INDOOR POSITION ESTIMATION USING FINGERPRINTING AND MINMAX APPROACH

by

Shakeel Ahmed

Supervised By

Dr. Fazli Subhan

Submitted for partial fulfillment of the requirements of the degree of MSCS to the Faculty of Engineering and Computer Science

NATIONAL UNIVERSITY OF MODERN LANGUAGES, ISLAMABAD

January 2019

NATIONAL UNIVERSITY OF MODERN LANGUAGES

FACULTY OF ENGINEERING AND COMPUTER SCIENCE

THESIS AND DEFENSE APPROVAL FORM

The undersigned certify that they have read the following thesis, examined the defense, are satisfied with overall exam performance, and recommend the thesis to the Faculty of Engineering and Computer Sciences.

THESIS TITLE: INDOOR POSITION ESTIMATION USING FINGERPRINTING AND MINMAX APPROACH

Submitted By: Shakeel Ahmed   Registration #: MSCS-AS16-ID-016

Master of Science
Degree Name in Full

Computer Science
Name of Discipline

Dr. Fazli Subhan
Name of Research Supervisor   Signature: ____________________

Name of Co-Supervisor (*If Any*)   Signature: ____________________

Dr. Muhammad Akbar
Name of Dean (FE&CS)   Signature: ____________________

Brig. Muhammad Ibrahim
Name of Director General (NUML)   Signature: ____________________

4th February, 2019
(Date)

CANDIDATE DECLARATION

I declare that this thesis entitled "*Indoor Position Estimation using Fingerprinting and Minmax Approach*" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature	:	______________________
Name	:	Shakeel Ahmed
Date	:	January 31st, 2019

ABSTRACT

Position estimation means locating position with reference to some coordinate system, i.e. two dimensional (x, y) or with reference of an object to some known land mark. This thesis focuses on indoor position estimation using Bluetooth, which is a low cost, easily available Radio Frequency (RF) based wireless technology. Most of the latest indoor positioning systems use Bluetooth due to its low cost and wide spread use in most of the wireless gadgets including smart phones, digital watches, and other handheld devices.

Accuracy is one of the most challenging issues in position estimation, which depends on accurate signal transmission and reception, conversion of received signal to distance estimates and modeling of distance estimates to localize object position. Position estimation consists of two main steps, signal measurements and position estimation based on signal. In this thesis, we have focused on both steps, i.e. signal modeling and localization or position estimation. In step one, we perform real time experiments to collect Bluetooth signal measurements, i.e. Received Signal Strength Indicator (RSSI), which is a parameter widely used for distance and position estimation. Experimental and simulation results conclude that there is 10 dBm variation in RSSI due to additive noise, multipath, shadowing, interferences with physical objects and hence affect distance estimation, which ultimately results in position estimation error. Real time experimental results validate this variation, and conclude that if optimized radio propagational constants are chosen, position estimation accuracy up to 1.32 m can be achieved in the presence of 10 dBm variation in the radio signal. In step two, we propose a new hybrid position estimation approach which integrates fingerprinting based K-Nearest Neighbors (K-NN) and lateration based MinMax position estimation technique. The novel idea in our proposed hybrid approach is use of Euclidian distance formulation instead of indoor radio propagation model to convert the signal to distance. We have tested our proposed hybrid position estimation technique in Matlab 7.1 using real time experimental data and compared its results with fingerprinting and lateration based position estimation techniques. Simulation results show that, the proposed hybrid approach performs better in terms of mean error compared to Trilateration, MinMax, K-NN, and existing Hybrid approach.

Keywords: Localization, Distance Estimation, Fingerprinting, K-NN, MinMax, Trilateration.

DEDICATION

This thesis work is dedicated to my parents and my teachers throughout my education career who have not only loved me unconditionally but whose good examples have taught me to work hard for the things that I aspire to achieve.

ACKNOWLEGEMENT

First of all, I wish to express my gratitude and deep appreciation to Almighty Allah, who made this study possible and successful. This study would not be accomplished unless the honest espousal that was extended from several sources for which I would like to express my sincere thankfulness and gratitude. Yet, there were significant contributors for my attained success and I cannot forget their input, especially my research supervisor, Dr. Fazli Subhan who did not leave any stone unturned to guide me during my research journey.

I shall also acknowledge the extended assistance from the administrations of Department of Computer Sciences who supported me all through my research experience and simplified the challenges I faced. For all whom I did not mention but I shall not neglect their significant contribution, thanks for everything.

Contents

CHAPTER 6

LIST OF TABLES

LIST OF FIGURES

List of Abbreviations

GPS	Global Positioning System
RSS	Received Signal Strength
RSSI	Received signal Strength Indicator
ToA	Time Of Arrival
TDoA	Time Difference Of Arrival
AoA	Angle Of Arrival
RF	Radio Frequency
UWB	Ultra Wide Band
WLAN	Wireless Local Area Network
SVM	Support Vector Machine
K-NN	K-Nearest Neighbour
K-WNN	K-Weighted Nearest Neighbour
MSE	Mean Square Error
MLE	Maximum Likelihood Estimation
Wi-Fi	Wireless Fidelity

CHAPTER 1

INTRODUCTION

This chapter discusses existing indoor position estimation techniques, its applications and challenges. Moreover, this chapter also highlights motivation, problem formulation, objectives of this research work, and our proposed methodology to further enhance position estimation accuracy.

1.1 Position Estimation

Position estimation refers to finding the actual coordinates of an object with reference to some coordinate systems. The term position estimation used in literature varies according to different domains. i.e sometime it is referred as location identification, localization, object tracking, indoor navigation, indoor guidance systems etc. For localization or object tracking, they are further classified as outdoor and indoor localization or position estimation. For outdoor localization, Global Positioning Systems (GPS) is most popular navigation and tracking system developed by the Department of Defense, United States for military purpose. GPS is mainly a navigation and guidance system [1, 2]. In case of indoor environment, the word position estimation refers to localization of an object actual position with reference to some coordinate system or known landmark. The word indoor navigation is used to guide someone with the help of a wireless handheld device equipped with location information. On the other hand, tracking means locating an object or human being inside the building with the help of wireless node or handheld device equipped with location information. In summary, the word position estimation depends on the environment and application domain.

1.2 Motivation

Due to the rapid advancement in wireless technology and smart phones, numerous new applications have been developed for variety of applications ranging from health monitoring to navigations and tracking. Position estimation acts an important role in our daily life, tracking objects, human beings, devices, surveillance of homes, offices and nearby surroundings are the demanding applications in smart phones. To categorize the environments, applications can be classified in to two categories, i.e indoor monitoring and outdoor monitoring. For outdoor monitoring or navigation GPS is the available technology but for indoor environment none of the technology so for considered a standard solution. The reason for this is the accuracy, which is one of the most important performances metric in building an accurate solution for indoor environments. The word accuracy in the domain of object tracking is defined as the difference between actual location of the object and estimated location. Accuracy also depends on the environment and application domain. For outdoor environment when tracking or navigation of vehicles are involved, 5 to 10 meter accuracy or position estimation error is acceptable or even in some cases 15 to 20 meters accuracy for finding the target location i.e landmark, is acceptable but for indoor environment even less than five meters accuracy is not acceptable. Other than this, in case of industrial application or automation finding the location of an object, needs accurate solutions. The reason for this difference in accuracy depends on environment. In outdoor environment GPS is available technology and it is based on satellites signals which require line of sight which is not a big issue. However for indoor environment 5 meter accuracy is not acceptable. In the recently developed position estimation techniques, accuracy depends on the wireless technology and position estimation technique. In case of radio based indoor position estimation techniques, some researcher's claims that even 1 meter accuracyis not sufficient for variety of applications [2, 3].

1.3 Indoor Position Estimation Techniques

Indoor positioning estimation techniques use sensing technology to estimate the object location. Among all sensing technologies, Radio Frequency is the most popular technology due to its low cost, easy accessibility and availability. Examples of such technologies are Bluetooth Zigbee and Wireless Local Area Networks (WLAN) [2]. This thesis uses Bluetooth, which is available in almost every smartphone and also in other handheld devices [4]. The range of Bluetooth devices varies from one meter to hundred meters according to Bluetooth specifications. The Indoor positioning estimation techniques which uses radio frequency can be classified in two major categories i.e. Pattern matching based fingerprinting and lateration based position estimation techniques. Fingerprinting based position estimation techniques estimates object position on pattern matching based approach. There are two phases in fingerprinting, offline phase and online phase, in offline phase, fingerprints of the desired locality are stored in an offline database and in online phase when the object enters the desired locality where we are going to locate that object, the sensors collect the readings and searches for its matching. If the readings match the fingerprints in already stored offline database, then the position is estimated. The problems in these techniques are the very tough phase of offline fingerprints, and specific environment, also each offline database reflects the selected environment. Any sort of change in the selected environment reflects on the final position estimation. This approach is a kind of static estimation. The most widely used fingerprinting based indoor position estimation techniques are K-Nearest Neighbors (K-NN) and K-Weight Nearest Neighbors (K-WNN). K, means nearest neighbors, the value of K, is random; we can fix it three, four, five and so on. It depends on the environment [5, 6, 7].

In Laterationbased approach, the position estimation depends on distance estimates and radio propagation model. Because radio propagation model is used to convert RSSI patterns in to distance estimates using specific radio propagation constants. Most popular lateration based position estimation techniques are Trilateration, Multilateration, and MinMax approach [8, 9, 10]. In all these techniques, distance estimates need optimal radio propagational constants, once the distance estimation results are accurate, position estimation error would also result in high accuracy. The main issues in these techniques are the variations in RSSI and conversion of RSSI to distance estimates. If the input parameters are within the acceptable range then, position estimation error will also be in acceptable range. The word acceptable means, for a blind person to locate the desired landmark, accuracy must be less than 1 meter but for normal positioning, acceptable range less than 3 meters is also acceptable. Other than these two approaches, researchers also developed hybrid approaches which combines fingerprinting, means the good features of fingerprinting and lateration approaches for better accuracy. The recent hybrid approach developed used Gradient filter for smoothing RSSI measurements and also used Kalman Filter after estimating object position to further enhance position estimation accuracy [11, 12]. This thesis carries the idea of hybrid approach further without the use of Gradient and Kalman filters. Real time experimental results validated our proposed hybrid approach in terms of mean error that, our proposed hybrid position estimation technique performs better than existing fingerprinting, lateration, and hybrid approach [12].

1.4 Applications of Indoor Positioning Systems

Position estimation plays an important role in human lives ranging from localization to surveillance. Following are the applications of indoor positioning systems [10-13].

1.4.1 Indoor Navigation

Indoor Navigation refers to tracking and guiding people working in indoor environments. For example, child tracking, guiding blind people to perform their daily activities etc. Indoor environment specifically when a person wants to explore the inside facilities. Indoor positioning systems help them to reach their destinations and perform their tasks with the help smart phones equipped with navigation systems.

1.4.2 Robotics for Industrial Applications

Robots are machines equipped with artificial intelligence features to perform industrial applications where humans are unable to work. For examples mines exploration, tunnels, even in medical fields robots are used in surgeries if their knowledge and location updates are available. Robots performs better in case of risk factors are involved. Navigation systems if equipped help robots to perform difficult tasks in wide range of industries ranging from automobiles to oil exploration.

1.4.3 Disaster Management Systems

Disasters happen and rescuing human lives is one of the difficult task to accurately drill that location from where the human presence detect. Objects if equipped with humans for example mobile phone equipped with Bluetooth, or mobile signals can be tracked in case of disasters and their lives can be saved. For this purpose device free and device based indoor positioning systems can be used to locate precious human lives after disaster happen. So indoor positioning systems play a vital role rescue management.

1.4.4 Augmented Virtual Reality Systems

Now a days augmented and virtual reality based solutions are available which resembles actual indoor or outdoor environments. Localization systems is an integral part of virtual reality based system which helps the visitors to navigate and locate actual place and update their knowledge.

1.4.5 Tourist Guiding Systems

Indoor positioning systems also helps in tourism industry. Navigation helps the tourists to reach their desired location hassle free. Now a days many application have been developed for outdoor tourist destinations. One of the most advance positioning systems developed for those who perform Hajj. They can reach their desired location with the help of an application installed on their smart phone which can work in indoor and outdoor as well.

1.4.6 Patient Monitoring Systems

Indoor positioning systems can also be used in hospitals. Doctors can monitor their patient's location history while roaming from one spot to another with in or out of hospital. Other than this, visitors can reach their desired location with the help of indoor positioning systems.

1.4.7 Employs tracking Solutions

Employers can track their employs within a specific premises for both indoor and outdoor environment. Similarly employs can also locate their officers live for smooth and fast operation.

1.5 Problem Formulation

Localization is the process to estimate the actual position of an object with reference to some coordinate system. For tracking an object in indoor environment, there are various constraints such as signal attenuation, multipath, presence of physical objects, walls, furniture's, temperature of the room, and much more which affects the received signal. These environmental conditions variate Bluetooth signal and due to variations in RSSI, position estimation error occur. Existing position estimation techniques based on fingerprinting and lateration approach also suffer from these environmental effects and until now there is no standard solution developed for indoor environmental which provides an optimal solution with high accuracy acceptable for the indoor environment. To summarize the problems in existing solutions based on position estimation error the following issues need to address [12, 19, and 22].

a. Variations in RSSI and its effect on distance estimates.
b. Modeling of Radio Propagation Constants which does not affect from the frequent changes by moving the physical objects inside the building.
c. Design of an accurate position estimation technique which support the variations in RSSI and provide an optimal solution acceptable for the desired location.

1.6 Research Objectives

Following are the main objectives of this research work.

a. To Study the relation between RSSI and Distance and its impact on accurate distance and position estimation
b. To Model the conversion of RSSI to distance using environmental specific radio propagation constants and its impact on accurate distance estimation.
c. To design a new hybrid based indoor position estimation technique which provide an optimal solution for indoor position environment.

1.7 Research Questions

In this thesis we will answer the following research questions.

a. Why there is a variation in RSSI? How to overcome this, so that distance estimation error become less or minimize.
b. Why distance estimation error occur, How to model the distance estimation process in the presence of noise?
c. How to minimize position estimation error? What are the weakness and strengths in the existing fingerprinting and lateration based as well as hybrid techniques to enhance position estimation accuracy.

1.8 Thesis Contribution

The main contributions in this thesis are as under.

In first phase we performed real time experiments using Bluetooth to measure signal strength and to know the reasons why there is a variation in RSSI. We performed series of experiments in 10 meters square area using four access points and one mobile unit and concluded that, there is a 10 dBmvariation in RSSI. There are multiple reasons for these variations such as effect of light, temperature of the room, presence of humans, existing of wireless signals etc.

In Second phase, we performed simulations to model the relation between RSSI and distance. This phase is very important because we need RSSI as an input parameter to localize or estimate the object position. So modeling the conversion process needs environmental specific radio propoagation constants. Propagation modeling is used to model RSSI and extract Distance estimates and for this we need specific environmental variables. So we performed extensive simulations for modeling RSSI to Distance estimates.

In third phase, we selected most popular fingerprinting and lateration based position estimation techniques. We implemented K-NN, Trilateration, MinMax, and existing hybrid position estimation technique which is a combination of fingerprinting and Trilateration approach using our own real time experimental data in order to know their weakness and strengths. We concluded that, position estimation error still not in acceptable range. Based on our analysis we have proposed a new hybrid position estimation technique which integrates Fingerprinting and MinMax approach which enhanced position estimation accuracy by 60% compared to the existing position estimation techniques.

