AN EVALUATION OF A PROTOTYPE SERVER-BASED INDOOR POSITIONING SYSTEM

by

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INDOOR POSITIONING SYSTEM

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ABSTRACT

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Mobile devices are used in every field in our lives. With the advancement of technology and telecommunication services, data consumption rates are increasing ever since. People started to prefer to use data-based applications with the help of contextual information to improve their user experience. Thus, providing a cross-platform location service to further enrich such applications has become a necessity. For this purpose, numerous client-based indoor location systems on mobile devices are developed to perform this task. Nevertheless, such systems can suffer from elimination of features from operating systems for security purposes and design choices in the long run. Indeed, with the current security trends, to ensure the privacy of mobile users, mobile operating system designers are progressively eliminating certain low-level features such as reading RSSI and introducing randomized MAC addresses. Thus, in this study, in order to eliminate platform dependency and to provide the location detection to a wide variety of devices, a server-based indoor positioning system is designed and implemented. Proposed systems performance and accuracy are compared with three client-based systems which uses classic RSSI and sensor-based methods. Our findings indicate that the proposed system performs in acceptable accuracy to client-based systems albeit a more complex and costly implementation.

ÖZET

SUNUCU TABANLI PROTOTİP İÇ MEKAN KONUMLANDIRMA SİSTEMİNİN DEĞERLENDİRİLMESİ

Mobil cihazlar hayatımızın her alanında kullanılmaktadır. Teknoloji ve telekomünikasyon hizmetlerinin ilerlemesiyle birlikte veri tüketim oranları günden güne artmaktadır. Kullanıcı deneyimini geliştirmek için içeriğe dayalı bilgiler yardımıyla veri tabanlı uygulamalar insanlar tarafından tercih edilmeye başlanmıştır. Böylece, bu tür uygulamaları daha da zenginleştirmek için bir platformlar arası yer hizmeti sağlanması bir zorunluluk haline gelmiştir. Bu amaçla, bu görevi yerine getirmek için mobil cihazlardaki çok sayıda istemci tabanlı kapalı konumlandırma sistemi geliştirilmiştir. Bununla birlikte, bu tür sistemler uzun vadede hem güvenlik amacı hem de tasarım seçimleri sebebiyle işletim sistemi özelliklerinin ortadan kaldırılmasına maruz kalabilir. Gerçekten de, mevcut güvenlik trendleri ile, mobil kullanıcıların mahremiyetini sağlamak için, mobil işletim sistemi tasarımcıları RSSI değerlerine erişim ve MAC adreslerini randomize etmek gibi bazı düşük seviyeli özellikleri aşamalı olarak ortadan kaldırmakta veya kısıtlamalar getirmektedir. Bunu göz önünde bulundurarak, bu çalışmada platform bağımlılığını ortadan kaldırmak ve çeşitli cihazlara konum tespitini sağlamak için sunucu tabanlı bir iç konumlandırma sistemi tasarlanmış ve uygulanmıştır. Önerilen sistemin performansı ve doğruluğu, klasik RSSI ve sensör tabanlı yöntemler kullanan üç istemci tabanlı sistem ile karşılaştırılmıştır. Bulgularımız, önerilen sistemin, daha karmaşık ve maliyetli bir uygulama olsa da, istemci tabanlı sistemlerde kabul edilebilir doğrulukta olduğunu göstermektedir.

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LIST OF SYMBOLS/ABBREVIATIONS

API	Application programming interface
BLE	Bluetooth low energy
CDF	Cumulative distribution function
FCC	Federal communications commission
HTML	HyperText markup language
IEEE	Institute of electrical and electronics engineers
MAC	Media access control
MU	Mobile unit
OS	Operating system
RSS	Received signal strength
RSSI	Received signal strength indicator
Wi-Fi	Wireless fidelity
WLAN	Wireless local area network

