INTELLIGENT ALGORITHMS FOR HIGH ACCURACY INDOOR POSITIONING AND TRACKING

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Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other University. This dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration, except where specifically indicated in the text.

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Abstract

The capacity to navigate and identify individuals and other devices is becoming increasingly common and more essential in the era of the Internet of Things and the blooming of Wireless Sensor Networks. Outdoor positioning has been shown very well and is commonly used in everyday life thanks to the well-known GPS scheme. However, owing to the unique problems and distinctive requirements in the indoor environment, indoor positioning is still undergrowth and has attracted a lot of research and development in recent times. It can be said that finding an extensive solution like GPS in outdoor positioning will be nearly impossible. We need to evaluate the demands of the application and system so that we can determine the appropriate technology for the navigation system. Not only diversified in demands and technology, but the range of appliances engaged in the system also affects indoor positioning. This heterogeneity covers different kinds of operating systems and communication protocols. Besides, the problems recognised for indoor conditions such as the fading impact, signal attenuation, signal blocking, noise, and interference still cause the navigation system many problems.

As a prospective technology candidate for indoor navigation devices, the Bluetooth Low Energy and iBeacon have appeared. The outstanding properties of Bluetooth Low Energy such as low consumption of energy, simplicity and elevated market penetration draw the attention of scientists. In this thesis, I develop an indoor positioning system using Bluetooth Low Energy technology. My scheme is based on a range-based technique that requires knowledge of beacons before positioning. Users with Bluetooth-enabled devices situated in the system region can be positioned by gathering RSSI signals. Then the information gathered will be filtered and processed through the proposed algorithm. Experiments demonstrate that my system achieves auspicious results with the error margin under half a metre for static devices. In addition, a mobile device sensor is used to measure inertial information. Applying pedestrian dead reckoning technique, direction and target position are estimated after that. Combining this outcome with my algorithms, the tracking results of my system achieved an error of about 0.2m.

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Nomenclature

Angle of Arrival	AoA
Bluetooth Low Energy	BLE
Body Area Networks	BAN
Deep Learning	DL
Electromagnetic interference	EMI
Global Navigation Satellite System	GNSS
Global Positioning System	GPS
Improved Lease Square Estimation	iLSE
Inertia Measurement Unit	IMU
Indoor Positioning System	IPS
Infrared	IR
Least Square Estimation	LSE
Line-of-Sight	LOS
Location-Based Services	LBS
Machine Learning	ML
Mobile Ad-hoc Network	MANET

Non-Line-of-Sight	NLOS
Near Field Commnunication	NFC
Open System Interconnection	OSI
Passive infrared	PIR
Pedestrian Dead Reckoning	PDR
Personal area network	PAN
Probability Hypothesis Density	PHD
Quality of Service	QoS
Radio Frequency	RF
Radio Frequency Identification	RFID
Radio Frequency Interference	RFI
Received strength signal indicator	RSSI
Simultaneous Localisation and Mapping	SLAM
Time division multiple access	TDMA
Time of arrival	ToA
Ultra-Wide Band	UWB
Visual Light Communication	VLC

Chapter 1 Introduction

The expansion of electronic mobile devices and wireless communication has been witnessed in the last decade. Wireless connection has become a fundamental characteristic of billions of computing devices ranging from low complexity ones such as Bluetooth beacons to high computational capability appliances such as laptops or smartphones. These devices are connected and communicated within a system or the coverage of any network. Also, they are carried by users while moving or travelling. This makes mobility one of the critical features of wireless communication and mobile computing. Besides that, mobility combined with localisation have been applied to a wide scale of applications in transportation, healthcare, guiding, homecare, logistics and much more. Hence, there is a high demand for effective location awareness in the wireless network. This chapter will provide an overview of indoor wireless networks – the Ad-Hoc network and indoor localisation, challenges, motivation as well as the objectives of the project.

1.1 Overview

In recent years, we have observed a large amount of wireless communication-related research. It is widely accepted that mobile wireless networks can be divided into two types: infrastructure network called Mobile IP and Ad-Hoc network. The Mobile IP enables a mobile device moving from one network to another without losing its IP addresses and connectivity. Ad-Hoc Networks (Sarkar et al., 2013) refer to infrastructure-less networks which do not require any base stations. This network contains two or more nodes with the wired or wireless interface to communicate with others. These devices can be either in a fixed location or moving around inside/outside the network. Hence, this characteristic creates a dynamic environment where a node might be shown up or disappear suddenly. Another requirement of an Ad-Hoc Network is that all the nodes should be able to contact each other anywhere and anytime within the network.

There are two types of Ad-Hoc Networks. The first one is the homogeneous network where all devices in the network have identical roles and capabilities, for example, two mobile phones transmit data to each other. The second one is the heterogeneous network. In this network, each device has different roles and capabilities like in the master-slave model (Conti et al., 2003). Both types are massively deployed nowadays due to their advantages (Ismail and Ja'afar, 2007) including cheap cost, simple to design, decentralised and robustness.

Moreover, in this age of mobile devices more than 2 billion smartphones and 1.20 billion tablets (Smart Insights, 2016) are being used all over the world, and hence the terminology MANETs. The mobile nodes in the MANET are designed to be self-configuring and self-organising in forming the network. The main tasks of each node in a MANET are to store, locate, retrieve and exchange data. MANET is currently deployed in the military battlefield, commercial sector, local level, and personal area network (PAN) (Bang and Ramteke, 2013). Body Area Networks (BANs) and PANs are rapidly expanding to include millions of electronic devices widely ranging in size, characteristics and capabilities.

One of the most recognised and vital BANs and PANs structures is the indoor localisation system. In fact, the term indoor positioning has become very popular in recent years. Localisation is the ability to determine the location information of users or an object in a closed environment. At present, the well-established positioning systems, such as Global Navigation Satellite System (GNSS) and the famous Global Positioning System (GPS) can only provide good performance in outdoor environments. The signal from satellites is blocked by walls, people and other objects. Moreover, the acceptable error range for outdoor positioning might be larger than for an indoor environment. This means that the available GPS chips on the market cannot adapt to the requirements of indoor positioning.

In terms of the commercial aspects, there are four main tasks offered by the indoor positioning in the market: proximity marketing, wayfinding and navigation, search and requesting help, asset or people tracking. Concerning the nature of these services, high accuracy symbolic position with a flexible frame of reference might be suitable for indoor mobile communication. In this regard, many wireless location technologies have been considered such as Visual Light Communication (VLC), Infrared (IR), Ultrasound, GPS, Simultaneous Localisation and Mapping (SLAM) and Radio Frequency (RF) Based (WLAN, Bluetooth, Zigbee, RFID). Each technology has its own advantages and disadvantages. Besides, the merging of devices' platforms, communication environments and systems components will introduce new concerns for accuracy, stability, compatibility and scalability in all infrastructures and services. Therefore, having a focus on developing and optimising system design as well as location algorithms could be an effective way to utilise positioning results and control system errors.

1.2 Problem statements

The general problem of this thesis is to answer the following question:

"What is the effective positioning solution to achieve high accuracy and low energy consumption in the noisy indoor environment?"

To answer this question, challenges in designing the indoor localisation have been defined. Such difficulties are also common problems faced in the design of MANETs.

A wireless network consists of various types of devices ranging from mobile phones, tablets, and smartwatches to small tags and sensors. They are mostly battery powered and operated by different operating systems. The rapid expansion in the divergence of devices being used causes many challenges in designing a MANET. In fact, those challenges depend on the actual application of a MANET, but there are some major challenges which are highlighted below:

- **Limited power source:** devices in the network are powered by batteries. Unfortunately, progress in battery technology is plodding compared to the development of mobile devices. This limitation of power source is a big issue in MANETs as some or all nodes might act as routers and end devices at the same time. The communication process including receiving and forwarding packets needed to be designed with the focus on energy conservation. Moreover, there is a trade-off between reducing a system's power consumption and optimising a system's performance. An optimisation based on unnecessary or irrelevant evaluation and features may lead to insufficient battery life.

- **Multi-hop routing protocol:** there is no default router, every node can act as a router to receive and forward data. This will make the routing process much more complicated than in the case of a single hop. Moreover, the dynamic topology may cause routing between two nodes to become challenging and consume more energy than usual.
- **Delay and time responding:** the mobility function may lead to a delay in the network in recognising the existence of the node and establishing nodes' communication. This will result in the challenge of the route selection.
- **Cross-platform issues:** each electronic device has a different hardware/software configuration, and they might have several radio interfaces available to them at the same time. This increases the complexity of network protocols and algorithms, especially in adapting to the dynamically changing conditions.

Other issues can be named, such as Quality of Service (QoS), Security, Scalability, Interference and Multicast.

- In MANETs, together with the mobility, indoor location-based services will enhance the user experience, improve business and increase sales in the retail, transportation or healthcare domains. Despite the need for indoor localisation, there does not exist any standard solution because of two major questions: "What is the ubiquitous technology for indoor positioning system?" and "How is the data collected and analysed?" Referring to the first problem, the currently well-established positioning systems, Global Navigation Satellite System (GNSS) and the famous Global Positioning System (GPS) can only provide excellent performance for outdoor environments. There is no such thing as a ubiquitous technology that identifies the indoor positioning. In fact, there are some options that can be used as a standard technology such as Wi-Fi-based positioning, RFID based positioning or Bluetooth based positioning due to their wide availability. However, there are some limitations such as huge power consumption, unique hardware installation or manual calibration. These need to be minimised in order to make any technology become feasible for standardisation. The second question is the huge and complex data obtained from numerous resources resulting in the uncertainty and complicated information processing. Moreover, data extraction and analysis are needed to meet some essential requirements:

- **Precision/Accuracy:** the requirements for accuracy and precision is much higher compared to that required in the outdoor scenario. Ideally, it should range from 2-3 metres to only a few centimetres depending on the application.
- **Coverage:** in theory, the most effective system is the one that has the widest coverage area. However, this term is strongly linked to energy efficiency. A sufficient system could provide a range of up to about 50-60 metres.
- **Interference:** the indoor environment consists of a mixture of radio wave signals such as the internet, mobile cellular, Bluetooth. They might operate at the same frequency. This leads to interference in the buildings.
- **Attenuation:** The propagation model for busy indoor environments is complicated. This is the result of multipath and Non-Line-of-Sight (NLOS) conditions and the presence of continuously moving objects/people within the area. On the other hand, it also depends on the material of building or subjects. Below is Table 1.1 of obstacle attenuation (Mautz, 2009)

Table 1.1 Object attenuation levels (Mautz, 2009)

Material	Attenuation [dB]
Dry Wall	1
Plywood	1 – 3
Glass	1 – 4
Human	3
Painted Glass	10
Wood	2 – 9
Iron Mat	2 – 11
Bricks	5 – 31
Concrete	12 – 43
Ferro-Concrete	29 – 33

- **Reflection, Diffraction, Scattering:** the signal within a building will experience these phenomena. This makes the modelling for indoor positioning systems much more complex and sensitive.
- **Energy consumption:** in the indoor environment, most devices are mobile or handhelds which are powered by limited batteries. Preserving energy consumption while maintaining the overall performance is one of the most challenging tasks for an indoor positioning system.

1.3 Research motivation

The research is motivated by the significant challenges of designing an indoor positioning in MANETs. First is the diversity in the requirements of an indoor positioning system. There is no specific standard for this system. This is very difficult for analysis and finding a solution. Thus, the first motivation is to propose a concept of an indoor positioning system framework in MANETs that can minimise difficulties posed by the diversity of devices and applications in MANETS. This study more focuses on the application in a large and busy indoor building.

In fact, researchers had been trying to solve the indoor positioning issue in a variety of ways. The leading GNSS technology performs poorly indoors. Some of the research and some commercialised products proposed some positioning systems using Wi-Fi, Bluetooth or RFID technology. Some authors such as Wu và Liu (2013) or Gu et al. (2019) use Wi-Fi and fingerprinting algorithms to solve the problem but this solution requires a lot of power usage and complex offline computation. Bluetooth solutions were also suggested by some authors (Basiri et al., 2017, Teran, Carrillo and Parra, 2018) and positive results achieved. However, the accuracy for small objects remains inadequate and the system may have problems with scalability. Additionally, RFID or Zigbee solutions are more suitable for locating sensors or very small items. It also has very short-range which is a problem even for indoor environments. Hence, there is no universal agreed solution.

Also, the motivation comes from the high demand for efficient indoor positioning in commercial use. According to the research of Nokia (Kalliola, 2011), 80% - 90% of human activities occurring inside a building and indoor communication accounts for 70% - 80% of the phone calls and data connection. Billions of handheld devices expect an intuitive, reliable and accurate location-based service. Moreover, customers will demand that great experience and service even when they change devices or enter any large and busy indoor facilities such as a hospital or underground station. Hence, the indoor positioning system should not only overcome the technical problem but also overcome non-technical issues such as low cost and low complexity in order to be widely implemented.

1.4 Aim and research objectives

The main aim of this research is to develop/design a high accuracy and energy-efficient indoor localisation system for MANET. The application to track both static and dynamic devices are considered in this research work.

The objectives of this research are summarised below:

- **Review of existing technology at both MANETs and indoor localisation**

To conduct an in-depth review of existing technologies, the accuracy aspects were focused. Details of properties and requirements of an indoor localisation were evaluated. In addition, there was a focus on energy-efficient.

- **Evaluate the capability of the potential technology and design an efficient hardware setup for the technology**

Indoor positioning has very unique characteristics. Thus this objective has a two-pronged purpose. First is to analyse the performance of the potential technology and technique in the indoor environment. The second phase is to design a recommended hardware setup for such situation following the evaluation and understanding of the potential technology

- **Design of an optimum localisation technique for indoor positioning for static device**

This is the main focus of this work. The technique was proved to achieve high accuracy with low energy consumption for tracking static devices.

- **Design a fusion system for indoor tracking based on the proposed technique**

Monitoring a static device might be not enough in the real-life application. Tracking an object or people is one of the most attractive topics in the recent market. Based on the developed approach for the static device, a system and algorithm for indoor tracking were proposed and evaluated.

- **Performance Evaluation of the system using experiment**

A testbed of different platforms and hardware was developed currently within my research group. Data was collected and analysed had been done using MATLAB software.

1.5 Contributions of the research to state of the art

There are three key contributions of this work. The first contribution is a comprehensive study of the indoor positioning system. There are comparisons between indoor positioning technologies and the different algorithms used. Besides, the review outlines the specific criteria and requirements of the indoor positioning system, paying particular attention to positioning in large building applications. More specifically, these are energy efficiency requirements for the system. There is also a conceptual model proposed for commercial indoor positioning systems This allows other researcher and engineer to understand which technology system should be exploited in their indoor positioning.

The second contribution is to demonstrate the suitability of Bluetooth Low Energy and iBeacon for indoor positioning systems. Experiments are performed with different conditions and configurations and evaluated thoroughly. Thereby showing that the ability of this technology is not only be demonstrated in theory but also, in reality, using correct setup topologies.

The third contribution of this study proposes a novel localisation algorithm call "Improve Least Square Estimation" that achieves high positioning accuracy with cross-platform capability. This algorithm is based on BLE technology and the iBeacon device has been shown to be effective. Evaluation and comparison have been made between our algorithm and other Bluetooth-based algorithms as well as other forms of technology. The findings show that with static devices, the algorithm works very well. Not just this, the algorithm proved to improve in real-time tracking capabilities the performance of the classical PDR. The overall results indicate the ability of the algorithm to achieve a high accuracy positioning while retaining relatively low power consumption. This experiment has been performed in the laboratory environment and in real-life (office) condition.

1.6 Methodologies

The methodology of the research process will be described in this section. It will clarify the methods used in the analysis, and discuss why this approach was selected. In general, the methodology was conducted to allow a detailed understanding of the problem posed as well as the objectives. The strategy to meet the aim is therefore drawn up. My research is based on experimenting and analysing studies and it uses the waterfall model system development life cycle (SDLC) (Vivek. 2015). It is made up of the following steps.

The first step is to identify the field of research that needs to be addressed. This study focuses on a highly accurate, indoor positioning system and energy conservation. By identifying this problem, an in-depth study was conducted to better understand both the system requirements and the solution being developed. From here, the remaining issues have also been identified. The questions are as follows:

- What are the requirements of an indoor positioning system and what are the key criteria?
- What are potential technologies which must fulfil the following points: energy efficient, high availability, cost-effective and relatively simple to exploit.
- Technology and solution should be easily implemented in reality.

Based on these questions, technologies that could be potential candidates were identified. The limitations of each technology were also addressed and discussed in further detail. A standard novel system had been designed to allow for the use of various types of technology where appropriate. This system will be described in chapter 5 of this thesis. With a careful analysis of each technology's advantages and disadvantages, focusing on large buildings such as hospitals and stations, Bluetooth Low Energy is chosen for its characteristics: low energy consumption, moderate coverage range, high compatibility and low-cost implementation.

The third step, after identifying potential technology which is BLE. We then approached the manufacturers: Bluecat, Locly and Estimote and discussed with them about the requirements of the research as well as the current market. Experiments were then carried out with a range of BLE devices. Real-life data were collected and carefully studied. Hence, the pros and cons of each device could be observed and evaluated.

After that, experiments were continuously organised to evaluate the capabilities of technology and algorithms. After that, experiments were continuously organised to evaluate the capabilities of technology and algorithms. Real information was collected and observed by different formats. The data collected then be filtered and added to the algorithm. The findings then studied and evaluated with other technologies and algorithms. Figure 1.1 demonstrates our methodology:

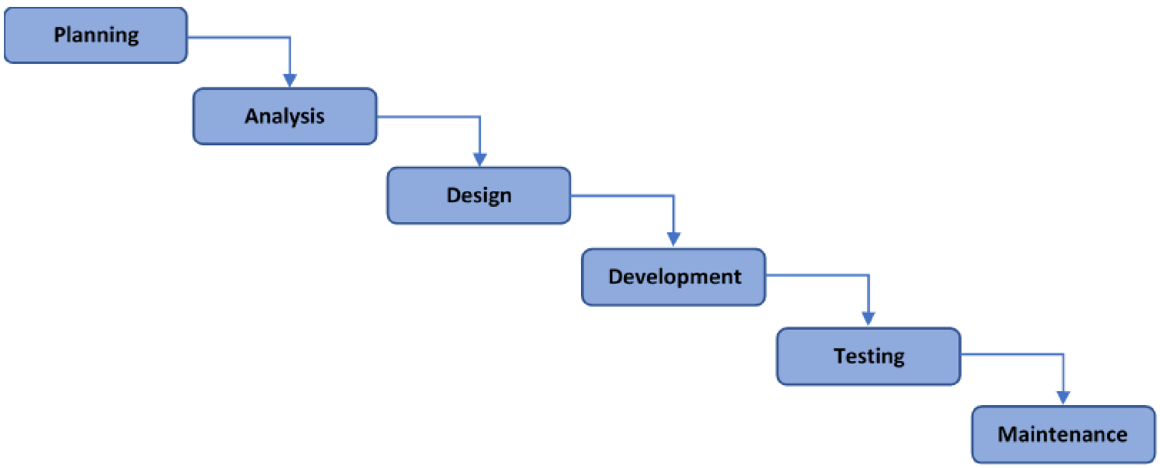


Figure 1.1 Thesis methodology – Waterfall model SDLC

1.7 Thesis structure

The thesis contains seven chapters. The present chapter gives an overview of this thesis, states challenges and difficulties. It also describes the aims and objectives, along with the contributions and outlines the structure of the document.

Chapter 2 introduces the essential background of MANET and indoor positioning. It provides foundation knowledge of this research. There is also a comparison between terms and metrics of an indoor positioning system.

Chapter 3 gives an in-depth literature review of state-of-the-art research of existing wireless technologies and indoor positioning systems. This chapter will compare these systems and technologies to analyse their advantages and disadvantages. Also, the gap between market and research is discussed.

Chapter 4 presents an evaluation of iBeacon and Bluetooth characteristics. Based on that a recommended Beacon setup topology is proposed

Chapter 5 proposes the "improved Least Square Estimation" for static devices. It describes the mathematical models and calculation. Then there will be an experiment and evaluation. Detailed discussion and results are also presented.

Chapter 6 is dedicated to the indoor tracking application. This suggests a hybrid model of the traditional PDR approach and my proposed solution. The system information will be given. An experiment was conducted to see evaluate the performance of this fusion system.

Chapter 7 concludes this study. It includes the summary of how this thesis answers the problem statements, limitations and recommend of potential future work.

Chapter 2 Background

In this chapter, the background of the study will be presented. The chapter begins with the knowledge and concepts of MANETs in Section 2.1. Later, in Sections 2.2 and 2.3, the technologies and metrics used in the indoor positioning system were covered and compared. Sections 2.4 and 2.5 will cover common methods and data filter used for the localisation purpose. Finally, there is an introduction to the technology chosen for this study: BLE and iBeacon.

2.1 Background of MANETs

MANETs stands for Mobile ad hoc network which is a network consisting of a set of mobile devices that is formed dynamically and randomly. It does not require any physical infrastructure configuration. Due to this nature, there are several notable characteristics of a MANET. First, it contains autonomous nodes, so the ad hoc network is decentralised. Hence, each node in the network behaves as a router that interconnects with its intermediate neighbours to forward the data packets. Intuitively, MANETs use the multi-hop routing process and have the self-configuring ability. Second, mobility nodes create a dynamic topology for MANETs. Nodes are free to join and leave the network at any time and any boundary, making the network topology unpredictable over time. Third, these networks have low capacity, low bandwidth link, high bit error rates and shorter communication due to the operation on the bandwidth-constrained variable capacity link. This leads to the fourth characteristic which is unreliable communication in terms of stability, high packet loss and re-routing instability. Fifth, the unreliable links and device heterogeneity make the network more vulnerable to physical attacks. It is prone to many types of physical threats varying from device damaged, device lost, device stolen to denial-of-service, interception or routing attacks. Final, nodes are small and handheld, so they are powered by batteries and other exhaustible sources. Therefore, energy efficiency and power conservation are crucial optimisation criteria of MANETs.

In order to design a sufficient MANET system, a general and simple architecture of a MANET network is shown in Figure 2.1 (Conti, 2003):

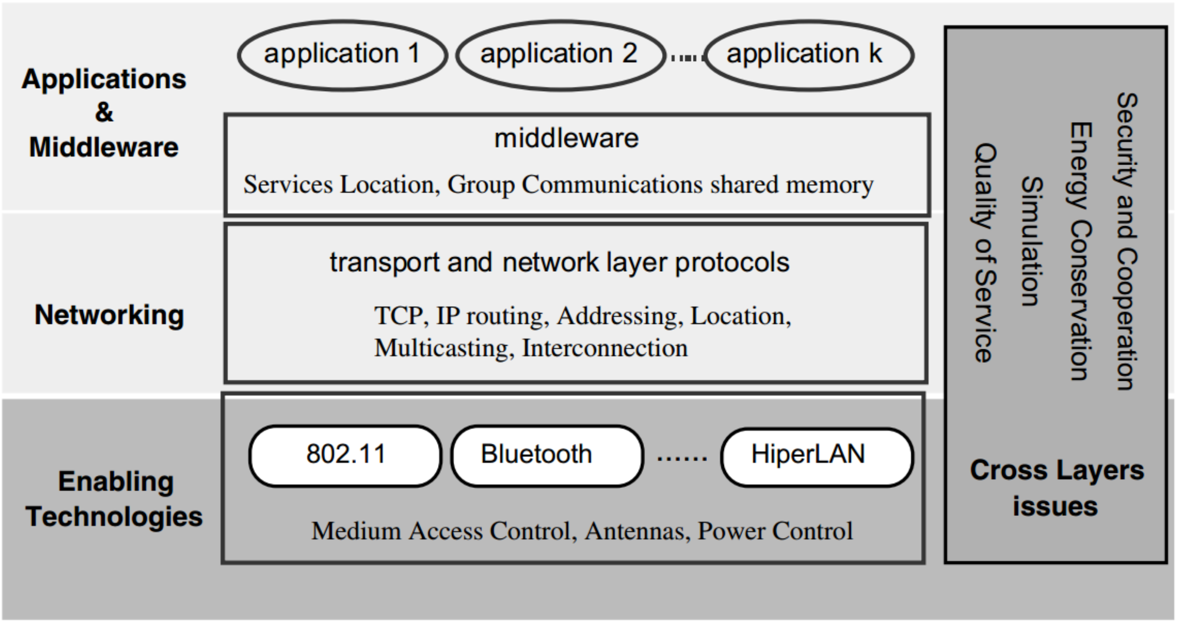


Figure 2.1 General MANET architecture (Conti, 2003)

As can be seen, there are three major areas to be considered in a MANET. The following sections will review each area separately. As the technologies are mainly based on wireless medium access, the discussion will be based on wireless technologies.

Enabling technologies

The enabling wireless technologies for MANETs were discussed by Conti (2003) and classified based on the network coverage area: Body (WBAN), Personal (WPAN), Local (WLAN), Metropolitan (WMAN) and Wide (WWAN) area networks. The author states that WAN and MAN are extremely complex in terms of addressing, routing, location management, security, etc. so their feasibility is not on the immediate horizon. Hence, this research will focus on three main application areas: WBAN, WPAN and WLAN including IEEE 802.15.1, IEEE 802.15.4, IEEE 802.15.3, IEEE 802.15.6 and IEEE 802.11

MAC protocol

As stated, the MAC protocol plays a vital role in designing a MANET. There are several points to be noted when choosing a suitable MAC protocol. First, wireless channels are unreliable with the path loss, fading and suffering interference. Secondly, as the nodes in MANETs are moving around, the network topology will change continuously. Thirdly, there is no central management in a MANET, each node can work as a router and can have its own view of the network. Lastly, energy management across multiple layers will play a pivotal role to achieve the desired energy conservation. Chlamtac et al., (2003) described the collisions/interference due to the hidden terminal as one of the main challenges of designing MAC protocols for MANETs. This will waste energy and cause delay by using too much unnecessary retransmission.

It is known that CSMA/CA is the most widely used choice for MAC protocol in MANETs as it is the standard used in both ZigBee and 802.11. CSMA/CA tries to avoid collisions with the RTS/CTS method before transmission. However, Chlamtac and his co-authors claim that the transmissions from a node out of range (this node may be moving into the network or have just gone out of the network) cannot be detected. Therefore, several types of MAC protocols have been proposed. In fact, Bluetooth and BLE use TDMA which allows collision-free medium access because it uses a reserved time slot for each node. However, this mechanism will cause delay, especially in a bursty traffic environment. Bharghavan et al. (1994) proposed MACAW, a mechanism that uses a four-way handshake method. This includes an ACK message from the receiver so the hidden terminals problem might be avoided but will make a trade-off with the delay time and may increase the energy consumption. Another MAC protocol proposed was Power Control MAC (PCM) (Jung and Vaidya, 2005). Basically, it uses the four-way handshake method but with the controlling of power. Each message is transmitted from a lower power level and periodically is increased up to a max power level. However, PCM's implementation is complex and costly at the moment.

Networking

In this domain, the main focus is on the routing protocol performance. The routing protocol for MANETs is classified into two main groups: proactive and reactive protocols.

Proactive routing protocols

In proactive protocols, each node maintains the routing information to every other node or the nodes within its area in the form of routing tables. These tables are updated periodically; hence, this type of routing protocol is also called table-driven protocol. Because of this feature, this protocol is unsuitable for an extensive network. Some well-known candidates from this type are Destination-Sequenced Distance-Vector (DSDV), Optimized Link State Routing (OLSR) and Hierarchical State Routing (HSR).

DSDV

DSDV protocol (Perkins and Bhagwat, 1994) is a distance-vector protocol. Each node has a routing table with a single route to the destination using the shortest path routing algorithm. A destination sequence number is used to avoid looping. This destination sequence is incremented by a node whenever there is a change to its neighbours. The greater destination sequence means the node has more recent information. Thus, nodes always choose the route with the most significant number. However, due to this frequent updating, there is a large amount of overhead to the network. Therefore, DSDV is not suitable for a large network.

OLSR

OLSR protocol (Jacquet et al., 2001) is a point-to-point routing protocol and is an optimisation of the traditional link-state algorithms. Each node maintains the routing information by exchanging the link state information among its neighbours. By using the multipoint relay (MPR) technique, OLSR can minimise the size of each control message and the number of rebroadcasting nodes. However, as DSDV, the limitation of OLSR is the high bandwidth consumption as a result of the periodic updating of the network topology.

HSR

HSR protocol (Pei et al., 1999) is another modified version of the link-sate algorithm. It maintains a hierarchical addressing and topology network. The network is divided into different clusters and each cluster has its own leader. The cluster leader exchanges the hierarchical topology with its peers. Then each node has this information stored in an HSR table. By using this method, the routing table size is much reduced, however, this also increases the complexity making it quite a challenge to implement.

Reactive routing protocols

In reactive routing protocols, each node discovers the routing information only when it is requested. This means the node maintains the routing information for active routes only. The route usually is discovered by flooding a route request throughout the network. When the message reaches the destination, a route reply will be sent back to the source node. Representatives for this type of protocol are Ad-Hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR) and Temporally Ordered Routing Algorithm (TORA).

DSR

DSR protocol is a source-based routing protocol and was proposed by Johnson B.D and his colleagues in 1999. If the source does not have the route information to the destination, then the discovery process will be started by sending out the REQUEST packets (RREQ) to its neighbours. Then the packet will be forwarded until it reaches the destination which will send back the REPLY message (RREP). In the case that the next-hop link is broken, an ERROR message (RERR) will be sent back to the source node. One important thing is that in the packets, the full route information to the destination is included. This leads to a large amount of overhead when the network gets bigger (Sharma and Lobiyal, 2015). Sharma also proved that in small size networks, the DSR protocol might perform better over the AODV and TORA. One advantage of this protocol is that a node can store multiple routes in the route cache, and if the source can find a suitable route to the destination then there is no need for the route discovery. In general, DSR performs best for low bandwidth and low power network.

AODV

AODV protocol (Perkins and Royer, 1999) is one of the most popular routing protocols in MANET. It is based on DSDV and DSR protocol. AODV uses the sequence numbering feature of DSDV while the route discovery is similar to that in DSR. There are a number of advantages with AODV, making it a popular choice in designing MANET. Firstly, each packet in AODV does not carry the full route information as in DSR, it only carries the destination address. Secondly, AODV is highly adapted to the dynamic topology of MANET. However, AODV requires more time for setting up. Using HELLO messages repeatedly may lead to the waste of bandwidth and it still has massive overhead in the big MANET. Therefore, several modified versions of AODV (MAODV) have been proposed to overcome these challenges. Zonghua et al. (2011) introduced a MAODV by changing the RREQ message to reduce the route overhead. Their results showed that the MAODV outperforms the traditional AODV under the conditions of increasing node mobility and traffic load. Rana. Y et al. (2015) proposed another version of AODV. Their approach uses the energy level on each node to decide whether to discard the RREQ or not. The results showed that their MAODV improves link stability as well as increasing the network lifetime.

TORA

TORA was invented by Park and Corson in 2001. It was designed for highly dynamic mobile and multi-hop wireless network. TORA includes three major tasks: route creation, route maintenance and route erasure. Several studied proved that TORA performs best in a large network, with a high-speed high mobility node. However, TORA has more delay and it creates more overhead issues.

Application

There is a wide range of applications using MANET ranging from transportation, military or, commercial, to entertainment or sensor networks. These are lists of some application examples:

- Military sector: battlefield communication, enhanced equipment…

- Emergency service: first responder, disaster discovery and recovery, hospital aiding and guiding…
- Sensor networks: smart sensors for body and home application, data tracking, movement tracking, machine-to-machine communication...
- Commercial application: e-commerce, e-payment, business database, airports and station aiding…

In this proposed research, the aim is to develop a communication supportive system in the area of transportation and healthcare. This system will automatically provide personalised guidance to the user, advertisement or notification in crowded places such as stations or hospitals. This is especially useful for people with health problems or marketing purposes. However, as mentioned earlier, the diversity of mobile devices' hardware and software makes the communication process between devices complex. It also raises a difficult task for optimising energy consumption across all aspects of communication. From the application perspective, there might be a need to develop different interfaces allowing the application to talk to different hardware and software effectively.

Cross-layer issues

De Felice (2008) stated that cross-layer design in MANET is very important to get the desired performance. The author proposed three integrations between MAC and clustering design and two joint designs for MAC and routing schemes. The result shows that these integrations reduce the overall overhead and may reduce the packet latency.

Varshavsky et al. (2005) introduced the cross-layer service discovery in MANETs. Their approach is to integrate the application layer and routing layer to improve energy efficiency. Authors state that by this integration, the node can know about the available services and choose the routing path in a more efficient way. Thus, it can reduce the overhead as well as energy wastage.

Ahmed et al. (2015) used the averaging Received Signal Strength (RSS) value method to find an effective route between source and destination. This benefits from allowing access to information between the MAC layer and the routing layer. The simulation shows that their method outperforms AODV in terms of packet delivery, routing overhead, end-to-end delay and energy efficiency.

2.2 Indoor positioning technologies

There are numbers of wireless-based technologies for positioning systems. Some of them are suitable for outdoor environments such as Cellular network or GPS; whereas some technologies are being considered for indoor areas. Figure 2.2 describes the outline of the current wireless technologies used for positioning.

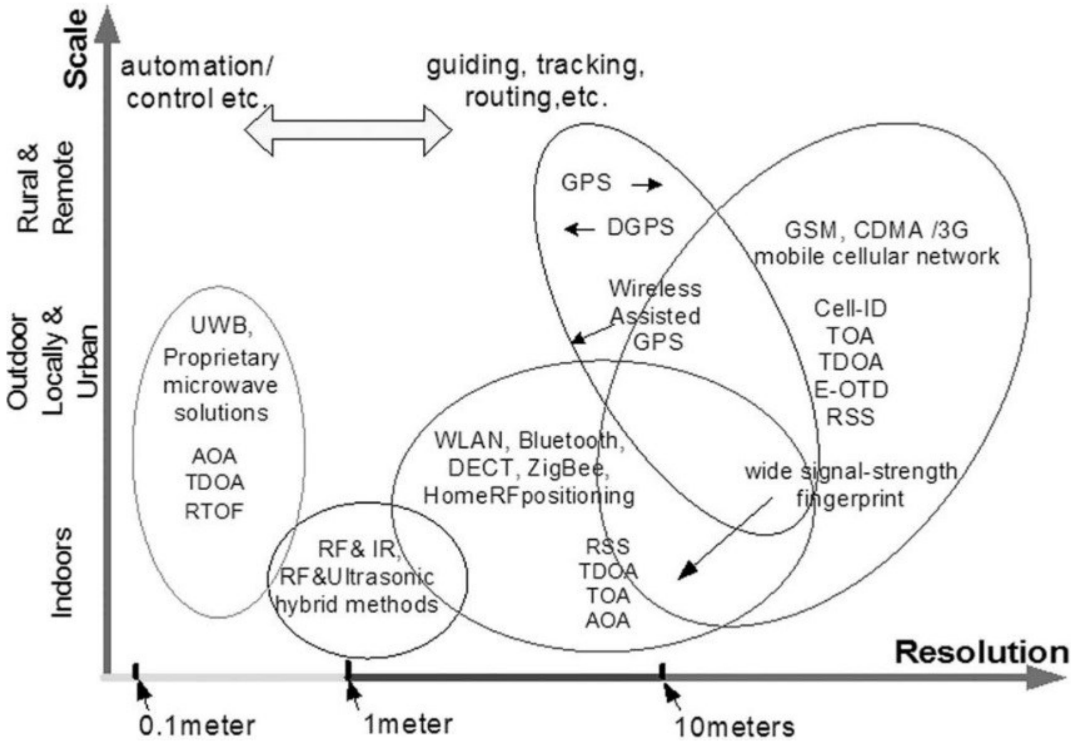


Figure 2.2 Available wireless-based positioning system (Liu. H et. al, 2007)

As the primary focus of my research is on the indoor positioning system with the scope of guiding and routing, this chapter will introduce and discuss well-known technologies that are available and most active for indoor positioning solutions. They are Infrared, Ultrasound, WLAN, Bluetooth, ZigBee, Visual Light Communication (VLC) and Radio Frequency Identification (RFID).

2.2.1 Infrared

Infrared (IR) is a type of radiant energy that is invisible to the human eye in most standard life environments, but it can produce heat. IR waves occur from 3GHz to about 400 THz in frequency and IR wavelengths range approximately from 700 nanometres (nm) to 1 millimetre (mm) which is longer than those of visible light but short than those of microwaves. In the context of positioning, IR and its invisibility can provide a less disruptive solution compared to other visible light sources.