1.9 Thesis Organization

This thesis is organized as follows: Chapter 2,discusses a detailed overview of the existing position estimation techniques and also discusses their advantages and disadvantages. Chapter 3, presents real time experimental analysis of RSSI, its relation with distance and modeling the environmental specific radio propagation constants. Chapter 4, presents the design of our proposed hybrid position estimation technique, chapter 5, presents the comparative analysis of our proposed hybrid position estimation technique with existing techniques and finally chapter 6 summarizes the research work, contributions, limitations and future research directions.

1.10 Summary

This chapter discussed the summary of the research work performed to develop location estimation technique with the help of RF based wireless technology i.e Bluetooth, which provide an accurate solution using our low cost wireless technology. This chapter also presented a brief overview of existing position estimation techniques, the motivation for needing more accurate solutions, problem formulation, research objectives, and the research contributions we achieved in our thesis. In the next chapter we will discuss the existing indoor position estimation techniques with reference to indoor and outdoor environments.

CHAPTER 2

POSITION ESTIMATION TECHNIQUES AND RELATED WORK

This chapter presents existing position estimation techniques based on radio frequency and its applications in various fields. Moreover, this chapter also highlight the research challenges specific to position estimation accuracy and related work.

2.1 Introduction

The word position estimation can be categorized as indoor and outdoor. For outdoor environment, the word position estimation is used in different contexts. i.etracking, navigation. When we use the word tracking it means monitoring someone live location with reference to a physical landmark for example. Currently in Islamabad, section H-9, near NUML university, or Higher Education commission, because for tracking Global Positioning System (GPS) is used which one of the most popular satellite based tracking system. Tracking devices normally equipped with GPS modules and now a days these modules are installed in handheld devices as well. For example digital watches for tracking children's, vehicles equipped with GPS modules, hand phones, Bluetooth devices having GPS functionality used for tracking purpose [1]. The term navigation is used in different context. The same GPS module equipped with google maps guiding people for finding places of their interest, landmarks, locations etc. These modules are user friendly having android operating systems and updated google maps guiding us for finding locations. These GPS modules equipped with updated maps even can guide us about road status, congestion on roads and time estimates for reaching desired locations. GPS was introduced by the US department of defense in world war-II for guiding their military for finding directions as the coordinates are already known. This technology is developed for outdoor applications. GPS is a satellite based navigation system which requires line of sight. For indoor environment this technology is not feasible due to its line of sight feature. This technology is further extended by adding hybrid features such as its combination with wireless technologies but still the researchers considered it unfeasible for indoor environments [2].

For indoor environments, the technology is not the GPS because the GPS signals are not available in indoor environment. For this purpose the researchers investigated different technologies which can be used for indoor position estimation or tracking purpose. In this regard technologies can be broadly classified in two three main categories i.e Infrared, ultrasound and radio frequency. Most of the researchers suggest radio frequency over infrared and ultrasound, the reason behind this is its easy availability and cost. Therefore, this thesis using Radio Frequency as a technology for indoor position estimation. Among all available technologies based on RF, Bluetooth is one of the cheaper and easily available technology[3]. Most of the handheld devices, including mobile phones, smart watches equipped with Bluetooth and is one most widely used and recommended positioning system for indoor environments [4]. The scope of this thesis is limited to Bluetooth based indoor positioning systems. Indoor positioning systems is a complete package, which include, signal measurement which is considered to be a technology module, position computation means position estimation technique, and signal parameters, i.e input signals and known coordinates. **Figure 2.1** showing a modular representation of indoor positioning system [11].

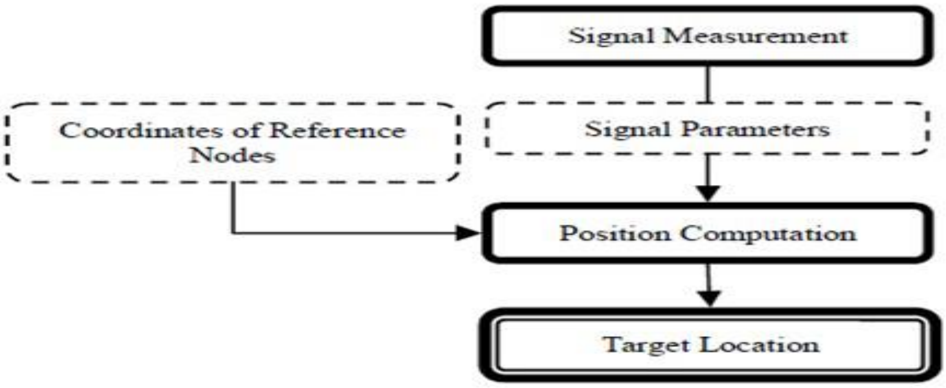

Figure 2.1 Indoor Positioning System, modular representation.

2.2 Position Estimation Techniques

Position estimation process consist of two steps as depicted in above picture, i.e signal measurements and position computation based on input signals. Signal measurements techniques measure the incoming signal and convert that signal to distance estimates. The problem in signal measurements is the reception accurate signals, because the signals transmitted from antenna does not received accurately due to multiple factors. Some factors are hardware dependents and some are environmental dependents [5, 6]. Following sub-section elaborates available signal measurements techniques and discusses its pros and cons.

2.1.1 Time of Arrival (ToA) and Time Difference of Arrival (TDoA)

These measuring techniques are based on time of arrival and time difference of arrival of signals at the receiving antenna. Both techniques can be used for measuring the estimated positions. These techniques have been used by many researchers. The drawback in these two techniques are the accurate estimation and reception of signals, which requires expensive hardware setup and time synchronization clocks. In case of time synchronization error position estimation will be suffered with error. Another main drawback of these techniques are the synchronization requires both antennas should be synchronized at the same time which is difficult task. Following figures explains further these two techniques. **Figure 2.2** explains when two antennas transmit signals to a central location T and **Figure 2.3** shows a complete localization system with three access points. The central location accept the signals from three access points. Time synchronization is important for both transmitters and receivers [7, 8]

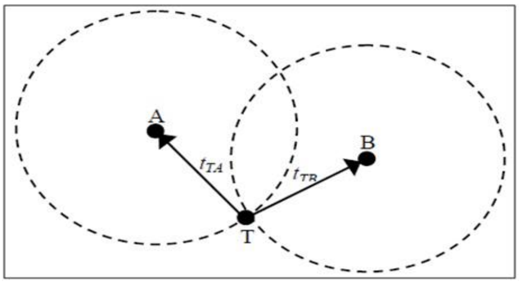

Figure 2.2: Time of Arrival (ToA) and Time Difference of Arrival (TDoA)

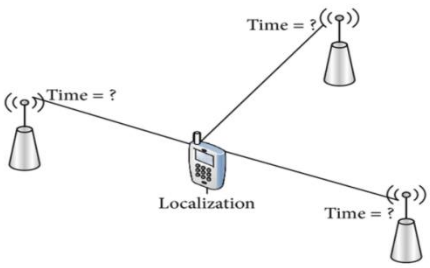

Figure 2.3: Localization System with three Access Points based on Time Synchronization features

2.1.2 Angle of Arrival (AOA)

This measuring technique measure the reception of signal with proper angle which requires expensive hardware to measure the reception of signal. Following figure explain the concept of AOA. Two antennas AoA1 and AoA2 are used and their intersection is considered to be the object position. There are two drawbacks in this technique, one is the expensive hardware capable to measure the angle of incoming or received signal, and other is the time synchronization of antenna as well direction of antenna for accurate signal measurements. **Figure 2.4** shows the received signal using Angle of Arrival position estimation approach [9].

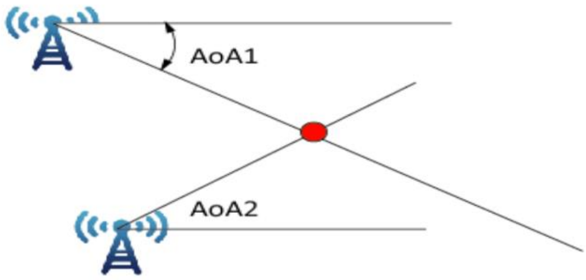

Figure 2.4: Angle of Arrival Antennas in case of position estimation using Angle of Arrival Position estimation Technique

2.1.3 Triangulation

Triangulation is a geometric based position estimation technique, uses the concept of basic geometric principles. Minimum three fixed stations are required to measure the incoming signal. The signal is then converted to distance estimates and the intersection of these distances is the estimated positon of the object. The other is the angulation which is a different concept. Following subsection explain triangulation based position estimation techniques [10, 11].

2.1.3.1 Lateration based Position Estimation Technique

Lateration is a Trigonometric based position estimation technique, which requires at-least three antennas to measure the incoming signal. These signals are then converted using radio propagation model to distance estimates. Once the distance estimates from three fixed antennas are recorded then position is estimated which is the intersection of these distances. If they intersect at one point, it means the distance estimation error is zero, in case of no intersection there is a position estimation error. This position estimation technique depends on signal measurement. If the signals are accurately measured i.e the antennas detect the object enabled with wireless handheld device or sensor, the signal is then converted to distance estimates using radio based propagation models. In lateration approach there are two sub-categories i.e. Trilateration and Multilateration. The idea of Trilateration and Multilateration approach is revealed in the below figures. **Figure 2.5** explains the idea of Lateration based position estimation technique

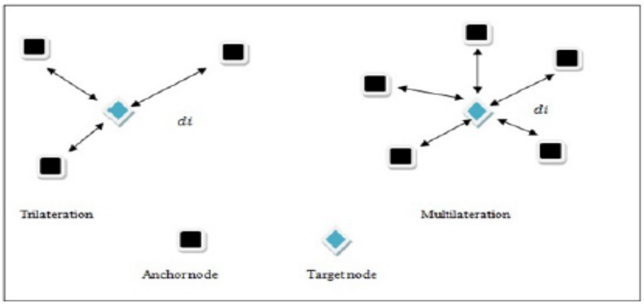

Figure 2.5: Position Estimation Process using Lateration based approach (Three and Four Access Points)

Trilateration approach locates the actual location of a target from three permanent points. Simply this approach concentrated on the crossing point of intersection [11,12]. The location of three anchor nodes are fixed in advance and known to the position system or database. In Multilateration, more than three i.e four access points or antennas. The lateration based approaches are widely used by for position estimation, where a radio propagation model is used for exchanging of RSSI to distance estimation. The location of an entity is calculated by Trilateration or Multilateration after captivating the RSSI at least from three anchor nodes in case of Trilateration and four in case of Multilateration approach.

2.1.3.2 Maximum Likelihood Estimation

The Maximum Likelihood estimation is one more kind of lateration base approach. The problem of ambiguity in dimension is address by MLE and is consider as iterative

Trilateration approach. The functioning rules of MLE depends upon statically consideration that a noise is produce in RSSI due to anchor nodes. It is a recursive method and the focal point of this approach is to decrease the Mean Square Error (MSE). By the use of RSSI, the distance estimation is resulting from each of anchor nodes. The error e_i among predictable and real distance is define by predictable target nodes and is given by following.

$$e_i(x_0 - y_0) = d_i - \sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^2} \quad i = 1,2,3,....n-1. \qquad (2.1)$$

Where b =(x_0, y_0) signify the location of a target node which is not known and (x_i, y_0) is the location of i_{th}node.

Where x is the resulting set of the above equation which calculate the distance of a target node. The major aim of MLE is to decrease the mean square error. For huge indoor system, this approach is used but for small indoor system this process is restricted. Consequently for three access node the result of this approach is not sufficient [12].

2.1.3.3 MinMax Algorithm

The comparable trigonometric result for location estimation is offer by the Min-Max approach, which is also a late- ration based location estimation. The radio propagation model is needed as similar to other location base position estimation approach for exchanging of RSSI into distance. A bounding box is produced for each anchor node by the use of given distance which is created from propagation model in Min-Max approach. The point where the bounding box are touching with one another from anchor node represents the location of the target. To add or subtract the estimated distance from permanent anchor nodes, for each anchor node a bounding box is created. The location of the target node is computed using Min-Max approach by using the formula. This similar formula is a mathematical representation of Min-Max approach [12, 13].

$$\left(\max{}_{(x_i - d_i)}, \max{}_{(y_i - y_i)}\right) * \left(\min{}_{(x_i + d_i)}, \min{}_{(y_i + y_i)}\right), \qquad (2.2)$$

Where (x_i, y_i) signify the position of anchor node and d_i represents the distance among anchor and target node.

The mean error in the concurrent situation of the Min-Max is enhance than in assessment to trilateration approach. However enhanced correctness is attainable due to the use of fingerprinting base approach. The late-ration base approach is discussed above which uses a radio propagation model for estimation of the distance between anchor node and target node. In direct to exchange the RSSI to distance estimation the radio propagation constant is needed. The tuning of distance estimation is very hard between anchor and target node. In addition the late-ration base location estimation approach assume that target node is deceitful at the point of intersection. On the other hand due to signal weakness problem in concurrent situation is dissimilar. The measurements taken by RSSI have a number of error as well as radio propagation model is also not correct. So as to the crossing point of intersection is not identical. The solution of the above equation is not present mathematically because the intersection point is not identical for this reason planned point of intersection is estimated location. Since the solution of the late-ration base approach is not correct forever. In an indoor position estimation the mean error of late-ration base approach is 3 to 5 meters which is unsatisfactory. So following are the disadvantages of late-ration base approaches.

The distance which is calculated by the RSSI is not correct due to the presence of noise in RSSI.The radio propagation model is suffer when the changes is coming in the environment. So creating the correct relationship among distance and RSSI, it is very hard to decide the improved radio propagation model constant.

2.2 Fingerprinting-based Position Estimation Techniques

In the area of position estimation, the fingerprinting is an approach which finds out the location of a mobile terminal with the help of signal fingerprint. It is also called pattern matching approach, in which the RSS measurement is matched with those RSS which are already stored in a database. There are two phases of fingerprinting approach. The online phase and off-line phase. In the training phase, the goal is to build an empirical training database for each reference position by sampling the WLAN signal strength from several access points. Then in the determination phase, the mobile user with a given RSS sample is estimated as the best matching location record in the training database [11, 12]. The most famous techniques which are introduce by the developer for fingerprinting is K nearest neighbours (KNN) [11]. The

KNN based fingerprinting approach consists on average signal strength which are taken in a unit of time at RPs.

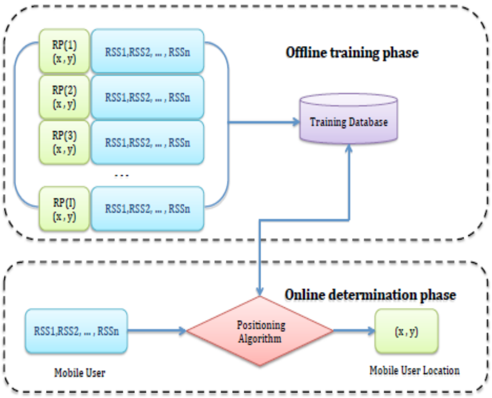

Figure 2.6: Fingerprinting based Position Estimation Technique [11]

2.2.1 K- Nearest Neighbors (K-NN)

K-NN is another type of fingerprinting based position estimation approach which find the actual location of a target node through RSS pattern [21, 22]. The word K denotes the total numbers of neighbors which are near to the target node. All fingerprinting based position estimation approaches find the actual location of a target node in two ways i.e. online phase and offline phase. In the first phase it uses the offline database which consist the RSS pattern, which are taken from the known location, while in the second phase it trace the actual location of the target node through K nearest neighbors. The actual location is the average value of the co-ordinates of the NNs. Therefore the actual location of an object is localized through the value of K which is already known. If a value of K is not permanent corresponding to the number of NNs. For example if K value is 2, then the sum of 2 NNs will compute. In the same way if n is the value of K, then the sum of NNs will be computed. There are two phases of position estimation process. Online phase and Offline phase. Offline phase need a database which consist on RSS pattern which are taken from the known location. This Offline phase consume a lot of time, because a more hard work is needed for the creation of database i.e. to divide the overall area into equal size of grids, gathering of hundred RSS measurements at every location, computing of the mean value to store them in the database. When the database is created then the position estimation process is completed in the online phase. The online phase needs the RSS signals from the target node and compares it with a store database by calculating the Euclidian space between measure and store RSS beside a well-known location. The distance between observed and store RSS are computed through the value of K, which is permanent. The shortest distance of K is computed, which is called NNs. When the NNs are computed, then the position of target is located through the NNs co-ordinates [21, 22].

