University of Technology Sydney

Faculty of Engineering & Information Technology

Development of Indoor Positioning System Using RSSI and Beacon Weight Approach in iBeacon Networks

A thesis submitted for degree of

Master (Computer Science)

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Certificate

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List of Abbreviation

AoA	Angel of Arrival
AWBCL	Averaged Weighted Based Centroid Localization
BLE	Bluetooth Low Energy
EKF	Extended Kalman Filter
FRBW	Filtered RSSI Based Weight
GIS	Geographic Information System
GPS	Global Positioning System
INS	Inertial Navigation System
IOC	Initial Operational Capability
IPS	Indoor Positioning System
LAN	Local Area Network
LBS	Location Based Services
LOS	Line Of Sight
MAC	Media Access Control
NLOS	Non Line Of Sight
RFID	Radio-Frequency Identification
RSSI	Received Signal Strength Indicator
SIG	Special Interest Group
TDoA	Time Difference of Arrival
ToA	Time of Arrival
ToF	Time of Flight
UKF	Unscented Kalman Filter
UWB	Ultra Wide Band
WCL	Weight Centroid Localization
WLAN	Wireless Local Area Network

Abstract

Increasing the location accuracy of the Indoor Positioning System (IPS) is an important research area in localization. Utilizing mobile beacons in IPS environment has made localization more accurate and cost-effective. This research developed a Filtered RSSI and Beacon Weight Approach (FRBW) based on improved Received Signal Strength Indicator (RSSI) using Kalman filter. This approach takes both the distance and improved RSSI measurements between beacon nodes into consideration. Kalman filter is applied on the RSSI measurements that eliminate noise of the signal and then applied on FRBW positioning algorithm. The developed approach was applied and validated in IPS experiments using Bluetooth Low Energy beacons. The results show that this FRBW approach has better positioning accuracy and minimum location error, and can be applied in IoT applications in smart city.

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1.

INTRODUCTION

1.1 Background

It is very important to locate objects in any place for many reasons, using the Global Navigation System; objects can be located in an outdoor environment, where walls or people do not obstruct the signal. However, this system loses its ability to accurately locate object positions in an indoor environment; hence, the importance of an Indoor Navigation System that can navigate in an indoor environment and locate objects.

Indoor navigation has become very important recently in order to locate people, devices and objects within the building where GPS signal does not pass due to walls and other factors.

Smartphones are nowadays equipped with many advanced technologies such as sensors and Bluetooth Low Energy (BLE). Utilizing existing technologies such as the Wi-Fi network or BLE for IPS system can significantly reduce the cost and complexity of IPS system deployment in an indoor environment.

Many technologies such as Wi-Fi and BLE have been adopted to locate objects in indoor environment with only hundreds of centimeters of error, however, using existing technologies such as Wi-Fi has minimized the deployment cost, but still the accuracy is the main concern for researchers.

In this research, we have adopted the Kalman filter in order to eliminate the noise in RSSI signal, and improve the RSSI signals quality. Furthermore, we have developed the Filtered RSSI (Received Signal Strength Indicator) based Weight

(FRBW) algorithm that utilizes the Beacon's weight along with the smoothed RSSI values to estimate the objects position in an indoor environment. The results show the position error was decreased to only a few centimeters.

The remainder of this section is organized as follows. The objectives and aims of this research are presented in Section 1.2 while. Section 1.3 explains the indoor positioning system problems. Contributions are in Section 1.4. Publications are listed in Section 1.5, and the overall structure of this thesis is outlined in Section 1.6.

1.2 Research Objective

The primary objective of this research is to develop an Indoor Positioning System using the Bluetooth Low Energy beacon network and smartphone.

The second objective of this research is to Improve Indoor Positioning accuracy by development of a Filtered RSSI and Beacon Weight algorithm.

The last objective of this research is to achieve navigation quality as required by user such as reliability, usability and cost.

1.3 Problems

Locating objects in an indoor environment has attracted many researchers in the last decade. The radio frequency signals cannot travel through walls, and objects such as furniture or people can obstruct the signal path and force the signal to travel more until it reaches the receiver, and therefore the outdoor positioning systems such as the GPS cannot locate objects in the indoor environment. Different technologies such as WiFi, UWB and ultrasonic signals have been used to estimate the objects coordinates in the indoor environment, however, these technologies were either expensive or hard to deploy or the positioning accuracy is very low. Due to this reason, our aim in this research is to develop a positioning algorithm that can use the existing technologies with a very low infrastructure cost with high accuracy in locating object position.

1.4 Thesis Contributions

The main contributions of this thesis are summarized as follows:

1. The development of indoor positioning system using existing technologies in smartphones; the BLE.

2. The development of a new indoor positioning system algorithm that uses Kalman filter as a RSSI signal smoother.

3. The developed indoor positioning system uses low cost and powerful beacons that serves as a reference point in the iBeacon network to estimate the mobile position.

4. The implementation and demonstration of the indoor positioning system is designed to allow easy and quick implementation.

5. The experimental validation of the developed system shows a high accuracy in locating the objects in an indoor environment.

6. The developed indoor positioning system using the Filtered RSSI and Beacon Weight (FRBW) algorithm has a minimum location error of up to 30 cm and can be applied in IoT applications in smart city.

1.5 Publications

Laial Alsmadi, Xiaoying Kong, Kumbesan Sandrasegaran "Improve Indoor Positioning Accuracy Using Filtered RSSI and Beacon Weight Approach in iBeacon Network" in "The 19th International Symposium on Communications and Information Technologies (ISCIT 2019), Vietnam

1.6 Thesis Layout

This section of the study shows the order of the topics, their importance and relationship to each other. This thesis is structured into five Chapters.

Chapter 2 gives an overview of the navigation systems, current indoor positioning systems algorithms and technologies, and the related work carried out in the area of the indoor positioning system using different radio frequency technologies.

Chapter 3 concentrates on the developed FRBW algorithm and gives a detailed description of its phases, which starts by smoothing and eliminating the noise in the RSSI signals using the Kalman filter. The idea of Centroid Localization algorithm and the Beacons' weight are also explained in this chapter. The estimated distance using the Path-Loss model based on raw RSSI values is explained in details.

Chapter 4 gives a full description of the equipment and tools that have been used in this study. This start with Estimote Beacons and applications such as the Matlab and Beacon Scanner. The validation of our developed FRBW algorithm is also discussed. The estimated position results of the 19 different mobile positions are given. In addition, a comparison of the FRBW results with other approaches such as the Estimote and Path-Loss are explained.

Chapter 5 presents the conclusions and proposes the future work in the field of Indoor Positioning Systems.

2.

LITERATURE REVIEW

2.1 Overview of Positioning Systems

Location Based Services (LBS) are increasingly becoming advanced with mobile and telecommunication technologies spewing out at an alarming rate (Raper et al. 2007). Mobile guides and navigation tools have thus become useful digital devices (Krisp & Keler 2015). These navigation systems help people with tasks in environments that are not familiar to them. (Zheng 2011) argues that location aware technologies such as the Global Positioning System (gps) have helped people in their social networks by geotagging contents such as videos and photos while at the same time others have used them to check in or leave reviews for the location of restaurants, schools, hospitals and social facilities.

Using the Global Navigation System, objects can be located in an outdoor environment, where the signal is not obstructed by walls or people. Outdoor navigation has assisted the transport industry by guiding drivers and even providing information about passengers as well as traffic flows (Li, Wang & Zhang 2015). Assistive technology has been enhancing the flexibility with which the elderly and the virtually impaired are able to move around their environments (Hakobyan et al. 2013). These devices have the ability to detect obstacles and redirect a virtually impaired person (Peng et al. 2010) as well as provide the measure of space (Shen et al. 2008) thereby smoothening navigation for the elderly and the disabled (Stepnowski, Kamiński & Demkowicz 2011). The Location Based Technology has also assisted in crime detection, disaster and emergency management, and social participation (Choy et al. 2016).

However, this system loses its ability to accurately locate object positions in an indoor environment due to inadequate indoor positioning methods and lack of Geographic Information System (GIS) data, hence, this shows the importance of an Indoor Navigation System that can navigate in indoor environment and located objects (Raper et al. 2007). Indoor navigation has become very important recently to locate people, devices and objects within the building where GPS signals don't pass due to walls and other factors. Supermarkets, national museums, airports and pharmacies require the location services while locating objects and artefacts and therefore the need to develop an indoor navigation system is increasing (Huang et al. 2018).

Many technologies such as NFC (Ozdenizci, Coskun & Ok 2015), Wi-Fi (Retscher & Roth 2017), UWB (Alarifi et al. 2016), RFID (Bai 2016), Bluetooth RRR, and Bluetooth Low Energy (BLE) have been adopted to locate objects in an indoor environment with only hundreds of centimeters of error. However, using existing technologies such as Wi-Fi has minimized the deployment cost, but still the accuracy is the main concern for researchers. In this research, we have adopted the Kalman filter that was able to eliminate the RSSI noise and improve the signal quality, and then the distance error reduced to only a few centimeters using our developed Filtered RSSI and Beacon Weight (FRBW) algorithm.

Navigation systems are used to locate any wanted object regardless of its current location, and the Global Positioning System (gps) is the most common system that can detect and find the exact location of any object in an outdoor environment. This is due to the standardization of the positioning of objects in the outdoor space as compared to the indoor space. The only limitation for outdoor navigation would be experienced in urban areas where the signals are obstructed due to high buildings and other similar barriers, which is a phenomenon, referred to as the canyon effect. However, the GPS loses its ability to provide accurate location due to signal problems in an indoor environment.

The first problem encountered is the indoor space model. Unlike the outdoor space, the indoor space has not been standardized. This may be due to a number of things including architectural factors that make buildings unique in their design and navigation patterns (Huang et al. 2009). For instance, one may simply look at You-Are-Here maps in order to locate a room in a building manually and without much technology. However, when it comes to technology in indoor navigation, much will be required. Complex computing, standardization and modelling of indoor space are beyond researchers (Afyouni, Ray & Claramunt 2016). This makes this area of research even greyer.

In addition, the Indoor Positioning System is a new technology that can provide precise location of any object, even when satellite signals are partially or completely blocked, especially inside the buildings. Besides, this indoor navigation technology suffers from lack of a universal solution such as the GPS that is witnessed with the outdoor positioning. To fill this gap, this research focuses on algorithms that would help in locating objects position within a building despite of these obstacles and reduce the positioning localization error to a few centimeters only using existing technologies that are embedded in smartphones.

2.1.1 Outdoor Positioning Systems

The outdoor navigation system uses the Global Navigation Satellite Systems (GNSS) such as GPS, Galileo, BeiDou and GLONASS to navigate and locate any object in the open space (Huang et al. 2018). The Global Positioning System (gps) which was developed by the US air force in 1973 is considered the standard outdoor navigation system. It provides users with location, navigation, and indicate the time (Chen 2012). The GPS system uses a constellation of 24 satellite called the initial operational capability (IOC) and consists of three segments: the space segment, the control segment; and the user segment (El-Rabbany 2002).

GPS satellites broadcast the signals with high accuracy; however the accuracy of the received signal depends on satellite geometry and receiver design features and quality (El-Rabbany 2002), which means the accuracy of GPS enabled smartphone is within 4.9 m under an open sky (van Diggelen & Enge 2015). Although it is easy to scale the GPS system, GPS does not work well in an indoor environment because the GPS signal can by blocked by building or any other physical barrier.

The GPS does not require the user to transmit any data, and it operates independently of any telephonic or internet reception, though these technologies can enhance the usefulness of the GPS positioning information. The GPS provides critical positioning capabilities to military, civil, and commercial users around the world. The United States government created the system, maintains it, and makes it freely accessible to anyone with a GPS receiver (El-Rabbany 2002).

2.1.2 Indoor Positioning Systems

Modern smartphones are rapidly becoming very important in our daily life not only for communication purpose, but also as a navigation, medical and learning device. The wireless indoor navigation system is a system to locate objects or people inside a building using radio waves, magnetic fields, acoustic signals, or other sensory information collected by mobile devices (Curran et al. 2011).

2.2 Indoor Positioning Systems: Technologies and Algorithms

2.2.1 IPS: Technologies

The wireless based communication requires two parts, the station that sends the wireless signals and the station that receives the wireless signals. Different technologies have been used in indoor navigation systems.

The propagation of the wireless wave can be influenced by reflection, scattering, and diffraction. The signal strength can be affected by multi path fading or shadow fading in the indoor environment (Li, Wang & Zhang 2015).

The wireless indoor navigation system is much cheaper and easier to deploy than any other approach, however, there are still problems in the accuracy, and many approaches and technologies have been used to minimize the error. In the following sections, we shall explore all the available wireless technologies that have been used in Indoor Positioning Systems.

2.2.1.1 Wi-Fi

Wi-Fi is a technology for radio wireless local area networking of devices based on the IEEE 802.11 (-Wi-Fi). The most common forms are IEEE 802.11b and 802.11g. It employs various bands in its operation such as 2.4 GHZ and 5 GHZ. The IEEE 802.11 standard is a set of media access control (MAC) and physical layer (PHY) specifications for implementing wireless local area network (WLAN) computer communication in the 2.4, 3.6, 5, and 60 GHz frequency bands (LAN). They are created and maintained by the IEEE LAN/MAN Standards Committee (IEEE 802). Wi-Fi allows wireless deployment of local area network (LANs) and areas where the connective cables cannot be placed. There are various hindrances to its accessibility such as the material used in building, whereby thick metals and bricks may block the accessibility of the signals (Ismail et al. 2008).

There are many factors, which determine the maximum range the Wi-Fi signal can achieve such as the transmitter antenna type, interference caused by the environment, the transmitter output power and the receiver antenna type. The output power of any transmitter that uses the radio frequency signals is measured in dBm. The transmitted signal in 802.11 b/g standard reaches 100 metres in an open space when transmitted at 30 dBm (Downey 2013).

The 802.11b and 802.11g function on the 2.4 GHz uses 14 channels spaced 5 MHz from each other except for a 12 MHz space before the channel 14 bandwidth to transmit over the 14 overlapping channels with 22 MHz length (IEEE 2012). The 2.4 GHz channels are depicted in Figure 2.1

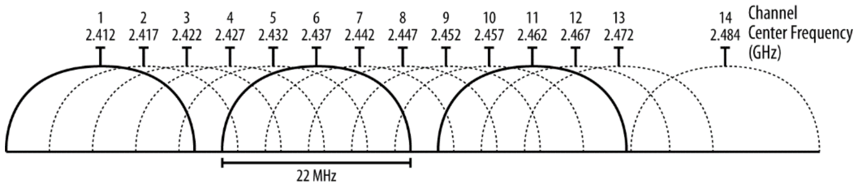

Figure 2.1: Wi-Fi channels on the 2.4 GHz frequency band (Wifi).

The 802.11ac standard can work on both 2.4 GHz and 5 GHz bands. In this version, the bandwidth was doubled from 20 MHz to 40 MHz per channel and supports multiple antennas (Christ & Wernli Sr 2013).

Wi-Fi Positioning Systems have a greater upper hand as compared to other positioning systems. This is because of its compatibility with almost every other device without necessitating installation of additional software. Following its comparative advantage, this system has been the most widespread for indoor localization and navigation systems (Ismail et al. 2008).

Wi-Fi hotspots have been employed in most commercial sites and buildings providing access network in the area. The leap in technology has made the production of devices that support Wi-Fi possible. These devices include laptops, tablets and mobile phones. This significantly reduces the cost of infrastructure and setting up the network coverage; therefore, making it a preference for most buildings (Li, Wang & Zhang 2015).

Many Indoor Positioning Systems have adopted Wi-Fi network to find objects in the indoor environment because of its high availability and low infrastructure cost.

However, due to many Wi-Fi networks security settings and restrictions in public places, the Wi-Fi based IPS system is not always the good option to deploy the IPS.

2.2.1.2 RFID

Radio-frequency identification (RFID) is a well-known technology that uses electromagnetic fields to identify and track tags. The tags contain electronically-stored information (Finkenzeller 2010). RFID systems consist of two elements: the transponder which is located in the object to be identified and the readers (Finkenzeller & Waddington 1999). The reader uses the radio-frequency electromagnetic field to read the data in the tag and get the identification of the tagged object.

There are various RFID tracking applications such as hospital patient tracking, asset tracking, supply chain, security, and medical and healthcare assets tracking. Recently, RFID technologies have been widely deployed in modern logistics and inventory systems for efficient monitoring and identification (Han et al. 2016). This is because RFID technology is considered low-cost, usable, and provide a reliable form of automatic identification, which makes it a cost effective technology to use for localization in indoor environments. Furthermore, RFID has favorable characteristics such as contactless communication, security and a high data rate and non-line-of-sight readability (Elkhodr, Shahrestani & Cheung 2016).

The main disadvantages of RFID technology are the data collisions, which happens while transmitting data between the tag and reader. When the RFID reader reads from more than one tag at the same time, the tag collision occurs, while the reader collision occurs when two readers read the same tag at the same time (Li, Wang & Zhang 2015). Another disadvantage of RFID is the communication range which is around 1 – 2 metres.

2.2.1.3 Inertial Navigation System

The Inertial Navigation System (INS) is a complete navigation system that does not depend on any external reference to calculate the position, orientation and the velocity of a moving object. The INS uses computer and various sensors such as the accelerometers, gyroscopes and magnetometers along with different algorithm such as Kalman filter to calculate the object parameters (Fu & Retscher 2009).

The INS system is composed of at least three gyrometer and three accelerometers that enable the system to drive a navigation solution. This navigation solution contains at least the position (normally latitude, longitude) (Christ & Wernli Sr 2013).

