MASTER

iBeacon localization

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iBeacon Localization

Master Thesis

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Abstract

Positioning technologies have been developed over the last few decades, by making use of technical advancement in digital circuitry, to provide location and navigation services to its users. One of the foremost positioning system developed was GPS (Global Positioning System). This system is a space-based navigation system which provides location information. At start it required special (expensive) hardware to make use of GPS but the age of smartphone has made it possible to use GPS on our hand held devices without any need of additional hardware component. We all are familiar with this, we use GPS on our smartphone in our daily life for navigation purpose. GPS has become the de facto standard for outdoor localization. But GPS cannot be applied in our indoor environments due to non-availability of Line-of-Sight (LoS) inside buildings. Since we spent more time indoors than outdoors, positioning systems targeted for indoor environments (market) are being developed. Extensive research has been conducted to develop indoor positioning systems by making use of different available signal technologies (like WiFi, ZigBee, Bluetooth, UWB etc.) depending upon the context and application scenario.

In 2010 the Bluetooth-Low Energy (or Bluetooth Smart) BLE protocol was introduced. This signal technology was developed to have low cost and low energy consumption characteristics. Apple Inc. introduced iBeacon technology making use of BLE protocol which can communicate with smartphone and provide context- and location- awareness. The fact that new smartphone (and tablets) all come with built in BLE protocol can be used to help develop low cost, energy efficient, precise and accurate indoor positioning system (by making use of iBeacon and smartphone). BLE protocol has the ability to become the de facto standard for the phenomena of Internet of Things and thus a BLE-based localization system can become an integrated part of IoT in indoor environments. The BLE devices will enjoy communication with each other all the time and as we move pass by them, they will be able to localize (smartphone and blind iBeacon) on the fly, provisioning us being context- and location-aware all the time.

This master thesis explores the applicability and suitability of developing an indoor positioning system using this technology. Range-based localization approaches and algorithms were chosen to explore, test, evaluate and compare in a testbed (depicting typical indoor environment) developed for this purpose. The received signal strength indicator (RSSI) is the parameter used as basis for these localization approaches namely; *Proximity Localization, Fingerprinting Localization, Conventional and Self-Adaptive Localization & Space based Localization*. The results obtained show that an *accuracy* of around *2 meters (RMSE)* can be achieved by making use of localization approaches such as Fingerprinting & Conventional localization. But these algorithms require prior calibration of environment and hence would work best for static environments or require new calibration if the environment changes (e.g. renovation, furniture displacement, human density and movement etc.). To account for dynamism of real-time environments a novel Self-Adaptive localization approach was used and it yielded an *accuracy of 2-3 meters (RMSE)*. These results were obtained for smartphone localization inside the localization space in our indoor environment. Space-based localization was used to localize blind (iBeacon) node by sampling signal space around a blind iBeacon using smartphone. The *accuracy* with this approach was found to be about *1 meter (RMSE)*. These evaluations show that Bluetooth-Low Energy is a viable alternative for indoor positioning system which offers widespread availability in society, very good accuracy, portability and low cost deployment.

Preface

زندگی آمد،برائے بندگی
زندگی بے بندگی شرمندگی

With devotion life becomes beauteous.
And without, what is life but blemish.
"Rumi"

I would like to thank my supervisor **Wouter van Kleunen** for his patience with me and excellent mentoring over last six months. Important mention to Jacob Kamminga, with whom I shared working space during the time of my graduate project. It was always good to discuss and share ideas with him and encourage each other in our work.

In the end I would like to thank my parents who have been a constant source of inspiration and motivation for me. It is through their blessings and sacrifice that me and my siblings have been able to live our dreams and be highly educated.

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Chapter 1

Introduction

Information is power. The more you know the better it is. This is true in many cases of our lives. One such case is having good knowledge and understanding of our daily environments. This means to be continuously aware of our own presence in the surroundings around us and have knowledge about "what" & "where" things, people etc. are in our current environment. Context- and location-awareness can be easily achieved with help of deploying a localization system in our chosen surroundings.

1.1 Localization

According to Merriam-Webster (an Encyclopædia Britannica Company) **localization** can be defined as; "**to find or identify the location of something**" (e.g. object or person) [1]. Localization can be seen as the starting point for navigation and other location aware services. The problem of determining the location of a person or an object is an ancient one. Many different methods were developed throughput the history of mankind to solve this problem. This meant many novel devices were invented to help mankind localize and navigate like Astrolabe[1], Backstaff[2], Compass[3], Reflecting Circle[4], The Sextant[5], and Traverse Board[6]. Most of these mentioned systems were developed for localization & navigation of ships in sea, but some systems also found application in land navigation. For perspective in more modern time, tracking the position/location of vehicles can be seen analogous to that of ships. The first built system for this purpose is the well known GPS system. But, the increase of digitalization meant that the need of localization solutions should not be just confined to vehicles alone these days. The age of Smartphones has been a game changer. Nowadays GPS technology is readily available on our Smartphones to help us with localizing our current location and navigation in daily life. The fact of presence of a powerful mobile computing device in our palm has enabled the possibility of personalized context- and location-aware applications.

[1] *A brilliant device used to determine Latitude by observing the altitude and position of the sun, stars, or other planets.*

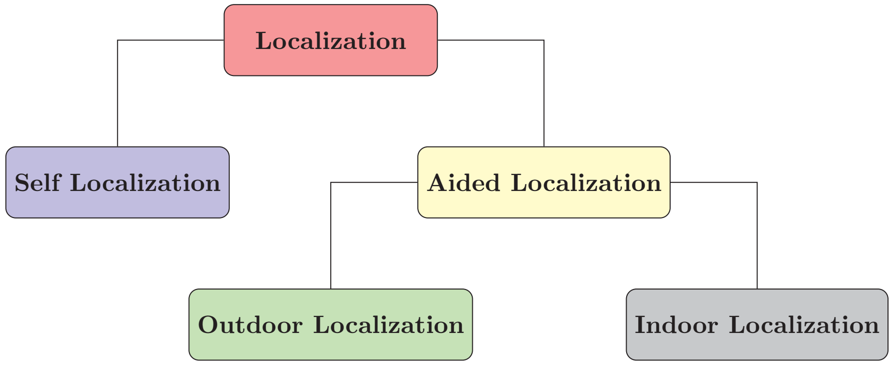
[2] *The back Staff or Back Quadrant is a navigational instrument that was used to determine the latitude by measuring the altitude of the sun in the sky.*

[3] *The most influential invention ever given to the age of exploration- The Mariner's Compass!*

[4] *19th century navigational instrument in the form of a graduated circle, used at sea to find the longitude by measuring the distance between the spotter and the moon.*

[5] *The pinnacle of nautical navigation, the sextant has been used for almost 300 years - even by NASA Gemini missions!*

[6] *Early device used to calculate speed, distance, direction and other navigational essentials in the 16th century.*



1.2 Motivation

Localization can be classified into two types; **Self localization** and **Aided localization**. *Self localization* is the innate ability of human beings to localize their current position w.r.t. surroundings around them. It also means the ability of humans to locate things around them using natural body sensors like eye, ear etc. *Aided localization* means using help from an external party to localize. Aided localization usually makes use of electronics to perform localization for humans. This way aided localization can help localize in global scheme of things. Aided localization can be further classified into two categories; **Outdoor Localization** and **Indoor Localization**. We all are familiar with *outdoor localization* since we almost use it every day on our smartphones (or tablets) to help us localize our current location, localize the location where we want to go and ultimately navigate. With help of GPS (yielding precision of 1-5 *meters*) and Google maps this has become a useful tool to use. *Indoor localization* stems from bringing this power into our indoor environments. But since GPS works best with Line-of-Sight (LoS) which makes use of GPS in indoor environment not feasible [28]; therefore, new methods of accomplishing indoor localization have been researched extensively over last 15 years. Indoor localization solutions on offer are diverse and make use of different information sources that reflect the constraints of various use-cases. Still

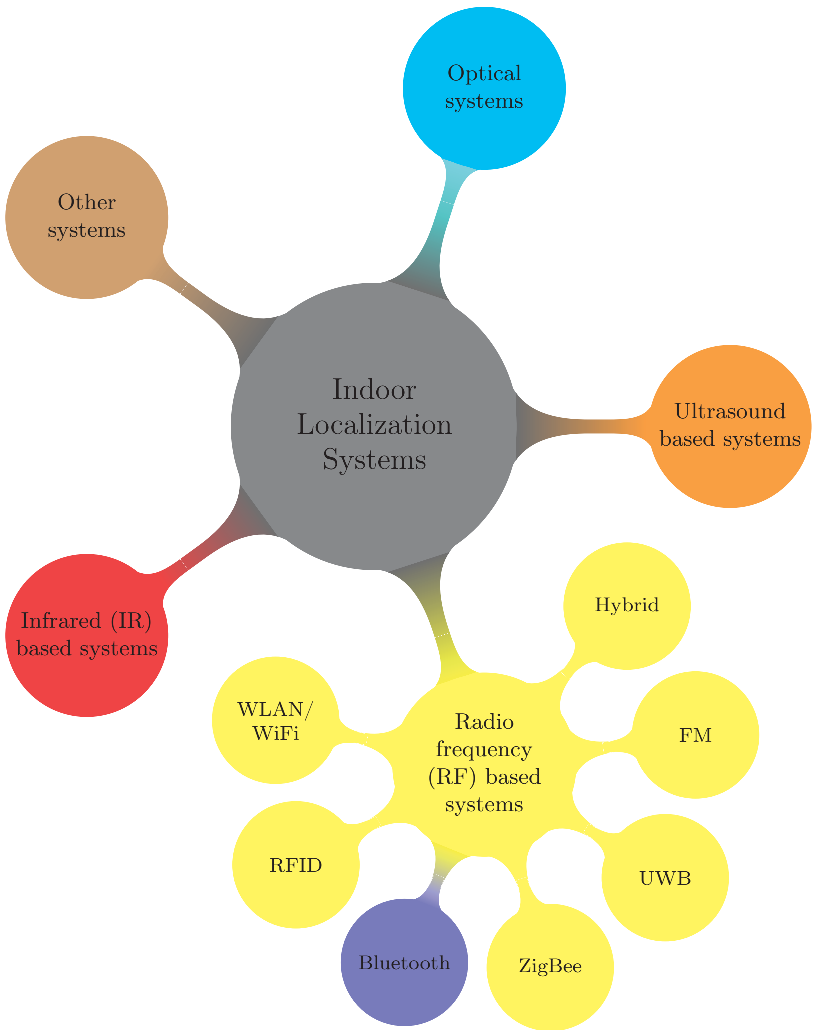
Accomplishment of an indoor localization which is low cost, adaptive, portable and robust is an open question.

Internet of Things (IoT) is a computing concept that describes a future, where everyday physical objects can be connected with each other and talk to each other. The IoT is significant because an object that can represent itself digitally becomes something greater than the object by itself. No longer does the object relate just to you, but is now connected to surrounding objects and database data. When many objects act in unison, they are known as having "ambient intelligence."

Therefore, a localization system which can help localize (our position and) the location of these many objects around us in our environment, without any help from us would be hugely beneficial. Indoor localization is an important aspect for future IoT and Wireless Sensor Network (WSN) applications.

1.3 Indoor localization

Over last 15-20 years significant research is being done in the field of indoor localization. This has lead to development of several indoor positioning systems (or solutions) using different signal technologies for both research and commercial purposes. These solutions are built with different measurement methods e.g. Lateration, Angulation, and Received Signal Strength. Therefore, when developing an indoor positioning system choice has to be made w.r.t. signal technologies available (as information source) and measurement methods that can be used with these technologies. These decisions are governed by the constraints of use-case and for what performance metrics the system is designed for. A mind map is presented here to distinguish between different indoor positioning systems based on the signal technology used as information source in these systems for the purpose of localization.



In chapter 2, we will explain in detail the measurement methods and signal technologies used in indoor localization systems. In recent times Radio Frequency (RF) signal technology has been vigorously researched and numerous indoor positioning systems have been developed using RF signal technology. The property of radio waves to penetrate through obstacles like walls, human bodies etc. make them an ideal information source to be used for indoor localization. Another important aspect of RF based localization systems is the further division of RF into narrow band based technologies (RFID, Bluetooth, WLAN/WiFi, and FM) and wide band based technologies (UWB).

The objective of this research work is to explore, and develop an indoor localization system based on RF signal technology which is:

- **Low cost,** both on hardware and implementation (software).

- **Adaptive,** implementable in different circumstances.
- **Portable,** not site specific, and applicable to different indoor scenarios.
- **Robust,** designed for dynamic environments.

This thesis will focus on the signals of Bluetooth Smart or Bluetooth-Low Energy protocol (which enjoys a new radio, new protocol stack, new profile architecture and a new qualification regime as compared to Bluetooth Classic) as the source of information to tackle the localization problem in an indoor environment. Bluetooth Smart has been designed to be low cost, easily implementable, and with very low energy consumption thus making it extremely desirable for future technological concepts. The most important advantage of Bluetooth Smart is its ready availability in digital devices (Smartphones, Tablets & Laptops) these days and it is a radio standard for a new decade, ability to become the de facto standard for the **"IoT"**.

1.4 Bluetooth Smart or Bluetooth Low Energy

Bluetooth Low Energy (BLE) is a wireless technology operating in 2.4 GHz ISM band developed by the Bluetooth Special Interest Group (SIG) for short range communication [13]. Bluetooth core specification v4.0 was adopted 30 June, 2010. Configured for low power consumption (devices operated with coin cell batteries), it has found applications in automotive, sports and fitness, healthcare, entertainment, home automation, security & proximity, and advertising. BLE uses Gaussian Frequency Shift Keying (GFSK) & Adaptive Frequency Hopping. It has 40 channels with 2 MHz spacing. It enjoys a physical layer bit-rate of 1 Mbit/s and transmission power between -20 dBm to $+10$ dBm (ensuring low power consumption). RF channels are classified into following two types:

- **Advertising physical channel:** (*three channels 37, 38, and 39*) used for discovering nearby devices, initiating connection between devices, and broadcasting data
- **Data physical channel:** (*the rest of channels*) for communication between connected devices

1.5 iBeacon

iBeacon is a protocol standardized by Apple Inc. It is Apple's version of a class of BLE devices that broadcast and receive tiny information within short distances from nearby portable electronic devices. This technology enables smartphones, tablets and other devices to perform actions when in proximity to an iBeacon (`https://support.apple.com/en-us/HT202880`). They also find application in indoor positioning systems which can allow smartphones to find their estimated position by providing relative location information of smartphone from an iBeacon in an Apple retail store. Thus providing proximity based indoor localization solution/system on the basis that an iOS device receiving signal strength from an iBeacon can approximate its distance to that iBeacon. This distance is categorized into 3 different ranges:

- **Immediate:** *within 2 meters*
- **Near:** *from 2-5 meters*
- **Far:** *from 5-10 meters*

The proximity localization concept is shown in Figure 1.1.

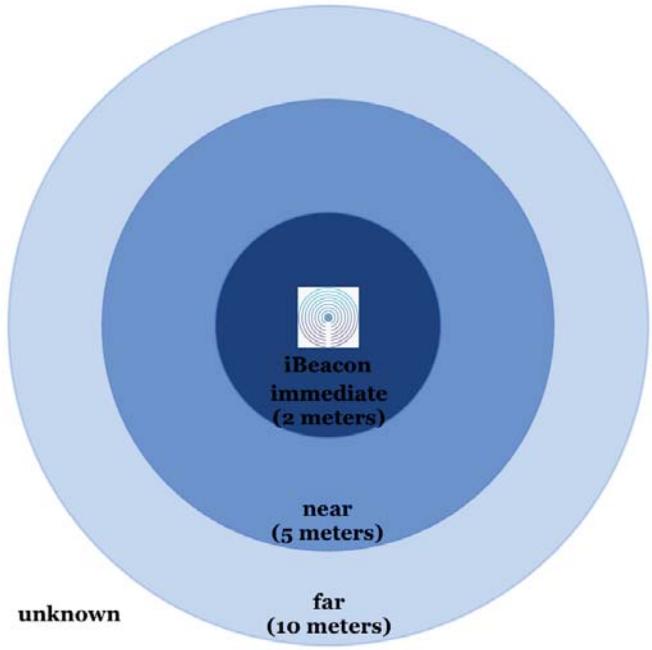


Figure 1.1: Indication of presence of smartphone w.r.t its closeness to an iBeacon in the nearby environment.

1.6 Problem

The feasibility of Bluetooth Low Energy (signal technology) as a viable information source for localization in an indoor environment is an interesting question. With help of iBeacon a positioning service for smartphone localization can be developed using BLE-protocol. Here current location of smartphone is given as a range estimate (immediate, near or far) via an App. as depicted in 1.1. This gives coarse grained (not a 2D) indoor localization solution. The question is can a more fine grained (2D) localization solution be developed in a practical indoor setup with iBeacons using BLE? Commercial-of-the-shelf BLE devices operate with low power transmission capability to have longer battery lifetime which results in smaller range and poor signal penetration. Therefore, when working under low cost & low power consumption constrains inherent in BLE devices can a BLE-protocol based positioning system be developed which is useful in diverse indoor scenarios w.r.t. following five system properties?

- *accuracy,*
- *adaptiveness,*
- *cost,*
- *complexity and*
- *localization time.*

The feasibility of this solution's applicability in typical indoor scenarios like Office buildings, Museums, Gym & Fitness center, Hospitals or Shopping Malls etc. where the indoor environment is continuously changing is also to be tested.

1.7 Research & Goal of Graduate Project

The goal of this graduate project is to investigate, develop and implement localization approaches based on received signal strength (RSS) measurement method in a practical indoor setup of iBeacons using BLE signal protocol. These localization approaches are:

i. *Proximity localization*,

ii. *Fingerprinting localization*,

iii. *Conventional localization*,

iv. *Self-Adaptive localization*,

v. *Space-based localization*.

These localization approaches will be explained in detail in chapter 3. The reason RSS-based localization approaches are used is the fact that data packets broadcast by iBeacons include received signal strength indicator (RSSI) value. The signal strength characteristics from an iBeacon can easily be measured on a smartphone without any additional HW capability via an App. that is able to scan BLE devices and retrieve RSSI value. Therefore using RSS-based localization approaches following localization goals are to be achieved:

i. ***Localization of a mobile node i.e. smartphone.*** The smartphone will be localized with help of reference iBeacons.

ii. ***Localization of a fixed blind iBeacon (static blind node)*** *using the already localized smartphone as reference.*

The Figure 1.2 describes the concept of BLE-based indoor positioning system. Here few reference iBeacons (with known locations) will help localize smartphone (unknown location) inside our localization space and then blind iBeacon node (unknown location), which is static and fixed, is localized using smartphone.

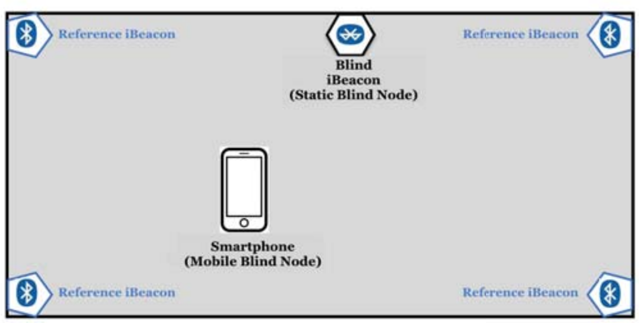


Figure 1.2: A simple graphical representation of bluetooth low energy (signal technology) based localization system for indoor environments.

1.8 Contributions

The main contributions of this graduate project are:

- Providing an overview and implementations of relevant localization algorithms based on RSS measurement method.

- Practical measurement setup which fully captures the characteristics of a general indoor environment.
- Results and evaluation of each localization approach on the basis of localization performance i.e. accuracy achieved.

Furthermore this thesis also provides comprehensive overview of localization methods (not related work).

1.9 Research Question

Based on the problem description, research and goal sections discussed earlier; the objective of this graduate project work is to answer the following main research question:

Can BLE-based fine grained (2D) localization solution (in terms of accuracy) be developed which can localize smartphone and blind iBeacon (static and fixed) in an indoor environment?

Following sub questions are to be answered as well:

1. Can BLE be used as an effective indoor localization technology?
2. What level of accuracy can be provided by such a system?
3. What is the most suitable localization algorithm best suited for a BLE based indoor localization system?
4. What is the maximum localization accuracy that can be achieved?
5. How do the dynamic changes in the environment affect the localization system?
6. What parameters most affect the localization performance?
7. What should be the minimum number of required number of reference iBeacons to start with?

1.10 Outline

The structure of this thesis is given as follows: After the Introduction **chapter** 1, **Chapter** 2 discusses the basics of indoor localization, the common algorithms which are used and the measurement methods associated with them. This chapter also discusses in detail the signal technologies which have been used to develop indoor positioning systems. The choice of appropriate signal technology for indoor localization depends on the use-case scenario. Application areas for indoor positioning along with performance metrics for our BLE-based indoor localization system are also provided in this chapter. In **chapter** 3, the making of our proposed BLE-based indoor localization system using different localization approaches and the working principle for these algorithms is described in detail. **Chapter** 4 will explain the measurement setup that was built to help implement and evaluate BLE-based (indoor) localization system developed with different lcoalization approaches. The results obtained using different algorithms (mentioned in chapter 3) are discussed and analyzed in **chapter** 5. An experimental evaluation of feasibility of BLE-based localization for outdoors is conducted and discussed in **chapter** 6. **Chapter** 7 is Conclusion & Future work and concludes this dissertation.

Chapter 2

Related Work

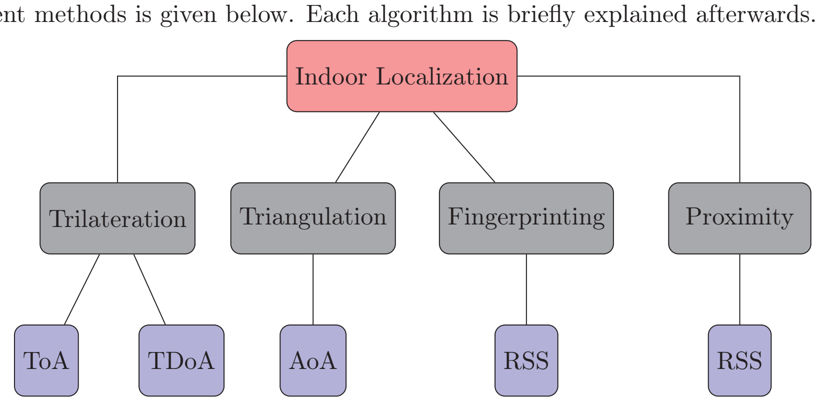
In this chapter, related work with respect to indoor localization is presented in great detail. This chapter starts off with section 2.1, introducing some basic concepts about indoor localization by explaining general algorithms used to solve localization problem. These algorithms can be used with wide variety of signal technologies and these signal technologies are discussed in detail in section 2.2. Section 2.3 provides an extensive list of application areas for indoor localization systems. This section highlights the significance of indoor positioning in our society and explains the importance for research efforts to put these applications into practice. As we will be developing BLE-based indoor localization system, potential application scenarios are presented for this system in section 2.4. Section 2.5 talks about the performance metrics that are used to evaluate indoor positioning systems. Here only few metrics are presented in accordance to the BLE-based indoor positioning system we are developing. There is whole list of other metrics which can be of extreme importance depending upon application context and user requirements. There is always a trade-off between these metrics when implementing.

2.1 Localization Algorithms

The general algorithms which are commonly used for indoor localization are listed below:

1. Trilateration & Triangulation
2. Scene Analysis (Fingerprinting)
3. Proximity
4. Dead Reckoning

These algorithms make use of different measurement methods for position estimation in indoor environments. A graph showcasing the above mentioned algorithms with their corresponding measurement methods is given below. Each algorithm is briefly explained afterwards.



2.1.1 Triangulation

The working principle of triangulation uses geometric properties of triangles to determine the target's location. It has two derivations (basic measurement principles):

- Lateration
- Angulation

Lateration

In lateration, position of an object is estimated by measuring its distance from multiple reference points. This technique is also referred as range measuring technique. In this approach *time of arrival* (ToA) or *time difference of arrival* (TDoA) measurement method is used and distance is derived by computing for the attenuation of signal strength or by simply using the relationship that signal velocity multiplied with time traveled gives distance. The common lateration (measurement) techniques (generally used) are:

- Time of Arrival (ToA) Method
- Time Difference of Arrival (TDoA) Method
- RSS (Received Signal Strength or Signal Attenuation) based Method
- RToF (Roundtrip Time of Flight) Method
- Received Signal Phase Method

ToA The principle of ToA is based on measuring absolute travel time of signal from transmitter to the receiver. This means that distance from mobile target to measuring unit is directly proportional to propagation time. For 2D estimation of position, ToA measurements must be made with at least three reference points, as shown in Figure 2.1. Localization systems based on ToA method would measure one-way propagation time and then the distance between measuring unit and signal transmitter is calculated. Generally using ToA approach yields two basic problems. First, the synchronization problem between all transmitters and receivers. All of them must be precisely synchronized. Second, a time-stamp must be labeled in the transmitting signal so that receiving device (measuring unit) can work out how much distance signal has travelled. ToA can be used with different signal technologies (signaling techniques) like direct sequence spread-spectrum (DSSS), or ultra wide-band (UWB) measurements. ToA has its difficulties for indoor environments as LoS cannot be guaranteed always and multipath effects are common.

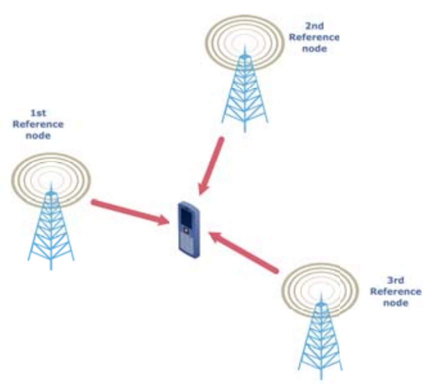


Figure 2.1: Time of Arrival (ToA) technique for localization

TDoA This technique finds the relative location of mobile transmitter by finding out difference in time at which the signal arrives at multiple measuring units, instead of absolute arrival time (as in ToA). For every TDoA measurement, the transmitter must lie on a hyperboloid with constant range difference between two measuring units. A TDoA measurement can be made with two emitters/transmitters on known locations and receiver located on hyperboloid. The target's location can be estimated in 2D from two intersections of two or more TDoA measurements as shown in Figure 2.2. The conventional method for computing TDoA estimates is to make use of correlation techniques. The drawback of this scheme is the non guarantee of LoS availability in indoors.