In indoor position estimation process the KNN technique is very efficient for motionless object, but due to the time consuming process of the offline phase, it is not mostly used. The RSS differences depend upon the environment, from where they are collected. The benefits of KNN based position estimation is that, it provides the high accuracy. But there are two major drawback of KNN. The first drawback is that it needs the time for a creation of offline phase which make the indoor environment unviable, while the second drawback is that the actual location of the target node is predicting through NNs. In case of large grid size the error becomes large. For example if the computed NNs deceits in the middle of the grid size, then the locating position will be on the midpoint of that grid, which is not usually in the same case. So the error of position estimation depends on the size of grid. If the size of the grid is small, then the time taken by the construction of the offline phase will be more than the normal. Hence due to these disadvantages, the fingerprinting based position estimation approaches are nor viable for real-time position estimation [13, 17, 18].

2.3 Neural Networks

In the biological neurons the Neural Network denotes the set of circuits. In the area of position estimation process the neural network take the RSS pattern as an input for the stored RSS in the database. The offline phase of fingerprinting technique which take the RSS as input, the neural network is biased with extra usage for position estimation. The position estimation which is created through neural network is not need a huge quantity of RSS pattern for viewing the correct position estimation. Hence neural network is slow and accuracy depends upon the correct tracking process [19, 20, and 24].

2.4 Support Vector Machine (SVM)

Support Vector Machine (SVM) is one more kind of position estimation process. This approach depends upon the RSS pattern which is near to the machine. Mainly this approach is used in the field of engineering, science and medicine with excellent practical result. The term SVM is used for statistical analysis and to investigate the pattern of data, but conversely this technique depends upon the offline phase of fingerprinting based position estimation. So SVM needs the training process to train the offline phase which ingests a lot of time [21, 22,24].

2.5 Proximity

Proximity is the fingerprinting based position estimation approaches which locate the exact location of the target in the form of symbols. The position estimation process rest on the multifaceted construction of antennas, which can be organized at a fix location. The position estimation process needs many antennas to generate the heavy power signals which are needed for position estimation process. Therefore the connection of antennas and the installation of the software make it expansive and it is hard for indoor position estimation. The accuracy of proximity depends upon the range and the variety of antennas. So proximity is not mostly used for indoor position estimation [22].

2.6 Scene Analysis

This approach is used to estimate the scene and to attain those topographies which are clearly coordinated and shown. A scene can be depicted both by images or the power of signals in that spot. The sense topographies are examined in the database in the permanent proximity to plans the position of an object, while in differential scene analysis the differences between successive scenes is placed. This disparity denotes that the entity is moving. Uncertainty topographies are predictable at specific positions; the observer can assess their location. The advantage of this approach is that it runs separately to store the database nearby which represent that a smaller amount power is needed for communication and the privacy of the client can be booked. The limitation of this approach is that it needs a database which is already crated, and checks the properties of the database, if the characteristics of scene is different [23, 24].

2.7 Hybrid Indoor Position Estimation Technique

The Hybrid Indoor Position Estimation means to combine the properties of fingerprinting and lateration base position estimation approaches for improving the accuracy of position estimation [14, 15, 16,17]. In [14], another hybrid approach was proposed which uses three steps to estimate an object position. In first step an offline database is used to correlate distance with RSSI readings. In step 2, a searching algorithm is used which is a binary search approach for distance between object and access point and finally in step 3, the most popular Trilateration approach is used for position estimation. Numerical results suggest that their proposed hybrid approach performs better than trilateration and almost similar to K-NN. The drawback of this approach is the lengthy three step process instead of two steps as compared to fingerprinting based position estimation technique.

In [15], the author proposed the hybrid indoor position estimation approach based on WLAN. The hybrid indoor position estimation finds the actual location of an entity in two phases. In the first step, it uses fingerprinting approach to compute the NNs, while in the second step it uses trilateration approach to find the actual location of the target node. Though lateration base position estimation approaches and pragmatic radio propagation model is used for exchanging of RSSI to distance estimate. This is nearly same as the radio propagation model. The author used the radio propagation model for the exchanging of RSSI to distance estimate in various situations and compared the accuracy of position estimation with fingerprinting and trilateration based K-NNs techniques. The numerical result shows that the accuracy of position estimation is enhanced than trilateration approach, because nodes deceit nearby to the NNs. Afterwards the distance between NNs and target nodes are computed through radio propagation model. The numerical result shows that the proposed approach is efficient from trilateration technique and less efficient than KNN.

The recent hybrid approach developed used Gradient filter for smoothing RSSI measurements and then integrated fingerprinting with Trilateration approach for position estimation. For accuracy improvement Kalman Filter is also used once the position is estimated [11]. This paper explores the idea of the most recent hybrid approach [11] further without the use of Gradient and Kalman filters. The next section presents the design of our proposed hybrid position estimation technique.

2.8 Literature Review

The organization of Microsoft Research was developed RADAR for localization purpose. RADAR locates the actual location of an object through radio frequency (RF). Fundamentally RADAR was developed to use Wireless Local Area Network (WLAN) and using the most famous fingerprinting technique such as K-NN [34]. In indoor positioning system, the concept of RF is tested experimentally and checked it to locate the position of motionless objects. According to the experimental result the accuracy of the motionless object is between 3 to 4 meters. To find the actual location of an object RADAR uses RSSI is a signal parameters with radio propagation model. Additionally the author claims that all positioning techniques which work on radio frequency have the capability of locating the actual position of an object an indoor environment. Finally the author suggested that the accuracy of position estimation approaches can be improved to control the changing in RSSI which occurs due to the environment [35, 36].

In [36] an Indoor positioning system is been developed which uses Bluetooth technology to track object or human location inside indoor environment. The accuracy obtained in two dimensional coordinate system was 2 meter only. The system topaz was later upgraded to Infrared based technology for achieving more accuracy. In [37] an indoor positioning system developed by Apple which also used Bluetooth low energy mainly for proximity monitoring. The name of the indoor positioning system is iBeacon, the main purpose of the system is to locate their products in stores. The beacons were placed at different distance varies from 50 cm to 3 meters. This application is also available on android and Apple store.

In [38] the authors developed an indoor positioning system using inertial sensors, WiFi and iBeacon which is a Bluetooth technology. The accuracy obtained using different indoor positioning systems are 1.9m using Fingerprinting based position estimation technique using WiFi, 1.4 meter using Dead Reckoning (DR) and WiFi, and 0.5 meter when combining all these position estimation techniques i.e Bluetooth, WiFi, and DR. In [39] the authors proposed a hybrid based indoor positioning system based on inertial sensors, particle filtering and WiFi. Their accuracy was 3 to 5 meters. The main advantage of this hybrid positioning systems is their easy to install and cheaper technology as compared to other available solutions but the drawback is the accuracy is not satisfactory for more specific applications. In [40], the authors developed a hybrid solution based on ultrasound and Radio Frequency which is almost similar to the other solutions. They used the most popular Triangulation and AoA position estimation technique.

In [41] the authors proposed indoor positioning system based on Ultra Wide Band technology. the system requires the target to attach UWB transmitter for location identification and a radio based transmitter to send signals to the network. The main disadvantage of the system is its cost and expensive technology. However the accuracy is very good i.e 15 cm reported but the problem is its cost.

The main objective of this thesis is to design an accurate indoor positioning system using low cost wireless technology which provides an optimal solution for variety of applications. Therefore, in this regard, we used Bluetooth as a wireless technology for indoor positioning system. The advantages of Bluetooth is its easy availability and cost. Most of the handheld devices ranging from smart phones to digital watches, almost every digital device support and equipped with Bluetooth.

2.9 Summary

This chapter highlighted the basic concepts of position estimation with reference to indoor and outdoor environments, existing indoor position estimation techniques and its advantages and disadvantages. The next chapter presents experimental setup and signal measurements in order to collect real time experimental data for position estimation.

CHAPTER 3

EXPERIMENTS AND DATA COLLECTION

Chapter 2, summarized the design of our proposed hybrid indoor position estimation technique. This chapter presents the real time experiments conducted for collection RSSI measurements and its relation with distance. Moreover, this also discusses the conventional fingerprinting and lateration based position estimation techniques.

3.1 Introduction

Bluetoothis a low cost wireless communication standard developed for short range communication [23, 24]. Due to its low cost and advance features for data transfer, almost every mobile phone have Bluetooth. Bluetooth latest version 5 have extended its range and data transfer rate. Normal range of Bluetooth in indoor environment is from 10 to 30 meters, however in line of sight and less obstacles its range can be extended to 100s meters [23]. Besides other applications of Bluetooth, Bluetooth is now widely considered for Indoor positioning systems and tracking purpose. In Bluetooth, the parameter used for distance estimation and indoor positioning is RSSI, which is the measurement of the power in the radio signal. In literature studies, there are many ranging techniques for distance estimation between two objects such as RSSI, Angle of Arrival (AOA), Time of Arrival (TOA), and Time Difference of Arrival (TDOA) [25]. Out of them, RSSI is one of the most cost effective ranging solution used in many position estimation techniques. In AOA, expensive hardwares are required for synchronization of time and angle measurements which increases the cost of indoor positioning systems, its deployment and maintenance. In TOA, the distance between two devices is proportional to the time the signal requires to reach from one device to another [3, 4, and 5]. TOA also needs precise synchronized equipment's. Another approach is TDOA, which is based on the time difference between more than one signals received from one to another antenna. These antennas must be equipped with specific hardware's to propagate multiple signals at the same time or even multiple types of signals at the same time. So all of these techniques require special hardware which directly affect installation and maintenance cost of indoor positioning systems. Among all these available techniques, RSSI is the most suitable cost effective solution [26, 27]. As discussed earlier, RSSI is a parameter available in almost every communication device including smart phones and other handheld devices [25, 26, 27].

This technique is referred to as range based technique, which requires radio propagation model to convert RSSI patterns to distance estimates. Besides radio propagation model, this method requires further iterative and non-iterative techniques for position estimation. There are certain issues as well in range based position estimation techniques which affect distance and position estimation accuracy. These issues are multipath fading, shadowing, noise and other interferences due to air, presence of radio signals, human bodies, temperature, inside furniture, walls, temperature as well [27, 28, 29].

There are different approaches proposed in the literature for improving distance and position estimation accuracy by minimizing the interference in RSSI such as Kalman Filter which can be used to minimize noise and increase accuracy. Kalman filter is widely used for position estimation especially in Bluetooth based solutions. Another approach is to make a system calibration to evaluate RSSI and distance ahead of time in a controlled environment [26]. Its advantage is its low cost. In this case the researchers investigated RSSI with respect to time and distance. In [27], an experimental study was performed which shows distance estimation error up to 3m. In summary, range based techniques provide a cost effective solution instead of few disadvantages but compare to other approaches, still it is one of the most widely used technique for indoor positioning systems [28, 29, 30].

In this Chapter, we have investigated RSSI with respect to time, its relation with distance, modeling indoor radio propagation model in order to calculate optimized radio propagational constants, and its effect on position estimation by using Trilateration approach with optimized radio propagation constants.

3.2 Experimental Setup

For position estimation, we need to get target node radio signal, once the signal is received then we need to convert these signals to distance estimates. In order to convert RSSI to distance estimates, we need to use radio propagation model which accept RSSI and convert RSSI to distance estimates. In the conversion process, we need to fix the radio propagation constants for better distance estimates. The position estimation process will start after getting distance estimates. So in this regard, we have conducted series of experiments. Fig 3.1 represents the experimental setup, which consist of four Access Points namely AP-1, AP-2, AP-3 and AP-4. All these APs were android based Samsung Mobile Phone. As depicted in the following figure, the area was 10 x 10 meter square. First of all the area was divided in to equal size grids of size one meter square. And from each AP-1, we took 100 readings of RSSI for each and every grid. i.e The average value of each grid point was calculated and stored in an offline database. Similary for each access point i.e AP-2, AP-3, and AP-4, the same procedure was adopted. The main idea behind collection of 100 reading was to calculate the average value of each grid.

Table3.1 shows the average RSSI vs. distance. These values represents average RSSI when a mobile phone is place at different places. These values are used to generate offline database using Euclidian distance formula which calculate the distance between two points. The respective RSSI readings are matched with distances. Table 3.2

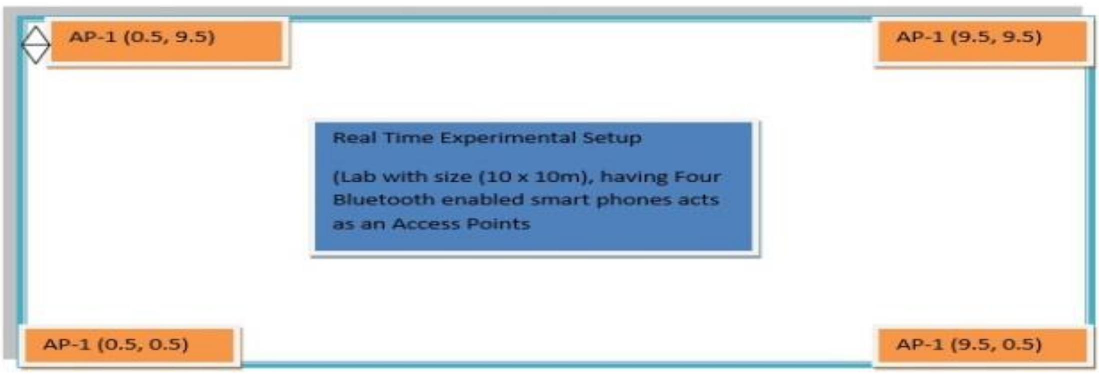

Fig. 3.1: Experimental Setup

Table 3.1: Distance vs. Average RSSI

Distance (m)	Distance vs. average RSSI (dBm) measurement using Bluetooth enabled hand phone
0	-15
1	-65
2	-68
3	-75
4	-76
5	-80
6	-77
7	-74
8	-84
9	-86
10	-87
11	-89
12	-88
13	-90

Table 3.2 RSSI data set at each grid point

(X-axis,Y-axis)	AP-1 (0, 9)	AP-2 (9,9)	AP-3 (9,0)	AP-4 (0,0)
(0, 0)	-86	-90	-86	15
(0, 1)	-84	-88	-86	65
(0, 2)	-74	-89	-86	68
(0, 3)	-77	-89	-86	75
(0, 4)	-80	-87	-87	76
(0, 5)	-76	-87	-87	80
(0, 6)	-75	-86	-89	77