Estimating objects position using the INS suffers from drift due to the fact the any error in acceleration measurement will cause position error because acceleration is integrated to find the position (Berrabah & Baudoin 2011). It has been reported by (Diaz, Ahmed & Kaiser 2019) that the position estimation error caused by using medium and low cost MEMS in inertial navigation systems is due to the z-axis gyroscope. However, (Christ & Wernli Sr 2013) suggests that using aiding device such as the GPS would solve the INS system drift problem.

2.2.1.4 Ultra Wide Band (UWB)

Ultra-wideband is a radio technology that is able to use a very low energy level for short-range, high-bandwidth communications over a large portion of the radio spectrum (UWB). The UWB frequency ranges between 3.1 to 10.6 GHz.

The UWB technology is very suitable for indoor localization because the UWB signals can go through any object and nothing can block the UWB signal. UWB utilizes the time difference of arrival (TDOA) of the RF signals to obtain the distance between the reference point and the target (Song, Jiang & Huang 2011).

Ultra-wide-band localization can achieve high accuracy of up to 20 centimeters in the indoor environment. Although the accuracy of UWB is high, it is a very expensive technology and it requires at least three receivers to receive signals from each tag. In addition, the readers must be synchronized correctly to achieve high position accuracy. The other drawback of using UWB for IPS system is the complexity of the system installation.

2.2.1.5 Bluetooth Low Energy (BLE)

The BLE is a very popular wireless communication that connects devices over small distances (SIG). The Special Interest Group (SIG) regulates and manages the Bluetooth technology. The Bluetooth channels starts at a frequency of 2402 MHz and ends at frequency 2480 MHz, which makes 79 channels during the data transmission phase.

The Bluetooth output power determines the maximum distance that Bluetooth device can connect with another Bluetooth device, based on this, three classes are used to classify the Bluetooth devices (Poole 2005) as shown in Table 2.1

Table 2.1: Bluetooth classes and their corresponding ranges

Class	Maximum Output Power (dBm)	Range
One	20	up to 100 m
Two	4	up to 10 m
Three	0	10 cm

Bluetooth version 4.0 also, called smart Bluetooth or Bluetooth Low Energy (BLE) version was developed in 2010 and released in 2011 and it comes with a low energy feature to collect data from the sensors of low rate devices, which allows Bluetooth module to reduce power consumption with the connected devices.

BLE enjoys a physical layer bit-rate of 1 Mbit/s and transmission power between -20 dBm to +10 dBm (ensuring low power consumption). The number of transmission channels has been reduced from 79 to 40 2 MHz wide channels (Figure 2.2), which are classified into two types (Instruments 2016):

- **Advertising physical channel:** The last three channels (37, 38, 39) used for discovering devices, and these initiate the connection between devices and broadcast data. The BLE advertising allows devices to broadcast information defining their intentions.

- **Data physical channel:** The remaining channels are dedicated for communication between connected devices

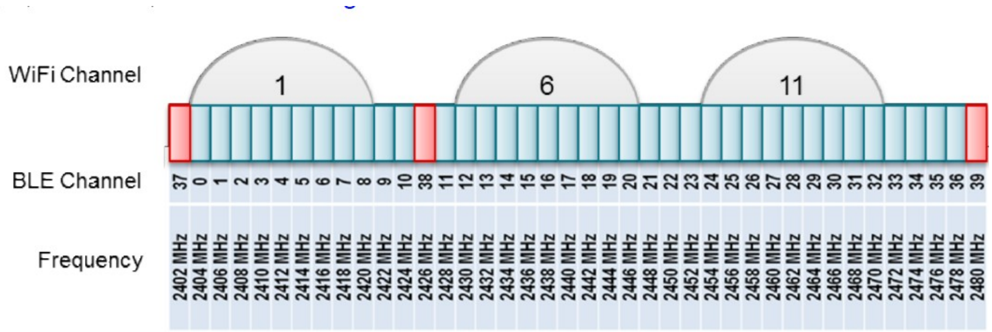

Figure 2.2: Adopted from (Instruments 2016)

The BLE devices can operate in four different roles (Instruments 2016) as following:

- Peripheral: An advertiser is connectable and operates as a slave in a connection such as the heart rate monitor.
- Central: It scans for advertisers, initiate the connections and operates as a master in one or more connection such as the smartphones.
- Broadcaster: A non-connectable advertiser that broadcasts the data such as the temperature sensor.
- Observer: It scans for advertisement but cannot initiate connections such as remote display. It' function is to receive data and present it.

2.2.2 IPS: Mechanism and Algorithms

There are many techniques used to estimate the distance between the mobile device and Beacon in the indoor environment; in addition, many algorithms are proposed in the literature to estimate the positioning and reduce the distance error. In this section, the main indoor positioning techniques and algorithms are explained.

2.2.2.1 Indoor Positioning System Mechanism

2.2.2.1.1 TIME OF ARRIVAL (TOA)

Time of Arrival (ToA) also referred to as the Time of Flight (ToF) is one of the simplest ranging technique used in outdoor and indoor positioning systems and it means the travel time of radio signal from transmitter to the receiver (ToA).

Three parameters are required to calculate the distance using this technique as per Equation (2.1) (Shi & Ming 2016):

- The exact time the signal transmitted at the transmitter.
- The exact time the signal arrives at the receiver.
- The signal speed.

$$d = c * (t_{arrival} - t_{sent}) \qquad (2.1)$$

2.2.2.1.2 TIME DIFFERENCE OF ARRIVAL (TDOA)

In this technique, the time the signal was sent is not important, so it is based on just the time the signal was received at two reference points and the signal speed, and then by finding the difference between the arrival time of the signal at both reference points, the distance can be calculated using Equation 2.2 (Roberts 2004):

$$\Delta d = c * (\Delta t) \qquad (2.2)$$

Where:

d:	distance
c:	signal speed
t:	the arrival time of the signal

2.2.2.1.3 ANGEL OF ARRIVAL (AOA)

The Angle of Arrival technique is defined as the angle between the propagation direction and its reference direction. The reference direction is known as orientation, which is the fixed direction against which the AOAs are measured (Rong & Sichitiu 2006) . The angle of arrival approach requires an antenna array at the receivers. Multiple receivers estimate the AoA of a signal RRR.

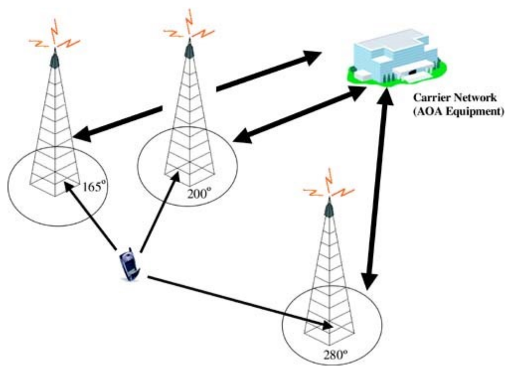

Figure 2.3: Adopted from (Oreilly)

2.2.2.1.4 RECIEVED SIGNAL STRENGTH INDICATOR (RSSI)

The RSSI, which stands for the Received Signal Strength Indicator, represents the measured power in the received signal. The RSSI values is measured in dBm, where dBm is the decibel milliwat. It is represented in a negative form, when the RSSI values is higher, then the signal is stronger and vice-versa. Based on this, the signal with -70 RSSI values is weaker than the signal with -10 RSSI values (RSSI).

2.2.2.2 Indoor Positioning System Algorithms

2.2.2.2.1 TRIANGULATION:

Triangulation is the process of estimating the objects location using the geometric properties of triangles (Triangulation). It has two techniques to estimate the position, the lateration and angulation.

In lateration technique, the TOA or TDOA mechanism are used to measure and estimate the distance between two nodes. However, this technique requires extra hardware for time synchronization. The angulation technique uses the AOS mechanism to estimate or measure the distance between two nodes and it does not require any time synchronization, which lower the deployment cost.

2.2.2.2.2 FINGERPRINT

Fingerprinting uses the RSSI values of a group of devices to create a signature (Fingerprint) of a specific location (Fingerprint). This is done by storing these values, along with the addresses of their corresponding devices in a database. Once several Fingerprints of different locations are created, continuous scans are performed and a runtime Fingerprint is generated every time. The last generated fingerprint is then compared to each one of the saved Fingerprints in order to obtain the closest match, which represents the location of the user.

2.2.2.2.3 PROXIMITY

The proximity approach is one of the easiest and simplest approaches in order to achieve meter level accuracy in an indoor environment. It just check the presence of an object within the specific area by measuring the strongest received RSSI value and then decides whether it's close or far.

The accuracy of the proximity method depends on the number of deployed Beacons in the designated area. This method suits applications that are proximity based in the navigation system.

The proximity approach does not provide the exact location of the object in the area; it just provides information such as near or far.

2.3 Related Work

Indoor positioning technologies in literature include Radio-frequency identification (RFID), WiFi, Bluetooth, ZigBee, inertial navigation, geomagnetic, and computing vision, etc. The RFID technology uses radio waves to identify and track objects automatically (*WiKi - RFID*). RFID systems consist of two elements: the transponder and the readers (Finkenzeller & Waddington 1999). Wi-Fi positioning uses devices of radio wireless local area networking based on the IEEE 802.11 (Chen 2012). Using the existing Wi-Fi network for indoor positioning can minimize the cost of deployment. There is no need for extra software or hardware (Ismail et al. 2008) . The Bluetooth (*Bluetooth Specifications*) is a personal area network standard that is widely used for short distance communications. Bluetooth is easy to deploy, requires low power consumption and is cheap (Zhou & Pollard 2006).

The positioning mechanisms include the time of arrival (ToA) method that depends on precise measurement of arrival time; and the time difference of the arrival

(TDOA) method that measures the relative time at each node, the angle of arrival (AOA) that measures the angle of the received signal; and the received signal strength indication (RSSI), which calculates the position based on the signal strength.

iBeacon is a new technology using Bluetooth Low Energy that was developed by Apple in 2013 (iBeacons) . The modern smartphones are equipped with BLE technology which can be utilized for indoor positioning based on their RSSI values (Boucaron, Coadou & de Simone 2010), (Faragher & Harle 2015). The advertisement packet that sent by iBeacon contains information such as broadcasting power, advertising interval, measured power and RSSI values (Newman 2014).

There is a very important relationship between the distance and RSSI value. This relationship can be modelled using the Path Loss Exponent Model as explained in the next section. Using the iBeacon to build an indoor positioning network is a new challenge to meet the indoor accuracy and reliability requirements in smart city applications.

The comparison of major current used indoor positioning technologies are demonstrated (Brena et al. 2017) in the table below:

Table 2.2: Comparison of indoor positioning technologies (Brena et al. 2017)

IPS Technology	Accuracy	Strengths	Weaknesses
Wi-Fi	1.5 m	Low cost, good precision	Vulnerable to access point changes
Bluetooth	30 cm–metres	Low cost, good precision	Intrusive; needs signal mapping
RFID	1–5 m	Very low cost passive side	Very low precision

Many algorithms were proposed so as to estimate the position of the objects in the indoor environment using RSSI approach. These include least square method (Wang et al. 2013), fingerprint and the weight centroid localization (WCL). The least square method uses the distance of the receiver to multi Beacons to compute the position of the receiver. The accuracy of the fingerprint approach is very high but the offline phase is time consuming and expensive (Chen et al. 2013), (Deepesh et al. 2016).

The WCL proposed by (Blumenthal et al. 2007) is a fast and simple algorithm that uses centroid algorithm to compute location of devices; whereby the localization is computed by taking the average value of known iBeacons coordinates. Research in (Zhao et al. 2018) proposed improvements based on the WCL algorithm; however the estimated error is still significantly high.

The Averaged Weighted Based Centroid Localization proposed by (ARUN et al.) uses weights that are dependent on the average value of the estimated location of the estimated mobile position and the actual mobile position. AWBCL has better positioning accuracy (the accuracy of finding object location or position) and reduced location error (the error of estimated object location or position) than the conventional simple WCL algorithm.

2.4 Conclusion

In summary, the Indoor Positioning System is a new technology that can provide the precise location of any object, even though satellite signals are partially or completely blocked, which is especially the case inside buildings. In this chapter, we have given a brief description of the current technologies and algorithms used in indoor positioning systems.

The accuracy of locating the objects in an indoor environment along with the system deployment cost are the main concern in IPS systems. In this research, we have developed a BLE Beacon base that utilizes the built-in BLE in almost all new smartphones to deploy IPS systems with high positioning accuracy and it is a relatively cheap system.

The IPS allows developing diverse applications in smart city such as guiding the users in a big shopping centers or airports. In addition, they can be used in museums as a virtual guide that provide contextual information based on the location. Another important application is the asset tracking.

3.

Development of Indoor Positioning Algorithm using Filtered RSSI and Beacon Weight approach in iBeacon Network (FRBW)

3.1 Overview

Positioning systems are used to locate any wanted object regardless of its current location, there are many positioning systems, however, the most common and well known positioning system is the Global Positioning System that can detects locations of objects in an outdoor environment (gps). Due to the signal problems with the GPS, the ability to find objects in an indoor environment is limited, and consequently the Indoor Positioning System is used, which is a relatively new technology that can find the exact location of any object where the GPS signal is lost or blocked. i.e. inside the buildings and tunnels (El-Rabbany 2002). Indoor positioning is one of the most important functions in smart city applications.

Indoor positioning using Bluetooth Low Energy (BLE) Beacons is an emerging technology. BLE Beacons have the advantages of small size, low cost and low energy consumption (SIG).

Positioning using Beacons is based on computing the distance between the positioning device and Beacons. Three distances from three Beacons will determine one’s position. There is no direct distance measurement from the Beacon signals. The measurement of the signal power using Received Signal Strength Indicator (RSSI) is used to indirectly compute the distance. However, the RSSI measurements and distance computing contain errors and many algorithms were developed in order to decrease this error.

Research efforts have been made to minimize the distance error and increase the position accuracy. The centroid localization algorithm proposed by (Bulusu, Heidemann & Estrin

2000) (Bulusu, Heidemann & Estrin 2000) uses the beacons coordination to estimate the position of the unknown mobile position using the centroid formula, however, the position accuracy using this algorithm is very low. The Weighted Centroid Localization algorithm(WCL) (Blumenthal et al. 2007) uses the weight as a factor to estimate position. The Average Weighted Based Centroid Localization (AWBCL) algorithm proposed by (ARUN et al.) which is based on the WCL algorithm has increased the location accuracy; however the position error is still high.

Increasing the location accuracy of the Indoor Positioning System (IPS) is an important research area in localization. Utilizing mobile Beacons in an IPS environment has made localization more accurate and cost effective. The cost of deploying IPS BLE based is very little when compared with other IPS technologies. For example, the main cost of deploying IPS BLE systems is the BLE Beacons, which costs between \$30 - \$50 depending on the hardware specifications. On the other hand, the IPS UWB based system tag started by \$250, in addition to UWB readers that costs a few hundred dollars.

This research develops a Filtered RSSI and Beacon Weight Approach (FRBW) based on improved Received Signal Strength Indicator (RSSI) values using a Kalman filter. This algorithm takes both the distance and improved RSSI measurements between beacon nodes into consideration. Kalman filter is applied on the RSSI measurements that eliminate noise of the signal and then this is applied to the FRBW positioning algorithm.

The developed algorithm was applied using eight Beacons. The results show that this FRBW approach has better positioning accuracy and minimum location error; and can be applied in IoT applications in a smart city.

3.2 Indoor Positioning Using Kalman Filter and Beacon Weight Positioning

The developed Indoor Positioning System algorithm is developed as the following two major phases: reducing measurement errors in RSSI using the Kalman filter; and computing the position using the Beacon Weight algorithm. The approach is designed as shown in Figure 3.1. Each phase is presented in this section below.

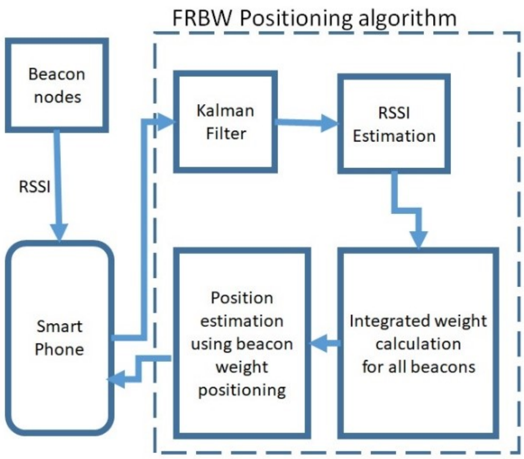

Figure 3.1: Positioning algorithm using Kalman filter and integrated Beacon weight

3.2.1 Filtering RSSI Measurements using the Kalman filter

The received RSSI measurements have high levels of noise. Therefore, to get better and precise information, the raw RSSI measurements need filtering. In the literature, researchers applied the Kalman filter to estimate RSSI errors in wireless LAN based positioning (Apte & Powar 2006). In the following sections, the Kalman filter is explained, followed by the discussion of measured RSSI values before and after applying the Kalman filter.

3.2.1.1 Measuring Distance using Estimote Beacons

The current iBeacons available in the market such as the Estimote iBeacons suffer from high distance error in the indoor environment localization; therefore, many algorithms have been developed to increase the localization accuracy and to decrease the localization error, however, the localization accuracy is still low and the error is too high.

In this thesis, we have developed a novel indoor positioning algorithm that has significantly decreased the distance error and increased the indoor positioning accuracy, as we will explain in Chapter 4.