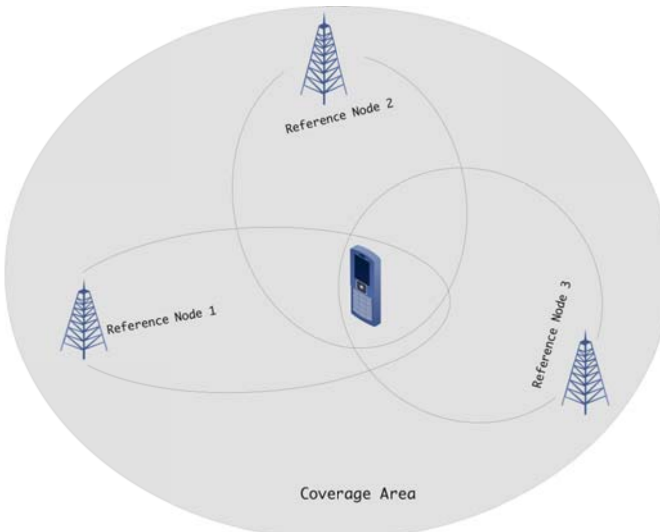


Figure 2.2: Time Difference of Arrival (TDoA) technique for localization

RSS In an indoor environment, radio propagation suffers from multipath effects. ToA & AoA measurement methods' accuracy is affected by this. An alternative approach is established based on attenuation of signal strength to estimate the distance of receiver from transmitter. Such method measures the signal's path loss component resulting from propagation. With help of theoretical and empirical methods the difference between the transmitted signal strength and received signal strength can be converted into range estimate, as shown in Figure 2.3. Since each indoor environment has its own characteristics of interference etc. therefore, the path loss models are always site specific. The accuracy with this can be enhanced via pre-measured RSS contours centered at receiver or using multiple measurements at several base stations.

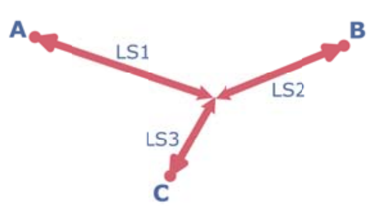


Figure 2.3: Localization based on received signal strength (RSS). Here LS1, LS2, and LS3 denote the measured path loss.

RToF This method measures time of flight from transmitter to the measuring unit and back again. In literature this method, also appears as Round Trip Time (RTT) and Two Way Ranging (TWR). This way synchronization requirement is not as strict as in ToA measurement method and

relative clock synchronization is good enough. Here, the measuring unit acts as a common radar. A target transponder responds to the interrogating radar signal, and the complete roundtrip time propagation is measured by the measuring units. But, there is a delay issue here with the responder which the measurement unit needs to know. This is not a big problem for long or medium range systems but for small range systems this cannot be ignored. The positioning algorithm used for ToA also applies for RToF.
Received Signal Phase method This method uses phase difference to estimate the range. It is also called Phase of Arrival (PoA) method. For indoor localization systems, the signal phase method can be used with ToA/TDoA or RSS methods to yield better localization results. But, the drawback with received signal phase method is LoS path requirement which if not fulfilled leads to more errors in indoor environment. There is also problem of ambiguous carrier phase measurements to overcome.

Angulation

In angulation measurement method, the position of an object is computed with help of measured angles relative to multiple reference points. This technique is usually implemented with Angle of Arrival method.

AoA In AoA, the position of a desired mobile target can be computed by finding the intersection of all pairs of angle direction lines, which are formed by the circular radius from a base or a beacon station (known locations) to the mobile target. The principle is explained in Figure 2.4. Generally AoA methods require at least two reference points and two measured angles in order to derive 2D location of the target. AoA estimation, also known by direction finding, is achieved either by virtue of directional antenna or with an array of antennae. The advantage of this measurement technique is no synchronization is required between the measuring units and amount of hardware required is also less (only two measuring units for 2D positioning and three measuring units for 3D). The disadvantages with this method are; requirement of complex and large hardware, performance digression because of target moving away, multipath reflections, shadowing effect and directivity of measuring aperture.

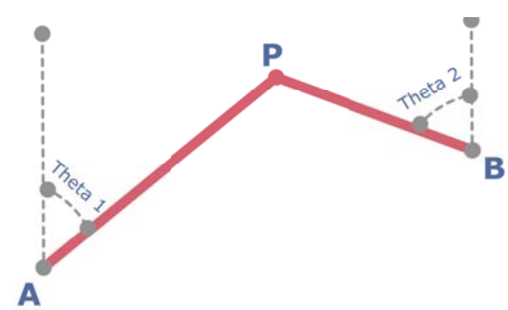


Figure 2.4: Localization based on angle of arrival (AoA) measurement.

2.1.2 Fingerprinting

Fingerprinting or Scene analysis is a type of algorithm used for indoor localization in which the first step is to gather features (fingerprints) of a scene and then estimate the location of object by matching current location's measurements with the closest apriori location fingerprints. Generally RSS based location fingerprinting is used in scene analysis. Location fingerprinting involves, matching of fingerprint of a signal's feature which is location dependent. This technique comprises of two stages: *an offline & an online stage*. Offline stage is about doing site survey of the environment. This involves taking signal strengths of various location points from the close-by base stations (reference units) and noting them down. Online stage would then be using a positioning algorithm to estimate the current location, based on the observed current signal strength and previously collected information. The main challenge for the positioning algorithms based on location fingerprinting is general problem with signal strength i.e. it being affected by diffraction, reflection, and scattering in its propagation in an indoor environment. There are multiple fingerprinting based localization algorithms using pattern recognition method, e.g. Euclidean distance, Probabilistic methods, K-Nearest neighbors (kNN), Neural networks etc.

The standard signal technology used is RF (Received Signal Strength Indication, RSSI) for fingerprinting but there are also fingerprinting localization systems with audio signals or visual images.

2.1.3 Proximity

The proximity method for localization finds the position of a mobile device just by its presence in a special area. Hence, proximity based algorithms provide symbolic relative location information. This method works by simply forwarding the location of an anchor (base or reference) point from where the strongest signal is received. Proximity measurement method has simple implementation, but accuracy of this method depends on how much anchor points are deployed and signal range. Proximity based localization systems are usually based on signal technologies like Infrared Radiation (IR) and Radio Frequency identification (RFID). General examples of proximity based localization systems are in detecting physical contact, automatic ID systems and mobile wireless positioning systems.

2.1.4 Dead Reckoning

In dead reckoning the position is estimated using knowledge of earlier determined positions and known or estimated speeds over the elapsed time. Usually, the main sensor type used is an inertial navigation system. The one problem with this system's usage is inaccuracy is cumulative; hence, deviation in the location fix grows with time. In the domain of indoor applications, a term called Pedestrian Dead Reckoning (PDR) is used in literature to indicate that external sensors like accelerometer are being attached with the user's body.

Table 2.1 ahead summarizes different algorithms and measurement methods used for indoor localization with respect to some key performance parameters.

Method	Measurement type	Accuracy	Coverage	LoS/NLoS	Multipath affect	Cost
Proximity	RSS	Low to high	Good	Both	No	Low
Direction	AoA	Medium	Good	LOS	Yes	High
Time	ToA,TDoA	High	Good	LOS	Yes	High
Fingerprinting	RSS	High	Good	Both	No	Medium
Dead reckoning	Acceleration, Velocity	Low to medium	Good	NLOS	Yes	Low
Map matching	Algorithm based on projection & pattern recognition based algorithms	Medium	Medium	NLOS	Yes	Medium

Table 2.1: Summary of different methods used in indoor localization systems.

2.2 Signal Technologies Used as Information Source for Indoor Localization

As mentioned earlier, indoor localization systems can be developed using different signal technologies. These signal technologies are listed below.

1. Infrared (IR) Localization Systems
2. Ultrasonic (US) Localization Systems
3. Radio Frequency (RF) Localization Systems
4. Optical Localization Systems
5. Other Localization Systems

They will be explained in detail one by one as follows.

2.2.1 IR Localization Systems

They are among the most common localization systems based on wireless technology. Infrared radiation (IR) based systems find applications for detecting or tracking objects or persons using the spectral region of infrared. They are readily available in various devices like mobile phones, PDAs and TV (both wired and wireless). The mechanism for IR-based systems is based on using LOS communication between the two nodes, i.e. transmitter and receiver, provided there is no interference form light/optical sources in environment. They are advantageous due to their small size, being light weight and thus easily carriable. But also have issues like security and privacy and require expensive hardware and maintenance cost. An example of a localization system based on Infrared technology is Active Badge System [48]. In the field of pervasive computing it was one of the very first indoor positioning system developed. Table 2.2 below summarizes some of the indoor localization systems based on IR technology, along with the characteristics they offer.

Name	Year	Accuracy	Covergae	Principle	Target illumination
Active Badges	1999	$6m$	scalable	Proximity	signal transmission
Lee and Song	2007	dm	$36m^2$	IR camera	retro reflective
Ambiplex	2011	20-30cm	$10m$	Angle of Arrival	natural IR radiation
Kinect	2011	$1cm$	$3.5m$	Structured light	passive

Table 2.2: Indoor localization systems based on IR technology.

2.2.2 Ultrasonic Localization Systems

Ultrasonic based localization systems use ultrasonic waves to measure the distance between the sound source and the mobile system (whose localization is required). Generally such systems have multiple ultrasonic receivers and synchronization between them is required which is usually done with IR or RF waves. The systems use ToA information of the sound signal from source to receiver to estimate for receivers' distance from source. The systems based on ultrasonic technology enjoy very good accuracy. Also low cost , ease of implementation and high accuracy makes such systems a good option for indoor localization. A disadvantage is they are also affected by multi path reception and can have large scale implementation complexity. Some examples of localization systems for indoor environments based on sound are Active Bat [49], Cricket [37], Losnus [41] & Alloula [3] etc. These systems provide *cm* level accuracy and enjoy application in smart tracking, monitoring and WSN. Table 2.3 below summarizes some of the indoor localization systems based on Ultrasonic technology, along with the characteristics they offer.

Name	Year	Accuracy	Carrier Frequency	Principle	Application
Active Bat	1997	$3cm$	40kHz	multilateration	smart tracking
Cricket	2005	$1\text{-}2cm$	40kHz	multilateration	smart tracking
Losnus	2010	$1cm$	35-65kHz	multilateration	WSN
Alloulah	2010	$3cm$	20-50kHz	multilateration	monitoring
Sato	2011	$4cm$	40kHz	multilateration	human motion

Table 2.3: Ultrasonic based indoor localization systems

2.2.3 Radio Frequency (RF) Localization Systems

Localization systems based on radio frequency (RF) technologies are most commonly used nowadays due to the property of radio waves to penetrate through obstacles like walls, human bodies etc. These systems thus provide better coverage and can be deployed with less hardware. Another useful aspect of RF based localization systems is the further division of RF into narrow band based technologies (RFID, Bluetooth, WLAN/WiFi, and FM) and wide band based technologies (UWB). RF based localization systems have attracted researchers interests over the last ten years and significant amount of work is done in this regard. The technologies are given below and will be subsequently explained.

- RFID
- Bluetooth (classic)
- Bluetooth Low Energy
- WLAN/WiFi
- FM
- ZigBee
- UWB
- Hybrid

RFID

Radio frequency identification (RFID) is one of the most promising technology for indoor localization systems build to locate people or objects. A basic system would consist of a reader(also known as RFID scanner) with an antenna which constantly scans for active transceivers or passive tags in its environment. Using radio signals as one way wireless communication of data is done from RFID tags to the reader. The most common approach used for localization is Proximity approach, i.e. system indicates presence of a person wearing RFID tag. For applications requiring coarse range localization RSSI can also be used. RFID based localization systems implementing ToA and AoA measurement method have proven difficult to develop. Fingerprinting implementation based on pre-measured signal maps can be applied for RFID scheme localization as well.

RFID technology based localization systems are used in many applications such as locating people, in automobile assembly industry, in warehouse management, in supply chain network etc. since the system works without line of sight requirement. Some examples of RFID based localization systems are from [42], [25] and "ways4all" developed by [21] and many others. Summary of some RFID technology based localization system is shown in the table 2.4 below.

Name	Year	Tag Range	Accuracy	Principle	Application
Dziadak	2005	$2m$	in $meters$	Proximity	burried asset detection
Seco	2010	$30m$	$1.5m$	RSSI, FP	person/object location
Peng	2011	$100m$	1-3m	RSSI + IMU	pedestrian navigation
Kimaldi	2011	$13m$	$room - level$	Proximity	hospital
Kiers	2011	11-30cm	dm	Proximity	navigation of blind

Table 2.4: RFID technology based indoor localization systems

Bluetooth

Bluetooth is a wireless standard for WPANs (Wireless Personal Area Networks) just like ZigBee. Bluetooth standard is a proprietary format managed by Bluetooth SIG (Special Interest Group). Bluetooth operates in the 2.4 GHz ISM band. The biggest advantage of using Bluetooth for an application is that nowadays almost every WiFi enabled mobile device, tablet, PDA or computer (laptop) comes with an embedded Bluetooth module in it. With Bluetooth standard also used for information exchange, there is also another benefit of this technology in form of provision of high security, low cost, low power and small size. Each Bluetooth tag comes with a unique ID, which can be then used to locate a Bluetooth tag. There is one potential drawback of using Bluetooth technology in the form of each bluetooth device having a latency thus making it unsuitable for real-time positioning applications. This is due to the fact that for each location finding, the device discovery procedure has to be run which in turn increases the localization latency and power consumption.

There has been research done in exploring the best possible positioning principle for Bluetooth based localization systems. The proximity method is the normally applied positioning approach. Time of flight (ToF or ToA) method is not favorable due to the standards and intrinsic characteristics of the (Bluetooth) protocol. One of the first implemented localization system using Bluetooth technology standard is Real-Time Navigational Assistance (URNA) system [2]. The objective was to enable the location-based information between Bluetooth-enabled mobile devices. It was based on Proximity approach. Another example is a commercial localization system called ZONITH (2011), which offers an indoor positioning module consisting of deployed bluetooth beacons (each covering one or more rooms) and Bluetooth devices e.g. mobile phones etc. worn by people to be tracked. It provides room-level accuracy. Table 2.5 summarizing some bluetooth based localization systems is given below.

Name	Year	Prior Calibration	Accuracy	Principle	Application
Aalto	2004	no	$20meters$	Proximity	advertising
Bargh	2008	yes	$room - level$	Fingerprinting	LBS
ZONITH	2011	no	$room - level$	Proximity	employee tracking

Table 2.5: Indoor Llocalization systems based on Bluetooth technology

Bluetooth Low Energy (BLE)

BLE has low power consumption than classic Bluetooth. With low power, applications can run on a small battery for four to five years. Just like Bluetooth, BLE operates in the 2.4 GHz ISM band. BLE has 40 channels equally spaced at 2 MHz apart and three of them are used for advertisement so that a BLE-enabled device can broadcast. Unlike classic Bluetooth, BLE remains in sleep mode constantly except for when a connection is initiated. The actual connection times are only a few ms, unlike Bluetooth classic which would take $100ms$. BLE has potential to become the de facto standard for Internet of Things (IoT) as BLE enables building of numerous basic services and profiles like proximity, battery, automation I/O, building automation, lighting, fitness, and medical devices. BLE-based indoor positioning systems usually use Proximity localization approach.

WLAN/WiFi

Using a WiFi based indoor positioning system is common practice because of low infrastructure cost and no need for line-of-sight (LOS). Any device with WiFi compatibility can be easily localized without any additional hardware or software manipulation. They are commercially available and are mostly based on received signal strength measurement principle, but there are also systems available with ToA, AoA & TDoA measurement methods (see table 2.6 for details). There are several advantages for designing a localization system using WLAN (WiFi) technology. Some of them include the readily availability of access points in indoor environments, no special hardware requirements, a 50-100 meters range making it more attractive in comparison to Bluetooth or RFID. An example of WiFi based localization system is RADAR [4]. It was designed as a user location and tracking system, addressing both the location and tracking problem. The implementation was done purely in software thus making it an easily implementable choice for indoor localization. The fundamental idea in RADAR was to use signal strength as a function of receiver's location and radio map. Fingerprinting approach has an offline and online phase. Summary of some WLAN/WiFi based localization systems is shown in the table 2.6 below.

Name	Year	Accuracy	Principle	Prior Calibration	Method
Bahl	2000	$5m$	fingerprinting	yes	offline training
Gunther	2004	5-15m	round trip time	no	-
Chen	2005	2-4m	fingerprinting & RFID	yes	offline training
Wong	2008	$2m$	angle of arrival	no	-
Ekahau	2009	$7m$	fingerprinting	yes	offline training
Gansemer	2010	2.1m	fingerprinting	yes	offline training
Hansen	2011	$4cm$	fingerprinting	yes	dynamic model

Table 2.6: Indoor localization systems based on WLAN/WiFi technology

FM

The FM radios are a well established broadcasting technology and the fact most households and cars (can) have them make them a good candidate for indoor navigation (and positioning) as audio signals of FM radio transmission can be used. Research has shown that fingerprinting (approach) based techniques are more feasible for FM radio based localization rather than ToA and TDoA methods. Not much work has been done in developing indoor based localization using FM radio signals but some of the implemented work is from [27] and is based on RSSI fingerprinting principle for an office environment. Another example is (PhD thesis) from [35] and FINDR by [30]. Table 2.7 below highlight some of the indoor localization systems based on FM technology along with their properties.

Name	Year	Prior Calibration	Accuracy	Principle	Application
Papliatseyeu (FINDR)	2009	yes	4.5m	Fingerprinting	indoor navigation
Popleteev	2011	yes	5m	Fingerprinting	employee tracking application
Moghtadaiee	2011	yes	3m	Fingerprinting	employee tracking

Table 2.7: Indoor localization systems based on FM technology

ZigBee

ZigBee is wireless technology standard popular for short and medium range communication applications. It can be regarded as a low rate Wireless Personal Area Network (WPAN). The standard is designed with applications requiring low power consumption in mind and not requiring large data throughput. For indoor environments ZigBee signal range is typically 20-30m. RSSI is the usual principle used for distance estimation between two ZigBee nodes. One drawback is that since ZigBee operates in the unlicensed ISM band , the designed localization system would be vulnerable to interference from other signal types consequently harming the radio communication. Some of the work done for ZigBee based indoor localization includes [19], [22] and MyBodygurad(2011), which is a commercial indoor tracking system for humans and objects. Table 2.10 given below helps describe some localization systems based on ZigBee technology.

Name	Year	Prior Calibration	Accuracy	Principle	Application
Tadakamadla	2006	minimal	3m	RSSI distance	context, LBS
Larranaga	2010	yes	3m	RSSI distance	WSN, tracking
MyBodyguard	2011	no	Proximity	Fingerprinting	tracking

Table 2.8: Indoor localization systems based on ZigBee technology

UWB

Ultra-wide-band is a radio technology for short range, high bandwidth communication holding the properties of strong multi path resistance. For localization systems with high accuracy demands (20-30 cm) UWB is widely used as other conventional wireless technologies such as RFID and WLAN/WiFi do not provide such high level of accuracy. A basic UWB based localization setup would include stimulus radio wave generators and receivers which can capture the propagated and scattered waves. UWB signals have property to penetrate through walls, glass and other obstacles making it extremely good for indoor localization because ranging is then free of LoS constraint and also inter room ranging is possible. The problem with UWB is that hardware is expensive thus making it unsuitable for large scale implementation. Some localization systems based on UWB technology are from [10], [46] and [12]. Table(2.11) summarizing UWB localization is shown below.

Hybrid

Hybrid localization systems use multiple different localization technologies for locating a mobile client. Localizing a mobile client is one of the most important service of a localization system and since some location technologies are primarily designed for indoor and GPS based positioning system is (by virtue of design) unsuitable for indoor, thus a hybrid system which works both indoors and outdoors would be highly desirable. This is how the concept of hybrid localization system came into being. Hybrid localization systems have thus been developed and some examples are Navizon, Xtify, SkyHook and Devicescape etc.

Name	Year	Noise Radar or IR (Pulse Duration)	Accuracy	Principle	Application
Stoica	2006	IR(750 ps)	$4cm$	ToA	sensor networks
Fischer	2010	IR(200 ps)	$4cm$	ToA, RTT	industrial application
Segura	2010	IR(2 ns)	$20cm$	TDoA	mobile robot
Kroell	2010	pseudo noise	$4cm$	Fingerprinting	office
UBISENSE	2011	IR(very short)	$<15cm$	TDoA, AoA	automation

Table 2.9: Indoor localization systems based on UWB technology

2.2.4 Optical Positioning Systems

Optical indoor positioning systems use camera as the main sensor. There are also optical positioning systems in combination with distance or mechanical sensors. Optical indoor localization systems using camera based system architectures are exclusively built on the Angle of Arrival (AoA) method. The advancement in CCD technologies, processing speed and image understanding has helped in developing camera based indoor localization systems. Optical localization systems can be categorized in terms of primary mode of reference. They are summarized in the table 2.10 below.

Name	Reference	Accuracy	Coverage	Object/Camera Positioning	Camera Cost
Hile	floor plan	$30cm$	scalable	cam., SR 4000	900 $
Ido	images	$30cm$	scalable	cam., IEEE 1394	-
Mulloni	coded markers	$m - dm$	scalable	cam., call phone	low
Popescu	projection	cm	$25m^2$	camera	1500 $
DEADALUS	none	$0.04mm$	$m - km$	obj., Guppy F80	high

Table 2.10: Optical indoor localization systems

2.2.5 Other Systems

There are other ways to do indoor localization as well. Some of the systems developed in this regard are discussed now. They can be specifically designed system with a certain application in mind and would make use of different available options including external (multiple sensors), different RF technologies etc. They are as:

- Inertial Navigation Systems (INS)
- Magnetic Localization
- Infrastructure Based Localization Systems

INS

An INS consists of an Inertial Measurement Unit (IMU) and a processing unit as the main components. But to provide for the location information it also makes uses of complementary sensors. An INS is an electronic device which is used to provide estimation of position, velocity and orientation of an IMU. The custom IMU consists of three orthogonally arranged accelerometers, three gyroscopes and/or a magnetometer. Summary of INS based localization systems helping in pedestrian navigation is given below in this table 2.11.

Name	Mounting Body Part or Device	Accuracy	Complimentary Sensors	Local Reference	IMU Sensors
Kemppi	waist/ pocket	17m	3 Accelerometers & Gyroscopes	map, beacon	Accelerometer
Seitz	phone	5m	3 Accelerometers & Magnetometers	WLAN RSSI	Bosch BMA150
Kligbeil	waist	1-6m	3 Accelerometers, Magnetometers & Gyroscopes and 1 Barometer	GPS, US, RF, CSS	Accelerometer
Jimenez	foot	1m	3 Magnetometers & Gyroscopes	RFID RSSI	MTI-G Xsens

Table 2.11: Pedestrian navigation approaches

Magnetic Localization

Localization systems using magnetic and electromagnetic fields are also developed. Permanent magnets or coils with AC or DC can be used as source of magnetic fields in such systems. One such system using AC magnetic field and 16 sensors to provide position and orientation of an object is the electromagnetic tracker system LIBERTY from Polhemus (2011). Another system is InfraSuvey (2011) which provides underground localization using UGPS based on low frequency AC magnetic fields. This system is designed to measure position and orientation of objects in underground environment such as mines, tunnels, caves or pipes. The system also finds application for indoor localization. There are also some other systems developed as well, some of them are given below in table 2.12.

Name	Year	Accuracy	Coverage	Principle	Application
Haverinen	2009	1mm	280m(1D)	Fingerprinting	robot localization
InfraSurvey	2011	1m	200m	AC magnetic field	caves, mines, tunnels
Q-Track	2011	50cm	23m	Near field	NLoS office & industry
Arumugam	2011	20cm	50m	DC field, coils	American football

Table 2.12: Magnetic Localization systems

Infrastructure Based Localization Systems

There are also localization systems which are not based on any of the technologies mentioned before instead they make use of already existing building infrastructure or embed additional infrastructure into building material for the sake of localization.

Power Lines Power Line Positioning (PLP) is a sub-room localization system in a household based on the fingerprinting method and using the existing electrical grid. PLP uses the power line infrastructure in a building. An example of such systems is [31] in which a location system based on battery-less tags using power lines is presented. An other example is [45], using wideband signals and fingerprinting based technique for localization. Here the drawback is electrical disturbance from other devices.

Floor Tile The multiple floor tiles presence can be used for passive, unobtrusive indoor tracking of human beings. These systems can be very advantageous as they are invisible to the user and users need not to be equipped with tags. A tile track system is presented by [47], which is based on measuring the capacitance between multiple floor tiles using the fact that when a person stands over a tile, the capacitance between human feet and transmitter increases. The system is good to use for multi-person tracking. Other examples include SensFloor developed by [44] and it is a large area capacitive system designed for ambient assisted living (AAL). There is also [40] & [39], who present a sensor floor system where electrical near field is used for fall-detection.

Fluorescent Lamps Such systems use the principle of optical communication for indoor guidance with help of lamps. The concept is proven by [24], which describes a system providing indoor guidance for the blind using fluorescent lights. Another example is from [29] where positioning systems is based on light communication in combination with an IMU based navigation system.

Summary of infrastructure based localization systems for indoors is given below in the table(2.13)

Name	Year	Accuracy	Coverage	Existing or Deployed infrastructure	Principle	Application
Stuntebeck	2008	1-3m	building	existing	power lines	location aware homes
SensFloor	2011	dm	$50m^2$	deployed	floor tiles	assistance for elderly
Nishikata	2011	10cm	building	existing	fluorescent lamps	robot guidance
Weber	2011	4m	40m	deployed	leaky feeder	indoor localization

Table 2.13: Infrastructure based localization systems

Comparison of different technologies (told before) which are used for indoor localization, with respect to accuracy and coverage is shown below in figure(2.5).