1. INTRODUCTION

Mobile devices are used in every field in our lives. With the advancement of technology and telecommunication services, data consumption rates have been increasing with exponential pace. People use data based applications with the help of contextual information to improve the user experience. Thus, providing an accurate location service to further enrich such applications has become a must. Although Global Positioning System (GPS) is widely adopted as the standard positioning system for outdoor environments, it lacks enough accuracy in dense urban areas and especially in indoor environments where a clear view of sky is not available. Therefore it is necessary to use different techniques for indoor location detection, such as Wi-Fi IEEE 802.11 radio signals, which become a de-facto standard in indoor positioning systems. Many of these system use client-based positioning system where location calculation is done on-device. However, with recent releases of mobile OS's, many low level functionalities are progressively being disabled or becoming harder to access due to security and privacy concerns or design choice of the developers. Such feature restrictions include the elimination of RSSI reading of wireless access points and randomized MAC addresses to disguise the device in iOS 7 and later [1]. Therefore, implementation of a functionality in an OS can become more cumbersome and harder to perform than other OS's. This could cause fragmentation between same versions of an application on different OS's especially if a functionality is held back due to development problems. On top of that, if the positioning system needs an upgrade on hardware level or an additional hardware is introduced, each change will need a software implementation on MU, which can further face with problems due to OS limitation.

In this thesis, a study is performed to evaluate the accuracy and performance of a centralized server-based positioning system, regarding the performance of client-based systems. The proposed server-based system uses sniffer devices to gather signal information from mobile devices. The position calculation is done on the server which enables platform independency. The proposed system is compared to the popular client-based systems implemented with Wi-Fi, Bluetooth and sensor-based approaches.

1.1. ORGANIZATION OF THE THESIS

Chapter 2 includes the background and literature review of the problem. Chapter 3 discusses the methodology used to design and implement the platform. Chapter 4 introduces Bluetooth Low Energy based positioning system and its comparison to conventional Wi-Fi based positioning system. Chapter 5 introduces a Wi-Fi based positioning system that has been implemented and tested in a large indoor environment to test positioning performance in real-world large indoor areas. Chapter 6 includes the Pedestrian Dead Reckoning positioning system which is based on mobile sensor data and discusses its results. Chapter 7 introduces the server-based positioning system and its implementation and also discusses its results. Chapter 8 discusses the results overall and concludes the thesis.

2. BACKGROUND AND LITERATURE REVIEW

This chapter includes information about the definition of location, context-awareness, history of positioning and positioning techniques. Section 2.7 consists of the literature review on the subject of positioning.

2.1. THE CONCEPT OF LOCATION

Location may be one of the most important elements in human history due to its importance related to our survival. It can be defined as the position or a particular place of a person or object in three dimensional space.

Throughout history, many aspects of our daily life are governed by the concept of location. Humans used prominent features around them to describe their positions, also they imposed religious importance on some natural places or formations that exhibit extraordinary features. Thus, location and places associated with them became an important part of human life. Nowadays we use popular landmarks, public parks or junctions to define our location.

But the true breakthrough of location usage is started within the last decade with the ever improving technology. Smartphones, with their integrated localization chips, changed our way of living. We now live in the age of applications that use internet and localization to serve us information and entertainment.

2.2. CONTEXT-AWARE SYSTEMS AND LOCATION-BASED SERVICES

According to Dey, “Context is any information that can be used to characterize the situation of an entity.” [2]. Thus, context aware systems can acquire information about a person and can answer some of the following questions;

- Who am I with?
- What am I doing?
- Where am I going?

- When do I need to leave?
- How am I feeling?
- Why am I here?

Using contextual information many applications can serve location-based services. Such applications can use location information to improve the content served by the provider or to provide a better user experience. Most popular applications that provide location-based services can be listed as below;

- Social network
- Real-time positioning
- Location sharing
- Health related
- Car or User Navigation
- Location-based advertisement

2.3. A BRIEF HISTORY OF POSITIONING

Since the beginning of the history, humanity, in order to increase their chance of survival, tried to expand their influence and conquer unknown lands to find new resources. Thus, exploration and reliable positioning quickly became a problem in early human societies.

Early travelers used the sight of known landmarks and geographical characteristics such as mountains, rivers, and valleys. This kind of navigation was of course very limited as it was generally tied to line-of-sight and proximity to a certain geographical feature. The need for a more reliable navigation is risen when humans started to use sea as way for transportation. The simple methods like staying within sight of land and studying wind patterns proved to be not enough.