To validate the measured distance using the Estimote iBeacons, eight BLE Beacons were deployed, and the mobile positions were chosen in three different places as shown in Figure 3.8, where (di) represents the distance between the Beacon (Bi) and mobile position (Poi), i = 1,2,…, 8:

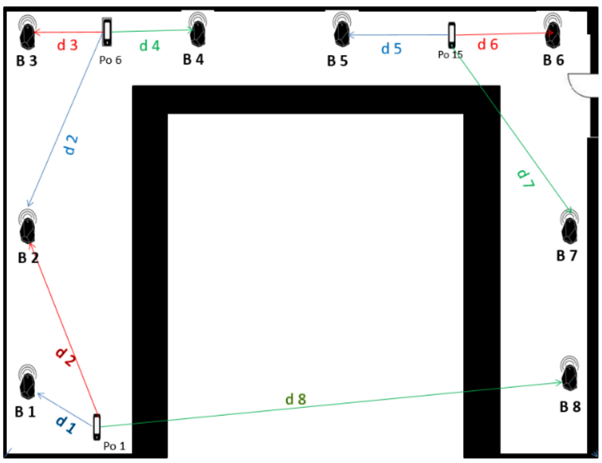

Figure 3.2: Mobile and Beacons positions

Based on mobile position 15, the measured distance between the mobile device and the Estimote Beacons is illustrated in Figure 3.3 using the Estimote model.

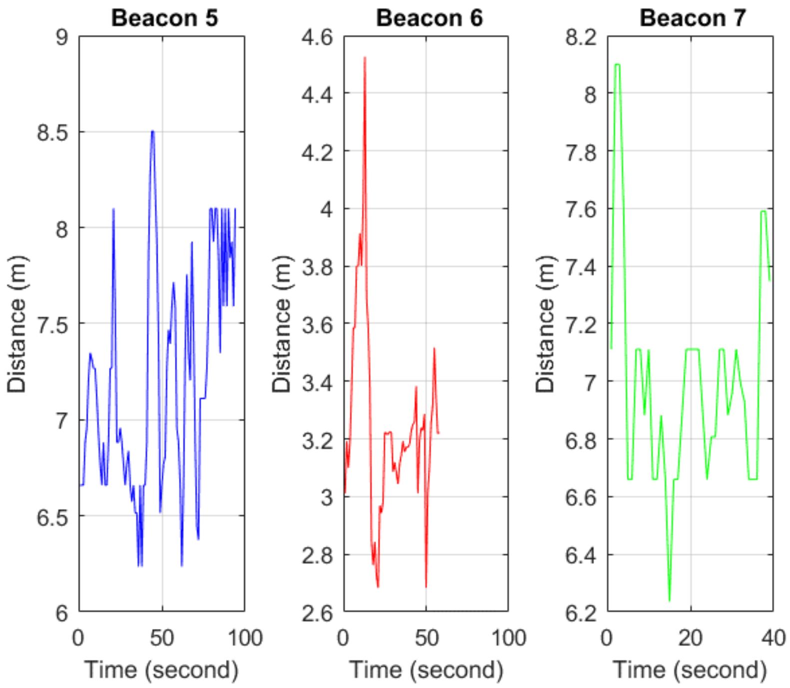

Figure 3.3: Estimated Distance using Estimote model

The average measured distance between Mobile at position 15 and the Beacons 5, 6 and 7 along with error is shown in Table 3.1:

Table 3.1: Beacons 5, 6, 7: Distances – Estimote Model

	True Distance (m)	Average Measured Distance (m)	Distance Error (m)
Beacon 5	6	7.2	1.2
Beacon 6	0	3.2	3.2
Beacon 7	4.6	6.9	2.3

The average measured distance error between the mobile and Beacons using the default Estimote model is very high. Using the Path-Loss model has significantly reduced the distance error, as we will explain in the next section.

3.2.1.2 Measuring Distance using Path-Loss Model

The wireless signals, which are an electromagnetic radio frequency, suffers an attenuation when transmitted due to many factors such as the distance and nature of the medium. When the transmitted signal experiences objects, it gets reflected, refracted, diffracted, and scattered.

The receiver can receive direct attenuated signal in an environment surrounded by buildings and trees which is also called line of sight (LOS) (Brena et al. 2017) or indirect attenuated signal due to other physical effects like reflection, refraction, diffraction and scattering, which is called non line of sight (NLOS). The free space propagation model is the simplest path loss model in which there is a direct-path signal between the transmitter and the receiver with no atmosphere attenuation or multipath components, based on the fact that the strength of a radiation field decreases by 1/d1. The Friis free space equation is used to measure the amount of power received relative to the power transmitted. Friis equation is expressed in the following formula:

$$P_r = P_t \frac{G_t G_r \lambda^2}{(4\pi R)^2} \qquad (3.1)$$

Where:

Pr: received power in Watts
Pt: transmitted power
Gt: transmitter antenna gain
Gr: receiver antenna gain

R: distance between the antennas in meters
λ: wavelength of the transmitted and received signal in meters

The log-distance propagation model is an extension to the Friis space propagation model. It incorporates a path-loss exponent that is used to predict the relative received power in a wide range of environments. The path loss is the reduction in power density of an electromagnetic waves as it propagates through space (Log-distance) and it can be expressed as the ratio of power of transmitted signal to the power of the same signal received by the receiver on a given path. It is a function of the propagation distance.

The log-distance path loss model assumes the path loss takes place exponentially with distance. The path loss in dB is given by Equation (3.2):

$$\overline{PL}\,(d) = \overline{PL}\,(d_0) + 10n\,log\left(\frac{d}{d_0}\right) \tag{3.2}$$

Where:

n: path loss exponent value.
d: distance (metres).
d0: reference distance (metres).

Table 3.2 lists some typical values for the path loss exponent. However, the path-loss exponent value varies according to the environment. In a free space environment, n is equal to 2. In practice, the value of n is calculated using empirical data.

Table 3.2: Path loss exponent for different environments.

Environment	Path Loss Exponent n
Free Space	2
Urban Area Cellular Radio	2.7 – 3.5
Shadowed Urban Cellular Radio	3 - 5

Line-of-Sight in Building	1.6 - 1.8
Obstruction in Building	4 – 6
Obstruction in Factories	2 - 3

The Log-Distance path-loss model can describe the relation between RSSI and distance (Oguejiofor et al. 2013) as following:

$$RSSI = -10\,nlog10(\frac{d}{d0}) + A0 \qquad (3.3)$$

Where:

d: distance in metres
n: path-loss exponent
d0: reference distance
A0: referenced RSSI value at d0

Let's assume:

A0 = 1
d0 = 1
n = 2 (for indoor location).

Based on the above assumption, Formula 3.3 can be rewritten as:

$$d = 10^{((TxPower - RSSI)/10n)} \qquad (3.4)$$

Where:

TxPower: Strength of the transmitted signal.

Based on mobile position 15, the measured distance between the mobile device and the Estimote Beacons using the Path-Loss model is illustrated in Figure 3.4.

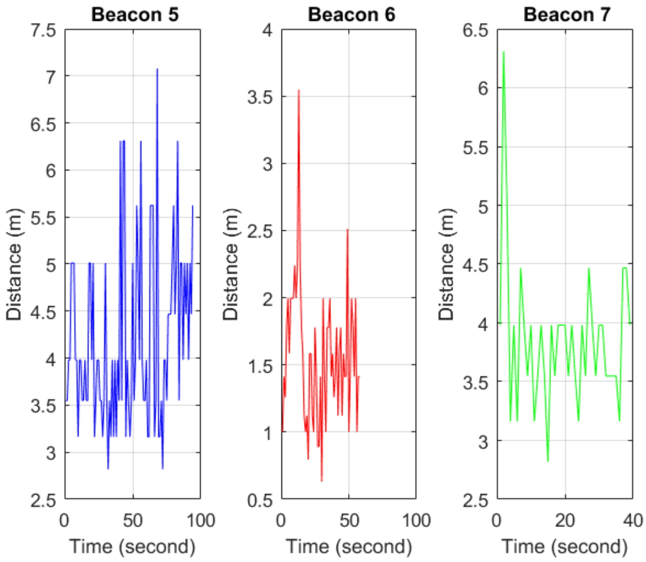

Figure 3.4: Estimated Distance at Position 13 using Path-Loss model

The average measured distance between Mobile at position 13 and the Beacons 5, 6 and 7 along with error is shown in Table 3.3:

Table 3.3: Average measured distance using Path-Loss model

	True Distance (m)	**Average Measured Distance (m)**	**Distance Error (m)**
Beacon 5	6	5	1
Beacon 6	0	1.5	1.5
Beacon 7	4.6	3.8	0.7

The average measured distance error between the mobile and Beacons using the Path-Loss model has achieved better results compared to the Estimote model. However, the positioning error is still high, and therefore smoothing RSSI values using the Kalman filter and integrating the Beacons weight will achieve an acceptable distance error as we will discuss in details in Chapter 4.

It is very important to mention here, the difference between the RSSI and TxPower. The RSSI value, as explained earlier, measures the received signal strength, while the TxPower is a factory-calibrated, read-only constant, which indicates what is the expected RSSI at a distance of 1 metre to the Beacon. The IEEE 802.11 standard specifies that RSSI can be on a scale of 0 to up to 255 and that each chipset manufacturer can define their own "RSSI_Max" value. The Estimote Beacon's RSSI ranges from -26 to -100 dbm. The signal strength depends on the distance and broadcasting power value (Technical).

The RSSI values are heavily influenced by different environmental factors such as absorption, interference or diffraction, and thus RSSI values tend to fluctuate and produce high levels of noise. To achieve a better estimation of the objects location in an indoor environment, the Kalman filter is applied on the raw RSSI values before computing the distance.

The measured raw RSSI values have a lot of noise. Figure 3.5 illustrates the RSSI values of Beacon 1 at position 1.

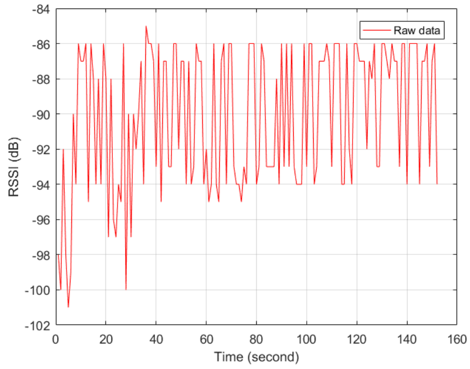

Figure 3.5: RSSI – Beacon 1 - Position 1

3.2.1.3 Kalman Filter

The Kalman filter which was proposed and developed by R.E. Kalman in 1960 to solve discrete data linear filtering problem (Kalman 1960). Since then, the Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous or assisted navigation.

The Kalman filter is an algorithm that uses a series of measurements observed over time, containing statistical noise and other inaccuracies, and produces estimates of unknown variables that tend to be more accurate than those based on a single measurement alone, and this is done by estimating a joint probability distribution over the variables for each timeframe (Maybeck & Siouris 1980), (Sorenson 1970).

The regular Kalman filter assumes linear models. The step from the current state to the next state, and the translation from state to measurement should be linear transformations. The Kalman filter has numerous applications in technology. A common application is for guidance, navigation, and control of vehicles, particularly aircraft, spacecraft and dynamically positioned ships (Sorenson 1970).

The basic Kalman filter assumes linear models, which means the step from the current state to the next state and the transition from each state should be linear. Extensions and generalizations to the Kalman filter have also been developed, such as the extended Kalman filter (EKF) and the unscented Kalman filter (UKF) which work on nonlinear systems. The underlying model is similar to a hidden Markov model except that the state space of the latent variables is continuous and all latent and observed variables have Gaussian distributions. The state-space model of the system is expressed as follows:

$$x_t = Ax_{t\_1} + Bu_t + w_t \qquad (3.5)$$

The current state x_t is defined as a combination of the previous state x_{t_1}, a control input u and noise w, and A, B are matrices.

The observation model of Kalman filter is expressed as:

$$z_t = CX_t + v_t \qquad (3.6)$$

Where:
C: is the transformation matrix.
v : is the measurement noise.

The Kalman filter has two steps: the prediction and update steps. In the prediction phase, the next state of the system is predicted based on the previous measurements, while in the update step, the current state of the system is estimated given the measurement at that time step (Welch & Bishop 1995). There are five equations in both steps which are as follows:

- Time Update (prediction):
  1. Project the state ahead :

$$\hat{x}_t^- = \hat{x}_{t-1} + Bu_t \qquad (3.7)$$

  2. Project the error covariance ahead:

$$\bar{P}_k = AP_{k-1}A^T + Q \qquad (3.8)$$

- Measurement Update (correction):

1. Computer the Kalman Gain:

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} \tag{3.9}$$

2. Updated the estimate via zk

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - H \hat{x}_k^-) \tag{3.10}$$

3. Update the error covariance:

$$P_k = (I - K_k H) P_k^- \tag{3.11}$$

Where:

$\hat{x}_t^-$ is the predicted state at time step t.

$\hat{x}_{t-1}$ is the state estimate at time step $t - 1$

Q is the covariance of the process noise.

R is the covariance of measurement noise.

P_t^- is the predicted error variance.

P_t is the updated error variance.

K_t is the Kalman gain at time step t.

3.2.1.4 Smoothed RSSI Values using Kalman Filter

The measured RSSI values are heavily influenced by the environment and have high levels of noise; therefore, applying the Kalman filter to all measured values eliminates the noise, which will affect positively the ability to find the objects position at later stages.

To begin with RSSI values filtration, first, we assumed that the matrices A, B and H are numerical constants and set them to 1, this is also, assuming that the mobile and position are static at a certain time frame; hence, the RSSI value is a constant in the measured time frame and other parameters are considered as a process noise. Based on these assumptions, the model can be constructed by ignoring u and set A to an identity matrix.

The Kalman filter for RSSI estimation is designed as follows:

1. State of interest x is designed to be RSSI at time step t:

$$x_t = RSSI(t) \tag{3.12}$$

2. The process model of the Kalman filter is designed as:

$$\dot{x}_t = Ax_t + \mathcal{E} \tag{3.13}$$

where A=1 in our design, $\mathcal{E}$ is the process noise.

3. The measurement model is designed using the relationship between the state of interest and the received RSSI measurement:

$$Z_t = Hx_t + \mathbb{F} \tag{3.14}$$

Where Z_t is the RSSI measurement at time step t. H=1 in our design. $\mathbb{F}$ is the measurement noise.

We use a time step from t-1 to t for the Kalman filter update, and update the Kalman filter process for state of interest, Kalman gain, and variance from time step t-1 to t.

In our approach, we have deployed eight Beacons in different positions. The following figure shows the RSSI values of Beacon 5 before and after applying the Kalman filter:

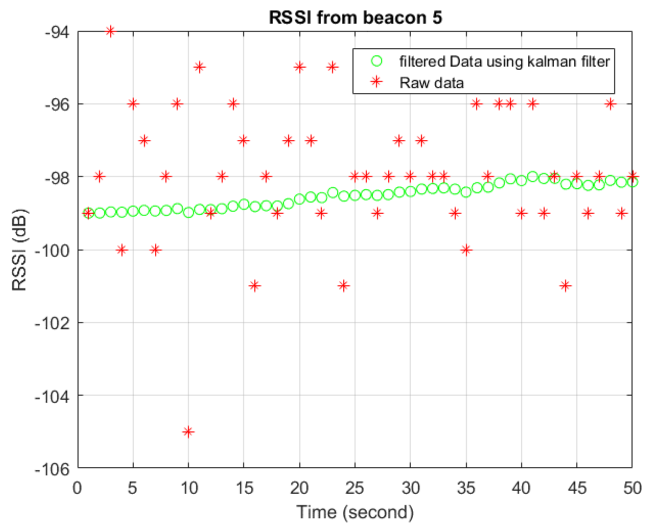

Figure 3.6: RSSI Comparison before and after Kalman filter for Beacon 5 at position 1

3.2.2 Computing Positioning using Beacon Weight

The Centroid Localization algorithm proposed by (Bulusu, Heidemann & Estrin 2000) uses the centroid to find the mobile position, while the Weighted Centroid Localization (WCL) algorithm proposed by (Blumenthal et al. 2007) uses the weight of each Beacon to estimate the mobile position. In this thesis, the concepts of CL and WCL algorithm have been expanded to be used with the smoothed RSSI values instead of using the raw RSSI values. In the following sections, we shall explore the centroid localization and then the Beacon's weight to estimate the mobile position using eight deployed Beacons.

