. The proposed dynamic localisation algorithm is better to deal with *continuous dead reading error* situations than *static* localisation algorithm for an RFID-Loc system.



(a) Error on X axis (b) Error on Y axis

Figure 7. 18 Errors Comparison on *continuous dead reading error* in five time intervals

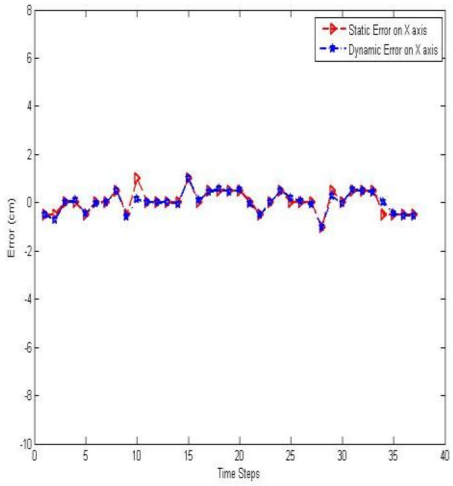


(a) Error on X axis (b) Error on Y axis

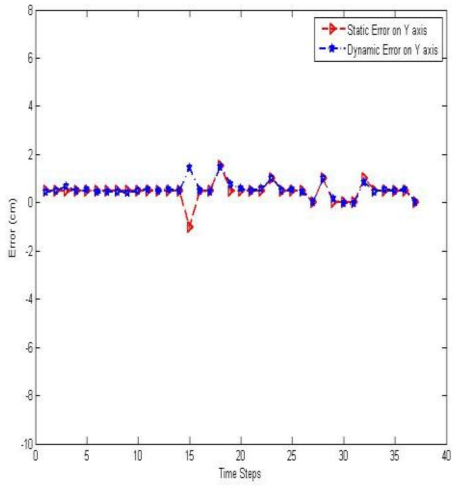
Figure 7. 19 Errors Comparison on *continuous dead reading error* in seven time intervals

c) Discrete repeated reading error

On this condition, it assumed that *repeated reading error* discretely occurs at the time interval 8, 17, 27; start position (-8.5, -3.5), radius length 30 centimetres. Figure 7.20 shows the error of estimated value along X axis and Y axis between dynamic and static algorithm and real simulated object moving path.



(b) Error on X axis



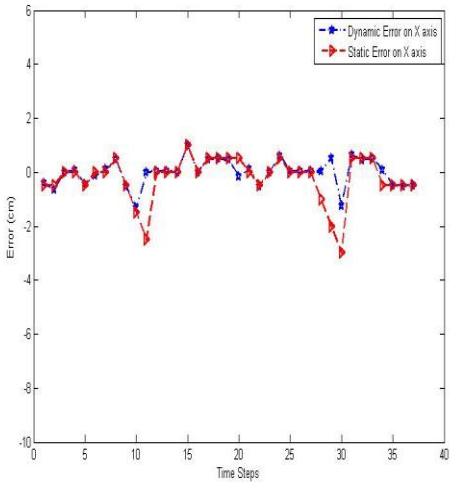
(b) Error on Y axis

Figure 7. 20 Comparison Errors on *discrete repeated readings error* situation

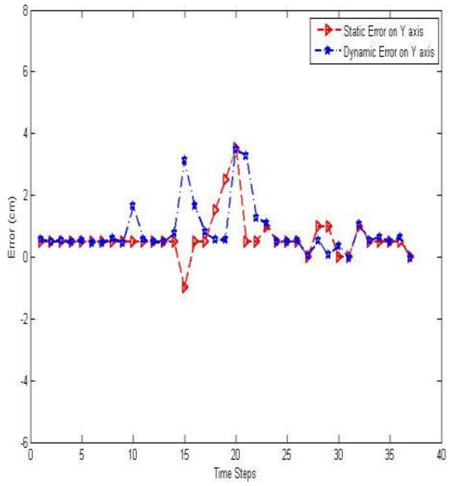
In comparison to conventional *static* localisation algorithm, dynamic localisation algorithm can have a roughly identical localisation performance on *discrete repeated reading error* situation. It is because on *discrete repeated reading error* situation, RFID reader practically observes some RFID raw data, only with the same value with previous time interval. On this condition, if the length of radius is enough to cover the object position of previous time interval, dynamic localisation algorithm would generate the same object position as *static* localisation algorithm at this time interval. However, due to the limited length of radius, the estimated object position on next time interval might have some errors.

d) Continuous repeated reading error

On this condition, it assumed that *repeated reading errors* continuously occur at the four continuous time intervals 8,9,10,11; 17,18,19,20; 27,28,29,30; start position (-8.5, -3.5), radius length 30 centimetres. Figure 7.21 shows the error of estimated value along X axis and Y axis between dynamic and static algorithm and real simulated object moving path.



(c) Error on X axis



(b) Error on Y axis

Figure 7. 21 Errors Comparison on *continuous repeated reading errors* in three time intervals.

From the results, it appears that the in comparison to conventional static localisation algorithm, dynamic localisation algorithm can effectively improve localisation precision on *continuous repeated reading errors* situations, especially on X axis.

To summarize four situations, dynamic localisation algorithm has a better performance on dealing with *unexpected false readings error* than conventional *static* localisation algorithm for an RFID-Loc system. The primary reason is that dynamic localisation algorithm is based on particle filter methods, which has a strong ability to recover the errors in localisation process. Secondly, dynamic localisation algorithm seems to be more efficient on dealing with continuous situations than *static* localisation algorithm, subject to a proper length of radius for distributing particles.

The reason is that dynamic localisation algorithm has the predicted and updated processes to connect continuous time intervals, but *static* localisation algorithm just has the individual processes on each discrete time interval.

7.3.3 Robustness of Algorithm

Although the proposed particle filter based dynamic localisation algorithm illustrates a better localisation performance than *static* localisation algorithm in an RFID-Loc system, the robustness of algorithm is still of importance to be concerned. There are two factors impacting the robustness of algorithm, the number of particles and the length of radius for distributing particles. Typically, as the increased number of particles, the localisation accuracy would be increased. If the environment is more complex, it required more particles, which cost much time on calculation. Thus, it is necessary to know how to choose the number of particles; the number of particles is chosen as 20, 50, 100, 200, 400, 800 to evaluate the robustness of algorithm, and the error of X and Y are standard mean. Meanwhile, due to the randomness of distributing particles, dynamic localisation algorithm would perform differently on varied distributions, so it requires running several times for comparing the difference. Table 7.4 and 7.5 separately show the results of dynamic localisation algorithm dealing with continuous dead-reading (5 time intervals) and discrete dead-reading situations.