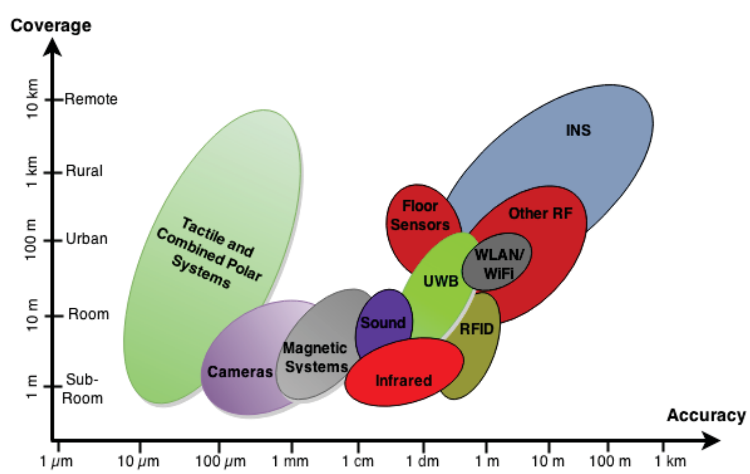


Figure 2.5: Overview of indoor technologies in dependence on accuracy and coverage

2.3 Indoor Localization Applications

Following is a list of applications highlighting the importance and need for indoor positioning in our modern way of life [26]. With innovation and continuous improvement in performance, next generation indoor positioning systems (like our BLE-based indoor localization system) will find more applications which are at the present time not feasible or thinkable.

2.3.1 Museums

Several applications in museums, such as visitor tracking for surveillance and study of visitor behaviour, location based user guiding and triggered context aware information services. All these things can be easily achieved with an indoor positioning system. The accuracy requirements are 2-3 meters.

2.3.2 Location Based Services in Indoor Environments

Location-Based Services (LBS) which makes use of the geographical position to deliver context-dependent information accessible with a mobile device can have huge commercial benefits. Such services are increasingly used indoors. Examples of indoor LBS are obtaining safety information or topical information on cinemas, concerts or events in the vicinity. These applications also include navigation to the right store in a mall or office in a public building. Within a store or warehouse, the location detection of products is of interest to the owner as well as to the customers. In particular, location-based advertisements, location-based billing and local search services have a high commercial value. There is a request to guide the visitors to correct exposition booths at large tradeshows and exhibitions these days. The positioning provider gets added value by making used of localization by resource tracking, fleet management and user statistics. These application require an indoor positioning system with an accuracy of couple of meters.

2.3.3 Private Homes

Applications at homes include the detection of lost items, physical gesture games and location based services at home. Ambient Assistant Living (AAL) systems provide assistance for elderly people in their homes within their activities of daily living. A key function of AAL systems is location awareness which requires an indoor positioning functionality. Applications at home are medical monitoring such as monitoring vital signs, detection of emergencies and fall detection, but also service and personalized entertainment systems, such as smart audio systems [52]. Here accuracy requirement can be very high, up to 1 meter.

2.3.4 Context Detection and Situational Awareness

Mobile devices provide a large variety of useful functions where it is desirable to have an automated adaptation of the mobile device depending on a change of the user's context. Such functionality spares the user additional effort by providing assistance in individual situations. To enable such an automatic adaptation the mobile user's context needs to be determined by the mobile device itself. The most significant criteria to determine the user's context is the current geographical location. For example a smart conference guide can provide information about the topic discussed in nearby auditoriums. Systems providing accuracy up to few meters work best in this application area.

2.3.5 Medical Care

In hospitals the location tracking of medical personnel in emergency situations has become increasingly important. Medical applications in hospital also include patient and equipment tracking, e.g. fall detection of patients. Precise positioning is required for robotic assistance during surgeries.

Existing analytical devices can be replaced with more efficient surgical equipment. High accurcay is demanded for positioning systems deployed inside hospitals.

2.3.6 Police and Firefighters

Indoor positioning systems can be used with great effect in law enforcement, rescue services, and fire services i.e. location detection of firemen in a building on fire. With help of indoor positioning the police benefits from several relevant applications, such as instantaneous detection of theft or burglary, detection of location of police dogs trained to find explosives in a building, locating and recovery of stolen products. Accuracy requirements vary from couple of meters to few meters.

2.3.7 Guiding of Vulnerable People

Systems specifically designed to help visually impaired with navigation and localization in indoor environments. High accuracy needed in this application area.

2.3.8 Surveying and Geodesy

Using positioning systems for surveying of the building interior. Positioning capbalities for this application demands global reference is needed for data input to CAD, GIS etc. Accuracy requirements vary from centimeters to millimeters.

2.3.9 Gym and Fitness Centers

there are several application in Gym and Fitness centers, such as tracking of users, behavioral study of gym users, location based user navigation and triggered context aware information services about gym machines and equipments. Accuracy of up to couple of meters is required in this application scenario.

2.3.10 Environmental Monitoring

With help of environmental monitoring it is easy to observe some phenomenon such as heat, pressure, humidity, air pollution and deformation of objects and structures. To monitor these parameters over a certain indoor or outdoor space, multiple sensor nodes are organized as a Wireless Sensor Network (WSN). A WSN consists of small, inexpensive, spatially distributed autonomous nodes with limited processing and computing resources and radios for wireless communication. A comprehensive literature review on WSNs can be found in [51]. Therefore the knowledge of nodes' position is determined by using localization algorithms. Accuracy requirements are up to couple of meters.

2.3.11 Structural Health Monitoring

Using sophisticated sensors incorporated into steel reinforcements within concrete can performing strain measurements can help detect strain changes and deformation caused by loading at various points. Centimeter accuracy is required in this case.

Indoor localization is an important aspect of all future WSN and IoT applications.

2.4 Application Scenario Example Envisioned for iBeacon Localization

Our iBeacon localization system can be deployed in many different indoor environments. As example, case scenario of **museums** is selected where our iBeacon localization system can be deployed and provides context- and location-aware services. People can be tracked moving around different parts of the museum via smartphone localization with this system. Blind iBeacons can be strategically placed near certain paintings or statue etc. and as people walk pass by them the blind iBeacons will be localized using (already localized) smartphone. Immediately after blind iBeacon is localized, people will get pop-up information about the thing (e.g. painting or statue) where that blind iBeacon was placed. This way people can have an interactive museum experience. Another case scenario would be, deployment of this system in **gym**. Here blind iBeacon can be hidden behind a gym machine. Blind iBeacon using its unique MAC address can help associate a unique ID to the machine and also characterize the machine it is placed behind. People in gym can localize this blind iBeacon using smartphone and will receive information via a popup about that gym machine (where blind iBeacon was hidden) and use machine, accordingly. This system can also help provide users with navigation service when inside a gym. Figure(2.6) tries to give idea about such an application of iBeacon localization for gyms.

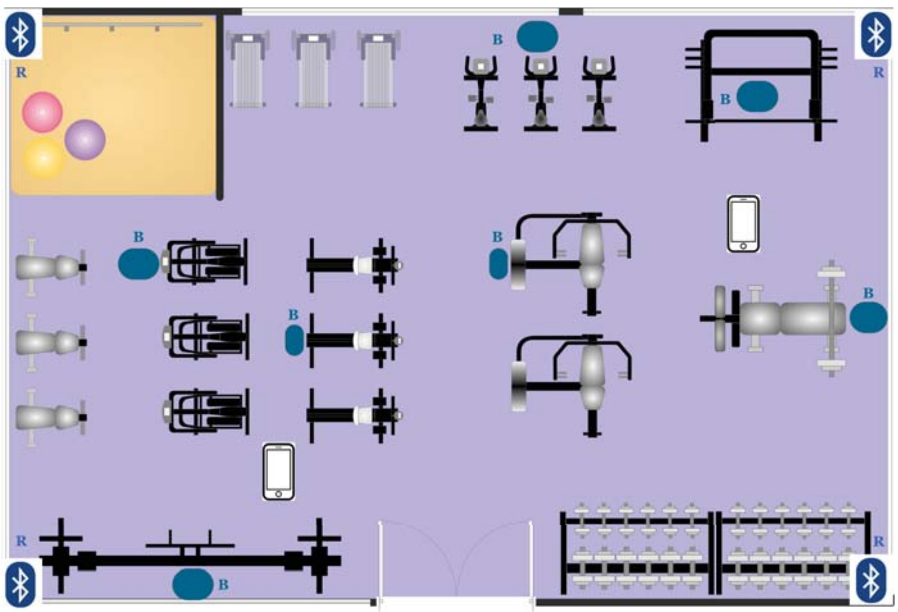


Figure 2.6: A BLE-based indoor positioning system deployed in Gym (indoor environment). Here **R** represent the reference iBeacons (with known locations) and **B** shows where blind iBeacons (with unknown locations) are placed. Gym users can localize these blind iBeacons using smartphone (localized with help of reference iBeacons) and immediately will get popup information about gym machines upon which these blind iBeacons are hidden.

2.5 Performance Metrics for Localization Systems

Following metrics are used to account for performance of an indoor localization system.

- **Accuracy:** Accuracy or location error is the most important performance metric for a localization system. Usually mean distance error is used as the performance metric, which is the euclidean distance between the calculated location and actual location. The higher the accuracy the better the system, however there is always a trade-off between accuracy and other system characteristics. A compromise has to be reached between accepted accuracy and other characteristics.

- **Precision:** Whereas accuracy describes the value of mean distance error, Precision is used to describe how consistently the system works i.e. it is a measure of the localization technique as it shows the variation in its performance over many trials. It can be described as distribution of distance error between the estimated location and true location and usually cumulative probability functions (CDF) of distance error is used for measuring the precision of a system.

- **Complexity:** The complexity of a localization system is attributed to hardware used, software implementation, and other factors in the system.
- **Cost:** The cost of a localization system depends on many factors. Important factors among these are; *money, time, space, weight & energy.* The time factor is in relation to installation and maintenance of the system. Mobile units may come with weight constraints and tight space requirements. Energy is also another important cost factor for a localization system.
- **Robustness:** A localization system with high degree of robustness would be able to function properly even in a scenario when some signals are not available, or when some of the RSS value or angle characteristics have never been seen before. Sometimes there is no signal availability from a transmitter unit (due to some blockage), measuring units can be out of function or damaged in a harsh environment. Nevertheless the localization techniques have to use this incomplete information to compute location.
- **Integrity:** This metric means the confidence which can be placed on certain localization system's output. An integrity risk is the probability that due to a malfunction (in the system) the calculated location differs from the required location by more than an acceptable amount.
- **Practicality:** This metric means how practical is the use of localization approaches chosen to develop the localization system for a certain indoor environment. This implies how practical is the deployment of hardware chosen, the implementation of localization algorithm and overall systems' functionality under dynamic indoor environments.

Chapter 3

Making of a BLE-based indoor localization system

In this chapter the main objective of the graduate project will be re-explained along with details of localization approaches based on received signal strength (RSS) measurement method that we plan to use in our BLE-based indoor positioning system implementation. These approaches: *Proximity Localization, Fingerprinting Localization, Conventional localization, Self-Adaptive Localization & Space based Localization* will be comprehensively discussed in this chapter. Starting with section 3.1, an Introduction into using Bluetooth-Low energy RSS range-based indoor positioning system is provided on the back of iBeacon technological innovation. Afterwards section 3.2 of this chapter will explain the objective of the graduate project's work. RSS Range-based indoor positioning make use of received signal strength measurements and section 3.3 helps explain RSS-based localization along with providing a formal localization definition in wireless networks (indoor positioning system) and explaining Log-Normal Shadowing Model (LSNM) which is used in range-based RSS-localization approaches as propagation model. Section 3.6 explain Maximum Likelihood Estimators (MLE) for range-based localization systems. Sections 3.4 to 3.10 wrap up the chapter by discussing in detail one-by-one the localization algorithms (mentioned earlier) with which our BLE-based indoor positioning system will be developed and results for these will be discussed in chapter 5.

3.1 Introduction

iBeacon is an example of technological innovation from Apple Inc. They are designed to work with Bluetooth-Low Energy protocol and come with characteristics of low energy consumption, low cost and longer battery times (in years). It is a new technology which is primarily designed to extend the location services in iOS. Apps. on your smartphone can be alerted when you approach or leave a location with an iBeacon. In addition to monitoring location, an App. can estimate users' smartphone proximity to an iBeacon thus providing a proximity based indoor positioning system see Figure 3.1.

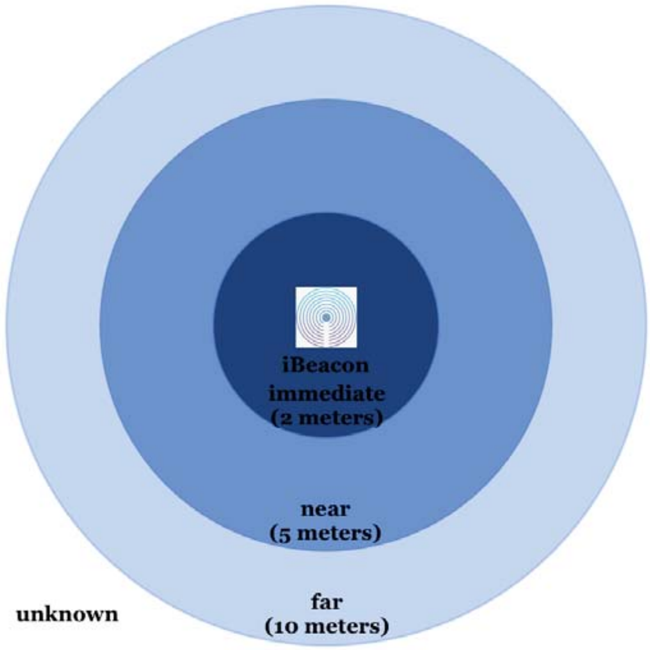


Figure 3.1: Indication of presence of smartphone w.r.t its closeness to an iBeacon in the nearby environment.

3.2 Objective

As evident from Figure 3.1 within an indoor environment an iBeacon provides location service with three ranges; *Immediate, Near and Far*. These ranges are attributed with received signal strength indication (RSSI) value that is received (or measured) on smartphone from the iBeacon. Usually some threshold on the measured RSSI values is used to define these distance ranges and an App. can notify the smartphone user about its proximity to an iBeacon (for example a display or checkout counter in a retail store). Thus we categorize this localization system (with iBeacon) as providing a coarse grained indoor localization solution, since only range estimation w.r.t information about closeness to a point (where an iBeacon is placed) is provided.

The objective of this master thesis work is to develop a more fine grained indoor localization system using iBeacons and a smartphone, where position estimation for smartphone can be described in more refined x- and y-coordinates within the (indoor) localization space (environment). The objective of the graduate work can be stated in two parts as:

Firstly; To localize smartphone with help of reference iBeacons (nodes with known location) in an indoor environment,

Secondly; To localize afterwards (single or multiple) blind iBeacons present in the localization space in our indoor environment. These blind iBeacons are meant to be static and fixed inside the localization space.

This objective can be explained with a simple graphical representation (see Figure 3.2). The generic idea is depicted in this figure, within an indoor environment e.g. a hallway or a big room etc. iBeacons placed at corners act as reference nodes. This way localization space is established inside the coverage area provided by these iBeacons. **The (2D) position estimate of**

smartphone and blind iBeacon inside this localization space is the end product of our localization system.

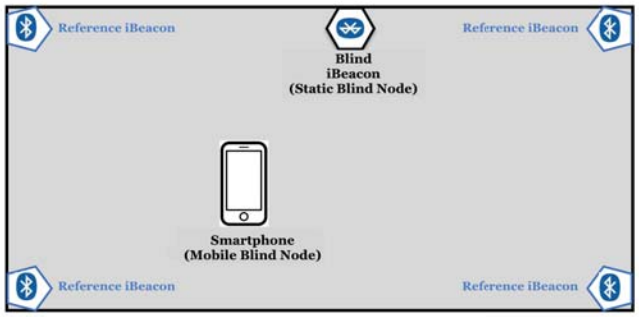


Figure 3.2: A simple graphical representation of bluetooth low energy (signal technology) based localization system for indoor environments.

The goal is to build a prototype BLE-based indoor positioning system which can be easily implemented in diverse indoors scenarios such as *a typical office environment* (as shown Figure 3.3), *museum, gym & fitness center, retail stores etc.*

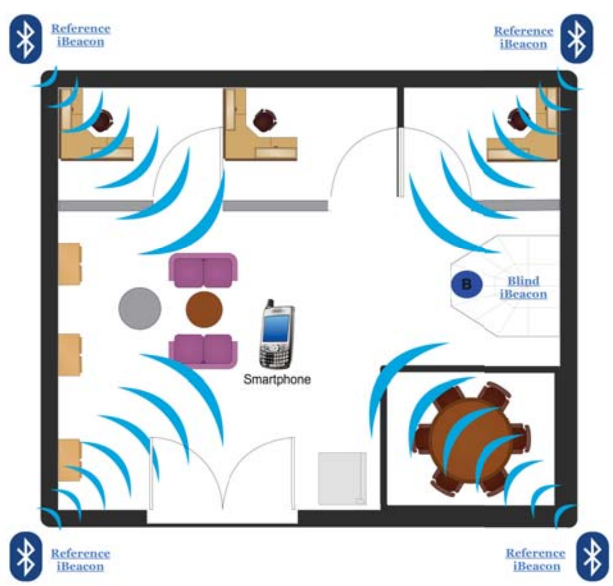


Figure 3.3: A Bluetooth low energy signal technology based indoor localization system

Real time indoor environments are always dynamic and continuously changing, thus making them challenging for precise and accurate position estimation. Different measurement methods like *ToA, TDoA, AoA, RSS* can be used to implement an indoor localization system. RSS range-based indoor positioning systems are usually based on RSS measurement method and thus we will make use of localization algorithms which are developed with received signal strength characteristics. We will be using five different algorithms based on RSS measurement method. These algorithms include *Proximity, Fingerprinting, Conventional Localization, Self-Adaptive Localization (SAL) &*

Space-based localization.

3.3 RSS Based Localization System

RSS range-based localization is a type of RSS-based localization approaches. It assumes that RSS is a function of distance [15]. Hence this function can be used to convert the RSS measurements to distance estimates, which are then used to estimate the position [33]. Therefore, range-based localization works with the assumption that RSS decay can be described by a function; hence, the signal strength over distance distribution is expressed with a propagation model. One of the parameter that appears in the propagation model is the position. Mathematically, localization then reduces to calculating field energies at the unknown location of the receiving antenna radiated from an antenna array at known positions. With a large enough antenna array and radiation in the environment adequately represented by the propagation model, localization reduced to a set of non-linear equations for the position estimation and possible parameters used in the propagation model. Usually the empirical Log-Normal Shadowing Model (in detail in section 3.3.1) is used in RSS based localization systems to describe the RSS over distance decay [15]. This model has two wave parameters; reference RSS power P_{d_0} & path loss exponent n (can be seen in Equation 3.1) which act as independent variables to account for the environmental influences and hardware differences. Log-Normal Shadowing Model is based on the assumption that RSS follows a log-normal distribution and is widely used model for position estimation in RSS-based localization systems.

3.3.1 Log-Normal Shadowing Model

We have adopted Log-Normal Shadowing Model (LNSM) as the propagation model for range-based localization approaches. The LNSM is used for modeling the signal strength over distance decay. This empirical model is widely used by RSS-based localization estimators (e.g. [32], [7] & [34]) and has shown to be a reasonable representation of reality [38]. The Log-Normal Shadowing Model works under the assumption that RSS follows a log-normal distribution. A log-normal distribution (see Figure 3.4) is a continuous distribution in which the logarithm of a variable (which will be RSS in our case) has a normal distribution. This means that:

- The average received signal strength (RSS) decreases logarithmically over distance.
- The received signal strength (RSS) follows a normal distribution at a certain distance.

The formula representing the Log-Normal Shadowing Model[15] is written below:

$$P_d = P_{d_0} - 10 \cdot n \cdot log_{10}(\frac{d}{d_0}) + X_\sigma \tag{3.1}$$

Where:

- P_d is the received signal strength in dBm at distance d.
- P_{d_0} is the received signal strength in dBm at reference distance d_0, which we will call as "Reference RSS power". In general, d_0 is relatively small. For simplification d_0 is considered as 1 meter [38].
- n represents the Path Loss Exponent (PLE). The path loss exponent represents the rate at which the path loss increases with distance.
- X_σ gives the deviation of the received signal strength due to shadowing effects and is invariant with distance [38]. X follows a zero-normal distribution with standard deviation σ:

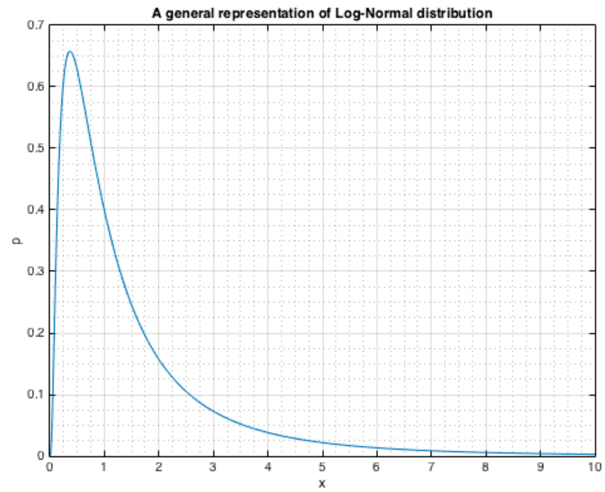


Figure 3.4: The Log-Normal Probability Distribution Function (LN-pdf) plot.

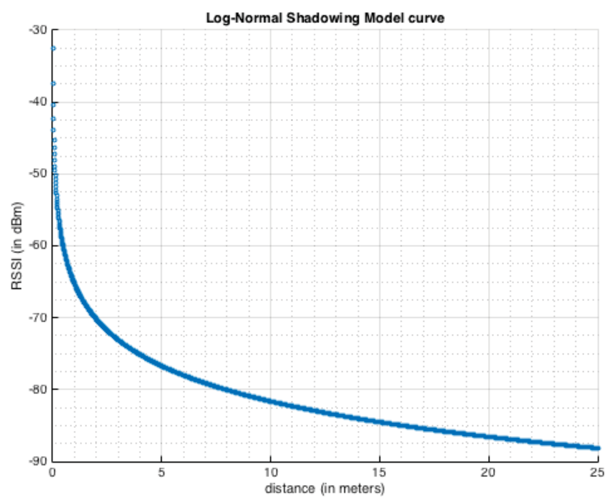


Figure 3.5: The Log-Normal Shadowing Model curve plot for received signal strength over distance distribution. In this curve the received signal strength power i.e. P_d is plotted as a function of distance based on Equation 3.1.

$$X \sim N(0, \sigma^2) \tag{3.2}$$

The Log-Normal Shadowing Model (see curve in Figure 3.5) when represented with this empirical model is widely accepted and has shown to be useful but it also come with certain limitations. The three major sources of error are interfering effects, shadowing [15] and hardware inaccuracies [17, 50]. The interfering effects are due to the adding up of multiple signals with different amplitude and phases resulting in either constructive or destructive interference. One way to address this issue is to perform RSS measurements over a relatively large frequency band, this way the error due to interference phenomena can be minimized. Shadowing also results in errors in RSS measurements. Shadowing is the attenuation of a signal due to obstructions, also called medium-scale fading [15].

3.3.2 Localization definition

Consider a wireless network, see Figure 3.6, that consists of N reference iBeacons (reference nodes in our case), a smartphone as mobile blind node and a blind iBeacon as a static and fixed blind node:

- **Reference nodes** know their position beforehand.
- **Blind nodes** do not know their locations and require localization. The whole objective of a positioning system is to estimate the position of blind nodes as accurately as possible. These blind nodes can be static or moving i.e. in our localization system we have two kinds of blind nodes;
  - **Mobile blind Node** is the **smartphone** (or tablet) which helps record RSS measurements from reference nodes. Afterwards these RSS measurements are used for position estimation of smartphone. The mobile node in our localization system will be referred as smartphone for convenience.
  - **Static blind Node** is the **blind iBeacon** in the environment whose position is not known before hand and it's position will be estimated using smartphone (already localized). This node will be mentioned as blind iBeacon. The number of blind iBeacons is one or more. They are always static in our indoor environment and shall be strategically place at a particular point of interest inside the localization space.

Our aim is to locate the blind nodes (smartphone and blind iBeacon) using RSS values measured on smartphone from all reference nodes.

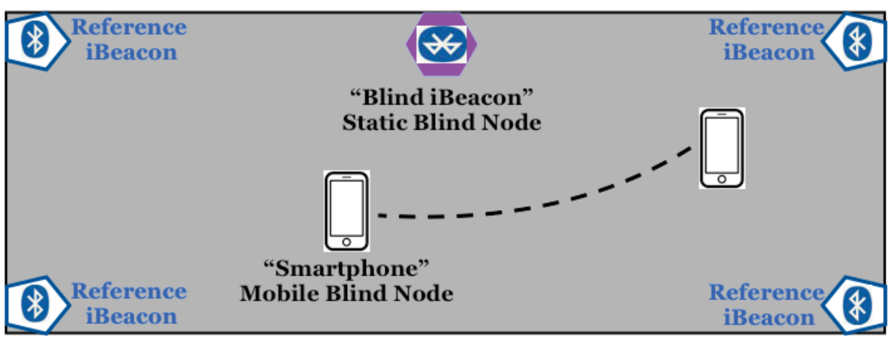


Figure 3.6: A generic wireless network shown here with reference and blind nodes in context of our BLE-based indoor positioning system. The reference nodes know their position beforehand and blind nodes are to be localized.

The major challenge for accurate RSS-based indoor localization comes from the variations of RSS resulting from the dynamic nature of radio channel indoors. In indoor environment the effects of shadowing, multipath, the orientation of devices, etc. make it difficult to properly capture the propagation model characteristics. One way to get around using a propagation model (which explains the relationship between RSS and its decay over distance) is to pre-built a radio map consisting of signal strength features collected over the coverage area in a method called *fingerprinting*, to locate a mobile device. This way a precise and accurate indoor positioning system can be developed which will work well for static (indoor) environments. In sections ahead we will discuss in detail algorithms that are developed with RSS measurement method. These algorithms are

- *Proximity localization*,
- *Fingerprinting localization*,

- *Conventional RSS-based localization*,
- *Self-Adaptive RSS-based localization*,
- *Space-based RSS-based localization*

3.4 Proximity

3.4.1 Introduction

Proximity is the simplest of localization algorithms. It is designed to provide "*symbolic relative location information*". The proximity method for localization is used to find the position of a mobile device just by its presence in a special area in range of a reference node nearby. This method works by simply forwarding the location of an anchor (reference node) point, from which the maximum signal strength is received, as the position estimate of mobile device. This method enjoy ease of implementation but in terms of localization system's performance (w.r.t accuracy), it is not good. Accuracy with this approach can be 5-10 meters. The more critical metric here is integrity i.e. how much confidence can be placed on localization systems' ability to correctly notify about smartphone's position with the correct distance range.