Based on methods that use IR signals, there are two types of IR based indoor positioning classified: use of active beacons and use of passive infrared.

2.2.1.1 Active Beacons

An active beacon is an approach using pre-configuration beacons set up at pre-known positions in a room or building. These beacons are fixed and attached with the infrared emitter(s). The unknown mobile nodes moving around within the defined space will be scanned and located. The unknown node's data is collected, and its position is calculated by triangulation or angle of arrival algorithms. One of the most well-known and early indoor localisation system is the Active Badge System (Want et al. 1992). Want and his co-authors proposed a novel positioning system that locates people at room level. Individuals wear "Active Badges" which transmit IR pulses with a unique code periodically. Pre-set-up network sensors collect these signals and process appropriately. They showed their system to provide an accuracy within 6 metres which is also the operating range of the IR emitter. In order to gain a high level of precision, more IR receptors were required to deploy in the area and the biggest prototype consists of around 200 badges and 300 sensors.

2.2.1.2 Passive Infrared Positioning

Passive infrared (PIR) positioning is the method to locate humans based on their thermal radiation. The PIR sensors operate in the long-wavelength (8 µm to 15 µm). They can detect the radiation emitted from other objects in the form of heat but do not transfer any signal. The collected heat radiation will be mapped into a passive image. It is not necessary for people or objects to wear any tags or emitters. Thus, one significant advantage of this method is the privacy due to the non-identification sensors. However, sun and other ambient heat sources will affect the system performance. One example of the Passive Infrared Positioning system was introduced by Kemper and Hauschildt (2010). They proposed a PIR system that allows simultaneous localisation and tracking multiple people. Authors presented a Sequential Monte Carlo (SMC) implementation of the Probability Hypothesis Density (PHD) filter. Four sensors were placed in four corners of a room in their testbed. Each sensor contained two thermophiles that can enable a field of view (FoV) of 90 degrees. Then the targets' heat data were collected, and their positions were estimated using the principle of AoA and Finite Set Statistics. The results showed that, with up to 3 people moving in the room, the mean error is less than 30cm and the update rate of more than 50Hz is achievable.

2.2.2 Ultrasound

Like the IR positioning system, the ultrasound/ultrasonic positioning system can provide accuracy at room level. There are some important properties of ultrasound. First, the ultrasound signal requires the line of sight between transceivers. Its signal is blocked by solid walls, obstacles or even humans. These signals will be reflected so if this reflection can be learned or predicted, and ultrasounds could be used to detect and monitor objects. Second, ultrasound has a short communication range (up to 10m). Third, the ultrasound signal can work in critical conditions such as high humidity or dusty conditions. However, these kinds of environmental conditions can affect the response of the ultrasound receiver. Fourth, ultrasonic waves do not interfere with other electromagnetic waves.

Based on these characteristics, ultrasound can be exploited for range location and indoor positioning systems. In nature, bats, whales and many other animals are famous for using echolocation to communicate, navigate and hunt. Using similar ideas, many research projects use ultrasound for proximity sensing. In brief, the ultrasonic positioning system estimates the location by measuring the time of flight of the signal from transmitters to receivers. This is actually very effective for applications only needing room-scale accuracy as the ultrasound does not penetrate walls. To achieve better accuracy, trilateration and multilateration are used with a more significant number of transceivers. This will increase the cost and complexity of systems.

Cricket indoor location (Balakrishnan. H and Priyantha. N, 2001) is one of the most well-known ultrasound-based positioning systems. It was designed with four aims which are privacy, decentralisation, low cost and room-level accuracy. The implementation involved pre-configured beacons and listeners. They transmitted a 40 kHz US pulse of 150 μs and the message contained the beacon's coordinate, temperature and identifier. Cricket provided space, position and orientation of target devices. Authors showed that their system can reach the accuracy of 10-15 cm.

2.2.3 WLAN

The most well-known and accessible technologies for WLAN is the IEEE 802.11 standard (IEEE, 2020). This standard has long dominated the market and is being supported by almost every mobile device. It is designed to achieve high data rates and for high-bandwidth customers. There are five commonly used specifications for the 802.11 PHY layers in MANET system.

IEEE 802.11a – was introduced in 1999. It uses the 5 GHz radio band and the maximum data link rate per channel is 54 Mbps. The range is up to 40m indoor.

IEEE 802.11b – was introduced together with the IEE 802.11a in 1999. It can achieve 11Mbps of maximum link rate in the 2.4 GHz radio band which is very similar specification to the traditional Ethernet. The power consumption is about 30mW and it can achieve up to 100m range outdoor.

IEEE 802.11g - was introduced in 2003. It is a combination of 802.11a and 802.11b. It uses 2.4 GHz and the maximum link rate is 54 Mbps. The range is about 50m.

IEEE 802.11n – was introduced in 2009 with the aim to improve the 802.11g standard by using MIMO technology and a wider radio channel. The maximum link rate can be 100 Mbps and it works on both 2.4 GHz and 5 GHz. It can reach up to 70m.

IEEE 802.11ac – was introduced in 2013 and is considered as the most popular used standard in the market nowadays. It is an extended version of 802.11n. The maximum throughput is 1Gpbs on 5 GHz band and 500 Mbps on 2.4 GHz band. The coverage indoor range is about 35m-40m.

The IEEE 802.11ac, also called Wi-Fi is currently leading the industry for MANET and indoor positioning. One of the main advantages of the Wi-Fi technology is that the Wi-Fi access points are widely deployed in almost all the business venues at present. The method called "Fingerprinting" is considered to be the most effective approach for a Wi-Fi signal to locate indoor objects and devices (Van Haute et al., 2016). Recent research has shown that despite being significant in terms of signal strength, the accuracy of this technology is relatively low. The resolution ranges from 5 to 15 metres. In order to resolve the positioning within 5 metres, many access points need to be installed. This is overkill because the Wi-Fi access point originally was designed to broadcast the Wi-Fi signal rather than for locating users. The processing is also more complicated which leads to higher latency compared to other technologies (Van Haute et al., 2016). This will lead to interferences and deployment cost problems. Moreover, most access points need to be plugged into an electrical outlet. Even with the latest technology Power over Ethernet (POE) for an access point, this still consumes a considerable amount of energy for a medium to large area such as train stations or hospitals compared to other technology like BLE or Zigbee.

2.2.4 Bluetooth

Originally invented by Ericsson in 1994, Bluetooth is a low tier wireless standard communication approach for low cost and short-range radio link. It is designed for small and mobile devices with low power consumption at approximately 100mW. Bluetooth signal operates at 2.4 GHz (Briere, Ferris and Hurley, 2006) and it can reach up to 10 metres at the standard 0dBm settings. At a much higher radio power of about 20dBm, Bluetooth radio can work in a range of 100 metres in theory. It supports both voice and data and is widely used in the market. It was estimated in 2016 that there would be around 10 billion Bluetooth enabled devices worldwide in 2018 (Smart Insights, 2016).

In 2010, Nokia proposed Wibree (Chavda et al., 2012) which is a radio technology based on traditional Bluetooth but with the lowest possible power consumption, low cost and low complexity. The technology operates in the same spectrum range of 2.4 GHz as Classic Bluetooth technology but uses a different set of channels. Then it is standardised by The Bluetooth Special Interest Group (SIG) and became Bluetooth Low Energy (BLE) (Townsend, 2014) in the market. The term BLE will be used to refer to this technology in this thesis. The most important features of BLE is that it has very low power consumption up to microwatts compared to the 1W (as reference threshold) of traditional Bluetooth. Thus, it poses much-decreased energy consumption of the Bluetooth system as well as offering a simple communication process based on the master/slave model. The operation range for this new Bluetooth varies between 10 and 100 metres distances and it has 1 Mbps data rate. As a result, the technology is not optimised for transferring files over a node, except for sending small chunks of data (exposed state). BLE is backwards compatible with the classic Bluetooth using dual-mode configuration according to Townsend. This allows the BLE to be implemented and join the market immediately thanks to the predominance of the Bluetooth device.

The operation of BLE consists of two main activities: advertising and connection, as shown in Figure 2.3 and Figure 2.4 (Townsend, 2014). In the advertising phase, broadcaster device sends advertising packets periodically to any device willing to receive them. These devices are called observers which keep scanning for advertisements. In the connection phase, after identifying the broadcaster device it wants to communicate with, the observer initiates and establishes the connection. The total connection time can take up to 15 seconds, but the connection link is often established within 5 seconds. It then becomes the central (master) device whereas the broadcaster becomes the peripheral (slave) device. A device can be either a slave or a master and can have multiple connections at the same time. In detail, a master can contact 7 slaves in real-time or be called “active slave” and up 255 “idling slave”. In idling mode, slaves are less sensitive but they still maintain the synchronisation between themselves and the master. This operation forms a piconet. In a defined area, if multiple piconets are overlapping, a scatter net will be formed. This kind of BLE scatters net offers a flexible and energy-efficient approach to dealing with the dynamic nature and the mobility of multiple devices. This simple operation makes BLE easy to set up, robust and reliable in such a complicated environment as inside a busy building.

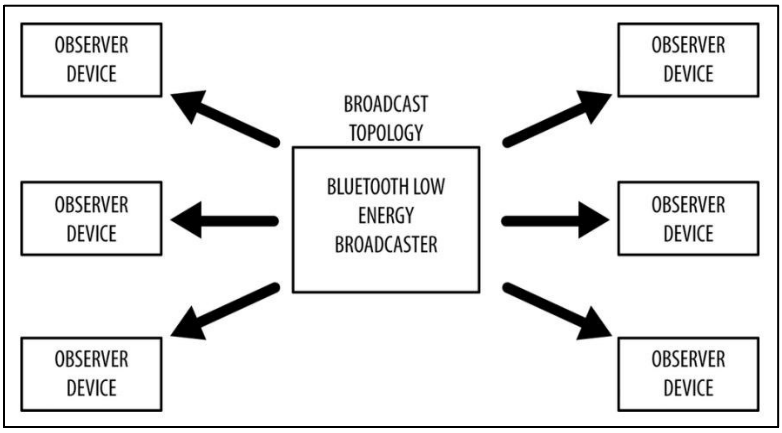


Figure 2.3 BLE Broadcast topology (Townsend, 2014)

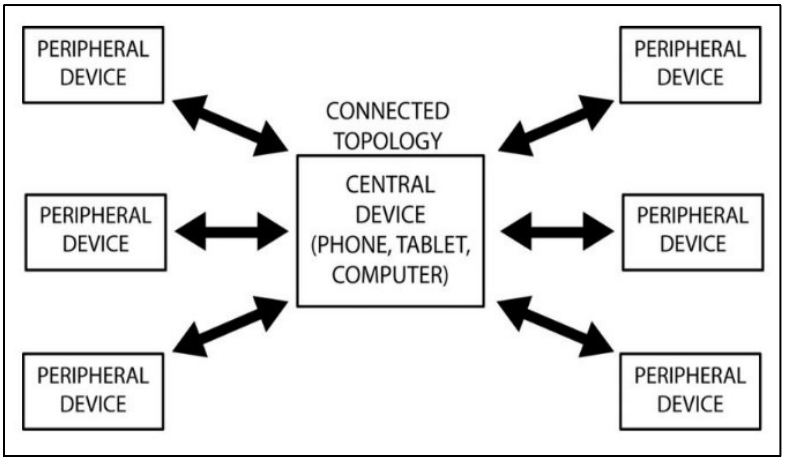


Figure 2.4 BLE Connection topology (Townsend, 2014)

Using Bluetooth in indoor positioning is not a recent approach. It had been introduced by Bruno and Delmastro (2003) and Muñoz-Organero et al, (2012). However, due to the limitations of the classic Bluetooth (Kriz, Maly and Kozel, 2016) devices, which has a long delay and unsatisfactory accuracy, this idea was not widely used. This has changed since Nokia announced their new Bluetooth based technology, Wibree (G. Chavda et al., 2012). Bluetooth or Bluetooth Low Energy are proximity networking. As mentioned, the master and slaves together create a cell, i.e. Pico-cell network. When a cell is formed, the position of these master and slave devices can be estimated within the given communicating cell. This is the basic idea of positioning using Bluetooth signal.

2.2.5 ZigBee

IEEE 802.15.4 (Bhaskar and Mallick, 2015) is a low cost, low rate communication standard for sensor and actuator device. This standard only defines lower layer protocol stacks which are the MAC layer and the PHY layer.

ZigBee (Ramya et al., 2011) is an enhanced version of IEEE 802.15.4 with the definition of upper layers: Network, Security, Application framework and Application Software. ZigBee was proposed in 1998 and then developed by the ZigBee Alliance which is an organisation consisting of hundreds of companies such as Ember, Freescale, Mitsubishi, AMI Semiconductors, ENQ Semiconductors etc. It then became a standard on December 14, 2004. The working range of ZigBee is about 20m to 50m in the indoor environment

In a ZigBee network, there are three supported topologies namely star, mesh and tree network and two types of devices as described in Ramya et al., (2011). Full-function device (FFD) is a device that can work in any topology and can perform all available operations within the network such as routing, coordination and management. The second type is the reduced function device (RFD). This kind of device can only work in a star topology and could perform only a simple task: talking to its coordinator. In each ZigBee network, it requires at least one FFD as the network coordinator. This one working as a master will control its connected nodes/children.

ZigBee offers many advantages for its purposes such as scalability, ease of deployment, very low power consumption, low cost and flexibility. However, this standard can only provide its best benefits for industrial applications. So, ZigBee is quite slow to be a popular choice in the market for commercial use compared to its competitor, the BLE.

2.2.6 IEEE 802.15.3, IEEE 802.15.6 – Ultra Wide Band

IEEE 802.15.3 is a standard for high data rate WPAN designed to provide the real-time distribution of content. It was described as a low-cost solution of moderate power consumption with very high data rate and QoS (Xin Wang et al., 2004). Whereas Bluetooth and ZigBee are end-to-end communication standards including a definition of how data is transmitted, received, managed, formatted; IEEE 802.15.3 at the moment defines only MAC and PHY layers that can be used as part of an overall standard. On the other hand, IEEE 802.15.3 was designed for multimedia wireless such as video streaming which requires very high data rates and low latency with the fair trade-off between bandwidth and energy.

IEEE 802.15.6 is a standard for a communication process designed for devices on, in or around the human body (Kwak et al., 2010). In general, it offers QoS, low power and security function but the ultimate purpose of this standard is for health monitoring application. IEEE 802.15.6 defines three PHY layers: Narrowband, Ultra-Wideband and Human Body Communications layers. On top of that, depending on the actual application, an appropriate MAC protocol can be chosen ranging from random access mechanism (CSMA/CA), unscheduled access or scheduled access. This is a promising standard for research and development in the area of real-time health monitoring and ambient living environment (Kwak et al. 2010).

As mentioned, UWB is under the IEEE 802.15.6 standard. It is an extremely short duration burst of the radio signal. Its frequency is defined at greater than 500Mhz. UWB is designed to transmit extensive data in short-range and low power consumption. These characteristics make UWB very promising for 3D and real-time indoor tracking. Zhang and his co-authors (2006) developed a UWB indoor positioning system that used a ToA method for position estimation. The mean error in 1D, 2D and 3D were 1.49mm, 2.61mm and 3.32mm respectively. However, note that the displacement in their experiment ranged from 0 to 50cm. Chu and Ganz (2005) carried out similar research. They took advantage of UWB properties such as multi-path fading robustness and multiple simultaneous transmission to propose a 3D indoor positioning that covered a larger indoor space, about 10m.

2.2.7 Visible Light Communication (VLC)

VLC is a new and interesting area of research on the positioning. It uses visible light signals for determining the location of objects. A VLC system consists of three main components (De Lausnay et al., 2016) namely, the LED (transmitter), the mobile device (receiver) and the optical channel (environment). The VLC is transmitted from an LED to a receiver which can be a photodiode and/or an image sensor. This receiver should contain the ID or any other geographical information useful for the positioning process. The light travel can be in a direct path (LOS) or reflected by walls or floors (NLOS). Figure 2.5 (Do and Yoo, 2016) shows how the system works. They stated that a VLC system could perform well in a range of 8 metres and strictly in the Line of Sight (LOS) condition. Authors also proved that an accuracy of up to 5 centimetres could be achieved using the VLC positioning.

Medina (2015) recommended VLC technology for hospitals as specific medical equipment requires isolation from EMI and RFI. Patients are also more vulnerable to the radio frequency signal. Also, VLC outperforms RF-based technology in underwater communications (Arnon, 2010) (Uema et al., 2015). However, this solution is still far from commercialisation. Firstly, it has not been fully standardised. Secondly, the set-up cost for this method is also very high at the moment while there are so many unsolved challenges such as modulation bandwidth, interference, nonlinearity, strictly LOS, multipath etc. Thirdly, it is only appropriate for certain scenarios and environments such as underwater, or hospitals where it has to operate within certain specific challenging conditions.

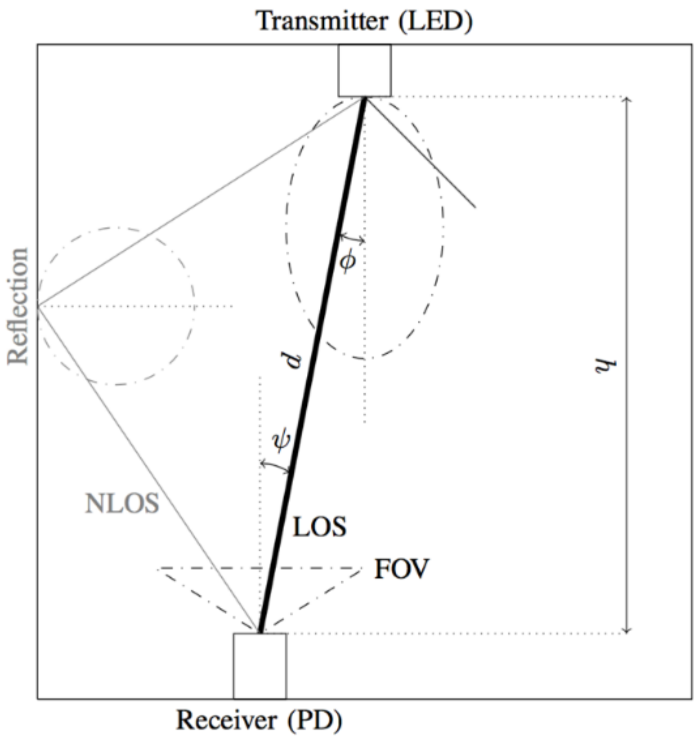


Figure 2.5 VLC technology (Do and Yoo, 2016)

2.2.8 Radio Frequency Identification (RFID)

RFID is a form of wireless communication that uses radio waves to identify and track objects. It was initially invented during World War II to identify whether a plane was a friend or a foe. RFID was introduced in the context of indoor positioning by Ahuja and Potti in 2010. An RFID system consists of tags, readers and a host or computer. They are classified into two main types: active and passive systems (Berthiaume, Donahue and Romme, 2017). The principle for both types is that the mobile device can estimate its location if it can notice the RFID tag whose location is pre-setup.

A passive tag does not require a power source as it is powered by the reader. When a tag enters the signal range of a reader, it will be turned on by this signal. Then the reader can collect information from the tag. This data will be sent to the host for processing. After processing, the output will be sent back to the reader and then the tag. Figure 2.6 (Ahuja and Potti, 2010) shows the communication methods for the passive tag RFID system.

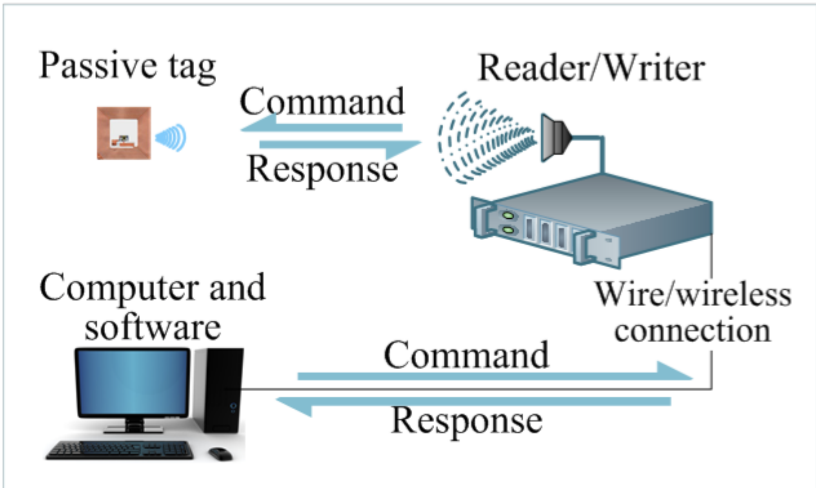


Figure 2.6 Passive tag working mechanism (Ahuja and Potti, 2010)

On the other hand, an active tag, powered by batteries, will periodically transmit information such as ID, location etc. Then the reader can scan this data and transmit it to the host. One main advantage of the active tag is that the reader can simultaneously scan the data from several tags at a time. Figure 2.7 shows this process.

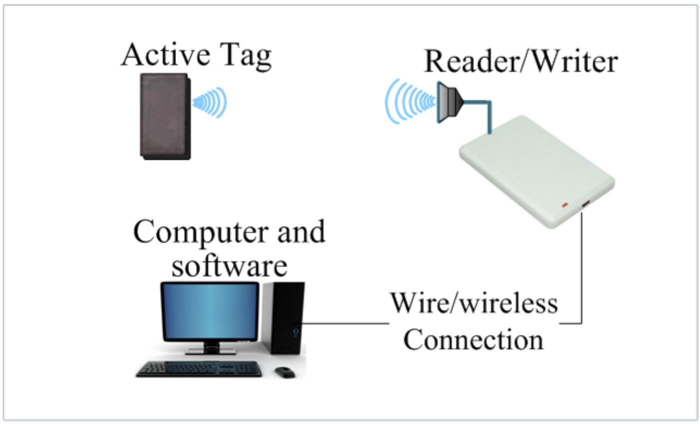


Figure 2.7 Active tag working mechanism (Ahuja and Potti, 2010)

The RFID system operates in one of three frequency bands (Lighthouse.io, 2017): Low Frequency (LF): 30 kHz – 300 kHz; High Frequency (HF): 3 – 30 MHz and Ultra High Frequency (UHF): 300 MHz – 3 GHz depending on the range and its application. RFID indoor positioning can achieve very high accuracy in theory (Lighthouse.io, 2017). However, it can only provide a static position, not real-time tracking or navigation. Moreover, the cost can be extremely expensive if a high-end reader and high-frequency active tag are required. A well-known form of the passive UHF RFID system in use today is NFC (Want, 2011). This method is expensive, accurate and highly energy efficient. Nonetheless, it can only work within a range of 10-20 cm and is not suitable for indoor positioning purposes.

2.3 Indoor positioning parameters

2.3.1 Absolute and Relative Position

The location awareness can be classified as physical position (or absolute location) and symbolic position (or relative location). The absolute location provides a coordinate-based position; for example, 53.4121° N, 2.9814° W is the location of the James Parson Building, LJMU. The relative location refers to a position relative to other objects; for example, a user is inside a building or next to a chair. Consequently, the resolution and accuracy requirement for indoor localisation are varied depending on each system. The application requiring absolute location demands a more definite position whereas the one requiring relative location only needs a coarser position.

2.3.2 Type of nodes

There are two types of nodes in the positioning system: known nodes and unknown nodes.

Known positions are defined as anchor nodes, beacons, access points or reference nodes. These points are physically known and typically fixed in a specific location with an exact coordination. In some rare cases, these nodes can move in a fixed pattern at a certain speed so that, the position of the node is defined.

On the other hand, unknown nodes are blind devices or mobile stations. These are the target whose coordinates needs to be determined by the system. Unknown nodes can be static or dynamic devices or tag. They are carried by humans or robots.

2.3.3 Line of Sight (LOS) and Non-Line of Sight (NLOS)

Line of Sight is the propagation when the transmitter can observe the receiver directly. It means the signal has a direct straight path between transceivers.

In contrast, Non-Line of Sight propagation describes the radio transmission that is obscured by obstacles such as walls, furniture or humans. This is very common in indoor environments and causes interference, reflection, deflection to the signals

2.3.4 Received Signal Strength Indicator (RSSI)

The received signal strength indicator (RSSI) refers to the measurement of the power level of a radio signal that a receiver is receiving from the emitter. Its unit is dBm and 1dBm = 1.3 milliwatt. In general terms, at a further distance, the signal is weaker and suffers through attenuation and other propagation. This makes the RSSI lower. In contrast, in the closer distance, the RSSI gets higher.

The RSSI has one vital downside, which is, that it is vulnerable to other parameters such as environmental conditions, radio frequency interference or noise. This leads to the RSSI being quite unstable over time. Nevertheless, it is still a widely chosen metric for an indoor positioning system. RSSI is very cost-effective, low complexity and can be used for many different pieces of equipment with various technologies. In order to achieve a satisfying accuracy, it requires suitable calibrations and filtering for RSSI in a given environment.

2.3.5 Time of Arrival (ToA)

Arrival time (ToA), or Time of Flight, is one of the most common range- metrics. It is used for outdoor positioning inside the popular GPS network. Parameters are determined based on the transmission speed, the exact time the transmission was transmitted and the exact time the signal was received. The distance is thus easily determined by the Formula (2.1) (Zafari, Gkelias and Leung, 2019):

$$d = \mathrm{c} \times (t_{arrival} - t_{transmit}) \tag{2.1}$$

Where c is the transmission speed, typically determined by the light speed, t is the absolute time the signal is being emitted and received and d is the distance between the transmitter and the receiver. The equation above can be transformed and used to measure the distance between two points by knowing the point's coordinates (Zafari, Gkelias and Leung, 2019). Formula (2.2) suggests this to us:

$$d = \sqrt{(x_{receiver} - x_{transmitter})^2 + (y_{receiver} - y_{transmitter})^2} \tag{2.2}$$

The TOA method requires a very precise synchronized clock between the transmitter and the receiver since the exact time is used to calculate the distance. Many TOA-based indoor positioning systems have been developed and can achieve the accuracy from a few centimetres to 40 m (Li, Han, Zhu and Sun, 2016)

2.3.6 Angle of Arrival (AoA)

Angle of Arrival (AoA) or sometimes referred to as Direction of Arrival (DoA) is also a popular method used to determine the location of an object. This approach offers two ways to accomplish the position. The first method is to use antenna arrays at the receiver side to measure the time the signal is transmitted from the source to each antenna, and then to estimate the source angle. The second method is more straightforward, the direction of each antenna at the receiving ends are pre-set, then adjust them incorporate with the source and measure the arrival angle. The strength of this method is that finding unknown objects only requires 1 or 2 nodes compared to at least 3 nodes like other methods. This approach, however, is best applied only under LOS conditions. And when the signal is reflected and diffraction the measuring angles can be hard to assess. Additionally, suitable equipment must be installed to determine the most precise measuring angle. AoA is often used in VLC indoor positioning systems.

2.3.7 Summary

In this study we want to identify with high accuracy the position of unknown objects in a simple way, requiring minimal hardware and low energy consumption. LOS and NLOS conditions also appear in complex indoor environments. ToA provides poor accuracy in such complex indoor environments since many obstacles and objects hit the signal (Mier et al. 2019). That is also the weakness of AoA. In addition to this, sufficient hardware is expected to be integrated into the sensor in order to obtain the AoA and ToA reliables. It is a conflict with the objectives of the project as well as beyond the study budget. As a result, RSSI with its advantages is very simple, can perform in the indoor environment and does not require additional hardware. This parameter is mostly used for indoor and BLE and Wi-Fi applications while AoA and ToA are best suited for outdoor use (F. Zafari, A. Gkelias and K. K. Leung, 2019). BLE has therefore been chosen as our focus in this study. In the next chapters, RSSI-based approaches and solutions for overcoming their drawbacks will be discussed. Table 2.1 shows key points of each metric.

Table 2.1 Metrics for indoor positioning summary

Method	Hardware	Minimum reference points	Synchronisation	Complexity	Disadvantages
AoA	Array of antennas	2	Required only at transmitter	High	Required precise hardware to calculate the angle Expensive antennas

					NLOS communication
ToA	Precise clock	3	Required at both transmitter and receiver	Medium	Clock synchronization among transmitter and receiver Multipath effect
RSSI	Low	3	No need	Low	Vulnerable to the environment NLOS communication

2.4 RSSI-based indoor localisation approaches

2.4.1 Fingerprinting

As mentioned earlier, fingerprinting is one of the most common methods for Wi-Fi indoor positioning. It includes two phases. First, is the offline calibration phase and mapping. A fingerprint map needs to be established. The strength of signals is measured, and the MAC address of a known access point is collected. These data will be used to locate the position of other access points or users' devices in the online phase by comparing with the object's signal strength. Hence, in order to achieve the best performance in fingerprinting, forming a very accurate and up-to-date fingerprinting map is the essential key. Figure 2.8 shows how Fingerprinting works (Ma et al., 2015).

One of the best algorithms according to Kriz, Maly and Kozel (2016) to compare between a subset of measurement in fingerprinting is k-NN. The authors describe that: "This method tries to find k of the nearest fingerprints from the database by means of Euclidean distance. In this way, we get locations and by their combinations we estimate the position of the device to be localised". For example, the Euclidean distance between $r_i = (r_1, r_2, \dots, r_N)$ measurements received from N different access points and the j^{th} predefined measurement value $c_i = (c_{j1}, c_{j2}, \dots, c_{jN})$ in the fingerprint database can be expressed as Equation (2.3):

$$d_j = \sqrt{\sum_{i=1}^{N} (r_i - c_{ji})^2} \tag{2.3}$$

where N is the number of access points. The first set of k neighbours are chosen. Then the weighted mean for a position x is estimated based on the known position x_j:

$$x = \left[\sum_{j=i}^{k} \frac{1}{d_i}\right]^{-1} \sum_{i=1}^{k} \frac{x_i}{d_i} \tag{2.4}$$

After that, by adding the weighted mean and calculating $d_{\min} = min(d_j)$, the estimated position is calculated.

The accuracy of the resolution of this approach can reach up to a metre depending on the number of access points per area.

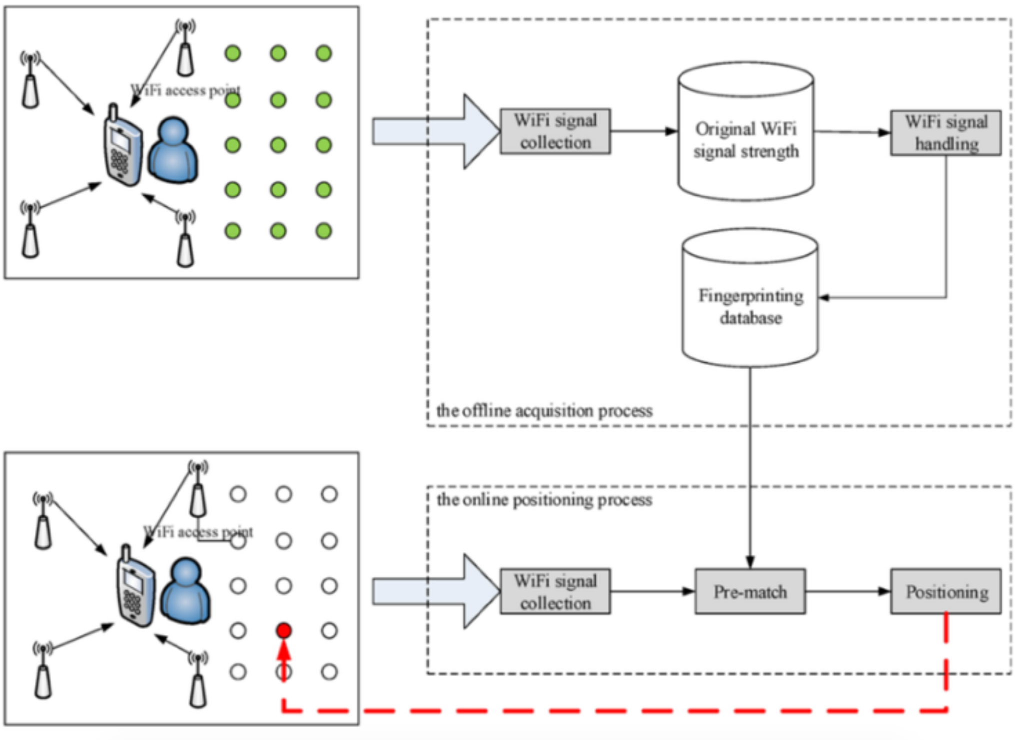


Figure 2.8 WiFi – Fingerprinting (Ma et al., 2015)

2.4.2 Trilateration

Trilateration will estimate the position from at least three anchor points (Anuradha et al., 2016). Three anchors could be beacons or access points each with a specific range $d,$ which is represented as a circle with radius d. The actual position will be where the three circles intersect, which can be calculated by solving the three-circle Equations (2.5) (Anuradha et al., 2016):

$$\begin{cases} {d_1}^2 = (x - x_1)^2 + (y - y_1)^2 \\ {d_2}^2 = (x - x_2)^2 + (y - y_2)^2 \\ {d_3}^2 = (x - x_3)^2 + (y - y_3)^2 \end{cases} \tag{2.5}$$

Where d_1, d_2, d_3 are the distance from anchors to the user's device, (x, y) is the coordinates of the user's location and (x_1, y_1),(x_2, y_2), (x_3, y_3) are the coordinates of three anchors points respectively. Figure 2.9 describes how the trilateration scheme works.

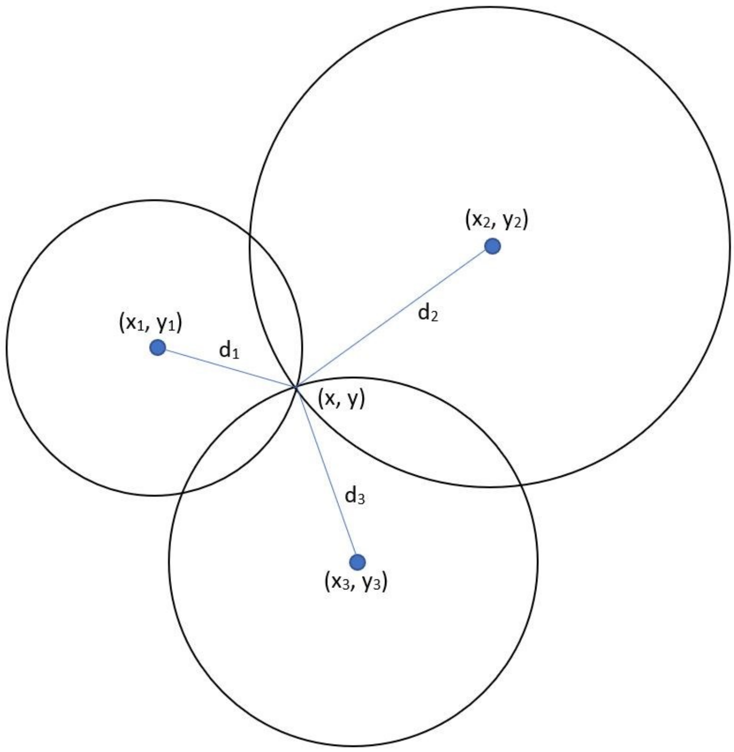


Figure 2.9 Trilateration scheme

2.4.3 Centroid

In real-life, the measurements from beacons or access point might vary and be randomly distributed, and therefore, the three circles might not intersect at a single point. To address this issue, two simple scenarios can be used to estimate the approximate location. The first method is increasing the number of anchors to narrow down the estimated area. However, this method will greatly increase the complexity of the whole system. The second method is to estimate the position by finding the centroid of the area. Figure 2.10 shows this situation. One way to do that is by taking the mean value of the polygon as given in Equation (2.6) (Anuradha et al., 2016):

$$(x, y) = \left(\frac{x_{D_1} + x_{D_2} + x_{D_3} + x_{D_4}}{4}, \frac{y_{D_1} + y_{D_2} + y_{D_3} + y_{D_4}}{4}\right) \tag{2.6}$$

Where, (x, y) is the coordinates of estimated position, (x_{D_i}, y_{D_i}) are the coordinates of intersecting points between two anchors working range.