(0, 7)	-68	-86	-89	74
(0, 8)	-65	-86	-88	84
(0, 9)	-15	-86	-88	86
(1, 0)	-86	-88	-84	65
(1, 1)	-84	-89	-84	65
(1, 2)	-74	-87	-84	68
(1, 3)	-77	-87	-84	75
(1, 4)	-80	-86	-86	76
(1, 5)	-76	-86	-86	80
(1, 6)	-75	-84	-87	77
(1, 7)	-68	-84	-89	74
(1, 8)	-65	-84	-89	84
(1, 9)	-65	-84	-88	86
(2,0)	-86	-89	-74	68
(2, 1)	-84	-87	-74	68
(2, 2)	-74	-87	-74	75
(2, 3)	-77	-86	-74	75
(2, 4)	-80	-84	-84	76
(2, 5)	-76	-84	-86	80
(2, 6)	-76	-74	-86	77
(2, 7)	-75	-74	-87	74
(2, 8)	-68	-74	-87	84
(2, 9)	-68	-74	-89	86
(3.0)	-86	-89	-77	75
(3, 1)	-84	-87	-77	75
(3, 2)	-74	-86	-77	75
(3, 3)	-74	-84	-74	76
(3, 4)	-77	-84	-74	80
(3, 5)	-80	-74	-84	77
(3, 6)	-76	-77	-84	77
(3,7)	-75	-77	-86	74
(3,8)	-75	-77	-87	84
(3,9)	-75	-77	-89	86

(4,0)	-87	-87	-80	76
(4, 1)	-86	-86	-80	76
(4, 2)	-84	-84	-80	76
(4, 3)	-74	-84	-77	80
(4, 4)	-77	-74	-77	80
(4, 5)	-77	-77	-74	77
(4, 6)	-80	-80	-84	74
(4,7)	-76	-80	-84	84
(4,8)	-76	-80	-86	86
(4,9)	-76	-80	-87	87
(5,0)	-87	-87	-76	80
(5, 1)	-86	-86	-76	80
(5, 2)	-84	-84	-76	80
(5, 3)	-84	-74	-80	77
(5, 4)	-74	-77	-77	77
(5, 5)	-77	-77	-77	74
(5, 6)	-77	-80	-74	84
(5,7)	-80	-76	-84	84
(5,8)	-80	-76	-86	86
(5,9)	-80	-76	-87	87
(6,0)	-89	-86	-75	77
(6, 1)	-87	-84	-75	77
(6, 2)	-86	-84	-76	77
(6, 3)	-84	-74	-76	74
(6, 4)	-84	-77	-80	74
(6, 5)	-74	-80	-77	84
(6, 6)	-74	-76	-74	84
(6,7)	-77	-75	-84	86
(6,8)	-77	-75	-84	89
(6,9)	-77	-75	-86	88
(7,0)	-89	-86	-68	74
(7, 1)	-87	-84	-68	74
(7, 2)	-87	-74	-75	74

(7, 3)	-86	-77	-75	74
(7, 4)	-86	-80	-76	84
(7, 5)	-84	-76	-80	84
(7, 6)	-84	-75	-77	86
(7,7)	-74	-68	-74	87
(7,8)	-74	-68	-84	87
(7,9)	-74	-68	-86	89
(8,0)	-88	-86	-65	84
(8, 1)	-89	-84	-65	84
(8, 2)	-89	-84	-68	84
(8, 3)	-87	-74	-75	84
(8, 4)	-86	-77	-76	86
(8, 5)	-86	-80	-80	86
(8, 6)	-86	-76	-77	87
(8,7)	-84	-75	-74	87
(8,8)	-84	-68	-84	89
(8,9)	-84	-68	-86	88
(9,0)	-90	-86	-15	86
(9, 1)	-88	-84	-65	86
(9, 2)	-89	-74	-68	86
(9, 3)	-89	-77	-75	86
(9, 4)	-87	-80	-76	87
(9, 5)	-87	-76	-80	87
(9, 6)	-87	-75	-77	89
(9,7)	-86	-68	-74	89
(9,8)	-86	-65	-84	88
(9,9)	-86	-15	-86	88

Once the RSSI data set is calculated, then we analyzed the RSSI readings based on varied distances. Following section discusses analysis of RSSI.

3.3 Analysis of RSSI

This section discusses the variation in RSSI due to different environmental conditions such as temperature, effect of human bodies and other physical objects inside room or lab, light, furniture, radio signals such as GSM, wifi signals also variate RSSI. Fig. 3.2 represents RSSI taken at a distance of 1 meter and 2 meters respectively. Here we must mention that, the readings were taken in the presence of human bodies inside the room, light bulbs, furniture and normal room temperature and many other physical objects which interfere RSSI. Here the variation is almost 10 to 15 dBm. The program used for measuring RSSI was inquiry based parameter which is one of the parameter used in Bluetooth to monitor RSSI of the device.

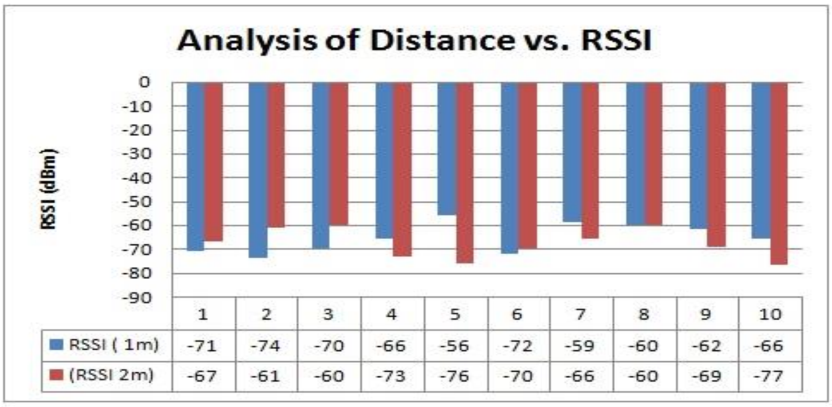

Fig. 3.2 Analysis of RSSI at distance 1 and 2 meter for 10 seconds

In Fig. 3.3, the readings were measured when the distance between the two devices were 3 and 4 meters. These readings are 10, which indicates the time and count of RSSI measurements as well. It is not necessary that every time the reading count would be 10 and also we will get 10 RSSI measurements. Sometime we got, 7 or 6 values and sometime we got 10 to 13 values in 10 seconds. The reason behind this difference depends on the Bluetooth module and its specification as well, but in average 10 values were received in 10 seconds. Here also the variation in RSSI is 10 dBm in average.

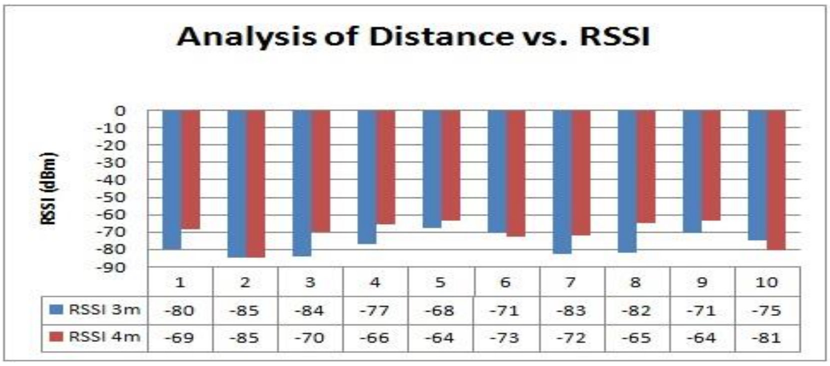

Fig. 3.3 Analysis of RSSI at distance 3 and 4 meter for 10 seconds

Similarly Fig. 3.4, 3.5 and 3.6 shows RSSI readings when distance between two devices are 5, and 6, 7, and 8 and 9, and 10.

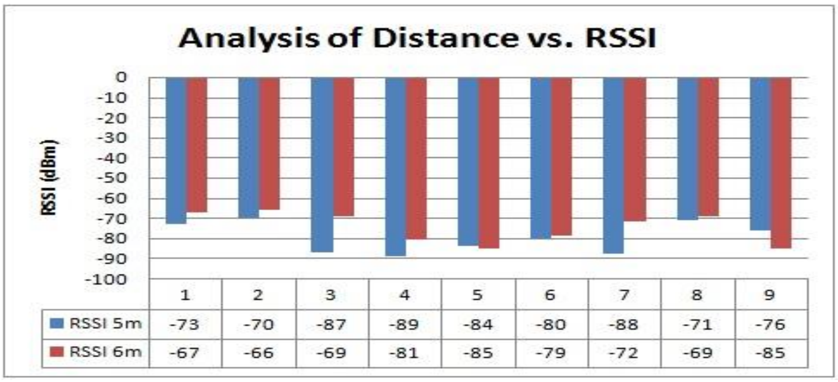

Fig. 3.4 Analysis of RSSI at distance 5 and 6 meter for 10 seconds

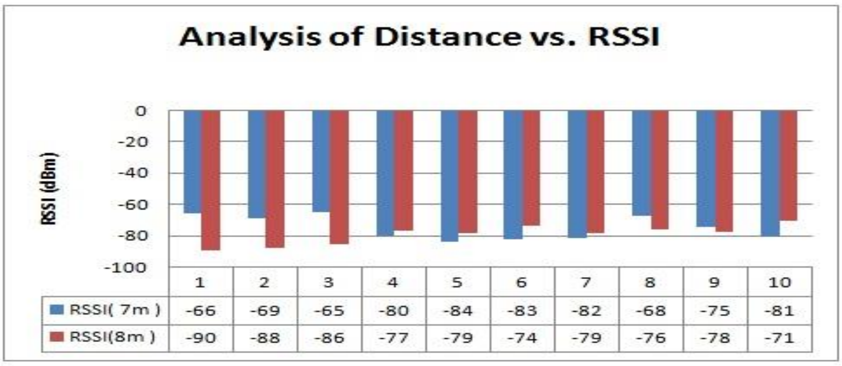

Fig. 3.5 Analysis of RSSI at distance 7 and 8 meter for 10 seconds

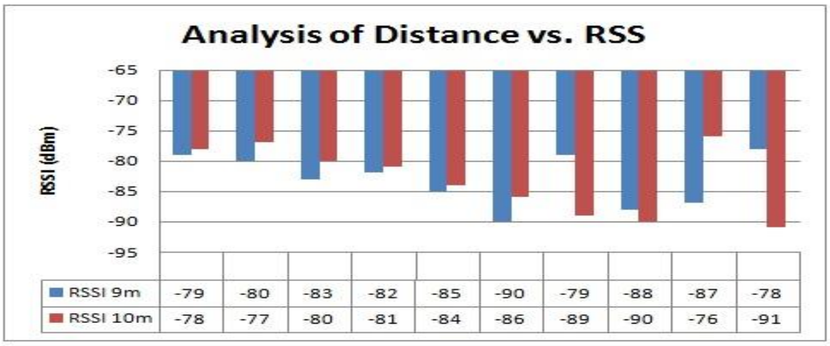

Fig. 3.6 Analysis of RSSI at distance 9 and 10 meter for 10 seconds

The next section discusses analysis of distance estimation using Bluetooth based RSSI measurements.

3.4 RSSI Distance Model

To convert RSSI measurements to distance estimates, we need Radio propagation model considering the indoor environmental conditions. For indoor positioning systems, the most common path loss models are the free space radio propagation model and logarithmic distance path-loss model. For RSSI to distance conversion, the algorithmic distance path-loss model is used in most of the literature [30-33]. The mathematical formulation is as under

$$RSSI = -10nlog(d) + A \tag{1}$$

Where *d*, is the distance between two devices, *n* is the path loss constant. The normal range of *n* is from 1 to 4. If there is more disturbance or obstacles, the value of *n* would be maximum for indoor environment. *A* is the numeric value of RSSI at a distance of 1 meter.

3.5 Distance Estimation from RSSI

Fig 3.7 shows real time experimental results. In this figure, there are three parameters selected i.e RSSI measurements at distance 1 to 14 meters and estimated distance when the radio propagation constants are A = -59 dBm, which is the value of RSSI fixed when the distance between two devices is one meter, and radio propagation constant "n" which is 3.5. Here it is important to mention that, the radio propagation model and constants used in this thesis are already been used by different researchers [30-33]. The range of “n” is from 1 to 4, which depends on different environmental conditions. Here we are turning these two values in order to get the best estimates according to our indoor environment. In this graph, the distance estimation error, which is the last row in a table shown in the following Fig. 3.6 presents distance estimation error. The error ranges from 0 to 5.4. The main objective behind this analysis is to find the best optimal radio propagation constants, which would be used for comparative analysis with our proposed position estimation technique.

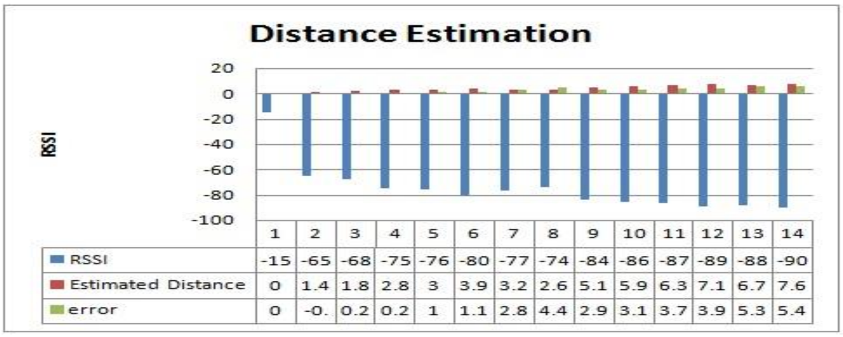

Fig. 3.7 Distance estimation using real time experimental RSSI measurements with A= -59, and n = 3.5

In Fig. 3.8 the same results are displayed with different radio propagation constants, i.e radio propagation constant A = -59, and we have fixe the value of n = 3. Again the graph shows distance estimation error. Here, the distance estimation error ranges from 0 to 2.3, which is better than the radio propagation constants used in previous graph. Results shows, distance estimation error depends also on radio propagation constants other than environmental conditions such as temperature, presence of human bodies, inside room furniture, air, light, and also humidity. Considering all parameters is a difficult task and beyond our scope, but we tried our best to fix the most suitable parameters.

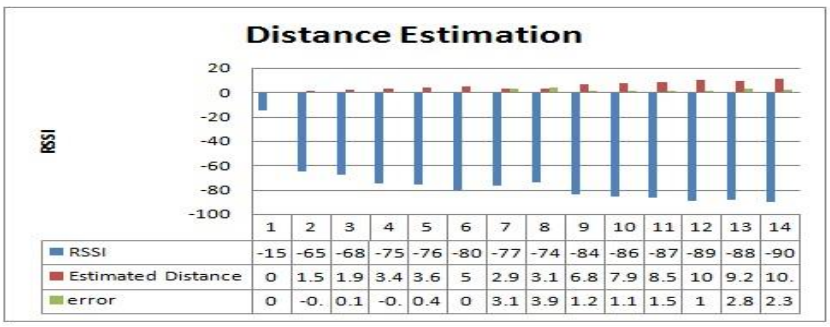

Fig. 3.8 Distance estimation using real time experimental RSSI measurements with A= -59, and n = 3

Fig. 3.9, shows distance estimation error when the radio propagation constants are once again changed. This time we fixed the value of n = 2.5 which shows the distance estimation error in negative direction. To make it absolute, still distance estimation error is above 4.

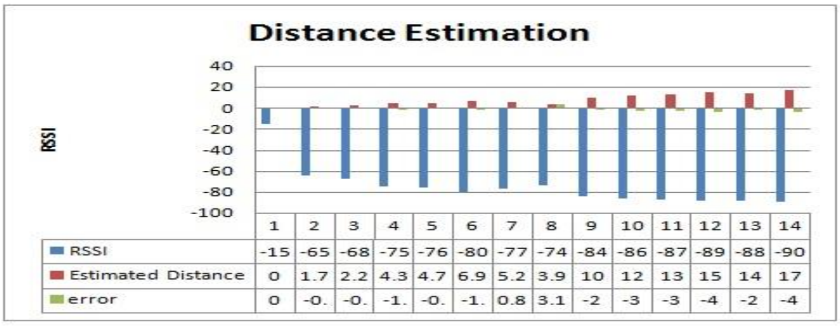

Fig. 3.9 Distance estimation using real time experimental RSSI measurements with A= -59, and n = 2.5

Similarly Fig. 3.10 and Fig. 3.11 also shows similar trends when we changed the radio propagation constants. When the value of n=1.5, the distance estimation error goes up and to an unacceptable range specifically for indoor environment. In case when we fixed the value of n=3.4, distance estimation error is almost similar to the results shown in Fig. 3.6 in which we fixed n= 3.5.