3.4.2 Working principle

As mentioned before iBeacon provides location service by informing user (on smartphone via App.) of their presence about an iBeacon, in the nearby environment, by using (distance) range estimates. The position of a mobile device is intimated as:

I. **Immediate;** *if the mobile device is within 2 meters of an iBeacon (acting as reference node)*

II. **Near;** *if the mobile device is within 5 meters of an iBeacon (acting as reference node)*

III. **Far;** *if the mobile device is within 10 meters of an iBeacon (acting as reference node)*

The three above mentioned ranges are set on the basis of already evaluated threshold on received signal strength indicator (RSSI) values from reference nodes. These threshold values are obtained for each distance range from RSSI (mean) values established during a quick measurement test over distance distribution in the localization space. This way when a mobile device is in range of an iBeacon, depending on the values of RSSI that are received over a short amount of time (and mean value taken), distance range estimate in terms of being immediate, near or far is assigned as position estimate of mobile device.

The advantages of using proximity-based localization approach in our BLE-based indoor positioning system, are: *simple implementation, no complex localization algorithm required, with a functional App. (e.g. on smartphone or tablet), a very plug & play solution and range-based localization scheme*. The disadvantages due to this approach are: *LoS requirement, its only coarse grained localization solution and does not provide 2D position estimation & the unreliability of RSS method to estimate distance due to reflections and unpredictable propagation fading.*

3.5 Fingerprinting

3.5.1 Introduction

Fingerprinting is the most used localization approach when it comes to indoor positioning. This is because this method requires no additional cost on infrastructure along with no prior knowledge of environment is required. This technique is sometimes also referred in literature as ***scene analysis***. As both the names suggest this algorithm starts with a comprehensive survey of the site (i.e. the indoor space which is to be localized) with respect to RSS readings that can be recorded over multiple points (distance distribution) in the coverage area. This results in a database of recorded signal strengths over numerous points (i.e. fingerprints of each point). The localization (of a mobile device) problem is then reduced to co-relating (matching) the currently measured RSS reading with those in database to estimate position. The system works on the assumption that each position in localization space can be associated with a unique signal strength feature and by virtue of this current location can be obtained relying on the difference of signal strength at different positions. Indoor positioning systems based on fingerprinting algorithm enjoy two phase implementation: The first phase is called ***offline phase*** and the second phase is called ***online phase***.

3.5.2 Working principle

The implementation of fingerprinting involves conducting *an offline & online phase*. These two phases are explained in detail ahead to develop a better understanding so that a BLE-based indoor localization system can be developed using fingerprinting localization approach, and its performance w.r.t. accuracy will be evaluated.

Offline phase

The offline phase starts with division of the indoor environment area (where localization of a mobile device is to be done) into a grid of cells. The Figure (3.7) helps explain this first step of offline phase. Consider a generic indoor environment, presented as a blank square box on left side in Figure (3.7). This indoor space is divided into small cells. Each cell enjoys a unique identification within the localization space. In the second step of offline phase, signal strength characteristic for each cell is recorded (usually at center of each cell) and associated with it. This way a database (or radio-map) is built where each cell will have its own unique RSS characteristic from each reference node and hence the word fingerprint. The radio-map (or database) can be created in two ways: mean value type radio-map and probability density function (p.d.f) type radio-map. Commonly mean value type radio-map (database) is created in offline case, which is also what we will be doing. In mean value type radio map, mean RSSI values from each reference node are gathered for each cell. More details on how this offline phase is conducted will be provided in the results chapter 5.

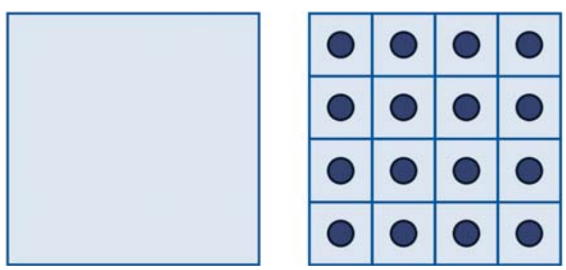


Figure 3.7: The division of (desired) localization area into small cells acts as first step of offline phase. For each cell mean RSS value from each reference node is measured and uniquely associated with that cell's identity.

The pseudocode for offline phase (also called calibration phase) is provided here for fingerprinting approach. The quality of radio-map would determine the precision and accuracy of position estimation of a mobile device. Therefore more the number of points where signal features are collected i.e. *the richer the database, better would be the outcome of localization results*. Hence for good localization performance, an extensive site survey (offline phase) should be conducted. This requires that fingerprints of numerous points (with high resolution) in the localization space should be gathered. This requires tedious amount of manual work, and thus the cost for this extensive

Algorithm 1 Fingerprinting localization approach offline phase conduction

```
procedure OFFLINE PHASE                                      ▷ Performed only once
    Divide localization space into K cells grid
    j ← cell ID where j ∈ [1:K]
    x_j ← x-coordinate jth cell
    y_j ← y-coordinate jth cell
    N ← Total reference iBeacons
    i ← identity reference iBeacon i ∈ [1:N]

    ▷ Fingerprints i.e. signal strength features are collected for each cell from all reference iBeacons
    N and RSSI database is created
    RSSI[] ← an empty list of length K                       ▷ Database created
    for cell j ∈ [1:K] do
        for reference iBeacon i ∈ [1:N] do
            P(i) = Measure power at x_j, y_j
        end for
        →RSSI_offline(j) = [P(i), ..., P(N)]                 ▷ RSSI Offline tuple
        RSSI[j] = [(id: j), (x: x_j, y: y_j), (→RSSI_offline(j))]
    end for
    Return: RSSI
end procedure
```

site survey in terms of manpower and time can be exhausting. During the experimentation work of Fingerprinting based BLE indoor localization system huge amount of time was spent in conducting offline phase (site survey), the author would propose using a self guided cleaning robot (like a vacuum cleaner robot) to collect the fingerprints. The time saved this way can be better utilized in improving the algorithm for position estimation.

Online Phase

In the online phase measurements taken at the current location (in the localization space) are matched with the already-established database (or radio-map) from the offline phase. The position estimation of a mobile device is done by matching the current position's signal feature with the fingerprint (signal features) of each cell in the database. The cell whose signal feature is closest to mobile device's current location's signal feature is obtained and the coordinates of midpoint of that cell are estimated as the 2D position of mobile device.

One problem with fingerprinting-based localization approach is that indoor environments are dynamic and collection of signal features in offline phase may not account for the change of indoor environment via indoor decoration, furniture, or walking of people which might have happened at the time of online phase measurements. This can severely effect localization performance.

Fingerprinting-based localization algorithms

There are numerous algorithms that have been developed to work with fingerprinting approach for indoor positioning systems. Extensive research has been done, and it has been proven that sophistication of algorithm help yield better localization results. Some algorithms are mentioned below; they range from very simple to complex in terms of computational understanding and implementation. These include:

- Euclidean Distance Algorithms, [11]
- Probabilistic methods, [18]

- K-nearest neighbor, [8]
- Neural networks, [5], [9], [43]
- Support vector machine (SVM), [20]
- Smallest M-vertex polygon (SMP) [36]

For simplicity the details of these algorithms are not discussed here except Euclidean Distance Algorithm which will be implemented in our BLE-based indoor localization system.

Euclidean Distance Algorithm

The Euclidean distance algorithm is an often used fingerprinting algorithm owed to its simplicity. The algorithm requires a set of RSSI values measured from several reference nodes at points (or cells) in localization space with known positions. This is achieved in the offline phase (or calibration phase) and RSSI database is created. In the online phase (or positioning phase) RSSI values from reference nodes are again measured at a point whose location is to be determined. For position estimation the RSSI-tuple of online phase is compared with the RSS-tuple of offline phase stored in the database (radio-map). A measure (Euclidean distance) for finding the similarity between the two tuples (online- and offline-tuple) is defined (see Equation 3.3). A small d indicates high similarity.

$$d = \sqrt{\sum_{i=1}^{n} (RSSI_{offline_i} - RSSI_{online_i})^2} \tag{3.3}$$

Here:

- $RSSI_{ci}$: RSSI value from reference node i during offline phase;
- $RSSI_{pi}$: RSSI value from reference node i during online phase;
- n: number of reference nodes received;
- i: denoted the identity of reference node.

This basic Euclidean Distance algorithm can be used for location estimation assuming indoor environment (in question) is static and small. For dynamically, changing environments the basic Euclidean Distance algorithm has to be modified by normalization. This normalization takes into account number of reference nodes received at a specific point (or cell) within the calibration phase and positioning phase. The resulting modified equation is:

$$d = \sqrt{\frac{1}{m}\sum_{i=1}^{m} (RSSI_{offline_i} - RSSI_{online_i})^2} \tag{3.4}$$

Here:

- $RSSI_{ci}$: RSSI value from reference node i during offline phase;
- $RSSI_{pi}$: RSSI value from reference node i during online phase;
- m: number of reference nodes received (matched);
- i: denoted the identity of reference node.

Again, a small d will indicate high similarity. After a localization measurement is made at current location, this fingerprint (signal strength feature from each reference node) is compared with the fingerprint of each cell obtained in calibration phase and a value for d is obtained. The cell which will give minimum value of d will be estimated

***as the current location of smartphone.*.**

The Equation 3.4 will be used for position estimation of blind node in our BLE-based indoor localization system developed with fingerprinting localization approach. Pseudo-code for online phase of Fingerprinting based localization approach is presented ahead. This phase explains how position estimation of smartphone can be done using Euclidean Distance Algorithm.

Algorithm 2 Fingerprinting localization approach online phase using Euclidean Distance Algorithm

procedure ONLINE PHASE ▷ Every time Localization is performed
  input($\overrightarrow{RSSI}_{offline}(j), \overrightarrow{RSSI}_{online}$)
  $x_{SP} \leftarrow$ unknown x-coordinate Smartphone
  $y_{SP} \leftarrow$ unknown y-coordinate Smartphone

  for reference iBeacon i ∈ [1:N] **do**
    $P(i)$ = Measure power at (x_{SP}, y_{SP})
  end for
  $\overrightarrow{RSSI}_{online} = [P(i), ..., P(N)]$ ▷ RSSI Online tuple
  difference-error[] ← an empty list of length K
  for j ∈ [1:K] **do**
    difference-error[j] $= \sqrt{\frac{1}{N}(\overrightarrow{RSSI}_{offline}(j) - \overrightarrow{RSSI}_{online})^2}$
  end for

  index j ← find index of minimum(difference-error) ▷ Finding minimum element value in difference-error
  index j MEANS j^{th} *cell fingerprints show most similarity with current location's fingerprints*
  Result: $x_{SP} = RSSI(j).x_j$, $y_{SP} = RSSI(j).y_j$
end procedure

3.6 Maximum Likelihood Estimators

In this section, the Maximum Likelihood Estimators (MLE) for range-based localization systems is defined. To start, a general MLE formula is formulated using the Log-Normal Shadowing Model [32]. The MLE of a position estimate equals the position estimate that maximizes the probability using function of Equation 3.1. The MLE for the blind node j equals:

$$\max_{\theta} \prod_{i=H_j} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(P_{i,j}-\hat{P}_{i,j})^2}{2\sigma^2}} \tag{3.5}$$

Here $\hat{P}_{i,j}$ represents:

$$\hat{P}_{i,j} = P_{d_0} - 10 \cdot n \cdot log_{10}(\frac{\widehat{d}_{i,j}}{d_0}) \tag{3.6}$$

$$\hat{d}_{i,j} = \sqrt{(x_i - \hat{x}_j)^2 + (y_i - \hat{y}_j)^2} \tag{3.7}$$

In Equation 3.6 & 3.7:

- $\widehat{d}_{i,j}$ represents the distance between reference node i and the position estimate of blind node j.
- θ is the set of parameters that maximizes the optimization function Equation 3.5. It is noted that θ always contains the position estimate i.e. $\hat{x}_j \in \theta$ and $\hat{y}_j \in \theta$.

As described before, the LNSM assumes that the variance remains constant over distance. Therefore, after some algebraic manipulation, Equation 3.5 reduces to:

$$\min_{\theta} \sum_{i=H_j} \left(P_{i,j} - \left(P_{d_0} - n \cdot 10 \cdot log_{10}(\frac{d_{i,j}}{d_0}) \right) \right)^2 \tag{3.8}$$

This equation above represents the MLE in its most general form using LNSM. This equation however does not define:

The values of the reference RSS power (P_{d_0}) and the path loss exponent (n).

3.7 Conventional RSS-based localization

As mentioned earlier indoor positioning system based on RSS measurement are usually implemented by making use of a propagation model to capture the radio signal's characteristics. A propagation model would help describe radio wave propagation as a function of frequency, distance, and other conditions. The propagation model when developed can ably predict the behaviour of propagation of radio waves from all the transmitters involve in the system. This way calibration of environment can be achieved. In literature it is proven that with an effective calibration of environment, performance (w.r.t. accuracy) of an indoor positioning system enhances. Therefore for accurate and precise positioning system finding an optimal propagation model is very important.

3.7.1 Introduction

Conventional RSS-based localization approach assumes to capture radio wave characteristics single propagation model is required that suffices for all the nodes (transmitters) present in the system. Therefore working with the presumption that optimal calibration of the propagation model is hardware- and space-invariant. Such systems also assume that these calibration settings do not change between calibration rounds. This is true when assuming a static (indoor) environment.

In range-based RSS localization, the position/location estimate for a mobile device appears as a parameter in the propagation model. These propagation models are mathematical representation of far-field solutions of the Navier-Stokes or Maxwell equations, depending on whether the network is based on the propagation of acoustic or electromagnetic waves. Mathematically, localization then reduces to calculating the field energies at the unknown position of the receiving antenna (of the mobile device) from an antenna array (no. of antennas proportional to no. of reference nodes) at known positions. When the antenna array is large enough (sufficient no. of reference nodes) and the propagation model adequately represents the radiation in the environment localization reduces to a set of non-linear equations for the position estimates and possible other parameters used in the propagation model. These other parameters are of significant importance as they account for reflection, refraction, diffraction, and the absorption affects in the environment. RSS-based localization usually employs the empirical Log-Normal-Shadowing model as the propagation model [15].

3.7.2 Working principle

Indoor positioning systems using RSS-based conventional localization approach are implemented in a two phase process; **Conventional Calibration & Conventional Localization Phase**. In the *"Conventional Calibration Phase"*, the optimal values of the propagation model parameters are estimated by performing calibration measurements (see Figure 3.8). The parameters calculated from the calibration measurements are usually called "nuisance parameters" as they only serve to help estimate the unknown position of mobile blind node (i.e. smartphone). In the second phase, *"Conventional Localization Phase"* the position of the blind node is estimated using the calibrated

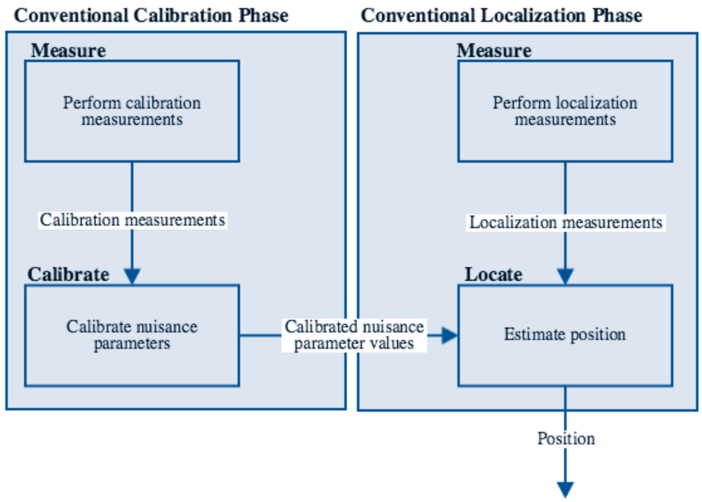


Figure 3.8: Conventional RSS-based localization approach

nuisance parameters as well as the localization measurements. There is a clear distinction between the two phases. The measurements made in calibration phase, named as *calibration measurements*, are used for calibration of nuisance parameters only; whereas the measurements made in the localization phase, named as *Localization measurements* are only used for the purpose of estimating the position.

We have adopted Log-Normal Shadowing Model (LNSM) as the propagation model for Conventional (RSS-based) localization approach. As mentioned before, the LNSM is used for modeling the signal strength over distance decay. This empirical model is widely used by RSS-based localization estimators (e.g. [32], [7] & [34]) and has shown to be a reasonable representation of reality [38]. Equation 3.8 represents the MLE in its most general form using LNSM. But this equation does not define the values of the reference RSS power (P_{d_0}) and the path loss exponent (n) i.e. the nuisance parameters. The conventional localization approach during its calibration phase, calibrate these nuisance parameters (i.e. P_{d_0} & n) and estimate value for each parameter either as one for whole system (all the transmitting nodes) or by estimating both parameter value for each transmitting node individually. Therefore the position estimation with the conventional localization approach assumes that the optimal values of reference RSS power (P_{d_0}) and the path loss exponent (n) are known before minimizing Equation 3.8 (as in [32]). So we write the Equation 3.8 as:

$$\min_{\theta=\hat{x}_j,\hat{y}_j,|P_{d_0}=\beta,n=\alpha} \sum_{i\in 1:N} \left(P_{i,j} - \left(P_{d_0} - n \cdot 10 \cdot log_{10}(\frac{\hat{d}_{i,j}}{d_0})\right)\right)^2 \tag{3.9}$$

This Equation above will be the cost function for conventional localization approach and results using this equation will be presented in chapter 5. The pseudocode to perform calibration phase of conventional localization approach is provided here.

Algorithm 3 Conventional localization approach using Maximum Likelihood Estimators

procedure CALIBRATION PHASE ▷ Performed once
    $N \leftarrow$ Total reference iBeacons
    $i \leftarrow$ identity reference iBeacon where i $\in$ [1:N]

▷ Collect RSSI values per each reference iBeacon over distance distribution (known locations) inside localization space.
    $K \leftarrow$ Total known locations
    $\overrightarrow{RSSI} = []$ ▷ an empty list to store measured power
    for K locations **do**
        for reference iBeacon i $\in$ [1:N] **do**
            $P_d(i)$ = Measure mean power at known Kth location
        end for
        $\overrightarrow{RSSI}[K] = [P_d(i), ..., P_d(N)]$
    end for

▷ Perform LNSM curve fit. Nuisance parameters *Reference RSS power and Path loss exponent* are estimated.
    $(P_{d_0}, n) \leftarrow$ Least Square fitting $(\overrightarrow{RSSI})$
    $P_{d_0} \leftarrow$ Reference RSS power in dBm
    $n \leftarrow$ Path loss exponent
▷ These parameters can be individually estimated for each reference iBeacon or estimated as one value for whole system (i.e. for all iBeacons together)
    Return: (P_{d_0}, n)
end procedure

procedure LOCALIZATION PHASE ▷ Every time Localization is performed
    $x_{SP} \leftarrow$ unknown x-coordinate Smartphone
    $y_{SP} \leftarrow$ unknown y-coordinate Smartphone
    $N \leftarrow$ Total reference iBeacons
    $i \leftarrow$ identity reference iBeacon where i $\in$ [1:N]

▷ Collect RSSI values per each reference iBeacon at (x_{SP}, y_{SP}) inside localization space.
    $\overrightarrow{RSSI} = []$
    for i $\in$ [1:N] **do**
        $P(i)$ = measured RSSI at (x_{SP}, y_{SP}) ▷ from each reference iBeacon
    end for
    $\overrightarrow{RSSI} = [P(i), ..., P(N)]$
    Grid-Search-Algo(P_{d_0},n,$\overrightarrow{RSSI}$)
▷ Call GRID-SEARCH ALGORITHM with P_{d_0}, n and RSSI values from each reference iBeacon at current unknown location as input parameters
    Result: x_{sp}, y_{sp}
▷ Estimated distance of smartphone from (0,0) and x,y coordinates for current location obtained
end procedure

3.8 Grid-Search Algorithm

A grid-search algorithm, variant of Particle filter approach was developed to estimate position of smartphone in our BLE-based localization system. This algorithm will be used with Conventional, Self-Adaptive and Space-based localization approach for position estimation.

3.8.1 Explanation

Grid-search algorithm assumes that node to be localized (i.e. smartphone and blind iBeacon in our case) can be at any point inside localization space. Hence any point in localization space can be chosen as the position estimate for smartphone. This algorithm starts with sampling the localization space into numerous points. The more the resolution the better it is. We sample the localization space with 1cm resolution both in x-axis (length of localization space) and y-axis (width of localization space). By doing this with one corner as reference, a distance array is calculated. The entries of this array are point to point distance value from current point (x, y) to origin/reference (0, 0). Since the location of each reference node is known w.r.t. origin, similar distance arrays are also created with respect to each reference iBeacon in the system. Afterwards using Equation 3.1, estimated power at each point inside localization space is calculated for each node by feeding in the nodes' distance array. The values of P_{d_0} & n are known for this procedure. With estimated power at each point inside localization space for each node known, least square error method is used (shown in Equation 3.10) to estimate the current location based on measured current power from each reference node.

$$\min_{\theta} \sum_{i=1}^{N} (P_{i,j} - \widehat{P}_{i,j})^2 \tag{3.10}$$

Here θ has the parameters of distance i.e. x- and y-coordinates. The result is the distance estimate of a point inside localization space for which current location's Received power and Estimated power give minimum error. This algorithm was implemented using MATLAB. The algorithm is explained with help of pseudocode below.

Algorithm 4 Grid search algorithm, variant of particle filter approach for localization

procedure GRID-SEARCH-ALGO
  INITIALIZATION ▷ Performed once
  Input: (P_{d_0}, n, l, w)
  $P_{d_0} \leftarrow$ Reference RSS power in dBm
  $n \leftarrow$ Path loss exponent
  $l \leftarrow$ length localization space ▷ x-axis
  $w \leftarrow$ width localization space ▷ y-axis
  $\overrightarrow{x1} = []$
  $\overrightarrow{y1} = []$
  $\overrightarrow{distanceGrid} = []$ ▷ distance vector localization space
  $x0 \leftarrow 0$
  $y0 \leftarrow 0$ ▷ Reference (x0,y0)
  $\overrightarrow{x1} = [0 : 0.01 : l]$ ▷ 1cm resolution along x-axis
  $\overrightarrow{y1} = [0 : 0.01 : w]$ ▷ 1cm resolution along y-axis
  $\overrightarrow{distanceGrid} = \sqrt{(x0 - \overrightarrow{x1})^2 + (y0 - \overrightarrow{y1})^2}$ ▷ euclidean-distance
  $N \leftarrow$ Total reference iBeacons with known locations $(x_R \& y_R)$
  $i \leftarrow$ reference iBeacons identity
  $x_R(i) \leftarrow$ known x-coordinate i^{th} reference iBeacon
  $y_R(i) \leftarrow$ known y-coordinate i^{th} reference iBeacon
  for i ∈ [1:N] **do**
    $\overrightarrow{distanceR}(i) = []$ ▷ distance vector for each reference iBeacon
    $\overrightarrow{distanceR}(i) = \sqrt{(x_R(i) - \overrightarrow{x1})^2 + (y_R(i) - \overrightarrow{y1})^2}$
    $\widehat{\overrightarrow{P}(i)} \leftarrow$ estimated RSSI at $(\overrightarrow{distanceR}(i))$
 ▷ $Using formula : P = P_{d_0}$ - 10 * n * $log_{10}(distance)$
    $\widehat{\overrightarrow{P}(i)} \leftarrow$ estimated RSSI at $(\overrightarrow{x1}, \overrightarrow{y1})$
 ▷ *Estimated power at each point inside localization space, size is (l X 100, w X 100)*
  end for
end procedure

Algorithm 5 Grid search algorithm, variant of particle filter approach for localization

procedure GRID-SEARCH-ALGO
  LOCALIZATION ▷ Every time Localization is performed
  $x_{SP} \leftarrow$ unknown x-coordinate Smartphone
  $y_{SP} \leftarrow$ unknown y-coordinate Smartphone
  $N \leftarrow$ Total reference iBeacons
  $i \leftarrow$ reference iBeacons identity
  for i ∈ [1:N] **do**
    $\overrightarrow{differenceError}(i) = []$
    $\overrightarrow{P}(i)$ = measured RSSI at (x_{SP}, y_{SP}) ▷ from each reference iBeacon
    $\overrightarrow{differenceError}(i) = (\overrightarrow{P}(i) - \widehat{\overrightarrow{P}(i)})^2$ ▷ The Method of Least Squares
  end for
  $\overrightarrow{Sum} \leftarrow \sum_{i=1}^{N}(differenceError(i))$
  size ← size of sum ▷ *size is (l X 100, w X 100)*
  index k ← *find index of minimum*$(\overrightarrow{Sum})$
▷ Finding minimum element value and its index
  estimated distance smartphone = distanceGrid[k]
▷ k^{th} *entry of distance array gives distance value of (unknown) location of smartphone w.r.t. origin*
  (row, col) = ind2sub(size(sum), k)
▷ Using MATALB ind2sub function to find the row and column for $\mathrm{k^{th}}$ value in distance grid
  $x_{est} = x1(row)$
  $y_{est} = y1(col)$
  Return: x_{est}, y_{est} ▷ estimated coordinates for smartphone's (blind node) current location
end procedure

3.9 SAL Algorithm

In conventional localization approach it is assumed that the optimal calibration settings of the propagation model do not change between the calibration rounds. But real environments are dynamic and continuously changing. In such environments, each node should be able to estimate its own optimal propagation model settings dependent on the node's hardware and location. We call this process as Self-Adaptive Localization (SAL).