Table 7. 4 Standard Error Mean of Different Number of particles on Continuous Dead-Readings

Times	***Standard Error mean***	***20 Particles***	***50 Particles***	***100 Particles***	***200 Particles***	***400 Particles***	***800 Particles***
1	**X**	**5.7183**	**3.3887**	**1.6898**	**2.1545**	**2.4313**	**4.9051**
	Y	**2.836**	**11.021**	**2.2502**	**1.6887**	**2.9541**	**2.5636**
2	**X**	**4.9873**	**3.36019**	**2.453**	**2.802**	**5.6722**	**3.4605**
	Y	**2.5292**	**3.0219**	**8.5965**	**1.9256**	**2.6206**	**2.4889**
3	**X**	**3.6204**	**6.0376**	**3.6389**	**5.0026**	**1.9846**	**4.0788**
	Y	**10.7526**	**8.9907**	**1.3014**	**5.0975**	**5.084**	**2.6942**
4	**X**	**12.0856**	**1.5671**	**4.4719**	**4.6668**	**3.5893**	**6.0933**
	Y	**7.9734**	**2.0616**	**2.2836**	**2.3384**	**8.8096**	**8.3007**
5	**X**	**3.5373**	**2.6858**	**2.3562**	**3.6663**	**1.5968**	**4.5654**
	Y	**2.7631**	**1.9723**	**1.0283**	**9.5804**	**1.5888**	**1.8237**
6	**X**	**1.1449**	**5.2231**	**3.8413**	**1.5196**	**2.2598**	**4.3468**
	Y	**2.9168**	**3.4289**	**5.085**	**2.4062**	**12.777**	**5.1622**

Table 7. 5 Standard Error Mean of Different Number of particles on Discrete Dead-Readings

Times	*Standard Error mean*	*20 Particles*	*50 Particles*	*100 Particles*	*200 Particles*	*400 Particles*	*800 Particles*
1	**X**	**0.8502**	**0.977**	**0.5762**	**0.6822**	**0.6785**	**0.5763**
	Y	**1.2817**	**1.7064**	**1.2179**	**1.0008**	**1.4473**	**1.3841**
2	**X**	**0.8007**	**0.6684**	**0.6878**	**0.7143**	**0.6311**	**0.9676**
	Y	**1.1405**	**0.673**	**2.128**	**0.9541**	**0.8065**	**1.0483**
3	**X**	**1.0815**	**0.5442**	**0.7579**	**0.6893**	**0.6574**	**1.0388**
	Y	**1.8567**	**0.7462**	**0.7229**	**1.3223**	**2.0474**	**1.0099**
4	**X**	**0.9568**	**0.5292**	**0.4966**	**0.5508**	**0.5836**	**0.6297**
	Y	**0.7068**	**1.8899**	**1.1677**	**1.1504**	**2.1328**	**0.8928**
5	**X**	**0.7079**	**0.616**	**1.0103**	**0.6045**	**0.7037**	**0.5608**
	Y	**1.1872**	**1.208**	**1.0125**	**0.8271**	**1.0106**	**1.9764**
6	**X**	**0.6959**	**0.5874**	**0.6139**	**0.5555**	**0.561**	**0.614**
	Y	**1.5173**	**1.5643**	**1.0058**	**0.9411**	**1.8575**	**1.0434**

The above Tables show that random distribution of particles would lead to varied standard error mean, even with the equal number of particles. So we would average the error value in the above Tables, and draw the trend in Figure 7.22 and 7.23.

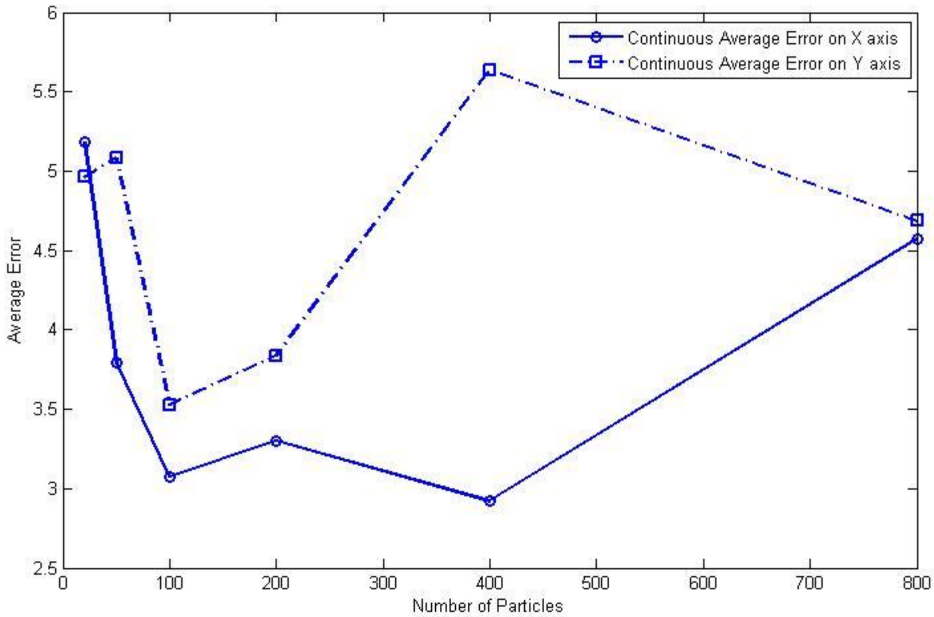


Figure 7. 22 Different number of Particles on *continuous dead reading error* situation

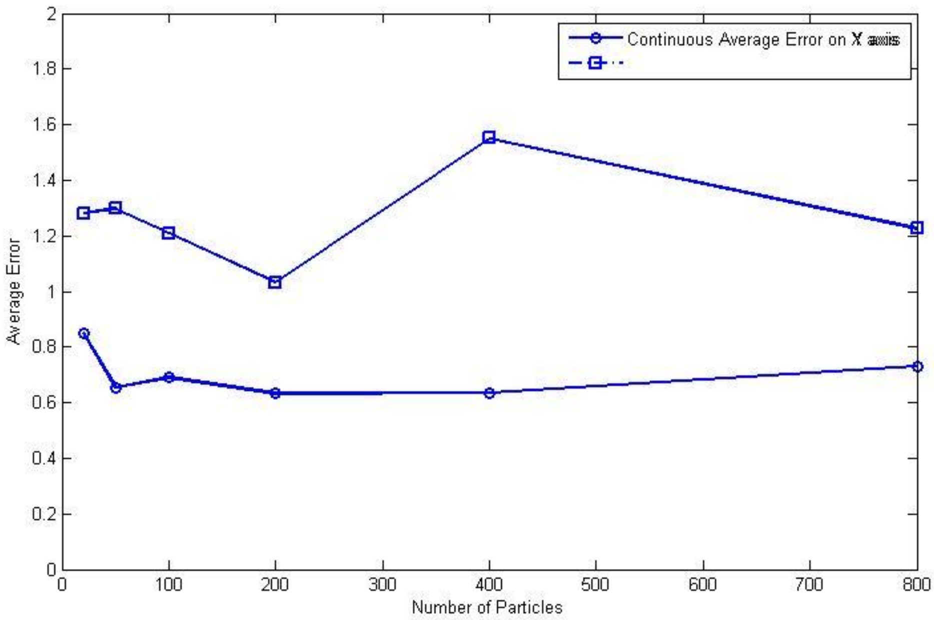


Figure 7. 23 Different number of particles on *discrete dead reading error* situation

From above two Figures, it shows that as the number of particles increase, the error of dynamic localisation algorithm would initially decrease, but then increase again. The reason is that the performance of dynamic localisation algorithm depends on the distribution of particles to a large extend. If the number of particles is small, the density of distributing particle area is very low, so as to the high probability of object position might not be covered. Oppositely, if the number of particle is large, the density of distributing particle area is high, although the high probability of object position is covered; the probability of covering unexpected false readings position is also increased. Consequently, on the condition of *unexpected false reading error* occurring, dynamic-localisation algorithm with a large number of particles would also be possible to generate big error. Therefore, the ideal number of particles in this case is between 100 and 200. With this number, the particle can be distributed fairly.