3.2.2.1 Centroid Location

The Centroid Localization Algorithm (Afyouni, Ray & Claramunt 2016) is a simple free-range localization algorithm that calculates the unknown objects coordinates based on other two known objects coordinates intersection points, which is mathematically represented by Equation 3.15:

$$(X_c, Y_c) = \left(\frac{x1+x2....+xn}{n}, \frac{y1+y2....+yn}{n}\right) \qquad (3.15)$$

In our approach, there are six intersection points that represents the centroid X and Y coordinates as following:

Intersection points between Beacon a and Beacon b:

The centroid points between Beacon a (X_a, Y_a) and Beacon b (X_b, Y_b) is (XC_{ab},YC_{ab}) and is shown in Figure 3.7 and represented in Equation 3.16:

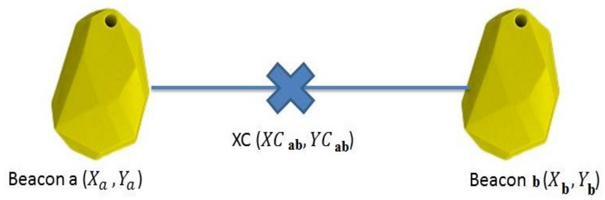

Figure 3.7: Centroid points between Beacon a and Beacon b

$$(XC_{ab}, YC_{ab}) = \left(\frac{X_a+X_b}{2}, \frac{Y_a+Y_b}{2}\right) \qquad (3.16)$$

Intersection points between Beacon a and Beacon c:

The centroid points between Beacon a (X_a, Y_a) and Beacon c (X_c, Y_c) is (XC_{ac},YC_{ac}) and is shown in Figure 3.8 and represented in Equation 3.17:

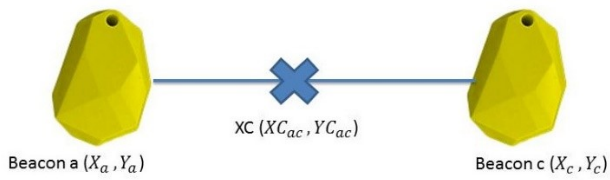

Figure 3.8: Centroid points between Beacon a and Beacon c

$$(\mathrm{XC_{ac}}, \mathrm{YC_{ac}}) = \left(\frac{X_a+X_c}{2}, \frac{Y_a+Y_c}{2}\right) \qquad (3.17)$$

Intersection points between Beacon b and Beacon c:

The centroid points between Beacon b (X_b, Y_b) and Beacon c (X_c, Y_c) is (XC_{bc},YC_{bc}) and is shown in Figure 3.9 and represented in Equation 3.18:

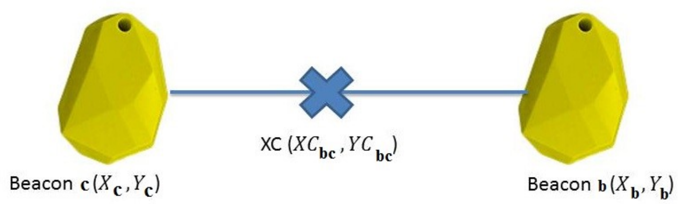

Figure 3.9: Centroid points between Beacon b and Beacon c

$$(\mathrm{XC_{bc}}, \mathrm{YC_{bc}}) = \left(\frac{\mathrm{X_b}+\mathrm{X_c}}{2}, \frac{\mathrm{Y_b}+\mathrm{Y_c}}{2}\right) \qquad (3.18)$$

Although the Centroid Localization Algorithm is easy to use, the accuracy is poor, so various forms of modification have been proposed to increase the localization. In this study, we have combined the Weight Centroid Localization Algorithm along with Centroid Algorithm to obtain better results as we will explain later.

3.2.2.2 Position Estimation using Beacon Weight

The Weight Centroid Localization (WCL) algorithm is an enhancement approach to the CL algorithm that considers the impact of the proximity between the Beacons and mobile device and assign weights for each Beacon to improve the objects position.

The smaller distance between the Beacon and smartphone will have a larger impact and therefore more weight, while the larger distance between the Beacon and smartphone will have less impact and therefore less weight. The impact of the Beacon and the smartphone is in inverse proportional to the distance. The value of Beacon weight is calculated based on Equation 3.19.

$$w_{ij} = \frac{1}{(d_{ij})^g} \qquad (3.19)$$

Where:

dij refers to the distance between Beacon and smartphone.
g refers to the adjustable degree, and it depends on the environments.

The WCL algorithm uses Equation (3.20) and Equation (3.21) to estimate the unknown mobile position based on the known Beacon position.

$$x_{est} = \frac{\sum_{i=1}^{n} w_i * x_i}{\sum_{i=1}^{n} w_i} \qquad (3.20)$$

$$y_{est} = \frac{\sum_{i=1}^{n} w_i * y_i}{\sum_{i=1}^{n} w_i} \qquad (3.21)$$

Although the WCL algorithm has significantly increase the localization accuracy, but the positioning error is still high. (ARUN et al.) have proposed enhancement to the original WCL algorithm which is called the Average Weighted Centroid Localization (AWCL) algorithm and it calculates the weight of each Beacon using the RSSI values only as per Equation 3.22:

$$w_{ij} = (P_{ref} * 10^{(\frac{RSSI}{20})})\hat{}g \qquad (3.22)$$

The AWCL algorithm uses the intersection between Beacons to find the average weight of each Beacon.

3.2.2.3 Position Estimation using Filtered RSSI and Beacon Weight (FRBW).

The smartphone position in an indoor environment is calculated using our developed Filtered RSSI and Beacon Weight (FRBW) algorithm that integrates the smoothed RSSI using the Kalman filter, CL, WCL and AWCL algorithms (Figure 3.10).

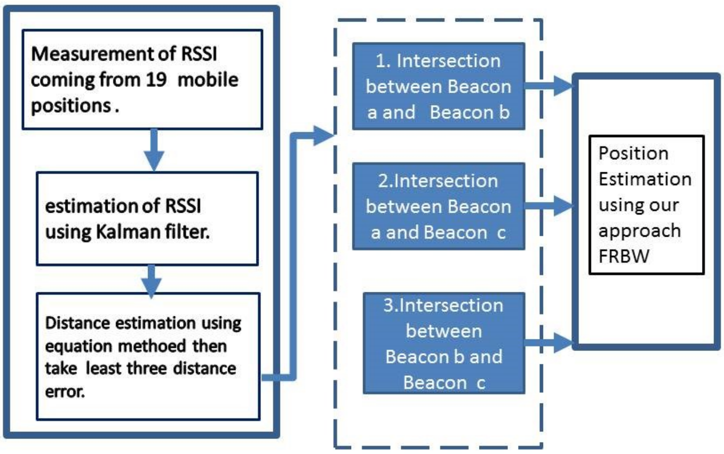

Figure 3.10: FRBW algorithm

The workflow of FRBW Algorithm is as following:

Step 1:

The first step in the FRWB algorithm is to smooth and eliminate the noise from the measured RSSI values by applying Kalman on all received RSSI values from all Beacons.

Step 2:

The distance between the smartphone and all deployed Beacons (in our scenario, we have deployed eight Beacons) is calculated using smoothed RSSI estimation by using the following Equation.

$$d_i = 10^{\left(\left(TxPower - RSSI\_KF\right)/10n\right)} \quad (i=1,2..8) \qquad (3.23)$$

Step 3:

The results of step 2 will be eight different distances between the smartphone and the deployed Beacons. The true distance is calculated using equation (3.24).

$$d_{true\_i} = \sqrt{(x_i - x_o)^2 + (y_i - y_o)^2} \quad (i=1,2..n) \qquad (3.24)$$

Step 4:

The error in distance is calculated using Equation 12.

$$\Delta d_i = d_i - d_{true\_i} \quad (i = 1,2, \dots n) \qquad (3.25)$$

Δd_i is the distance error between the smartphone and the Beacons.

As we have deployed eight beacons, there will be eight distance error; the FRWB algorithm considers only three beacons with the least distance error for the next step. The other Beacons data are discarded at this stage.

Step 5:

The following calculations are carried out at each intersection:

- The weight of each Beacon using Equations 3.19.
- The average of Beacon's weight.
- The centroid coordinates between each Beacon.

Intersection between Beacon a and Beacon b

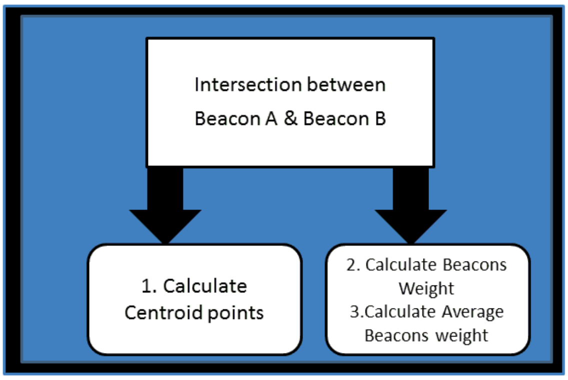

Figure 3.11: Calculations at Beacon a and Beacon b intersections

The weight of Beacon a and Beacon b is calculated using Equation 3.19 and named W_a and W_b respectively. The average weight of Beacon a and Beacon b is then calculated using Equation 3.26.

$$w1_{avg} = (W_a + W_b) / 2 \qquad (3.26)$$

The centroid points of Beacon a and Beacon b are calculated as explained earlier in Section 3.2.2.1 using Equations 3.27.

Two centroid points between Beacon a (X_a, Y_a) and Beacon b (X_b, Y_b) is (XC_{ab},YC_{ab})

$$(XC_{ab}, YC_{ab}) = \left(\frac{X_a+X_b}{2}, \frac{Y_a+Y_b}{2}\right) \qquad (3.27)$$

Intersection between Beacon a and Beacon c

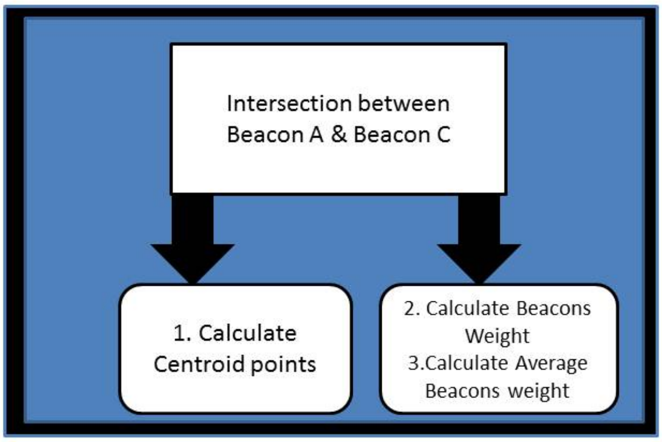

Figure 3.12: Calculations at Beacon a and Beacon c intersections

The weight of Beacon a and Beacon c is calculated using Equation 3.19 and named W_a and W_c respectively. The average weight of Beacon a and Beacon b is then calculated using Equation 3.28.

$$w2_{avg} = (W_a + W_c)/2 \qquad (3.28)$$

Where:

W_a: Beacons' a weight

W_c: Beacons' b weight

The centroid points of Beacon a and Beacon c are calculated as explained earlier in Section 3.2.2.1 using Equations 3.29.

Two centroid points between Beacon a (X_a, Y_a) and Beacon c (X_c, Y_c) is (XC_{ac},YC_{ac})

$$(\mathrm{XC_{ac}}, \mathrm{YC_{ac}}) = \left(\frac{X_a+X_c}{2}, \frac{Y_a+Y_c}{2}\right) \qquad (3.29)$$

Intersection between Beacon b and Beacon c

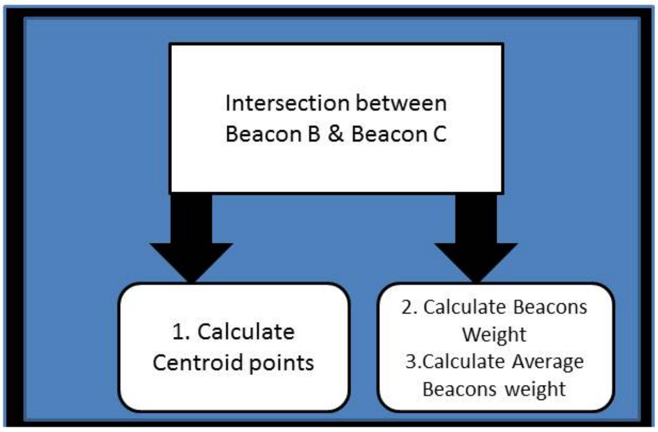

Figure 3.13: Calculations at Beacon b and Beacon c intersections

The weight of Beacon b and Beacon c is calculated using Equation 3.19, named W_b and W_c respectively. The average weight of Beacon b and Beacon c is then calculated using Equation 3.30.

$$\mathrm{w3_{avg}} = (W_b + W_c)/2 \qquad (3.30)$$

Where:

W_b: Beacons’ b weight

W_c: Beacons’ b weight

The centroid points of Beacon b and Beacon c are calculated as explained earlier in Section 3.2.2.1 using Equations 3.31.

Two points intersection between Beacon b (X_b, Y_b) and Beacon c (X_c, Y_c) is (XC_{bc},YC_{bc})

$$(\mathrm{XC_{bc}}, \mathrm{YC_{bc}}) = \left(\frac{X_b+X_c}{2}, \frac{Y_b+Y_c}{2}\right) \tag{3.31}$$

Step 6:

The estimated mobile coordinates are then calculated as per Equation 3.32 and Equation 3.33 as following:

$$X_{est} = \frac{w1_{avg} * XC_{ac} + w2_{avg} * XC_{ab} + w3_{avg} * XC_{bc}}{\sum_{i=1}^{n} wi_{avg}} \quad \text{Where n=1, 2, 3} \tag{3.32}$$

$$Y_{est} = \frac{w1_{avg} * YC_{ac} + w2_{avg} * YC_{ab} + w3_{avg} * YC_{bc}}{\sum_{i=1}^{n} wi_{avg}} \quad \text{Where n=1, 2, 3} \tag{3.33}$$

Step 7:

The estimated position error is calculated using equation 3.34:

$$Position_{error} = \sqrt{(x_{est} - x_0)^2 + (y_{est} - y_0)^2} \tag{3.34}$$

3.3 Conclusion

In this chapter, the Filtered RSSI Beacon Weight (FRBW) algorithm was introduced and explained in details. The first stage of this algorithm is smoothing the measured RSSI values received by each Beacon using the Kalman filter. The centroid points and the weight of each Beacon are then calculated to estimate the smartphone position.

The FRBW algorithm improves the positioning precision and accuracy in indoor environments using a different technique.

The results of our developed FRBW algorithm has achieved a higher accuracy level when compared with the current algorithms, as we will show in the next chapter.

4.

FRBW Algorithm Validation using Beacon Experiments

4.1 Introduction

The Filtered RSSI and Beacon Weight (FRBW) algorithm consists of two main stages; in stage one, the Kalman filter is applied on all measured RSSI values to eliminate the signal noise and to get a smooth and filtered signal, and the second stage computes the weight of each Beacon and estimates the object position in indoor environment.

To validate our indoor positioning approach, we deployed eight Beacons sensors from Estimote and smart phones in an indoor environment. The mobile was tested on eight different locations and then calculated and then estimated mobile positions were compared with the actual mobile positions.

4.2 Experiment Design

4.2.1 Equipment and Tools

This section gives details of all equipment, devices and software used in implementing the Indoor Positioning System algorithm throughout the design and validation phases.

4.2.1.1 Estimote iBeacons

The Estimote Beacons is built on BLE and iBeacon technologies and it has been used in this research to estimate the position of the objects in an indoor environment.

Beacons are BLE devices that broadcast small data packets at regular time intervals and commonly operate on coin-cell batteries. The BLE devices operates in sleep mode most of their time, however, at a predefined intervals, they wake up and transmit the data packet. The Beacon manufacturer provides a software tool that enable the developers to either increase or decrease the broadcast interval that best suits the application needs. This method allows the BLE device to operate for months and years.

According to the Bluetooth Core Specification (SIG), the data broadcasted by a BLE beacon is contained into packets and are formatted as shown in Figure 4.1

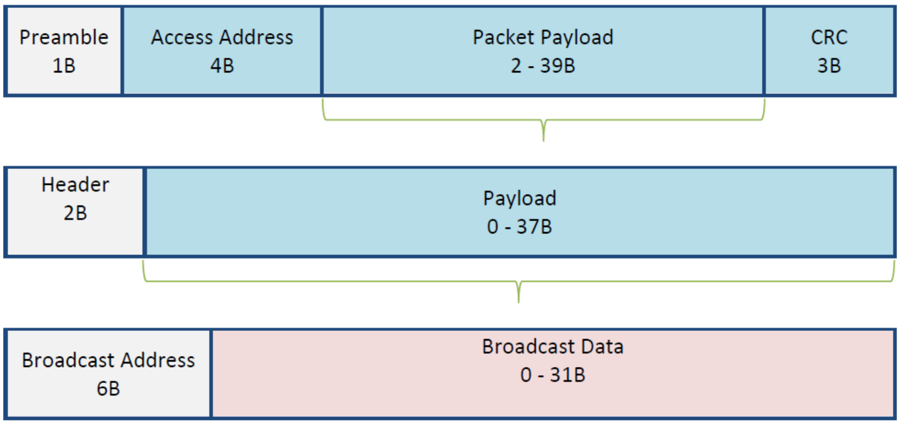

Figure 4.1: BLE Packet Structure (SIG)

The iBeacon protocol, developed by Apple in 2013, was the first Beacon technology made available. Its uses BLE technology to transmit data to other BLE enabled devices. It started as a way of turning iOS devices into advertisers that can transmit data to other listening iOS devices. This system was also used to estimate the distance between broadcasting and receiving devices (iBeacons).

The iBeacon packet consists of three-part identifiers of the Beacon (Technical) as shown in Table 4.1:

Table 4.1: iBeacon Data Frame

ID	Data Size	Data Type
UUID	16 bytes	String
Major	2 bytes	Unsigned short number
Minor	2 bytes	Unsigned short number

The iBeacon data field is shown in Figure 4.2 as following:

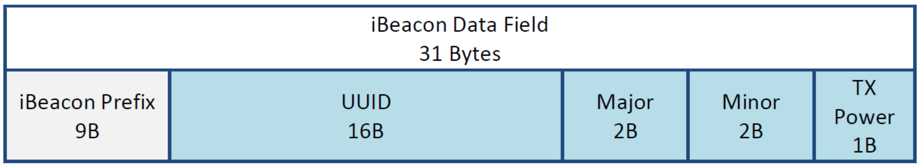

Figure 4.2: iBeacon Data Field (Herrera Vargas 2016)

These values provided by the advertisement can be modified according to the applications settings and requirements. The hierarchical configuration of these values provides identifying information about the Beacon. While the UUID can be distinguished to a corporation, major and minor values can be used to distinguish between regions and sub-regions of a corporation.