3.9.1 Introduction

In SAL systems the parameter settings are estimated directly from the available localization measurements. Such systems perform these localization measurements in the order of tens of milliseconds so that the environmental dynamics can be considered as static. In general, it is not easy to estimate the optimal parameter settings in an automated way for each time a node localizes itself. In theory the optimal values of these parameters depend on the locally varying electromagnetic permittivity and permeability of localization space. This is to say that the propagation model needs to account for local changes in the localization environment. In a more realistic model, optimal propagation model should be estimated for each node individually depending upon the node's hardware and location, this process is termed as Self-Adaptive Localization (SAL). SAL in order to adopt for the local spatial influences in the environment applies a multivariate propagation.

3.9.2 Working principle

Self-Adaptive Localization (SAL) is designed to continuously adapt to a dynamic environment.The main difference between "Self-Adaptive Localization Approach" and the "Conventional Localization Approach" is that in SAL, localization measurements are used for both estimating the *nuisance parameters* as well as for estimating the *position* of the nodes. This implies that in the SAL Approach calibration settings are updated every time a node estimates its position. Therefore:

The SAL approach allows that the optimal calibration settings vary over space and time, and are assumed to be static during the localization measurements.

As compared to the conventional approach, SAL requires less or no online/offline calibration measurements. The broken line in the Figure 3.9 indicates this improvement. This idea of estimating nuisance parameters on the basis of localization measurements is discussed in these papers [23] & [14]. However, it has not been applied in dynamic environments. Position estimation with SAL approach also makes use of MLE (discussed earlier). The Equation 3.8 represents the MLE in its most general form using LNSM. This equation however does not define:

- The values of the reference RSS power (P_{d_0}) and the path loss exponent (n).
- In SAL implementations, the different definitions of θ define the difference between the conventional and SAL approach.

The MLEs of 3 different implementations of the SAL approach are discussed ahead.

Reference RSS Self-Adaptive Localization (RR-SAL) estimates the reference RSS power (P_{d_0}) on the basis of localization measurements. In comparison with the conventional localization approach, RR-SAL assumes that value of the reference RSS (P_{d_0}) is not known before minimizing Equation 3.8. This results in this version of the equation:

$$\min_{\theta=\hat{x}_j,\hat{y}_j,\widehat{P}_{d_0}|n=\beta} \sum_{i\in 1:N} \left(P_{i,j} - \left(\widehat{P}_{d_0} - n \cdot 10 \cdot log_{10}(\frac{\hat{d}_{i,j}}{d_0}) \right) \right)^2 \tag{3.11}$$

Path Loss Exponent Self-Adaptive Localization (PLE-SAL) estimates the path loss exponent (n) on the basis of localization measurements (as in [23]). In comparison with the

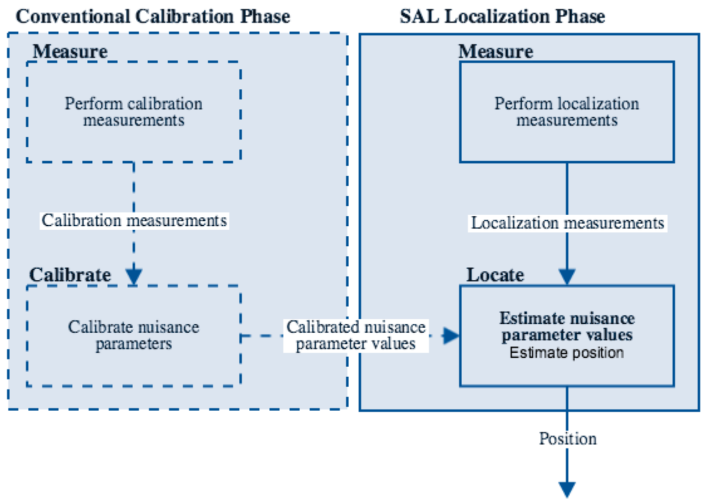


Figure 3.9: Self-Adaptive Loclaization approach

conventional localization approach, PLE-SAL assumes that value of the the path loss exponent (n) is not known before minimizing Equation 3.8. This results in this version of the equation:

$$\min_{\theta=\hat{x}_j,\hat{y}_j,\widehat{n}|P_{d_0}=\alpha} \sum_{i\in 1:N} \left(P_{i,j} - \left(P_{d_0} - \hat{n} \cdot 10 \cdot log_{10}(\frac{\widehat{d}_{i,j}}{d_0})\right)\right)^2 \tag{3.12}$$

Log-Normal Self-Adaptive Localization (LN-SAL) estimates the reference RSS power (P_{d_0}) and the path loss exponent (n) on the basis of localization measurements. This is shown in work done by [14]. In comparison with the conventional localization approach, LN-SAL assumes that value of the reference RSS (P_{d_0}) and of the path loss exponent (n) is not known before minimizing Equation 3.8. This results in this version of the equation:

$$\min_{\theta=\hat{x}_j,\hat{y}_j,\widehat{P}_{d_0},\widehat{n}} \sum_{i\in 1:N} \left(P_{i,j} - \left(\widehat{P}_{d_0} - \hat{n} \cdot 10 \cdot log_{10}(\frac{\widehat{d}_{i,j}}{d_0})\right)\right)^2 \tag{3.13}$$

These Equations 3.11 to 3.13 above will be the cost functions for mentioned SAL localization approaches and results using them equation will be presented in chapter 5.

3.10 Space-based RSS Localization

3.10.1 Introduction

The space based RSS radio localization finds its root idea from spatial image reconstruction in Fourier Optics. This approach samples RSS over space and can produce as good performance as other localization systems such as TOF-based & phase-based. Space-based RSS localization approach samples signal intensities (RSS) over space with a mobile node (with unknown position) to reconstruct the signal and the position of transmitter (i.e. blind node with unknown position). The position of mobile node is estimated by measuring signal intensities from an array of fixed transmitters with known positions.

3.10.2 Working principle

This method is also based on the Log-Normal Shadowing Model. The Figure 3.10 tries to explain the working of space-based localization algorithm. The idea is to sample signal space around the blind iBeacon node which is static and fixed. This is achieved by placing the measuring mobile node (i.e. smartphone in our case) at discrete points around blind node. The mobile node (smartphone) measures RSS from all the reference iBeacons and a fixed blind iBeacon and position estimation for both the mobile and blind iBeacon is performed. The output result is the 2D localization of fixed blind iBeacon.

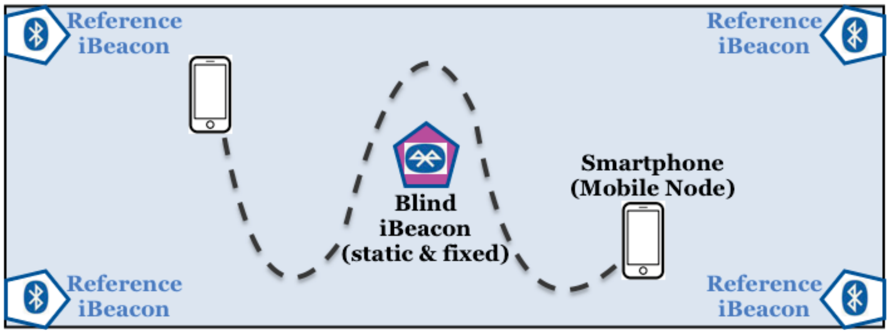


Figure 3.10: Space based localization algorithm approach, the signal space around the blind iBeacon is sampled and position estimation of blind iBeacon is performed along with smartphone localization.

3.10.3 Optimization Definition

Consider a wireless network that consists of R reference nodes (infrastructure nodes), one fixed blind iBeacon and one mobile smartphone node:

- We identify the locations of R reference nodes by: x_1, y_1 ... x_R, y_R. These locations are known.
- We identify the location of fixed iBeacon node by: x_{R+1}, y_{R+1}. This location is unknown and is to be estimated.
- One mobile node that does not know its location and changes its location every time instance. We identify the positions of the mobile blind node over T time instances by: $x_{1,M}, y_{1,M}$ ... $x_{T,M}, y_{T,M}$. These locations are unknown and are to be estimated as well.

The mobile node measures the RSS values from the reference nodes and the fixed blind nodes at each of the time instance t. Here, we distinguish between measurements from reference nodes and blind nodes by identifying them as:

- The RSS measurements from reference nodes are identified as: $RSS_{t,1}$ ... $RSS_{t,R}$.
- The RSS measurements from fixed blind nodes are identified as: $RSS_{t,R+1}$ ... $RSS_{t,R+F}$.

Using these notations, the optimization problem is expressed as:

$$\min_{\theta} \sum_{t=1}^{T} \sum_{i=1}^{R} \left(\widehat{RSS}_{t,i} - RSS_{t,i} \right)^2 + \sum_{t=1}^{T} \sum_{j=R+1}^{R+F} \left(\widehat{RSS}_{t,j} - RSS_{t,j} \right)^2 \tag{3.14}$$

Here:

$$\widehat{RSS}_{t,i} = P_{d_0,i} - 10 \cdot n_i \cdot log_{10} \sqrt{(\hat{x}_{t,M} - x_i)^2 + (\hat{y}_{t,M} - y_i)^2} \tag{3.15}$$

and:

$$\widehat{RSS}_{t,j} = P_{d_0,j} - 10 \cdot n_j \cdot log_{10} \sqrt{(\hat{x}_{t,M} - \hat{x}_j)^2 + (\hat{y}_{t,M} - \hat{y}_j)^2} \tag{3.16}$$

It is noted that here $P_{d_0,i}, n_i, P_{d_0,j}$ and n_j represent the parameters of the Log-Normal Shadowing Model. We assume that these parameters are individually calibrated for each transmitter (reference nodes and fixed blind nodes). For this purpose a calibration round is conducted before localization to estimate these parameters. These parameters can also be estimated for whole system as one values via calibration round. But results with individual calibration of nodes (reference iBeacons and fixed blind iBeacon) will always be better than whole system calibrated as one. Another procedure can be to automatically calibrate these parameters via the localization process itself as in [6] and [16]. θ represents the set of parameters that minimizes Equation 3.14. This set contains position estimates of mobile and blind nodes:

$$\theta = \hat{x}_{1,M}, \hat{y}_{1,M} ... \hat{x}_{T,M}, \hat{y}_{T,M}, \hat{x}_{R+1}, \hat{y}_{R+1}$$

Pesudocode which helps explain how localization of blind iBeacon is performed using space-based localization approach is decribed ahead.

Algorithm 6 Space-based localization approach using Maximum Likelihood Estimators

procedure CALIBRATION PHASE ▷ Performed once
    $N \leftarrow$ Total reference iBeacons
    $i \leftarrow$ identity reference iBeacon where i ∈ [1:N]

▷ Collect RSSI values per each reference iBeacon over distance distribution (known locations) inside localization space.
    $K \leftarrow$ Total known locations
    $\overrightarrow{RSSI} = []$ ▷ an empty list to store measured power
    for K locations **do**
        for reference iBeacon i ∈ [1:N] **do**
            $P_d(i)$ = Measure mean power at known Kth location
        end for
        $\overrightarrow{RSSI}[K] = [P_d(i), ..., P_d(N)]$
    end for

▷ Perform LNSM curve fit. Nuisance parameters *Reference RSS power and Path loss exponent* are estimated.
    $(P_{d_0}, n) \leftarrow$ Least Square fitting $(\overrightarrow{RSSI})$
    $P_{d_0} \leftarrow$ Reference RSS power in dBm
    $n \leftarrow$ Path loss exponent
▷ These parameters can be individually estimated for each reference iBeacon or estimated as one value for whole system (i.e. for all iBeacons together)
    Return: (P_{d_0}, n)
end procedure

Algorithm 7 Space-based localization approach using Maximum Likelihood Estimators

procedure LOCALIZATION ▷ Every time Localization is performed

▷ RSSI values from reference iBeacons and blind iBeacon collected at unknown locations around the blind iBeacon at discrete time instances t where t ∈ [1:T]

    $j \leftarrow$ identity of blind fixed iBeacon
    $x_{SP} \leftarrow$ unknown x-coordinate Smartphone
    $y_{SP} \leftarrow$ unknown y-coordinate Smartphone
    $x_{blind} \leftarrow$ unknown x-coordinate blind iBeacon
    $y_{blind} \leftarrow$ unknown y-coordinate blind iBeacon
    $\overrightarrow{RSSI}_{ref} =[]$
    $\overrightarrow{RSSI}_{blind} =[]$
    for t ∈ [1:T] **do**
        for i ∈ [1:N] and j **do**
            $P_{ref}(i) \leftarrow$ measured RSSI value from each reference iBeacon i
            $P_{blind}(j) \leftarrow$ measured RSSI value from blind iBeacon j
        end for
        $\overrightarrow{RSSI}_{ref}(\mathrm{t}) = [P_{ref}(i), ..., P_{ref}(N)]$
        $P_{blind}(\mathrm{t}) = P_{blind}(j)$
        Call GRID-SEARCH ALGORITHM
        Input: $\left(\overrightarrow{RSSI}_{ref}(t), length, width, P_{d_0}, n\right)$ ▷ Input parameters to Grid-search-algorithm
        RESULT: $x_{SP}(t), y_{SP}(t)$ obtained at instance t
    end for
    $\overrightarrow{RSSI}_{blind} = [P_{blind}(1), ..., P_{blind}(T)]$
    $\widehat{\overrightarrow{x}}_{est} = [x_{SP}(1), ..., x_{SP}(T)]$
    $\widehat{\overrightarrow{y}}_{est} = [y_{SP}(1), ..., y_{SP}(T)]$ ▷ x_{SP}, y_{SP} obtained at each instance t

▷ Estimated smartphone positions acts as reference for blind iBeacon localization. These estimated positions act as reference points and formulate localization area for blind iBeacon localization.

    $length = |x_{SP}(1) - x_{SP}(T)|$
    $width = |y_{SP}(1) - y_{SP}(T)|$
    Call GRID-SEARCH ALGORITHM
    Input: $\left(\overrightarrow{RSSI}_{blind}, length, width, P_{d_0}, n\right)$ ▷ Input parameters to Grid-search-algorithm
    Result:
    blind iBeacon coordinates $= x_{blind}, y_{blind}$
end procedure

Chapter 4

Measurement Setup

In this chapter description of the measurement setup; i.e., the testbed is provided. Different localization approaches using this testbed will be performed to develop our BLE-based indoor positioning system. The localization approaches which were discussed in previous chapter; *Proximity, Fingerprinting, Conventional localization, Self-Adaptive localization & Space-based localization algorithms* will be implemented using this measurement setup. In the first section 4.1, the chosen localization area (an indoor environment) is introduced where our BLE-based indoor positioning system can be deployed. This localization space can be used under different configurations see section 4.2. In our BLE-based indoor localization system, we will be using clones of iBeacon. There are many iBeacon clones present in the market and we will be using the clone named BEACONinside. Brief discussion about these nodes (iBeacon clone) is done in section 4.3 and from now on whenever the word iBeacon will be mentioned it will mean BEACONinside nodes. An App. is developed for android OS based smartphones to help scan BLE devices, present in the surroundings of smartphone. This App. is introduced in section 4.4. The measurement setup developed to implement proximity localization approach for our BLE-based indoor positioning system is described in section 4.5. Some localization algorithms like fingerprinting, conventional localization and space-based localization require calibration of the environment before localization process can be performed. Section 4.6 explains the measurement setup used to do calibration of environment for these localization approaches. We finish the chapter by describing the measurement setup for space-based localization approach for our BLE-based indoor positioning system in last section, 4.7.

4.1 Localization Space

The localization space was chosen to be the Hallway of Pervasive Systems group in Zilverling building (see Figure 4.2), in University of Twente. The dimensions of hallway were found to be 2.5 *meters* in width and 27 *meters* in length. A cross sectional view of the hallway is also presented graphically in Figure 4.1.

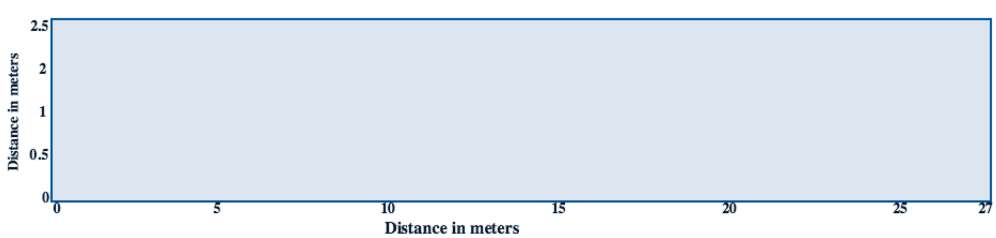


Figure 4.1: Graphical representation of the measurement setup.

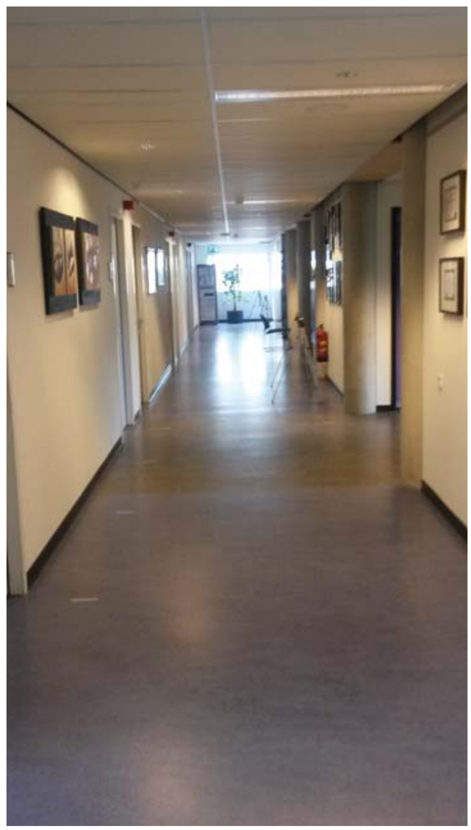
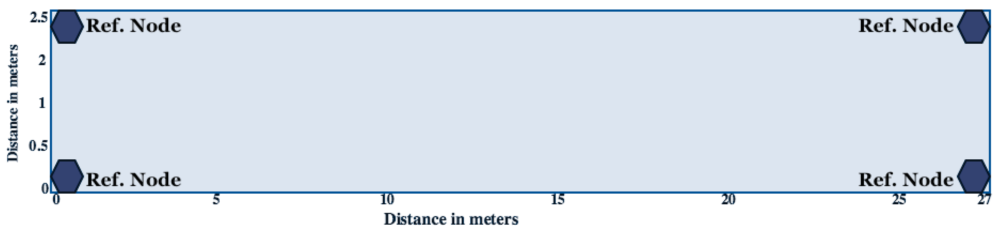


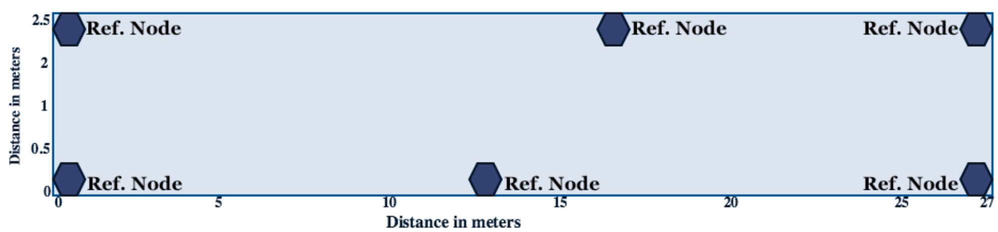
Figure 4.2: Picture taken from camera of the test environment (Hallway of PS group)

4.2 Measurement Setup Configurations

The measurement setup was used with two different configurations (in terms of number of reference nodes used) i.e. with 4 reference nodes and with 6 reference nodes (see Figure 4.3 for graphical view). The reason for conducting experiments with different number of reference nodes is to explore how few (i.e. minimum number of) reference nodes are required for satisfiable localization performance. Usually the more the number of reference nodes the better are localization results. For *Fingerprinting and Conventional Localization* approaches implementation was performed under both configurations. For *SAL and Space-based localization* approaches measurement setup with 6 reference nodes was used only.



(a) With 4 reference nodes



(b) With 6 reference nodes

Figure 4.3: A graphical view of the measurement setup with reference nodes (polygons).

4.3 BEACONinside

They are one of many clones of iBeacon present in the market. These nodes will be used in our indoor BLE-based indoor localization system. These nodes will serve two purposes in our indoor localization system;

I. **To be used as reference nodes** (a fixed minimum number of them with apriori known position) to help accomplish the task of smartphone localization.

II. **To be used as blind iBeacon** (blind nodes with unknown position), that is to be localized in reference to smartphone.

The BEACONinside nodes (see Figure 4.4) run on AAA battery or Micro-USB and are used for long term deployment due to their good battery time. They are easily install-able and enjoy signal range of around 40 *meters* and come with a BEACONinside App. This App. allows you to modify the characteristics of a BEACONinside node such as *Major and Minor ID, advertisement period & transmission power level etc.* (`http://www.beaconinside.com/`). Some characteristics of a typical BEACONinside node are described in table 4.1 below.

Figure 4.4: BEACONinside node, a clone of iBeacon.

Characteristic	Value	Comment
Range	0-40 *meters*	Suitable for indoors application
Device ID	MAC-Address (unique per device)	Not configurable
UUID	F0018B9B-7509-4C31-A905-1A27D39C003C	Configurable
Major	Random value btw. 1 - 65,536	Configurable
Minor	Random value btw. 1 - 65,536	Configurable
TX Power Level	0 dBm (default), -6 dBm, -23 dBm	Configurable
Advertising Interval	100 ms - 10 s (400 ms default)	Configurable
Advertising Packet	Apple iBeacon compatible	Not configurable

Table 4.1: Some product information about a BEACONinside node

4.4 BLE App. for our indoor positioning system

To collect Received Signal Strength Indication (RSSI) measurements from each of the reference node, an App. for android OS was developed. This App. scans for Bluetooth-Low Energy devices nearby (i.e. iBeacon in the surroundings of smartphone) and log data packets received and write them in a text file. This text file would then be feed into Laptop in order to perform localization processing. Usually the App. was configured to record a log of 2500 samples and then write a text file, for each measurement round on smartphone. This self-designed App. can only scan BLE devices, it cannot connect with the BEACONinside nodes and modify their configuration settings (this can be something for future works). The App. was run over Samsung Galaxy S4 mini (smartphone), see Figure 4.5 to log measurement data.

Figure 4.5: Samsung Galaxy S4 mini used as the smartphone.

4.5 Measurement setup Proximity approach

BEACONinside nodes (see chapter 4) can provide a range of around 40 $meters$ when operated with transmission power level of 0 dBm, based on this knowledge three separate regions of intimation were created to notify user about it's estimated proximity to the reference iBeacon. Each of these regions are based on certain distance range (see Table 4.2). Received Signal Strength Indication (RSSI) from a reference iBeacon is used to associate the presence of smartphone (i.e. user) in one of the three regions:

i. Near,

ii. Far, and

iii. Very far.

Proximity notification	Distance (range) w.r.t. smartphone
Near	0 - 5 $meters$
Far	5 - 20 $meters$
Very far	20 + $meters$

Table 4.2: The distance range associated with each of the three regions, used to intimate presence of smartphone w.r.t. reference node nearby.

Multiple BEACONinside nodes were used to record RSSI measurements over distance distribution (from 0 - 25 $meters$). This way an attempt was made to establish a clear threshold, based on the recorded mean RSSI measurements over multiple distances from reference node (see Figure 4.6), for each distance region.

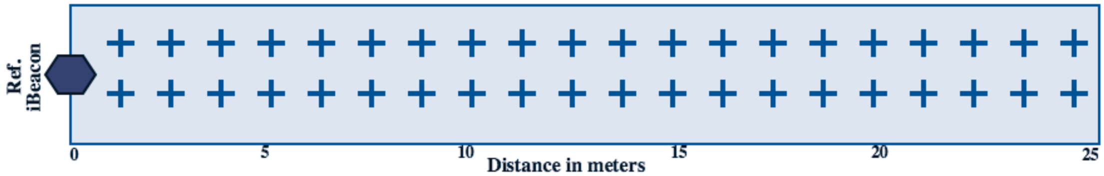
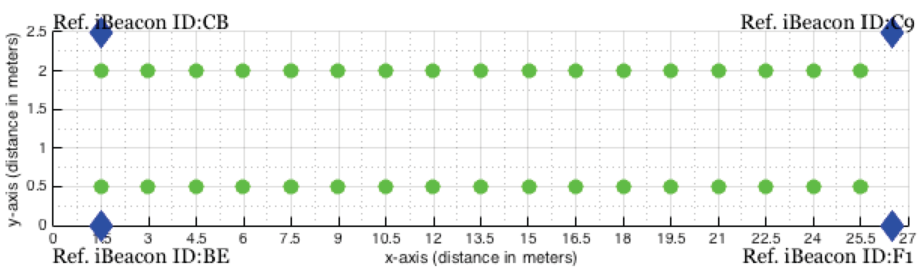


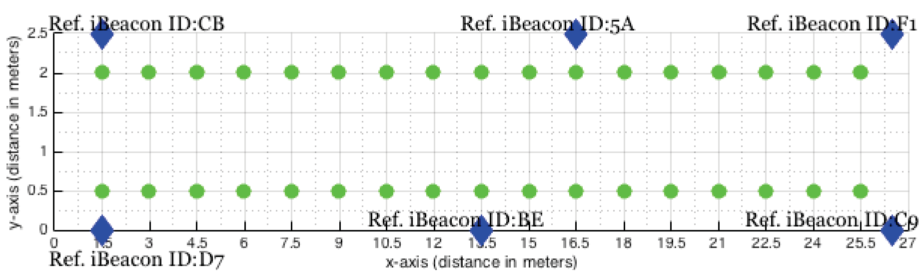
Figure 4.6: Graphical view of measurement setup for proximity approach. Here the plus sign denote positions over distance distribution where mean RSSI value from reference iBeacon was recorded on smartphone to establish RSSI mean value range (threshold) for different distance regions.

4.6 Calibration Phase Setup

Since the aforementioned indoor localization algorithms (like fingerprinting, conventional and space-based) require calibration phase. Therefore, measurement setup to perform calibration phase was constructed and is depicted in Figure 4.7. Here the green dots are the points where measurements are logged on a smartphone form iBeacons (acting as reference nodes) in the localization space. In total 34 points inside the localization space were chosen to gather measurements for calibration. The RSSI measurements from each reference node were collected on a smartphone placed over tripod at 1 m height from ground level. The calibration phase was repeated twice with different number of reference nodes, firstly with 4 reference nodes (see Figure 4.7a) and then with 6 reference nodes (see Figure 4.7b). An App. (Android OS-based) was developed for the purpose of recording measurements on a smartphone from the iBeacons present in our test-bed.