7.4 Validation RFID-Loc Solution

This section considers verifying the RFID-Loc framework with both proposed RFID Tag Arrangement and localisation algorithm to localize the moving object in a basic and simple indoor environment as a case study.

The first issue needs to be verified is the predictive capacity on accuracy and precision of an RFID-Loc framework by using proposed RFID infrastructure and algorithms. The traditional passive RFID tags based localisation system relies on highly dense grid tag pattern and *static* localisation algorithms. RFID-Loc framework in this thesis has provided an optimal RFID button tag arrangement pattern, a rectangle based feature selection method and a dynamical particle filter based localisation algorithm. The accuracy and precision delivered by proposed RFID-Loc framework has to be compared with the accuracy and precision of traditional RFID based localisation system, to see if it has a better performance than traditional RFID based localisation system.

Secondly, moving speed of object has to be concerned in an indoor environment. In this thesis, Chapter 2 has reviewed that in a dense RFID tag environment, RFID reader needs a sufficient response time to observe a basically enough RFID data for processing. On this case, the time period of object keeping on one step $\boldsymbol{T}$, which is defined in Chapter 4, is more important than object moving speed to accuracy and precision delivered by an RFID-Loc framework. Therefore, the experiment also has to verify the impacts of different value of $\boldsymbol{T}$ on the accuracy and precision delivered by a localisation solution based on RFID-Loc framework.

7.4.1 Localisation Accuracy and Precision

For verifying the predictive capacity on accuracy and precision of an RFID-Loc framework by using proposed RFID infrastructure and algorithms, two typical passive RFID based localisation solutions are compared. The typical RFID localisation solution is based a regular grid passive RFID tag pattern, as shown in Figure 7.24. Localisation algorithm in this solution is usually a simple average method in Equation

4.7 in Chapter 4. The second RFID-Loc localisation solution is based a triangular passive RFID tag pattern, as shown in Figure 7.25. Localisation algorithm in this solution is usually a simple average method in Equation 4.8 in Chapter 4. The proposed RFID-Loc based localisation system is to use a sparse RFID tag pattern, as shown in Figure 7.26. The localisation algorithm is to use the methods proposed in Chapter 6.

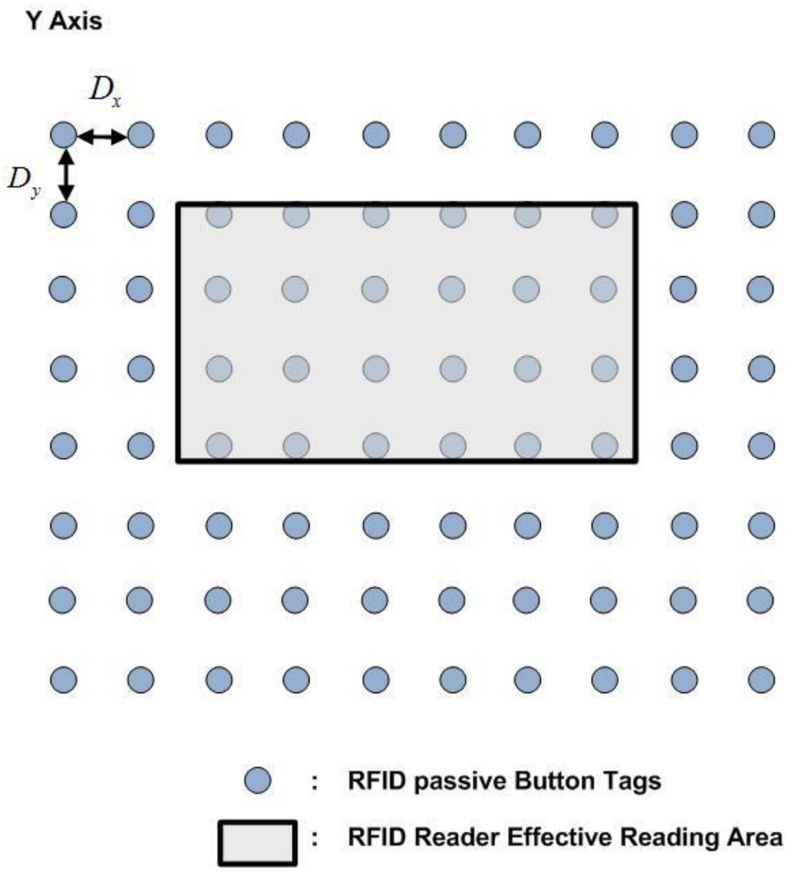


Figure 7. 24 Grid based passive RFID localisation solution

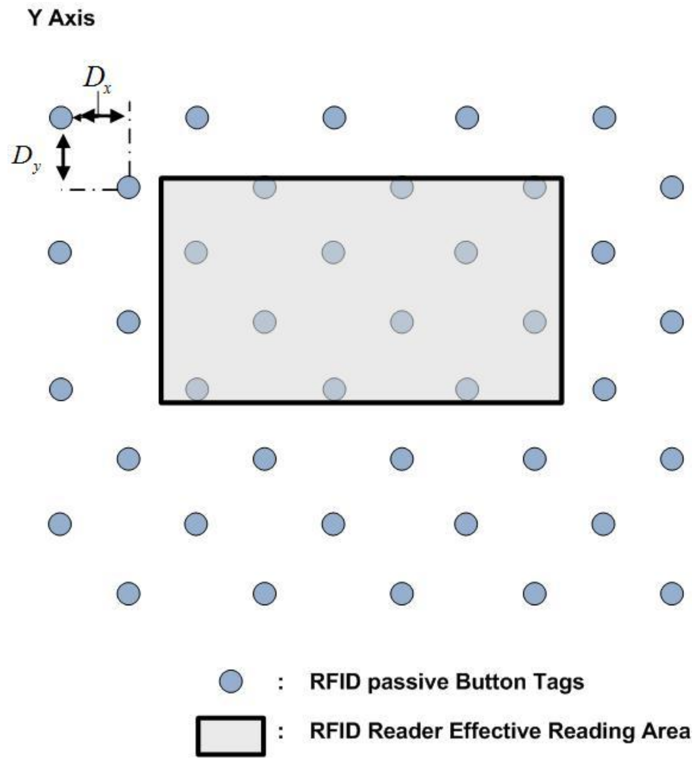


Figure 7. 25 Triangle based passive RFID localisation solution

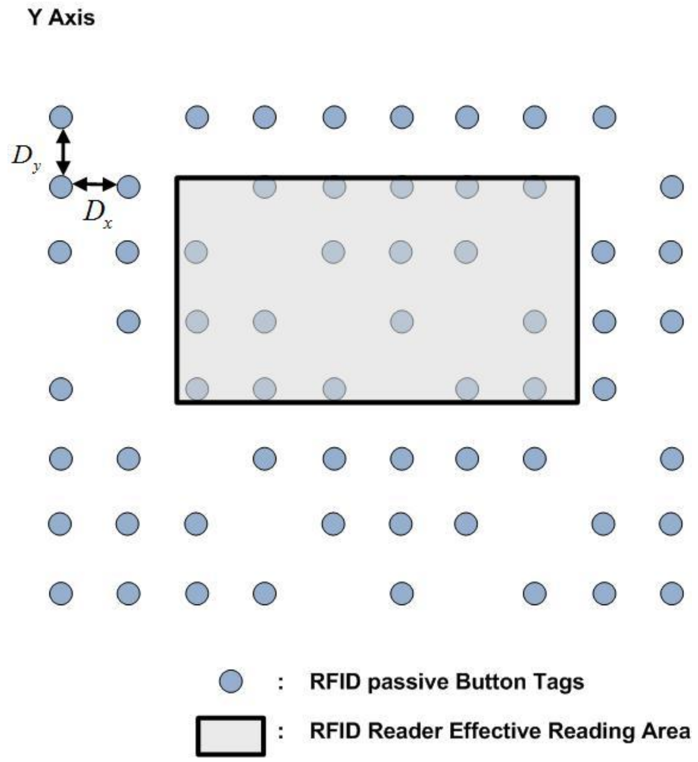


Figure 7. 26 Sparse RFID tag pattern delivered by an RFID-Loc framework

Of above three patterns, RFID tag distance is already assumed as 10 centimetres, thus localisation accuracy in the above three solution would be identical. As for localisation precision, these three solutions are validated into two typical objects moving trajectories in an indoor environment, which are Truck (along X axis), Dolly (along Y axis). In each experiment, time intervals of object moving are assumed as 50, which is larger than the assumed time intervals in Chapter 6. Standard Error of Mean is adapted to measure localisation precision, by Equation 5.6 in Chapter 5.