Eddystone is an open Beacon format developed by Google in 2015, the latest version of Eddystone, which was announced in April 2016 added a cryptographically secure method to configure the Beacon broadcasted message called Eddystone - EID. Eddystone protocol is discoverable by Android and iOS devices. The Eddystone data field is limited to 31 bytes as shown in figure 4.3:

Eddystone Data Field 31 Bytes									
Len 0x02	Type 0x01	Flags 0x06	Len 0x03	Type 0x03	Eddystone UUID 0xAA, 0xFE	Len 0x??	Type 0x16	Eddystone UUID 0xAA, 0xFE	Eddystone Frames Up to 20B

Figure 4.3: Eddystone Data Field (Herrera Vargas 2016)

The Eddystone protocol (GitHub) describes several different frame types that can be used individually or in combinations to create Beacons for a variety of applications.

- Eddystone - UID: A unique and static ID with a 10-byte Namespace and a 6-byte Instance component.
- Eddystone – URL: A compressed URL that is usable by the client once parsed and compressed.
- Eddystone – TLM: Contains Beacon status data such as battery voltage and uptime.
- Eddystone – EID: Encrypted UID and accessible by authorized apps only.

The BLE Beacons such as Beacon from Estimote is a dedicated hardware Beacons that are compatible with iBeacon and Eddystone protocols.

Estimote Beacons are small wireless sensors that can be easily placed anywhere in a physical location, The Estimote Beacons consists of a 32-bit ARM Cortex M0

CPU with 256 KB flash memory, accelerometer, temperature sensor and a 2.4 GHz Bluetooth Low Energy (BLE) module. The BLE module broadcasts information within a range of 70 metres (SDK). Though the signals are often distracted under real world conditions, a range of about 40-50 metres can be expected. As stated in (Technical), the battery is able to last more than three years on default settings on a single CR2477 battery. Figure 4.4 shows an Estimote Beacon and its board.

Figure 4.4: Estimote Beacons – Hardware structure (Hardware 2014)

The Estimote Beacons technical details (Technical) are shown in Table 4.2:

Table 4.2: Estimote BLE Beacons Technical Specifications

Parameter	
Processor	1. ARM® Cortex®-M4 32-bit processor with FPU 2. 64 MHz Core speed 3. 512 kB Flash memory 4. 64 kB RAM memory
Radio: 2.4 GHz transceiver	1. Bluetooth® 4.2 LE standard 2. Range: up to 200 meters (650 feet) 3. Output Power: -20 to +4 dBm in 4 dB 4. Sensitivity: -96 dBm 5. Frequency range: 2400 MHz to 2483.5 MHz 6.No. of channels: 40
Sensors	1. Motion sensor (3-axis) 2. Temperature sensor 3. Ambient Light sensor 4. Magnetometer (3-axis) 5. Pressure sensor

Using the Estimote SDK (SDK), mobile applications are enabled to receive and understand BLE Estimote signals in order to calculate the proximity of nearby locations and objects. The Beacons specifics provide information about their type, ownership and approximate locations, temperature or motions.

Based on Estimote documentation, there are four fixed proximity zones for estimating the distance to a Beacon (SDK) as following:

- Immediate:
  The Immediate proximity state represents a high level of confidence that the device is physically very close to the Beacon. This is for example the case when holding the smart- phone directly onto a Beacon.

- Near:
  The Near proximity state indicates a proximity of about 1-3 metres, if there are no obstructions between the device and the beacon that might cause distractions.
- Far:
  The Far proximity state indicates a detected Beacon without much confidence in the accuracy that is too low to determine whether it is Near or Immediate. The Far proximity state relies on the accuracy property to determine the potential proximity to a Beacon.
- Unknown:
  The Unknown proximity state indicates a state where Beacons can not be determined. This might happen if the ranging has just begun or if the accuracy level is insufficient for measurements to determine a state that is either Far, Near or Immediate.

4.2.1.2 Smartphone

Since the introduction of the first consumer mobile phone in 1980s by Motorola, there have been continuous developments in the technology used to make mobile phones. Nowadays, mobiles are very powerful and equipped with many sensors such as Accelerometers, Gyroscope and other sensors, which can ease our daily life tasks.

Thanks to these developments, nowadays, mobile phones are built using very advanced technologies. For example, they are equipped with fast CPUs, large RAMs and different wireless technologies. As a result, mobile phones have become capable of performing complex tasks. In the past, these tasks would require conventional computers.

Mobile phones are commonly equipped with Radio Frequency (RFID) technologies, specifically Bluetooth (IEEE 802.15.1) and Wi-Fi (IEEE 802.11). Many researchers have implemented IPSs using smartphones due to their high computational capabilities and their availability with almost everyone.

In this research, we have utilized the HUAWEI Y7 mobile to implement our IPS system using our developed FRWB algorithm.

The HUAWEI smartphone running Android is used to connect data in positioning experiment such as timing and RSSI values.

Figure 4.5: HUAWEI Mobile

4.2.1.3 Beacon Scanner Application

An Android Beacon Scanner application (Figure 4.6) that can capture the Radio Signal Strength Indicator (RSSI) has been used in this study.

The main benefit of this application is that it can capture the RSSI values, the RSSI values are then smoothed using the Kalman filter and using our developed FRBW algorithm, we have achieved better position accuracy as will show in section 4.4.

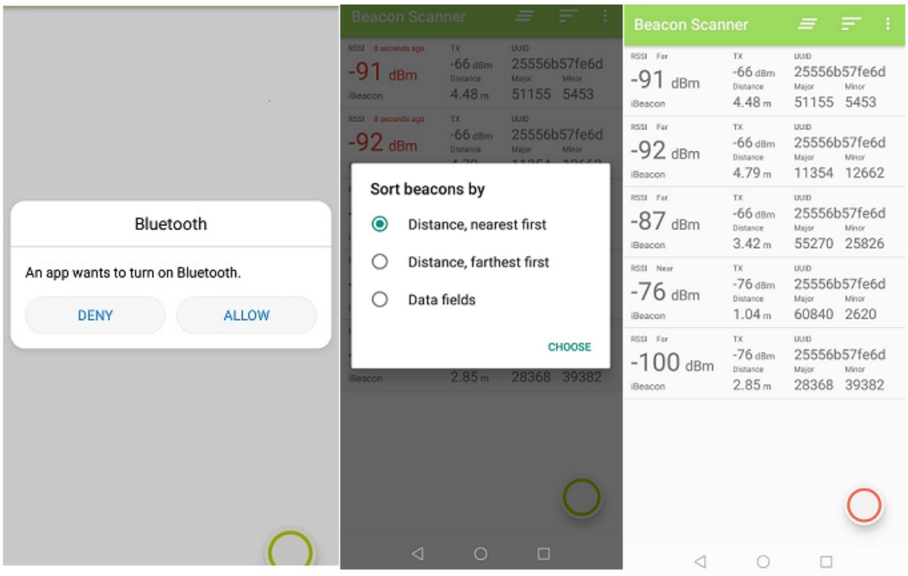

Figure 4.6: Beacon Scanner Application

The application capture data such as RSSI, UUID, Major, Minor and Estimated distance (Figure 4.7). The distance measured using the Estimote model is not accurate; hence, there is a need to achieve a better and more accurate positon estimation.

TimeFormatted	UUID/Namespace	Major/Inst	Minor	TX	RSSI	Distance
2/25/2019 13:05	b9407f30-f5f8-466e-aff9-25556b57fe6d	31594	49037	-66	-83	2.6
2/25/2019 13:05	b9407f30-f5f8-466e-aff9-25556b57fe6d	11354	12662	-66	-104	10.4
2/25/2019 13:05	b9407f30-f5f8-466e-aff9-25556b57fe6d	31594	49037	-66	-95	5.8
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	31594	49037	-66	-83	3.9
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	31594	49037	-66	-86	3.1
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	16034	60821	-76	-85	1.4
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	16034	60821	-76	-85	1.4
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	31594	49037	-66	-98	4.3
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	16034	60821	-76	-84	1.4
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	31594	49037	-66	-97	4.9
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	16034	60821	-76	-88	1.5
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	31594	49037	-66	-86	4.4
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	16034	60821	-76	-90	1.5
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	31594	49037	-66	-97	4.8
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	16034	60821	-76	-88	1.5
2/25/2019 13:06	b9407f30-f5f8-466e-aff9-25556b57fe6d	31594	49037	-66	-86	4.5

Figure 4.7: Data collected using the Beacon Scanner Application

4.2.1.4 Estimote Beacon Application and Cloud

Estimote provides developers with two important tools. First, the Cloud service enables the developers and researchers to manage Estimote Beacons remotely allowing them to access settings of Beacons and locations saved with Indoor Location SDK (Figure 4.8).

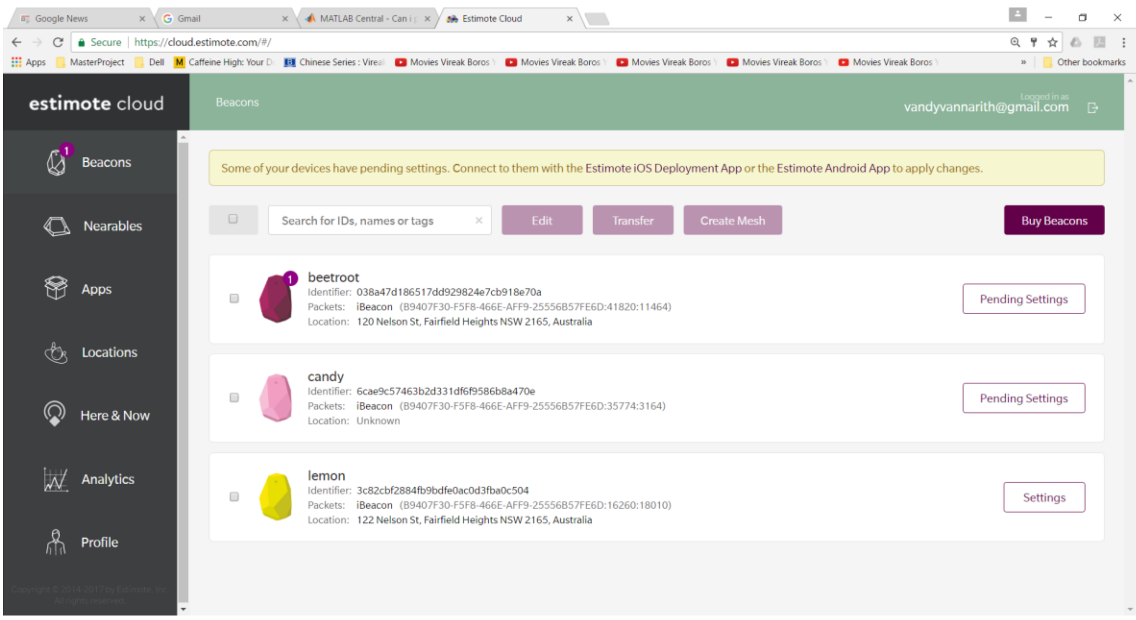

Figure 4.8: Estimote Cloud Tool

Second, the Estimote scanner application (Figure 4.9) allows the developer to develop applications for indoor environments

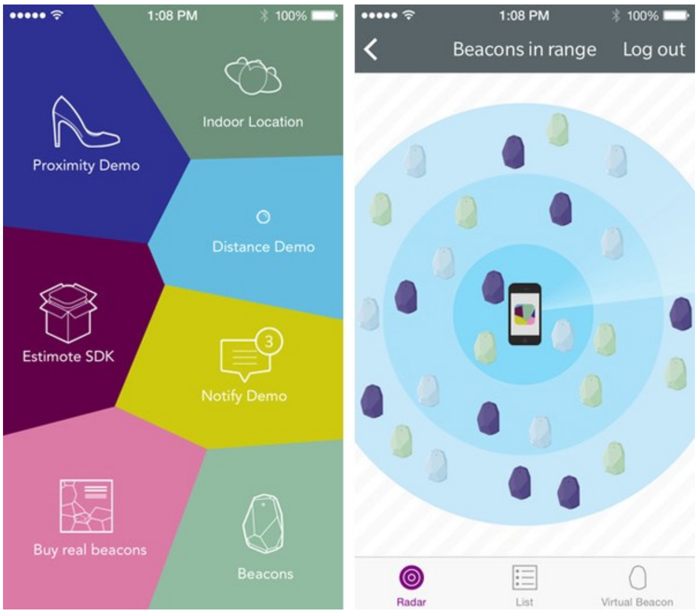

Figure 4.9: Estimote Scanner Application

4.2.1.5 Matlab Software

MATLAB is a multi-paradigm numerical computing environment and proprietary programming language developed by Mathworks. The Matlab software is used in this research to import the Beacon Scanner software data. The data has been manipulated and the Kalman applied to reduce the RSSI noise, as we will explain in details in the next section.

4.2.2 Experiment Environment

Eight Beacons from Estimote with known coordination named B1(x1,y1), B2(x2,y2), … Bi(xi,yi) (i = 1,2, … 8) were deployed in the experiment area. The mobile device was positioned in 19 different locations to validate our approach. The Beacons RSSI values were collected using a smart phone application. The collected RSSI values were then smoothed using the Kalman filter. The weight of each Beacon then is calculated and applied to the mobile position estimation. (Figure 4.10) shows the deployed Beacons position and the 19 different mobile locations.

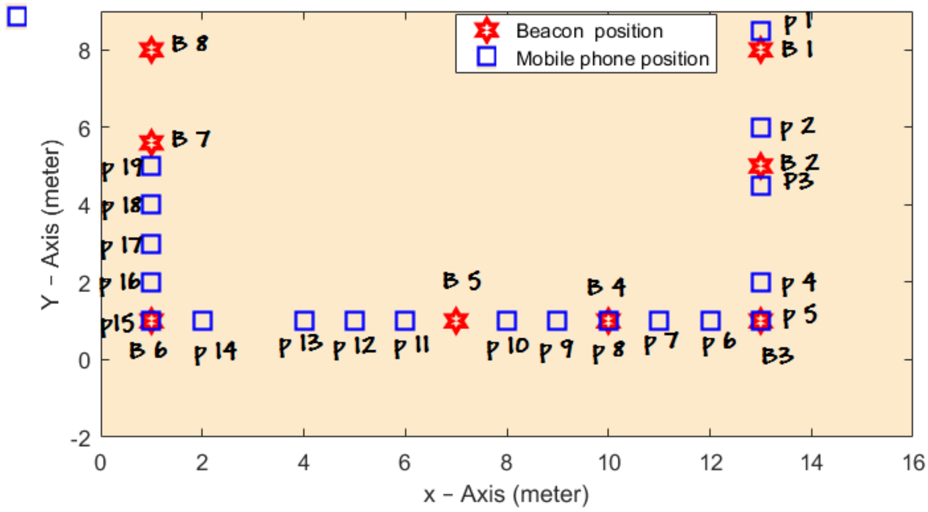

Figure 4.10: Experiment Setup

The Estimote Beacons coordinates are shown in Table 4.3:

Table 4.3: Estimote Beacons Coordinates

Beacon Name	X – Axis (m)	Y – Axis (m)	Z – Axis (m)
Beacon 1	13	8	210
Beacon 2	13	5	210
Beacon 3	13	1	210
Beacon 4	10	1	210
Beacon 5	7	1	210
Beacon 6	1	1	210
Beacon 7	1	5.6	210
Beacon 8	1	8	210

The mobile position coordinates are shown in Table 4.4

Table 4.4: Mobile Positions Coordinates

Position Name	X – Axis (m)	Y – Axis (m)
Position 1	13	8.5
Position 2	13	6
Position 3	13	4.5
Position 4	13	2
Position 5	13	1
Position 6	12	1
Position 7	11	1
Position 8	10	1
Position 9	9	1
Position 10	8	1
Position 11	6	1
Position 12	5	1
Position 13	4	1
Position 14	2	1
Position 15	1	1
Position 16	1	2
Position 17	1	3
Position 18	1	4
Position 19	1	5

The following table shows the experiments condition and algorithm parameters.

Table 4.5: Experiment Parameters

Parameters	Value
Number of iBeacons	8
iBeacons Z coordinate (Beacon height)	210 cm
Receiver	Android mobile
Filtering approach	Kalman Filter
Path loss exponent (n)	2

Each iBeacon has its unique name, UUID, Major and Minor attributes that helps in identifying each one and collects the required data such as RSSI values. Table 4.6 shows the deployed Estimote Beacons attributes.

Table 4.6: Estimote Beacons Attributes

UUID B9407F30-F5F8-466E-AFF9-25556B57FE6D			
Beacon name	**Beacon Colour**	**Major ID**	**Minor ID**
Beacon 1	candy	31594	49037
Beacon 2	beetroot	16034	60821
Beacon 3	beetroot	51155	5453
Beacon 4	lemon	28368	39382
Beacon 5	beetroot	50056	41317
Beacon 6	candy	60840	2620
Beacon 7	lemon	55270	25826
Beacon 8	candy	11354	12662

4.3 Reduced RSSI Measurement Error using Kalman Filter

The raw RSSI measurements contain a lot of noise that affect on the estimated mobile position. We applied the Kaman filter on all received RSSI values to eliminate the noise and smooth the signal.

In our experiment, there are 19 different mobile locations during the validation phase. The beacons coordinates are fixed during the whole experiments and are provided in Table 4.3, while the mobile locations are given in Table 4.4.