(a) Calibration phase with 4 reference nodes



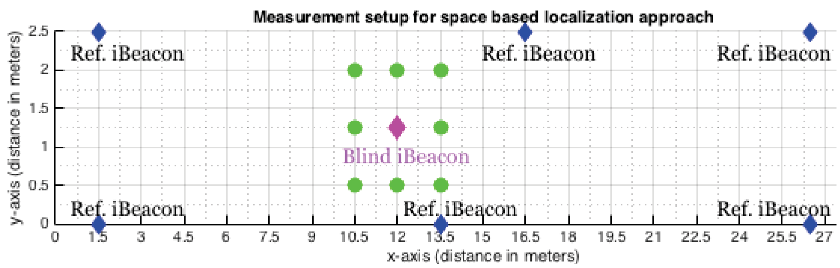
(b) Calibration phase with 6 reference nodes

Figure 4.7: Calibration phase measurement setup with reference nodes (shown by blue diamonds). The green dots represent the points in localization space where smartphone was placed to gather RSSI measurements from reference nodes to help calibrate environment.

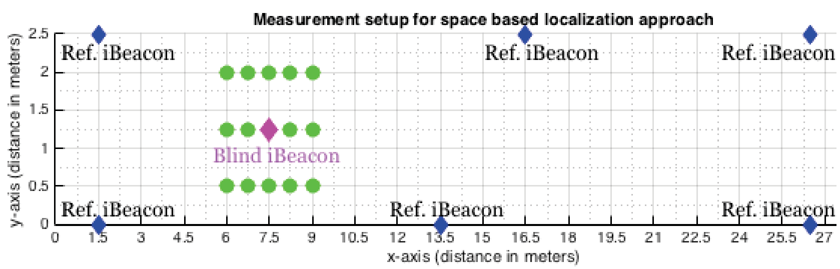
This measurement setup in Figure 4.7 was used to perform calibration phases (required) for *Fingerprinting, Conventional & Space-based localization algorithms*.

4.7 Setup for Space-based localization algorithm

The working principle for space-based localization approach was discussed in detail in 3. Since space-based localization requires sampling the signal space around the blind node with a mobile node therefore a new measurement setup is required. Here the measurement setup for space-based localization approach is presented in Figure 4.8. The sampling of signal space is performed by placing smartphone at discrete positions around the blind iBeacon. The measurement setup was used with 6 reference nodes and used twice to deduce localization performance results. For first experiment (see Figure 4.8a) signal space around blind iBeacon was sampled at 8 points and in the second experiment (see Figure 4.8b) signal signal space was sampled at 14 points around blind iBeacon by recording RSSI measurements from all nodes (reference and blind iBeacons) on smartphone.



(a) Space based localization experiment 1



(b) Space based localization experiment 2

Figure 4.8: The implementation of space base localization approach for our BLE-based indoor positioning system. Here the green dots represent the discrete points around blind iBeacon, shown by magenta polygon, where smartphone was placed to sample the signal space (RSS intensities). The blue diamonds represent the reference iBeacon nodes.

Chapter 5

Results

In this Chapter the performance evaluation of our proposed BLE-based indoor localization system will be performed using different localization algorithms. These algorithms are; *Proximity Approach, Fingerprinting Approach, Conventional Localization Approach, Self-Adaptive Localization Approach & Space-based localization Approach* (details in chapter 3). Our BLE-protocol based indoor positioning system will be developed on top of these localization algorithms (all of) which are based on received signal strength (RSS) measurement method. The primary performance metric used to evaluate the indoor positioning system's performance is *accuracy*. In section 5.1 the BLE based indoor localization system will be developed using proximity approach. Section 5.2 will discuss the localization of smartphone using fingerprinting approach based on Euclidean distance algorithm (as introduced in chapter 3). Smartphone localization is performed using conventional localization approach and results are presented in section 5.3. Since real-time (indoor) environments are dynamic, therefore a novel Self-Adaptive localization approach is proposed to localize smartphone in section 5.4. Section 5.5 discusses results for space-based localization approach to localize the smartphone and blind iBeacon. We finish the chapter by summarizing results from each localization approach and evaluating them with respect to key performance metrics for indoor localization system (which were introduced in chapter 2).

5.1 Proximity Approach

The basic localization procedure for proximity approach for indoor localization was explained in chapter 3. For our BLE-based indoor positioning system the proximity approach for localization of smartphone is developed using the characteristics of BEACONinside node and measurement setup as described in chapter 4.

Proximity intimation	Distance (range) w.r.t smartphone	Estimated RSSI threshold (mean) value from reference iBeacon	Associated range for RSSI (mean) value from reference iBeacon
Near	0 - 5 $meters$	-69.76 dBm	if under -75 dBm
Far	5 - 20 $meters$	-80.59 dBm	if between -75 to -85 dBm
Very far	20 + $meters$	-86.24 dBm	if over -85 dBm

Table 5.1: The distance range associated with each of the three regions, used to intimate presence of smartphone w.r.t reference node nearby.

5.1.1 Implementation

The characterization of each region with a certain RSSI (mean value) threshold for a reference node can be seen in Table 5.1. The associated range for RSSI (mean) value for each distance region was established on the basis of found standard deviation of measured values over points in these ranges from iBeacon. This BLE-based indoor localization system is depicted in Figure 5.1.

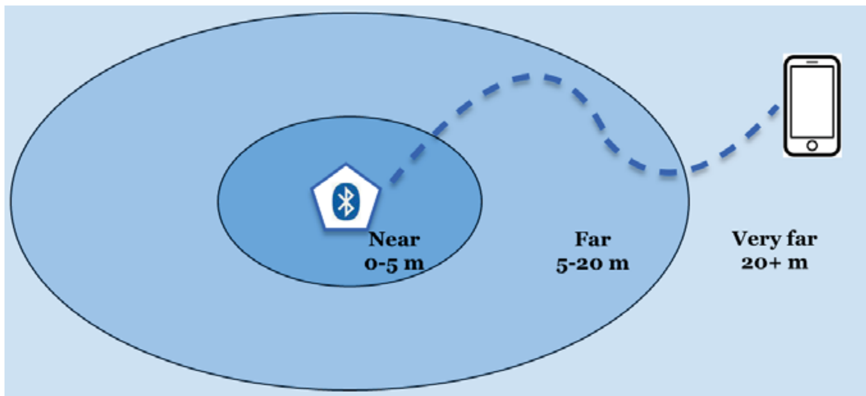


Figure 5.1: Presentation of a BLE-based indoor localization system using proximity approach. When in range, smartphone can be intimated to be in one of the three regions around that iBeacon.

Pseudocode explaining proximity based localization approach is given ahead. This explains how user is notified about distance range (Near, Far, and Very Far) from reference iBeacon in his surrounding area.

Algorithm 8 Proximity localization approach

procedure CALIBRATION ▷ Performed once
  Measure mean RSSI values over distance distribution inside localization space from a single reference iBeacon
  Define distance ranges
  $Near \leftarrow 0$ to 5 meters
  $Far \leftarrow 5$ to 20 meters
  $VeryFar \leftarrow 20 +$ meters
end procedure

procedure LOCALIZATION ▷ Every time localization is performed
  Measure mean RSSI value from reference node at current location
  $P_d \leftarrow$ Mean RSSI value in dBm
  if $P_d <$ *-75 dBm* **then**
    Result: *Near* $\leftarrow$ smartphone's proximity notification
  else if $P_d >$ *-75 dBm* and $<$ *-85 dBm* **then**
    Result: *Far* $\leftarrow$ smartphone's proximity notification
  else$P_d >$ *-85 dBm*
    Result: *VeryFar* $\leftarrow$ smartphone's proximity notification
  end if
end procedure

5.1.2 Summary

BLE-based indoor positioning system with proximity approach can be easily implemented. It is the simplest of localization algorithms and iBeacon were designed to provide such a localization solution. With help of an App. users can easily calibrate the threshold values for their chosen indoor environment and implement the system in quick time.

5.2 Fingerprinting Approach

Described in detail in chapter 3, the working principle of Fingerprinting based localization approach constitute of on *Offline & Online phase*. In context of our BLE based indoor positioning system's localization space these phases are performed and explained ahead.

5.2.1 Implementation

The first step with fingerprinting approach is conducting the offline phase. The localization space is divided into thirty-four cells (see Figure 5.2) The measurement setup was configured with dif-

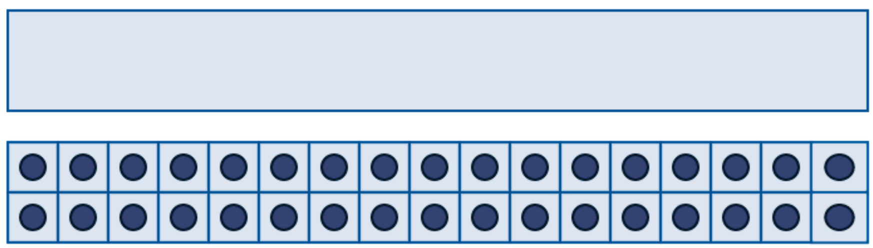


Figure 5.2: The localization space of $2.5m$ x $27m$ divided into a grid of 34 cells. Measurements were taken inside each cell to assign it with a distinguished signal feature (mean RSSI value). Each cell here has an area of $0.5m$ x $1.5m$.

ferent number of reference nodes (4 and 6). The ***offline phase;*** i.e., the calibration phase was performed and the collection of mean value of RSSI for each node in each cell was performed to build a database (radio-map) of fingerprints for each cell.

After completing the calibration phase (i.e. offline phase), the ***localization phase*** was performed to estimate the current location of smartphone. Euclidean Distance algorithm is used ([11]) (see 3 for details) and results obtained can be seen in tabular form (see table A.1) in appendix.

Localization performance with 4 reference nodes:

Localization performance is measured by finding the error between actual position of smartphone and estimated position of smartphone.

The results obtained for fingerprinting with 4 reference nodes yielded an accuracy of RMSE of 3.6 meters.

This can be further bettered with following improvements:

- with more sophisticated and complex localization algorithm usage.
- increasing the number of reference nodes.

Another set of experiment was conducted to test the suggested improvement number two i.e. increasing the number of reference nodes (from *4 to 6*) and comparing the RMSE values. It was observed that the results indeed get better. They are summarized in the tabular form (see table A.2) in appendix.

Localization performance with 6 reference nodes:

Localization performance is measured by finding the error between actual position of smartphone and estimated position of smartphone.

The results with 6 reference nodes were significantly better than previous results with 4 reference. The localization performance improved with 6 reference nodes and we got RMSE of 2.1 meters for our smartphone position estimation.

5.2.2 Summary

The results obtained with Fingerprinting turned out to be good. But they should be considered with a degree of caution; where there is more scope for optimism (improved localization performance) with this approach as sophistication of algorithm (using neural networks or K-nearest neighbour) in theory may be able to provide even better accuracy, there is also an important consideration to be made about correlation between offline and online phase. How closely the environment resembles during both phases is critical, as it happens in our case the online and offline phase measurements were taken on weekends and environment was as closed to static and similar as it gets (interference from human walking was also at its minimal).

Fingerprinting can be a highly effective way for indoor positioning but it comes with a big drawback of calibration phase and being site specific. If more number of points or cells (high resolution) at which signal features from each reference node can be gathered, a more refined rich database (or radio-map) can be established in offline phase which will help increase the localization performance w.r.t. accuracy. But this will also increase the overhead in terms of manual labour and time consumption. Also each time the environment changes (furniture displacement, renovation happens, human density or movement etc.) new round of calibration (offline phase) would be required. This would mean the overall solution will never be a portable solution and always be site specific.

Finally we summarize the results obtained via fingerprinting approach for our BLE-based indoor positioning system in table 5.2.

No. of reference nodes	Algorithm used	Accuracy (in meters)
4	Euclidean Distance Algorithm	3.6
6	Euclidean Distance Algorithm	2.1

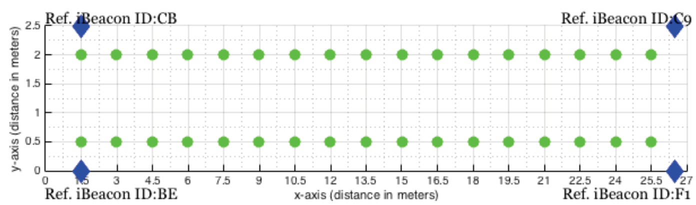
Table 5.2: The summary of results with fingerprinting approach.

5.3 Conventional Localization Approach

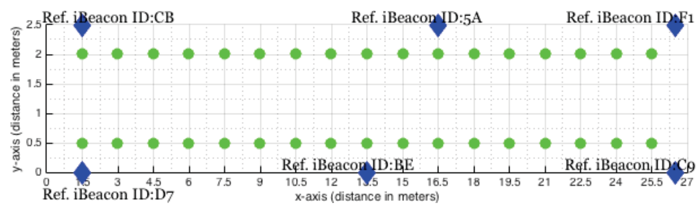
Indoor positioning systems using RSS-based conventional localization approach are implemented in a two phase process; **Conventional Calibration & Conventional Localization Phase** (see chapter 3 for details).

5.3.1 Calibration Phase

In conventional localization systems, calibration phase is performed to estimate the value of nuisance parameters which are; reference RSS power (P_{d_0}) and path loss exponent (n). These parameters can either be calibrated with one single value for whole system (i.e all the transmitters in the localization system) or can be individually calibrated for each transmitter (reference node) present in the system. We will be calibrating our localization space both individually and as a whole. Since our measurement setup can be operated under two different configurations w.r.t. number of reference nodes (4 or 6), calibration phase is performed for both configurations (see Figure 5.3).



(a) With 4 reference nodes

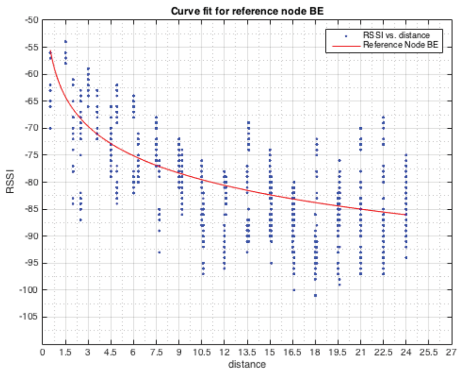


(b) With 6 reference nodes

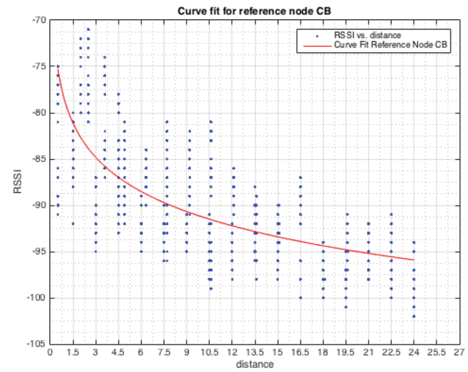
Figure 5.3: The calibration phase of Conventional Localization approach for our BLE-based indoor positioning system. Here the green dots represent the points at which RSSI measurements from each reference iBeacon is gathered to help estimate nuisance parameters. The blue diamonds show the fixed position of reference iBeacons along with their IDs in this measurement setup.

Individual Calibration with 4 reference nodes:

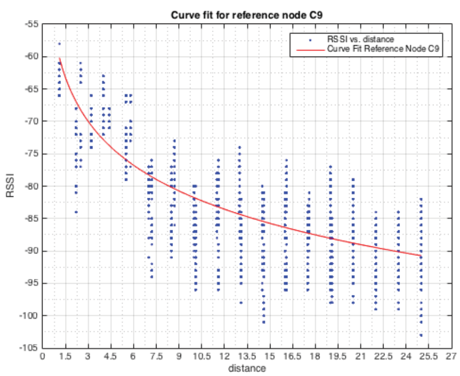
Inside the localization space 34 distinct points were chosen and calibration measurements were performed (the green dots in Figure 5.3a). The RSSI values obtained at each calibration point from each reference node were plotted separately and curve fitting of LNSM was performed (Figure 5.4). We used the "cftool" in MATLAB to do the curvefit and estimate P_{d_0} and n. This way values for P_{d_0} and n were estimated for each node. These values are shown in Table 5.3 along with goodness of the curve-fit.



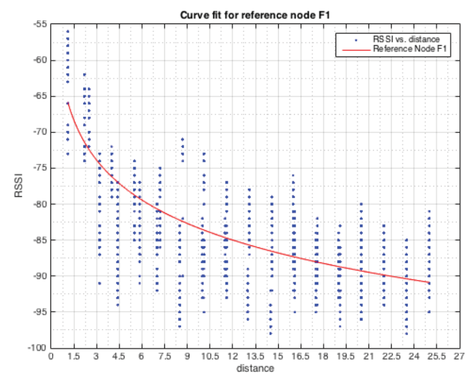
(a) Reference node BE



(b) Reference node CB



(c) Reference node C9



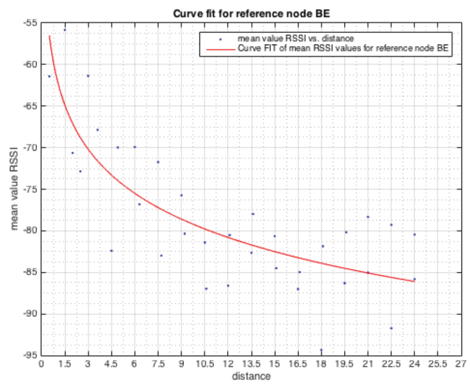
(d) Reference node F1

Figure 5.4: Curve Fitting with LNSM for all reference nodes (measured) RSS values in a configuration of measurement setup with 4 reference nodes over distance distribution. Here RSSI is in dBm and distance is in $meters$.

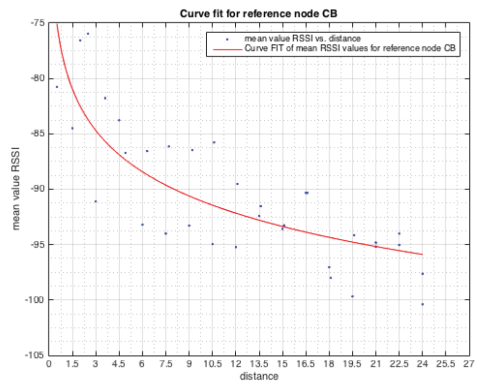
Node ID	Estimated value of RSS power i.e. P_{d_0} in dBm	Path loss exponent i.e n	Goodness of fit
BE	-61.01	1.814	RMSE: 6.839
C9	-59.25	2.252	RMSE: 5
CB	-78.96	1.228	RMSE: 4.372
F1	-65.07	1.845	RMSE: 5.186

Table 5.3: The estimated values for reference RSS power (P_{d_0}) and PLE (n) from curve fitting of data for each reference node.

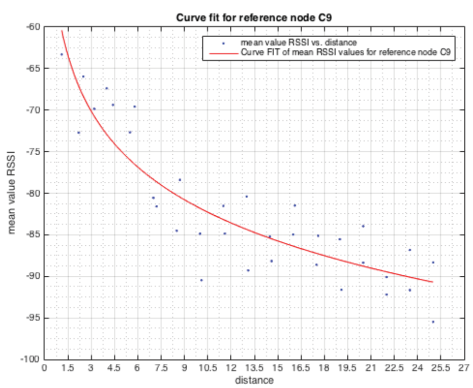
For ease of implementation usually mean value of recorded RSSI measurements is used. In view of this, the curve fitting of LNSM using “cftool” in MATLAB for each reference node was also done with mean (value) RSSI measurements obtained from each reference iBeacon on the 34 points inside the localization space (see Figure 5.5).



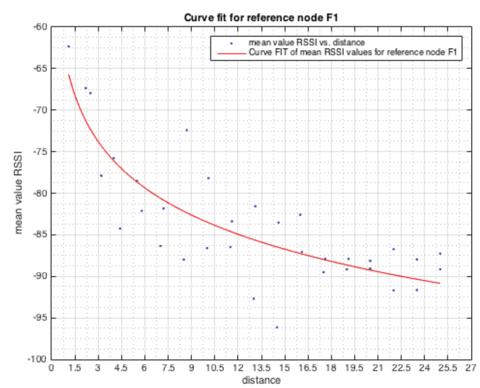
(a) Reference node BE



(b) Reference node CB



(c) Reference node C9



(d) Reference node F1

Figure 5.5: Curve Fitting with LNSM for all reference iBeacons (measured) mean RSSI value over distance distribution. Here RSSI is in dBm and distance is in $meters$.

The nuisance parameters reference RSS power and PLE were again estimated with respect to the mean value measurements from each reference iBeacon over the distance distribution using "cftool" in MATLAB. The estimated values for these parameters are formulated in the table 5.4 along with goodness of fit.

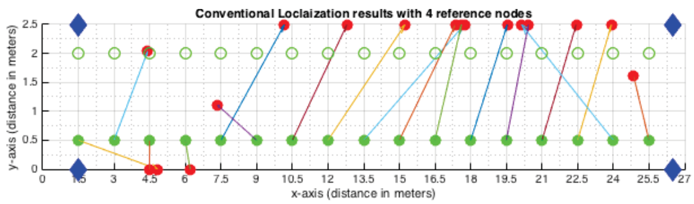
Node ID	Estimated value of RSS power i.e. P_{d_0} in dBm	Path loss exponent i.e. n	Goodness of fit
BE	-61.79	1.761	RMSE: 5.144
C9	-59.47	2.234	RMSE: 3.758
CB	-78.79	1.24	RMSE: 3.751
F1	-64.94	1.853	RMSE: 4.203

Table 5.4: The estimated values for RSS power and PLE from curve fitting of data for each reference node.

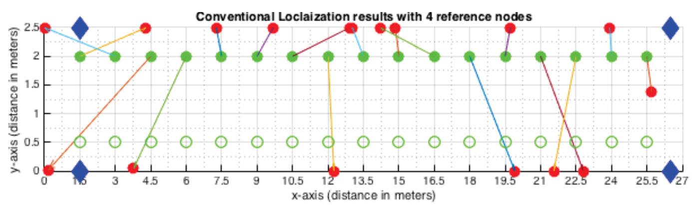
5.3.2 Localization Phase

Localization phase with individually calibrated 4 reference nodes

After performing calibration phase the localization phase was conducted using nuisance parameter values from table 5.4 for each node. Making use of Maximum Likelihood Estimators (MLE, see chapter 3), the cost function was derived and position estimation of smartphone (i.e. blind node) was performed. Smartphone was placed at 34 different positions inside the localization space. For each location the position estimate was performed and can be seen for all 34 locations (divided in 2 rows) in Figure 5.6. The results are also given in a tabular form (see table A.3) in appendix.



(a) Position estimates for current location in Row 1



(b) Position estimates for current location in Row 2

Figure 5.6: The localization phase of Conventional localization approach for our BLE-based indoor positioning system. Position estimates for current location of smartphone are shown for 34 distinct locations inside the localization space. Here the green dots represent the current location of smartphone and red dots are the estimated positions of smartphone. The setup has 4 reference nodes (individually calibrated) shown with blue diamonds.

Localization performance with 4 reference nodes:

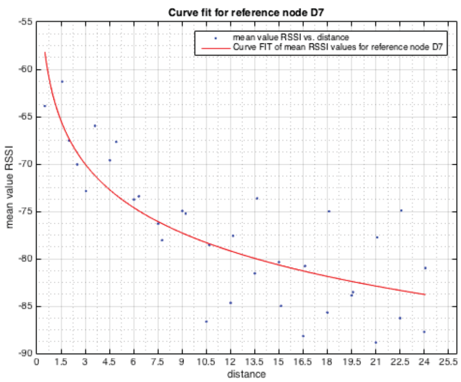
The localization performance is measured by finding the error between actual position of smartphone and estimated position of smartphone.

The localization performance of conventional localization approach with 4 reference nodes was found to be with an accuracy of RMSE 2.555 meters. The RMSE on y-axis was found to be 1.4894 meters and RMSE on x-axis was 2.0783 meters.

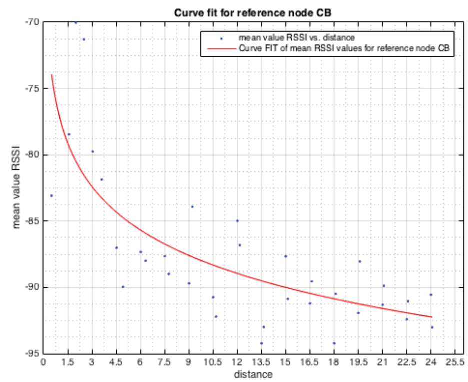
The conventional localization approach was also implemented with increase in number of reference nodes, from 4 to 6.

Calibration phase (individual) with 6 reference nodes

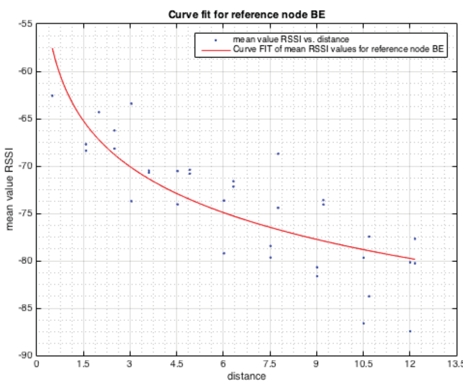
The calibration phase was conducted with 6 reference nodes using the measurement setup shown in Figure 5.3b. The mean value RSSI signal characteristic (for each reference node) was plotted over the distance distribution in the localization space and fitting of the LNSM was performed to estimate the values of *reference RSS power & path loss exponent* (see Figure 5.7). The values for reference RSS power (P_{d_0}) and PLE (n) obtained after the curve fit are presented in the table 5.5.