Table 7. 6 Comparison by mean of localisation precision

Methods	***RFID-Loc Solution***		***Grid Solution***		***Triangle Solution***	
	Error on X	***Error on Y***	***Error on X***	***Error on Y***	***Error on X***	***Error on Y***
Truck Movement	**0.92 cm**	**4.35 cm**	**6.95 cm**	**5.63 cm**	**8.15 cm**	**6.68 cm**
Dolly Movement	**2.23 cm**	**2.38 cm**	**3.42 cm**	**7.63 cm**	**4.12 cm**	**8.36 cm**

Table 7. 7 Comparison by range of localisation precision

Methods	***RFID-Loc Solution***		***Grid Solution***		***Triangle Solution***	
	Error on X	***Error on Y***	***Error on X***	***Error on Y***	***Error on X***	***Error on Y***
Truck Movement	**(-5,10) cm**	**(4,5) cm**	**(-3,9) cm**	**(-14,2) cm**	**(-5,10) cm**	**(0, 8) cm**
Dolly Movement	**(-5,10) cm**	**(-10,5) cm**	**(-4,9) cm**	**(-10,17) cm**	**(-6,12) cm**	**(-12, 8) cm**

Table 7.7 and 7.8 show that the accuracy and precision of an RFID-Loc framework by using proposed RFID infrastructure and algorithms can give a higher precision than two typical RFID based localisation solutions, particularly on X axis value of object position. On Truck movement, precision of RFID-Loc system can reduce to 0.92 centimetres on X axis value of object position, 4.35 centimetres on Y value of object position. On Dolly movement, precision of RFID-Loc system can reduce to 2.23 centimetres on X axis value of object position, 2.38 centimetres on Y value of object position. The precision is obviously improved than the other typical RFID based localisation system. Apart from that, according to practically observed RFID data, it illustrates that *unexpected false reading error* mentioned in Chapter 6 sometimes occurs on each trajectory. However, frequency of their occurrence within 50 time intervals is very low, which is 2 or 3 times for each trajectory. The occurrence of *unexpected false reading error* is all discrete, not continuous. Figure 7.27 and 7.28 illustrates the truck, dolly and movement of object trajectory separately.