In this section, we will show the results of applying the Kalman filter on the collected RSSI values from different mobile positions named position 4, 6 and 13 and are follows:

4.3.1 Processing Result at Mobile Position 4:

In our experiment, the mobile position 4 coordinates are (13, 2). We have collected the RSSI values of Beacons. Table 4.7 shows a sample of the collected RSSI values of two Beacons named Beacon 3 and Beacon 4 from this location.

Table 4.7: Beacons RSSI - Position 4

time	Beacon 3 – Position 4		Beacon 4 – Position 4	
	RSSI – Raw	RSSI – Kalman	RSSI – Raw	RSSI - Kalman
1	-96	-96	-90	-90
2	-98	-96.6	-85	-89
3	-91	-95.6	-93	-90.2
4	-93	-95.9	-96	-90
5	-87	-96	-94	-89.5

The RSSI values before and after applying Kalman filter on Beacon 3 at mobile position 4 is represented in Figure 4.11:

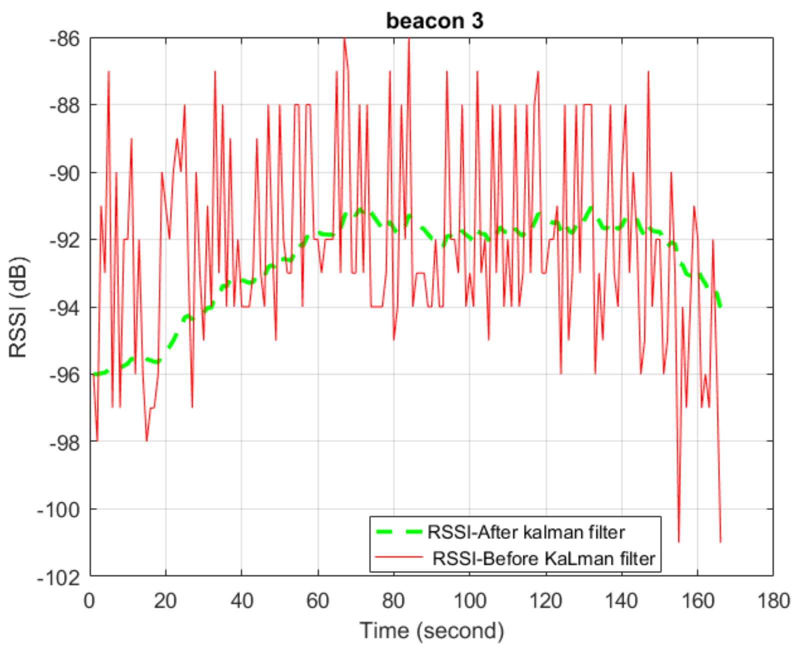

Figure 4.11: Kalman filter results - Beacon 3 - Position 4

Applying the Kalman filter on the received raw RSSI values (-86 dB -101 dB) of Beacon 3 at mobile position 4 (13, 2) has significantly improved the RSSI values (-93 dB - -96 dB). The RSSI error was decreased from 15 dB to 3 dB, and the average RSSI after Kalman filter is -92.6.

The RSSI values before and after applying the Kalman filter on Beacon 4 at mobile position 4 is represented in Figure 4.12:

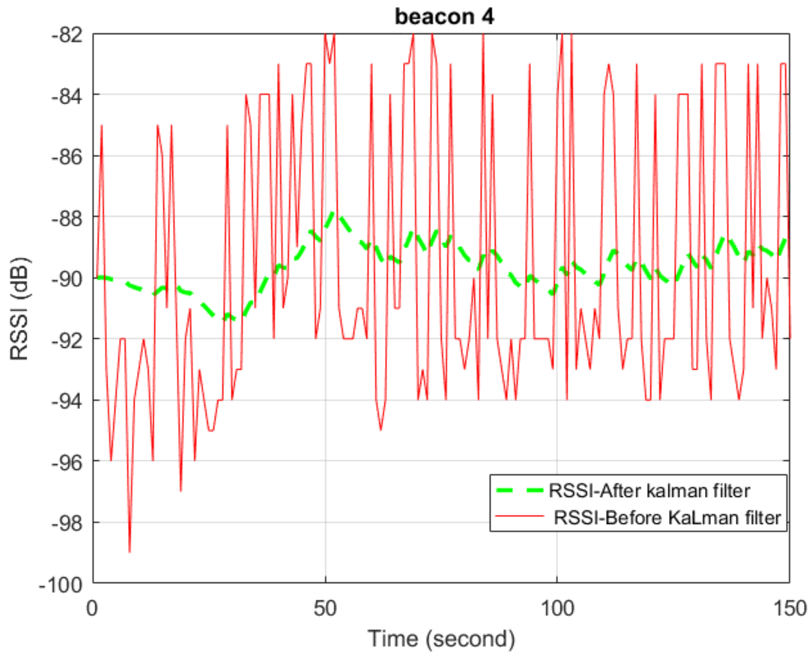

Figure 4.12: Kalman filter results - Beacon 4 - Position 4

Applying the Kalman filter on the received raw RSSI values (-82 dB -99 dB) of Beacon 4 at mobile position 4 (13, 2) has significantly improved the RSSI values (-88 dB - -91 dB). The RSSI error was decreased from 17 dB to 3 dB, and the average RSSI after the Kalman filter is -89.6.

4.3.2 Processing Result at Mobile Position 6:

In our experiment, the mobile position 6 coordinates are (12, 1). We have collected the RSSI values of all Beacons. Table 4.8 shows a sample of the collected RSSI values of two Beacons named Beacon 2 and Beacon 4 from this location.

Table 4.8: Beacons RSSI - Position 6

time	Beacon 2 – Position 6		Beacon 4 – Position 6	
	RSSI – Raw	RSSI – Kalman	RSSI – Raw	RSSI - Kalman
1	-101	-101	-101	-100
2	-94	-100.9	-99	-100.9
3	-93	-100.9	-94	-100.9
4	-99	-100.8	-102	-100
5	-94	-100.9	-96	-100.7

The RSSI values before and after applying the Kalman filter on Beacon 4 at mobile position 6 is represented in Figure 4.13:

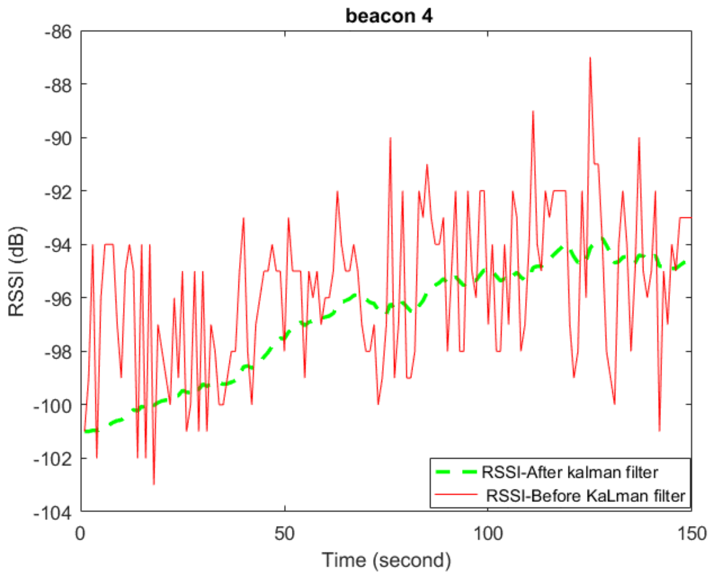

Figure 4.13: Kalman filter results - Beacon 4 - Position 6

Applying the Kalman filter on the received raw RSSI values (-87 dB -103 dB) of Beacon 2 at mobile position 6 (12, 1) has significantly improved the RSSI values

(-101 dB - -94 dB). The RSSI error was decreased from 16 dB to 7 dB, and the average RSSI after Kalman filter is -96.1.

The RSSI values before and after applying the Kalman filter on Beacon 2 at mobile position 6 is represented in Figure 4.14:

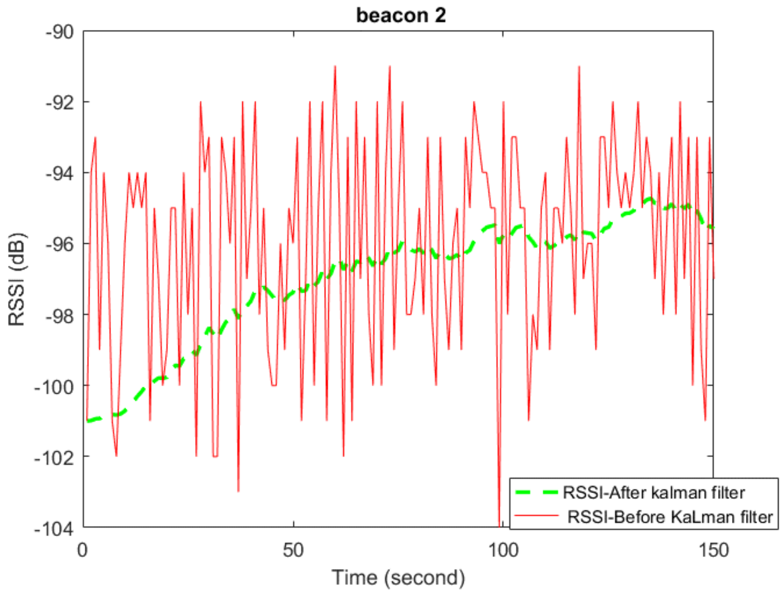

Figure 4.14: Kalman filter results - Beacon 2 - Position 6

Applying the Kalman filter on the received raw RSSI values (-93 dB -104 dB) of Beacon 2 at mobile position 6 (12, 1) has significantly improved the RSSI values (-97 dB - -101 dB). The RSSI error was decreased from 11 dB to 4 dB, and the average RSSI after the Kalman filter is -95.8.

4.3.3 Processing Result at Mobile Position 13:

In our experiment, the mobile position 13 coordinates are (4, 1). We have collected the RSSI values of all Beacons. Table 4.9 shows a sample of the collected RSSI values of two Beacons named Beacon 6 and Beacon 7 from this location.

Table 4.9: Beacons RSSI - Position 13

time	Beacon 6 – Position 13		Beacon 7 – Position 13	
	RSSI – Raw	RSSI – Kalman	RSSI – Raw	RSSI - Kalman
1	-98	-98	-98	-98
2	-101	-98.1	-100	-98.2
3	-101	-98.1	-92	-97
4	-95	-97.8	-98	-97.9
5	-99	-97.9	-101	-97.5

The RSSI values before and after applying the Kalman filter on Beacon 6 at mobile Position 13 is represented in Figure 4.15, and applying the Kalman filter has significantly improve the RSSI signal and removes noise. The average RSSI value is now -97.85 dB.

Figure 4.15: Kalman filter results - Beacon 6 - Position 13

The RSSI values before and after applying the Kalman filter on Beacon 7 at mobile Position 13 is represented in Figure 4.16, and applying the Kalman filter has significantly improve the RSSI signal and removes noise. The average RSSI value is now -91.6 dB.

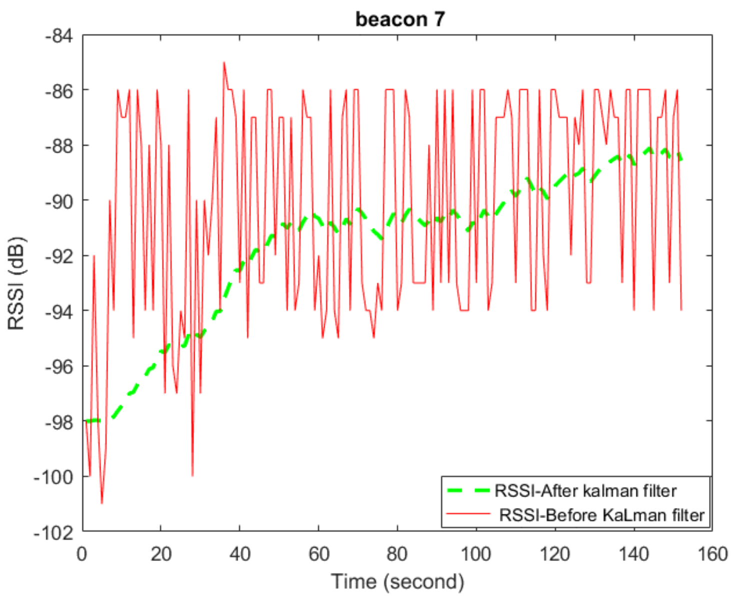

Figure 4.16: Kalman Filter Results - Beacon 7 - Position 13

4.4 Experiments Results and Discussion for Distance Processing

4.4.1 Measured Distance:

The measured distance between the mobile and the Beacons is calculated using different approaches. In this section, we will show the results of measured distance using the Path-Loss model and our developed FBRW algorithm. The results show a reasonable improvement in measuring distance after applying the Kalman filter on the RSSI values as shown in the next sections.

4.4.1.1 Measured Distance using Raw RSSI and Path-Loss Model:

Each Beacon transmits a set of data packets that include the UUID, Major ID, Minor ID, TxPower and its RSSI value. As we have explained earlier in Chapter 3, using the Path-Loss Exponent model, the distance can be calculated using the raw RSSI values. Equation (3.4) is used in this section to calculate the distance between the mobile device and Estimote Beacons.

In our experiment, we have deployed the mobile in 19 different positions, while the Estimote Beacons were fixed at specific coordinates as per Section 4.2.2. In the next sections, we have chosen three random mobile positions called Position 4, Position 6 and Position 13, and at each position the measured distance of each Beacon is shown, in addition, the average measured distance and the error are displayed in a table.

4.4.1.1.1 Position 4:

In our experiment, the mobile position 4 coordinates are (13, 2). The measured distance of each Beacon is shown in Figure 4.17.

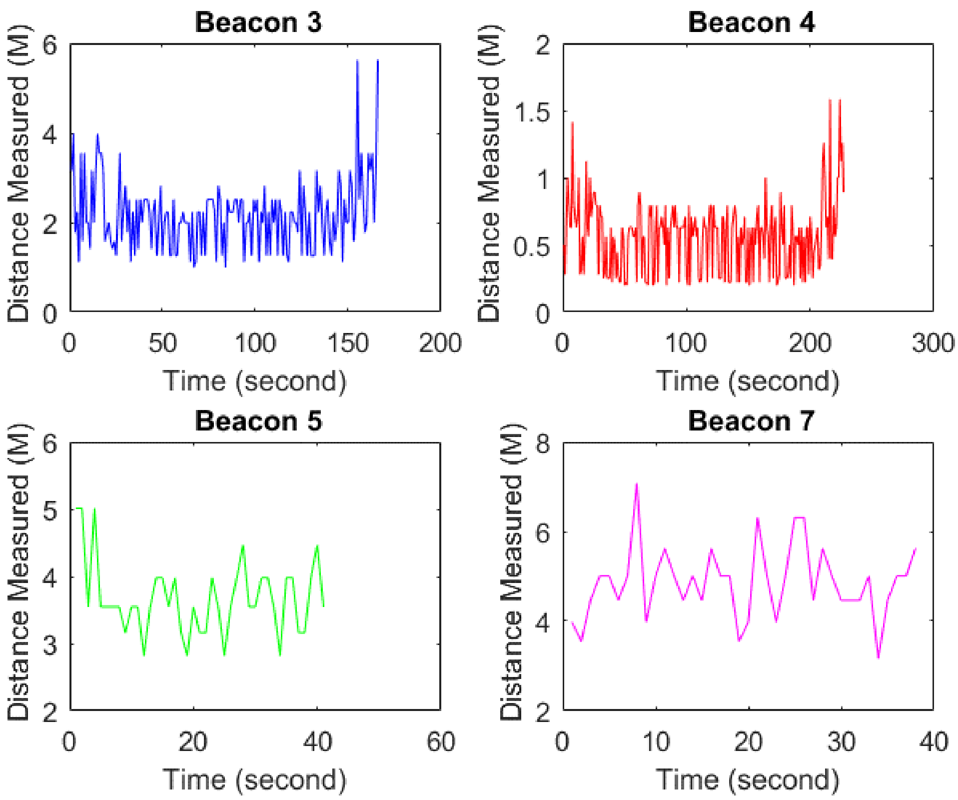

Figure 4.17: Measured Distance – Path-Loss Model – Position 4

The average measured distance using each Beacon data with the error is shown in Table 4.10

Table 4.10: Distances using Path-Loss Model (Beacons 3,4,5,7)

Beacon	Distance – True (m)	Distance - Measured (m)	Distance – Error (m)
Beacon 3	1	2.1	1.7
Beacon 4	3.1	0.5	2.6

Beacon 5	6	3.6	2.4
Beacon 7	12.5	4.8	7.6

4.4.1.1.2 Position 6:

In our experiment, the mobile position 6 coordinates are (12, 1). The measured distance of each Beacon is shown in Figure 4.18

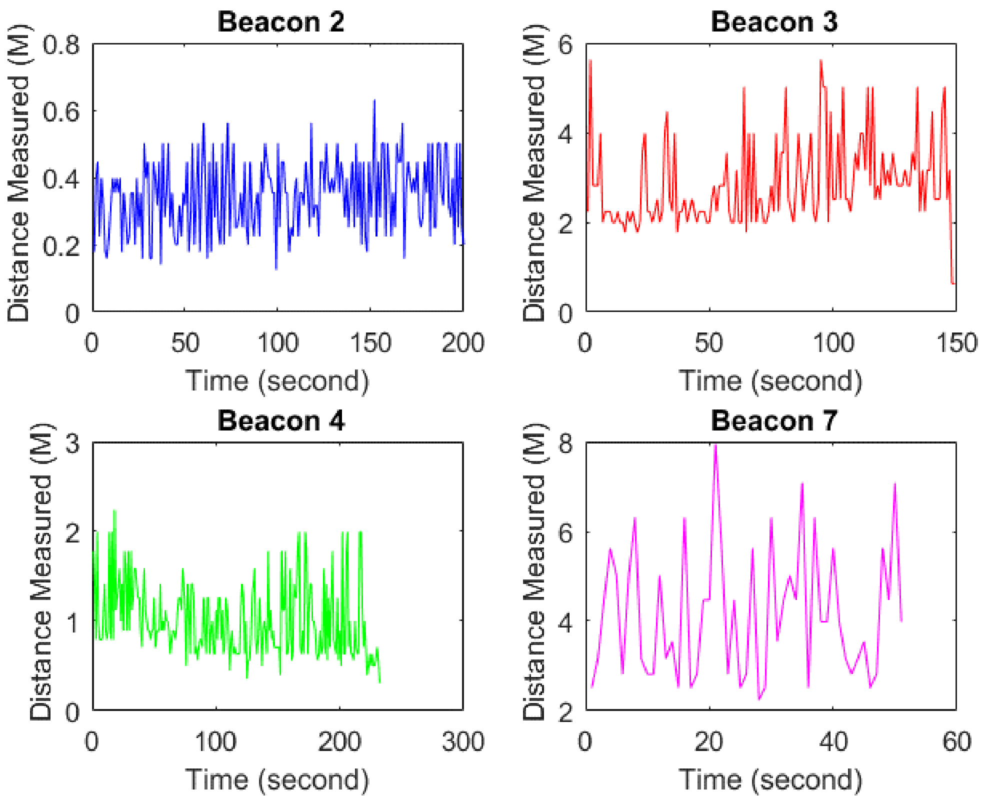

Figure 4.18: Measured Distance – Path-Loss Model – Position 6

The average measured distance using each Beacon data with the error is shown in Table 4.11

Table 4.11: Distances using Path-Loss Model (Beacons 2,3,4,7)

Beacon	Distance – True (m)	Distance - Measured (m)	Distance – Error (m)
Beacon 2	4.1	0.3	3.7
Beacon 3	1	2.8	1.8
Beacon 4	2	1.0	0.9
Beacon 7	11	4.1	6

4.4.1.1.3 Position 13:

In our experiment, the mobile position 13 coordinates are (4, 1). The measured distance of each Beacon is shown in Figure 4.19.