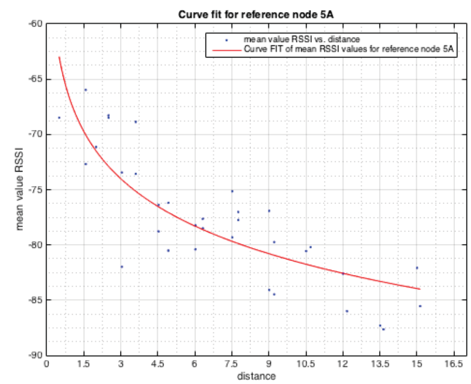
(a) Reference node D7



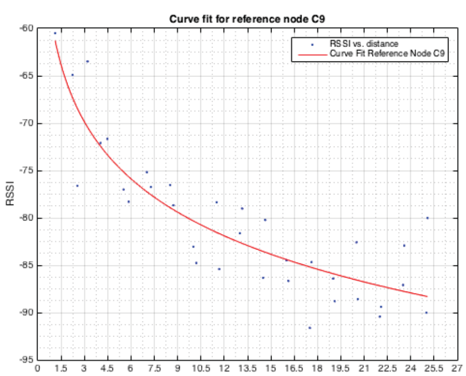
(b) Reference node CB



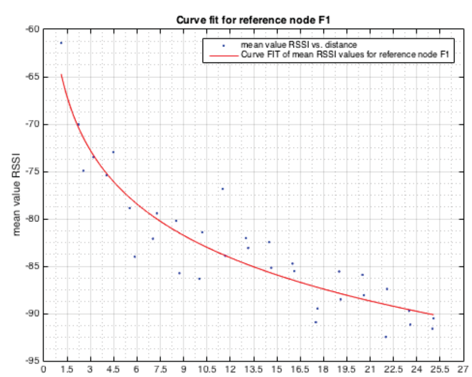
(c) Reference node BE



(d) Reference node 5A



(e) Reference node C9



(f) Reference node F1

Figure 5.7: Curve Fitting with LNSM for all reference nodes (measured) mean RSSI values over distance distribution. Here RSSI is in dBm and distance is in $meters$

Node ID	Estimated value of reference RSS power i.e. P_{d_0} in dBm	Path loss exponent i.e. n	Goodness of fit
D7	-62.75	1.523	RMSE: 4.297
CB	-77.2	1.088	RMSE: 3.945
BE	-62.39	1.608	RMSE: 3.836
5A	-67.23	1.421	RMSE: 3.312
C9	-60.32	2	RMSE: 3.597
F1	-63.81	1.88	RMSE: 2.688

Table 5.5: The estimated values for RSS power and PLE from curve fitting of data (mean values) for each reference node.

Calibration phase (as a whole) with 6 reference nodes

All the reference nodes comprising the system can also be calibrated for nuisance parameters at once as whole. This way a single value of P_{d_0} & n is found which suffices for all the reference iBeacons. The curve fitting with LNSM was done for plotted mean RSSI values from each reference iBeacon together (see Figure 5.8). The estimated values for reference RSS power and path loss exponent are shown in table 5.6.

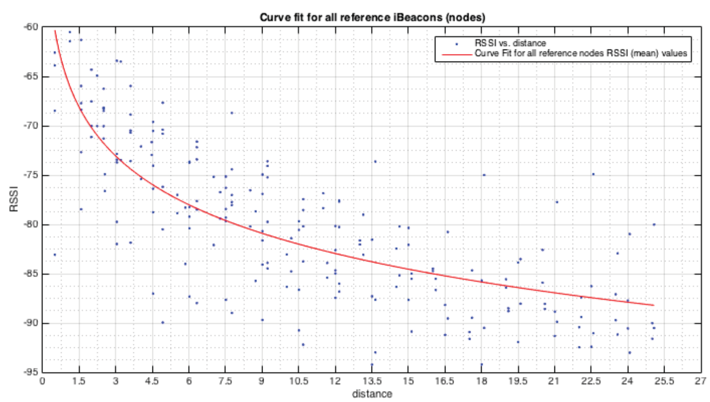


Figure 5.8: Curve Fitting with LNSM for all reference nodes as a whole system based on (measured) mean RSSI values over distance distribution. Here RSSI is in dBm and distance is in $meters$

Parameter	Estimated value
Reference RSS power i.e. P_{d_0} in dBm for whole system	-65.27
Path loss exponent i.e. n for whole system	1.6370
Goodness of fit	RMSE: 5.064

Table 5.6: The estimated values for RSS power and PLE from curve fitting of data (mean values) for whole system.

Localization phase with 6 reference nodes:

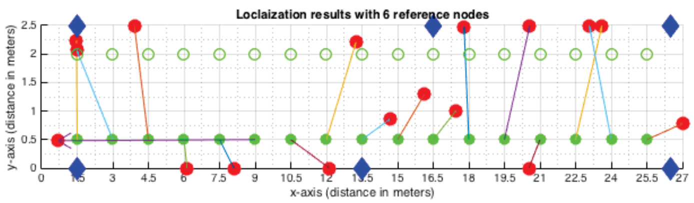
The smartphone localization was performed using the calibration results obtained for reference nodes. These results are plotted for the both cases i.e. case of individual calibration of the nodes and case of whole system calibrated as one using estimated values of nuisance parameters from tables 5.5 & 5.6. The position estimates are also summarized in tabular form (see table A.4) in appendix.

Localization performance with 6 reference nodes, when nodes individually calibrated:

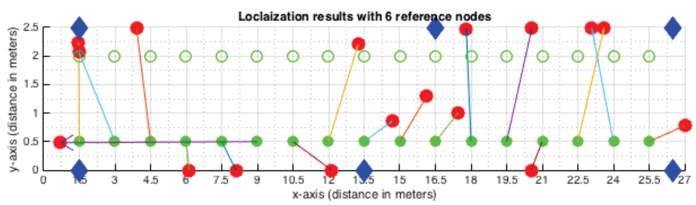
The localization performance is measured by finding the error between actual position of smartphone and estimated position of smartphone.

The localization performance of conventional localization approach with 6 reference nodes, each individually calibrated, was found to be with an accuracy of 2.270 meters. The error on x-axis was found to be 1.7784 meters and for y-axis was 1.4109 meters.

The results obtained are plotted in Figure 5.9.



(a) With 6 reference nodes, each individually calibrated



(b) With 6 reference nodes, each individually calibrated

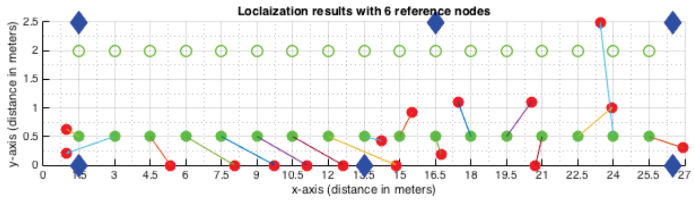
Figure 5.9: The localization phase of Conventional localization based BLE indoor positioning system. Position estimates for current location of smartphone are shown for 34 distinct locations inside the localization space. Here the green dots represent the current location of smartphone and red dots are the estimated positions for smartphone. The setup has 6 reference nodes (individually calibrated) presented by blue diamonds.

Localization performance with 6 reference nodes, whole system calibrated as one:

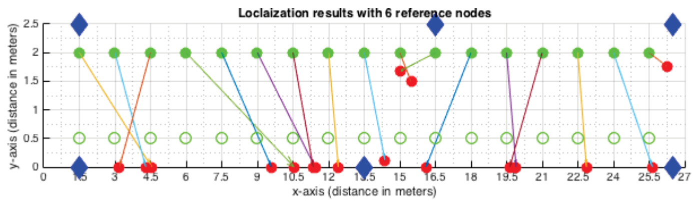
The localization performance is measured by finding the error between actual position of smartphone and estimated position of smartphone.

The localization performance of conventional localization approach with 6 reference nodes, when whole system, was calibrated as one was found to be with an accuracy of 2.156 meters. The error on x-axis was found to be 1.7784 meters and for y-axis was 1.6341 meters.

The results obtained are plotted in Figure 5.10.



(a) With 6 reference nodes, whole system calibrated as one



(b) With 6 reference nodes, whole system calibrated as one

Figure 5.10: The localization phase of Conventional localization based BLE indoor positioning system. Position estimates for current location of smartphone are shown for 34 distinct locations in the localization space. Here the green dots represent the current location of smartphone and red dots are the estimated positions for smartphone. The setup has 6 reference nodes (individually calibrated) presented by blue diamonds.

It can be seen that there is not much difference between individual calibration of nodes and whole system calibrated as one. But the localization performance increase with increase in number of reference iBeacons. An error of around 2 meter for smartphone localization can be regarded as a very good outcome.

5.3.3 Summary

The objective of developing a fine grained Bluetooth-Low Energy based indoor positioning system was successfully achieved with help of conventional localization approach. It is shown that the localization performance can be achieved with an ***accuracy*** of around ***2.2 - 2.75*** *meters*. The localization performance is summarized in 5.7 table below. It is also observed error for smartphone estimation was more significant in y-direction than in x-direction. This has to do with the dimensions of localization space i.e. more length vertically than horizontally. Therefore positioning in y-direction is less accurate than in x-direction.

Conventional Localization approach for BLE indoor positioning system				
No. of reference Nodes	Calibration of P_{d_0} and n	RMSE in *meters*	RMSE in x-direction	RMSE in y-direction
4	Individually	2.55	2.07	1.48
4	As a whole	2.75	-	-
6	Individually	2.27	1.77	1.41
6	As a whole	2.15	1.77	1.63

Table 5.7: Summary of localization performance with conventional localization approach for our BLE based indoor positioning system.

5.4 Self-Adaptive Localization Approach

"Self-Adaptive Localization (SAL) Approach" is designed to continuously adapt to a dynamic environment. For details see chapter 3. The results for 3 different implementations of the SAL approach (as discussed in chapter 3) are provided ahead.

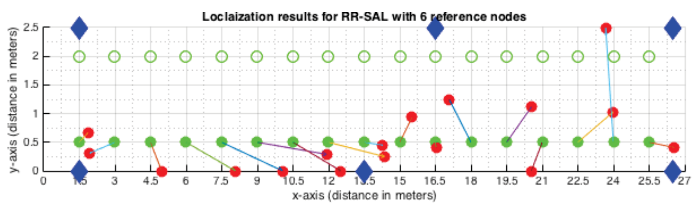
5.4.1 Reference RSS Self-Adaptive Localization (RR-SAL)

Localization Performance

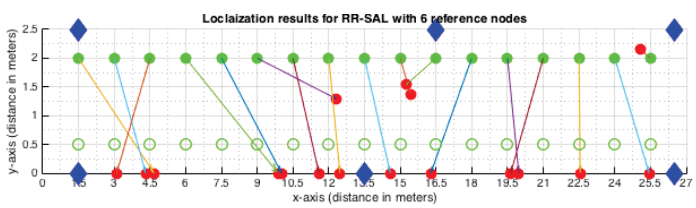
The localization performance is measured by finding the error between actual position of smartphone and estimated position of smartphone.

The position estimation of smartphone with RR-SAL approach was found to be with RMSE of 2.1343 *meters* ***(see Figure 5.11 for 2D plot of results). The error on x-axis was found to be 1.6706 meters and for y-axis was 1.3282 meters.***

The results obtained are also presented in tabular form in appendix (A.6).



(a) RR-SAL results plot Row 1



(b) RR-SAL results plot Row 2

Figure 5.11: The results for localization of smartphone with RR-SAL approach.

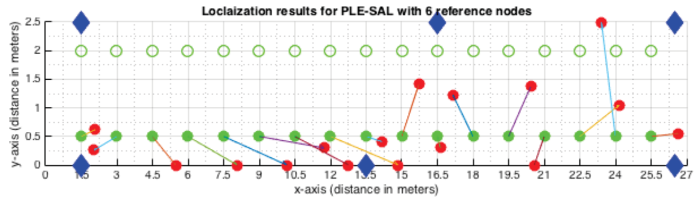
5.4.2 Path Loss Exponent Self-Adaptive Localization (PLE-SAL)

Localization Performance

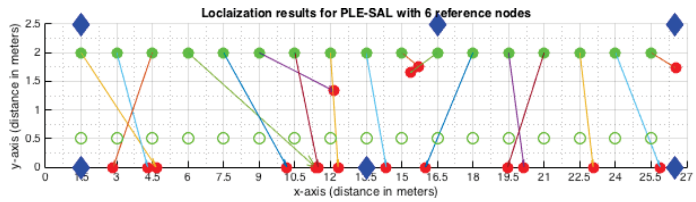
The localization performance is measured by finding the error between actual position of smartphone and estimated position of smartphone.

The position estimation of smartphone with PLE-SAL approach was found to be with RMSE of 2.2871 *meters* ***(see Figure 5.12 for 2D plot of results). The error on x-axis was found to be 1.8554 meters and for y-axis was 1.3373 meters.***

The results obtained are also presented in tabular form in appendix (A.7).



(a) PLE-SAL results plot Row 1



(b) PLE-SAL results plot Row 2

Figure 5.12: The results for localization of smartphone with PLE-SAL approach.

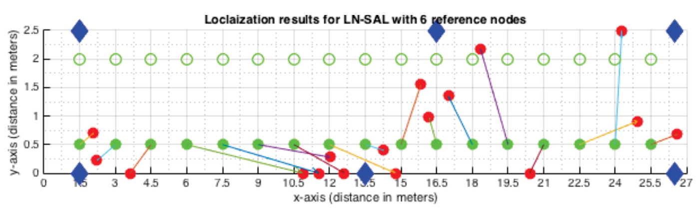
5.4.3 Log-Normal Self-Adaptive Localization (LN-SAL)

Localization Performance

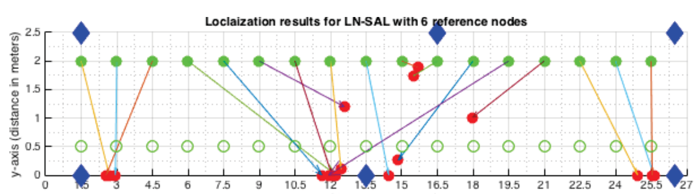
The localization performance is measured by finding the error between actual position of smartphone and estimated position of smartphone.

The position estimation of smartphone with LN-SAL approach was found to be with RMSE of 2.9786 *meters* ***(see Figure 5.13 for 2D plot of results). The error on x-axis was found to be 2.6489 meters and for y-axis was 1.3622 meters.***

The results obtained are also presented in tabular form in appendix (A.8).



(a) LN-SAL results plot Row 1



(b) LN-SAL results plot Row 2

Figure 5.13: The results for localization of smartphone with PLE-SAL approach.

Summary

Table 5.8 summarizes the characteristics of the different SAL approaches and comparison with each other. The table columns represent the following:

Type	Article	θ	Calibrated parameters	RMSE in *meters*
RR-SAL	5.4.1	(x, y, P_{d_0})	(n)	2.1343
PLE-SAL	[23]	(x, y, n)	(P_{d_0})	2.2871
LN-SAL	[14]	(x, y, P_{d_0}, n)	$()$	2.9786

Table 5.8: Summary Conventional and SAL systems.

- The ***"Type"*** columns contains the type of localization system.
- The ***"Article"*** column gives the reference to the articles that describe these localization systems.
- The ***"θ"*** column contains the set of parameters that are estimated by the localization measurements.
- The ***"Calibration parameters"*** column shows the set of parameters that are calibrated before localization.
- The ***"RMSE"*** column shown the accuracy that can be achieved with SAL approaches.

5.5 Space-based Localization Approach

The space-based localization approach (described in detail 3) will be used to estimate the position (x- and y-coordinate) of blind iBeacon.

5.5.1 Implementation

The measurement setup described in chapter 4 for Space-based localization was used.[1]

5.5.2 Localization performance

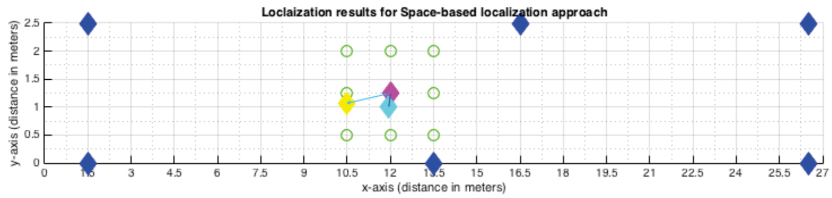
The blind iBeacon was placed inside the localization space at two different points and signal space around it was sampled by placing smartphone at different points around the blind iBeacon. The results obtained can be seen in Figure 5.14. Here

- The magenta diamond shows the actual position of blind iBeacon,
- The yellow diamond indicates the estimated position of blind iBeacon w.r.t actual positions of smartphone when placed around (at multiple points) blind iBeacon, and
- The cyan diamond indicates the estimated position of blind iBeacon w.r.t estimated positions found for smartphone when placed around (at multiple points) blind iBeacon.

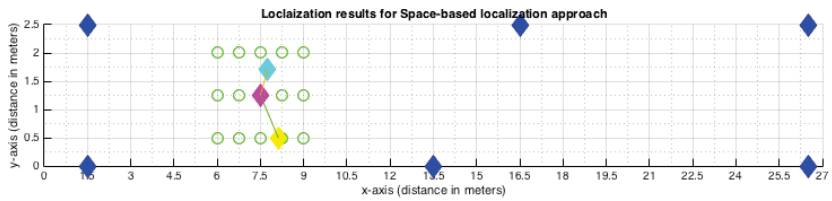
Using Space-based localization approach the blind iBeacon localization was performed with an accuracy of RMSE of 1.2419 $meters$ ***when signal space around blind iBeacon was sampled with 8 points. The localization performance improved and RMSE of 0.9731*** $meters$ ***was found when signal space was sampled with 14 points around blind iBeacon.***

The results obtained with space-based localization are provided in tabular form in appendix.

[1] *Individually calibrated values for nuisance parameters $P_{d_0})$ and n for all the reference nodes iBeacon was used in space-based localization approach.*



(a) Space based localization experiment 1, SBL-01



(b) Space based localization experiment 2, SBL-02

Figure 5.14: The results plot of blind iBeacon localization with space base localization approach in our BLE-based indoor positioning system. Here the green circles represent the discrete points around blind iBeacon (shown by magenta polygon) where smartphone was placed to sample the signal space (RSS intensities). The blue diamonds represent the reference iBeacon nodes.

5.6 Conclusion

In this chapter our proposed BLE-based indoor positioning system was implemented with 5 range-based algorithms. In this section we will recap the algorithm with respect to localization performance and evaluate them on the basis of performance metrics, described for indoor positioning systems in chapter 2. The most important performance metric is accuracy, table 5.9 summarized all the localization approaches with this metric. The performance metrics used to evaluate our

Localization approach	Accuracy in m
Proximity	-
Finger-printing	about 2-2.5 m
Conventional Localization	about 2 m
Self-Adaptive Localization	about 2-3 m
Space-based Localization	about 1 m

Table 5.9: Summary of localization approaches, for our BLE-based indoor positioning system, based on accuracy of these approaches.

BLE-based indoor positioning system are as follows:

- Accuracy (most important) & Precision
- Adaptiveness
- Complexity & Cost
- Practicality & Integrity
- Localization time

We have summarized the localization performance for each algorithm w.r.t performance metrics above in table 5.10.

Localization approach	Accuracy & Precision	Adtaptiveness	Complexity & Cost	Practicality & Integrity	Localization time
Proximity	−−	−	++	++	++
Fingerprinting	+	0	+	+	0
Conventional Localization	++	+	0	+	−
Self-Adaptive Localization	++	++	−	+	0
Space-based Localization	+++	++	0	+	−−

Table 5.10: Summary of localization approaches, for our BLE-based indoor positioning system, w.r.t different localization performance metrics.

Chapter 6

BLE-based Outdoors Localization

The previous chapters discuss in detail how an effective BLE-based indoor positioning system can be successfully developed. In this chapter we will try to find out the feasibility of developing a localization system for outdoors involving iBeacons and a smartphone. We will try to answer the effectiveness of iBeacons for outdoor localization.

6.1 Model and Measurement Setup

This section will discuss the propagation model and measurement setup used in order to build a BLE-based outdoors positioning system. Fist we discuss the measurement setup, a grass field nearby University of Twente's campus was selected as the experimentation environment (see Figure 6.1).

Figure 6.1: The outdoor site where experiment was conducted for BLE-based out door localization system.

A measurement setup was established using 16 tripods each 4 m displaced apart (see Figure 6.2). As discussed before with indoor localization system implementation, here also we can either use the conventional localization approach or apply Self-Adaptive localization (these were described in detail in chapter 3). Conventional localization approach was used to gather results for outdoor positioning.

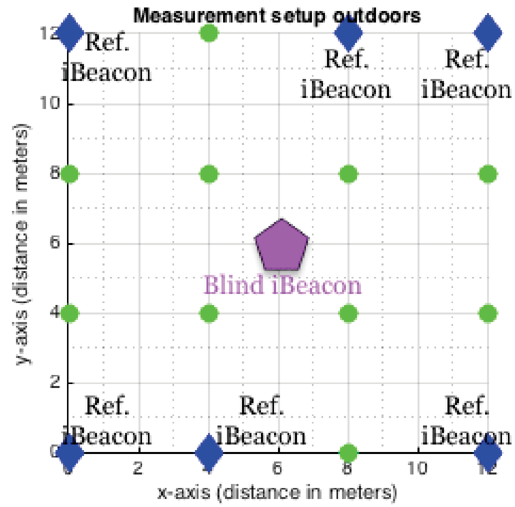


Figure 6.2: Measurement setup outdoors, here the polygons represent reference iBeacon nodes and green dots show the positions of tripods in the setup.

6.2 Conventional Localization Approach.

Since conventional localization approach performs localization in two phases; a calibration phase and then localization phase (see Figure 3.8). We first conducted the calibration phase in which we calibrated for the nuisance parameter reference RSS power P_{d_0} where the value for path loss exponent n was assumed to be 2 (i.e. in free space) for simplicity. The calibration phase measurement setup can be seen in Figure 6.3). The resulting curve fit with LNSM yielded value of P_{d_0} as -65.69 dBm (see table 6.1).

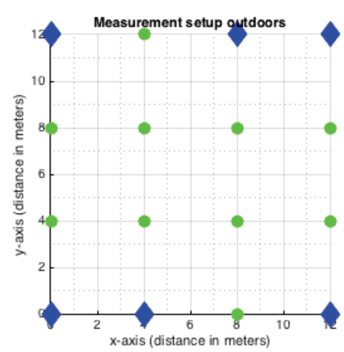


Figure 6.3: Calibration phase outdoors, here blue diamonds show the positions (known) of reference nodes where as green dots indicate the points where measurements for calibration were recorded on a smartphone.

Parameter	Estimated value
Reference RSS power i.e. P_do in dBm for whole system	-65.69

Table 6.1: The estimated values for reference RSS power from curve fitting of data (mean values) for whole system.

Afterwards localization phase was conducted where smartphone was placed at 8 different points (we call them point of interest, POIs) inside the localization space and position estimation for smartphone was performed. The results obtained are shown in tabular form in appendix A.10. The **RMSE** is obtained for smartphone and is presented in the table 6.2. Figure 6.4 provides the results plot for smartphones' position estimation.

Position estimation	RMSE error
Smartphone	8.5181

Table 6.2: The estimated values for RSS power from curve fitting of data (mean values) for whole system.

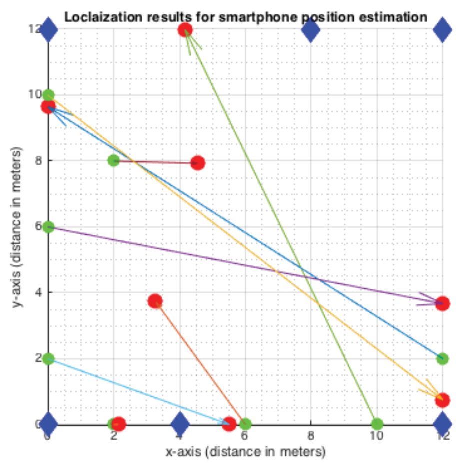


Figure 6.4: The result plot for smartphone localization outdoors. Here the green dots represent the actual position of smartphone and red dots show the estimated position. The blue diamonds show the positions of reference iBeacon nodes.

6.3 Summary

The localization performance achieved outdoors was well below the expectation. There can be several reasons for it. Some of them can be; presence of high level of grass, the fact that nodes were placed only 0.75 m from ground level etc. We assume higher placement of nodes (both reference and blind) w.r.t ground may yield better results. Also the number of tests done were not enough, more tests should be performed to have a better understanding of feasibility and effectiveness of BLE-based outdoor localization. Only conventional localization approach was used to implement the localization system and obtain results. We believe that with space-based localization approach better results can be achieved. But this remains to be tested and can be done as part of future works.

Chapter 7

Conclusion and future work

In this chapter we present conclusions reached after implementing our Bluetooth-Low Energy based indoor positioning system. The first section 7.1, would give an overall conclusion about the work done. The section 7.2 would discuss the potential application scenarios for our BLE-based indoor positioning system. The last section 7.3 will provide some advice for future work that would be of interest in this area.

7.1 Conclusions

In this thesis work an indoor localization system based on Bluetooth-Low Energy technology, making use of iBeacon and smartphone, was developed, tested and evaluated with several well known localization approaches. The goal was to evaluate the suitability and the applicability of building a fine grained indoor positioning system using BLE devices (i.e. iBeacon) which can successfully demonstrate localization of smartphone along with blind iBeacon(s) in the chosen indoor environment. After a comprehensive study of earlier research in indoor positioning systems based on different signal technologies, an indoor positioning system based on Bluetooth-Low energy (or Bluetooth Smart) protocol was developed. BLE signal technology was chosen because of its characteristics of low cost, low energy consumption and the fact that it is readily available in digital devices (like smartphone, tablets etc). The infrastructure nodes (BLE devices) in this system namely iBeacon (clones) are also cheap and have long battery life. Research was conducted to see with which localization algorithms, this indoor positioning system can be developed and received signal strength measurement method was used. RSS range-based localization algorithms were chosen to develop our BLE-based indoor positioning system. The localization approaches used were; *Proximity Localization, Fingerprinting Localization, Conventional and Self-Adaptive Localization & Space based Localization*. The conclusion of the evaluation is that Bluetooth-Low energy can be considered as a viable (candidate) signal technology depending on the requirements. The system developed can deliver accuracy of **2-3** *meters* with relatively high precision with Fingerprinting, Conventional & Self-Adaptive localization approach for smartphone localization. Whereas with Space-based localization approach an accuracy of **1-1.5** was achieved for blind iBeacon localization. These results are good enough to facilitate building other additional services; like context aware location services, navigation & tracking of humans and goods. For now the the measurements were taken on smartphone and feed into a central processing unit (Laptop) for localization processing.