Thus, Minoans, one of early civilizations from Crete started to use celestial features such as stars and constellations. This enabled them to travel during night and reach places far from their land of origin. In the case of Minoans, they travelled to Thera (present day Santorini Island) and Egypt [3].

For almost over 2500 years, basic celestial navigation served humanity until the first use of magnetic compass. Although it was developed around 200 BC by Han dynasty in China, the first use for navigational purposes occurred in 11^{th} century by Song dynasty. The compass later adopted by Islamic world and brought to Europe during 1300s which later flourished the age of exploration. With the help of compass and improved navigational techniques, Europeans discovered unknown lands and continents as well as riches. During this age, the first circumnavigation of Earth is accomplished by the expedition of Magellan, a Portuguese explorer [4].

During and after the age of exploration, the need for accurate latitude measurement has paved way to enhanced tools such as cross-staff, astrolabe, sea charts by magnetic compass, and sextant. Accurate longitude determination is made possible by the invention marine chronometer in mid 1700s [5].

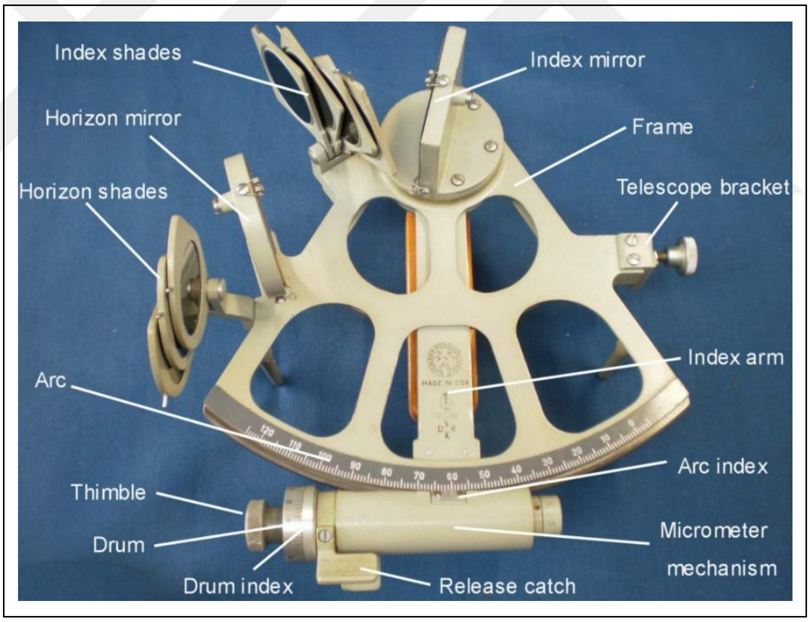


Figure 2.1. Parts of sextant [6]

At the turn of 20^{th} century, the first radio installations are implemented in navigation. With the help of technological advancements, 20^{th} century has witnessed the invention of many radio based technologies, such as radio direction finder in 1906, radar systems in 1937, and LORAN the first electronic air navigation system developed by MIT in 1940 [7].

The launch of the first artificial satellite Sputnik into orbit by Soviet Union in 1957 paved the way to new positioning methods. For the first time in history, seven artificial satellites are placed into Earth's orbit to provide fairly accurate (80 feet) location estimation. This system is called TRANSIT and it was made operational in 1962 [8].

2.4. THE AGE OF SATELLITE POSITIONING

In line with the development of several independent navigational systems such as TRANSIT [8], SECOR [9] and LORAN [10], a more superior system is planned for development that embodies the best aspects from each system. Thus, in 1973 Defense Navigation Satellite System, later to be called Navstar-GPS, was born by as a military project by Pentagon. The first prototype block of ten satellites was made operational by launches between 1978 and 1985 [11].