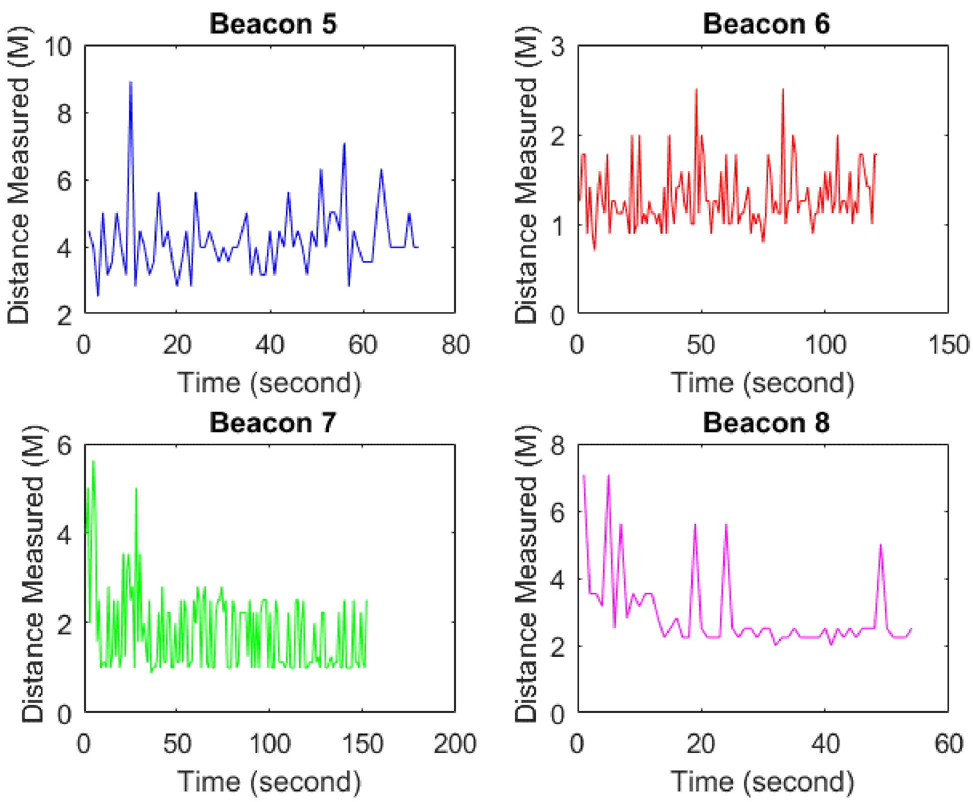

Figure 4.19: Measured Distance – Path-Loss Model – Position 13

The average measured distance using each Beacon data with the error is shown in Table 4.12

Table 4.12: Distances using Path-Loss Model (Beacons 5,6,7,8)

Beacon	Distance – True (m)	Distance - Measured (m)	Distance – Error (m)
Beacon 5	3	4.9	1.9
Beacon 6	3	1.2	1.7
Beacon 7	5.4	1.7	3.69
Beacon 8	8	2.9	4.69

4.4.1.2 Measured Distance using Smoothed RSSI:

The raw RSSI measurements suffer from high noise, due to this fact and in order to minimize the positioning error and increase the accuracy of the measured distance, the Kalman filter is applied on all received RSSI measurements. In addition, the weight of each Beacon was calculated based on this measured distance at each mobile position.

In our experiment, we have deployed the mobile in 19 different positions, while the Estimote Beacons were fixed at specific coordinates as per Section 4.2.2. In the next sections, we have chosen three random mobile positions called Position 4, Position 6 and Position 13, and at each position the measured distance of each Beacon is shown, in addition, the average measured distance and the error are displayed in a table.

4.4.1.2.1 Weight and Distance Computing for Position 4:

In our experiment, the mobile position 4 coordinates are (13, 2). The measured distance of each Beacon is shown in Figure 4.20.

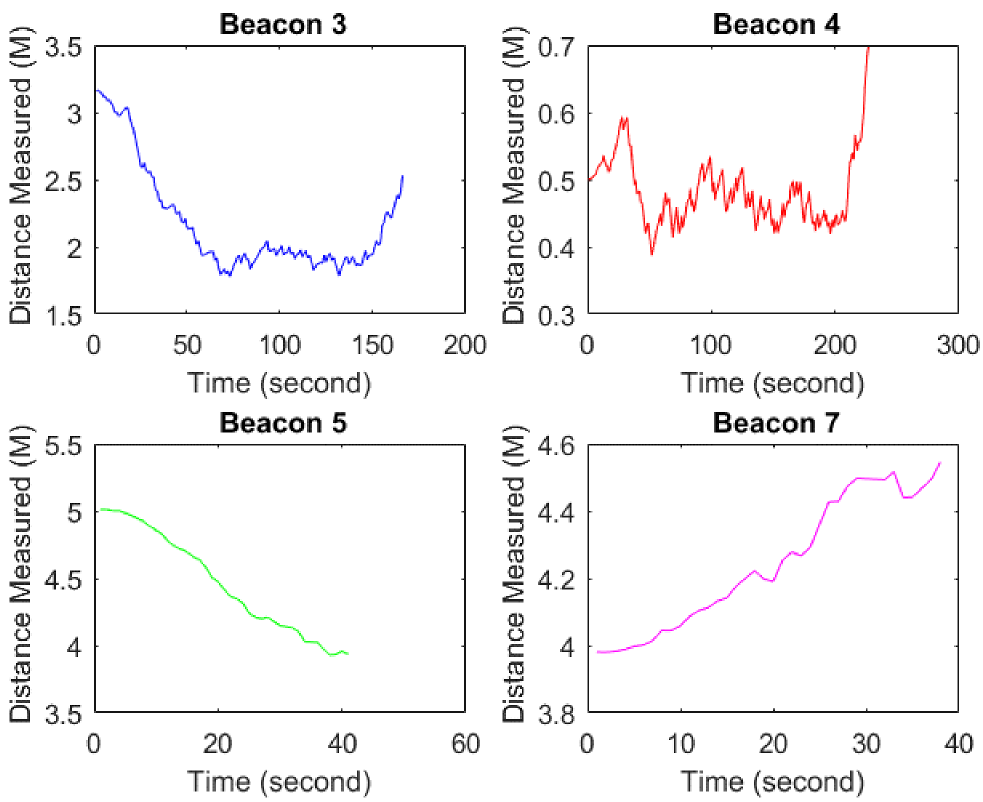

Figure 4.20: Measured Distance – Smoothed RSSI – Position 4

The average measured distance using each Beacon data with the error is shown in Table 4.13

Table 4.13: Distances using Smooth RSSI values – Position 4

Beacon	Average Smoothed RSSI (dB)	Distance – True (m)	Distance – Average Measured (m)	Distance – Error (m)
Beacon 3	-92.64	1	2.15	1.1
Beacon 4	-89.61	3.1623	0.47	2.6
Beacon 5	-98.9	6.0828	4.448	1.63
Beacon 7	-98.5	12.528	4.2413	8.28

The weight of three Beacons with the least distance error was calculated using Equation (3.19). Figure 4.21 shows Beacon 3, Beacon 4, and Beacon 5 weight at this mobile position. The weight of Beacon 7 was not calculated because its distance error is high.

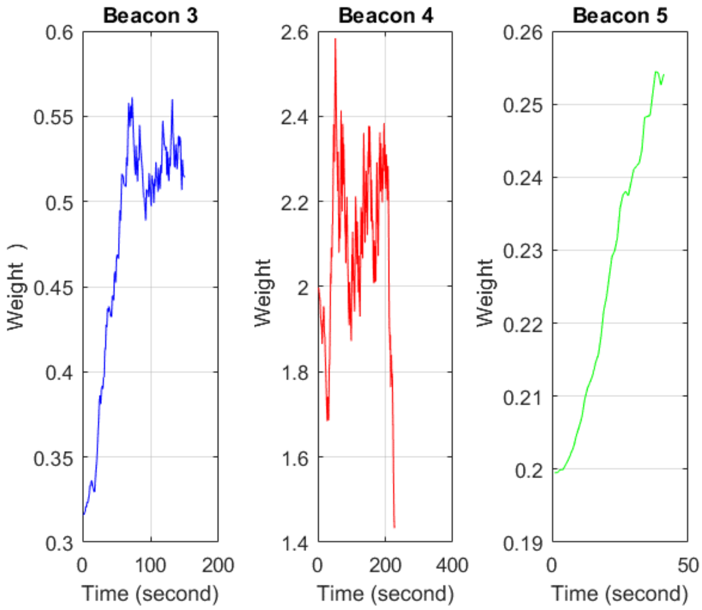

Figure 4.21: Beacons Weight – Position 4

The average Weight of Beacon 3, Beacon 4 and Beacon 5 is given in Table 4.14.

Table 4.14: Average Beacons Weight - Position 4

Beacon	Average Weight
Beacon 3	0.47
Beacon 4	2.0
Beacon 5	0.2

4.4.1.2.2 Weight and Distance Computing for Position 6:

In our experiment, the mobile position 6 coordinates are (12, 1). The measured distance of each Beacon is shown in Figure 4.22.

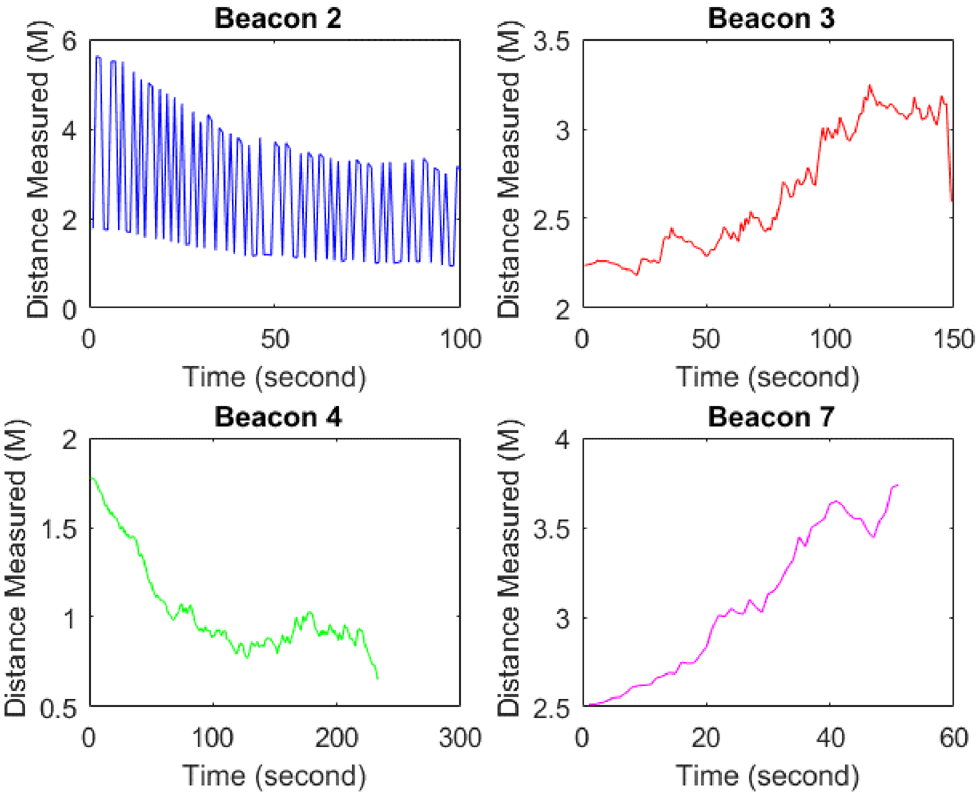

Figure 4.22: Measured Distance – Smoothed RSSI – Position 6

The average measured distance using each Beacon data with the error is shown in Table 4.15

Table 4.15: Distances using Smooth RSSI values – Position 6

Beacon	Average Smoothed RSSI (dB)	Distance – True (m)	Distance – Average Measured (m)	Distance – Error (m)
Beacon 2	-95.8	4.1	2.0	2.1
Beacon 3	-94.3	1	2.6	1.6

Beacon 4	-96.1	2	1.04	0.9
Beacon 7	-95.6	11.9	3.07	8.85

The weight of three Beacons with the least distance error was calculated using Equation (3.19). Figure 4.23 shows the Beacon 2, Beacon 3 and Beacon 4 weight at this mobile position. The weight of Beacon 7 was not calculated because its distance error is high.

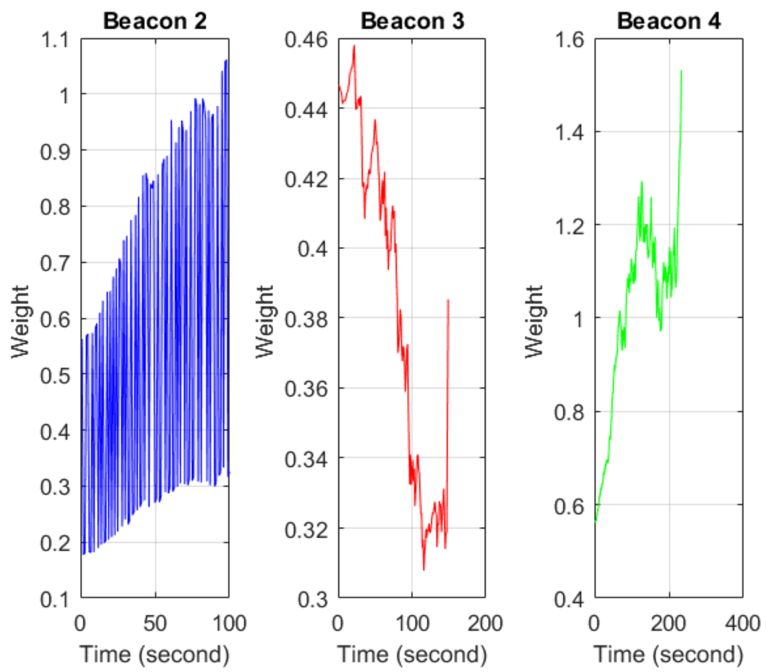

Figure 4.23: Beacons Weight – Position 6

The average Weight of each Beacon 2, Beacon 3 and Beacon 4 is given in Table 4.16.

Table 4.16: Average Beacons Weight - Position 6

Beacon	Average Weight
Beacon 2	0.7
Beacon 3	0.38
Beacon 4	1.0

4.4.1.2.3 Weight and Distance Computing for Position 13:

In our experiment, the mobile position 13 coordinates are (4, 1). The measured distance for each Beacon is shown in Figure 4.24.