The system deployment is simplified by low cost of BEACONinside (iBeacon clones) nodes [1], combined with the fact that no additional extra infrastructure needs to be deployed, since these nodes can run for one year on AAA batteries. It was observed that with calibration of environment beforehand high localization performance can be achieved, but this increases the workload and

[1] *used in our BLE indoor positioning system*

will work best for static environments. But since indoor environments are usually dynamic and continuously changing, each time a new calibration round will be required. To do away with this extra work, Self-adaptive localization was introduced and evaluation with this approach yielded good localization performance as well. The localization of blind iBeacon in indoor environment yielded excellent results with space-based localization approach. In the end it can be concluded that BLE introduces several improvements to inexpensive indoor positioning. Fast response time, no need of fixed infrastructure, advertisement support, simple deployment, low cost and power efficiency are important and worthy improvements to be mentioned. Since BLE is to become the de-facto IoT wireless technology, thus a BLE-based indoor localization system would have huge commercial implications. In next section we will discuss some of these possibilities.

7.2 Commercial Implications

In this section potential commercial application scenarios where our BLE-based indoor positioning system can be successfully deployed is discussed. Along with this major thesis work, some time was also spent in writing a minor thesis exploring commercial potential of this work done. The details for this can be studied in a separate report written by author. A thorough market research was done and multiple market segments were found to be good target for our product. Here for simplicity only one market segment i.e. **Gym & Fitness Centers** is discussed. This market segment showed overwhelming willingness to make use of an indoor positioning system in order to provide its users with unique consumer experience. With help of further customization on the LocusPositioning BLE App. a highly interactive app. (for user) can be created. In an indoor environment hidden iBeacon can be placed on different work out equipment and machines, user's smartphone can localize this blind iBeacon and get information about gym equipment and machine in an interactive way on smartphone screen. Figure (7.1) tries to give idea about such an application of iBeacon localization for gyms & fitness centers.

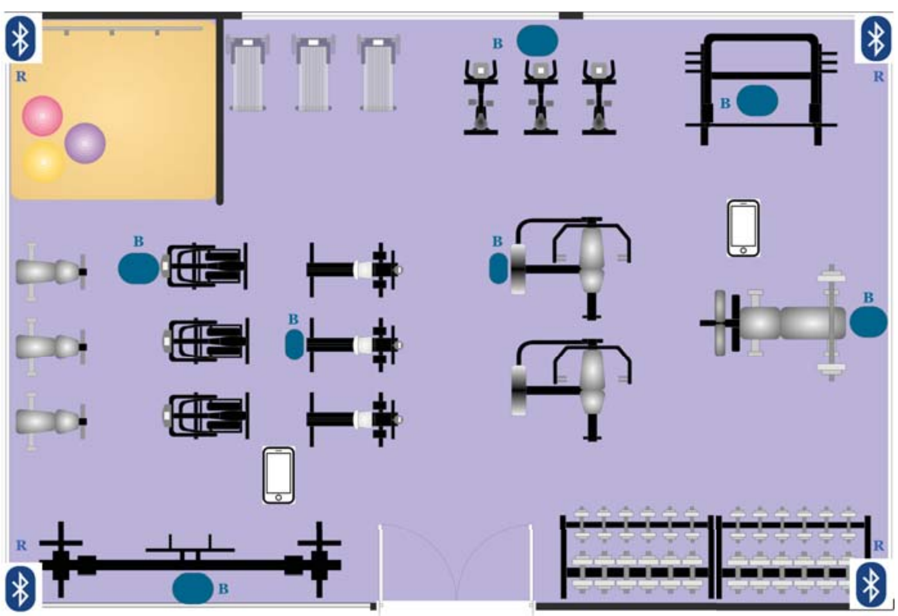


Figure 7.1: A BLE-based indoor positioning system deployed in Gym (indoor environment). Here **R** represent the reference iBeacons and **B** shows where blind iBeacons are placed. Users while moving inside gym area will be able to localize these blind iBeacons and get pop up information about the machine on which blind iBeacon is placed.

7.3 Future work

Although the evaluation of our proposed BLE-based indoor localization system was done according to plan, several improvements could have been made if time would have permitted. Using commercial of the shelf BLE devices results in some limitations. These limitations in BLE in general are due to the effect of implementation choices made by vendors. An example of this would be the transmission power levels. In our system we worked with the maximum power transmission level (i.e. 0 dBm) which was available on the iBeacon clone (BEACONinside) nodes that we had used. Since Bluetooth is a wireless technique which enjoys low penetration signal characteristics, increasing power transmission level would result in an increased range and signal penetration in indoor environment.

The localization computation was performed using particle filter approach (implemented using Matlab), which required the measurements to be feed into laptop to get results (position estimate). Since we envision the localization system to be implemented on smartphone, therefore it would be interesting to build a software solution which is more efficient and can be easily performed using smartphone processing capabilities. Another direction for future works is to work on App. development and integrate localization processing capabilities in it.

Another potential improvement would be to explore possibility of using *Time of Flight* (ToF) *& Angle of Arrival* (AoA) measurement method-based (BLE) positioning system. This can be achieved by customizing the hardware used by using new radio and directional antennas or an antenna grid.

Another related topic would be to explore if a hybrid solution can be deployed making use of cheap BLE devices (i.e. iBeacon) and other infrastructure nodes or different signal technology (like WiFi etc.). Making use of machine learning approaches and data fusion algorithms to help ease of deployment, expansion or repair of already in-placed system could also help improve RF based localization.

Since for now the localization computation was performed on a laptop after gathering measurement data on a smartphone, and results were deduced for smartphone and iBeacon localization. The author propose developing BLE based indoor localization system on the mobile node i.e. smartphone itself. This way whole processing can be done on the users' smartphone and a 2D map outcome can be produced intimating user of its current location and the estimated location of blind iBeacon in the environment.

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Appendix A

Table

Current Location coordinates (x, y)	**Smartphone localized in cell no.**	**Estimated Coordinates (x, y)**
(0.5 , 1.5)	*Cell 19*	(2 , 3)
(0.5 , 3)	*Cell 06*	(0.5 , 9)
(0.5 , 4.5)	*Cell 20*	(2 , 4.5)
(0.5 , 6)	*Cell 06*	(0.5 , 9)
(0.5 , 7.5)	*Cell 08*	(0.5 , 12)
(0.5 , 9)	*Cell 07*	(0.5 , 10.5)
(0.5 , 10.5)	*Cell 28*	(2 , 16.5)
(0.5 , 12)	*Cell 28*	(2 , 16.5)
(0.5 , 13.5)	*Cell 12*	(0.5 , 18)
(0.5 , 15)	*Cell 11*	(0.5 , 16.5)
(0.5 , 16.5)	*Cell 09*	(0.5 , 13.5)
(0.5 , 18)	*Cell 09*	(0.5 , 13.5)
(0.5 , 19.5)	*Cell 09*	(0.5 , 13.5)
(0.5 , 21)	*Cell 14*	(0.5 , 21)
(0.5 , 22.5)	*Cell 16*	(0.5 , 24)
(0.5 , 24)	*Cell 13*	(0.5 , 19.5)
(0.5 , 25.5)	*Cell 16*	(0.5 , 24)
(2 , 1.5)	*Cell 19*	(2 , 3)
(2 , 3)	*Cell 19*	(2 , 3)
(2 , 4.5)	*Cell 20*	(2 , 4.5)
(2 , 6)	*Cell 05*	(0.5 , 7.5)
(2 , 7.5)	*Cell 26*	(2 , 13.5)
(2 , 9)	*Cell 26*	(2 , 13.5)
(2 , 10.5)	*Cell 23*	(2 , 9)
(2 , 12)	*Cell 23*	(2 , 9)
(2 , 13.5)	*Cell 23*	(2 , 9)
(2 , 15)	*Cell 23*	(2 , 9)
(2 , 16.5)	*Cell 23*	(2 , 9)
(2 , 18)	*Cell 29*	(2 , 18)
(2 , 19.5)	*Cell 13*	(0.5 , 19.5)
(2 , 21)	*Cell 14*	(0.5 , 21)
(2 , 22.5)	*Cell 32*	(2 , 22.5)
(2 , 24)	*Cell 33*	(2 , 24)
(2 , 25.5)	*Cell 34*	(2 , 24)

Table A.1: Results of a Fingerprinting-based BLE protocol solution for indoors positioning. The position of smartphone is estimated is localized in an area of 2.5m x 27m with four reference iBeacon nodes.

Current Location coordinates (x, y)	**Smartphone localized in cell no.**	**Estimated Coordinates (x, y)**
(0.5 , 1.5)	*Cell 01*	(0.5 , 1.5)
(0.5 , 3)	*Cell 03*	(0.5 , 4.5)
(0.5 , 4.5)	*Cell 03*	(0.5 , 4.5)
(0.5 , 6)	*Cell 04*	(0.5 , 6)
(0.5 , 7.5)	*Cell 03*	(0.5 , 4.5)
(0.5 , 9)	*Cell 06*	(0.5 , 9)
(0.5 , 10.5)	*Cell 07*	(0.5 , 10.5)
(0.5 , 12)	*Cell 08*	(0.5 , 12)
(0.5 , 13.5)	*Cell 08*	(0.5 , 12)
(0.5 , 15)	*Cell 08*	(0.5 , 12)
(0.5 , 16.5)	*Cell 28*	(2 , 16.5)
(0.5 , 18)	*Cell 11*	(0.5 , 16.5)
(0.5 , 19.5)	*Cell 13*	(0.5 , 19.5)
(0.5 , 21)	*Cell 13*	(0.5 , 19.5)
(0.5 , 22.5)	*Cell 11*	(0.5 , 16.5)
(0.5 , 24)	*Cell 16*	(0.5 , 24)
(0.5 , 22.5)	*Cell 15*	(0.5 , 24)
(2 , 1.5)	*Cell 01*	(0.5 , 1.5)
(2 , 3)	*Cell 01*	(0.5 , 1.5)
(2 , 4.5)	*Cell 20*	(2 , 4.5)
(2 , 6)	*Cell 22*	(2 , 7.5)
(2 , 7.5)	*Cell 22*	(2 , 7.5)
(2 , 9)	*Cell 05*	(0.5 , 7.5)
(2 , 10.5)	*Cell 22*	(2 , 7.5)
(2 , 12)	*Cell 25*	(2 , 12)
(2 , 13.5)	*Cell 11*	(0.5 , 16.5)
(2 , 15)	*Cell 10*	(0.5 , 15)
(2 , 16.5)	*Cell 28*	(2 , 16.5)
(2 , 18)	*Cell 25*	(2 , 12)
(2 , 19.5)	*Cell 14*	(0.5 , 21)
(2 , 21)	*Cell 31*	(2 , 21)
(2 , 22.5)	*Cell 32*	(2 , 22.5)
(2 , 24)	*Cell 33*	(2 , 24)
(2 , 25.5)	*Cell 15*	(0.5 , 22.5)

Table A.2: Results of a Fingerprinting-based BLE protocol solution for indoors positioning. The position of smartphone is estimated in an area of 2.5m x 27m with six reference iBeacon nodes.

Row 1			Row 2		
POI	**Actual-coordinates (x, y)**	**Estimated-coordinates (x, y)**	**POI**	**Actual-coordinates (x, y)**	**Estimated-coordinates (x, y)**
1	(0.5, 1.5)	(0, 4.84)	18	(2.0, 1.5)	(2.5, 4.3)
2	(0.5, 3)	(2.04, 4.42)	19	(2.0, 3)	(2.5, 0)
3	(0.5, 4.5)	(0, 4.49)	20	(2.0, 4.5)	(0.01, 0.15)
4	(0.5, 6)	(0, 6.2)	21	(2.0, 6)	(0.04, 3.77)
5	(0.5, 7.5)	(2.5, 10.17)	22	(2.0, 7.5)	(2.5, 7.27)
6	(0.5, 9)	(1.11, 7.34)	23	(2.0, 9)	(2.5, 9.68)
7	(0.5, 10.5)	(2.5, 12.8)	24	(2.0, 10.5)	(2.5, 12.92)
8	(0.5, 12)	(2.5, 15.24)	25	(2.0, 12)	(0, 12.25)
9	(0.5, 13.5)	(2.5, 17.74)	26	(2.0, 13.5)	(2.5, 13.03)
10	(0.5, 15)	(2.5, 17.36)	27	(2.0, 15)	(2.5, 14.85)
11	(0.5, 16.5)	(2.5, 17.61)	28	(2.0, 16.5)	(2.5, 14.23)
12	(0.5, 18)	(2.5, 19.54)	29	(2.0, 18)	(0, 19.91)
13	(0.5, 19.5)	(2.5, 20.43)	30	(2.0, 19.5)	(2.5, 19.72)
14	(0.5, 21)	(2.5, 22.44)	31	(2.0, 21)	(0, 22.81)
15	(0.5, 22.5)	(2.5, 23.92)	32	(2.0, 22.5)	(0, 21.56)
16	(0.5, 24)	(2.5, 20.13)	33	(2.0, 24)	(2.5, 23.93)
17	(0.5, 25.5)	(1.61, 24.85)	34	(2.0, 25.5)	(1.37, 25.7)
Root Mean Square Error (RMSE)		**2.8192**m	**Root Mean Square Error (RMSE)**		**2.2644**m

Table A.3: The results for 34 Points of interest (POIs) inside the localization area, and their estimated positions.

Row 1			Row 2		
POI	**Actual co-ordinates (x, y)**	**Estimated co-ordinates (x, y)**	**POI**	**Actual co-ordinates (x, y)**	**Estimated co-ordinates (x, y)**
1	(0.5, 1.5)	(2.24, 1.47)	18	(2.0, 1.5)	(0, 3.7)
2	(0.5, 3)	(2.07, 1.48)	19	(2.0, 3)	(2.5, 2.93)
3	(0.5, 4.5)	(2.5, 3.91)	20	(2.0, 4.5)	(1.06, 2.84)
4	(0.5, 6)	(0, 6.13)	21	(2.0, 6)	(0, 7.58)
5	(0.5, 7.5)	(0, 8.1)	22	(2.0, 7.5)	(0, 7.83)
6	(0.5, 9)	(0.48, 9.7)	23	(2.0, 9)	(2.39, 11.13)
7	(0.5, 10.5)	(0, 12.13)	24	(2.0, 10.5)	(0.38, 10.31)
8	(0.5, 12)	(2.21, 13.25)	25	(2.0, 12)	(1.2, 12.38)
9	(0.5, 13.5)	(0.86, 14.68)	26	(2.0, 13.5)	(0.47, 14.75)
10	(0.5, 15)	(1.29, 16.13)	27	(2.0, 15)	(1.97, 15.77)
11	(0.5, 16.5)	(1.01, 17.47)	28	(2.0, 16.5)	(2.5, 15.19)
12	(0.5, 18)	(2.48, 17.47)	29	(2.0, 18)	(0.26, 17.36)
13	(0.5, 19.5)	(2.5, 20.57)	30	(2.0, 19.5)	(0, 19.76)
14	(0.5, 21)	(0, 20.3)	31	(2.0, 21)	(0, 19.72)
15	(0.5, 22.5)	(2.5, 23.61)	32	(2.0, 22.5)	(0.25, 22.43)
16	(0.5, 24)	(2.5, 23.08)	33	(2.0, 24)	(0, 24.93)
17	(0.5, 25.5)	(0.78, 27)	34	(2.0, 25.5)	(1.86, 26.01)

Table A.4: The results for 34 Points of interest (POIs) inside the localization area, and their estimated positions.

POI	SP actual coordinates (x, y)	SP estimated coordinates (x, y)	Blind iBeacon actual coordinates (x, y)	Actual (direct) distance between SP and blind iBeacon	Estimated (direct) distance between SP and blind iBeacon
1	(1.25, 11.25)	(0 , 12.45)	(2.5, 15)	(3.95)	(4.67)
2	(2, 26)	(1.21, 25.14)	(2.5, 15)	(11.01)	(9.90)
3	(0.5, 13.5)	(0.23, 15.53)	(2.5, 15)	(2.50)	(2.20)
4	(2, 4.5)	(0, 2.29)	(2.5, 15)	(10.51)	(13.16)
5	(0.75, 27)	(0.98, 26.49)	(2.5, 15)	(12.12)	(9.64)
6	(1.25, 3)	(0, 0.6)	(2.5, 15)	(12.06)	(11.96)
7	(1.25, 6)	(0, 8.38)	(2.5, 15)	(9.08)	(7.53)
8	(0.5, 15.75)	(2.5, 13.31)	(2.5, 15)	(2.13)	(3.14)
9	(0.5, 17.25)	(0, 19.83)	(2.5, 15)	(3.01)	(4.43)
10	(0.5, 18.75)	(0, 19.69)	(2.5, 15)	(4.25)	(6.35)
11	(0.5, 20.25)	(2.5, 20.32)	(2.5, 15)	(5.61)	(1.86)
12	(0.5, 21.75)	(0, 23.63)	(2.5, 15)	(7.04)	(7.02)
13	(0.5, 23.25)	(2.5, 25.3)	(2.5, 15)	(8.48)	(5.47)
14	(1.25, 9)	(2.5, 10.96)	(2.5, 15)	(6.12)	(8.35)
15	(2, 11.25)	(0, 11.02)	(2.5, 15)	(3.78)	(6.23)
16	(2, 17.25)	(0.93, 14.73)	(2.5, 15)	(2.30)	(1.03)
17	(2, 18.75)	(0, 17.44)	(2.5, 15)	(3.78)	(5.01)
18	(2, 20.25)	(2.5, 21.91)	(2.5, 15)	(5.27)	(10.95)
19	(2, 21.75)	(1.03, 19.79)	(2.5, 15)	(6.76)	(7.57)

Table A.5: The results for 34 Points of interest (POIs) inside the localization area, and their estimated positions with optimal calibration parameter settings for whole system.

Row 1			Row 2		
POI	**Actual-coordinates (x, y)**	**Estimated-coordinates (x, y)**	**POI**	**Actual-coordinates (x, y)**	**Estimated-coordinates (x, y)**
1	(0.5, 1.5)	(0.67, 1.87)	18	(2.0, 1.5)	(0, 4.67)
2	(0.5, 3)	(0.31, 1.93)	19	(2.0, 3)	(0, 4.32)
3	(0.5, 4.5)	(0, 4.97)	20	(2.0, 4.5)	(0, 3.1)
4	(0.5, 6)	(0, 8.08)	21	(2.0, 6)	(0, 9.87)
5	(0.5, 7.5)	(2.5, 10.07)	22	(2.0, 7.5)	(0, 10.02)
6	(0.5, 9)	(0.29, 11.92)	23	(2.0, 9)	(1.29, 12.33)
7	(0.5, 10.5)	(0, 12.52)	24	(2.0, 10.5)	(0, 11.59)
8	(0.5, 12)	(0.25, 14.36)	25	(2.0, 12)	(0, 12.47)
9	(0.5, 13.5)	(0.45, 14.28)	26	(2.0, 13.5)	(0, 14.58)
10	(0.5, 15)	(0.94, 15.52)	27	(2.0, 15)	(1.37, 15.43)
11	(0.5, 16.5)	(0.41, 16.53)	28	(2.0, 16.5)	(1.54, 15.25)
12	(0.5, 18)	(1.24, 17.09)	29	(2.0, 18)	(0, 16.28)
13	(0.5, 19.5)	(1.12, 20.55)	30	(2.0, 19.5)	(0, 19.97)
14	(0.5, 21)	(0, 20.54)	31	(2.0, 21)	(0, 19.63)
15	(0.5, 22.5)	(1.03, 23.99)	32	(2.0, 22.5)	(0, 22.55)
16	(0.5, 24)	(2.5, 23.67)	33	(2.0, 24)	(0, 25.44)
17	(0.5, 25.5)	(0.41, 26.56)	34	(2.0, 25.5)	(2.15, 25.07)
Root Mean Square Error (RMSE)		**1.6076**m	**Root Mean Square Error (RMSE)**		**2.5546**m

Table A.6: The results for 34 Points of interest (POIs) inside the localization area, and their estimated positions. Reference RSS power P_{d_0} is estimated on the basis of localization measurements.

Row 1			Row 2		
POI	**Actual-coordinates (x, y)**	**Estimated-coordinates (x, y)**	**POI**	**Actual-coordinates (x, y)**	**Estimated-coordinates (x, y)**
1	(0.5, 1.5)	(0.62, 2.08)	18	(2.0, 1.5)	(0, 4.66)
2	(0.5, 3)	(0.26, 2.04)	19	(2.0, 3)	(0, 4.30)
3	(0.5, 4.5)	(0, 5.48)	20	(2.0, 4.5)	(0, 2.85)
4	(0.5, 6)	(0, 8.07)	21	(2.0, 6)	(0, 11.37)
5	(0.5, 7.5)	(0, 10.16)	22	(2.0, 7.5)	(0, 10.17)
6	(0.5, 9)	(0.3, 11.73)	23	(2.0, 9)	(1.33, 12.15)
7	(0.5, 10.5)	(0, 12.75)	24	(2.0, 10.5)	(0, 11.48)
8	(0.5, 12)	(0, 14.85)	25	(2.0, 12)	(0, 12.32)
9	(0.5, 13.5)	(0.41, 14.16)	26	(2.0, 13.5)	(0, 14.35)
10	(0.5, 15)	(1.42, 15.73)	27	(2.0, 15)	(1.75, 15.73)
11	(0.5, 16.5)	(0.3, 16.63)	28	(2.0, 16.5)	(1.65, 15.36)
12	(0.5, 18)	(1.23, 17.15)	29	(2.0, 18)	(0, 16)
13	(0.5, 19.5)	(1.37, 20.43)	30	(2.0, 19.5)	(0, 20.15)
14	(0.5, 21)	(0, 20.58)	31	(2.0, 21)	(0, 19.46)
15	(0.5, 22.5)	(1.05, 24.16)	32	(2.0, 22.5)	(0, 23.06)
16	(0.5, 24)	(2.5, 23.41)	33	(2.0, 24)	(0, 25.88)
17	(0.5, 25.5)	(0.55, 26.65)	34	(2.0, 25.5)	(1.73, 26.54)
Root Mean Square Error (RMSE)		**1.7066**m	**Root Mean Square Error (RMSE)**		**2.7476**m

Table A.7: The results for 34 Points of interest (POIs) inside the localization area, and their estimated positions. Path Loss Exponent n is estimated on the basis of localization measurements.

Row 1			Row 2		
POI	**Actual-coordinates (x, y)**	**Estimated-coordinates (x, y)**	**POI**	**Actual-coordinates (x, y)**	**Estimated-coordinates (x, y)**
1	(0.5, 1.5)	(0.7, 2.08)	18	(2.0, 1.5)	(0, 2.68)
2	(0.5, 3)	(0.23, 2.23)	19	(2.0, 3)	(0, 2.94)
3	(0.5, 4.5)	(0, 3.62)	20	(2.0, 4.5)	(0, 2.55)
4	(0.5, 6)	(0, 10.87)	21	(2.0, 6)	(0, 12.23)
5	(0.5, 7.5)	(0, 11.54)	22	(2.0, 7.5)	(0, 11.64)
6	(0.5, 9)	(0.28, 12.01)	23	(2.0, 9)	(1.2, 12.58)
7	(0.5, 10.5)	(0, 12.62)	24	(2.0, 10.5)	(0, 12.06)
8	(0.5, 12)	(0, 14.77)	25	(2.0, 12)	(0.1, 12.44)
9	(0.5, 13.5)	(0.4, 14.28)	26	(2.0, 13.5)	(0, 14.45)
10	(0.5, 15)	(1.55, 15.84)	27	(2.0, 15)	(1.89, 15.67)
11	(0.5, 16.5)	(0.98, 16.18)	28	(2.0, 16.5)	(1.74, 15.49)
12	(0.5, 18)	(1.35, 16.99)	29	(2.0, 18)	(0.26, 14.85)
13	(0.5, 19.5)	(2.18, 18.34)	30	(2.0, 19.5)	(0, 11.91)
14	(0.5, 21)	(0, 20.41)	31	(2.0, 21)	(1.01, 17.98)
15	(0.5, 22.5)	(0.91, 24.94)	32	(2.0, 22.5)	(0, 24.94)
16	(0.5, 24)	(2.5, 24.28)	33	(2.0, 24)	(0, 25.62)
17	(0.5, 25.5)	(0.68, 26.61)	34	(2.0, 25.5)	(0, 25.55)
Root Mean Square Error (RMSE)		**2.2376** m	**Root Mean Square Error (RMSE)**		**3.5689** m

Table A.8: The results for 34 Points of interest (POIs) inside the localization area, and their estimated positions. The reference RSS power P_{d_0} and Path Loss Exponent n is estimated on the basis of localization measurements.

Experimental Setup	RMSE for blind iBeacon w.r.t actual smartphone positions	RMSE for blind iBeacon w.r.t estimated smartphone positions	RMSE for smartphone position estimation
SBL-01	0.245 m	1.5108 m	3.0923 m
SBL-02	0.510 m	0.9731 m	2.099 m

Table A.9: Summary of space-based localization results

POI	Smartphone actual co-ordinates (x, y)	Smartphone estimated coordinates (x, y)	Blind iBeacon actual co-ordinates (x, y)	Actual (direct) distance between Smartphone and blind iBeacon	Estimated (direct) distance between Smartphone and blind iBeacon
1	(2, 0)	(2.14 , 0)	(6, 6)	(7.21)	(19.71)
2	(0, 2)	(5.52, 0)	(6, 6)	(7.21)	(4.97)
3	(6, 0)	(3.27, 3.74)	(6, 6)	(6)	(12.39)
4	(10, 0)	(4.16, 12.0)	(6, 6)	(7.21)	(5.44)
5	(12, 2)	(0, 9.65)	(6, 6)	(7.21)	(6.07)
6	(0, 6)	(12, 3.67)	(6, 6)	(6)	(3.92)
7	(2, 8)	(4.55, 7.93)	(6, 6)	(4.47)	(2.22)
8	(0, 10)	(12, 0.75)	(2.5, 15)	(7.21)	(12.69)

Table A.10: The results for Smatphone positioning and blind iBeacon w.r.t smartphone when smartphone is placed at 8 different Points of interest (POIs) i.e. distinct positions inside the localization space.