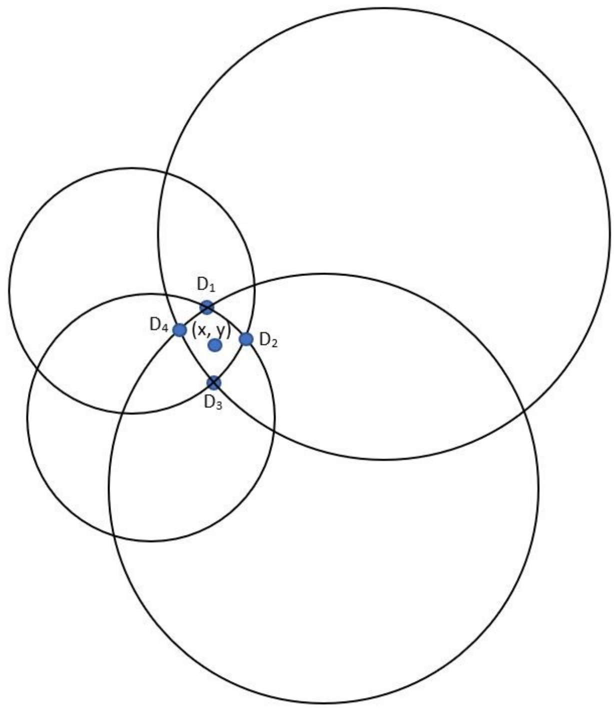


Figure 2.10 Centroid scheme

2.4.4 Least Square Estimation

Least Square Estimation (LSE) is a well-known method to solve the lack of GPS for positioning objects (Sharp and Yu, 2013). It is based on the following Equation (2.7) (Sharp and Yu, 2013):

$$y = Ax + w \tag{2.7}$$

where x is the object's estimated position, y is the measured position, w is the error or noise, ith row of A characterises ith measurement. The approach is to choose an appropriate value for estimated $\hat{x}$ so that the norm value $||A\hat{x} - y||$is minimum. Cheung et al. (2004) proposed a 4-anchor system to solve this issue shown in Figure 2.11.

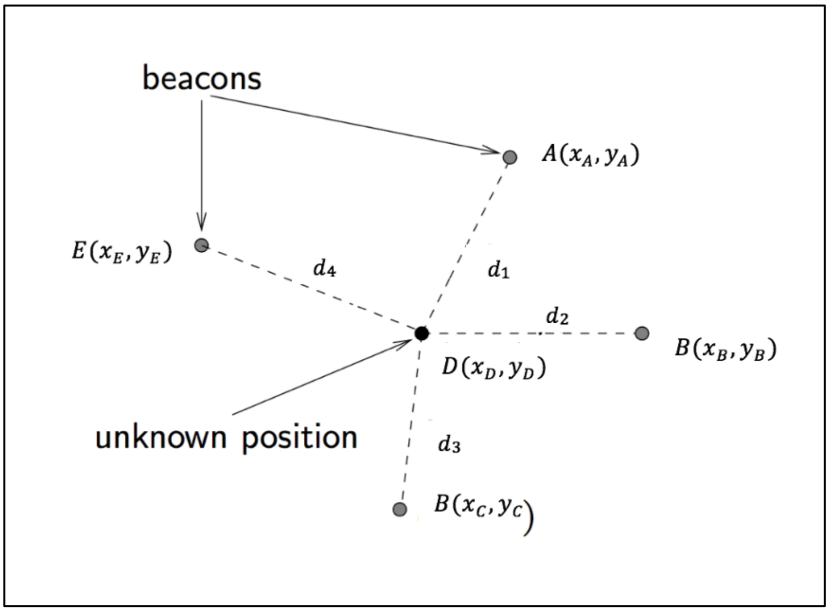


Figure 2.11 LSE scheme (Cheung et al., 2004)

Below, the Equation (2.8) is used to determine the coordinates of users (Cheung et al., 2004):

$$Ax \approx b \tag{2.8}$$

where $x = (x_D - x_{D_0}, y_D - y_{D_0})$ with x_{D_0} and y_{D_0} are the initial position of users; b is a $ix1$ matrix and A is $ix2$ matrix with Equation (2.9), (2.10) and (2.11) : (Cheung et al., 2004)

$$b_i = d_i - \sqrt{\left(x_{D_0} - x_i\right)^2 + \left(y_{D_0} - y_i\right)^2} \tag{2.9}$$

$$a_{i1} = \frac{x_{D_0} - x_i}{\sqrt{\left(x_{D_0} - x_i\right)^2 + \left(y_{D_0} - y_i\right)^2}} \tag{2.10}$$

$$a_{i2} = \frac{y_{D_0} - y_i}{\sqrt{\left(x_{D_0} - x_i\right)^2 + \left(y_{D_0} - y_i\right)^2}} \tag{2.11}$$

Where i is the number of anchors, (x_i, y_i) is the coordinates of each anchor and d_i is the distance between the user and the i^{th} anchor.

2.4.5 Dead Reckoning

Dead reckoning is a technique that calculates the current positioning by knowing the previous position, its velocity and direction. Begin with the starting point, after a short period of time, a change will be added and track. This change can be the coordinate or velocity. This process is repeated for real-time tracking. However, because of this change and track process, the possibility of causing errors will increase after each interval. Therefore, it requires a suitable adjustment to reduce the error and improve the accuracy after each turn. In this project, dead reckoning and the proposed method are combined to provide a real-time tracking application. This method will be detailed discussed in cooperate with the proposed algorithm in Chapter 6 of this thesis.

2.4.6 Summary

In this subsection, 5 methods have been introduced for using RSSI to predict the location of unknown objects. They can be divided into 2 groups in particular: offline approach and online approach. Fingerprinting is a typical offline-method. It is often used in conjunction with Wi-Fi and gives a high level of accuracy. However, this method requires extensive offline calibration, and it is highly vulnerable if the indoor environment layout is changed. Within the context of this study, we focus on online approaches such as trilateration, centroid, LSE and dead-reckoning.

2.5 Filter for data

The use of filters is crucial for smooth data and precise data, but it is also an essential problem in designing indoor navigation systems to select which filters to use. As mentioning earlier, RSSI is chosen as the primary data of the research. Hence, average filters, feedback filters, Gaussian filters and Kalman filters were considered in this study.

2.5.1 Averaging filter

This is the most intuitive method to smooth the data signal. RSSI values are measured for one node and the average value is calculated using Equation (2.12) given below:

$$\overline{\mathrm{RSSI}} = \frac{1}{\mathrm{m}} \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{RSSI}_{\mathrm{i}} \tag{2.12}$$

where $\overline{\mathrm{RSSI}}$ is the mean RSSI; m is the number of measurements (window) and $\mathrm{RSSI}_{\mathrm{i}}$ is the RSSI of the i^{th} beacon. This median value represents the whole set of collected neighbouring RSSI.

2.5.2 Feedback filter

Feedback filter as described in (Halder, Giri and Kim, 2015) and (Anuradha et al., 2016) to eliminate the large differences in the measured value of RSSI. Its principle is to add a weighted value α to the RSSI to correct RSSI values. In addition, the feedback filter considers the previous RSSI measurement to make sure the RSSI can be smoothed. Formula (2.13) shows this solution:

$$\mathrm{RSSI}_{\mathrm{smoothed}} = \alpha \times \mathrm{RSSI}_{\mathrm{k}} + (1 - \alpha) \times \mathrm{RSSI}_{\mathrm{k}-1} \tag{2.13}$$

In this equation, k is the current measurement, whereas k-1 is the previous measurement. The current RSSI value is based on the previously validated RSSI value. The α parameter demonstrates this connection. In research of Anuradha and his co-author (2016), α typically varies from 0.65 to 0.8. Average and feedback filters are very useful in areas with LOS between beacon and object, such as outdoor environments or wide-open indoor areas, according to the literature. However, when the signal suffers multi-paths and attenuates in more complex environments, they both underperform and need to be re-adjusted.

2.5.3 Gaussian filter

As stated, the findings of taking average filters are not great when the volatility of the signal is too significant. Applying Gaussian filters can fix this issue as the value of RSSI follows the standard distribution. The concept of the Gaussian filter is to calculate the region with a high probability of the RSSI signal value falling into. The filter selects and retains these RSSI values and takes the average. Its formula for RSSI is represented by Equation (2.14):

$$f(\mathrm{RSSI}) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(\mathrm{RSSI}-\mu)^2}{2\sigma^2}} \tag{2.14}$$

where μ is the mean $\overline{\mathrm{RSSI}}$ and σ^2 is the variance and defined by the Formula (2.15):

$$\sigma^2 = \frac{1}{m-1} \sum_{i=1}^{m} (\mathrm{RSSI}_i - \mu)^2 \tag{2.15}$$

The Gaussian filter limits the RSSI within the range of one standard deviation σ from the mean. This is presented in Equation (2.16):

$$P(\mu - \sigma < \mathrm{RSSI} < \mu + \sigma) = \int_{\mu-\sigma}^{\mu+\sigma} f(\mathrm{RSSI}) d\mathrm{RSSI} \approx 0.682 \tag{2.16}$$

RSSI values outside the limit region are regarded as noise and are eliminated.

2.5.4 Kalman filter

The Kalman filter (Lee, Lim and Lee, 2016) is proposed to cope with noise obeying the normal distribution. The basic principle of this filter is implementing a predictor and a corrector to minimize the error covariance. It will revise the past, present and future state which includes noise to correct/predict the RSSI measurement. As stated, there are two main stages in Kalman filtering: prediction and updating and they are represented in the following set of Equations (2.17) to (2.21):

Prediction phase:

State Model: $$\widehat{x_k} = Fx_{k-1} + B_{k-1}u_k \tag{2.17}$$

Error covariance: $$\widehat{p_k} = Fp_{k-1}F + q_k \tag{2.18}$$

Correction phase:

Kalman Gain: $$K_k = \widehat{p_k}H(H\widehat{p_k}H^T + r_k)^{-1} \tag{2.19}$$

Updated covariance: $$p_k = (I - K_kH)\widehat{p_k} \tag{2.20}$$

Updated state: $$x_k = \widehat{x_k} + K_k(z_k - H\widehat{x_k}) \tag{2.21}$$

where F is the state transition matrix; Bu is the control input if applied; q is the system noise covariance; I is the identity matrix; r is the measurement noise covariance and z is the measurements or true observation.

2.5.5 Summary

Filters commonly used to smooth RSSI data have been introduced in this subsection. Each filter has its way of working and expected to remove unwanted noise and provide stability for RSSI data in the indoor environment. In chapter 4 and 5 of this thesis, filters will be applied to real-data and details evaluation will be presented in order to find out the optimum filter for this study.

2.6 Introduction to BLE Beacon and iBeacon

A beacon is a standalone BLE device powered by batteries or USB. It repeatedly transmits a small data packet that other devices can pick up. One beacon can operate for months or years thanks to the low energy consumption of BLE technology. They are built in different shapes and colours but most of them are small and portable.

Beacons broadcast data packets periodically. The time interval will determine how often the beacon wakes up and sends its message. These intervals are predefined and usually depend on the actual purpose of beacons. Shorter intervals will increase the chance other devices pick up the message as well as improve the data readings. However, it will reduce battery life. Other metrics need to be considered such as the transmission power. It determines how far the signal can reach in theory. Again, stronger transmission power gives a more significant beacon's working range, but it costs more energy consumption. Thus, configuring a suitable interval value and transmission power is critical for any indoor positioning system.

These data are formatted into a packet which is specified by Bluetooth Core Specification (Bluetooth.com, 2019). Figure 2.12 shows this payload (Bluetooth.com, 2019).

As we can see, the broadcast data of a BLE packet is minimal, only 31 bytes. It is usually a string of text of numerical values. This can be a beacon identification, signal strength or time interval. Some manufacturers integrate beacons with other sensors such as accelerometer, gyroscope or movement sensors to provide more information. One of the most popular beacons on the market is iBeacon.

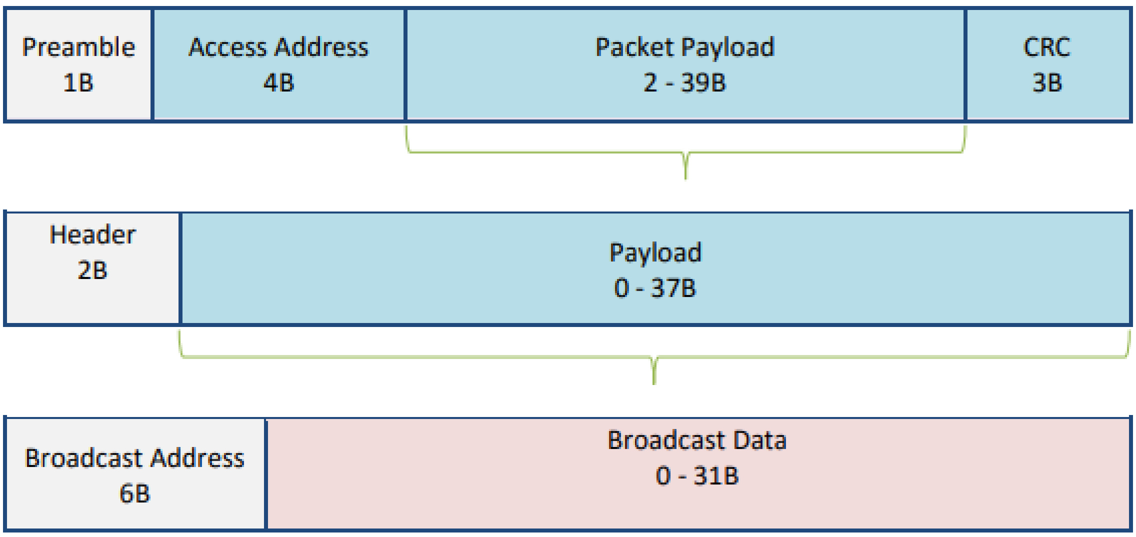


Figure 2.12 Beacon payload (Bluetooth.com, 2019)

iBeacon was first introduced by Apple in 2013. Its data field is described in Figure 2.13.

iBeacon Data Field 31 Bytes				
iBeacon Prefix 9B	UUID 16B	Major 2B	Minor 2B	TX Power 1B

Figure 2.13 iBeacon data field (Bluetooth.com, 2019)

iBeacon data consists of four values. The first value is called Universally Unique identifier (UUID) which identifies the beacon manufacturer or application or owner. This means all beacons belonging to one manufacturer or owner will share the same UUID. In some cases, some manufacturers allow developers to change this value to a dedicated application. The second value is major. It identifies the group within the manufacturer. The third value is minor. It determines the beacon within a group. Major and minor are unsigned integers ranging from 0 to 65535. The final value is called the TX power. This is the calibrated transmission power at the distance of 1m. This value is set by the manufacturer and cannot be changed.

iBeacon is a proximity device. It defines three ranging states of a target: “immediate” means the target is very close to the beacon; “near” means the target is about 1m-3m away from the beacon; “far” indicates that the target can be detected but over 3m from the beacon. However, these ranging indicators are not reliable for a high accuracy indoor positioning system. Another drawback of iBeacon is its compatibility. It requires Apple products to be fully used and integrated into a system. Fortunately, Google provides an alternative solution called Eddystone in 2018 (Google Developers, 2019), which has a very similar specification to iBeacon. In the context of this research, iBeacon is defined as our beacons.

Chapter 3 Literature Review

Research and applications on indoor positioning will be covered in this chapter with great details. This chapter begins with section 3.1 by introducing the indoor localization system architecture. Two architectures have been presented and compared. This is the basic model that has been developed later. Section 3.2 shall include the properties and characteristics expected by an indoor positioning system. Section 3.3 then features an extensive listing of applications for indoor localisation. This section underlines the importance of this system in the industry and the latest market trend. Systems using various algorithms and technologies will be reviewed and outlined in section 3.4

3.1 Indoor positioning system architecture

Localisation is one of the most popular application systems of MANETs. Despite various purposes of localisation systems, there are some essential components suggested by Pahlavan et al. (2002). Figure 3.1 shows these functional blocks:

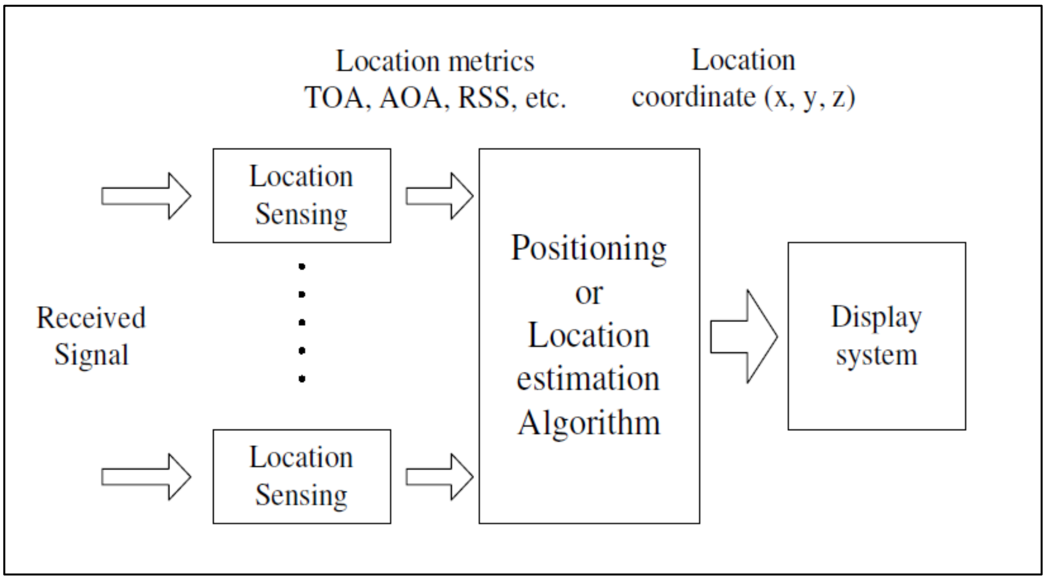


Figure 3.1 Localisation system block

There are three stages in a positioning system. First, the location sensing device collects useful data using an appropriate sensing signal such as infrared, ultrasound, LIDAR or radio frequency. The useful data can be time of arrival (ToA), angle of arrival (AoA) or received strength signal (RSS). They are fed into the location estimation algorithm in stage 2. There are a number of positioning techniques such as trilateration, fingerprinting, triangulation or neural networks. In this stage, data from the sensed signal will be filtered and calculated to estimate the position of the unknown node. Finally, there will be a display system to convert calculated results into a readable format for the end-user.

Alternatively, Hightower and his co-author (2002) presented a different perspective of a location system. The location stack is their point of view about localisation as a software engineering model. It is based on the famous Open System Interconnection (OSI) layered to the network model and shown in Figure 3.2:

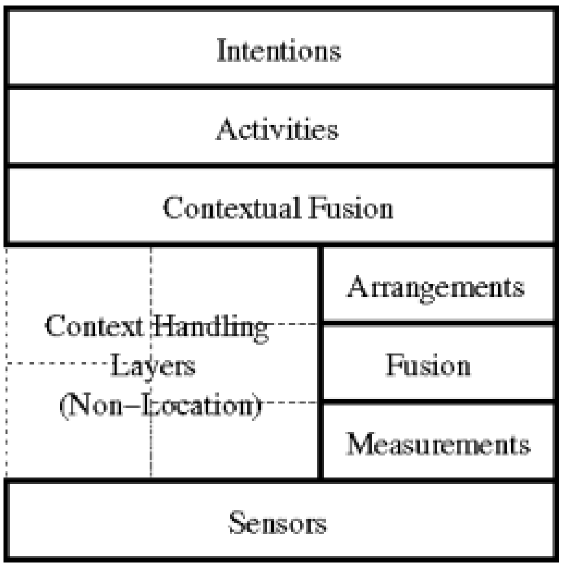


Figure 3.2 Seven layered location stack (Hightower. J, 2002)

In the first layer, “Sensors” contain sensor hardware and a software driver for detecting raw data such as GPS signal or proximity beacon. The second layer “Measurement” is algorithms to convert raw sensor data into canonical data such as distance, angle or proximity. The “Fusion” layer is a method to merge data into time-stamps probabilistic representations of positions and orientations of nodes. “Arrangements” is an engine to perform the relationship between two or more objects such as the relative position of a user in a room. “Contextual Fusion” is the layer to merge the position with other non-location contextual information such as calendar, colour or temperature. “Activities” and “Intentions” are two layers which take responsibility for categorising all the information into activities using machine learning.

These are the two widely used architectures to construct an indoor positioning system. The Hightower model (2002) is generally presented from the software engineering perspective, using the location stack. This system has the advantage of breaking down tasks in the design of an indoor positioning system, making it easier and more practical for future development and maintenance. Nonetheless, the system's drawback is that communication interfaces between layers are required, which may be complex when there is no standardisation in indoor positioning. Pahlavan's system, on the other hand, aims to provide components required for the indoor positioning system. Every element may be customised, depending on the application. It can be seen as layers 1, 2 and 5 of the Hightower (2002) structure. Within the scope of this research, a typical framework architecture based on these two basic studies will be introduced and discussed in Chapter 5.

3.2 Positioning System properties

Understanding requirements and applications is crucial before carrying any research and/or development. There were a number of studies in this field (Mautz, 2012) that show that in order to serve the market in any application, an indoor positioning system should be low-cost, low-complexity, low-power, short latency, high integrity, relatively low-maintenance and with a minimal amount of required infrastructure. These should be used to drive the direction of research and design.

- Accuracy: centimetres, decimetres or metres level. The standard definition of positioning accuracy is used during this thesis for the comparison of systems' performance. It defines the closeness between a measured or estimated quantity at a given time and the true quantity. This is the key criterion for various phenomena such as signal propagation, multipath or positioning. In terms of positioning accuracy, there are two types: which are relative and absolute accuracy. These terms will be explained further in the next section.

- Coverage area: it identifies the conceptual range in which a positioning system ensures its efficiency. In this thesis, this area is defined as a limited and defined area that rarely would be extended such as a room or a building.
- Complexity: a positioning system should be sufficiently easy for widespread deployment, integration, connection and configuration. It should require minimum-to-nonspecial cabling. Also, the manual setting up should be as little as possible. Any tags or beacons in the system are desired to be small and energy-efficient.
- Cost: this could be installation cost, maintenance cost, operation cost or time cost. All stages will be involved in calculating the cost such as initial set-up hardware and software, the staffs or the system complexity.
- Interface/Output: text-based, graphic display, audio. This is how an operator/engineer will work with systems and how users will interact with systems. In general, it should user-friendly for both operators and users.
- Update rate/latency: per-hour, per-day or real-time. This could be periodic, on event or on-demand. In some applications, it even is post-processing which means there is no specific time be defined (log collection).
- Scalability: systems that can expand the working area by inserting components. It can be scaled in terms of node deployment, supported users or devices.
- Privacy and security: the ability to protect personal data or a device's information from theft or any unauthorised access. It also includes the restriction of outward data leakage.
- Infrastructure: tags, beacons, server, etc.
- Compatibility: cross-platform system (Android, iOS), support multiple devices (phone, tablet, watches, speaker, screen, etc.)
- Power conservation: to preserve the energy on the transmitter, there are several important design issues. First, it is the signal rate. In general, the higher the signal rate and the update rate, the higher the accuracy. However, it will cost too much regarding the energy consumption especially if the tags and mobile devices in the wireless infrastructure are battery-powered. Reducing signal rate will improve the battery life but this needs to be done wisely in order to maintain the quality of the signal. The

second issue is the signal strength. Stronger signal strength provides better coverage area but again, it demands a lot of energy. Other design issues can be named as algorithms optimisation or data processing.

- Technology: optical, magnetic, light, sound, etc.
- Signal used: radio frequencies, infrared, electromagnetic waves, etc.
- Measured quantity: distance, time, transmitted power, etc.
- Measuring algorithm: trilateration, triangulation, centroid, least-square, etc.
- Coordinate reference: object, sensor or wall reference.
- Application: which application will the system be deployed on. This will be discussed in more details in the next section of the report.
- Legal and approval: how users' data are collected and used and what level of information will the system need from users are two important questions. It should be under the acceptance of users and be encrypted before being transferred.

3.3 Localisation application

Applications of indoor positioning called Location-Based Services (LBS). They all use the knowledge of geographical location to provide useful context data visible via mobile gadgets. In fact, this offers enormous business advantages. The requirements of an indoor positioning system are determined by the actual application. For example, in the healthcare sector, an application to provide navigation for patients or staffs around a hospital will require an indoor positioning system with an accuracy of meters. On the other hand, an asset tracking or medicine tracking application will require much higher accuracy which is just about centimetres.

In general, the applications offered by the indoor positioning in the current market can be classified into four main categories (Haverinen, 2017): Proximity marketing/advertising, Wayfinding/navigation, Search/Requesting help and Asset or people tracking.

The list below enumerates those application areas in the industry and their use cases.

Location-based services and indoor navigation in the railway station/airport.

- Search: orientation in a new station (platform, help points, ticket office); trains' event/schedule/alerts in a familiar station; show places in real-time; available services
- Indoor navigation: dynamic real-time routing to destination; distance/time to destination; personal recommendations (to shop/store; to tax-free kiosks)
- Advertising: push personal advertisement based on preference.
- People tracking for station operators: getting information about the stream of visitors, peak hours, and security.

Location-based services and indoor navigation in hospital.

- Search: orientation in the hospital. This helps patients know the way to where they need to be.
- Indoor navigation: vulnerable patient, patient with visual impairment can be aided by real-time guiding with their personal device.
- People tracking: tracking the patient for their safety.

Location-based services and indoor navigation for police, firefighter or militaries.

- Search: orientation in a building on fire or warfare.
- Indoor navigation: routing to the crime scene, navigation through minefields.
- Tracking: tracking enemy, statistics and logs for training and analytical use.

Location-based services and indoor navigation for office use:

- Search/navigation: for a large office and industrial building; or for a new employee. This also offers guiding for robotic machines.
- Asset and tracking: determine the location of the warehouse, pallets; monitoring staff and robots.

Location-based services and indoor navigation for the shopping centre:

- Search/ navigation: guiding customers through the centre with detailed shop location.
- Proximity marketing/advertising: advertisements can be displayed based on customers' preferences or based on their actual location. This improves the overall users' shopping experiences.

- Tracking people: for operators to improve shop allocation, knowing busy hours…

These are some of the applications that can benefit from indoor navigation. This research particularly focuses on the station and hospital venues.

3.4 Indoor localisation technologies

As mentioned in the previous chapter, indoor localisation systems can be built using different technologies. Many studies and systems have been developed by researchers. There are many promising outcomes but there are also some drawbacks. They will be discussed as follows.

3.4.1 Infrared

Infrared is one of the most popular and early technologies developed not only for wireless technology but also for localisation. One benefit of this technology can be defined as requiring only small, easy-to-integrate sensors. However, issues remain unresolved, such as requiring LOS communication, a short working range, security and accuracy. Researchers have been working to address these problems.

Kostromins and Osadcuks (2014) proposed a novel mobile robot localisation system in agriculture using active infrared beacons. The system contains stationary infrared active beacons and a robot which has a rotary infrared light detection. The authors stated that there are external factors that affect the system: sun, other ambient light, ambient temperature, etc. (Kostromins and Osadcuks, 2014). Also, the system set-up geometry is another critical design criterion. This includes the beacon placements and the antennas' direction and orientation. Their experiment shows that the system can achieve an error margin within 7 cm with the processing time of 7 seconds.

Yang et al. (2015) offered a PIR system that produces an accessibility map. The proposed method is based on the particle filter for human tracking and long-time observation for the map. Then the fusion of two results is used to give the final estimation. The simulation shows that their system can achieve the error ranging from 0.1 m to 0.6 m. However, conditions for creating the accessibility map are quite strict: 3 types of static activities (lying, sitting and standing) 6 specific types of furniture (sleeping bed, living room couch, dining table, kitchen sink, front door and bathroom basin). Authors claimed this can be improved by implementing the system in the real environment and the dynamic map will be investigated.

Cahyadi et al. (2019) developed an indoor positioning system using infrared technology and invisible beacons. Authors used surveillance cameras capable of capturing IR in both bright and low-light conditions. The beacons used here were mobile phones equipped with IR proximity sensors. The strength of this method is that the range depends on the field of view of the camera, meaning that it has a very large working range. The experiment concluded that the system was capable of detecting static beacons with an error of less than 5 cm. Although the accuracy is good, the system will only function effectively if the camera is in night mode. Many external light sources interfere with the signal obtained in daytime conditions. It also needs more sophisticated image processing to be able to locate the beacon. Additionally, the use of the camera makes it clear to see that LOS communication between the camera and the beacon is mandatory.

3.4.2 Ultrasound

Ultrasound positioning system, like the IR indoor positioning system, can also deliver impressive short-range performance. Besides, LOS communication between transmitter and receiver is not necessary in Ultrasound communication. Another Ultrasound bonus is that this mechanical wave does not interfere with other electromagnetic waves like Wi-Fi or Bluetooth. Ward's "Active Bat" (1997) and "Cricket" (Balakrishnan and Priyantha, 2001) systems are considered to be the most popular and laid the foundation for IPS operating on ultrasound. They use TOA to estimate an object's location. Nevertheless, they acknowledged that there are some problems generally encountered by the ultrasonic positioning system, including relatively low resolution, limited working range and external noise exposure.

Lopes and his colleagues (2012) introduced a high accuracy 3D indoor positioning system using ultrasonic. The typical challenges initially make the ultrasound-based localisation system achieve bad results in a 3D application. Inspired by the idea of GPS, the authors use synchronised ultrasound anchors and a time division multiple access (TDMA) scheme to overcome these problems. The experiment shows that their system can achieve a stable result in a 3D environment. The absolute error is 20.2cm and the update rate is 350ms in a room of 200m^3. However, while the range has been significantly enhanced, the use of GPS is still not appropriate for indoor applications.

Qi and Liu (2017) proposed another novel ultrasound positioning system. The author used preset beacons, combined with Wi-Fi, and suggested a novel Time of Flight (ToF) estimation. This ToF calculation is used by the author to improve time synchronisation between nodes. The highest accuracy achieved by simulation was 0.61 mm, which was very impressive. Nevertheless, the accuracy of the robot experiment was more than 10.2 mm, despite the presence of LOS communication between the transceiver. The reason for this inconsistency is believed to be due to ambient noise and radio signal interference with Wi-Fi. In addition, in order to achieve high accuracy and synchronisation, this system requires very precise sensors placement. This is because of the natural ultrasound wave that is diverse over the distance. The complexity of the data processing is also increased on a large scale.

3.4.3 WLAN

WLAN, also known as Wi-Fi, is one of the most popular solutions introduced for indoor positioning systems. Like many other technologies, various approaches are available to locate objects using Wi-Fi technology, such as ToA, RSS or AoA. However, a study, which was done by Zafari, Gkelias and Leung (2019), indicates that methods of using ToA or AoA are not widely employed. Many Wi-Fi based indoor localization systems use the popular "Fingerprinting" technique. Not only because of its accuracy but also it can use existing infrastructure to minimise costs.

The fundamental part of the "Fingerprinting" technique is the construction of a database system. Nonetheless, this is a very labour-intensive and time-consuming process, so researchers have been focused on solving this problem. Wu and Liu (2013) proposed a Wi-Fi-based indoor localisation called WILL. They developed a logical map structure to be used for the offline training phase of the database construction process. This system used smartphone sensors such as accelerometer, gyroscope and magnetometer to classify user actions. By doing so, they combine the RSS data obtained with the user movement and place them in a virtual room and create a logical map accordingly. Experiments showed that the room-level accuracy rate was 86%.

In 2019, Gu and colleagues introduced another approach to tackle the difficulty of the site survey process. The authors proposed a "landmark graph-based" approach to automating the fingerprint collection. Devices such as smartphones or sensors would have to be mounted initially, but the system does not require active users to participate. Experimental testing showed that the accuracy of the device was approximately 1.5 m.

Researchers also work to boost the performance of Wi-Fi-based indoor positioning systems regarding accuracy. Kim et al. (2012) developed an improved Wi-Fi fingerprinting algorithm called semi-supervised affinity propagation Weighted K-nearest neighbour (WKNN-SAP) This helped to resolve the inconsistency between the offline process and the online RSS process. In addition, isolated access points and data outliers have been eliminated using clustering methods. Noise and interference are therefore minimised. Experiments found that the mean error was approximately 1.85 m.

Wang et al. (2016) applied deep learning and channel state information to the positioning system. This device has been labelled DeepFi. Through studies, DeepFi has shown that it can achieve accuracy of about 1.36 m, which is claimed to be better than other approaches. However, the complexity of the training process is very high, making it difficult to expand. Li et al. (2019) proposes a division area approach to reduce process time and system complexity, as well as to improve accuracy. The author presented an offline training method called Improved Fuzzy C-means (IFCM). Experimental results indicated that the overall processing time is decreased by 94.13% compared to other methods. The average accuracy was approximately 2.53 m.

3.4.4 ZigBee

Zigbee has many features similar to Bluetooth, especially low-cost and low power consumption, making it also a candidate for indoor positioning technology.

Uradzinski et al. (2017) deployed ZigBee technology to evaluate the accuracy of their proposed fingerprint algorithm. They boost the fingerprint ZigBee database by filtering the interference data and applying the Bayesian algorithm to estimate the position. The standard deviation error of 0.51 m was achieved. And the maximum working distance is approximately 40 m. Zhao et al. carried out another analysis in 2010. They presented a cooperative positioning algorithm tailored to ZigBee applications. By using the link quality and the received signal strength of the ZigBee signals, the distance between paired devices can be determined more precisely. Simulation tests indicate that their algorithm is capable of achieving 0.06 m of positioning errors.

At the other hand, the Zigbee working mechanism is sleep and awake to preserve energy, so nowadays, this technology is often used to locate robots or devices for home automation systems where so many devices and sensors are involved. There are some commercial initiatives that have been use Zigbee to connect and locate devices in smart home ecosystems such as NetVox (NETVOX, 2020) và Samsung (Smartthings, 2020). Within the range of this study, we concentrate on locating users with handheld devices. Due to this sleep and awake mechanism, the requirement for real-time positioning might be achieved.

3.4.5 IEEE 802.15.3, IEEE 802.15.6 – Ultra Wide Band

UWB as mentioned has the potential to overcome NLOS communication and multipath effects. In 2018, Ridolf and his collaborators performed an in-depth research to understand the capabilities of UWB. They ranked UWB as one of the most promising indoor positioning systems candidates. In their analysis, the authors stated that the accuracy could be up to a centimetre. In addition, accuracy can be increased up to 31 per cent if the system is able to predict user movements. The UWB-based positioning system often consumes less power than other systems such as WLAN or Bluetooth (Mautz, 2012; Liu et al., 2007). It has therefore recently actractted researchers for developing an indoor positioning system using this technology.

Kok et al. (2015) presented a fusion approach of intertial sensors with UWB to boost the efficiency of the indoor positioning system. They combined data from accelerometer, gyroscope and ToA measurements to make a 6D pose prediction. Synchronization of clocks between the intertial sensor and the UWB sensor is mandatory to resolve the multipath effect and NLOS communication. Experimental tests showed that the error is just 2.3cm-3cm.

Another approach suggested by Arsan and Hameez in 2019. To maximise the accuracy of UWB-based localization, authors used the concept of clustering algorithms. Based on their assessment, K-means algorithms are accredited to produce the best results for their systems and to achieve an accuracy of approximately 14 cm.

Retscher et al. (2019) integrated UWB and WLAN in order to build an indoor navigation system. The goal of this combination is to exploit existing WLAN infrastructure and improve UWB accuracy. The experiment was conducted under laboratory conditions. Initial results showed that the minimum accuracy can be up to 0.3 m. The average error, however, is up to 6.5 m.

Although UWB has great potential for an indoor navigation system, UWB is not yet supported by handheld devices (Mautz, 2012 and Bespoon, 2020). This technology will therefore be very costly to deploy, particularly on a large scale.

3.4.6 Visible Light Communication (VLC)

VLC is described as a new and modern device-based indoor positioning solution. It uses Light Emitting Diodes (LEDs) which transmit visible light between 400 and 800 THz. The light is picked up by the devices and measures the location accordingly. AoA is likely the most common and reliable approach used with VLC (Armstrong, J, 2014). However, other methods are being studied and the accuracy of the centimetres is being achieved (Afzalan and Jazizadeh, 2019, Zhuang et al, 2018).

Lv et al. (2017) implemented a RSSI-based VLC system. The authors considered using a differential detection algorithm to address LED signal instability. The algorithm also helps to increase the working range of the LED. The accuracy of the experiment was 4.0 cm and the authors noted that the working range could be increased by 46 times if the light setup could be optimised for the environment.

Li et al. (2018) implemented another system. The traditional VLC technology was combined with the smartphone camera. The camera on the smartphone records the LED signal and uses the Perspectrive-n-point algorithm proposed by the authors to determine the position of the smartphone. The results indicated that the average error ranged from 4.81 cm to 6.58 cm.