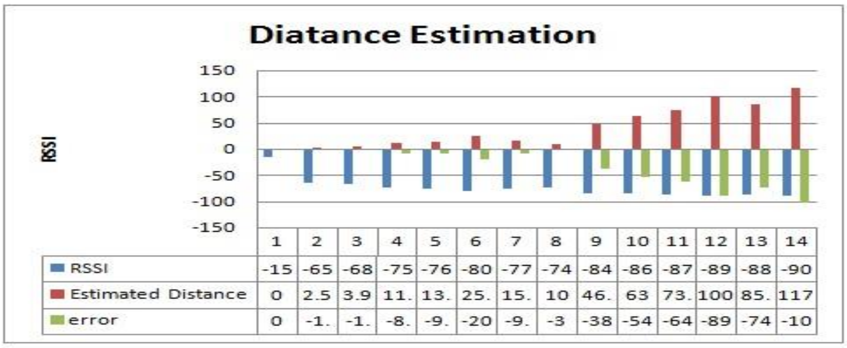

Fig. 3.10 Distance estimation using real time experimental RSSI measurements with A= -59, and n = 1.5

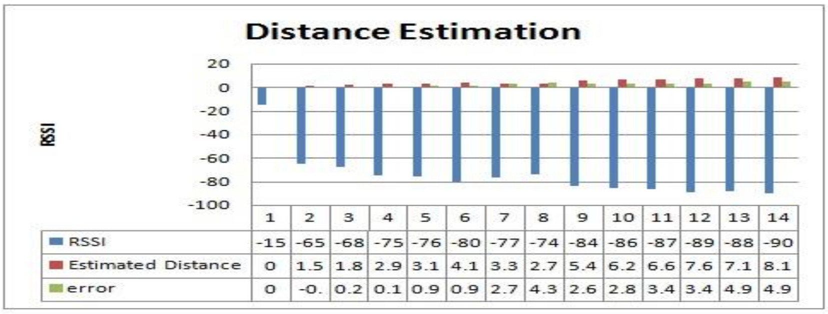

Fig. 3.11 Distance estimation using real time experimental RSSI measurements with A= -59, and n = 3.4

In all the above graphs we fixed the value of A = -59 dBm which has not been changed, the reason behind this is the distance estimation error and its combination with the value of “n”. We analyzed the value of A as well but the distance estimation error went beyond the acceptable range for indoor environment.

3.6 Position Estimation Error due to Variation in RSSI

Position estimation is the process of finding actual location of the object with reference to some coordinate systems. Position estimation techniques are classified as distance and fingerprinting based. In distance based position estimation techniques, the RSSI signals are converted to distance estimates and then position estimation techniques are applied once the distance estimates are available. Fingerprinting based approaches use fingerprints of the indoor location using a database and then the object is traced by comparing the measured patterns from different sensors. Fingerprinting based position estimation technique is a two step process. In phase 1, the offline database is generated by taking a fingerprint of the desired location. This phase is one of the most difficult and challenging task. Fingerprints of each grid point is required in order to track or estimate the position of the target node. This fingerprint depends on the indoor environment. Any kind of change in the indoor environment will affect the whole offline database. Once the database is generated, then position estimation is performed by comparing the RSSI fingerprints. When the object enters the locality, the sensors collect RSSI patterns and compare these patterns with offline database using position estimation technique. K-NN is the most popular position estimation technique used in fingerprinting based approach.

In this paper, we have selected the most widely used distance based position estimation technique i.e. Trilateration. Trilateration is a trigonometric based position estimation technique, which require three or four access points to locate an object by measuring the radio signal attached to the estimated object. If three access points are used that is called Trilateration and in case of four access points that is called Multilateration depicted in the following figure.

As discussed earlier, we used Bluetooth as available technology for position estimation. Table 3.3 presents numerical results if the object is placed in the middle of the room i.e. (5, 5). We took real time 10 RSSI patterns when the object is placed at the same location, the readings of four access points are mentioned in Table 3.3, column 2 respectively as depicted in Figure 1 section 2. The estimated coordinates are shown in column 4 and their mean error in column 5. Row 1 shows the average RSSI value with a mean error of 0.3 m while the sub-sequent rows showing RSSI patterns with different variation. These readings are observed in real-time considering the real time indoor environment. The average variation in RSSI observed is 10 dBm with position estimation error of 1.32 m. The worst error observed is 2.4 meters in real time. The radio propagation constants used for conversion of RSSI to distance estimates are A =-59 dBm and the value of n= 3.5. These two propagational constants are the ideal values we observed in distance estimation for our indoor environment. The next section summarizes our analysis using Bluetooth.

Table 3.3. Position estimation using Trilateration with RSSI variation

S.No	RSSI pattern (Four Access Points)	Real location	Estimated location	Mean error (m)
1	-77 -77 -77 -77	(5, 5)	(4.8, 4.8)	0.3
2	-72 -85 -70 -90	(5, 5)	(6.4, 6.4)	2.9
3	-82 -80 -90 -80	(5, 5)	(3.2, 5.4)	1.27
4	-86 -84 -87 -84	(5, 5)	(4.4, 4.7)	0.74
5	-83 -88 -87 -89	(5, 5)	(4.9, 5.8)	0.72
6	-89 -80 -83 -79	(5, 5)	(5.1, 3.5)	1.34
7	-87 -87 -87 -87	(5, 5)	(4.8, 4.8)	0.32

8	-90 -82 -77 -74	(5, 5)	(5.3, 2.6)	1.93
9	-80 -76 -90 -77	(5, 5)	(3.1, 5.5)	1.33
10	-90 -77 -77 -90	(5, 5)	(7.5, 4.8)	2.4
	Average Error			**1.325**

3.7 Summary and Contributions

This chapter presented extensive analysis of RSSI as a parameter for position estimation. Following are the key observations and findings based on real time experimental analysis.

a) There is a 10 dBm variation in RSSI with respect to time. This variation is being observed in a dense indoor environment, considering room temperature, presence of human bodies, physical objects such as furniture, presence of radio signals such as WIFI, GSM signals, Bluetooth, effect of sun light etc.
b) We also performed different experiments for distance estimation by changing the numerical values of logarithmic radio propagation distance model in order to calculate optimize radio propagation constants which give reasonably accurate distance estimation. We concluded that, if the value of "A" is -59 dBm and "n= 3.5", the distance estimation error is minimum.
c) After analyzing RSSI variation and modeling of radio propagational constants, we estimated real time object position with optimize radio propagation constants using traditional position estimation technique i.e. Trilateration Approach. We have come to the conclusion that in the presence of dense indoor environment, considering 10 dBm variation in RSSI, still we can estimate object position with 1.32m error which is an acceptable range for indoor environment.

The next chapter will present the design of our proposed hybrid position estimation technique which is an extension of the previous hybrid position estimation technique.

CHAPTER 4

DESIGN OF HYBRID INDOOR POSITION ESTIMATION TECHNIQUE USING FINGERPRINTING AND MINMAX

Chapter 2 presented an introduction to existing position estimation techniques, as well as detail discussion on fingerprinting, lateration and hybrid indoor position estimation techniques. Moreover, we have compared existing fingerprinting and lateration based position estimation techniques and also the research gap. This chapter presents the design of an new hybrid indoor position estimation technique, which combine fingerprinting and MinMax algorithm. The proposed hybrid indoor position estimation technique is compared with existing techniques such as K-NN, Trilateration, MinMax, and one of the existing hybrid approach which combined Fingerprinting and Trilateration approach while considering communication holes and Kalman filter as well.

4.1 Concept of Hybrid Indoor Position Estimation Technique

The term hybrid mean combination of two existing techniques. In our thesis, we examined first both position estimation techniques using independently, using real time experimental data that we collected during our experiments. We also implemented existing lateration based position estimation techniques and performed real time position estimation using lateration based techniques. Then we implemented existing hybrid position estimation technique i.eKalman filter based hybrid position estimation technique [12] using our own experimental data. The concept of our proposed hybrid position estimation technique is based on the existing hybrid indoor position estimation technique which is based on combination of fingerprinting and trilateration approach. The difference between existing hybrid approach and our hybrid approach is, they used fingerprinting with trilateration and used Kalman filter after calculating position of the target node, another difference is, they considered communication holes, which mean if there is no signal, how the hybrid approach will estimate the position. In our proposed approach, we assumed that, there is no communication hole and the data is already filtered. For this purpose we took 100 reading at each grid and then used their average value for a specific point. Also we combined fingerprinting with MinMax approach and used radio propagation model. They have not used radio propagation model. So our proposed hybrid approach is an extension of the existing hybrid technique with new features. The next section discusses proposed hybrid approach in detail with the help of a flow chart, its mathematical model, and algorithm.

4.2 Proposed Hybrid Indoor Position Estimation Technique using Fingerprinting and MinMax Approach

The proposed hybrid indoor position estimation technique consist of two stages. In first stage, our proposed hyrbid approach uses Fingerprinting approach and in second stage it uses MinMax Approach. In first phase, we have used Fingerprinting approach, using K-NN which calculates Nearest Neighbors, once the nearest neighbors are calculated then, the distance between the nearest neighborsare calculated using Euclidian distance formula, once the distances are calculated, then the target position is calculated using MinMax approach. The design of the proposed algorithm is depicted in the following flow chart.

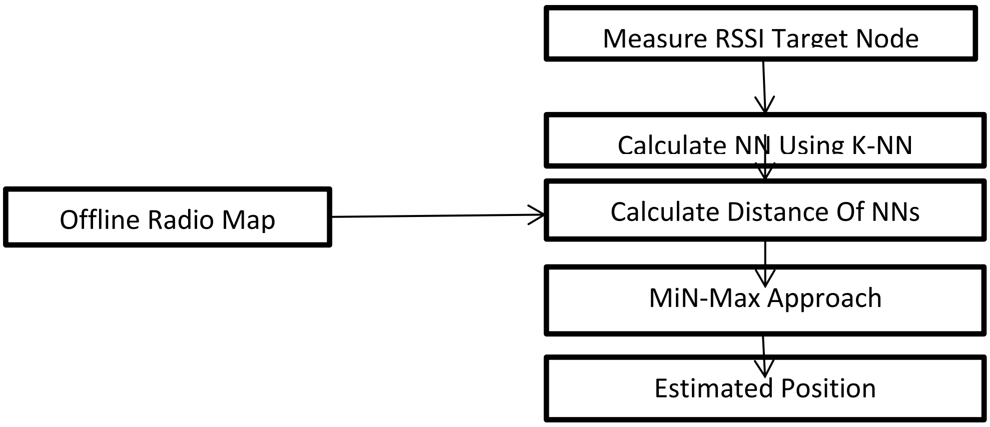

Figure 4.1 Flow Chart of Hybrid Indoor Positioning System

4.2.1 Mathematical Model of the Proposed Hybrid Approach

As discussed in previous section, the proposed hybrid approach consist of two steps, in step 1, we have used Fingerprinting approach, which is one the most popular pattern matching position estimation technique. In step 1, we have only calculated the nearest neighbors of the target position which is going to be estimated. For this purpose K-NN algorithm is used to calculate the nearest neighbors. The mathematical formula for calculating the nearest neighbors as under.

$$d = \sqrt{\sum_{i=1}^{n} (si - si')^2} \qquad (4.1)$$

Where d shows Euclidian distance, $s_i$represents RSS reieved at the target location and s_i^0shows the corresponding RSS in the database , while n is the number of anchor nodes for which the Euclidian distance are calculated.

In step 2, we have used MinMax approach, which is a lateration based position estimation technique. Unlike Trilateration approach, MinMax algorithm works differently, i.e instead of drawing circles, MinMax draw bounding boxes/rectangles for every access point which is fixed already. The radii of each bounding box i.erectangles is the distance calculated from NNs. Here the difference between conventional MinMax and other lateration based position estimation techniques is the use of Euclidian distance formula for finding the distance for radii of the bounding boxes. In conventional approaches, the radio propagation model is used to convert RSSI measurements in to distances, but in hybrid approach, once the NNs are calculated, then the distance between NNs are calculated using Euclidian distance formula, which acts as a radii for MinMax and there is no need to use radio propagation model. This will enhance position estimation accuracy and will also minimize the effect of noise over position estimation. The main reason behind using the hybrid approach is to minimize the effect of noise, which can affect the position estimation process. The mathematical formulation of MinMax approach is as under.

$$\left(\max{}_{(x_i - d_i)}, \max{}_{(y_i - y_i)}\right) * \left(\min{}_{(x_i + d_i)}, \min{}_{(y_i + y_i)}\right), \qquad (4.2)$$

Where (x_i, y_i) represent the fixed position of access point and $d_{i,}$ represents distance between estimated target position and access point. The pseudo code of our proposed hybrid algorithm is as under.

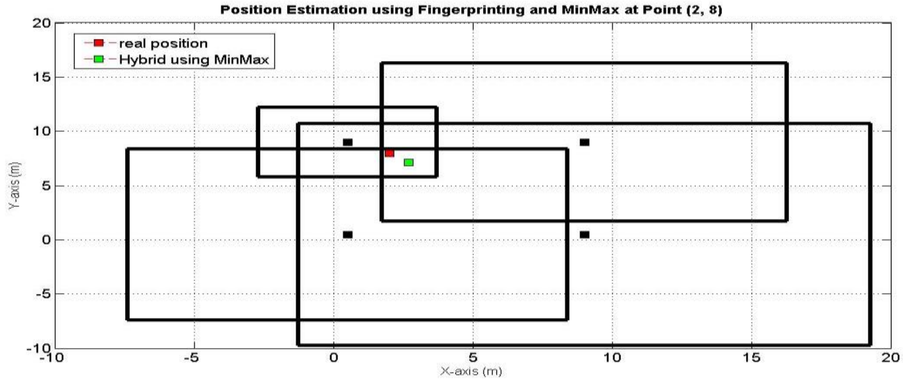

Figure 4.2: Proposed Hybrid Indoor Position Estimation Technique using Fingerprinting and MinMax(Case Study)

4.3 Summary

This chapter presented the concept of hybrid indoor position estimation technique, which is an extension of the previous hybrid approach. As discussed earlier, our proposed hybrid approach is the combination of most popular fingerprinting and K-NN approach. Other than this, this chapter discussed the complete design of our proposed hybrid approach with the help of flow diagram, its mathematical formulation as well as its pseudocode. The next chapter will discuss, the experimental setup, data collection process and analysis of conventional positon estimation techniques.

CHAPTER 5

RESULTS AND DISCUSSIONS

This chapter presents real time experimental results conducted for comparative analysis of the existing position estimation with our proposed hybrid position estimation techniques, which is a combination of K-NN and MinMax approach.

5.1 Comparative Analysis with Existing Position Estimation Techniques

Position estimation can be generally categorized as fingerprinting and lateration based position estimation techniques. In fingerprinting based approach normally, a radio map is created from experimental data set and then the object position is determined based on pattern matching approach. Fingerprinting technique is already discussed in detail in chapter 2. We have implemented K-NN approach which is a fingerprinting based position estimation technique in order to validate the numerical result of our proposed approach. Other than this, another category is lateration approach position estimation techniques, which are based on distance estimates. In our thesis we have implemented two approaches i.e Trilateration and MinMax approach. Trilateration and MinMax both are based on trigonometric principles. In case of trilateration, each access point is considered as the center of circle and the point of intersection if so is the estimated position. If there is a unique point of intersection, it means the position estimation error is zero. If the circles do not intersect at single point, it means there is a position estimation error. Similarly, in MinMax approach, instead of circles, rectangles are drawn for each access point and the point of intersection is considered as the estimated position. If the point of intersection is unique then it means there is no position estimation error or in other words it is almost zero. We can zero because, it is very difficult to accurately estimate an object in the presence of noise. Moreover, we have also implemented one of the recently developed hybrid approach, which is combination of K-NN and Trilateration approach. The following sub-section discusses comparative analysis of our proposed hybrid approach with existing position estimation techniques.