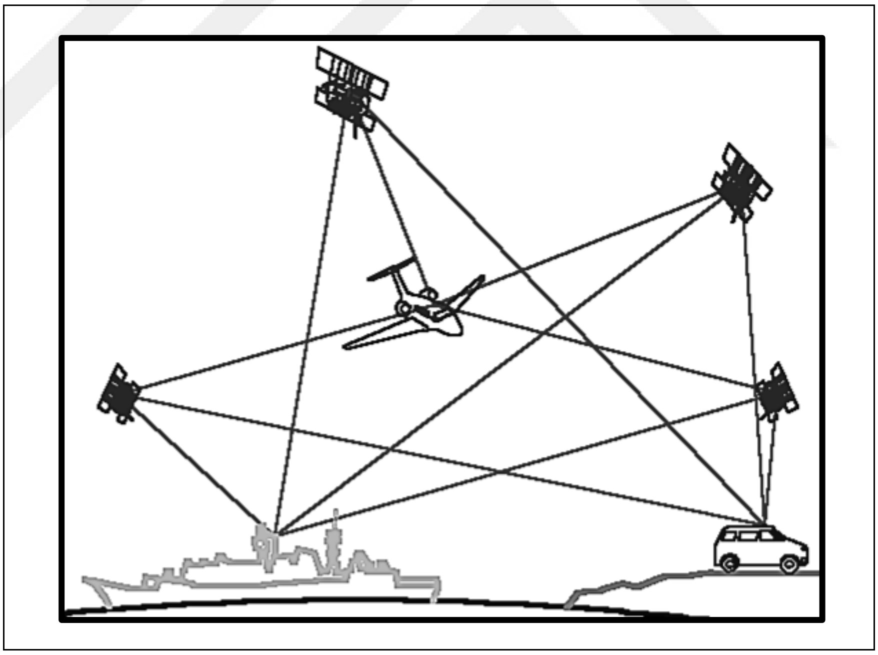


Figure 2.2. GPS overview [12]

GPS is based on basic principle of known position of satellites and accurate time keeping. The satellites have a very accurate atomic clocks which are synchronized across all of the satellite constellation and ground (Earth) clocks. The receiver, in order to estimate its location, must solve equations by the information acquired from constantly transmitting satellites, to obtain its position and its deviation from atomic clocks. Thus, in order to system to work, the receiver need to acquire signals from four satellites in order to solve four unknown variables – x, y, z and Δt [13].

Approximately at the same time with the development of GPS, a similar Russian satellite navigation system is planned for development. Prior to this system, several other positioning systems were in use by the Russians. In order to combine the best aspects from these systems and improve the localization accuracy, a single system for a navigation was planned by the cooperation of Russian Ministry of Defense and Russian Army in 1970. The system was called Global Navigation Satellite System (GLONASS). The first satellite for the system was launched in 1982. Although the system suffered several problems throughout its deployment, the constellation continued to be operational in Russian territory. By the end of the year 2011, the 24 satellite constellation completed successfully and the worldwide coverage is achieved [14, 15].

Nowadays there are other global satellite navigation systems in development by different countries such as Galileo by European Union and BeiDou by China. They are being developed to become global navigation systems having full satellite constellations. There are also regional systems like NAVIC (Navigation with Indian Constellation) by India, and Quasi-Zenith Satellite System (QZSS) by Japan.

2.5. PATH TO INDOOR LOCATION DETECTION

The satellite navigation systems performs best and are mostly reliable in outdoor environments. The clear view of sky and direct line-of-sight to satellites provide reliable system operation. Satellite navigation devices sometimes cannot acquire a fix in dense urban areas due to the signal attenuation caused by high skyscrapers. Even in these situations, high elevation satellites can help to acquire a fix to improve the system operation.

The problem becomes evident when the satellite-transmitted signal is attenuated and approaches to the noise floor. These kind of attenuation can happen in dense urban and of course in indoor environments. In indoor environments the roof of the buildings and floors above cause total signal attenuation where a navigation device simply cannot acquire a fix.

To overcome the positioning problem in indoors, various technologies and methods have been proposed. Some of these technologies are Ultrasound, RFID, Infrared, Bluetooth and WLAN. Among these technologies the IEEE 802.11, which is also known as WLAN, was the most popular and one of the most published location detection technologies in literature due to its widespread prevalence. Every single mobile device ranging from smart watches to laptops has a WLAN module that enables it to access wireless networks. As a result, this enables exploitation of the radio signals properties, such as signal powers with various WLAN infrastructures. This made distance determination between the device and the point of signal measurement possible, which is the first step for position estimation.