Generally, VLC-based indoor positioning systems often achieve very high accuracy, up to centimetres level. Nevertheless, most authors only performed room-level experiments (Li, Y et. Al 2018, Lv et al., 2017, Han et al., 2016, Afzalan and Jazizadeh, 2019) and yet clearly demonstrated that their systems would work on a larger scale. In addition, the VLC-based indoor positioning system has another requirement that requiring strictly LOS communication (Mier, Jaramillo-Alcázar and Freire, 2019), which is very difficult in the indoor positioning context. In addition, the installation costs of new LED may be very high or not appropriate for use in old buildings, as they may interfere with the existing lighting system.

3.4.7 Radio Frequency Identification (RFID)

RFID in an indoor positioning system is traditionally formed of electromagnetic connectivity between RFID tags and RFID readers. This system is commonly used in security control or monitoring equipment (Ahsan et al. 2010). There are two models to construct an indoor positioning system based on RFID. One possibility is that the user carries the tag and the tags will be read by a pre-setup reader installed in the infrastructure. It is called an active system; another alternative called a passive system is that the user holds the reader and the tags are attached to the structure. In particular, the active device draws more interest from researchers because the tag is cheaper and very small, easier to scale and carry.

Ni et al. (2004) presented an active RFID indoor positioning system called LANDMARC.The author used the nearest neighbour algorithm to process the signal received from the reader and then calculate the location of each tag. The author stated that the accuracy is around 1 metre. Although the accuracy is not great and the system has other disadvantages, such as only signal strength indicator (detectable and not detectable) and good delay. But this is the foundation for the later development of active RFID-based indoor positioning systems.

Zhang et al. (2016) proposed an active indoor positioning RFID system for a large-scale IoT network. The new algorithm called iLocate had achieved accuracy of up to 30 cm with a transmission distance of up to 1000 m. In 2019, Shen et al. developed another active system in which the reader is placed on a rotary table and collects data accordingly. The system can achieve accuracy of up to 9.34 cm in 2D and 13.01 cm in 3D through experiments.

However, according to surveys conducted by Zafari and Mier in 2019, RFID-based indoor positioning systems often deliver a low working range and unreliable accuracy. A lot of tags are required to achieve reliable accuracy and longer working range. This would increase costs, increase power consumption and increase the complexity of the system. In addition, RFID also has security and connectivity issues (Mier, 2019).

3.4.8 Bluetooth Low Energy

Like mentioned above, there are a number of well-known advantages of BLE compared to other competitors such as low cost and deficient power consumption. Another advantage of BLE technology is that the communication link between two devices in the system does not need to be visible so they can be blocked or even in different rooms. However, there are two notable disadvantages which need to be understood when studying Bluetooth based positioning. First, the communication process of Bluetooth is quite time-consuming especially for various numbers of devices and platforms. This needs to be optimised in order to use Bluetooth technology in a real-time tracking application. Second, because the position of target devices is estimated within a cell, the smaller the cell, the better the accuracy. This will lead to an increase in the number of cells and number of devices. As a result, the proximity-based network as BLE will have to deal with confliction and noise. Furthermore, the 2.4 GHz spectrum is unlicensed, so it is free and widely used. BLE operating under this radio frequency will interfere with other radio signals. Consequently, according to Basiri and his colleagues in 2017, BLE is potentially the most suitable technology for an indoor positioning system. At present, iBeacon is a well-known application of BLE for indoor positioning. A lot of research has been done on this topic.

One of the greatest benefits of BLE over Wi-Fi is that it has the ability to create a dedicated positioning system. Nevertheless, identifying an effective topology and a selection of beacons is a challenge to overcome. One of the early BLE-based indoor positioning studies on this issue was completed by Faragher and Harle in 2014. They had shown that the accuracy of the system could be improved with the number of beacons used per unit area increases, and the number is up to 6 to 8 beacons. Beyond this point, their analysis showed that there has been no change in positioning accuracy. The authors also reported that due to low bandwidth, BLE is vulnerable to fast fading, which will result in varying overall performance. Also, active Wi-Fi scanning and Wi-Fi network can cause BLE measurement errors (Huang, He and Du, 2019).

Budina et al. (2015) provided instructions on how to determine the number of beacons in a building. Authors recommended dividing the space into smaller areas and optimise the localisation result in each area. Rezazadeh (2018) presented an analysis of the environment and adjust positions the beacon accordingly. Their system achieved 21,7 percent higher precision than the standard iBeacon placement. However, the position of beacons and number of beacons is dependent not only on the environment, but also on the characteristics of the beacon. It will be one of the main goals and the focus of this study.

Table 3.1 provides a review of several BLE-based indoor positioning systems which have been studied and presented. In general, authors agree that the design and deployment of the beacon in the building is very critical and greatly affects the accuracy of the beacon. Accuracy is normally lies between 0.7 m and 8 m. Nevertheless, in order to obtain an accuracy of about 0.7 m, Paterna et al. (2017) and Huang, He and Du, (2019) need to use a lot of beacons (6-8) for a small office area. In addition, Paterna's system is a passive system, which will incur more installation costs and energy usage when there are more users and in a larger environment. NLOS communication and multipath effects have not been well addressed. In addition, it is worth to note that the accuracy can also be enhanced by combining it with an effective Kalman filters (Huang, He and Du, 2019).

Table 3.1 Recent BLE-based indoor positioning system review

Author	Method	Accuracy	Environment	Beacons	Comments
Faragher, R and Harle, R, 2015	Fingerprinting	2.6m – 8.5m	50m x 15m	19	The error will be decreased as the number of beacons increased in one area Need to perform fingerprinting training No tracking ability

Paterna, V. C, et. al 2017	Weighted Trilateration	0.7m – 1.82m	5m x 5m	4 - 6	Authors use the "passive" system where the receivers are placed in the infrastructure and the user keeps the BLE tag and transmits the signal. The findings are fairly good, but this approach is complicated when there are a lot of active users in the network. LOS communication is required. Tag and reader must be at the same altitude
Radoi et al., 2017	Particle filtering	2m-6m	8m x 6m	5	Author claim that the accuracy can be improved by study the characteristics of the room and the beacon.
Teran, Carrillo and Parra, 2018	Fingerprinting Machine learning	1m	8m x 8m	4	Pairing with Wi-Fi helps to achieve significant coverage while retaining a low number of beacons needed.
Zuo, Liu, Zhang and Fang, 2018	Fingerprinting	1.27m – 3.94m	90m x 37m	48	The author has suggested an indoor positioning system using BLE and Wi-Fi. Experiments in a large area give positive outcomes.
Silva. M, et al, 2019	RSS Fingerprinting	4.43m – 4.88m	121.65m^2	24	Authors suggested the concept of combining BLE and Wi-Fi to perform positioning in a very complex environment like a library. The accuracy is not high, but the RSSI data set is designed to help further research.
Huang, He and Du, 2019	Trilateration Kalman filter	0.757m - 2.23m	5.6m x 8.8m	8	Accuracy improved with Kalman filtering.
Huang, Liu, Sun and Yang, 2019	Weighted Lateration	2.2m	9m x 12m	4	Authors stated the accuracy can be improved by utilising the beacon deployment. NLOS effect has not been considered.

3.4.9 Summary

Typically, each technology has its own advantages and disadvantages. After a comprehensive review and evaluation, as well as engaging with stakeholders on current industry trends and markets, the following points are provided to select the most appropriate technology:

- Wi-Fi is a well-known, well-matured technology, and many researchers have studied the Wi-Fi indoor positioning systems. It is capable of providing high precision and great coverage. In fact, Wi-Fi is present in almost every place of modern life. However, Wi-Fi is normally used for purposes other than positioning and there is no dedicated Wi-Fi localization system. It affects system scalability and performance. Besides, Wi-Fi also requires high power consumption, and the most commonly used "fingerprinting" algorithm involves comprehensive training data. It becomes troublesome when the layout or interior of the building changes.
- RFiD, like Wi-Fi, has been around for a long time. The low cost and high accuracy make this technology widely incorporated into the object tracking application in the market. The maximum operating distance is however too short: less than 1 m. RFiD is thus not suitable for this type of study.
- Infrared and ultrasound systems are both inexpensive and well documented. It is capable of providing both relative accuracy and a moderate link range. The major downside though is that these two systems are unable to penetrate walls and obstructions. As a result, people may experience many difficulties in tracking individuals.
- VLC is a state of the art technology. It's environmentally friendly and potentially very effective. However, since it is new, VLC needs a lot of time to develop and grow. Furthermore, this technology is vulnerable to interference and noise generated by other ambient lights.
- Zigbee, it has very similar characteristics to Bluetooth. This is capable of providing reasonable precision and a sufficient range for indoor systems. Another advantage is the generally low cost. However, this system is not as readily implemented as Bluetooth. The sleep and waking process is not suitable for real-time applications.

- Bluetooth or its new version, Bluetooth Low Energy, has the advantage of being a low-cost, simple, highly energy-efficient operating mechanism. This has also been widely integrated into existing devices. This makes this technology very appropriate for our research. Accordingly, BLE was chosen in this study. Disadvantages such as noise instability risk of inconsistent accuracy can be addressed in combination with proper filtering, algorithms, and iBeacon settings will be the main focus of the research.

Potential technologies are compared in Table 3.2:

Table 3.2 Technologies advantages and disadvantages

Technology	Advantages	Disadvantages
Bluetooth Low Energy	Low cost, high availability. Integrated into most smart handheld devices. Simple working mechanism. Low power consumption	Vulnerable to the environment. The signal is blocked by obstacles More beacons cover wider coverage and more accuracy but increasing cost and power. Not sufficient for a very large area. Interference with other sources because BLE using 2.4 GHz spectrum
Wi-Fi	Widely available Mature development High speed, high throughput No need LOS	Requires data training but it can be changed easily by building changed or even furniture moved. High power consumed compared to other technology. Likely has no dedicated system for IPS.
RFID	Cheap, accurate and low complexity Very low energy consumption Pass through objects, no need LOS	Coverage is too small. Not suitable to position human or large object. Costly in large scale. Security issue. Low accuracy
Zigbee	Low cost, low energy	Interference with Wi-Fi and Bluetooth

	Already deployed for IoT application	More suitable for a communication link occurs within second because of the sleep mode working mechanism to preserve energy.
Infrared	Quite mature as early development. Low energy consumption.	Does not penetrate wall and obstacles, so it is more suitable for proximity application. Interfere with other light sources LOS communication is strictly required
Ultrasound	Low cost No interference with other electromagnetic waves Can work in aggressive conditions	Require LOS between transceiver. High delay. Very short range Solid walls create too many echos, therefore noise. Sound pollutions issue.
Visual Light Communicat ion (VLC)	Precise Easy to be installed	High cost Low availability, low flexibility

Table 3.3 is a comparison of technologies based on their ability to meet the key requirements of indoor positioning systems as defined in section 3.2.

Table 3.3 Technologies for indoor positioning summary

Technology	**Metric**	**Accuracy**	**Range**	**Complexity**	**Cost**	**Update rate**	**Scalability**	**Privacy**	**Compatibility**	**Power**
BLE	TOA, RSSI	Medium	< 20m	Low	Low	Medium	Medium	Medium	High	Low
Wi-Fi	RSSI, TOA	Low	< 100m	High	High	High	Medium	Medium	High	High
RFID	RSSI	Low	<1m	Medium	Medium	Medium	Low	Low	Medium	Low
Zigbee	RSSI, TOA	Medium	< 40m	Medium	Low	High	High	Medium	Medium	Low
Infrared	TOA	Medium	< 10m	High	Low	Medium	Medium	Low	Medium	Low

Ultrasound	TOA, AOA	Low	< 10m	Medium	Low	Low	Medium	Medium	Medium	Low
VLC	AOA, TOA	High	< 10m	High	High	High	High	High	Low	High

Chapter 4 Design and evaluation of iBeacon topology for optimal signal to noise ratio

In the recent market, a varied range of handheld devices has been integrated with Bluetooth making this technology very highly applicable. In this project, Bluetooth Low Energy and iBeacon devices are used to develop an indoor positioning system. Because of the complex characteristics of the indoor environment, it is vital to understand and evaluate Bluetooth characteristics in this environment, so that we can verify that Bluetooth and iBeacon are suitable for indoor tracking applications. This chapter will investigate and evaluate Bluetooth properties in many practical experiments. The environment was changed from a free space area to a noisy room, from natural conditions to artificial conditions. At the end of this chapter, a suitable topology of iBeacon infrastructure for optimal signal to noise ratio is designed and presented.

4.1 Test area

The main parameter of the research, as mentioned in the previous chapters, is the RSSI of BLE technology. Experiments to explore the properties of RSSI and BLE are therefore set up. There are two areas chosen for the experiments. The long corridor on the 5th floor of the James Parsons building was chosen to represent the ideal environment with no object and obstacle (Figure 4.1). The dimensions of the testbed area were set to around 1.5 m x 30 m and are shown in Figure 4.2. The LOS contact in this testbed is assured.

Figure 4.1 Corridor on 5th floor James Parsons Building

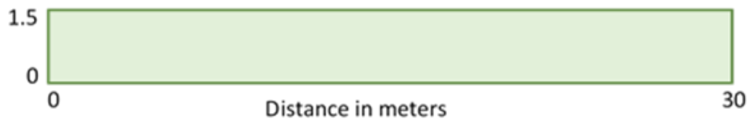


Figure 4.2 Dimension of the testbed area on 5th floor JP Building: Testbed 1

On the other hand, Room G04/05 on the ground floor of the building was considered as a more complicated environment with many obstacles, potential interference sources such as Wi-Fi Access Points, work station, lab machine and people present during working hours. Its graphical representation is shown in Figure 4.3.

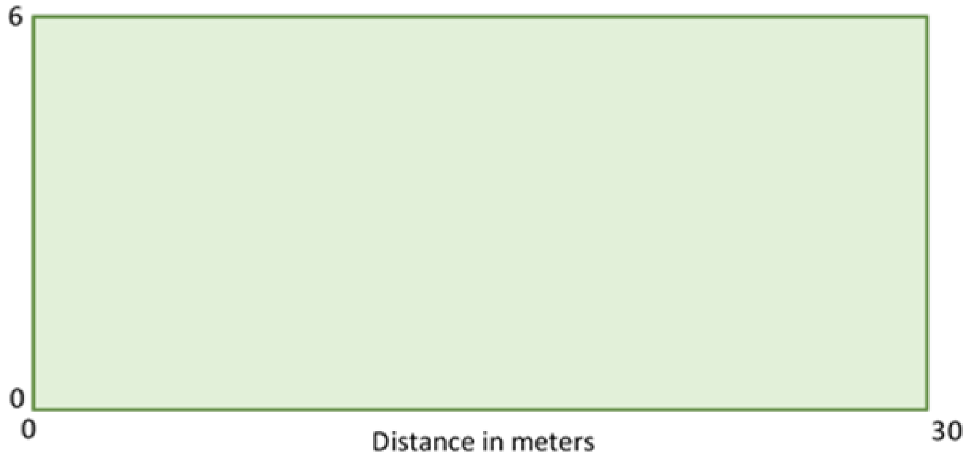


Figure 4.3 Graphic Representation of testbed in Room G04/05: Testbed 2

4.2 Equipment and tools

The equipment and tools, including software and hardware used for data collection and analysis, will be presented as follows.

4.2.1 iBeacon

iBeacon can be considered to be one of the most significant parts of this study. They are the known nodes deployed and pre-installed on the infrastructure at pre-calculated locations. Each iBeacon has two key tasks: it is used as a reference node to find users, and it is used to calibrate parameters.

There are many types of iBeacons on the market today. Most of them are powered by the battery. After approaching manufacturers and reviewing the beacon available in the UK, three variants of iBeacon are chosen: Estimote iBeacon (Estimote, 2020), Locly iBeacon (Locly, 2020) and BlueCats iBeacon (BlueCats, 2020). The settings and characteristics of the type of beacons used are shown in Table 4.1.

Table 4.1 iBeacon Vendors

	Estimote	**Locly**	**BlueCats**
Range	Up to 40m	Up to 40m	Up to 60m
MAC address	Unique per device Not Configurable	Unique per device Not Configurable	Unique per device Not Configurable
Major	Random between 0 – 65,535 Configurable	Random between 0 – 65,535 Configurable	Random between 0 – 65,535 Configurable
Minor	Random between 0 – 65,535 Configurable	Random between 0 – 65,535 Configurable	Random between 0 – 65,535 Configurable
Tx Power level	-4 dBm	-4 dBm	-4 dBm
Advertising Interval	400 ms	400 ms	400 ms
Battery type	3V Coin battery	3V Coin battery	Double AA
Battery life	14.6 months using these settings	~12 months using these settings	23.1 months using these settings

4.2.2 Handheld devices and the application

An application for iOS using the SDK provided by Apple (Apple Developer, 2019) has been developed to collect RSSI from the reference points. This SDK offers seamless communication between Apple's smartphones and iBeacon. Application searching for the UUID, major and minor, to locate a beacon within the scan range. When detected, the RSSI value is registered and logged into an excel file.

Figure 4.4 shows RSSI how data were stored. The key information was major, minor of the iBeacon and RSSI measured from the beacon to the device. However, in the version only the timeline (starting from zero), the MAC address and the iBeacon format were collected along with the RSSI index. However, we realised that the iBeacon with an undetected signal is not shown in this format and that it is difficult to determine the exact time to collect this data to facilitate future research. The second version was created to solve these problems. Figure 4.5 presents this version. The number of beacons detected and the actual time recorded had been added. Furthermore, the estimated distance from the RSI calculated by the Apple SDK was also shown in the data for ease of comparison and calculation. This application is run over an iPad 2 to collect the data.

Timestamp	MAC	Major	Minor	RSSI(dBm)
34	8C04B050-	1162	18359	-73
52	0C5B9B13-	51886	21323	-84
54	0D69328B-	46972	29716	-79
128	8C04B050-	1162	18359	-74
233	8C04B050-	1162	18359	-74
261	0C5B9B13-	51886	21323	-83
265	0D69328B-	46972	29716	-78
334	8C04B050-	1162	18359	-74
366	0D69328B-	46972	29716	-79
480	0C5B9B13-	51886	21323	-80
580	0C5B9B13-	51886	21323	-81
801	0C5B9B13-	51886	21323	-81
802	0D69328B-	46972	29716	-77
865	8C04B050-	1162	18359	-71
897	0D69328B-	46972	29716	-77
1218	0C5B9B13-	51886	21323	-80
1219	0D69328B-	46972	29716	-79
1295	8C04B050-	1162	18359	-71
1321	0C5B9B13-	51886	21323	-82
1398	8C04B050-	1162	18359	-70
1425	0D69328B-	46972	29716	-78
1432	0C5B9B13-	51886	21323	-83
1542	8C04B050-	1162	18359	-71

Figure 4.4 RSSI data collected version 1

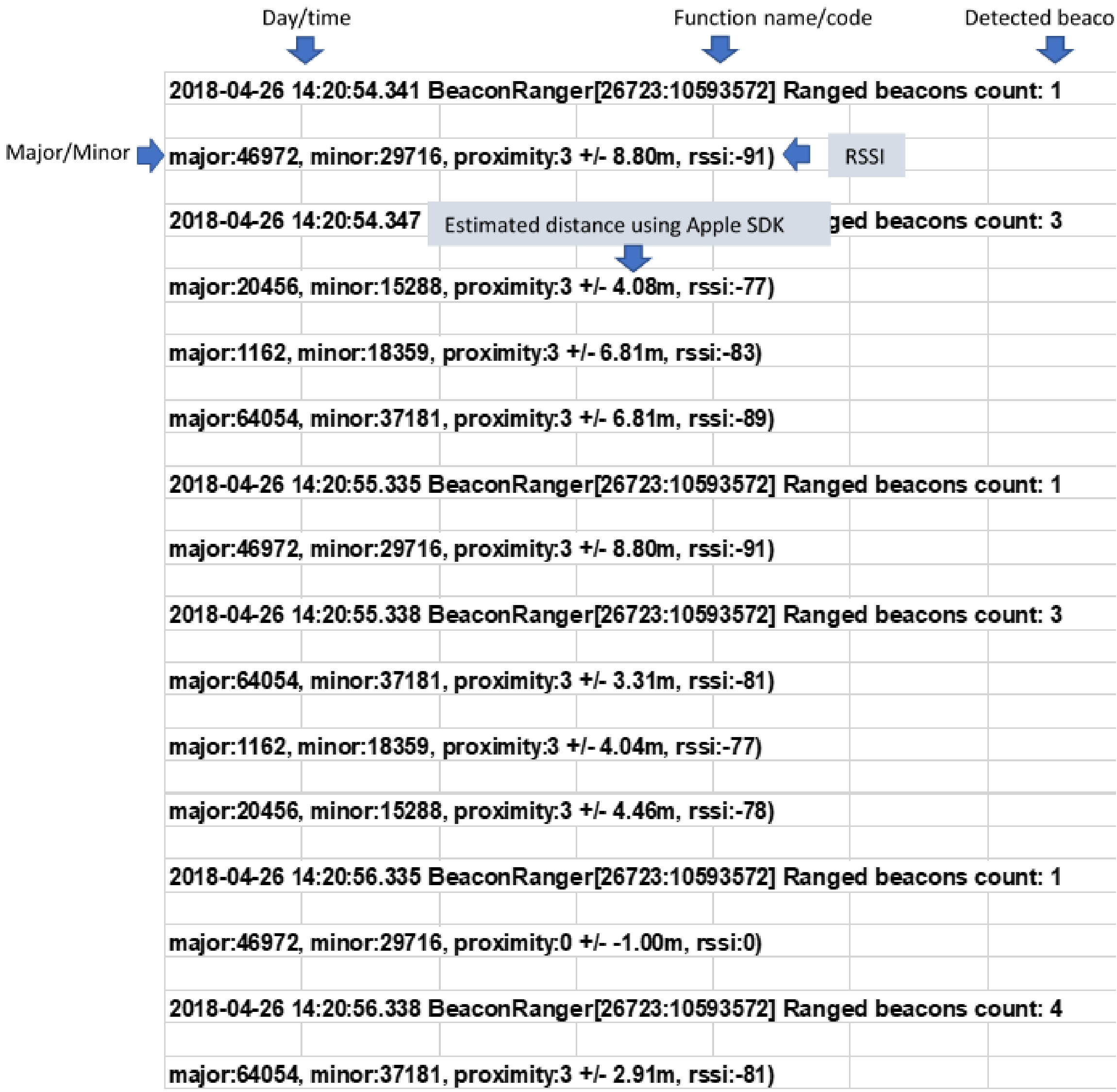


Figure 4.5 RSSI data collected version 2 - updated format

To expand the research, the Samsung Galaxy S6 is used as an Android OS candidate. However, unlike iOS, Android does not have native iBeacon support. The Estimote programme on the Google Play Store (Estimote, 2020) is then used to collect data. This programme can print the logged data to the Excel file. Figure 4.6 displays the data sample.

1A37DFFD-1866-423D-A1B8-0C848948C498	D3C41C9E-3DE8-4B54-9C71-D11320D01085	8D91DA4F-76A9-4003-964B-D92771BE6234	1A37DFFD-1866-423D-A1B8-0C848948C498
-36	-61	-61	-65
-34	-58	-64	-67
-39	-58	-65	-65
-38	-56	-65	-65
-37	-58	-66	-65
-37	-57	-67	-65
-37	-57	-67	-65
-36	-59	-68	-65
-36	-60	-70	-65
-36	-59	-70	-65
-36	-59	-70	-65
-36	-59	-70	-65
-36	-58	-69	-65
-36	-57	-69	-65
-36	-57	-68	-65
-37	-57	-68	-65
-37	-56	-67	-64
-36	-56	-67	-64
-37	-56	-67	-64
-37	-56	-67	-64
-37	-55	-66	-64
-37	-55	-66	-64
-37	-55	-66	-64
-37	-55	-66	-64
-36	-55	-66	-64

Beacon MAC-address

Figure 4.6 RSSI data collected Android

Table 4.2 is a summary of the devices and apps used in the study.

Table 4.2 Devices and apps

Operating System	iOS	Android
Device	iPad 2	Samsung Galaxy S6
Manufacturer	Apple	Samsung
Settings	iOS 9.3.5 Wi-Fi: On Bluetooth: On	Android 7.0 Wi-Fi: On Bluetooth: On

SDK	Provided by Apple	Provided by Estimote
Support iBeacon	Native	Not native
Other Apps	Xcode Matlab	Android Studio Matlab

4.3 Bluetooth stability in the indoor environment

As mentioned, the indoor environment has distinctive characteristics that affect radio signals emitted by sensors. The first factor is the strong multipath effect. This phenomenon is caused by walls, furniture or equipment. These obstacles block the signals making them reflected and diffracted. Thus, it will influence how well the receiver behaves. The second factor is the interference from other radio sources. Inside a building, there are many radio signals operating in the same frequency such as WLAN or Bluetooth.

Furthermore, in a big building, the number of wireless emitters and electronic devices can be huge leading to a very noisy environment. This disrupts and disturbs the usual pattern of the Bluetooth signal. The final relevant factor can be named as humans. A significant part of the human body is water which has a resonance frequency at 2.4 GHz. The Bluetooth signal, therefore, is weakened. Another impact of humans is their mobility. Users and carried devices might move around a building in an unpredicted pattern and inconstant speed. This also causes the signals to fluctuate. There are other factors such as heat, humidity or temperature. Therefore, in this subsection, the stability of the Bluetooth signal in the indoor environment will be verified.

In the first experiment, an iBeacon and an iPad were set up in two fixed positions in the first testbed. Figure 4.7 shows the setup.

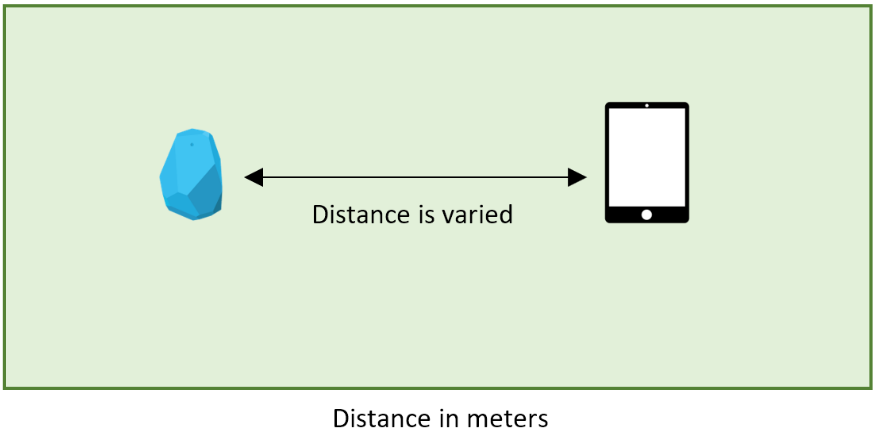


Figure 4.7 Experiment setup for testing signal stability

This experiment aims to study the quality of the Bluetooth signal between static devices. Both devices were placed on the floor, opposite, and directly in line-of-sight, each other from 50 cm away. There were no other radio noise sources near them. The Bluetooth signal emitted from the iBeacon and picked up by the iPad was observed for 10 minutes, the reading frequency is 1 sample/sec. Figure 4.8 shows the observation. In the first 200 samples, the Bluetooth signal fluctuated from -55 dBm to -61 dBm. Then the RSSI became more stable and only varied between about -57 dBm and -59 dBm. The reason for the instability in the beginning can be estimated as two devices needing time to discover each other and be stable.

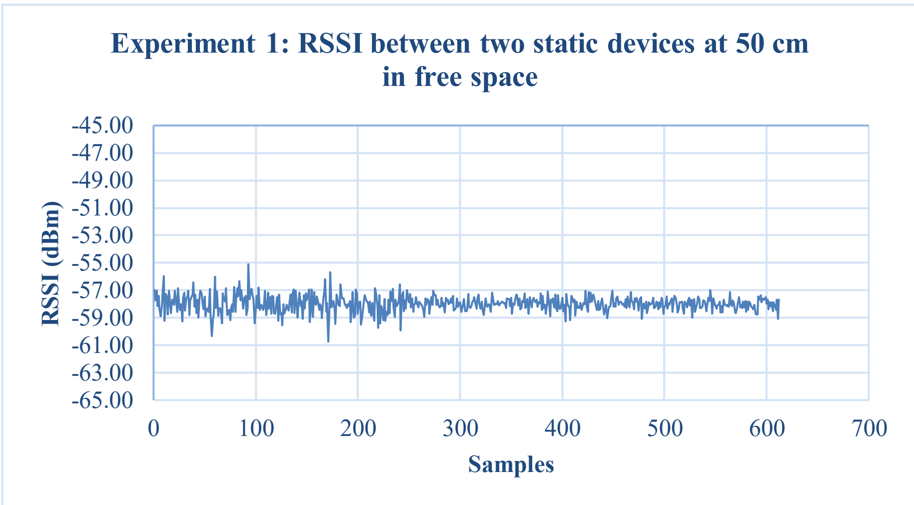
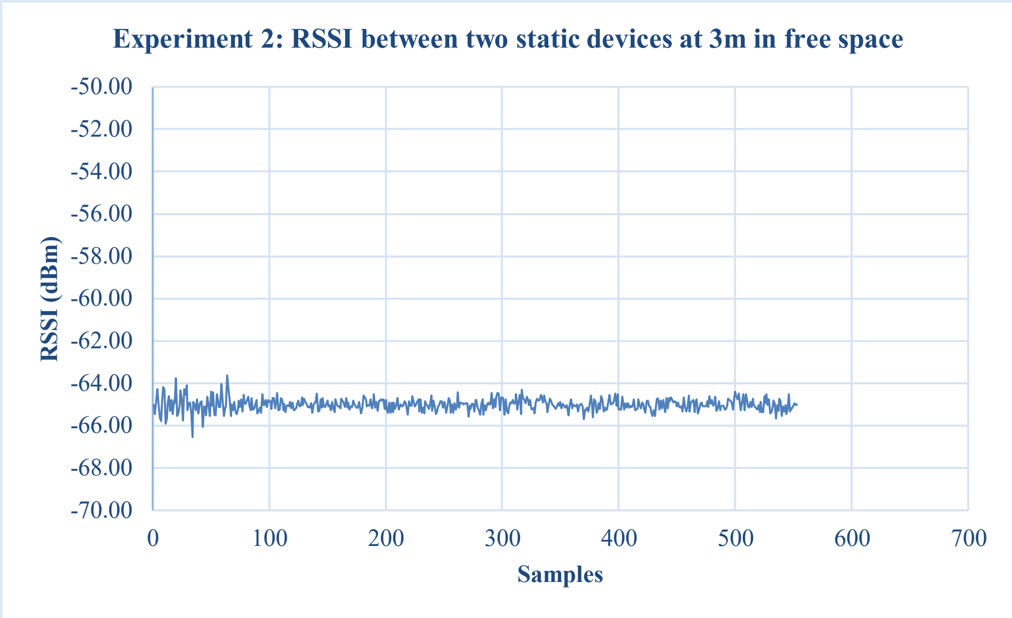


Figure 4.8 Bluetooth RSSI at a distance of 50 cm

Based on this initial experiment, the experiment was modified to approve the performance of the Bluetooth signal. In the second experiment, the distance between the two devices was changed to 3m and 6m respectively. Similar observations had been done over 10 minutes. Figure 4.9 shows results for this experiment. It can be seen in both cases, that the overall shape of the RSSI signal is similar to the first experiment. At the beginning of the measurements, the signal is quite unsteady, but it becomes firmer after a period of time. However, there are some points to notice in these results. When the distance between the two devices is 3m, the signal only fluctuated in about the first 60 readings, which is equivalent to about 1 minute, ranging from -63.6 dBm to -66.6 dBm. Then it was stabilised in the region of -64 dBm to -66dBm. In the set-up with 6m separation between devices, there were about 110 readings which varied from -72.6 dBm to -75.3dBm in the beginning. The signal firmed up at around -74 dBm with only 1 dBm variation. It can be seen that, out of three experiments, the results in experiment 2, when the two devices are 3m apart, give the most stable performance. Furthermore, it was interesting to see that there were 612 RSSI samples collected in the first test compared to 553 samples in the two later experiments despite being recorded in the same period of time. The reason for this might be the connection between beacon and device was lost, result in the RSSI collected is 0. These values were discarded. Nevertheless, in all three experiments, after the stabilisation period, the RSSI signal varied only within 2 dBm, which will make no difference for later position calculation.



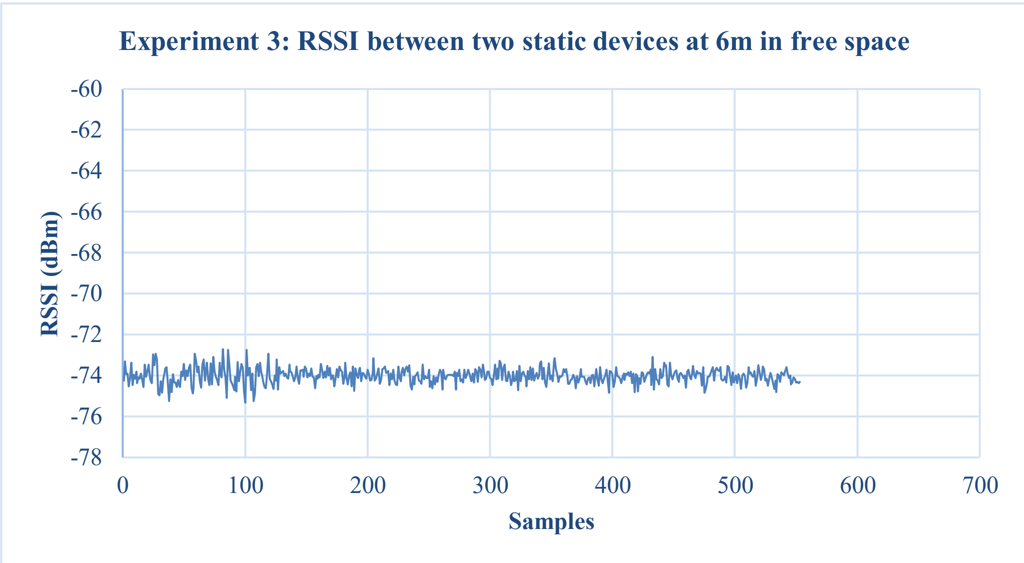


Figure 4.9 Bluetooth RSSI at distance of 3 m and 6 m

However, the first session just made evident that iBeacon and Bluetooth signals can maintain their stability over a short distance and when there is LOS between devices. In fact, these conditions only happen in the laboratory. In the real scenario, the distance between devices can be further and there are many obstacles and interference sources in the indoor environment. Also, in order to verify the relationship between the beacon-target distance and the RSSI signal and to find the optimum distance threshold between them, another experiment with some alterations was carried. The first change in the experiment is shifting the distance between the iBeacon and the mobile device up to 30m. The RSSI signal is collected while moving further from the iBeacon. In every 1m which is the assumption for a human's stride length at normal walking speed, the user stopped and recorded the signal for 1 minute. The mean value of these measurements will be taken for the observation. The second modification of this experiment is the environment. The experiment was then conducted in the second testbed – room G04/05.

Figure 4.10 presents my observations from the test on the 5th floor corridor of the James Parsons building. The first point we can notice from the result is the number of samples in each stop are not equal. Within a 1-minute recording, there are about 60 samples expected to be recorded. However, the number of readings is varied, and it became much less than expected when the iPad went further away from the iBeacon, especially after 20 metres. The mean value of these readings was taken, which is the red line, and confirm that the Bluetooth signal decreases over distance in the quadratic trend, which is the green line on the graph. It obeys the Friis' Free Space Loss. This can be explained that in this environment, where there are no obstacles or any other noticeable noise sources, the Bluetooth signal can reach the target in a straight line. The signal variation for each distance is from 1 dBm in the nearer distance to 3 dBm in the further distance. Although this is an acceptable range, it shows that Bluetooth and iBeacon might not work well when two devices are separated too far.