5.1.1 Position estimation at Point (1,1)

Table 4.1 shows the mean error of estimated position at point (1,1) using K-NN, Trilateration, Hybrid Trilateration, MinMax and our proposed hybrid approach. As shown in the following table, the position estimation error of K-NN is 0.5 m which is almost similar to our proposed hybrid position estimation technique. The reason behind this is as our proposed technique is a hybrid approach combination of K-NN and MinMax. So similarity may happen out of 100 grid points. Other than this, the position estimation error of MinMax is 3.80 meters and Trilateration is 4.5 meters. Fig. 4.1 represents graphical representation of real position in two dimensional coordinate system (x, y) and estimated position using Trilateration, K_NN and Hybrid based on trilateration. Similarly, Fig. 4.2 represents real position, and estimated position using MinMax, K-NN and our proposed hybrid approach. As discussed in previous chapter, Trilateration is a trigonometric based position estimation technique which estimate target position by drawing circles, on the other side, MinMax approach draw rectangles. If the point of intersection in both cases are unique, it means there is no position estimation error or the estimated position is the same as real position.

Table 5. 1 Comparative Analysis of Position Estimation Techniques at Point 1 (1, 1)

S.No	**Position Estimation Techniques**	**Mean Error (m)**
1	K-NN	0.50
2	Trilateration	4.5
3	Hybrid Trilateration	0.84
4	MinMax	3.80
5	**Proposed Hybrid MinMax**	**0.56**

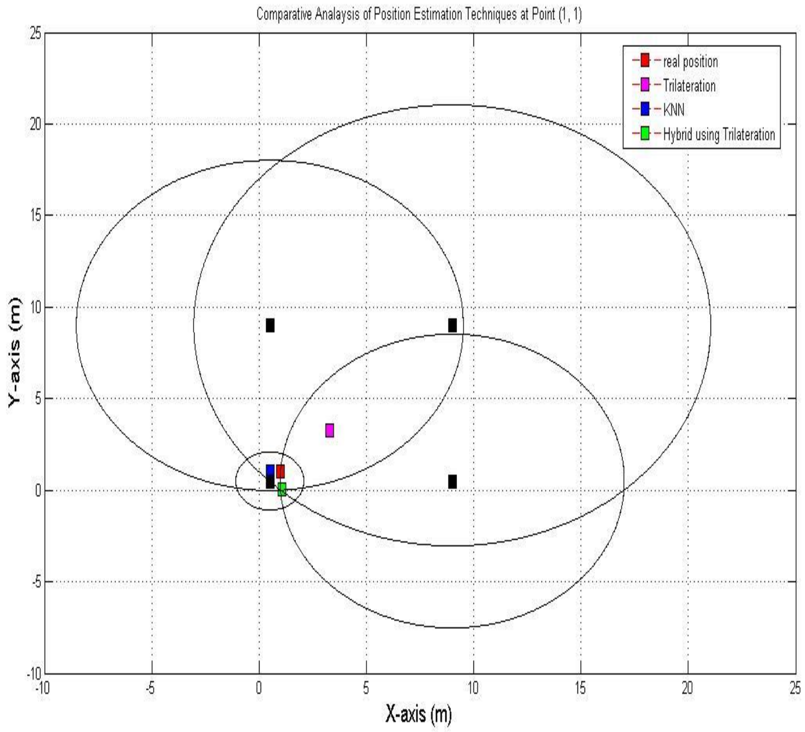

Fig. 5.1 estimated position at (1, 1) using Trilateration, K-NN and Hybrid Trilateration

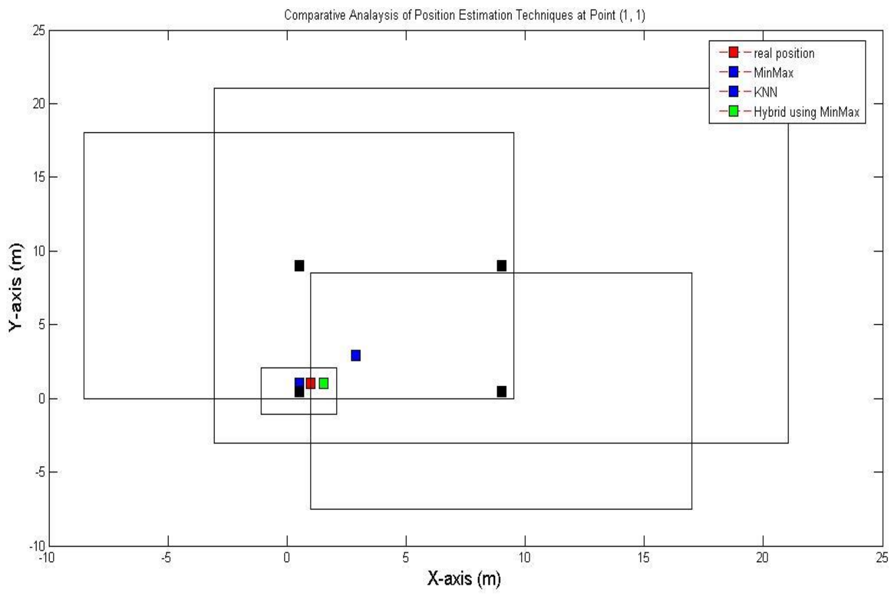

Fig. 5.2 Estimated position at (1, 1) using MinMax, K-NN and Proposed hybrid technique

5.1.2 Position estimation at Point (7, 5)

Table 5.2 shows numerical results when the object is placed at (7, 5). Here it is important to mention again that the estimated position error using K-NN and our proposed position estimation is similar, but position estimation error of other techniques are different from each other. The reason behind this is effect of environmental conditions and noise. Similarly in Fig. 5.3 shows estimated position using Trilateration, K-NN, and existing hybrid position estimation technique based on Trilateration. The figure clearly indicates that, the point of intersection is not unique. Same situation in Fig. 4.4 which shows estimated position using MinMax, and our proposed hybrid MinMax.

Table 5.2 Comparative Analysis of Position Estimation Techniques at Point 1 (7, 5)

S.No	**Position Estimation Techniques**	**Mean Error (m)**
1	K-NN	0.5
2	Trilateration	1.8
3	Hybrid Trilateration	0.9
4	MinMax	1.1
5	**Proposed Hybrid MinMax**	**0.5**

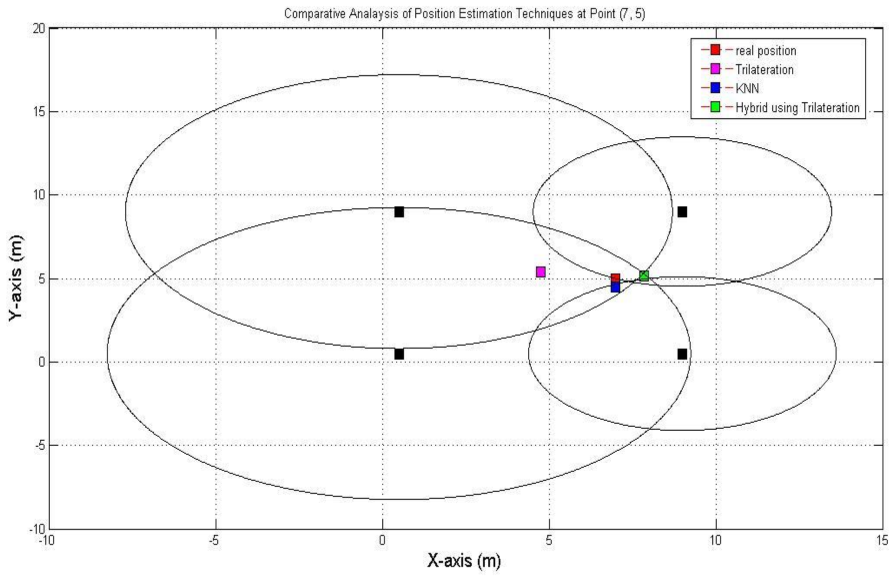

Fig. 5.3 estimated position at (7, 5) using Trilateration, K-NN and Hybrid Trilateration

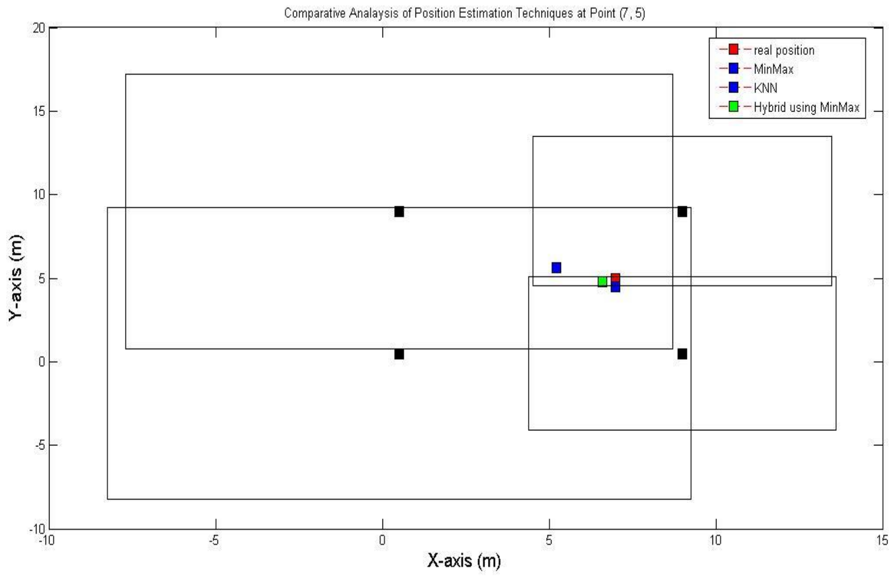

Fig. 5.4Estimated position at (7, 5) using MinMax, K-NN and Proposed hybrid technique

5.1.3 Position estimation at Point (5, 7)

Table 5.3 shows numerical results at grid point (5, 7), which means when the real target position is placed when the x-axis is 5, and the y-axis is 7. The mean error analysis shows that, K-NN performs better than all position estimation techniques. The position estimation error of K-NN is 0.2 meters which is the lowest one, while the position estimation error of our proposed hybrid based on MinMax is 0.5 m. On the other hand again position estimation error of existing hybrid position estimation technique is poor than our proposed approach.

Table 5. 3 Comparative Analysis of Position Estimation Techniques at Point 1 (5, 7)

S.No	**Position Estimation Techniques**	**Mean Error (m)**
1	K-NN	0.2
2	Trilateration	1.5
3	Hybrid Trilateration	2.0
4	MinMax	0.9
5	**Proposed Hybrid MinMax**	**0.5**

Fig. 5.5 and 5.6 depicts graphical representation of existing and our proposed hybrid techniques. In both figures, the circles and rectangles have different size. Due to position estimation error, none of the circles and rectangles intersect at one point.

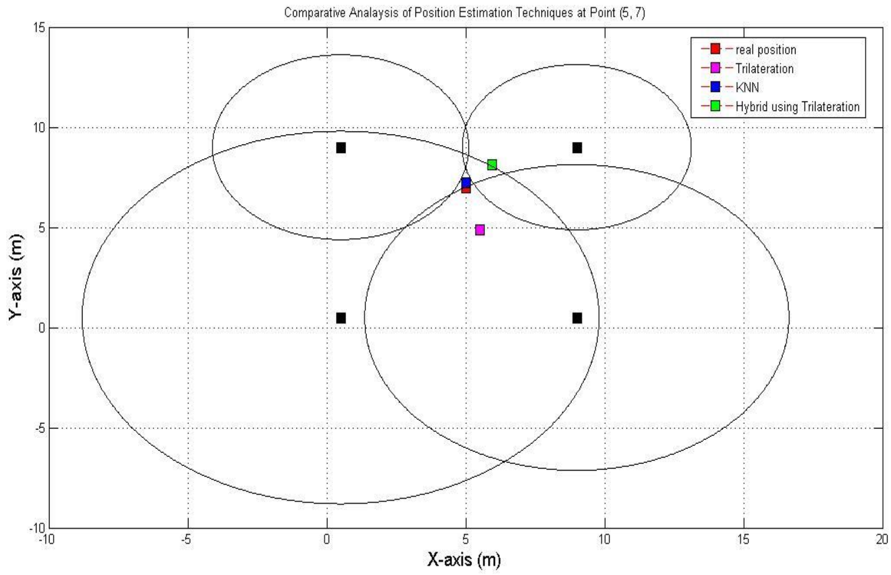

Fig. 5.5 estimated position at (1, 1) using Trilateration, K-NN and Hybrid Trilateration

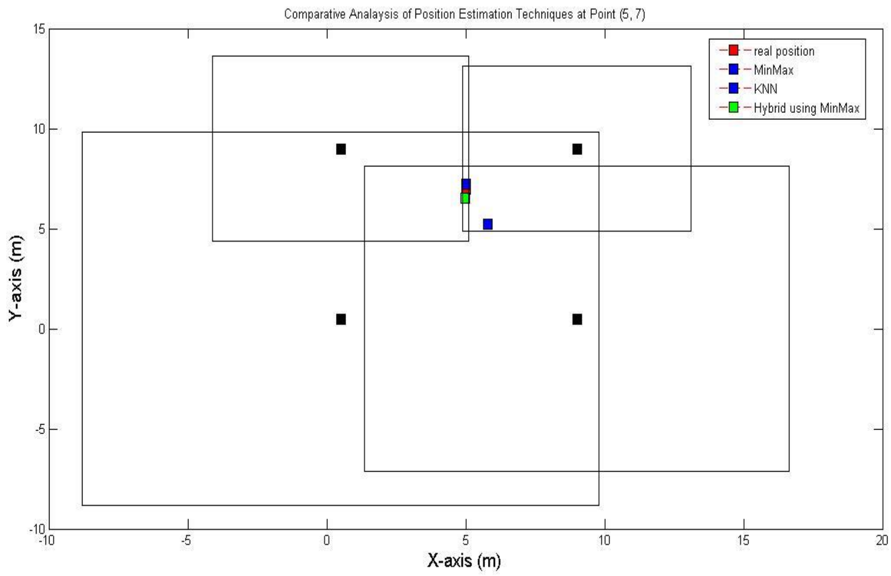

Fig. 5.6 estimated position at (1, 1) using Trilateration, K-NN and Hybrid Trilateration

5.1.4 Position estimation at Point (9, 9)

Similarly Table 5.4 shows means error analysis existing and our proposed hybrid position estimation technique. Here position estimation error of K-NN is poor than our proposed hybrid approach which is 1.7m while position estimation error of K-NN is

2.2 m. In our experiments, we have used Bluetooth modules embedded in our smart phones. As per Bluetooth Specification, the range of Bluetooth is from 1 meter to 100 meters for class A devices. As mention in chapter 3, our experiments were conducted in a computer lab and the RSSI readings were collected when the maximum distance between two devices was 10 meters. So point (9, 9) is the cornor location, that's why, the position estimation error is 1.7 meters. Fig. 5.7 and 5.8 graphically represents the real position and estimation position using existing and our proposed hybrid approach.