Indoor positioning techniques follow more or less the same notion with GPS to estimate the location. However, the culprit here is that the stationary and moving obstacles also affects the indoor positioning systems by attenuating the transmitted signal. The problem then lies into overcoming the attenuation problem by either increasing or re-positioning the signal-transmitters or incorporating sophisticated algorithms that can partially eliminate this disadvantage.

2.6. INDOOR POSITIONING

The indoor positioning systems can be categorized into radio signal based, sensor-based and server or client based systems. There are also device-free systems where position estimation done without the need for a mobile device.

2.6.1. Signal-Data Based Systems

Signal-Data based positioning utilize the information carried or possessed by the received radio signals. Such information can be specifically embedded by the implementer of the system or can be simply the result of the signal propagation in the medium.

Time-of-Arrival [16] (ToA) and Time-Difference-of-Arrival [17] (TDoA) are two techniques where precise time information is used to determine time-of-flight duration of the received signal. Using this precise time value, the distance to the transmitter can be calculated. The transmitter embeds its own time information just when the signal is about to leave, and the receiver compares the origin time with the received time to make a calculation. In order for these systems to work, precise time keeping and synchronization is a necessity. This requirement increases both the complexity and cost of the system.

Angle-of-Arrival [18] (AoA) is another technique where the source of the signal can be calculated using the angle information of the incoming radio waves to a receiver. The technique relies on TDoA, where multiple wave measurements at a single antenna array can result in small but discernible time differences. This phenomena can be used to calculate the angle of an incoming radio wave.

2.6.2. Signal-Magnitude Based Sytems

Signal-Magnitude based positioning utilize the received signal strength powers to calculate the signal propagation distance, which is the path signal travelled to arrive to the receiver. In ideal conditions, the signal propagation in free space dictates that power received is inversely proportional to the square of the distance in meters (Eq. 2.1). In other words, the power received decreases relative to increase in the distance to the transmitter. By using this principle, the approximate distance between two points on radio path can be evaluated.

$$P_r = P_t D_t D_r \left(\frac{\lambda}{4\pi d}\right)^2 \tag{2.1}$$

Trilateration [19] was the first technique to be utilized for indoor positioning by making use of the signal powers due to its simplicity. It does so by mapping radio signal powers as a function of distance. The position information can be obtained by measuring received signal powers from three transmitters with known positions. The gathered information is then used to calculate the estimated location.

Fingerprinting [20] is another technique to utilize signal powers. This is a much more powerful technique because it involves two phases to eliminate the signal fluctuations and real-time sampling errors. The positioning process is divided into a learning (offline) phase and positioning (online) phase. In the learning phase, pre-determined points are selected with a set distance in between them (such as two meters) and received signal powers are sampled at these locations to construct signal map of the environment. In the positioning phase, the real-time signal readings are compared to the sampled points in the signal map and the position estimate is selected among these points.

2.6.3. Client or Server Based Model

Indoor positioning systems can be further categorized by their processing locations. The majority of them are client-based systems where position determination is done at mobile terminals such as smartphones, tablets and laptops. The mobile device performs the calculation onboard, by the help of the information received from peripheral sources. These sources can be radio signal emitters, such as WLAN access points.

On the other hand, server-based systems provide much higher processing power due to a diverse configuration options as well as cloud computing. In these systems, the position determination is performed on the remote server and the mobile device itself is used as a signal source. The signal transmitted from the mobile device can be measured at more than one location and can be fed to the server to accomplish the position estimation.

The main benefits of server-based positioning systems are mobile operating system independence and scalability. In recent releases of mobile operating systems many low level functionalities are progressively being disabled or becoming harder to access due to security concerns or OS implementations. For example, iOS operating system blocked accessing received radio signal strength values and uses randomized MAC addresses for probing access points as a security measure [1]. This results in fragmented software across mobile platforms or in some cases completely hinders ability to perform third-party positioning. Thus, using a server-based solution eliminates any client-side obstacles, and improves mobile-side maintenance by minimizing the necessary requirements. Also, if needed any improvement in positioning process and simple maintenance can be done in real-time on server without hindering users experience or imposing a new app version requirement on users.