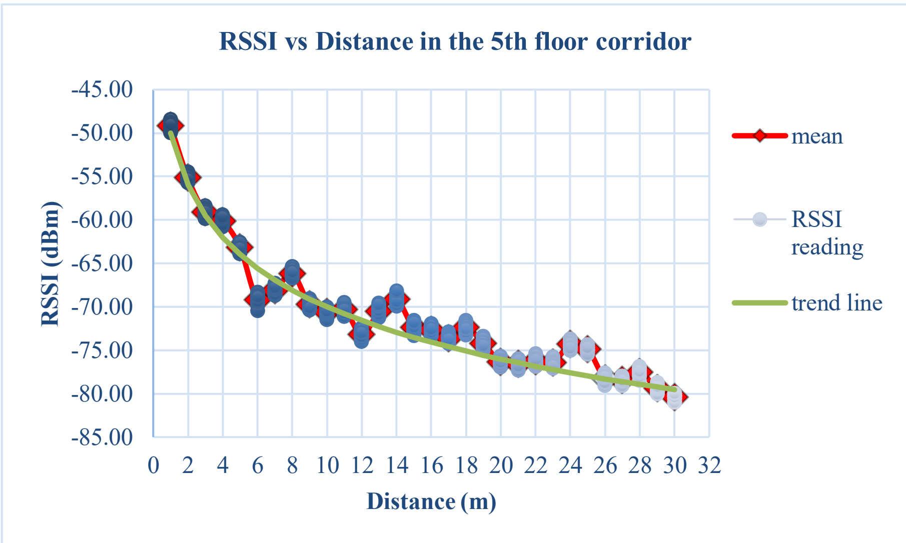


Figure 4.10 RSSI vs Distance in the 5th floor corridor

The next experiment took place in room G04/05. Its results are presented in figure 4.11. Observation shows us that the RSSI signal also decreases in the quadratic trend. Nonetheless, this trend is different compared to the previous result. Overall, although being recorded at the same distance, the signal strength is lower than in the previous experiment. For example, at 1m, the RSSI is about -56 dBm compared to -48 dBm in the test in the 5th-floor corridor. It is also be noticed that after 10 m, the RSSI signal becomes much more fluctuating. This may be the effect of noise sources in room G04/05. Wi-Fi access points and other electronic equipment such as oscilloscope, signal generator, amplifier and computer may interfere with the Bluetooth signal. Furthermore, from 16 m, only about 15 samples per minute were recorded and the maximum distance was 21 m with only 2 samples recorded. It is a noticeably shorter distance than the 5th-floor corridor experiment results. Bluetooth signal suffers a multipath fading effect as there are many chairs, table and humans present in the room. The signal had to bounce off, reflect and diffract when coming into contact with obstacles. Therefore, it becomes weaker. Furthermore, the signal variation is also more extensive than the preceding test. It was about 10 dBm at 16 m and even at 20 m, the variation is about 16 dBm. This will cause a significant error in the later position calculation. Fortunately, under 8 m, the signal only varied less than 3 dBm, which is still within my expectation.

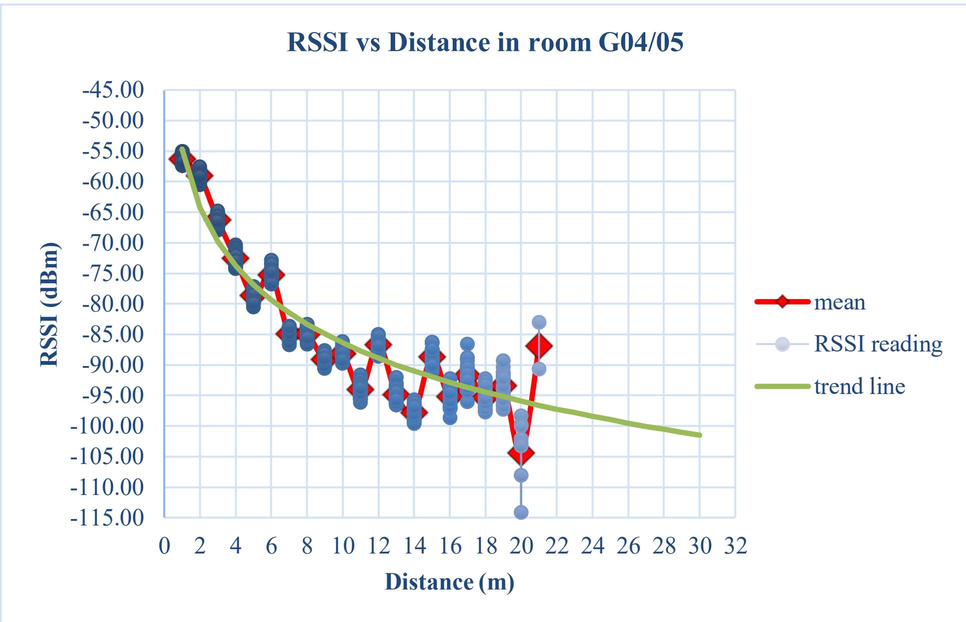


Figure 4.11 RSSI vs Distance in Room G04/05

In summary, results made evident that iBeacon and Bluetooth signals can maintain their robustness over distance in both a free space area and “noisy” indoor environment. The Bluetooth signal will decrease over distance obeying a quadratic trend. However, the model for the “noisy” indoor environment needs to be considered and appropriately chosen. Also, the result showed that Bluetooth and iBeacon work best within the range of 5 m to 8 m.

4.4 Impact of height and orientation

In a real-life indoor environment, there are numerous structure and layout set-ups. Thus, beacons might be placed at different positions with different heights or different orientations. This is also the case for mobile devices when users are moving around and carrying them in different postures. Signals experience the multipath fading effect in the indoor environment. They bounce off obstacles and be reflected before reaching targets. Because iBeacons periodically emit signals, this effect will cause interference if two or more transmit reflected signals across others. This experiment aims to evaluate the effect of height and orientation to the Bluetooth signal, reflection and multipath fading effect. This section is going to give a recommendation on the beacon height placement and a suitable calibration for the indoor localisation system to reduce the effect of the multipath fading effect.

In the first experiment of this section, the beacon was placed at three different heights from the ground. First, the iBeacon was placed on the ground, i.e. 0-metres height. Then it was placed at the height of 1 m, which is my assumption for the height of a mobile device when a user is carrying it. Finally, the same iBeacon was placed at 2 m height. This is the assumption when the iBeacon is installed in the ceiling in real case scenarios. In three cases, the RSSI signals were collected from the iPad moving from 1m to 30 m in room G04/05. Note that room G04/05 is the testbed for a real-life indoor environment. Figure 4.12 describes the experiment:

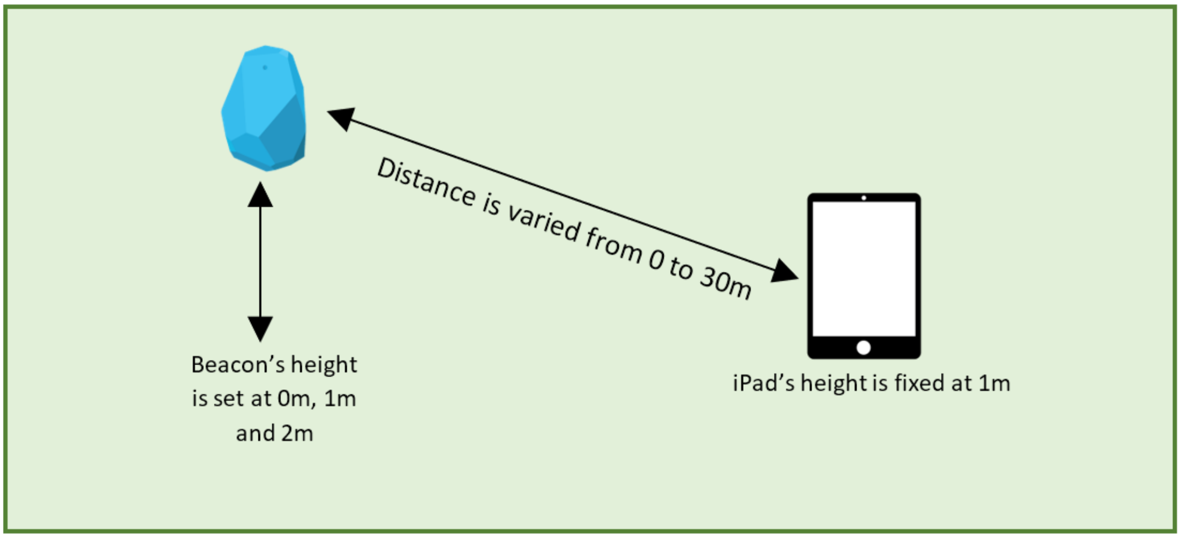


Figure 4.12 Experiment: RSSI at different heights

Figure 4.13 shows the results. Although beacon and mobile settings were identical, we can see that there are differences in terms of distance and value fluctuation for the three cases. Surprisingly, in the case of 1m height, the signal experiences lots of noise and can only reach 20m. In comparison at the 0-metre height, the signal fluctuates less, and the maximum distance is also 20 m. And in the case where beacons were installed at 2 m high, the signal recorded at 30 m was quite acceptable and the overall shape was much more stable. This set-up outperforms other previous set-ups. This can be explained as when the iBeacon is placed higher such as on the ceiling, the emitted signal has a straight path to reach the target mobile. Therefore, it suffers a less multipath fading effect. On the other hand, in the 1 m height set-up, sometimes, the signal can reach the target mobiles directly, but most of the time it meets other reflected signals as this is the height of most obstacles in the room such as chairs, tables, computers... These signals may be in phase which causes a stronger signal, or if they are out phase, these will be cancelled. These effects lead to the most fluctuation of RSSI as we can see.

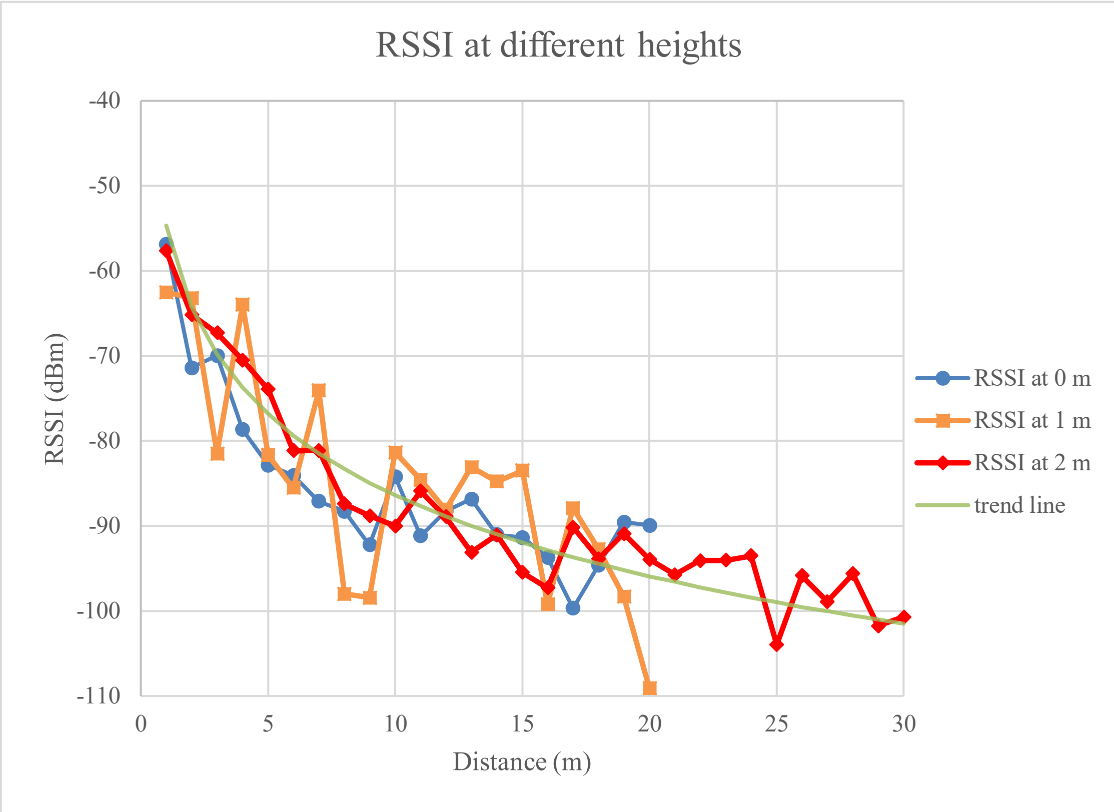


Figure 4.13 RSSI at different heights

The second experiment was set that placed the iBeacon and the iPad at the same height and in a straight line at the distance of 1m as shown in Figure 4.14. The iBeacon was then turned clockwise in 8 directions in the space. In each direction, 50 RSSI samples were collected and took the average value. Figure 4.15 shows the observations. When the two devices were facing each other, i.e. iBeacon points to East direction, the signal collected was the strongest. However, the difference when the iBeacon was turned is quite small, it was only within 1.2 dBm. In fact, the antennas of Estimote's iBeacon and other major current manufacturers are omnidirectional (Estimote.com, 2019), which broadcast signal in a doughnut-shaped as figure 4.16 (Estimote.com, 2019). Thus, the signals collected are considered identical.

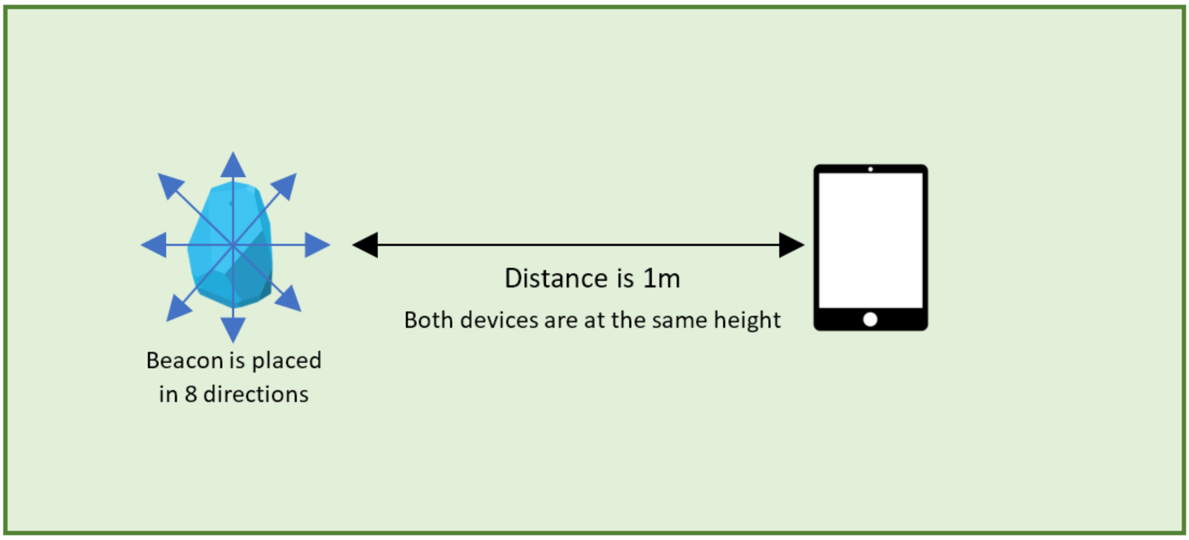


Figure 4.14 Experiment: RSSI with 8 orientations

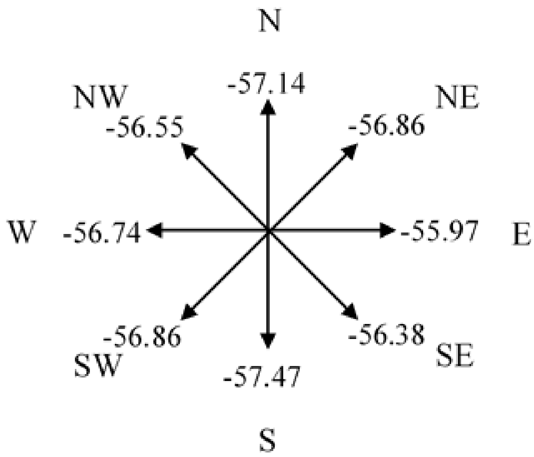


Figure 4.15 RSSI with 8 orientations

In summary, after two experiments, we can see the effect of height placement on the Bluetooth signal. This significantly affects how the signal approaches the destination and therefore affects the signal quality. My test suggests that the signal is more reliable when the beacons are placed higher than other obstacles and moving objects. In such a set-up, there is a high possibility that signals can reach the device target in a straight path without interference with other reflected signals. On the other hand, the effect of orientation between beacon and device is negligible. Thus, in this project, this parameter is not considered in order to reduce system complexity.

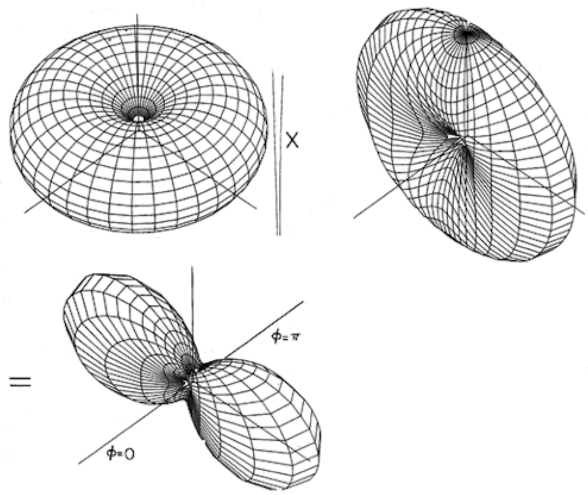


Figure 4.16 Bluetooth antennas (Estimote, 2019)

4.5 Bluetooth signal for cross devices and cross-platform

In the current market, there is various type of devices with different OS and different functions. Furthermore, more and more beacon manufacturers are joining the market. In this section, the cross-platform and cross-devices performance of the BLE signal will be in the indoor environment. The experiment was amended as follows.

- Different beacons from the same manufacturer – Estimote - were used.
- Different beacons from different manufacturers were installed: Locly and BlueCats beacons are used to verify the result.
- The mobile device was replaced by a different one: a Samsung S6 with Android OS is used instead of the iPad. This collected data from the initial Estimote beacon.

Figure 4.17 and figure 4.18 display results from the experiment. In the first test, two Estimote iBeacons at 50 cm from the iPad was placed and the signal was measured for 10 minutes. Results collected share a very similar shape to each other. The RSSI signals from two iBeacons are almost identical with the average of 57.6 dBm.

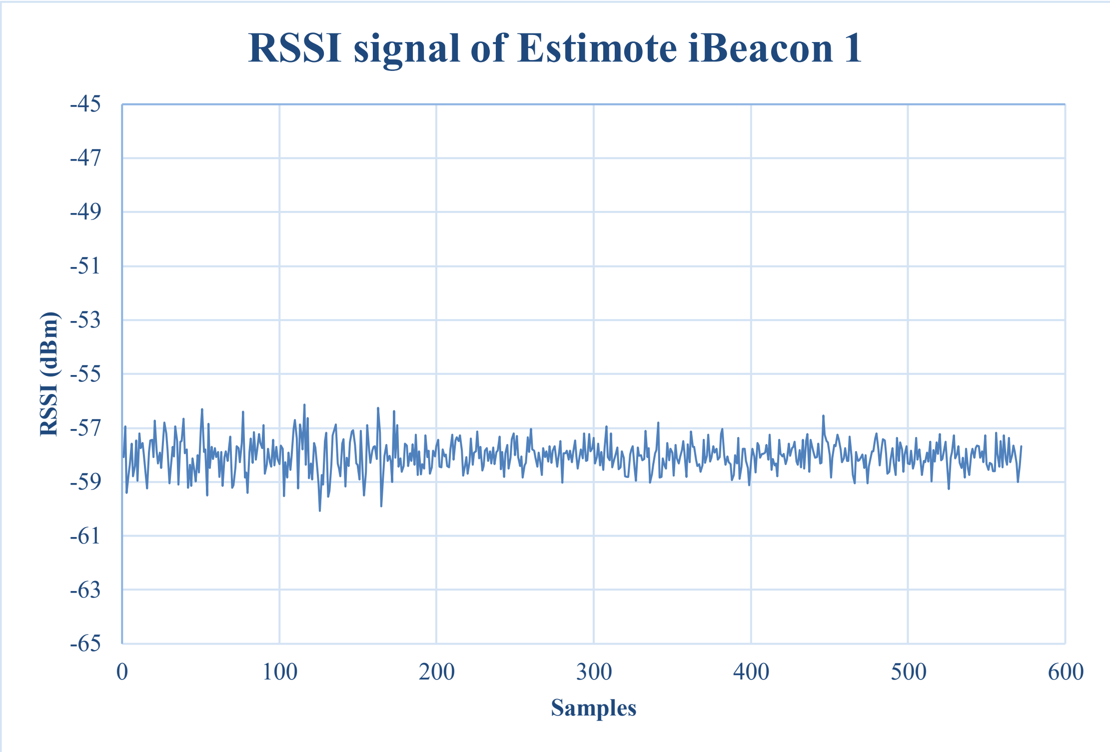


Figure 4.17 RSSI collected from Estimote iBeacon 1

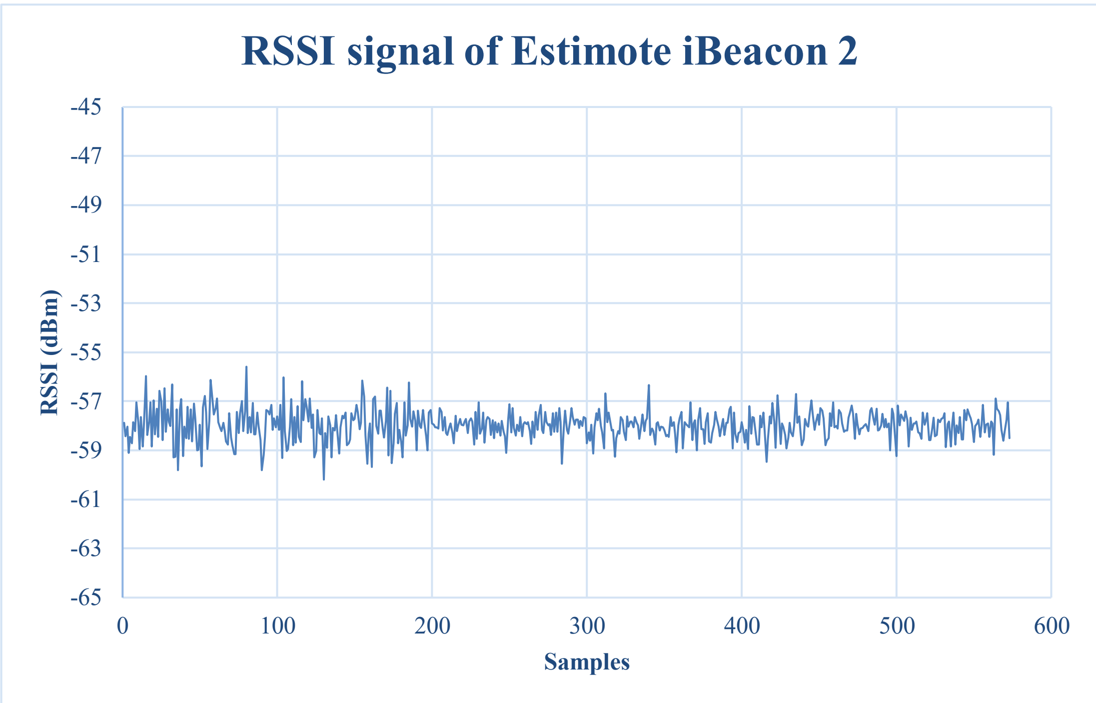


Figure 4.18 RSSI collected from Estimote iBeacon 2

In the second experiment, again the signal from iBeacons to iPad device was inspected at 50 cm for 10 minutes but with three different manufacturers: Estimote, Locly which are coin battery-powered and Bluecats which is powered by two AA batteries. Figure 4.19 and figure 4.20 present our observation. Although three beacons were placed in the same position with the same time transmission power settings, the overall collected signals were notably different. First, Estimote and Locly's signal fluctuated for about the first 180 readings before becoming stable. On the other hand, Bluecats iBeacon needs about 4 and a half minutes, equal to 270 readings, to be stabilised. Second, it is interesting that despite the shortest stable signal time, Bluecats's signal has the highest average RSSI at -51 dBm whereas this value of Locly's beacon is -59 dBm and Estimote's beacon is -58 dBm.

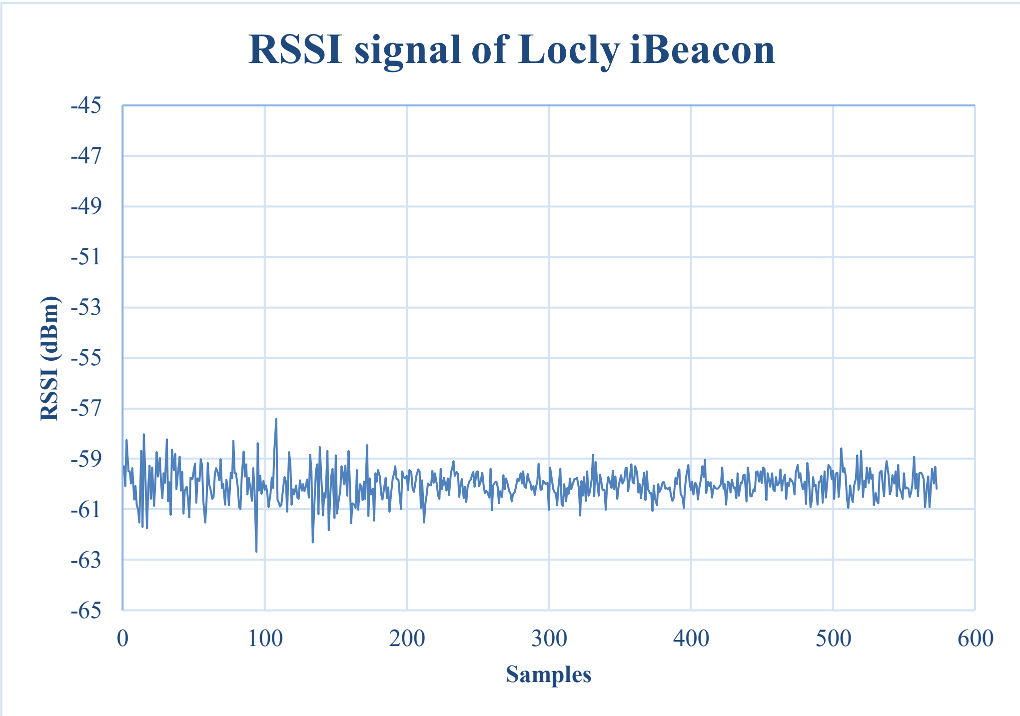


Figure 4.19 RSSI collected from Locly iBeacon

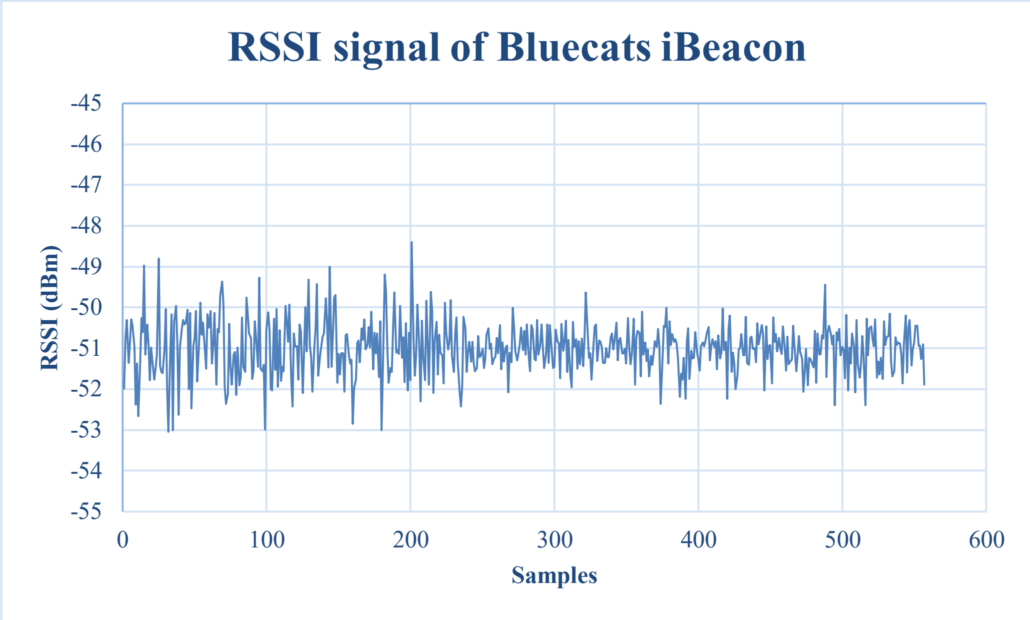


Figure 4.20 RSSI collected from Bluecats iBeacon

In the last experiment, the performance of the Bluetooth signal of the two most popular OS for mobile devices: iOS and Android, was studied. An Estimote iBeacon was placed from 1 m to 20 m away from an iPad and a Samsung S6. The reading frequency is about 1 sample/sec and at each metre distance, signals were measured for 10 seconds and took the mean. Figure 4.21 is my report. It shows that there are some differences between the two signals. The average RSSI value collected from the iPad is higher than from the Samsung device. Also, the signal from the iOS handheld is more stable than the competitor: variation is about 3 dBm compared to 3.8 dBm. However, two signals follow the same quadratic trend line as described throughout the experiment. This result shows that the differences of Bluetooth signals in two major mobile OS are quite small and they share the same characteristics as discussed in the previous experiments.

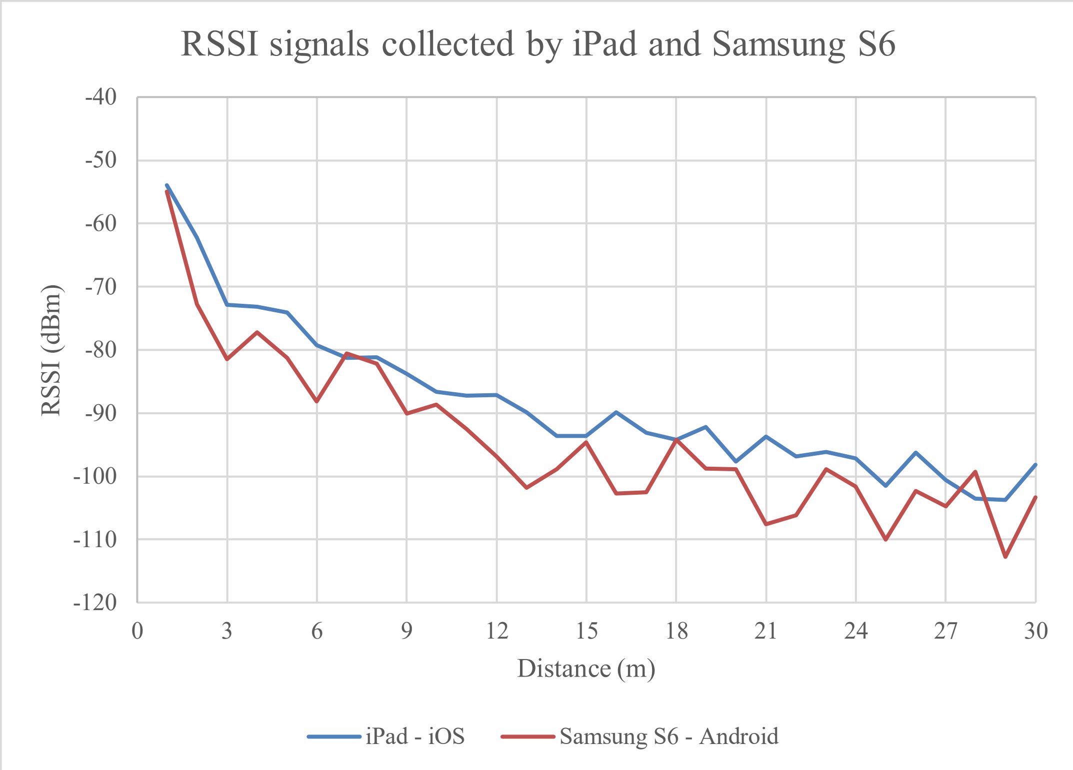


Figure 4.21 RSSI collected by various devices

Briefly, observations verified that there is diversity in signal performance between beacons from different manufacturers. This indicates that, in one system and one environment such as one building, using the same beacons is a crucial design criterion to achieve a satisfactory positioning result. On the other hand, the Bluetooth signals gathered from multiple OS, i.e. Android and iOS are dissimilar. Fortunately, they performed almost identically regarding the shape and the signal movement. Thus, a calibration in each OS needed to be done before calculating positions. In this project, a calibration using the appropriate propagation model is developed. Then, the evaluation is done using the iOS system. However, this can be applied to be used in an Android positioning system as the parameters can be changed accordingly.

4.6 Bluetooth signal characteristics summary

From experiments, it is noticeable that the Bluetooth signals are varied in the indoor environment. Fortunately, this variation is only about 2-3 dBm which might not affect the result of positioning at a shorter distance. However, in this environment, the signal experiences a multipath fading effect especially when transceivers are further away from each other. The signal fluctuation can be as significant as 5 dBm after 6 metres and even larger than 10 dBm after 20 metres. Thus, keeping the Bluetooth signal varying within the variation threshold with appropriate distance from beacons to devices is an important basis for the design. It is also found that the height between beacon and devices, between beacon and ground and beacon and other obstacles, plays an impactful role for the signal collected. By placing beacons at a suitable height, a clear path can be created, and then the signal from the beacons can go straight to devices as expected without experiencing too much propagation and attenuation. Another interesting element is that mixing beacon manufacturers in one system might lead to noisy data measurement. Each manufacturer has its own settings and design such as antennas, batteries, etc., which notably influences the signal transmitted. Thus, it is recommended that only beacons from the same manufacturer should be used in one system or in one area. This will reduce the system complexity and utilise the performance of system calibration.

On the other hand, it is discovered that the effect of device orientation to data measured is quite small. This is thanks to the omnidirectional antennas design in the most recent iBeacons in the market. Finally, the Bluetooth signal performs quite similarly across devices and platforms. There is minor dissimilarity such as in signal strength or signal variation, but they share all the same other characteristics such as robustness, reliability, multipath fading effect. A simple adaptive calibration for each platform might solve this difference and be able to provide a satisfactory positioning result in that platform.

4.7 iBeacon topology suggestion for indoor position systems

In this section, a recommended topology for iBeacon in an indoor positioning system is proposed. There are some points to note in the design:

- Each beacon covers a circle area which has a radius equal to its range. Within this range, the beacon’s signal must be reliable and stable. In one area or building, it is recommended to use all beacon from 1 manufacturer with same settings.

- Each target point, i.e. user's device, must be surrounded by at least three beacons for reliable positioning. In addition, based on BLE specification, the maximum parallel connections is 7 (Townsend, 2014). Thus, to maintain the connection and avoid the interference, the number of neighbour beacon should not exceed 7.
- The number of deployed beacons in the system should be minimised to save the cost.

Under condition 3, the densest circle packing (Graham et al., 1998) is used as the base topology to maximise the covered area. It was proved (H.C. Chang, L.C. Wang. 2010) that the regular hexagonal packing is the densest packing. In my proposal, it is assumed that all beacons have the same settings, i.e. they will cover the same circle area with equal radius. In order to obey point 1, beacon transmission range will be configured to around 5 metres for reliability which requires the transmission power only about -12dBm (Estimote.com 2019). In fact, throughout the experiment, it was able to measure data up to 11m at this transmission level but within 6m, signals were stable as predicted. This small amount of required energy also increases the battery life of the beacon.

Then, comply with point 2, the set-up topology is created using 4 beacons, which are placed five metres apart. This created a parallelogram as shown in figure 4.23. Five metres distance between beacons is also the expected circle radius. This topology setup will cover the area up to $25m^2$. As in the regular procedure, it is assured that each target point will be covered by at least 3 beacons.

In fact, there are applications where localization is only necessary for small spaces such as small meeting rooms or offices, where the distance between beacons is not far away and there will be little noise from beacons outside the area or interference from external sources. Therefore it is required only a minimum number of 3 beacons with 5 meters away from each other as shown in Figure 4.22 to enforce the trilateration or LSE algorithm for positioning. This setup covers an area of $10.8m^2$. However, for wider areas, such as the hall or the airport or the large office, the optimum topology needs to be specified as 3 beacons can not cover the entire field. At the same time, more potential noise is possible, so 4 beacons are recommended in each $25m^2$ region to ensure that the user can pick up the most reliable signal.

The extension for a large area is shown in figure 4.24. As mentioned, in the normal manner of my recommended setting, the reliable signal can be collected when the distance between beacon and device is 6m. Then the maximum number of beacons, that produce a strong signal and reliable signal, surrounding one point in the topology is 6. This topology is used and evaluated in my project.