Table 5. 4 Comparative Analysis of Position Estimation Techniques at Point 1 (9, 9)

S.No	**Position Estimation Techniques**	**Mean Error (m)**
1	K-NN	2.2
2	Trilateration	6.3
3	Hybrid Trilateration	4.3
4	MinMax	2.6
5	**Proposed Hybrid MinMax**	**1.7**

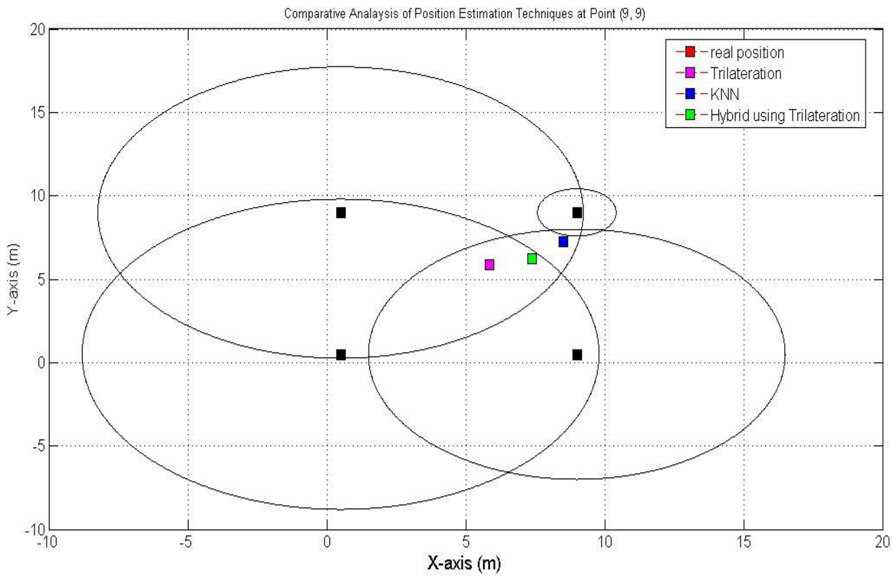

Fig. 5.7 estimated position at (9, 9) using Trilateration, K-NN and Hybrid Trilateration

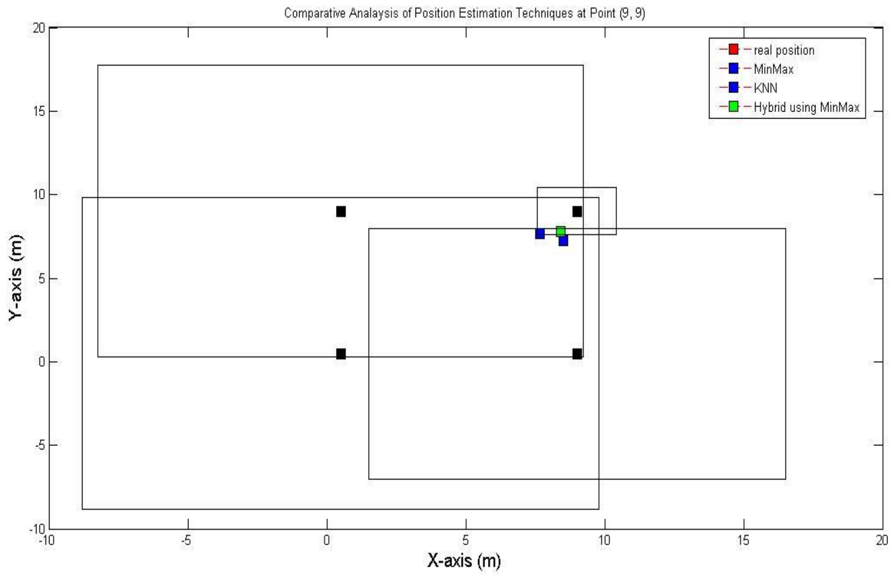

Fig. 5.8 estimated position at (9, 9) using Trilateration, K-NN and Hybrid Trilateration

5.1.5 Position estimation at Point (8,3)

This, section further elaborates means error analysis of existing and our proposed hybrid approach. As shown in Table 5.5 , the mean error of K-NN is 0.5 while the mean error of existing hybrid approach is 2.2 meters, while the mean error of our proposed hybrid approach is better than all existing position estimation techniques i.e 0.3 meters. Here it is important to mention that, we did extensive analysis of K-NN and we found that, when the nearest neibhbours that is if the value of K= 4, then the results are much better, if we fix the value of K, 2, 3 or 5 the results are not satisfactory. For our proposed hybrid approach, we have fixed the value of K= 2, because we need four access points to locate the object. The radii of each circles and rectangles are calculated using Euclidian distance formula instead of radio propagation models. Fig. 5.9 and 5.10 visualize the estimated and real positions. Again the figures clearly indicates that, the point of intersection is not unique due to position estimation error in existing and our proposed hybrid position estimation technique.

Table 5.5 Comparative Analysis of Position Estimation Techniques at Point 1 (8,3)

S.No	**Position Estimation Techniques**	**Mean Error (m)**
1	K-NN	0.5
2	Trilateration	0.7

3	Hybrid Trilateration	2.2
4	MinMax	0.5
5	**Proposed Hybrid MinMax**	**0.3**

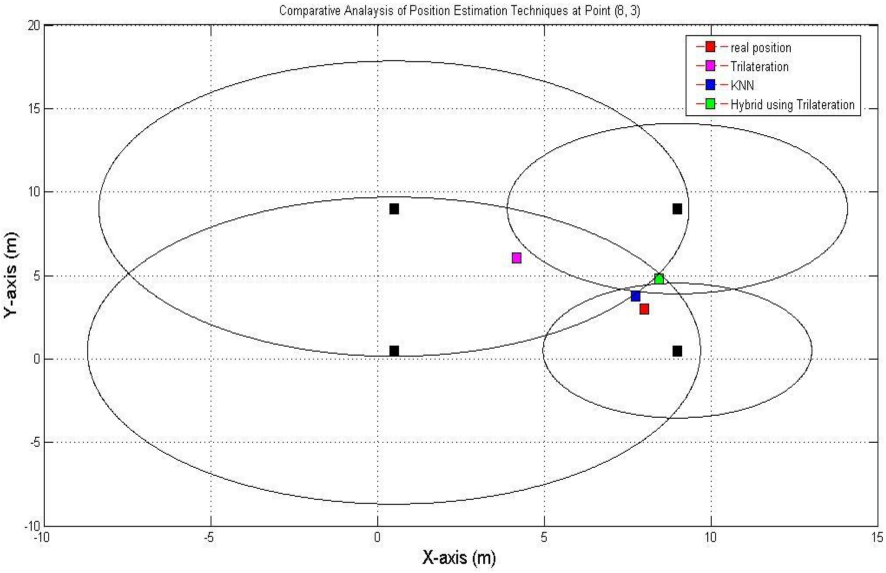

Fig. 5.9 estimated position at (8,3) using Trilateration, K-NN and Hybrid Trilateration

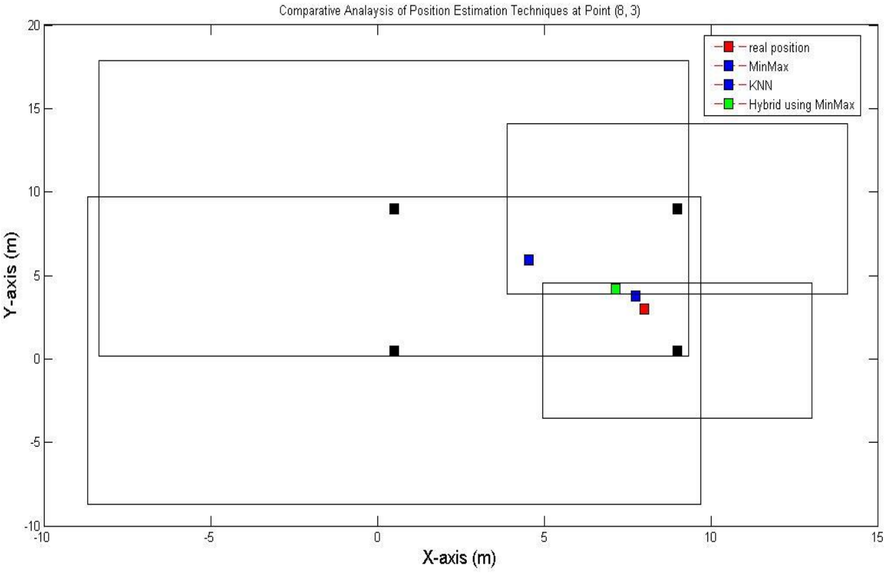

Fig. 5.10 estimated position at (8,3) using Trilateration, K-NN and Hybrid Trilateration

5.1.6 Position estimation at Point (2,8)

Table. 5. 6 is the ideal situation for K-NN, and existing hybrid technique based on trilateration. As shown in Fig. 5.11 the point of intersection is unique as the position estimation error is zero while Fig. 5.12, the position estimation error is also near to zero. So the point of intersection is not unique. Numerical results here shows that, our proposed hybrid technique is better than MinMax and Trilateration but comparatively a bit lower than K-NN and existing Trilateration approach.

Table 5. 6 Comparative Analysis of Position Estimation Techniques at Point 1 (2, 8)

S.No	**Position Estimation Techniques**	**Mean Error (m)**
1	K-NN	0
2	Trilateration	0.4
3	Hybrid Trilateration	0.0
4	MinMax	0.7
5	Proposed Hybrid MinMax	0.1

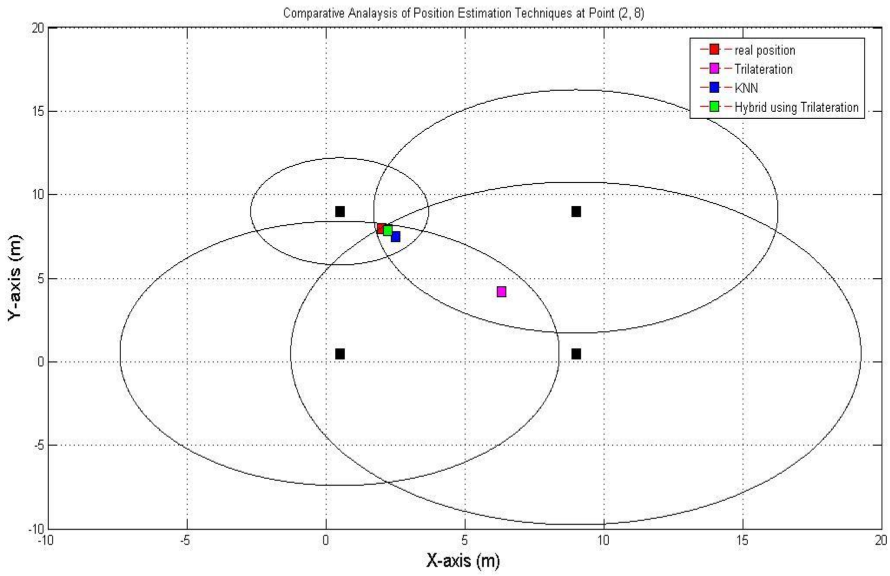

Fig. 5.11 estimated position at (2, 8) using Trilateration, K-NN and Hybrid Trilateration

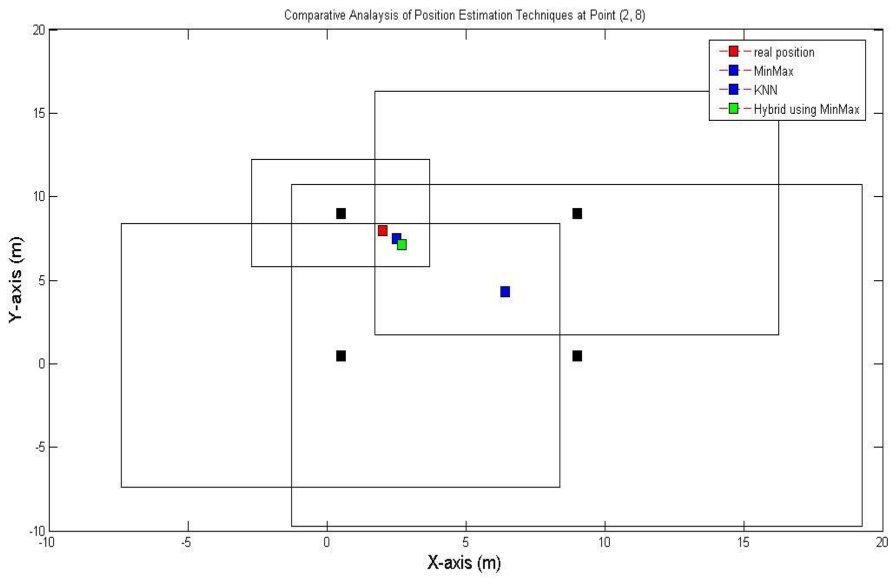

Fig. 5.12 estimated position at (2,8) using Trilateration, K-NN and Hybrid Trilateration

5.1.7 Position estimation at Point (5,5)

Table 5.7 shows numerical results obtained at the center of the (10x10) grid, i.e when the real position or target position is fixed at the center of the grid. Here, our proposed hybrid approach performs better than K-NN, Trilateration, existing hybrid approach, and MinMax. Still we believe that, the position estimation error exist and we can only minimize it. Moreover, the previous hybrid approach used Gradient filter to clean the RSSI measurements prior to position estimation. Also the existing hybrid approach used the most popular Kalman Filter which further enhances position estimation error. In our case, we used RSSI average measurements, and implemented all position estimation techniques with the same data and parameters. Fig 5.13 and 5.14 depicts the graphical representation of real position and estimated position.

Table 5. 7 Comparative Analysis of Position Estimation Techniques at Point 1 (5,5)

S.No	**Position Estimation Techniques**	**Mean Error (m)**
1	K-NN	1.2
2	Trilateration	0.7
3	Hybrid Trilateration	0.8
4	MinMax	1.0
5	**Proposed Hybrid MinMax**	**0.7**

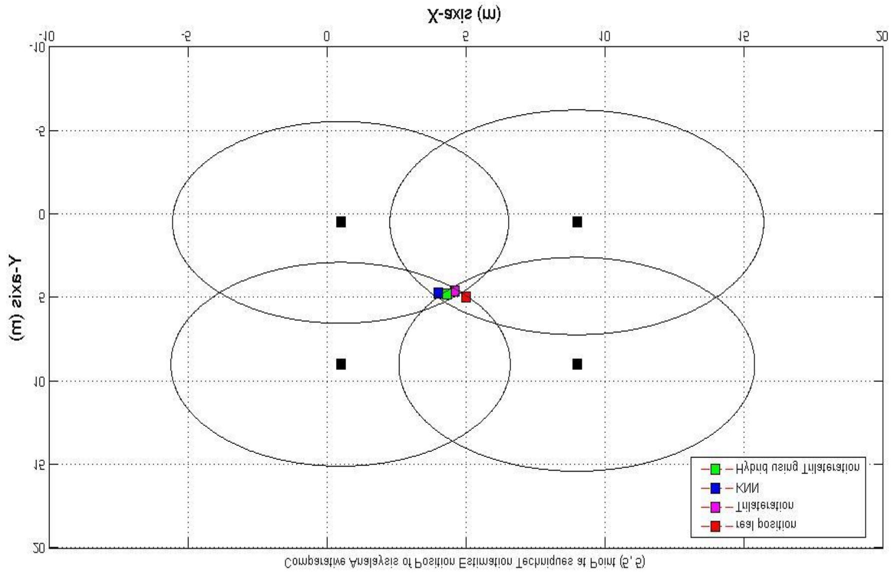

Fig. 5.13 estimated position at (5, 5) using Trilateration, K-NN and Hybrid Trilateration

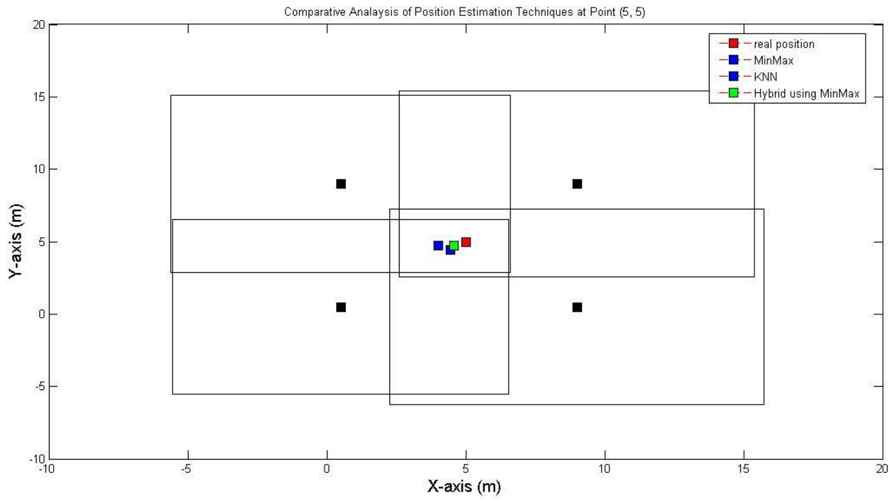

Fig. 5.14 estimated position at (5, 5) using Trilateration, K-NN and Hybrid Trilateration

Table 5.8 shows average mean error of existing position estimation techniques and our proposed hybrid approach. The numerical results obtained from seven different points clearly indicates that, our proposed hybrid approach is better than existing position estimation techniques in terms of average mean error.