The drawbacks in server-based positioning systems is its complexity and operating cost. Client-based systems can operate with minimal hardware such as already prominent access points. Whereas, server-based systems require a centralized server to perform positioning calculation and the peripheral sensing equipment specialized for capturing or “sniffing” airborne WLAN packets. The maintenance of the server also plays an important role, if the server faces a downtime, the entire system becomes unavailable. Client-based systems, on the other hand can continue to function with lesser peripheral units albeit at a lower accuracy.

2.6.4. Device-Free Positioning

Like many positioning techniques, device-free positioning utilizes various methods ranging from radio signal based to sound and visual guided systems. These systems do not require a signal emitting or receiving device on the user, and function using radio signal, ultrasonic [21] or visual motion detection by the use of a camera. For this purpose, passive infrared (PIR) sensors detecting changes in infrared spectrum can also be used to capture the heat generated from human subjects for tracking and detecting movements [22].

2.7. LITERATURE REVIEW

The lack of consistent and reliable location detection mechanism for indoor environments attracted a lot of interest from both academia and industry. As a result, over the last decades many localization techniques were developed and tested with various properties. Among the proposed techniques, the most popular ones utilized radio signals as their key component.

In 2001, the Bat location sensor system (Figure 2.3) [23] is developed by AT&T Laboratories in Cambridge using ultrasonic personalized badges known as Bats. Trilateration technique works by emitting an ultrasonic signal from the badge and using the receivers on the ceiling to calculate time-of-flight values of the signal. Using these values, the distance of the Bat and the ceiling mounted sensor are determined. Trilateration technique is then utilized to perform location detection. The test results indicated that the Bat location sensor system estimated the location of badge wearing personnel with 3 cm error rate 95 per cent of the time.

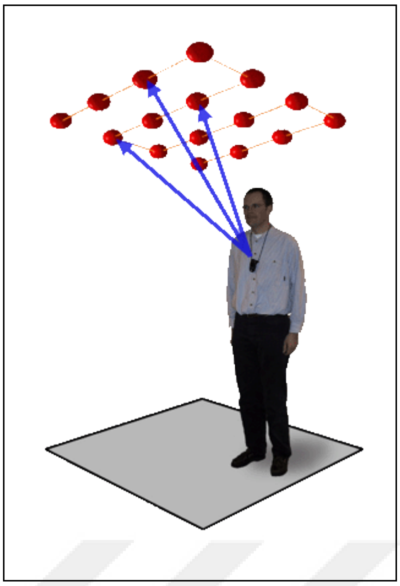


Figure 2.3. Bat location sensor system [23]

Triangulation technique is also used by another early implementations of a indoor positioning system. This system was implemented by Bergamo and Mazzini [24], which used triangulation on Wireless Sensor Networks by the received signal powers from two wireless beacons that were placed to two known locations. Their work focused on improving accuracy by modeling wireless fading when movement is present.

Another venue that has been looked into using trilateration was the Bluetooth technology. Accordingly, Castano et al. [25] used received-signal-strength levels to determine the distance for triangulation calculation and achieved an error rate of 3 meters in an 225 square meter indoor environment.

Although being a relatively simple and widely adopted technique, triangulation can be unreliable in many environments where the free-space propagation of radio signals is susceptible to scattering and reflection due to uneven placement of objects and human activity. To overcome these problems, fingerprinting map creation using received-signal-strength levels have been proposed which was very popular approach in academia due to its successful results. Following this trend, Bahl and Padmanabhan [20] designed an RF based localization system based on empirical and signal propagation models in location estimation and compared several methods in each model. Empirical method based on fingerprinting achieved distance error of just under three meters and their findings concluded that it was the best among the ones they compared in their study.