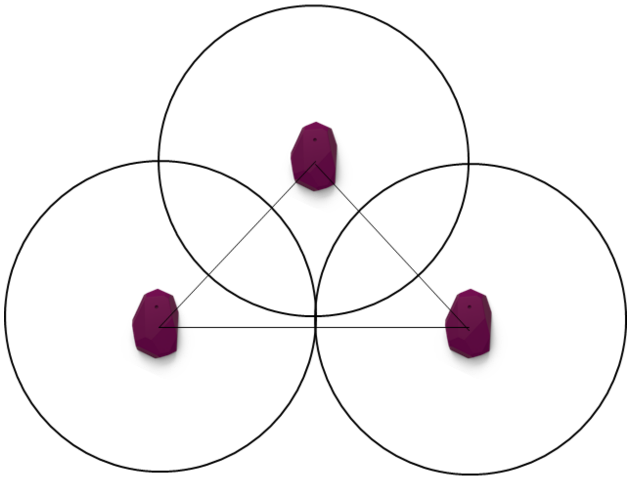


Figure 4.22 Minimum iBeacon topology for a small area up to 10.8m^2

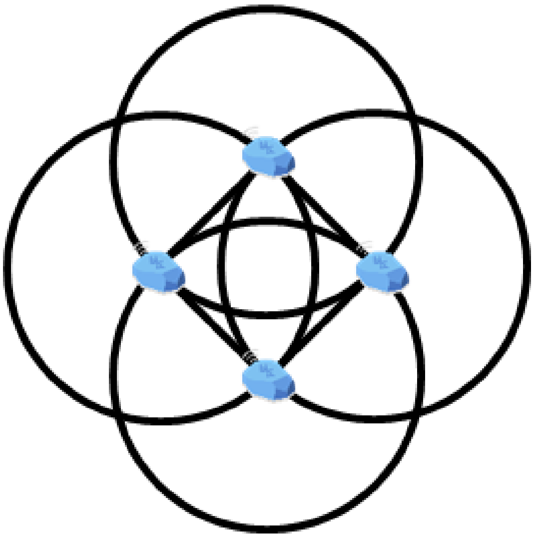


Figure 4.23 Recommended iBeacon topology to cover an area up to 25m^2

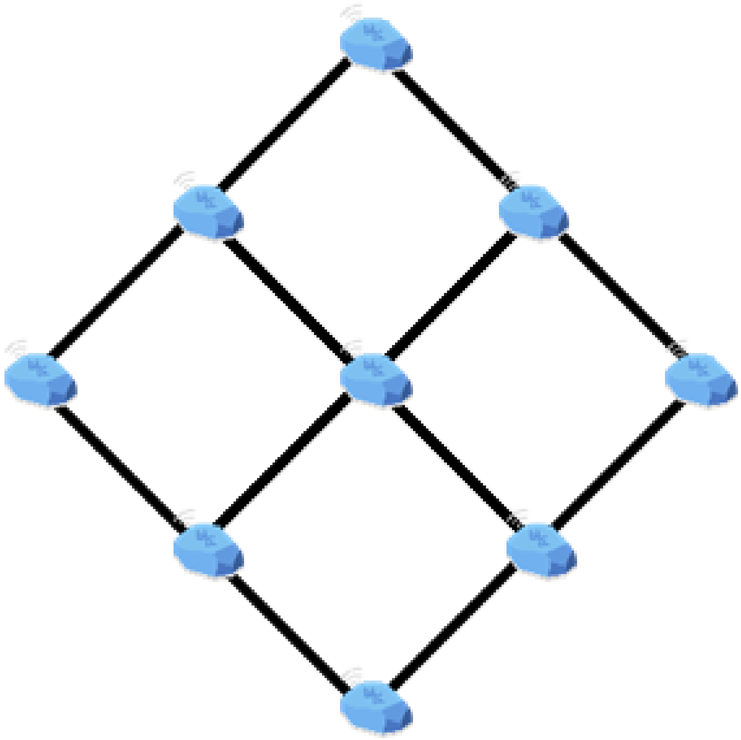


Figure 4.24 iBeacon topology for an area larger than $25m^2$

Chapter 5 Intelligent Algorithms for high accuracy positioning of static objects

A highly accurate algorithm to estimate the positioning of the static object will be proposed in this chapter. It starts with the introduction of relevant research and model. The proposed system model is then defined. Finally, the algorithm is introduced and evaluated via experiment.

5.1 Related work

5.1.1 Log-Normal Shadowing Model

The most commonly used indoor propagation model is the log-normal shadowing (LNS). It represents and simplifies the relationship between RSSI, distance and “noise” term as shown in Equation (5.1). This is an extension of the Friis’s free space model. The received signal strength suffers an exponential loss in the indoor environment. This loss is predicted in the model over distance d and path loss exponent η. The path loss exponent represents the shadowing effect and multipath propagation. Its value is dependent on the environment with different obstacles and material. In the indoor open space, the shadowing effect is neglected and η value is equal to approximately 2. In this thesis, the value of η is obtained by measurements and the calibration.

$$\mathrm{RSSI} = \mathrm{A} - 10 \times \eta \times \log_{10}(\mathrm{d}/\mathrm{d}_0) + X_\sigma \tag{5.1}$$

Another factor in the model is A, which is the received signal strength at the reference distance d_0. Typically, in the building environment, d_0 is set to be 1m whereas the A value is set by the beacon manufacturer. However, the A value depends on the actual receiver and transmitter. One single value cannot represent a various set of devices in real life, therefore, it needs to be measured on the specific device in the system. X_σ is the zero-mean Gaussian random variable. If the error has no zero-mean, it will be reflected in the measured reference received signal strength A. Thus, for simplicity, this parameter is removed in the following calculation.

5.1.2 RSSI filtering

The Bluetooth signal was found reliable, over the short-range and when the target is static, through experiments in the former chapter. However, mobile nodes move, and the environment can be altered in a real scenario. We saw how vulnerable RSSI signals are when the environment and other circumstances change. Mainly due to the current complexity of the multi-path fading of the indoor environment, the signal is dispersed and gets noisy. This variation may cause an error in distance calculation and the high precision position estimation. Signal filtering is, therefore, one of the most important criteria for a reliable data value of an indoor positioning system.

RSSI filters are being assessed to identify the best solution for the indoor positioning system. The experiment was conducted in room G04/05, with a wide range of noise sources, in order to assess the ability of each filter. Beacons are situated 1 m and 5 m apart from the mobile device. At each position, the RSSI from each beacon was observed 100 times, which is equivalent to about 2 minutes. This is the highest schedule for RSSI information collection for a single static node. Following the application of feedback filters, Gaussian filters and Kalman filters at 1 m and 5 m, the measures of raw RSSI and RSSI information are shown in Figure 5.1 and Figure 5.2.

The primary problem of RSSI is the fast fading impact. RSSI information collected varies rapidly over time. The filter requires, therefore, to remove this oscillation, creating smooth information by decreasing standard deviations. However, RSSI filtered must be able to show the RSSI features with regard to slow fading, mainly owing to mobility and displacement. The observation results were assessed with these requirements. At 1m, the Feedback filter gives the variance of 1.97 whereas the Gaussian filter gives the variance of 0.62 and Kalman filter gives the least variance at 0.11. At 5m, the Feedback filter has 2.73 variances, whereas the Gaussian filter and Kalman filter achieve 1.62 and 1.13 variance respectively. The feedback filter is not suitable for smoothing the signal with rapid deterioration, as mentioned in the preceding section. The filtered signal remains gross and the standard deviation is quite significant. The

Gaussian filter shows a bit better, but the Kalman filter outperforms its competitors. The Kalman filter filtered signal has a very small standard deviation and is close to the average RSSI value at that range. The average value measured at the same place with the same environments in 8 hours should be noted.

This chapter utilises experiments to select the Kalman filter as the principal filter in my indoor positioning system. In other conditions and systems, however, different types of filters may be used.

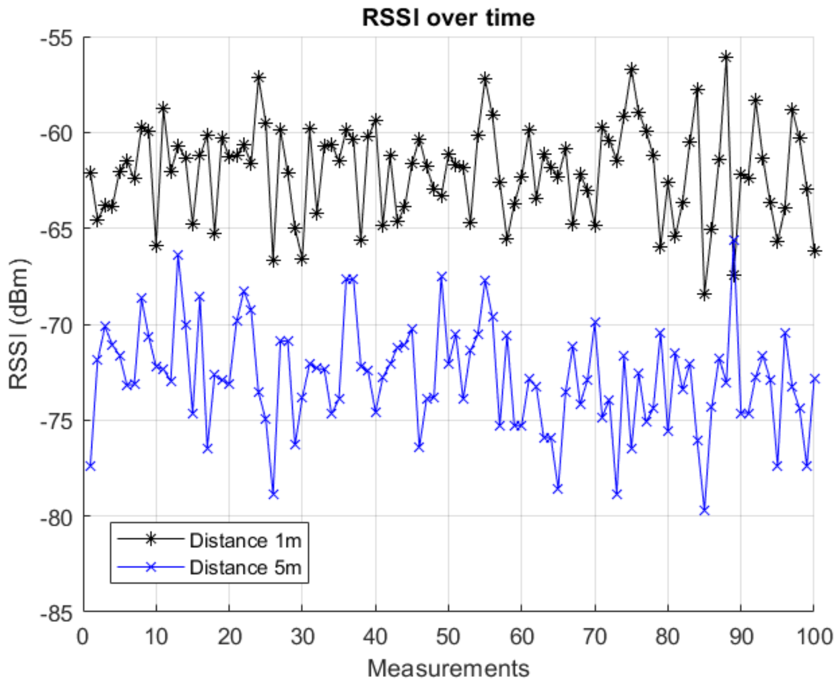


Figure 5.1 Raw RSSI at 1m and 5m

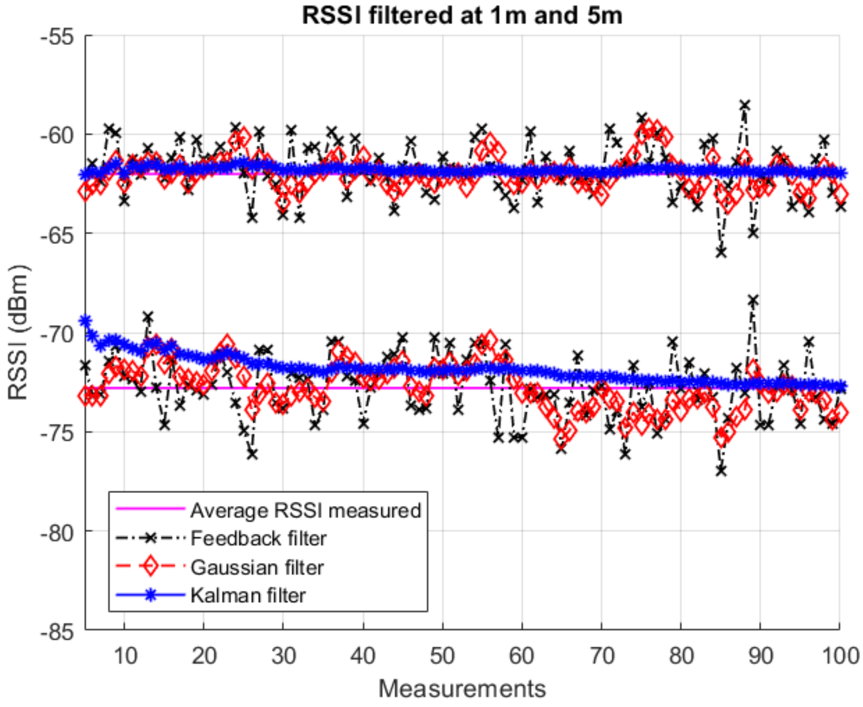


Figure 5.2 Comparison of RSSI filtered at 1m and 5m

5.1.3 RSSI- Distance estimation model

The distance between beacons and a device can be obtained using the log-normal shadowing and calibrated factor. From Equation (5.9), the conversion between RSSI and distance can be expressed by the formula (5.2) below:

$$d = 10^{\frac{\overline{RSSI} - \overline{A}}{10\eta}} \tag{5.2}$$

Where $\overline{RSSI}$ is the averaged measured RSSI at distance d, $\overline{A}$ is the averaged measure RSSI at reference distance and η is the environment and noise factor. From Equation (5.2), it can be seen that A and η are mathematically related and need to be carefully calibrated to improve the accuracy. All beacons and devices are considered static, then it can be seen that after the factor calibration and RSSI smoothing, there is no noticeable noise in the distance calculation. In section 5.2, a method for obtaining the value of A and η by fitting a large number of experiment measurement will be introduced.

5.1.4 Least Square Estimation

Least Square Estimation (LSE) is a well-known method to solve the lack of GPS for positioning objects (Sharp and Yu, 2013). It is based on the following Equation (5.3):

$$y = Mx + \epsilon \tag{5.3}$$

The approach is to choose an appropriate value for estimated $\hat{x}$ so that the norm value $||M\hat{x} - y||$is minimised. Then the general linearised solution is:

$$M\hat{x} \approx \beta \tag{5.4}$$

Applying into the classic positioning problem, the matrices can be represented as in Equations (5.5)(5.6) and (5.7):

$$M = 2\begin{bmatrix} x_1 - x_2 & y_1 - y_2 \\ x_1 - x_3 & y_1 - y_3 \\ x_1 - x_4 & y_1 - y_4 \end{bmatrix} \tag{5.5}$$

$$\beta = \begin{bmatrix} d_2^2 - d_1^2 - (x_2^2 + y_2^2) + (x_1^2 + y_1^2) \\ d_3^2 - d_1^2 - (x_3^2 + y_3^2) + (x_1^2 + y_1^2) \\ d_3^2 - d_1^2 - (x_3^2 + y_3^2) + (x_1^2 + y_1^2) \end{bmatrix} \tag{5.6}$$

$$\hat{x} = \begin{bmatrix} x \\ y \end{bmatrix} \tag{5.7}$$

The solution is given by:

$$M\hat{x} \approx \beta \tag{5.8}$$

5.2 Proposed system

5.2.1 System model

The positioning system is designed to be used in the indoor environment, i.e. hospitals, in an IoT network. Figure 5.3 presents the system architecture overview. There are two main tasks which are: collecting and exchanging data with operator and users and applying different technologies and algorithms to provide location tracking and monitoring based on data collected. It consists of four primary communication interfaces:

- Interface 1: data collection and exchange data with the database within the IoT network of operators.
- Interface 2: application to interact with users: users input or automatically collect the required data.
- Interface 3: enable communication between different platforms, various types of devices suitable for the indoor environment.
- Interface 4: applying suitable technology and calculation to analyse data to provide tracking results as well as other required health monitoring.

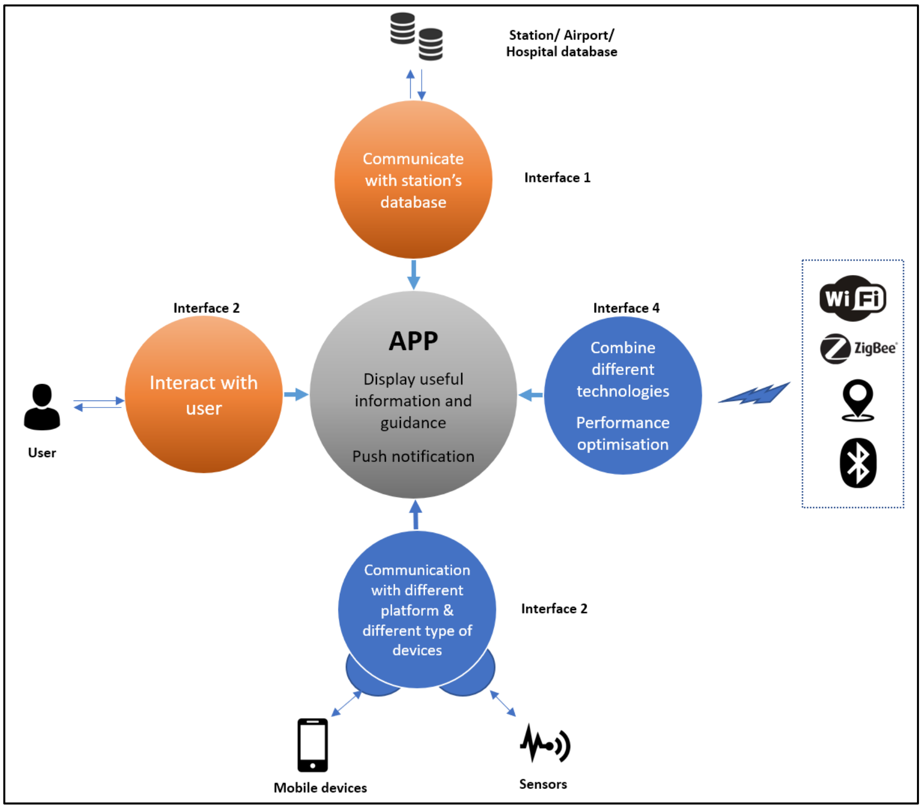


Figure 5.3 System architecture overview

In this thesis, my proposed architecture is focusing on interface 4 which will identify the location of users and objects, with timestamps of their movement, in the indoor environment.

Taking an insight into the architecture for interface 4, of my proposed tracking system, Figure 5.4 describes the general working flow of the system. There are three main stages:

- Modelling and collecting data: beacons are pre-installed in appropriate positions (as identified in my earlier work) (Nguyen et al., 2017). Their positions and the reference RSSI value will be collected, measured and calibrated. Users with BLE-enabled devices/tags will communicate with these beacons. Useful information such as RSSI, timestamp, height, etc. are collected and will be analysed in the next stage.
- Data processing and position calculation: the RSSI value collected in the previous stage is filtered and processed through a set of improved LSE calculations (Nguyen et al., 2017) in order to estimate the actual position of devices. Other integrated data will be analysed in this stage.
- Output: the position is provided after achieving satisfactory error correction. Real-time tracking in a grid map, 2D map or 3D map is presented. Other metrics such as fall detection, heart rate, etc. will be communicated to appropriate staff.

As mentioned earlier, BLE is chosen as the primary technology for the tracking system due to its advanced technical capability compared to other competitors available on the market. Figure 5.5 illustrates the schematic of my implementation. The BLE-enabled beacons are used as anchors. They advertise their identity and transmission power periodically. This advertisement will be picked up by the user's device when they enter within the range of a beacon. On receiving the data from beacons, the APP in the user's device will process the data and calculate the distance between itself and the beacons. If the device is offline, i.e. there is no internet connection, the Offline Positioning module in the APP should estimate the position of the device and display it in the offline map. The tracking/navigation and any guidance will be based on this offline data. If there is an internet connection, all collected and calculated data would be transferred to a server. This server will execute the localisation and other data processing in real-time. A comparison process between estimated positions in the server will be made in order to select the most satisfactory result based on the actual application. The positioning technique used at this stage of research is my hybrid Centroid-Least Square Estimation (Nguyen et al., 2017) and it is named iLSE.

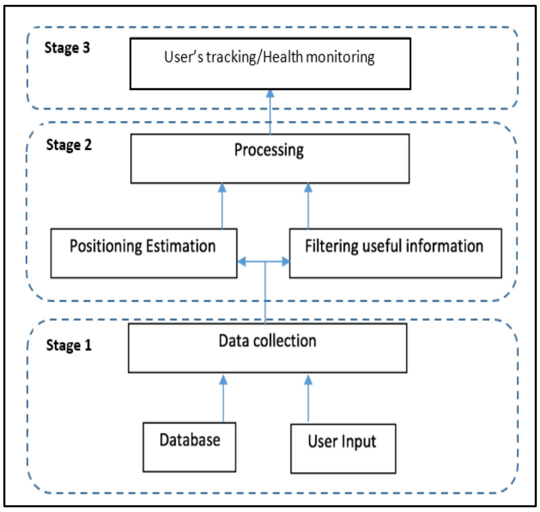


Figure 5.4 Indoor Positioning working flow

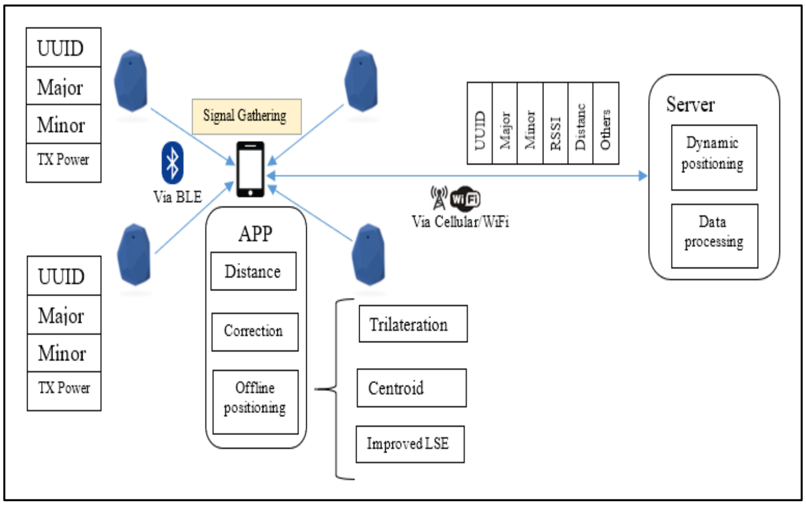


Figure 5.5 BLE positioning overview

5.2.2 Positioning step

The detailed steps of the proposed optimised indoor positioning approach using iBeacon and Bluetooth are also shown in Figure 5.6. There are four steps which obeys our general working flows preparation, which includes mapping and beacon deployment; collect data and modelling, position calculation and output.

Below is the step by step breakdown of the experiment result.

- Collect RSSI values from beacons at pre-defined position.
- Find environment factor η and calibrate A.
- Measure RSSI value from beacons to devices.
- Smoothing RSSI uses Kalman Filter.
- Calculate distance estimate from the log-normal shadowing model.
- Position estimation (x_0, y_0) using Trilateration-Weighted Centroid approach as the initial state.
- Position estimation (x, y) using improved Least Square Estimation for t number of times until Δx and Δy are satisfied.
- Measure and calculate errors. Get feedback and output.

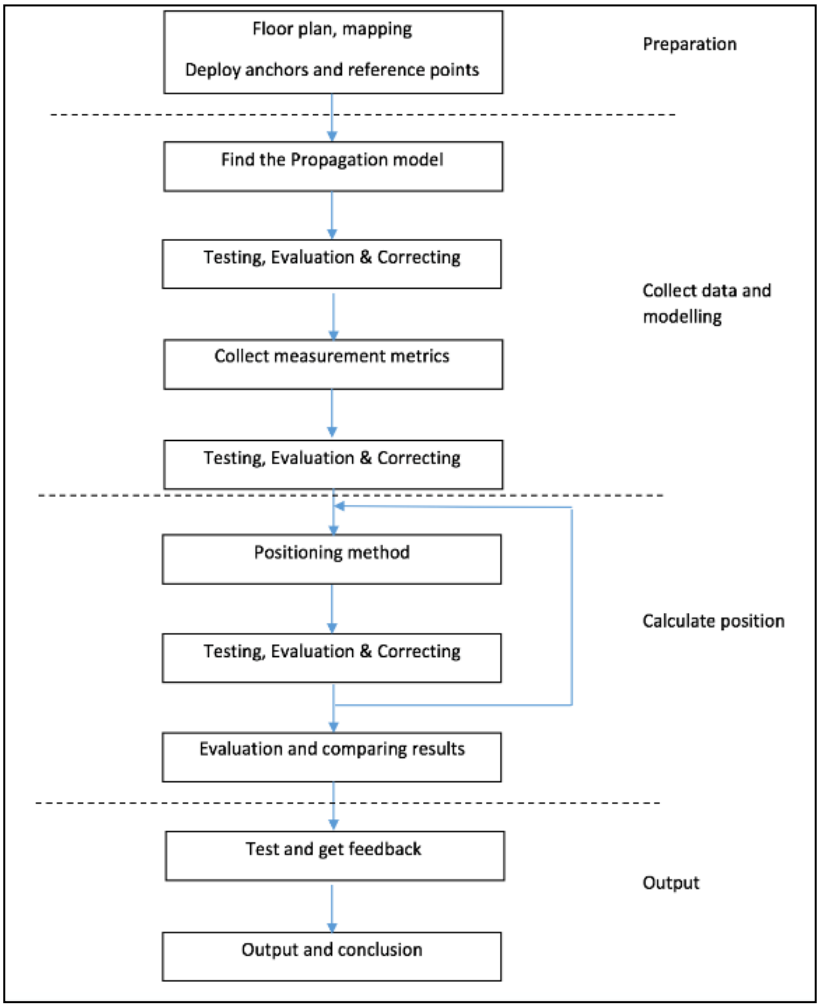


Figure 5.6 Optimized Indoor Positioning step

5.2.3 Calibrated localisation

Using the reference distance as 1 metre, we see that the distance and RSSI are dependent on A and η as given by formula (5.9):

$$\mathrm{RSSI} = \mathrm{A} - 10 \times \eta \times \log_{10}(\mathrm{d}/\mathrm{d}_0) \tag{5.9}$$

Under the complexity of different indoor environments such as multipath, human body, interference etc., and the device's condition such as battery life, antenna direction, choosing a generic set value of A and η can cause errors in ranging estimation later. Hence, these factors should be calibrated and corrected.

In the given area where the localisation of a device is to be calibrated, $[\mathrm{d}]_\mathrm{n}$ is a set of n known reference distances $[\,\mathrm{d}_1, \mathrm{d}_2 \ldots \mathrm{d}_{\mathrm{n}-1}, \mathrm{d}_\mathrm{n}]$ and $[\mathrm{RSSI}]_\mathrm{n}$ is a set of n pre-measured RSSI $[\mathrm{RSSI}_1, \mathrm{RSSI}_2 \ldots \mathrm{RSSI}_{\mathrm{n}-1}, \mathrm{RSSI}_\mathrm{n}]$. This is shown in figure 5.7. Using a linear regression method, the relationship between A and η can be expressed by the formula (5.10):

$$[\mathrm{RSSI}]_\mathrm{n} = \eta \times [\mathrm{d}]_\mathrm{n} + \mathrm{A} \tag{5.10}$$

Solving (5.10) gives the value of A and η for a specific area and a device. The pseudo-code for the calibration is shown as below:

```
Algorithm 1: CALIBRATION

// This program can be used to calibrate the environment factor and
reference power for each node or the whole environment for
simplicity.

Input:  number of iBeacons NB

        number of known device's location n

        distance between K iBeacons and n devices locations d

Output: environment factor η

        reference power A

1.  INITIAL: RSSI to zero

2.  INPUT: NB, n, d

// Measure RSSI from each known device's location to each reference
iBeacons
```

```
FOR n device's location DO
    FOR NB beacons DO
        P = measure the mean received power at known location
    ENDFOR
    RSSI = calculated P for n device's locations and K beacons
ENDFOR
// Execute linear regression to calculate the output
WHILE true DO
    η, A  ← linear regression RSSI and d
ENDWHILE
OUTPUT η, A
```

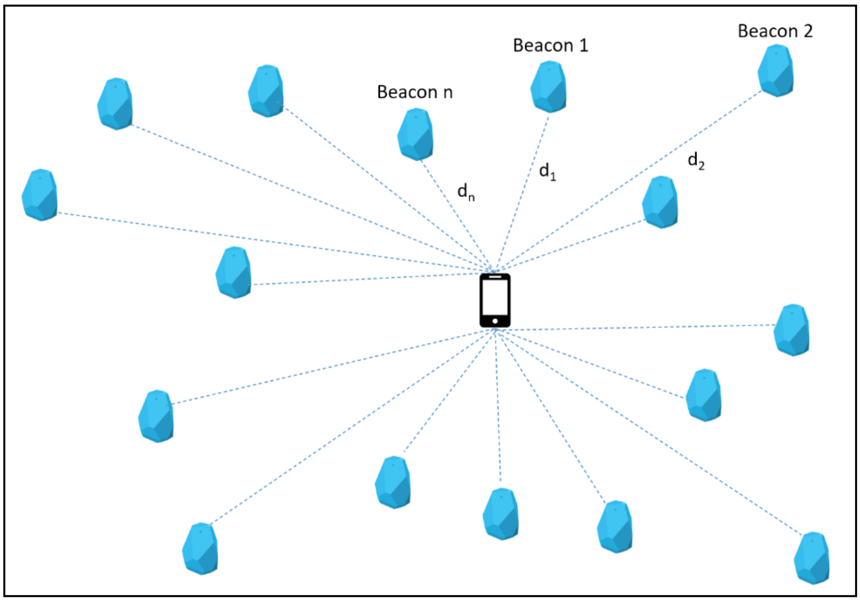


Figure 5.7 Calibration phase measurements

5.2.4 Positioning calculation

Weighted Centroid

In practical calculation of Formula (2.5) a scenario may arise where the distance between two beacons is larger than the sum of distances from these beacons to the device. For example,

$L_{AB} > d_1 + d_2$, i.e. the Euclidean distance between beacons A and B is larger than the sum of distances from A and B to the device. Figure 5.8 describes this scenario. This leads to values in the imaginary quadrant, which in turn will require more complex processing when finding the intersection. Furthermore, in the centroid calculation, all the beacons and devices are treated equally regardless of their distance from the device. Hence, it may lead to error in the position calculation. The RSSI or the estimated distance can be used to overcome this issue of the Trilateration–Centroid approach without increasing the complexity.

The RSSI from each beacon to device shows the contribution of each beacon to the positioning. Furthermore, RSSI represents the relationship in terms of signal strength and distance between beacons and devices. Hence, the weighted factor w can be expressed with distance to represent the contribution of each beacon as Formula (5.11):

$$w_i = \frac{1}{{d_i}^{\omega}} \tag{5.11}$$

where ω is the degree representing the contribution of each beacon. In the testbed, as the distance under 10m so the ω is set to be 1 (Blumenthal et al., 2007). The weighted factor for intersection points D_1 , D_2 and D_3 can be expressed as follows (5.12):

$$\widetilde{w_1} = \frac{1}{{d_1}^{\omega} + {d_2}^{\omega}} \qquad \widetilde{w}_3 = \frac{1}{{d_3}^{\omega} + {d_4}^{\omega}}$$
$$\widetilde{w_2} = \frac{1}{{d_2}^{\omega} + {d_3}^{\omega}} \qquad \widetilde{w}_4 = \frac{1}{{d_4}^{\omega} + {d_1}^{\omega}} \tag{5.12}$$

However, in these weighted distances, if one distance is much larger than another, the beacon with the smaller distance to the device might be considered as unimportant. In fact, this should be understood in the opposite situation. The smaller distance the more major role a beacon should play. Hence, resolving (5.11) and (5.12), the weighted centroid algorithm is modified in (5.13) as agreed with (Shi, 2012):

$$w_1 = \frac{1}{{d_1}^{\omega}} + \frac{1}{{d_2}^{\omega}} \qquad w_3 = \frac{1}{{d_3}^{\omega}} + \frac{1}{{d_4}^{\omega}}$$
$$w_2 = \frac{1}{{d_2}^{\omega}} + \frac{1}{{d_3}^{\omega}} \qquad w_4 = \frac{1}{{d_4}^{\omega}} + \frac{1}{{d_1}^{\omega}} \tag{5.13}$$

And the final position results in the following formula (5.14):

$$x = \frac{\sum_{i=1}^{h} x_{D_i} w_i}{\sum_{i=1}^{h} w_i} \qquad y = \frac{\sum_{i=1}^{h} y_{D_i} w_i}{\sum_{i=1}^{h} w_i} \tag{5.14}$$

where h is the number of intersection points, (x_{D_i}, y_{D_i}) are the intersection points.

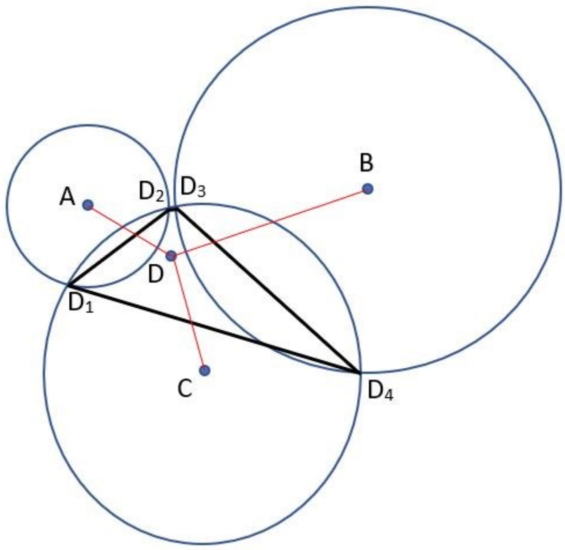


Figure 5.8 Weighted centroid

Improved Least Square Estimation

In the classic LSE, it always uses the position (0, 0) as the initialisation. The main idea of this improvement is cooperating with the prior positioning result from the trilateration – weighted centroid algorithm and finding the value of change in distance between two immediate states. Resolving Equation (2.5), the Euclidean distance between the beacon and device can be found, which is represented as a function of x and y, shown below:

$$d_i^k = f(x^k, y^k) = \sqrt{(x^k - x_i)^2 + (y^k - y_i)^2} \tag{5.15}$$

where d_i^k is the distance from beacon i to the device at the time state k (x^k, y^k) is the estimated position and (x_i, y_i) is the beacon i position.

Using Taylor expansion to find the distance in the next time state k+1 as expression (5.16):

$$f(x^{k+1}, y^{k+1}) = f(x^k, y^k) + \frac{\partial f(x^k, y^k)}{\partial x^k} \Delta x^k + \frac{\partial f(x^k, y^k)}{\partial y^k} \Delta y^k \tag{5.16}$$

As $f(x^k, y^k)$ is the first-order function, the Taylor expansion results in (5.17):

$$d_i^{k+1} = f(x^{k+1}, y^{k+1}) = d_i^k - \frac{x_i - x^k}{d_i^k}\Delta x^k - \frac{y_i - y^k}{d_i^k}\Delta y^k \tag{5.17}$$

In this equation, $\Delta x^k = x^{k+1} - x^k$ and $\Delta y^k = y^{k+1} - y^k$ are the change in distance between time k and k+1. If either of these values is 0, it can be considered as the classic Least Square problem.

For n beacons in 2D dimension and static devices, we can express (5.17) as a series of matrices representing the coordinates over the Euclidean distance, change in Euclidean distance and change in time states of coordinates (5.18), (5.19) and (5.20):

$$M = \begin{bmatrix} \frac{x_1 - x^k}{d_1^k} & \frac{y_1 - y^k}{d_1^k} \\ \vdots & \vdots \\ \frac{x_n - x^k}{d_n^k} & \frac{y_n - y^k}{d_n^k} \end{bmatrix} \tag{5.18}$$

$$\beta = \begin{bmatrix} d_1^{k+1} - d_1^k \\ \vdots \\ d_n^{k+1} - d_n^k \end{bmatrix} \tag{5.19}$$

$$\hat{x} = \begin{bmatrix} \Delta x^k \\ \Delta y^k \end{bmatrix} \tag{5.20}$$

This becomes a Least Square problem with the solution of finding: $M\hat{x} \approx \beta$. Solving this problem gives us the change in distance between two immediate states.

The pseudo-code for this algorithm is described as:

```
ALGORITHM 2: iLSE FOR STATIC DEVICE

// This program is used to estimate the position of a static device
using iLSE approach.

Input:  number of iBeacons NB

   i = (1,2,…,NB)

   coordinate of each iBeacon (Xᵢ,Yᵢ)

   time measurement K in seconds

Output: device’s position X,Y
```

1. **INITIAL**: RSSI, R, D, X_0,Y_0 to zero, ω, threshold

2. **INPUT**: NB, (X_i,Y_i), K

3. **FOR** i from 1 to NB beacons **DO**

4.   **FOR** time k from 1 to K **DO**

5. $RSSI_i^k$ = measure the RSSI from device to the i^{th} iBeacon

6.   **ENDFOR**

//Measure the RSSI from the device to i^{th} beacon

7. $RSSI_i$ = $RSSI_i^k$ ← Kalman filter

//Calculate the distance from the device to i^{th} beacon

8. R_i = 10**(($RSSI_i$ – A)/ η)

9. **ENDFOR**

//Calculate all the intersection point of all circles

10. D = intersection_circles(X_i,Y_i,R)

//Calculate initial position value after time K

11. **FOR** h from 1 to length of D **DO**

12. $\left(X_0 = \frac{\sum_{i=1}^{\mathrm{length(D)}} x_{D_i} w_i}{\sum_{i=1}^{\mathrm{length(D)}} w_i},\ Y_0 = \frac{\sum_{i=1}^{\mathrm{length(D)}} y_{D_i} w_i}{\sum_{i=1}^{\mathrm{length(D)}} w_i}\right)$

13. **ENDFOR**

14. (X,Y) = (X_0,Y_0)

//Calculate delta x and delta y using iLSE and update (X,Y)

15. **WHILE** running time t **DO**

16.   (Δx_t,Δy_t) <- improve_LSE(X,Y,R,X_i,Y_i)

17.   **IF** Δx > threshold **AND** Δy > threshold **DO**

18.   X = X + Δx_t

19.   Y = Y + Δy_t

20.   **ENDIF**

21. **OUTPUT** X,Y

22. **ENDWHILE**

5.3 Experiment and observation

5.3.1 Positioning for one device

Testbed set up

Figure 5.9 shows the testbed environment for my experimentation. Four beacons are placed in a grid area of 5x5 meters. They are placed at fixed positions as followed: iBeacon_1 (coordination 0, 0), iBeacon_2 (0, 5), iBeacon_3 (5, 5) and iBeacon_4 (5, 0). There are five different positions of devices Position A (0, 3), Position B (2, 4), Position C (1, 1), Position D (3, 2), Position E (5, 5). There are ten tables randomly placed around the testbed, but all devices can see each other directly.