Table 5. 8 Average mean error analysis

Position estimation Technique	Average Mean error (m)
K-NN	1.02
Trilateration	3.18
MinMax	2.12
Hybrid based on Trilateration	2.2
Proposed hybrid based on MinMax	**0.86**

5.2 Summary

In this chapter, we presents the comparative analysis of existing and our proposed hybrid approach, which is a combination of K-NN and MinMax approach. As discussed in chapter 4, our proposed hybrid approach is an extension of previous hybrid position estimation technique based on K-NN and Trilateration. Numerical results shows our proposed hybrid approach performs better than existing techniques discussed here.

CHAPTER 6

CONCLUSION AND FUTURE WORK

This chapter summarizes a brief overview of the research work performed to design a position estimation technique based on fingerprinting and MinMax approach. Also this chapter presents the contributions, limitations and future research directions in order to carry forward the research work in the field of position estimation or localization.

6.1 Summaryof The Research Issues And Our Proposed Solution

Position estimation is the process of finding the object location with respect to some coordinate systems. In literature, the word position estimation is referred as localization, object tracking, indoor positioning, or simply position estimation. Position estimation process can be categorized as outdoor and indoor. For outdoor environment, GPS is the one of the standard navigation system deployed in most of vehicles, mobile phones, handheld devices. GPS is a sattalite based navigation system developed by the United States for guiding their military in war. However, GPS is line of sight technology works in outdoor environment. For indoor environment GPS is not an ideal solution, so the researchers are working on indoor environment. Currently there is no standard solution so for developed specifically for indoor environment. The reason for this is the effect of noise on distance estimation and if there is an error in distance estimation, the accurate solution is yet to be developed. The main idea behind this research work is to design a position estimation technique which provide an optimal solution for object tracking in indoor environment. In this thesis we have proposed a hybrid position estimation technique, which is an extension of the previous hybrid position estimation technique, which uses Fingerprinting and Trilateration approach and Kalman filter for better position accuracy. In our proposed technique, which is a combination of Fingerprinting approach and MinMax approach without using Kalman filter.

Real time experimental results concludes that, our proposed hybrid position estimation technique performs better than traditional Trilateration, K-NN, MinMax and also performs better than previous hybrid technique. Other than this, prior the design of our proposed hybrid approach, we have also analyzed the variation in RSSI, and its relation with distance in order to calculate optimal propagation constants. We have used Bluetooth as a wireless technology and performed real time experiments in our lab. The measurements were taken in a size of 100 m^2 with one meter grid size. Four access points and one mobile unit were used in our experiments. The RSSI measurements were recorded for 10 to 15 seconds and we stored 10 values for each grid, then we calculated the average RSSI for each grid and for each of the access point. In previous studies, they used Gradient filter to eliminate communication holes, i.e when the RSSI measurements are not received. But in our study, we used the average values. Then existing traditional and hybrid approach were implemented in Matlab 7.0 with our real time experimental data. Numerical results concludes our proposed hybrid technique performs better in terms of mean error. The next section briefly summarizes our achievements.

6.2 Achievements

Position estimation techniques are compared in terms of accuracy, and for accuracy mean error analysis is the parameter used in the literature. We have implemented the existing traditional position estimation techniques which are Trilateration, MinMax, K-NN and one of the recently developed hybrid position technique. The RSSI measurements and input parameters we used in comparative analysis were the same as we have used in our proposed hybrid position estimation techniques. Our main contributions in this thesis are as under.

a. Real time experiments for RSSI analysis
b. Distance estimation analysis in order to know the variation in RSSI and its effect on distance for tuning radio propagation constants which are used for converting RSSI measurements in to distance estimates. The optimal radio propagationconstants are then selected.
c. Implementation of existing position estimation techniques.
d. Design of a new hybrid position estimation technique.
e. Extensive real time comparative analysis of existing and our proposed hybrid position estimation technique.

6.3 Limitations

Our proposed hybrid position estimation technique have some limitation which are highlighted as follows.

I. We have performed experiments and took the RSSI measurements in a limited area of
100 m^2 , the numerical results are based on the actual measurements, however we observed significant variations in RSSI with respect to time. Numerical results may show difference in position estimation process due to various environmental conditions such as presence of human bodies, effects of furniture and so many physical objects if the size of the indoor environment change. This limitation has been addressed in most of the literature as well and it is according to our observations as well.

II. Also we have tested our proposed hybrid approach on Bluetooth enabled hand phones as well which are commonly used in our daily life. Other hand phones having different Bluetooth specifications, the RSSI measurements may change.

6.4 Future Work

Future research is required to design more and more accurate solution which eliminates the variations in RSSI measurements accordingly. Moreover, we observed that, RSSI even one percent variation can effect distance estimates and if there is an error in distance estimation, then the position estimation greatly suffers. So it is highly recommended to design such position estimation technique which simultaneously smoothen RSSI measurements and also the final position estimation variations.

REFERENCES

[1] Curran K, Furey E, Lunney T, Santos J, Woods D, McCaughey A. An evaluation of indoor location determination technologies. *Journal of Location Based Services*. 2011 Jun 1;5(2):61-78.

[2] Dardari D, Closas P, Djuric PM. Indoor Tracking: Theory, Methods, and Technologies. *IEEE Trans. Vehicular Technology*. 2015 Apr 1;64(4):1263-78.

[3] Riga P, Kouroupetroglou G. Indoor Navigation and Location-Based Services for Persons with Motor Limitations. *InDisability Informatics and Web Accessibility for Motor Limitations 2014* (pp. 202-233). IGI Global.

[4] Subhan F, Hasbullah H, Rozyyev A, Bakhsh ST. Analysis of Bluetooth signal parameters for indoor positioning systems. *InComputer& Information Science (ICCIS), 2012 International Conference* on 2012 Jun 12 (Vol. 2, pp. 784-789). IEEE.

[5] K. Yu, I. Sharp, and Y.J. Guo, Ground-Based Wireless Positioning, *Wiley-IEEE Press*, 2009.

[6] D. Milioris, L. Kriara, A. Papakonstantinou, G. Tzagkarakis, P. Tsakalides,and M. Papadopouli, "Empirical evaluation of signal strengthfingerprint positioning in wireless LANs," *in Proc. 13th ACM Int. Conf.Modeling, Anal. Simulation of Wireless and Mobile Syst.*, Bodrum,Turkey, Oct. 2010, vol. 24, no.4, pp. 5-13.

[7] Han Y, Shen Y, Zhang XP, Win MZ, Meng H. Performance limits and geometric properties of array localization. *IEEE Transactions on Information Theory*. 2016 Feb;62(2):1054-75.

[8] Kypris O, Abrudan TE, Markham A. Magnetic Induction-Based Positioning in Distorted Environments. IEEE Trans. Geoscience and Remote Sensing. 2016 Aug 1;54(8):4605-12.

[9] He S, Chan SH. Wi-Fi fingerprint-based indoor positioning: *Recent advances and comparisons. IEEE Communications Surveys & Tutorials*. 2016 Jan 1;18(1):466-90.

[10] Farid Z, Nordin R, Ismail M. Recent advances in wireless indoor localization techniques and system. *Journal of Computer Networks and Communications*. 2013;2013.

[11] Subhan, Fazli, HalabiHasbullah, and Khalid Ashraf. "Kalman filter-based hybrid indoor position estimation technique in bluetooth networks." *International Journal of Navigation and Observation* 2013 (2013).

[12] Subhan F, Hasbullah H, Rozyyev A, Bakhsh ST. Indoor positioning in bluetooth networks using fingerprinting and lateration approach. *InInformation Science and Applications (ICISA), 2011 International Conference* on 2011 Apr 26 (pp. 1-9). IEEE.

[13] Costilla-Reyes O, Namuduri K. Dynamic Wi-Fi fingerprinting indoor positioning system. *InIndoor Positioning and Indoor Navigation (IPIN),* 2014 International Conference on 2014 Oct 27 (pp. 271-280). IEEE.

[14] Pormante L, Rinaldi C, Santic M, Tennina S. Performance analysis of a lightweight RSSI-based localization algorithm for Wireless Sensor Networks. *InSignals, Circuits and Systems (ISSCS), 2013 International Symposium* on 2013 Jul 11 (pp. 1-4). IEEE.

[15] Lloret, Jaime, Jesus Tomas, Miguel Garcia, and Alejandro Canovas. "A hybrid stochastic approach for self-location of wireless sensors in indoor environments." *Sensors 9*, no. 5 (2009): 3695-3712.

[16] Hongpeng, W. A. N. G., and FeiJia. "A hybrid modeling for WLAN positioning system." *In Wireless Communications, Networking and Mobile Computing*, 2007. WiCom 2007. International Conference on, pp. 2152-2155. IEEE, 2007.

[17] Wang Y, Yang X, Zhao Y, Liu Y, Cuthbert L. Bluetooth positioning using RSSI and triangulation methods. *InConsumer Communications and Networking Conference (CCNC)*, 2013 IEEE 2013 Jan 11 (pp. 837-842). IEEE.

[18] Brena RF, García-Vázquez JP, Galván-Tejada CE, Muñoz-Rodriguez D, Vargas-Rosales C, Fangmeyer J. Evolution of indoor positioning technologies: *A survey. Journal of Sensors*. 2017;2017

[19] Mashuk MS, Pinchin J, Siebers PO, Moore T. A smart phone based multi-floor indoor positioning system for occupancy detection. *InPosition, Location and Navigation Symposium (PLANS)*, 2018 IEEE/ION 2018 Apr 23 (pp. 216-227). IEEE.

[20] Chun SB, Lim S, Lee MS, Heo MB. Indoor Location Tracking for First Responders using Data Network. *The Journal of Advanced Navigation Technology*. 2013;17(6):810-5.

[21] Deak G, Curran K, Condell J. A survey of active and passive indoor localisation systems. *Computer Communications*. 2012 Sep 15;35(16):1939-54.

[22] He S, Chan SH. Wi-Fi fingerprint-based indoor positioning: *Recent advances and comparisons. IEEE Communications Surveys & Tutorials*. 2016 Jan 1;18(1):466-90.

[23] Nguyen K, Luo Z. Evaluation of bluetooth properties for indoor localisation. *In Progress in Location-Based Services* 2013 (pp. 127-149). Springer, Berlin, Heidelberg.

[24] Yan, Jun, Lin Zhao, Jian Tang, Yuwei Chen, Ruizhi Chen, and Liang Chen. "Hybrid Kernel Based Machine Learning Using Received Signal Strength Measurements for Indoor Localization." *IEEE Transactions on Vehicular Technology* 67, no. 3 (2018): 2824-2829.

[25] Batistić L, Tomic M. Overview of indoor positioning system technologies. *In 2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)* 2018 May 21 (pp. 0473-0478). IEEE.

[26] Jung J, Kang D, Bae C. Distance estimation of smart device using bluetooth. *Personal Computing Platform Research Team*. 2013:13-8.

[27] K. Whitehouse and D. Culler, "Calibration as Parameter Estimation in Sensor Networks," *Wireless Sensor Networks and Apps*., 2002, pp 59-67.

[28] A. Savvides, C.-C. Han, and M. B. Strivastava, "Dynamic Fine-Grained Localization in Ad-Hoc Networks of Sensors," *7th ACM/IEEE Int'l. Conf. Mobile Computing and Networking*, Rome, Italy, 2001, pp. 166–179.

[29] T. He, C. Huang, B. M. Blum, J. A. Stankovic, and T. Abdelzaher, "Range-Free Localization Schemes for Large Scale Sensor Networks," *MobiCom '03, ACM Press*, 2003, pp. 81-95.

[30] Li G, Geng E, Ye Z, Xu Y, Lin J, Pang Y. Indoor Positioning Algorithm Based on the Improved RSSI Distance Model. *Sensors*. 2018 Aug 27;18(9):2820.

[31] Golestani A, Petreska N, Wilfert D, Zimmer C. Improving the precision of RSSI-based low-energy localization using path loss exponent estimation. *In Positioning, Navigation and Communication (WPNC)*, 2014 11th Workshop on 2014 Mar 12 (pp. 1-6). IEEE.

[32] Nowak T, Hartmann M, Zech T, Thielecke J. A path loss and fading model for RSSI-based localization in forested areas. *In Antennas and Propagation in Wireless Communications (APWC)*, 2016 IEEE-APS Topical Conference on 2016 Sep 19 (pp. 110-113). IEEE.

[33] Nguyen HA, Guo H, Low KS. Real-time estimation of sensor node's position using particle swarm optimization with log-barrier constraint. *IEEE Transactions on Instrumentation and Measurement.* 2011 Nov;60(11):3619-28.

[34] P. Bahl and N. V. Padmanabhan, "Radar: An in-building rf-based user location and tracking system," Proceedings IEEE 19th INFOCOM Conference on Computer Communications and Communications Societies, vol. 2, pp. 775–784, 2000.

[35] Jang, Beakcheol, and Hyunjung Kim. "Indoor Positioning Technologies Without Offline Fingerprinting Map: A Survey." *IEEE Communications Surveys & Tutorials* (2018).

[36] Batistić, Luka, and MladenTomic. "Overview of indoor positioning system technologies." In *2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, pp. 0473-0478. IEEE, 2018.

[37] Topaz, 2018, http://www.tadlys.co.il/

[38] iBeacon, 2018, https://developer.apple.com/ibeacon/

[39] H. Zou, Z. Chen, H. Jiang, L. Xie, and C. Spanos, "Accurate Indoor Localization and Tracking Using Mobile Phone Inertial Sensors, WiFi and iBeacon," IEEE International Symposium on Inertial Sensors and Systems, 2017

[40] H. Leppäkoski, J. Collin, and J. Takala, "Pedestrian Navigation Based on Inertial Sensors, Indoor Map, And WLAN Signals," IEEE Inernational Conference on Acoustics, Speech and Signal Processing (ICASSP), 2012.

[41] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The Cricket Location-Support System," 6th ACM International Conference on Mobile Computing and Networking, Boston, MA, 2000

[42] Ubisense, 2018, https://ubisense.net/en