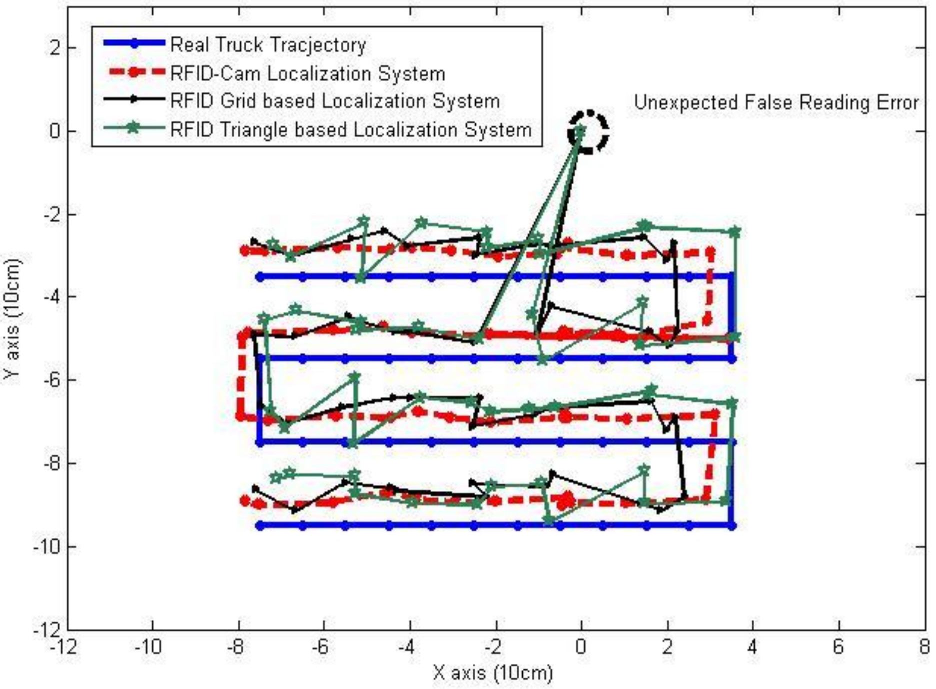


Figure 7. 27 Comparison on Truck Movement

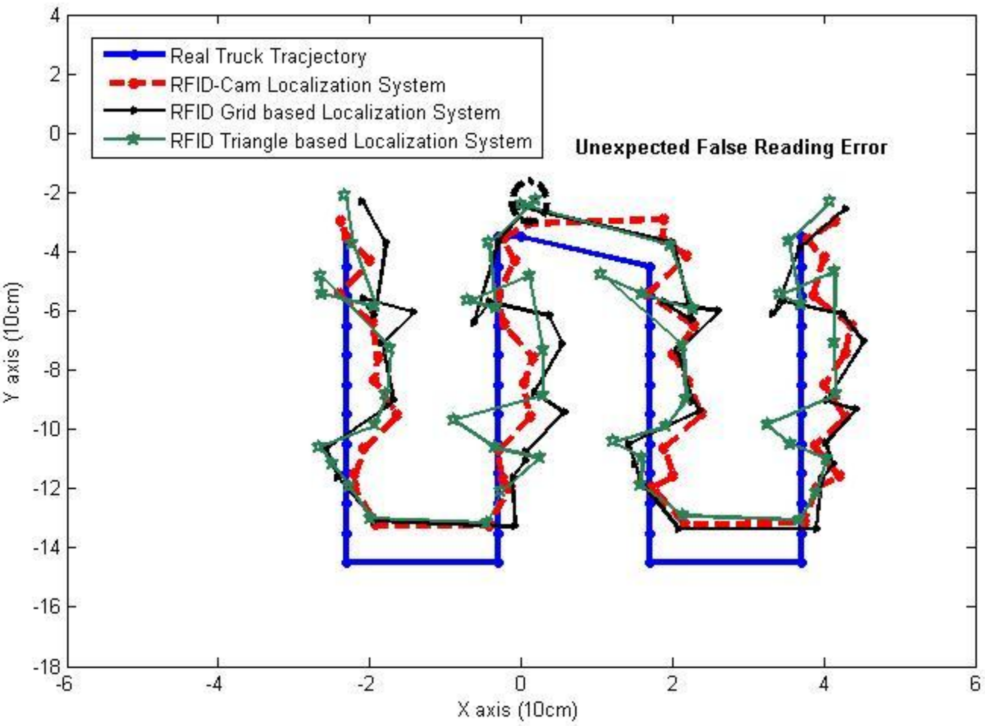


Figure 7. 28 Comparison on Dolly Movement

From Figure 7.27 and 7.28, the red dash line represents the performance of a localisation solution based on RFID-Loc framework; the blue line represents the real object movement trajectory. It can conduct that compared to typical RFID based localisation system, the localisation solution based on proposed RFID-Loc framework can resist *unexpected false reading error* to some extent, so that improve localisation precision of an RFID-Loc system. Although the occurrence of *unexpected false reading error* in an indoor environment is rare, the impact of its occurrence is obviously fatal to the performance of the localisation solution based on proposed RFID-Loc framework. To sum up the results in Table 7.7 and 7.8, the localisation solution based on proposed RFID-Loc framework can offer localisation accuracy up to 10 centimetres, with an approximate precision 2 centimetres on X position of object and 3 centimetres on Y position of object.

7.4.2 Impact of time period *T*

This section verifies the impact of time period of object keeping on one step ***T*** on localisation accuracy and precision delivered by the localisation solution based on proposed RFID-Loc framework. As mentioned in Chapter 4, under given experimental platform, ***T*** is assumed as 40 seconds per each time interval, because *system reading efficiency* of a given RFID-Loc infrastructure cannot improve obviously when ***T*** is over 40 seconds. So it means that at each time interval, moving object has to keep in a position for 40 seconds so that RFID reader can observe a sufficient RFID data to localize its position. In this section, it would verify the performance of RFID-Loc system on assuming different value of ***T*** as 60, 40, 20, 10, 5 seconds. And localisation accuracy has been assumed as 10 centimetres, so mean of localisation precision is used as a Figure to verify the impact of ***T.*** Figure 7.29 illustrates *mean of localisation precision* in a RFID-Loc system with different time period ***T***.

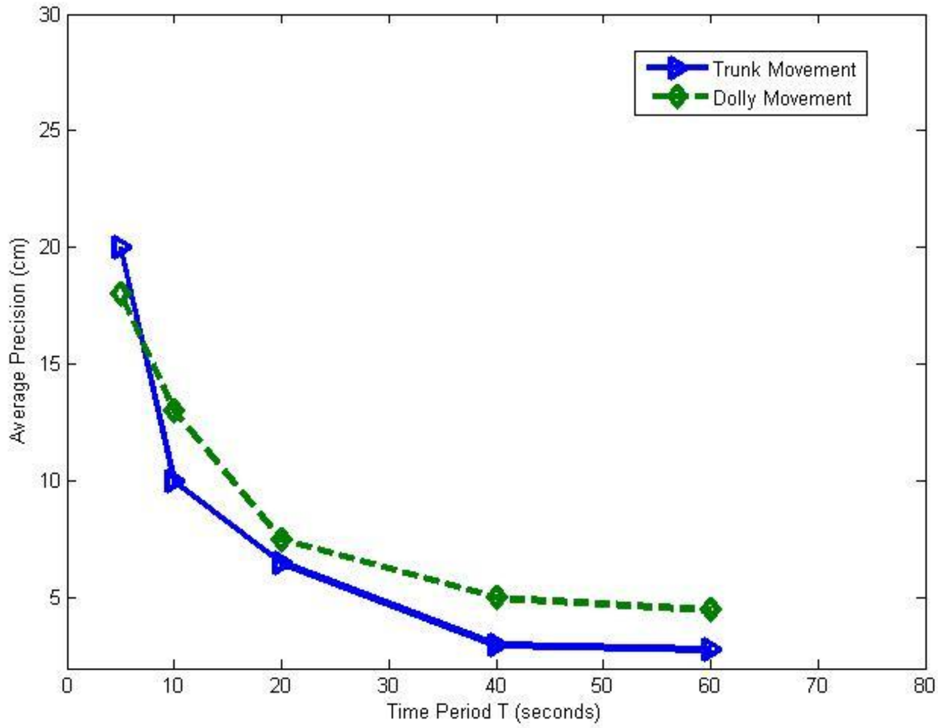


Figure 7. 29 *Mean of localisation precision* in the localisation solution based on proposed RFID-Loc framework with different time period *T*.

From Figure 7.29, it represents that time period of object keeping on one step ***T*** has a tremendous impacts on the performance of the localisation solution based on proposed RFID-Loc framework. Based on a given RFID-Loc infrastructure platform, object localisation precision would be only achieved as the object moving speed is quite slow, approximately 5 centimetres per minute. If the object moving speed is beyond it, the tracking error will obviously increase due to the lack of adequate RFID data observation.

7.5 Discussion

While the previous sections have carried out a few experiments to validate the predictive capacity on accuracy and precision of an RFID-Loc framework into a indoor object localisation environment, the results show that under given RFID experiment devices, it can basically reach localisation accuracy up to 10 centimetres and precision up to 3 centimetres.

The primary reason impacting the improvement of the predictive capacity on accuracy and precision of an RFID-Loc framework is that current RFID hardware devices cannot remove *regular false reading error* completely. So it leads to a lower *system reading efficiency* of RFID based localisation system, which cannot ensure the reliability of observed RFID data. Regarding to our validating results, with a given *system reading efficiency* up to 50%, localisation precision is approximately up to 3 centimetres, with 2 pixels error on a 1024×768 output images. If we would like to reduce pixels error to 0.5, localisation precision has to be reduced to at least 7mm, which can basically satisfy an object position requirement in indoor applications. On other words, the relative value of *system reading efficiency* in an RFID-Loc infrastructure module probably has to be improved up to 80% or 90%. It is a challenging task in terms of current RFID manufacture state of art.

Secondly, the distance of RFID tag limits the improvement of the predictive capacity on accuracy of an RFID-Loc framework. It is possible to achieve localisation accuracy up to 10 centimetres in an indoor application. The improvement of localisation accuracy depends on the distance between RFID tags; also, passive RFID tag pattern has to been a non-overlapped pattern. Thus, to satisfy these conditions requires the area of passive RFID tag as smaller as possible. However, current two popular passive RFID tags (button and card) both have an area over 10 centimetres square, which is too larger than 1 mm. The future development of RFID devices can provide a feasible passive RFID tags to use in an RFID-Loc system.

Thirdly, the time period of collecting RFID data is also a key barrier to limit the application of RFID-Loc framework into indoors. In terms of the experimental validation, the suggested time period of collecting RFID data is 40 seconds. However, the ideal requirement of object tracking system indoor is expected to work in a real-time mode, which means to response object position parameters at least 24 frames per second. It is a hard task for current localisation solution based on RFID-Loc framework to achieve because the time period of collecting RFID data cannot ensure to observe sufficient RFID data to localize moving object position within 1/24 second.

7.6 Summary

In this Chapter, the application of a RFID-Loc framework in indoor environment is discussed and verified. The proposed sparse RFID Tag Arrangement and dynamic localisation algorithm in RFID-Loc framework are both verified by using available RFID hardware device with different object moving trajectories in an indoor. The results show that under current RFID devices, the RFID-Loc system with proposed solutions can reach accuracy up to 10 centimetres, with a precision up to 3 centimetres. However, the time period of object keeping on one step $\boldsymbol{T}$ would significantly influence the performance of localisation solution based on RFID-Loc framework, since the increased time period would reduce the loss of RFID raw data.