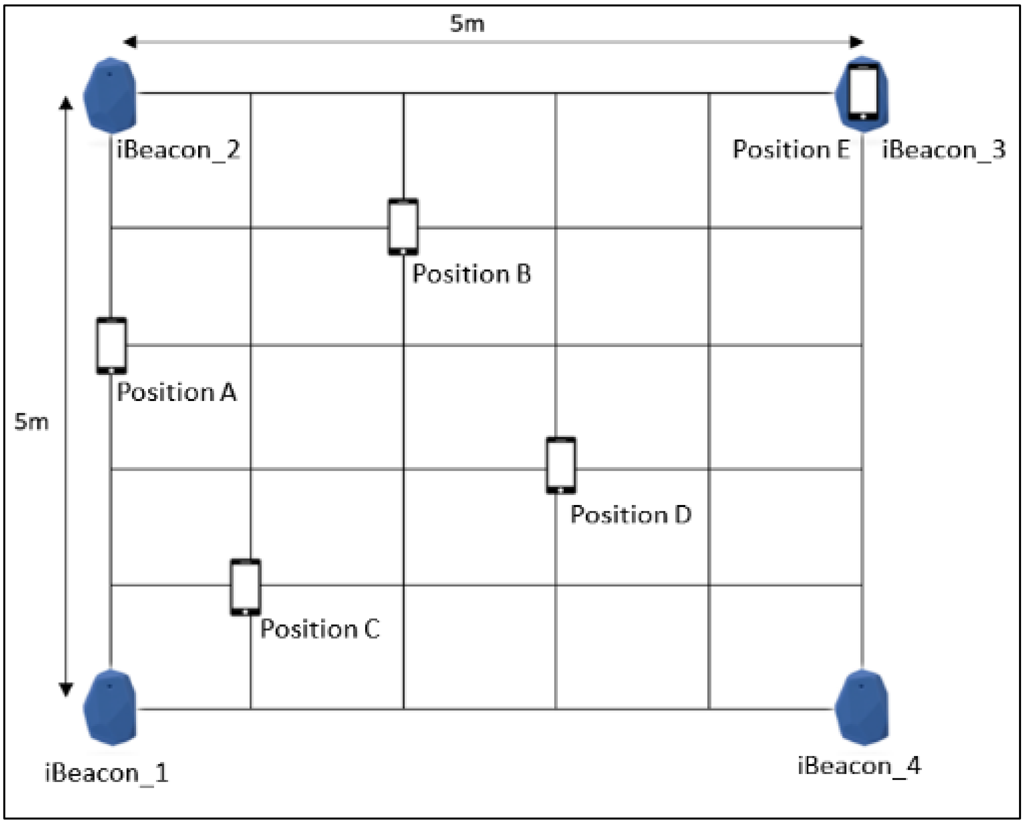


Figure 5.9 Testbed set up

Table 5.1 lists devices used in my experiment for measurements:

Table 5.1 Devices used in the testbed

Items	Details	
	Manufacturer	**Settings**
iBeacon	Estimote	Transmit power: -4 dBm Advertising interval: 400ms
iPad 2	Apple	iOS 10.2.1 Wi-Fi: On - Bluetooth: On

There are several assumptions made for this experimentation as listed below:

- All the devices are static.
- All the antennas are omnidirectional.
- All the devices are at the same height of 1.2m.

Calibration

The RSSI measurements were collected 100 times using Estimote application at predefined locations and fixed distances varying from 0 to 10m on the iPad device. Figure 5.10 shows the calibration results.

The calibrated result gives the environment factor for the testbed as $\eta = 2.6472$. The received signal strength at 1m is A = -54.6476 dBm compared with the Estimote documentation (Estimote.com, 2019), with a transmission power of 4dBm, in theory, A will be approximate -60dBm.

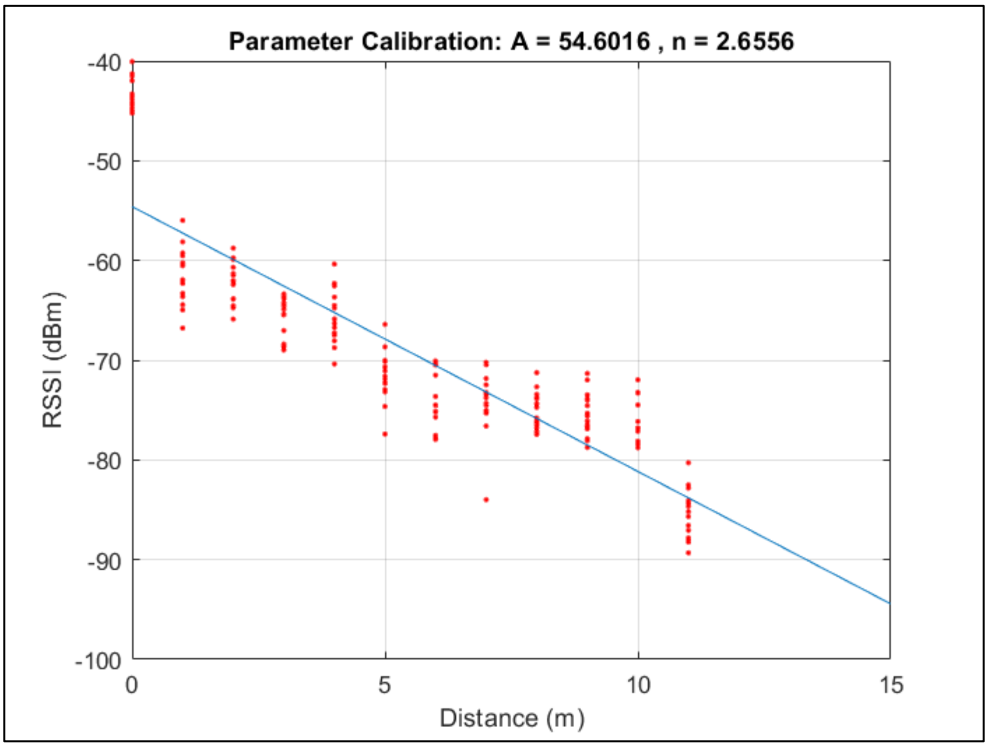


Figure 5.10 Factor Calibration

Positioning result

Figure 5.11 shows the experimental results for the three positioning calculations when applying the Kalman filter for RSSI measurements. Table 5.2 compares the accuracy among approaches.

As can be seen, my proposed approach has the best performance of all three approaches in terms of positioning for a static device in my specific testbed. The mean error for Trilateration-weighted Centroid is 0.375m. The mean error for classic LSE is 0.333m. The improved LSE performs the best with a mean error of 0.192m. This is the result of correcting factor and smoothing the RSSI value. The experiment was replicated 10 times and the average error is about 0.3374m. It is a very promising result considering the area is 25m^2. The precision, therefore, is about 98%. Table 5.3 shows the details of these repetitions.

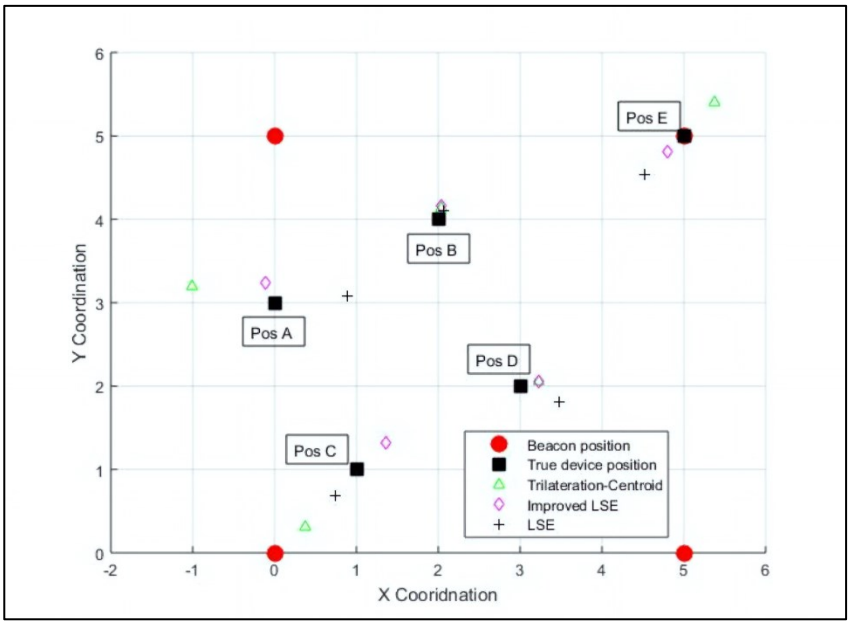


Figure 5.11 Test 1: Static positioning Results

Table 5.2 Positioning Accuracy

Method	**Mean error**	**Maximum error**
Trilateration-weighted Centroid	0.375 m	1.009 m
LSE	0.333 m	0.89 m
Improved LSE	0.192 m	0.354 m

Table 5.3 iLSE repetition result

Improved LSE	**Run 1**	**Run 2**	**Run 3**	**Run 4**	**Run 5**	**Run 6**	**Run 7**	**Run 8**	**Run 9**	**Run 10**
Average Error (m)	0.192	0.302	0.447	0.714	0.451	0.349	0.154	0.136	0.414	0.215

5.3.2 Scalability evaluation

The experiment was expanded to test the scalability and cross-platform capabilities of the proposed algorithm. Using the same testbed introduced in 5.3.1 and iBeacons' placement and configuration is similar, 4 handsets were used including: Samsung Galaxy S6 at position A (0.3), iPad at position B (2.4), Samsung Galaxy S10 at position C (1.1) and iPhone X at position D (3.2). Data were obtained and analyzed using Matlab. Figure 5.12 shows the observation:

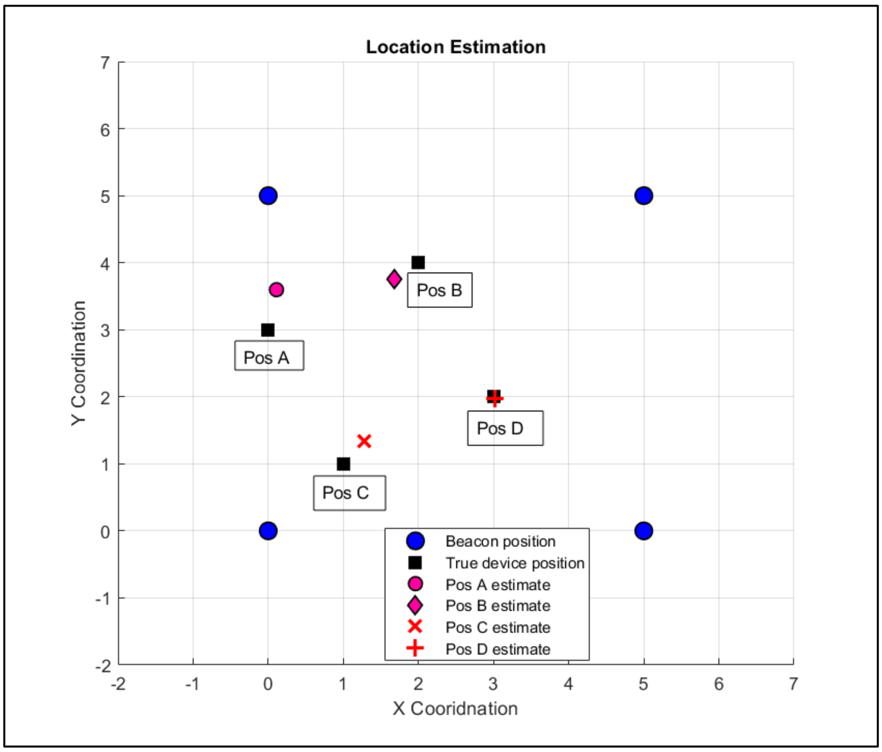


Figure 5.12 Test 2: Static positioning Results for multiple devices

It can be seen that the findings are very positive and the accuracy is still very good. In particular, the findings are shown in Table 5.4. Apart from position D, the average error is around 0.48 m, higher than when only one active user is being tracked. Interestingly, the estimated position at position D is almost perfect, with an error of just 0.031 m. The explanation may be that the iPhone X is a modern device, the Bluetooth antennas and the OS are much improved, so the signal collected is more reliable. This can also be seen by comparing the performance of both Android devices. Samsung Galaxy S10, which is the newer unit, offers better performance than Samsung Galaxy S6 does. In addition, we can see that two iOS devices perform better than

Android devices. The reason may be the iOS native support for iBeacon, which makes the signal more stable.

Table 5.4 Multiple devices tracking result

Result	**Position A**	**Position B**	**Position C**	**Position D**
Device	Samsung Galaxy S6	iPad 2	Samsung Galaxy S10	iPhone X
True Position	(0, 3)	(2, 4)	(1, 1)	(3, 2)
Estimate Position	(0.1096, 3.597)	(1.68, 3.756)	(1.276, 1.332)	(3.022, 1.978)
Error (m)	0.609	0.402	0.43	0.031

We expanded the experiment with a larger testbed and an additional beacon. Four beacons are placed at 4 corners of the testbed, each beacon is 10 m apart: Beacon_1 (0.0), Beacon_2 (0.10), Beacon_3 (10.10), Beacon_4 (10.10). Another Beacon_5 is located in the middle spot (5,5). This experiment simulates the case that the devices are at the edge of the topology and in a broader area. The three devices are positioned at three locations: the iPad at position A, the iPhone X at position B, and the Samsung Galaxy S10 at position C. Again, RSSI data is obtained and processed in the Matlab. Figure 5.13 Test 3: Space Expanded positioning Results the result. In this experiment, the handheld device can receive signals from all 5 beacons at each position. Nevertheless, only three of the strongest RSSI signals were selected and then filtered and processed. We can see that the result is still very good, with a mean error of 0.51 m as expected. In details, the error at positions A, B and C is 0.65 m, 0.065 m and 0.819 m respectively. In particular, the device could gather very strong and reliable signals from all beacons at position B, so the result is very impressive. This indicates that the system has the potential to expand. But, due to the small budget of the report, we have not been able to explore this further. This is going to be discussed in the future with the real-life environment and even more beacons.

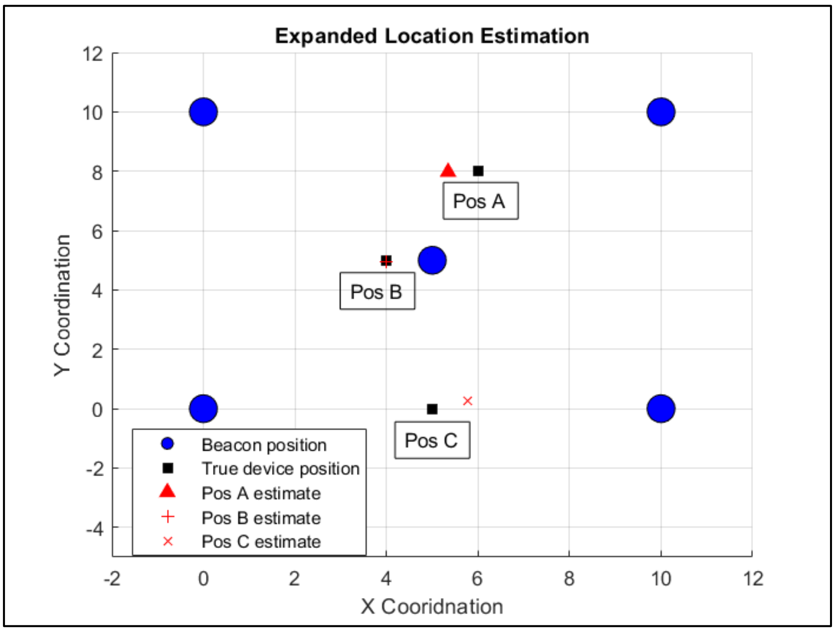


Figure 5.13 Test 3: Space Expanded positioning Results

Table 5.5 Expanded positioning Results

Result	Position A	Position B	Position C
True Position	(6,8)	(4,5)	(5,0)
Estimate position	(5.3466,7.9751)	(4.0009,4.9344)	(5.7747,0.2676)
Error(m)	0.653874	0.06506	0.8196

5.4 Discussion and summary

As seen in the experiments above, the performance of the algorithm is very encouraging with an average accuracy of about 0.3374 m for tracking one device in the testbed and 0.48 m for tracking multiple devices. First, this is because the Kalman filter stabilized the RSSI signal at the calibration stage. Second, especially when the device is on the edge of the testbed or on the side of the testbed, the improved LSE method outperforms its competitors. For example, in position A (0, 3), my method gives the positioning result of (-0.115, 3.233) whereas Trilateration-weighted Centroid results is (-1.009, 3.196) and classic LSE results is (0.8917, 3.078). In position E (5, 5), the Trilateration-Centroid and classic LSE results are (5.382, 5.394) and (4.525, 4.537) respectively. The improved LSE estimates (4.804, 4.807) as the coordinate. This is because, in this position in the testbed, distances from beacons to the device are the farthest, it leads to more fluctuation in RSSI even with the filtering. Furthermore, at larger distances, even small changes in RSSI will result in larger error distance estimations. However, using improved LSE and by incorporating the trilateration-weighted centroid approach results as the initial guess, this error is minimised. In addition, repeated tests were carried out and the accuracy obtained by less than 0.5 mm for 90% of the number of experiments also illustrated the reliability of the algorithm. The system was also tested on a larger scale with a wider testbed and one more beacon were added. Findings indicated that the precision was up to 98%. In particular, the outcomes are very good with a modern device or place that has the ability to obtain strong and stable signals. The error in these scenarios is only about 3-6 cm.

Concerning power consumption, the setting of each beacon is advertising interval of 400ms and transmitting power of-4dBm. We measured the average current consumed by an Estimote beacon is about 0.09mAh in the application and the Estimote beacon is powered by a 1000mAh - 3VCR2477 coin battery. Thus, the total power consumed is just about 27 microwatts. Thus, it can operate for about 10658 hours which is about 14.6 months while maintaining the continuous connectivity. Compared this to other proposing BLE-based indoor positioning which also focuses on the energy-efficient, we can see its advantages. Table 5.6 presents this comparison:

Table 5.6 Power consumption comparison

Author	**Method**	**Power consumption**
Nguyen, 2019	RSSI-based iLSE	27μW
Paterna et al. 2017	RSSI-based Trilateration	54 μW
Sadowski and Spachos, 2018	RSSI For IoT	367 μW

Although, the settings were recommended by the manufacturer. we also varied it to evaluate the effect on power consumption. Table 5.7 presents the findings. It is worth to note that decreasing the advertising interval will increase real-time communication capability but will conduct much more power consumption.

Table 5.7 Power consumption on different settings

Advertising interval (ms)	**Transmitted power (dBm)**	**Average current (mAh)**	**Power consumption** (μW)
100	0	0.35	135
100	-4	0.22	88
200	0	0.17	34
200	-4	0.115	0.345
400	0	0.098	29.4
800	0	0.04	12
800	-4	0.029	8.7

We also do not notice any significant power consumption during data collection and processing. The battery of the smartphone only drops about 2% when collecting data for 10 minutes. Note that smart handhelds still operate other functions in regular use.

We explore another primary aspect of the indoor positioning system, which is processing time as computational complexity. We measured the computational time of the data processing in experiment 1, experiment 2 and experiment 3. The histogram of computational time is shown in Figure 5.14. And the average computational time are presented in Table 5.8

Table 5.8 Computational Time of the algorithm

Experiment	**Test 1: classic LSE algorithm**	**Test 1: improved LSE algorithm**	**Test 2: improved LSE algorithm**	**Test 3: improved LSE algorithm**
Average Computational time (sec)	0.14182	0.20326	0.85034	0.59461

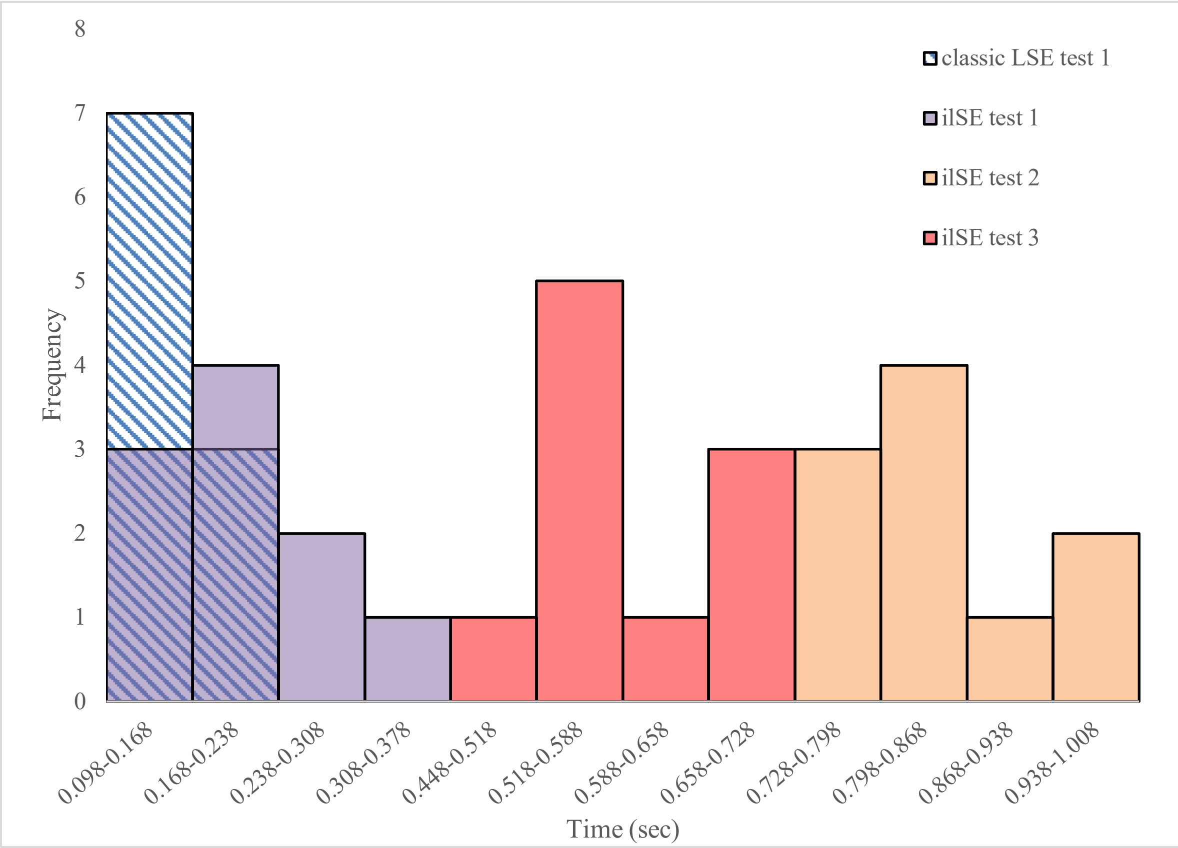


Figure 5.14 Histogram of Computational Time

Looking at the results recorded for experiment 1, the average computational time of the iLSE algorithm is around 0.203s for tracking one device, while the average running time of the classic LSE algorithm is 0.142s. In experiment 2, as the number of mobile nodes increased by 4 times, the processing time also increased by about 4 times and an average of about 0.85 seconds. On the other hand, it was interesting to look at the third experiment, a 3-fold increase in the number of mobile devices and one additional beacon make the data point obtained around 3.75 times. Though, the computational time just increases about 3 times to around 0.595s. The histogram reflects the same observation. While the number of beacon increases or the covered area increases, the processing time does not raise at the same rate. However, in general, the computational time increases with the number of active mobile nodes. This matter will be studied further in future research.

It's not straightforward to compare our system with other systems. This is because each system uses very different criteria, such as beacon manufacturers or environmental factors, even though it is possible to use the same metric as RSSI. Nonetheless, Table 5.9 demonstrates the accuracy and precision of recent BLE-based indoor positioning systems. It can be shown that, with recent testing, BLE-based indoor positioning systems produce very good accuracy. Our proposed system also proved its potential while achieving high accuracy of 0.3m-0.5 m with a working area can be comparable to other systems. This is because implementing the recommended topology setup optimizes the layout of the beacons, as well as the iLSE algorithm, helps to improve the accuracy of the beacons compared to the traditional method.

Table 5.9 Algorithms comparison

Author	**Method**	**Accuracy**	**Range**	**Note**
Nguyen, 2020	RSSI Improved LSE	0.3 -0.5 m	$25m^2$ – $100m^2$	
Insoft, 2020	RSSI	0.5-1 m	Range up to 75m	Commercialised
Huang et al, 2019	RSSI Wi-Fi- fingerprinting	2.2m	$108m^2$	
Huang, He, Du, 2019	RSSI Modified Trilateration	0.757m	$50m^2$	
Mekki et al., 2019	Trilateration	0.5m	$25m^2$	For IoT application.

Chapter 6 Intelligent algorithms for High Accuracy Tracking of Objects

Nowadays, the development of large infrastructures such as airports, railway stations, commercial centres or hospitals requires adequate positioning and navigation at the same standard as GPS for outdoor navigation. The proliferation of smart handheld devices makes it possible to become a reality. Handheld device localisation can help users identify their position in the building in real-time and navigate precisely in the building. Besides, it may also be used in other ways, such as the identification of assets and objects or monitoring of the number of people entering and leaving the building for security reasons. In order to do this, it is essential to have a high precision indoor object tracking system. In this section, an indoor object tracking system based on the system proposed in Chapter 5 will be presented.

6.1 System Overview

At present, solutions for indoor monitoring are primarily divided into two main groups:

- The solution relies on radio frequency signals such as Wi-Fi, RFID and Bluetooth in the same way as the approach described in Chapter 5.
- The solution uses sensors attached to the tracked object.

Each approach has its own advantages and disadvantages. In the first group of the solution, as discussed in the last chapter, static devices work very well. Also, with my proposed method, it does not require the planning of a complex database or intensive data training. It needs only the pre-installed iBeacon and the calibration in the corresponding region and is still capable of achieving high efficiency. Nevertheless, the solution does not work well with high mobility objects and in the application that demand real-time tracking. Fortunately, this is the strength of the second group of solutions. The second set of solutions can predict and calculate the position of an object in real-time with properly installed sensors. However, with only one incorrect prediction, usually at the start or at the turning points, the error of this process will increase as it relies on previous predictions. Thus, a small error can lead to a substantial error when tracking an object. I propose a fusion between the two solutions to monitor objects in the indoor environment method. It will combine the results of the algorithm developed in Chapter 5 for static devices and the results of a pedestrian dead reckoning technique for handheld devices. Figure 6.1 presents my system overview. Details of the system will be present in the next sections.

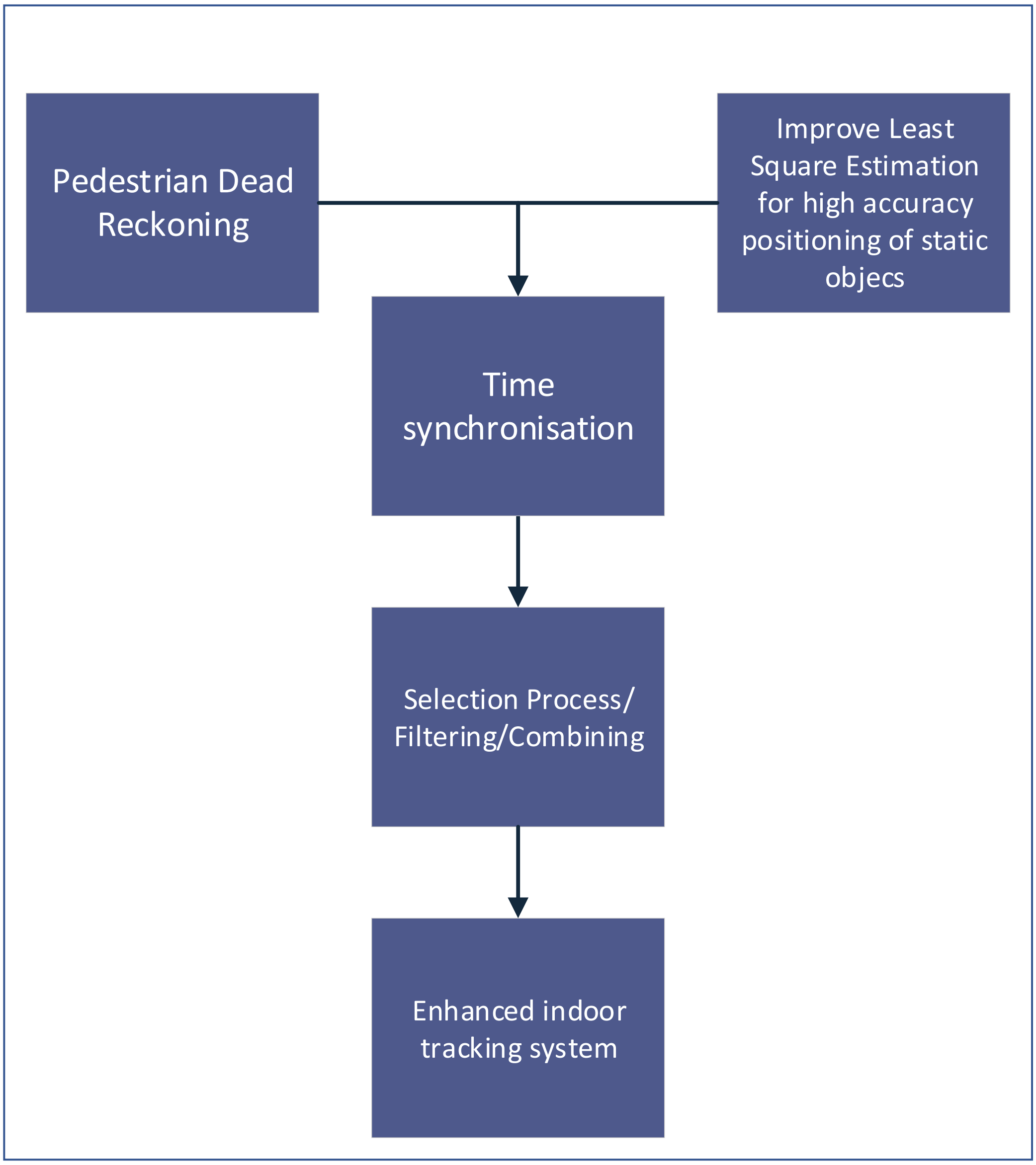


Figure 6.1 Overview of fusion indoor tracking system

6.2 Pedestrian Dead Reckoning

Pedestrian Dead Reckoning is a method used to estimate the movement of an object usually person. This method uses information from the Inertial Measurement Unit (IMU) to detect motion, estimate stride length and direction of motion. This is the foundation of many localisation approaches, such as Simultaneous Localisation and Mapping (SLAM). One of the ways to collect sensor data and execute the PDR as mentioned above is to use an IMU that has been incorporated into smartphones, tablets or smartwatches currently on the market. The IMU in smartphones usually consists of three main types of accelerometer, gyroscopes and magnetometers. Accelerometer information is used for Phase and Step Detection Estimation. The magnetometer is used as a compass to determine the orientation of the object. Lastly, the gyroscope is used to decide the altitude and change the direction of motion of the device. Of course, information from the sensors will be gathered simultaneously and in conjunction with each other to make the most accurate predictions.

As noted, the method can be divided into four main parts: step estimation, estimation of step length and estimation of orientation and estimation of position. My indoor tracking system is also based on these main components.

6.2.1 Step Detection

Step detection is one of the subjects that has recently attracted much study. Many studies are showing good results, but, they share the same fundamentals as using the accelerometer data. The accelerometer is usually embedded into smart handsets. When a user walks, there is a change in the speed and acceleration due to the human motion mechanism. At average walking rates and regular moves, the acceleration will increase and decrease periodically. Calculation of these parameters is the answer to step identification.

Wang et al. (2007) and Jimenez et al. (2009) proposed one way to detect the step. They pointed out that while going forward, the acceleration would go through the zero marks two times in one step. Therefore, a zero-crossing can be counted, and the step can be identified. Based on this, these authors developed and proposed a zero-crossing detection algorithm. All articles presented that their approach achieved excellent results. However, the basic rule is that IMU must be placed on the user's foot, or at least that users can hold a handheld device and walk with swing hands. This study concentrates more on the case of a user using an IMU Integrated Device such as a mobile phone and walking, or a small unit, such as a tag attached to a user's body or the smart device is put in a pocket.

Another way to detect step is to determine the peak magnitude of the acceleration. Mladenov and Mock, 2009 did find the peak value by way of measuring fixtures sample data, averaging it and taken out the peak. As described in the research of Wang and Jimenez, (2007, 2009) while moving, the recurrence of the swing process can produce both positive and negative peaks. The peak can be identified by looking for a maximum or minimum point in a sliding window. After that, the bandpass filter can be used to reduce the defect. If the readings in the window surpass the threshold value of the bandpass filter, a peak is identified. Two peaks establish one step. This will be used in this thesis due to its simplification as well as its well-performance in many cases including walking and running (Ho, Truong and Jeong, 2016). Figure 6.2 presented the step detection algorithm used in the system.

6.2.2 Step Length Detection

Step length estimation is another critical factor in the process. In fact, this parameter varies on each individual, depending on the speed of walking, step frequency and other physical characteristics such as gender age, height, weight, etc. (Renaudin, Susi and Lachapelle, 2012) As a consequence, the measurement of step length is quite difficult in a real application. In several newspapers and magazines (Nina, 2019), the writer provided figures on the average stride length based on age and gender. Of course, the data is still generic and can hardly be used in applications that require very precise accuracy, such as object tracking. Weinberg (2002) proposed a formula for the measurement of user stride length based on a maximum accelerometer founded in the step detection stage. Equation (6.1) shows this:

$$steplength = K \times \sqrt[4]{a_{max} - a_{min}} \tag{6.1}$$

Where a_{max} is the maximum in speed in vertical, a_{min} is minimum in speed in vertical and K is a constant. Ladetto (2000) observed that when the device is in a fixed position relative to the user the relationship between step length and step frequency will be linear. Also, this connection can be applied to this project as users keep and use it in hand or place it in a bag. Step length can be calculated as Equations (6.2) and (6.3):

$$f_{step} = \frac{1}{\Delta_t} \tag{6.2}$$

$$steplength = a \times f_{step} + b \times var + c \tag{6.3}$$

In these, Δ_t is the time interval of a step, (a, b, c) is the coefficient, f_{step} is walking frequency and var is the acceleration variance. Figure 6.3 presented the step length calculation process.