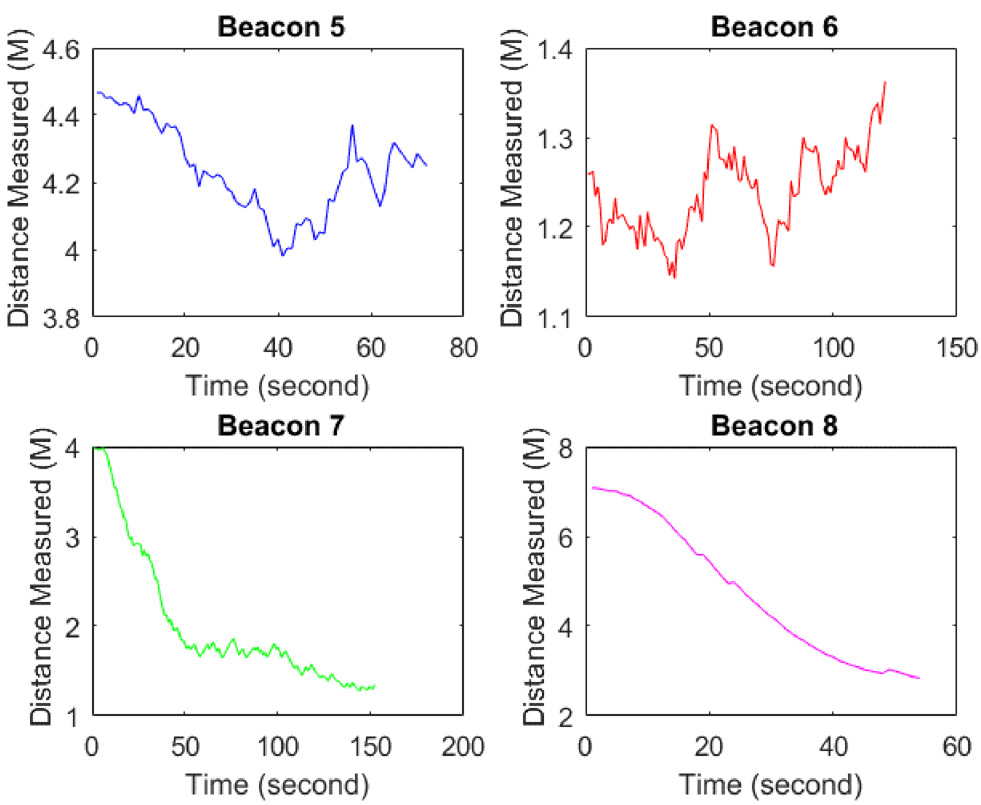

Figure 4.24: Measured Distance – Smoothed RSSI – Position 13

The average measured distance using each Beacon data with the error is shown in Table 4.17

Table 4.17: Distances using Smooth RSSI values – Position 13

Beacon	**Average Smoothed RSSI (dB)**	**Distance – True (m)**	**Distance – Average Measured (m)**	**Distance – Error (m)**
Beacon 5	-98.5	3	4	1
Beacon 6	-97.8	3	1.2	1.8
Beacon 7	-91.6	5.4	2	3.4
Beacon 8	-99.0	8	4.4	3.6

The weight of three Beacons with the least distance error was calculated using Equation (3.19). Figure 4.25 shows the Beacon 5, Beacon 6, and Beacon 7 weight at this mobile position. The weight of Beacon 7 was not calculated because its distance error is high.

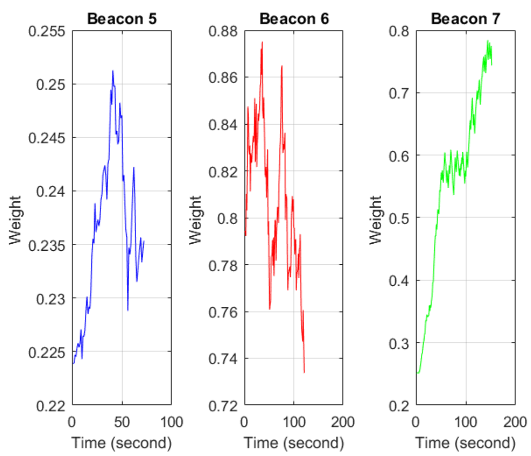

Figure 4.25: Beacons Weight – Position 13

The average Weight of each Beacon 5, Beacon 6 and Beacon 7 is given in Table 4.18.

Table 4.18: Average Beacons Weight - Position 13

Beacon	Average Weight
Beacon 5	0.2
Beacon 6	0.8
Beacon 7	0.5

4.4.2 Positioning Estimation

4.4.2.1 Positioning using FRBW Algorithm:

The developed Filtered RSSI Beacon Weight (FRBW) algorithm has achieved improved accuracy in an indoor environment. The FRBW uses the smoothed RSSI values along with the Beacons weight to estimate the mobile coordinates as explained in Chapter 3.

Figure 4.26 shows the estimated mobile positions using our developed FRBW algorithm and how close it is to the actual mobile position.

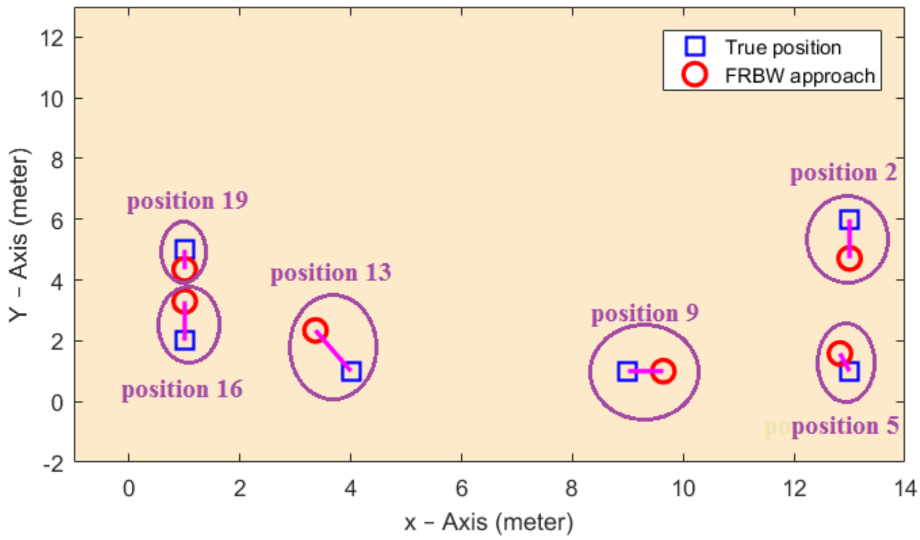

Figure 4.26: Mobile Positions Estimation using FRBW algorithm

Table 4.19 shows the actual mobile positions coordinates, and the estimated mobile coordinates at each position along with the positioning error.

Table 4.19: Estimated Mobile Coordinates and Error at each Position

Mobile Position	X-Axis (m)	X-Axis (m) - Estimated	Y-Axis (m)	Y-Axis (m) – Estimated	Position Error (m)
Position 1	13	13	8.5	6.5	2.000
Position 2	13	13	6	4.714	1.286
Position 3	13	11.9019	4.5	4.6146	1.104
Position 4	13	12.0696	2	2.9851	1.355
Position 5	13	12.8266	1	1.5827	0.608
Position 6	12	12.1124	1	1.5198	0.5318
Position 7	11	9.7177	1	1	1.282
Position 8	10	10.3608	1	1	0.361
Position 9	9	9.6392	1	1	0.639

Position 10	8	9.3272	1	1	1.327
Position 11	6	4	1	1	2.000
Position 12	5	6.155	1	1	1.155
Position 13	4	3.3607	1	2.343	1.487
Position 14	2	3.3623	1	2.2686	1.862
Position 15	1	3.1403	1	1.6591	2.239
Position 16	1	1	2	3.3	1.300
Position 17	1	2.6861	3	2.8473	1.693
Position 18	1	2.6261	4	2.7965	2.023
Position 19	1	1	5	4.354	0.646

4.4.2.2 Comparison between FRBW and Estimote Distance Signals:

Figure 4.27 shows the estimated mobile positions using our developed FRBW algorithm and the Estimote algorithm.

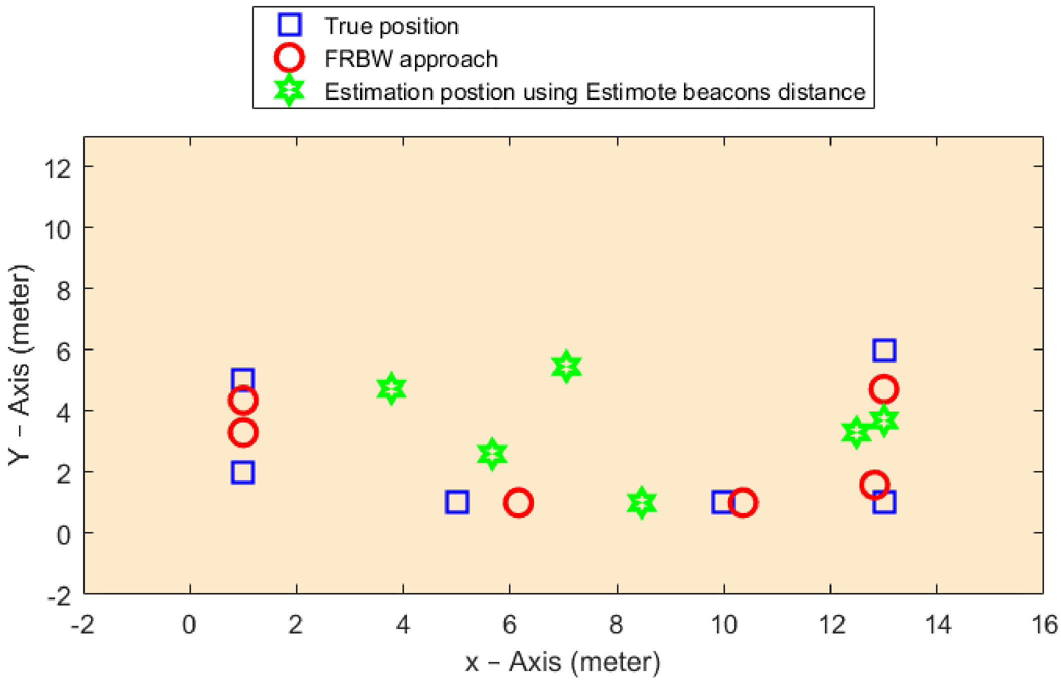

Figure 4.27: Mobile Positions Estimation using FRBW and Estimote algorithms

Table 4.20 shows the distance error using the Estimote and FRBW algorithms.

Table 4.20: Comparison in Position Error – Estimote and FRBW

Mobile Position	**Estimote Algorithm**		**FRBW Algorithm**	
	Position Error (m)	Percentage (%)	Position Error (m)	Percentage (%)
Position 1	7.177	15%	2.000	13%
Position 2	2.3084	8%	1.286	4%
Position 3	1.184	8%	1.104	8%
Position 4	2.8224	10%	1.355	9%
Position 5	4.5358	12%	0.608	7%
Position 6	1.3986	7%	0.5318	6%
Position 7	2.0178	9%	1.282	4%
Position 8	3.3875	10%	0.361	7%
Position 9	1.5132	7%	0.639	6%
Position 10	2.0835	8%	1.327	4%
Position 11	5.4645	13%	2.000	7%
Position 12	1.7251	7%	1.155	4%
Position 13	2.548	8%	1.487	4%
Position 14	3.7454	9%	1.862	8%
Position 15	3.0888	9%	2.239	12%
Position 16	6.9685	14%	1.300	6%
Position 17	4.1226	11%	1.693	4%
Position 18	3.7034	10%	2.023	13%
Position 19	2.7879	9%	0.646	5%

4.4.2.3 Comparison between FRBW and Path-Loss with raw RSSI Model:

Figure 4.28 shows the estimated mobile positions using our developed FRBW algorithm and the Path-Loss Model using the raw RSSI values.

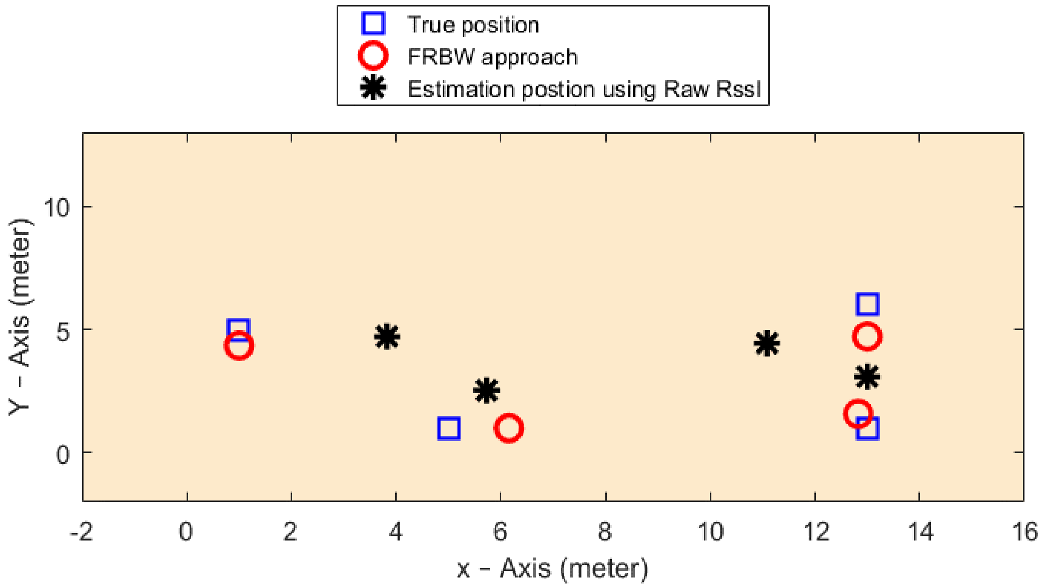

Figure 4.28: Mobile Positions Estimation using FRBW algorithm and Path-Loss Model

Table 4.21 shows the distance error using the Path-Loss Model and FRBW algorithm.

Table 4.21: Comparison in Position Error – raw RSSI and FRBW

Mobile Position	**Raw RSSI Algorithm**		**FRBW Algorithm**	
	Position Error (m)	Percentage (%)	Position Error (m)	Percentage (%)
Position 1	8.6069	25%	2.000	13%
Position 2	2.9135	17%	1.286	4%
Position 3	1.7417	9%	1.104	8%
Position 4	3.1053	18%	1.355	9%
Position 5	5.0498	21%	0.608	7%
Position 6	1.4586	9%	0.5318	6%

Position 7	2.7263	10%	1.282	4%
Position 8	3.4898	18%	0.361	7%
Position 9	0.9006	7%	0.639	6%
Position 10	2.2353	9%	1.327	4%
Position 11	5.68	22%	2.000	7%
Position 12	1.6969	9%	1.155	4%
Position 13	2.432	8%	1.487	4%
Position 14	4.2835	16%	1.862	8%
Position 15	3.2069	15%	2.239	12%
Position 16	7.1908	23%	1.300	6%
Position 17	1.9628	6%	1.693	4%
Position 18	4.1141	15%	2.023	13%
Position 19	2.8411	9%	0.646	5%

4.5 Conclusion

In this chapter, the results of applying our developed Filtered RSSI and Beacon Weight (FRBW) algorithm on 19 mobile positions were shown and compared with the Estimote algorithm and raw RSSI values.

The results show a significant increase in locating mobile positions in the indoor environment when compared to other algorithms. In addition, the distance error was decreased and at some mobile positions reached 30 cm error only using relative and existing technology.

5.

Conclusion and Future Work

5.1 Conclusion

The positioning systems are used to locate any wanted objects regardless of its current location, and there are many positioning systems, however, the most common and known positioning system is the Global Positioning System that can detects locations of objects in an outdoor environment. Due to the signal problems with the GPS, the ability to find objects in indoor environment is limited, hence the Indoor Positioning System. which is a relatively new technology, can find the exact location of any object where the GPS signal is lost or blocked i.e. inside the buildings and tunnels . Indoor positioning is one of the most important functions in smart city applications.

Indoor positioning using Bluetooth Low Energy (BLE) Beacons is an emerging technology. BLE Beacons have the advantages of small size, low cost and low energy consumption.

The accuracy of locating the objects in an indoor environment along with the system deployment cost are the main concern in IPS systems. Increasing the location accuracy of the Indoor Positioning System (IPS) is an important research area in localization. Utilizing mobile Beacons in an IPS environment has made localization more accurate and cost-effective.

In this research, we have developed a BLE Beacon based IPS system that utilizes the built-in BLE in almost all new smartphones in order to deploy the IPS system with high positioning accuracy and a cost-effective solution.

The received RSSI measurements have high levels of noise. Therefore, to obtain better and precise information, the raw RSSI measurements need filtering. In this research, we have applied a filter on RSSI values in order to eliminate the signal noise and get a smoother signal.

The developed Filtered RSSI and Beacon Weight Approach (FRBW) algorithm applies the Kalman filter on all received RSSI signals, then the centroid points between two Beacons along with their weight are calculated as so to estimate the smartphone position in the indoor environment.

The first stage in the developed Filtered RSSI and Beacon Weight (FRBW) algorithm is smoothing the measured RSSI signals received by each Beacon using the Kalman filter. The centroid points and the weight of each Beacon are then calculated to estimate the smartphone position.

The developed algorithm was applied using eight Beacons. The results show that the FRBW approach has better positioning accuracy and minimum location error, and can be applied in IoT applications in smart city.

The results of applying our developed FRBW algorithm show a significant increase in locating mobile positions in an indoor environment when compared to other algorithms. In addition, the distance error was decreased and at some mobile positions reached 30 cm error only using relative and existing technology.

5.2 Future Work

There are some problems that remain open to future research. Although the developed algorithm has achieved high positioning accuracy in an indoor environment, the algorithm needs more tuning to achieve high positioning accuracy at all positions all the time.

One of the parameters, which we think might affect the accuracy level, is the measured degree (g) in the Beacons weight using equation 3.4.

The developed indoor positioning system algorithm will be deployed for both Android and IOS applications and will integrate the GPS in its next version to serve as both an indoor and outdoor navigation and positioning system.

Another important issue to consider when implementing the indoor positioning system is the number of deployed Beacons as; the density of deployed Beacons increases the positioning accuracy. Increasing the number of Beacons will increase the cost of the system; however, prices are currently dropping rapidly, so it will not be an issue in the near future.

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