Chapter 8:

Conclusions and Future Works

By now, it has reached the end of our investigation into the optimal use of RFID technique for accurate and precise object position localisation in an indoor environment. In this chapter, it would give a brief discussion about the merits and demerits of the methodologies developed in this thesis, and some ideas for future directions in RFID-Loc tracking indoor.

8.1 Conclusions

As reviewed in chapter 2, localization and tracking technique is a hot topic in indoor application. However, due to the various limitations, none of the current localization and tracking technique perfectly satisfies the ideal requirements of indoor moving object localisation application. For instance, the existed electromechanical tracking systems in indoor applications suffer from jitter and drift, such as electromechanical, infrared sensors. And the optical tracking systems suffer from the problems that the referenced feature points are out of focus, occlude or even out of view. The wireless indoor localisation techniques are mostly with a low and instable accuracy. The motivation of this research work is to investigate the possibility of utilizing RFID technique as an accurate and precise indoor moving object localisation solution.

In order to reach this goal, it is firstly necessary to investigate the issues which would potentially influence the performance of RFID technique based object position localisation system. A formal framework named *RFID-Loc* in Chapter 3 offers a coherent and consistent solution with three modules: RFID-Loc Infrastructure, RFID-Loc Data Filter and RFID-Loc Localisation Algorithm, to study the factors impacting the performance of RFID based moving object localisation in an indoor environment application. This framework can guide the research and design of methods used in a passive RFID based object localisation system with enhanced localisation accuracy and precision.

Meanwhile, the issues of each module and the investigation procedure of them are analyzed and defined. In Chapter 4 of RFID-Loc infrastructure module, by carrying on an empirical and theoretical evaluation on RFID hardware device characteristic, the high radio frequency range and regular passive RFID tag pattern are initially determined by the preliminary RFID infrastructure. Later on, experiment findings show that global tag density has a major impact on *system reading efficiency* of RFID Infrastructure. A sparse RFID Tag Arrangement is proposed in Chapter 5 aiming at reducing the impacts of *regular false reading error* from RFID hardware level on localisation precision. The efficiency of this methods and the assumptions upon which it relies, are investigated empirically. While sparse RFID Tag Arrangement strategy can reduce the impacts of *regular false reading error* on localisation accuracy and precision from RFID-Loc hardware level, it is impossible to eliminate it completely. Subsequently, in section 6.2 of RFID-Loc Date Filtering module, it attempts to use a feature selection method to reduce the impact of *regular false reading error* from RFID-Loc software level. An explicit comparison of RFID Date Filter algorithms to remove *regular false reading errors* from RFID software level has been carried out. A rectangle-based feature selection method is justified as the major RFID Data Filter algorithm, with the capability of maximally reducing *regular false reading errors*. Also, the possibility to resist *unexpected false reading error* in an RFID-Loc system is investigated in section 6.3 by discussing and comparing several RFID-based localisation algorithms. Due to the complexity and randomness of *unexpected false reading error*, it is hard to manage them from RFID hardware level. A detailed discussion and comparison of localisation algorithms is addressed to evaluate their performance on robustly and accurately localising object. A dynamic localisation algorithm for RFID-Loc system is proposed to accurately and precisely extract object position parameters overtime in an RFID-Loc system. This algorithm is shown to have a better capability of resisting *unexpected false reading error* than conventional localisation algorithms used in RFID-based localisation systems, while having a higher computational complexity.

The verification of RFID-Loc framework in Chapter 7 illustrates that with proposed RFID infrastructure and algorithms, the RFID-Loc framework can offer localisation accuracy up to 10 centimetres, with a localisation precision up to 3 centimetres. This accuracy and precision is superior to the current state-of-art RFID based localisation techniques. The main contributions are:

1. A formal framework is proposed for investigating the problem of use of RFID technique to accurately and precisely localize the moving object in an indoor environment. This framework can guide the research and design of the optimization methods used in an RFID based 2D localisation technology with enhanced accuracy and precision.
2. A sparse RFID Tag Distribution is proposed for the RFID infrastructure module, with the capability of enhancing the system reading efficiency from RFID infrastructure level, so as to improve the accuracy and precision of the 2D RFID based moving object localisation.
3. A rectangle-based feature selection method is selected and justified as the major algorithm in RFID data filter module, with the capability of maximally reducing the regular false reading errors from RFID infrastructure level.
4. A dynamic localisation algorithm for an RFID localisation algorithm module is proposed, which can accurately and precisely extract 2D position parameters of a moving object over time, also with the resilience to unexpected false reading error in indoor environments.

8.2 Future Directions

The main contributions of this research work are simply in paying significant attention to the improvement of accuracy and precision on applying RFID techniques for indoor moving object localisation. There are still a lot of work needs to do in next stage.

Firstly, RFID-Loc framework requires overcoming *false reading* problem and localising moving object in a stable performance. While the dynamic tracking algorithm can solve some uncertainty detection problem by using other observation model or resampling method, it cannot deal with *false reading* problem completely. It is necessary to evaluate more methods from hardware level to software level to manage and reduce *false reading* problem.

Secondly, the problem of object orientation tracking requires a method to solve. The monocular anti-collision RFID reader can possibly achieve the object orientation tracking to some extent. However, due to the limitation of the shape of the effective detection area shape from RFID reader, the accuracy of object orientation tracking is very low. Thus, it would extend RFID-Loc framework into multiple reader situations. By estimating the relative position moving of each reader, it could achieve the object orientation tracking, with a potential higher accuracy.

Finally, the proposed RFID-Loc localisation solution merely solves the problem of 2D moving object localisation and tracking. In future, it can be extended into 3D environment, but the RFID-Loc framework is still valid to be used.

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Appendix A : Bayes Theorem

Bayes Theorem: (See DeGroot 2002) Let $B_1, B_2......, B_k$ from a partition of space S such that $\Pr(B_j) > 0$, for $j = 1,......,k$ and A is an event such that $\Pr(A) > 0$, Then, for $i = 1,......,k$:

$$\Pr(B_i \mid A) = \frac{\Pr(B_i)\Pr(A \mid B_i)}{\sum_{j=1}^{k}\Pr(B_j)\Pr(A \mid B_j)}$$

Where:

The nominator $\sum_{j=1}^{k}\Pr(B_j)\Pr(A \mid B_j) = \Pr(A)$

Appendix B : Kalman Filter

Motion model: $s_t = F_{t-1}s_{t-1} + v_{t-1}$

Observation model: $d_t = H_t s_t + w_t$

Where s_t is the system state, v_{t-1} and w_t are mutually independent zero-mean with white Gaussian noises (Ristic et al. 2004) with noise covariance Q_t and R_t, F_{t-1} and H_t are known matrices, specifying the linear relationships of motion model and observation model. And t is time interval. This two Equation implements the $\Pr(s_t \mid s_{t-1})$ and $\Pr(d_t \mid s_t)$ respectively in Bayes Filter.