6.2.3 Orientation Estimation

Orientation or heading Estimation is an indispensable step in the PDR process and must be achieved from the very first step of the algorithm. Headings can indicate the direction of travel of the system in the next frame. There are a number of ways to determine the direction of the device. The most basic approaches are to use the compass. The gyroscope is used in modern equipment as an alternative. This will provide the position of the device according to the true magnetic north of the earth, and the output of the device will be in the spherical coordinates (roll, pitch, and yaw). In the sense of this study, indoor 2D tracking is the main focus. The rotation of the yaw provides sufficient data to predict the device direction. A gyroscope and an accelerometer can accomplish this angle. The matrix of rotation is defined as Equation (6.4) with θ is the yaw angle or angle of direction:

$$R(\theta) = \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix} \tag{6.4}$$

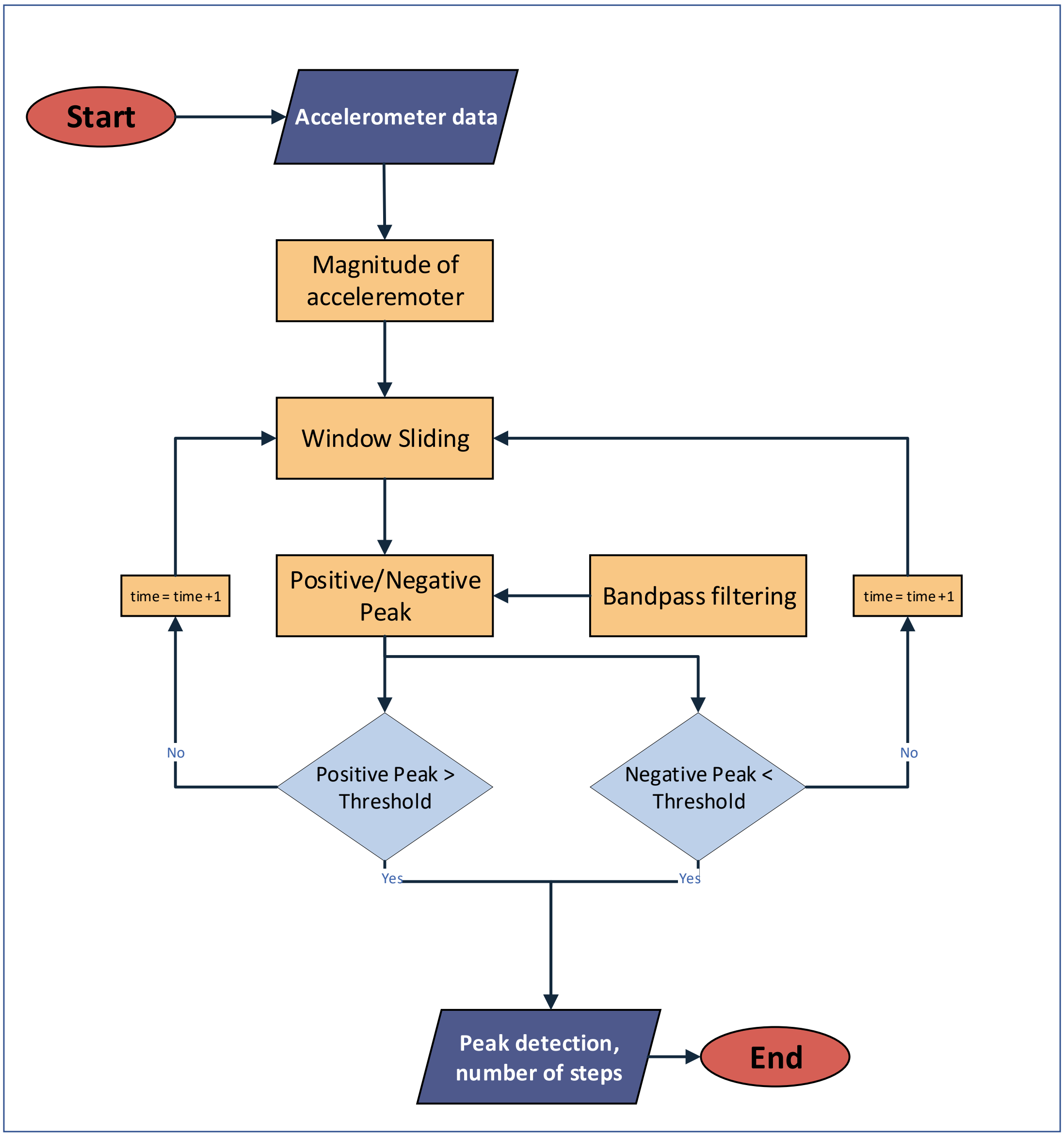


Figure 6.2 Step detection process

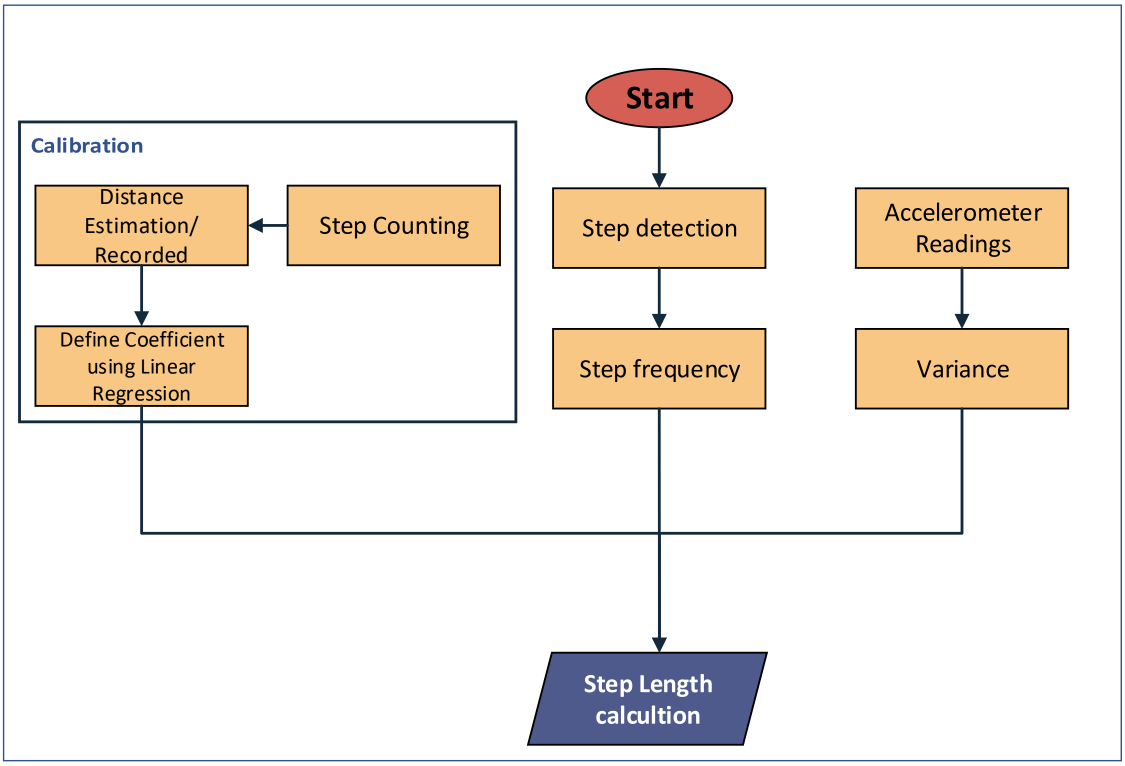


Figure 6.3 Step length calculation process

6.2.4 Indoor tracking by Merging IMU-based PDR and improved RSSI-based BLE positioning

The final step of the indoor tracking system is the calculation of the position for each period. On the basis of measurements taken from the previous stage, including step identification, step sizes, orientation and velocity, the customer's location is calculated in the PDR system. A Kalman filter as described in chapter 5 will be applied for a finer resolution. The position is estimated based on the Equation (6.5).

$$\begin{cases} Pos_t(x) = Pos_{t-1}(x) + SL_t cos(\theta) \\ Pos_t(y) = Pos_{t-1}(y) + SL_t sin(\theta) \end{cases} \tag{6.5}$$

Where θ is yaw angle but also is an angle of direction. Figure 6.4 describes this calculation:

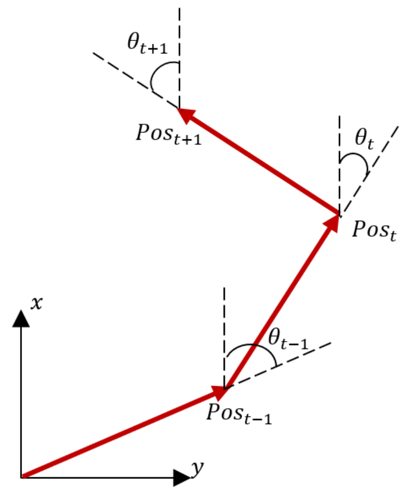


Figure 6.4 PDR position calculation

Nonetheless, the main problem with PDR is volatile. The mistake occurs at any point due to the calculation in each time frame. Apparently, the final error can be high and irrational if the error occurs at the beginning of the measurement process, i.e. at the first few measures, because the PDR uses the previous estimate in order to measure the next estimate. The initial point is often set at (0, 0), which is quite impractical. For example, it creates a significant error if the user's starting point is in the middle of the room. Orientation is another issue because the user may rotate and adjust the direction of the device during the motion. This may make the later orientation estimation incorrect, as the PDR is based on the previous calculation.

In the last chapter, I proposed an RSSI-based approach using iBeacon and BLE to identify the user location. As described and evaluated, the proposed solution has a very positive outcome for static devices with an error of only 0.25 m. We also know that this approach performs poor in real-time and high accuracy tracking application. This is due to the BLE and iBeacon tolerance and update rates. It takes around 8 sec-10 sec to provide the most reliable RSSI signal. Therefore, during the tracking, the position can only update every 10 sec, which is much less than the PDR. However, in each point estimated, the direction and position are satisfied.

A fusion system using my BLE RSSI-based approach and PDR technique to track an object in real-time will be developed. Each approach will perform its own task with the time synchronisation. Then the output will be filtered through a noise filter to eliminate any unwanted interference and spike. The step-by-step method is described in figure 6.5 and pseudo code is presented below:

```
Algorithm 3: FUSION TRACKING

//This program combines PDR and iLSE algorithm to track moving object

Input: sensors information: accelerometer acc, gyroscope g,
magnetometer m

       Timestamp T, beacon position

       received power strength RSSI

Output: Pos(X), Pos(Y)

1.  INITIAL: coefficient a, b ,c, acceleration peak threshold pth,
beacon position (Xi,Yi)

2.  Pos0(X) , Pos0(Y) ← execute iLSE algorithms with (Xi,Yi), RSSI

3.  FOR t from 1 to T DO

4.      INPUT: acc, g, m ,t ,RSSI

// Perform the PDR tracking, take advantage of its update rate

5.      Peak detection ← bandpass filtering, pth, a

6.      Δtt = time of peak p – time of peak pt-1

7.      SL = a * 1/ Δtt + b * var(acc) + c

8.       Extract yaw rotation from gt: θt

9.       Post(X) = Post-1(X) + SLt*cos(θt)

10.      Post(Y) = Post-1(Y) + SLt*sin(θt)

11.     PDR = [PosPDRt(X) PosPDRt(Y) t]

// iLSE tracking, take advantage of its exact orientation and
position

12.     PosLSEt(X), PosLSEt(Y) ← execute iLSE with (Xi,Yi), RSSIt

12.     iLSE = [PosLSEt(X) PosLSEt(Y) t]

// Fusion tracking

13.    Pos(X),Pos(Y) ← apply extended Kalman Filter with more weight
       on iLSE(PDR,iLSE)

14.  OUTPUT Pos(X), Pos(Y)
```

15. **ENDFOR**

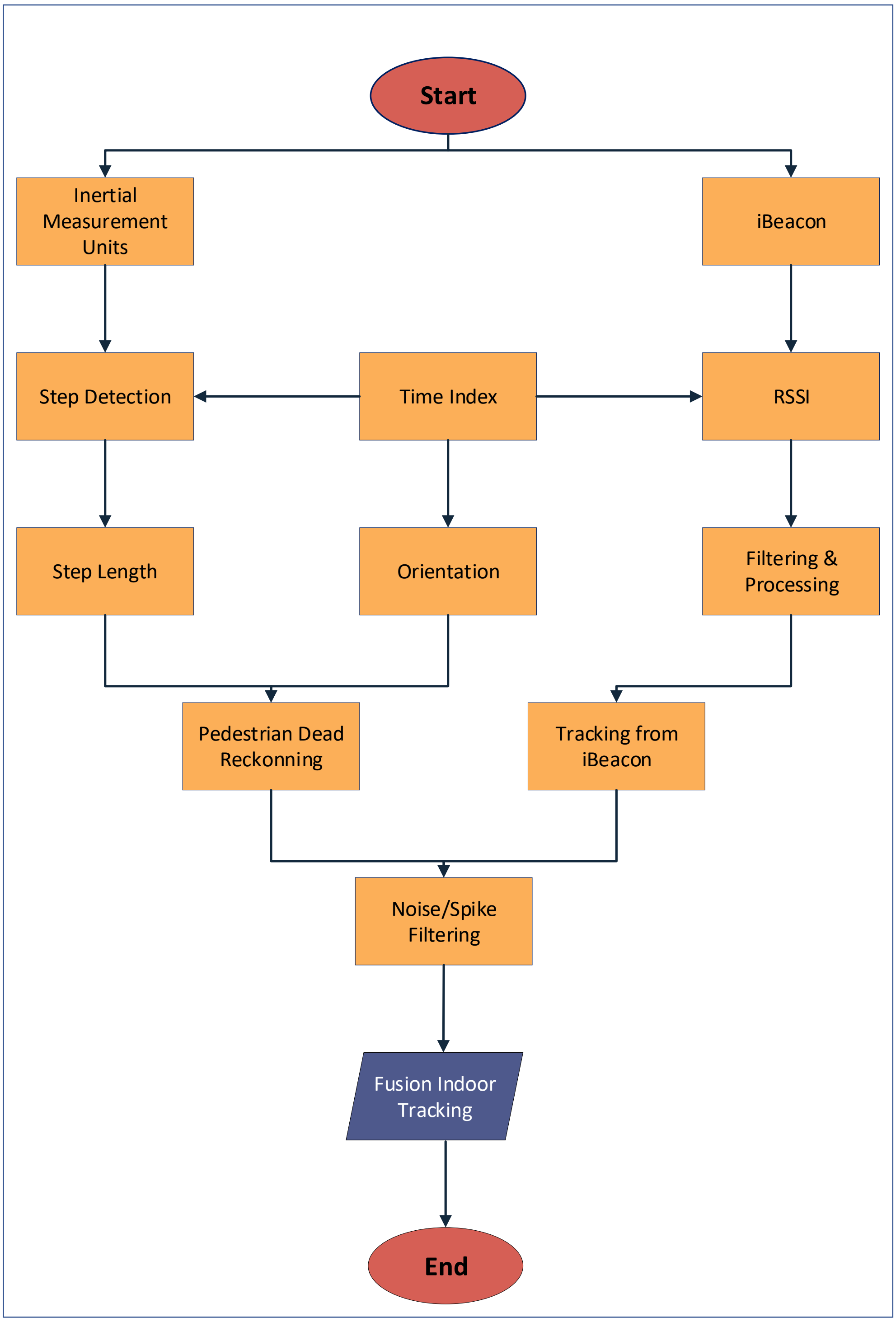


Figure 6.5 Fusion indoor tracking system

6.3 Experimental results

To evaluate the performance of the proposed system, we equate the outcome of the fusion system with the results of the PDR and the result of the proposed solution to chapter 5 for tracking application.

The same testbed but larger as defined in Chapter 5 is used. Thus, to follow the suggestion topology in Chapter 4, two more iBeacons were placed to create 2 equal parallelograms. A person was carrying an iPhone X and was walking at an average speed. Data are collected and transferred from the IMU sensors to the PC in real-time. In order to have the MATLAB compliant format log file without further testing, the MATLAB software on iOS was used to capture these data. Figure 6.6 describes the testbed and the walking path. Table 6.1 presents our devices and software used

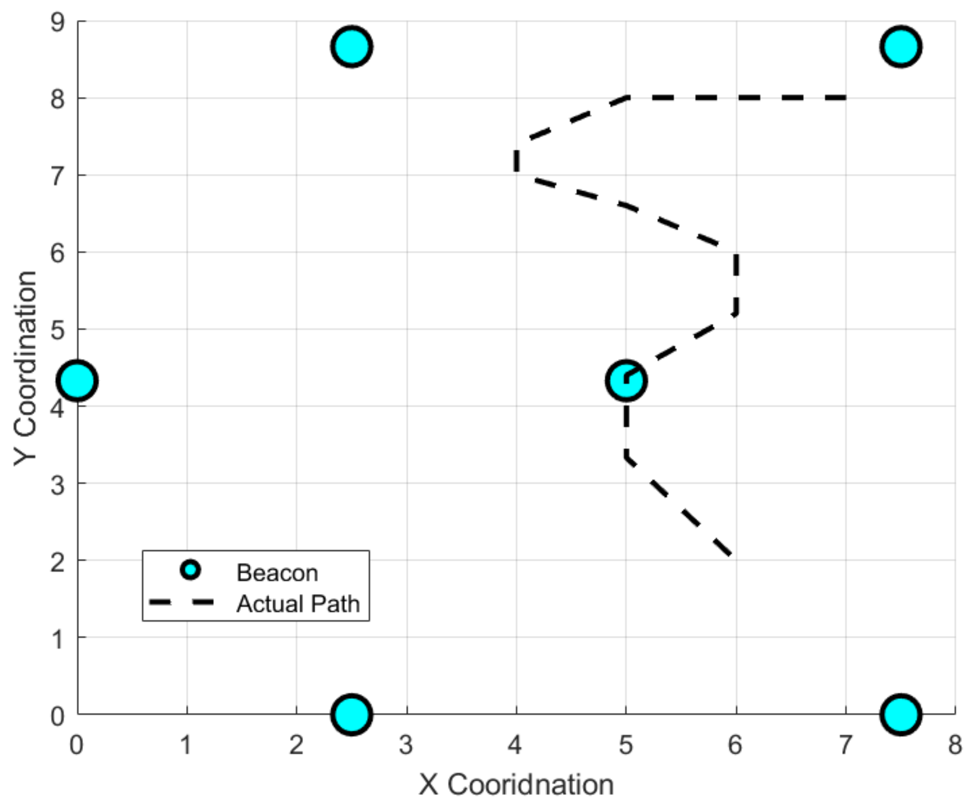


Figure 6.6 Indoor Tracking Testbed and Walking path

Table 6.1 Devices used in the testbed

Items	Details	
	Manufacturer	Settings
iBeacon	Estimote	Transmit power: -4 dBm Advertising interval: 400ms
iPad 2	Apple	iOS 10.2.1 Wi-Fi: On - Bluetooth: On

For this experiment, there are several assumptions:

- All the antennas are omnidirectional.
- All the devices are at the same height of 1.2m.
- The Earth's rotation effect is negligible
- The Earth's force is negligible.

In the scope of this project and experiment, we do not examine the function and performance of PDR solutions. We centred on how the fusion model enhances the performance compared to the traditional PDR in terms of positioning and direction. Therefore, the detailed results of the PDR was not addressed or debated.

My approach is tested in the first experiment. One of the problems identified for my BLE-based approach is the response of the RSSI in real-time. Although the beacon update frequency was set to 1ms, it is found that the phone had picked up the same RSSI value for about 8-9 seconds. This was clarified in chapter 4 that BLE and iBeacon need a few seconds to execute the communication process and a few minutes to become sufficiently stable. Nevertheless, we have also stated that the instability caused by this operating mechanism is acceptable. Therefore, in order to reduce interference and boost battery life, the update rate of the beacon was increased to 20ms as the vendor defaults. The data of the RSSI then be logged every 10 sec. Figure 6.7 shows the tracking result of my proposed algorithm for the static device. As can be seen, although the measured path is not smooth, it achieves entirely appropriate consistency as the route observed followed very close to the actual walking path. The mean error of my modified LSE model is about 0.35 meters, but the peak error is almost 1 meter.

We then tested the PDR tracking methodology with data collected from IMU embedded into the iPhone. Surprisingly, the result was fairly average as shown in figure 6.8. The initial point was found wrongly, and, at some points, the orientation of the route was not right. The average error is roughly 0.84 meters and the peak error is 1.4 meters. There are several explanations for this finding. In the first place, the implemented PDR may not be tailored for the condition used on a mobile phone. The tuning and calibration of the PDR may have taken too much effort and time, so the basic and standard PDR methodology was used for this study. Second, we observed that the orientation of the phone can be changed at any time due to the ordinary handling of the human to the device. It makes the final mistake uncertain. For future work, the solution to these problems could provide an additional and improved approach for the indoor tracking system. Nevertheless, as stated above, in the scope of my research, this finding is used as a reference point for examining the fusion system.

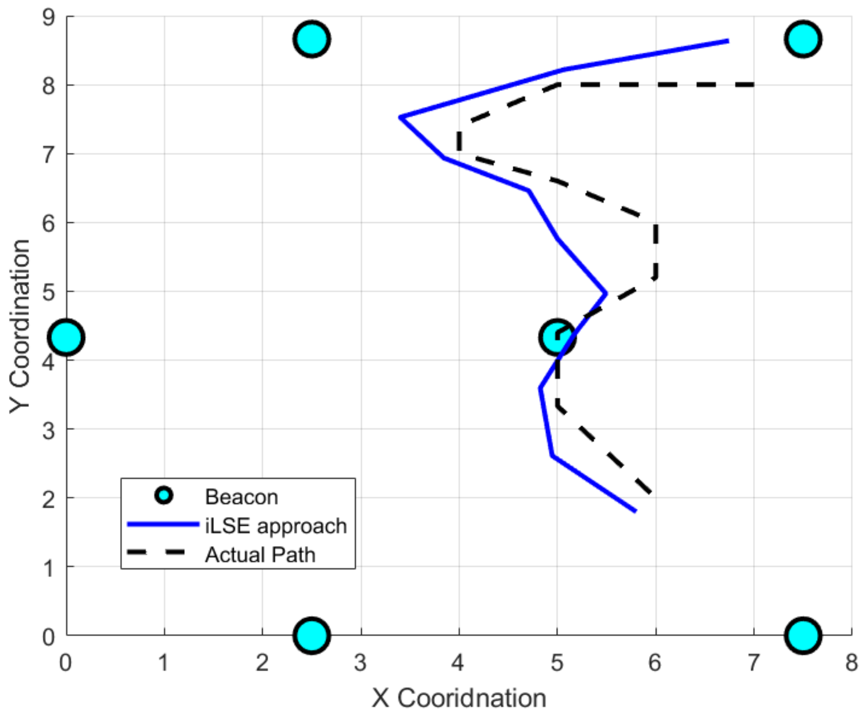


Figure 6.7 iLSE Positioning Tracking Results

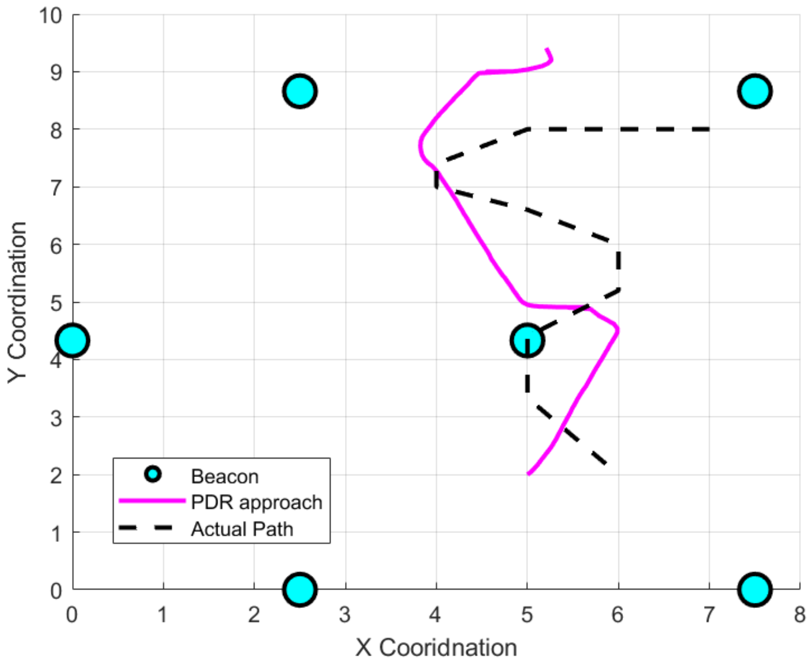


Figure 6.8 PDR Tracking Results

Final, the outputs of two methods were integrated into a single product using an extended Kalman filter. Figure 6.9 shows the outcome. The tracking performance is noticeably improved both in terms of position and orientation. The minimum error is now around 0.2 metres, while the peak error is 0.4 metres. The direction of the walking path is also improved as more weight was put on the iLSE result than the PDR result in the filter. This experience indicates that the quality of an indoor tracking system can be improved by a hybrid model between the classic PDR and my iLSE method. In specific, the iLSE approach plays an important role in the use of user orientation regardless of their movement or handling of smartphones.

In addition, Table 6.3 contrast our proposed approach with other approaches to enhance the PDR. It can be seen that, with the ability to improve the PDR tracking accuracy by 76%, our proposed system is comparable to other proposed systems in terms of accuracy. However, this fusion system is at an early stage, so it has not been tested for practical use. By contrast, for example, the algorithm proposed by Yan et al. 2018 uses PDR in combination with a smartphone camera to provide visual support to the user. Our system will continue to develop in a project to assist first responders. This project is funded by Innovate, UK (KTP, 2020)

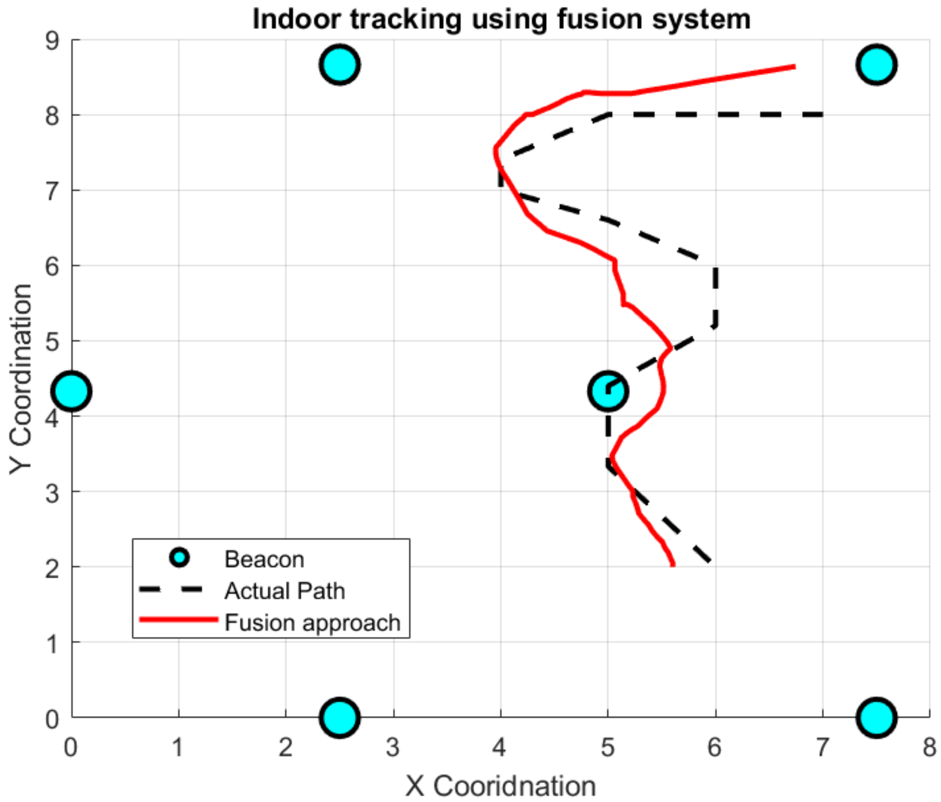


Figure 6.9 Fusion tracking Results

Table 6.2 Positioning Accuracy

Method	**Average error**	**Maximum error**
Improved LSE tracking	0.35 m	1 m
PDR tracking	0.84 m	1.4 m
Fusion tracking	0.2 m	0.4 m

Table 6.3 Compare with other solutions

Author	**Method**	**Improvement**	**Application**
Nguyen, 2020	Fusion with Improved LSE	76%	
Yan et al. 2018	Fusion with Camera	70%	Visual aiding

Yu et al, 2019	Fusion with Wi-Fi	66.4%	
Shi et al, 2018	Fusion with RSSI fingerprint	30%	

Chapter 7 Conclusion and Future work

7.1 Conclusion

I will provide an overview of the outcomes of the system and highlight its outstanding aspects and drawbacks in this chapter.

In summary, an indoor positioning system using Bluetooth Low energy technology and iBeacon has been established and examined using the proposed localisation algorithm. An in-depth survey and extensive assessment of past research and the current market were performed. Studies indicate that each technology has its own advantages and disadvantages, but Bluetooth Low Energy is a prospective candidate for an unique indoor positioning system in hospitals or stations. First, it is the upgrade of Bluetooth Low Energy compared to the traditional Bluetooth. Its operating mechanism means that only installed beacons periodically transmit advertisements, and mobile nodes in the scheme conduct passive scanning and do not need to respond back to the beacon. It would benefit if the number of mobile targets in a region increased considerably. Besides, Bluetooth Low Energy does not involve 10.25 seconds for full scanning and communicating like traditional Bluetooth. Processing time then is considerably decreased and meets the real-time demand of the contemporary indoor positioning system. Another benefit compared to other rivals can be stated as the market accessibility of this technology. Bluetooth and Bluetooth enabled equipment, particularly handheld devices, are penetrating very deeply into the current market. It enables any application created to be able to be applied to the market in a very brief time. This also improves the usability of cross-platform and cross-devices. In fact, this has been verified in my studies in previous sections. The cost also reflects high availability. Devices such as iBeacon and BLE antennas are inexpensive and are commonly powered by the battery. In contrast to Wi-Fi, deployment costs for BLE technology are much cheaper and less power is consumed. Furthermore, by using handheld devices, the localisation scheme can benefit from the available sensors mounted on these phones. Sensors such as accelerometer, gyroscope, etc. can play a significant role in navigating and predicting locations, particularly in complicated circumstances. Together, Bluetooth and iBeacon meet the various demands of indoor navigation systems, such as navigation, which only require a coarser positioning or human/object localisation which requires to be very precise.

The purpose of this study is to develop and propose systems and intelligent indoor positioning algorithms using Bluetooth Low Energy. Therefore, experiments were conducted to verify the characteristics of Bluetooth in indoor localisation. Through tests, it demonstrates that Bluetooth has enough reliability and efficiency to satisfy very high accuracy requirements of my developed indoor positioning system. An optimal set-up of topology based on the experiment was also proposed. It is a topology consisting of 4 beacons and capable of covering an area of around $25m^2$. It helps maintain signal reliability while reducing deployment costs and energy consumption for the entire network.

However, the vulnerability of the RSSI signal in complicated environments or quickly altering objects causes some system issues. We used a suitable filter and appropriate techniques of calibration to solve this instability. The system was developed using iBeacon and the proposed improved Least Square Estimation algorithms. In general, the system and my algorithms gave very positive results with only less than 0.5 m of positioning errors. The test was performed 10 times and for 90 per cent of the measured time, the system achieved the error of less than 0.5m. Maximum error was 0.714 m. In comparison to other system algorithms in which the error ranges from 0.5 m to 2.2 m, the potential of this system can be seen. The processing time is only about 0.20s and does not increase too much as space is increased. Also, the power consumption for each beacon is about 27 microwatts which is relatives low compared to other studies.

A fusion system was also developed and proposed for indoor tracking application. It is a combination between the classic PDR and the improved Least Square Estimation. The experiment shows that despite the underperform of PDR in the testbed, the system is still able to achieve 0.2m average error. The performance is boosted by about 70% compared to classic PDR.

7.2 Limitation

The proposed system has shown positive results and has been successfully tested, but there are still problems that need to be addressed. In the first place, the major limitation of this work is scalability. It can become a concern as the number of users in the region increases. Around that time, the server had to manage more users and the amount of RSSI data collected increased dramatically. This makes the processing time also increased in proportion to the number of users. This issue needed to be addressed and optimised. However, a straightforward solution is building an application so that the RSSI data can be processed within the handheld device. Also regarding the scalability, although the experiment has shown that when the number of beacons increased, the computational time is not greatly increased as the size of the localisation area. However, adding more and more beacons and spreading into a very large area can lead to over-deployment and trigger many waves. Applying big scales also makes maintenance difficult because the beacons can be too dense and at the position that is difficult to reach. At the same time, mixing between old and new beacons can also prompt system efficiency degradation and require more calibration effort. Secondly, in real conditions, the environment can be changed by subjective or objective factors. Beacons may be shifted or damaged, or obstacles may move too often. This makes it possible to mislead the necessary manual calibration at the start and cause mistakes in predicting target locations. This requires manual re-calibration if there are too many changes to the area or environment. Third, the iLSE algorithm alone does not perform well in real-time tracking and updating the user's location. This, therefore, needs to be integrated with other algorithms in order to be able to monitor the user's location in real-time. A solution to this problem is to use the PDR as stated in Chapter 6. Promising findings were presented. However, further design of the PDR fuse with iLSE in both hardware and software is needed for practical use. Fourth, the suggested system uses beacon from the same manufacturer. It is ideal, but it is difficult to implement broadly in practice. However, due to the small budget for studies, this has not been investigated.

7.3 Future work

The project and objectives were concluded as expected. However, there are improvements can be established if more time is allowed to overcome the limitation.

The first is to extend the experiment with various types of beacons, such as Google's Eddystone, AltBeacon's Radius Network, or Tecno-World's GeoBeacon. Each beacon is provided with different communication protocols by different manufacturers. Cooperating with multiple beacon manufacturers would help to improve the efficiency of the system and to qualify for the market. Not only this, research can also be carried out in a range of different environments to further improve and evaluate.

Second, it would be easy and useful to introduce a complete software solution on the smartphone for both Android, iOS or any other popular operating system. Data can be stored locally on devices, making the system work better when scaled up. Third, it is important to tackle the problem of scalability and reduce the time complexity of multiple users. This can be overcome by integrating it with other technologies by using other methods, such as ToA and AoA. Applying ToA and AoA techniques also possible to open the system to a new route: a pre-deployed beacon is not required. It can be achieved by combining the available sensors on the mobile device and integrating a timer into the beacon. The concept of this scheme is to integrate the transceiver straight into the mobile device. By collecting data on ToA and AoA, the system can predict the distance and position of a mobile relative to other existing obstacles. It is beneficial if the system used in the building is not prepared in advance.

Fourth, exploring the use of machine learning and deep learning in the system is another direction. The system can thus adapt to the evolving environment such as shifting obstacles. Adaptability to failure is also enhanced at the same time. Besides, ML / DL can assist the system in reconstructing the map of the region as a map grid or as a 3D map by constructing an appropriate database. Fifth, an appropriate PDR approach or similar technique can be developed in order to exploit the best benefit from the fusion system. Finally, enhancing topology and scalability, as well as hybrid technology, will make the system more comfortable and more efficient to adopt and use in the future. From the industry perspective, the system principle can also be used by offering friendlier and rich data output such as picture or audio.

On the other hand, we would recommend a more comprehensive approach to this research after having had this experience. We recommend that we create a virtual simulation environment, for example, using the Robotics Operating System (ROS) platform. In this environment, we can place different beacons from different manufacturers in different circumstances, including height, noise, orientation, topology, speed, number of beacons etc. Other sensors like the accelerometer, the gyroscope can also be integrated easily. Beacons' model and its library can be obtained by collaborating with the manufacturers for sample raw data. This platform allows for convenient, cost-effective and time-effective testing of different beacon installations and the impact of different conditions compared with actual tests. In addition, different algorithms can be tested and optimised in this simulated environment to give an understanding of their performance. Having these results and understanding will help to experiment with real beacons and sensors in a much more efficient manner.

Publication

1. **Q. H. Nguyen**, P. Johnson, T. T. Nguyen and M. Randles, "Optimized indoor positioning for static mode smart devices using BLE," *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, Montreal, QC, 2017, pp. 1-6.
2. **Q. H. Nguyen**, P. Johnson, T. T. Nguyen and M. Randles, "A novel architecture using iBeacons for localization and tracking of people within healthcare environment," *2019 Global IoT Summit (GIoTS)*, Aarhus, Denmark, 2019, pp.1-6.

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Appendix A: improve_LSE.m

improve_LSE(X,Y,R,X_i,Y_i)

```
function [delta_x,delta_y] =
improve_LSE(initial_pos,distances,known_pos)
i=1;
temp_pos(i,:) = initial_pos ;
temp_error = 0 ;
for j = 1 : size(known_pos,1)
temp_error = temp_error + abs((known_pos(j,1) -
temp_pos(i,1))^2 + (known_pos(j,2) - temp_pos(i,2))^2 -
distances(j)^2) ;
end
estimated_error = temp_error ;
while norm(estimated_error) > 1e-2
for j = 1 : size(known_references,1)
m_matrix(j,:) = -2*(known_pos(j,:) - temp_pos(i,:)) ;
f(j) = (known_pos(j,1) - temp_pos(i,1))^2 +
(known_pos(j,2) - temp_pos(i,2))^2 - distances(j)^2 ;
end
estimated_error = -inv(m_matrix' * m_matrix) *
(m_matrix') * f' ;
temp_pos(i+1,:) = temp_pos(i,:) + estimated_error' ;
i = i + 1;
end
delta_x = temp_pos(i,1) ;
delta_y = temp_pos(i,2) ;
```
Z