The iteratively calculation of Kalman Filter has two phases: predict and update, which exactly reflect the same stages of Bayes Filter, as shown below:

Prediction:

$s_{t|t-1} = F_{t-1}s_{t-1|t-1}$ State Prediction

$P_{t|t-1} = Q_t + F_{t-1}P_{t-1|t-1}F_{t-1}^T$ Covariance Prediction

Update:

$y_t = z_t - H_t s_{t|t-1}$ State Innovation

$S_t = H_t P_{t|t-1} H_t^T + R_t$ Covariance Innovation

$K_t = P_{t|t-1} H_t^T S_t^{-1}$ Kalman Gain

$s_{t|t} = s_{t|t-1} + K_t y_t$ State Update

$P_{t|t} = P_{t|t-1} - K_t S_t K_t^T$ Covariance Update

Appendix C : MatLab Code

Motion Model Prediction file: Motion.m

```
function Predict_M = Motion(Location, rad, numParticle);
P = numParticle;
P_s = rand(P,1);
PI = 3.1415926;

for i = 1:P
   P_s(i,1) = P_s(i,1)*2*PI;
end
r = rad ;

P_predict(P,2)=0;

x = Location(1,1);
y = Location(1,2);

for i = 1:P
   %P_predict(i,1)= x + 2*cos(P_s(i,1));
   %P_predict(i,2)= y + 2*sin(P_s(i,1));
   P_predict(i,1)= x + sqrt(2)*r*rand()*cos(P_s(i,1));
   P_predict(i,2)= y + sqrt(2)*r*rand()*sin(P_s(i,1));
end

Predict_M = P_predict ;
```

Particle Filter Localisation algorithm file: PF_Main_Function.m

```
function S = PF(numParticle, Trajectory, steps, rad, noise, f1);

% Trajectory means the input data trajectory (X axis, Y axis or Random)
% The start point would be varied

%Initialize and Define the features and position
t_s = steps ;
state_location(t_s,2) = 0 ;
feature_predict(t_s,4) = 0;
f_ob(t_s,4) = 0;
r = rad;
num = numParticle;
length = 4 ;
width = 3 ;
n = noise ; % noise usually 0 - 1
PI = 3.1415926 ;

for i = 1:t_s
    f_ob(i,:) = f1(i,:);
end

%Apply motion estimation into location state on step 1
if(Trajectory == 2)  % random trajectory
location = [2.5,-3];
end
if (Trajectory == 1)  % Y trajectory
location = [-2.5,-3.5];
end
if (Trajectory == 0)
location = [-7.5,-3.5];  % X trajectory
end

Predict_M = Motion(location, r, num);

%Estimate the feature position on step 1
 f_pre_particle(num,4)= 0 ;
for i = 1:num
   f_pre_particle(i,1) = Predict_M(i,2)+ length;
   f_pre_particle(i,2) = Predict_M(i,1)+ width;
   f_pre_particle(i,3) = Predict_M(i,2)- length;
   f_pre_particle(i,4) = Predict_M(i,1)- width;
end

%Calcuate the weight of observation
%Weight(num,4)= 1;
for i = 1:num
   Weight(i,1) = sqrt(2*PI*n^2)*
exp((-(f_ob(1,1)-f_pre_particle(i,1))^2)/(2*n^2));
   Weight(i,2) = sqrt(2*PI*n^2)*
exp((-(f_ob(1,2)-f_pre_particle(i,2))^2)/(2*n^2));
   Weight(i,3) = sqrt(2*PI*n^2)*
exp((-(f_ob(1,3)-f_pre_particle(i,3))^2)/(2*n^2));
   Weight(i,4) = sqrt(2*PI*n^2)*
exp((-(f_ob(1,4)-f_pre_particle(i,4))^2)/(2*n^2));
   Local_Weight(i,1) =
(Weight(i,1)+Weight(i,2)+Weight(i,3)+Weight(i,4));
end
```

```
%Resampeling to delete some weight which are not useful, and get the largest
weight.
Weight_high = 0 ;
Weight_low = 0 ;
Weight_left = 0 ;
Weight_right = 0 ;
Weight_Large1 = 0 ;  % max weight for feature 1
Weight_Large2 = 0 ;
Weight_Large3 = 0 ;
Weight_Large4 = 0 ;

for i = 1:num
    %Weight_high = Weight_high + Weight(num,1);
    %Weight_low = Weight_low + Weight(num,2);
    %Weight_left = Weight_left + Weight(num,4);
    %Weight_right = Weight_right + Weight(num,3);
    if(Weight(i,1) >= Weight_Large1)

           Weight_Large1 = Weight(i,1) ;
           Max_number_1 = i   ;
    end;

    if(Weight(i,2) >= Weight_Large2)

           Weight_Large2 = Weight(i,2);
           Max_number_2 = i    ;
    end;
    if(Weight(i,3) >= Weight_Large3)

           Weight_Large3 = Weight(i,3);
           Max_number_3 = i     ;
    end;
    if(Weight(i,4) >= Weight_Large4)

           Weight_Large4 = Weight(i,4);
           Max_number_4 = i
    end;
end;

%using weight and Max number
state_location(1,1)= (Predict_M(Max_number_2,1)+
Predict_M(Max_number_4,1))/2;
state_location(1,2)= (Predict_M(Max_number_1,2)+
Predict_M(Max_number_3,2))/2;

%start_loop
for j = 2:t_s
location(1,1) = state_location(j-1,1);
location(1,2) = state_location(j-1,2);

Predict_M = Motion(location, r, num);

%Estimate the feature position on step 1
 f_pre_particle(num,4)= 0 ;
for i = 1:num
    f_pre_particle(i,1) = Predict_M(i,2)+ length;
    f_pre_particle(i,2) = Predict_M(i,1)+ width;
    f_pre_particle(i,3) = Predict_M(i,2)- length;
```

```
    f_pre_particle(i,4) = Predict_M(i,1)- width;
end

%Calcuate the weight of observation
%Weight(num,4)= 0;
for i = 1:num
    Weight(i,1) = Weight(i,1) * sqrt(2*PI*n^2)*
exp((-(f_ob(j,1)-f_pre_particle(i,1))^2)/(2*n^2));
    Weight(i,2) = Weight(i,2) * sqrt(2*PI*n^2)*
exp((-(f_ob(j,2)-f_pre_particle(i,2))^2)/(2*n^2));
    Weight(i,3) = Weight(i,3) * sqrt(2*PI*n^2)*
exp((-(f_ob(j,3)-f_pre_particle(i,3))^2)/(2*n^2));
    Weight(i,4) = Weight(i,4) * sqrt(2*PI*n^2)*
exp((-(f_ob(j,4)-f_pre_particle(i,4))^2)/(2*n^2));

    %Weight(i,1) = sqrt(2*PI*n^2)*
exp((-(f_ob(j,1)-f_pre_particle(i,1))^2)/(2*n^2));
    %Weight(i,2) = sqrt(2*PI*n^2)*
exp((-(f_ob(j,2)-f_pre_particle(i,2))^2)/(2*n^2));
    %Weight(i,3) = sqrt(2*PI*n^2)*
exp((-(f_ob(j,3)-f_pre_particle(i,3))^2)/(2*n^2));
    %Weight(i,4) = sqrt(2*PI*n^2)*
exp((-(f_ob(j,4)-f_pre_particle(i,4))^2)/(2*n^2));
end

%Resampeling to delete some weight which are not useful, and get the largest
weight.
Weight_high = 0 ;
Weight_low = 0 ;
Weight_left = 0 ;
Weight_right = 0 ;
Weight_Large1 = 0;  % max weight for feature 1
Weight_Large2 = 0 ;
Weight_Large3 = 0 ;
Weight_Large4 = 0 ;

for i = 1:num
    %Weight_high = Weight_high + Weight(num,1);
    %Weight_low = Weight_low + Weight(num,2);
    %Weight_left = Weight_left + Weight(num,4);
    %Weight_right = Weight_right + Weight(num,3);
    if(Weight(i,1) >= Weight_Large1)
           Weight_Large1 = Weight(i,1);
           Max_number_1 = i   ;
    end;

    if(Weight(i,2) >= Weight_Large2)

           Weight_Large2 = Weight(i,2);
           Max_number_2 = i    ;
    end;


    if(Weight(i,3) >= Weight_Large3)

           Weight_Large3 = Weight(i,3);
           Max_number_3 = i     ;
    end;
```

```
    if (Weight(i,4) >= Weight_Large4)

           Weight_Large4 = Weight(i,4);
           Max_number_4 = i      ;
    end;
end;


weight1 = 0 ;
f1_x = 0;
f1_y = 0;
weight2 = 0 ;
f2_x = 0 ;
f2_y = 0 ;
weight3 = 0 ;
f3_x = 0;
f3_y = 0;
weight4 = 0 ;
f4_x = 0 ;
f4_y = 0 ;

for i = 1:num
   if(Weight(i,1) > 0.75 * Weight_Large1)
     f1_x = f1_x + Predict_M(i,1) * Weight(i,1);
     f1_y = f1_y + Predict_M(i,2) * Weight(i,1);
     weight1 = weight1 + Weight(i,1);
   end;
   if(Weight(i,2) > 0.75 * Weight_Large2)
     f2_x = f2_x + Predict_M(i,1) * Weight(i,2);
     f2_y = f2_y + Predict_M(i,2) * Weight(i,2);
     weight2 = weight2 + Weight(i,2);
   end;
   if(Weight(i,3) > 0.75 * Weight_Large3)
     f3_x = f3_x + Predict_M(i,1) * Weight(i,3);
     f3_y = f3_y + Predict_M(i,2) * Weight(i,3);
     weight3 = weight3 + Weight(i,3);
   end;
   if(Weight(i,4) > 0.75 * Weight_Large4)
     f4_x = f4_x + Predict_M(i,1) * Weight(i,4);
     f4_y = f4_y + Predict_M(i,2) * Weight(i,4);
     weight4 = weight4 + Weight(i,4);
   end;
end;

Dec1 = 0 ;
Dec2 = 0 ;
Dec3 = 0 ;
Dec4 = 0 ;

for i = 1:num

    Dec1 = Dec1 + Weight(i,1) ;
    Dec2 = Dec2 + Weight(i,2) ;
    Dec3 = Dec3 + Weight(i,3) ;
    Dec4 = Dec4 + Weight(i,4) ;

end

i
```

```
Dec1 = 1/ Dec1
Dec2 = 1/ Dec2
Dec3 = 1/ Dec3
Dec4 = 1/ Dec4

%using weight and Max number
if(Weight_Large2 ~= 0 && Weight_Large4 ~= 0 )
%if(Weight_Large2 >=1 && Weight_Large4 >= 1 )
state_location(j,1) = (f2_x / weight2 + f4_x / weight4)/2 ;
%state_location(j,1)= (Predict_M(Max_number_2,1)+
Predict_M(Max_number_4,1))/2;
else
state_location(j,1)= (f_ob(j,2)+ f_ob(j,4))/2;
for i = 1: num
   Weight(i,2) = 1 ;
   Weight(i,4) = 1 ;
end;

end;

if(Weight_Large1 ~= 0 && Weight_Large3 ~= 0 )
%if(Weight_Large1 >= 1 && Weight_Large3 >= 1 )
state_location(j,2)= (Predict_M(Max_number_1,2)+
Predict_M(Max_number_3,2))/2;
state_location(j,2) = (f1_y / weight1 + f3_y / weight3)/2 ;
else
state_location(j,2)= (f_ob(j,1)+ f_ob(j,3))/2;
for i = 1: num
   Weight(i,1) = 1 ;
   Weight(i,3) = 1 ;
end;
end;

end;

S = state_location;
```

Error Generation file: ErrorGeneration.m

```
function MeasureError = ErrorGeneration(S, R_Rec, or, t_s);

MeasureError(3,4) = 0;

% Mean Error
Rec_ME_x = 0 ;
Rec_ME_y = 0 ;
Dx_ME_x = 0 ;
Dy_ME_y = 0 ;
for i = 1:t_s
Rec_ME_x = Rec_ME_x + or(i,1) - R_Rec(i,1) ;
Rec_ME_y = Rec_ME_y + or(i,2) - R_Rec(i,2) ;
Dx_ME_x = Dx_ME_x + or(i,1) - S(i,1) ;
Dy_ME_y = Dy_ME_y + or(i,2) - S(i,2) ;
end

Rec_ME_x = Rec_ME_x /t_s ;
Rec_ME_y = Rec_ME_y /t_s ;
Dx_ME_x = Dx_ME_x /t_s ;
Dy_ME_y = Dy_ME_y /t_s ;

MeasureError(1,1) = Rec_ME_x ;
MeasureError(1,2) = Rec_ME_y ;
MeasureError(1,3) = Dx_ME_x ;
MeasureError(1,4) = Dy_ME_y ;

% Mean Absolute Error
Rec_MAE_x = 0 ;
Rec_MAE_y = 0 ;
Dx_MAE_x = 0 ;
Dy_MAE_y = 0 ;
for i = 1:t_s
Rec_MAE_x = Rec_MAE_x + abs(or(i,1) - R_Rec(i,1) ) ;
Rec_MAE_y = Rec_MAE_y + abs(or(i,2) - R_Rec(i,2) ) ;
Dx_MAE_x = Dx_MAE_x + abs(or(i,1) - S(i,1) ) ;
Dy_MAE_y = Dy_MAE_y + abs(or(i,2) - S(i,2) ) ;
end

Rec_MAE_x = Rec_MAE_x /t_s ;
Rec_MAE_y = Rec_MAE_y /t_s ;
Dx_MAE_x = Dx_MAE_x /t_s ;
Dy_MAE_y = Dy_MAE_y /t_s ;

MeasureError(2,1) = Rec_MAE_x ;
MeasureError(2,2) = Rec_MAE_y ;
MeasureError(2,3) = Dx_MAE_x ;
MeasureError(2,4) = Dy_MAE_y ;

% Root-Mean-Squared Error
Rec_RMSE_x = 0 ;
Rec_RMSE_y = 0 ;
Dx_RMSE_x = 0 ;
Dy_RMSE_y = 0 ;
for i = 1:t_s
Rec_RMSE_x = Rec_RMSE_x + (or(i,1) - R_Rec(i,1))^2 ;
Rec_MRMSE_y = Rec_RMSE_y + (or(i,2) - R_Rec(i,2))^2 ;
Dx_RMSE_x = Dx_RMSE_x + (or(i,1) - S(i,1))^2 ;
```

```
Dy_RMSE_y = Dy_RMSE_y + (or(i,2) - S(i,2))^2 ;
end

Rec_RMSE_x = sqrt(Rec_RMSE_x /t_s) ;
Rec_RMSE_y = sqrt(Rec_RMSE_y /t_s) ;
Dx_RMSE_x = sqrt(Dx_RMSE_x /t_s) ;
Dy_RMSE_y = sqrt(Dy_RMSE_y /t_s) ;

MeasureError(3,1) = Rec_RMSE_x ;
MeasureError(3,2) = Rec_RMSE_y ;
MeasureError(3,3) = Dx_RMSE_x ;
MeasureError(3,4) = Dy_RMSE_y ;
```