Similarly, Sanchez et al. [26] used the fingerprinting technique as a baseline and proposed an improvement by adding trilateration and probability distributions to improve the standard fingerprinting approach's accuracy. In their proposed method, Sanchez at al. used Baye's theorem to perform the localization and used triangulation technique to narrow down the search area ultimately to eliminate the addition of unnecessary fingerprint data.

Taheri et al. [27] designed a platform independent tool for computers to evaluate different wireless NICs and the performance of two positioning algorithms utilizing the fingerprinting technique.

Martin et al. [28] developed the first system that entailed both offline and online phases of the fingerprinting approach on a smartphone. Accordingly, the proposed system developed by Martin et al. was tested using four algorithms including nearest neighbor and closest point. Their system achieved an error rate of less than 2 meters with an accuracy of 39 to 48 percent.

Farshad et al. [29] implemented an indoor positioning system utilizing Wi-Fi signals to examine the effect of Virtual Access Points (VAP) in fingerprinting-based indoor localization. The findings showed that using VAP approach has a significant impact on the quality of location detection in a setup where multiple devices with different specifications are in use.

From a different perspective, Ni et al. [30] worked with Radio Frequency Identification (RFID) tags and developed a prototype system using RFID for indoor location detection called LANDMARC. Rather than using RFID readers at predetermined locations, they placed passive reference tags as a way to identify the location much like landmarks in daily life and achieved less than 3-meter localization accuracy.

On the other hand, some researchers also worked on ToA technique on WLAN, and more specifically on the IEEE 802.11a version. Reddy et al. [16] used embedded time information on 802.11a frames as a way to perform a ToA estimation. Within a 802.11a frame, short training symbols (STS) and long training symbols (LTS) were manipulated with the help of correlation to achieve the positioning estimation.

Research on other techniques such as TDoA and AoA were also undertaken by various authors. Yamasaki et al. [17], developed a TDoA based positioning system using IEEE 802.11b WLAN. In their work, they used the clock information within a WLAN frame to measure the clock error caused by the inadequate synchronization between access points. They resolved these errors by using known coordinates of the access points. Their findings indicate an error-rate of 2.4 meters within 67 per cent accuracy. Similarly, Tay et al. [18], developed an AoA system using Ultra-Wide band (UWB) technology, where they used a biased estimator to perform AoA positioning. The results of the test conducted yield maximum error-rate of only 11.91 centimeters.

Using similar technology Yang and Fathy [31] developed a UWB-based radar system in 2005, which operated at 10 GHz. The main reason for choosing the UWB technology was its strong penetration capabilities so that it can be used to create a through-wall image reconstruction with high precision. Counter to its attractiveness, their initial system suffered a low sampling rate. In 2009 they improved the capabilities of their previous system by designing a real time see-through wall system with a custom FPGA firmware. This custom firmware solved the sampling problem that they faced in their initial system and allowed them to achieve 100 Msamples/s. The upgraded version of the proposed system allowed motion tracking too.

Generally the positioning systems are designed and tested in relatively small or controlled environments where systems behave optimally. Hence, the test results do not always reflect the real life performance of these proposed systems. Therefore, nowadays there are increasing number of studies that look into the performance and the issues faced when the evaluations are conducted in large real-world indoor environments. Accordingly, Wirola et al. [32] has comparatively highlighted the requirement and methodology differences between implementing indoor positioning system in a large and small scale indoor environments. Li et al. [33], developed a positioning system at Queen Mary University in London which aims to identify room the user is currently in. The system is deployed on the second and third floors of Electronic Engineering building. In this study, they incorporated Wi-Fi RSSI positioning system with GSM-based approach and their results indicate that the proposed system achieved room level positioning with 72 per cent accuracy.

In a larger scale test environment, Mathisen et al. [34] evaluated several positioning techniques utilizing the existing Wi-Fi infrastructure in a university hospital floor of

160,000 square meters. In this study, the authors propose a new approach to evaluate the problems associated with large scale positioning systems over time and elaborate on different techniques to interpret the positioning. The study also reports on the experience with implementing and utilizing the system. Their proposed system, for various algorithms, achieved a mean error-rates from 8 to 15 meters relative to ground positions.

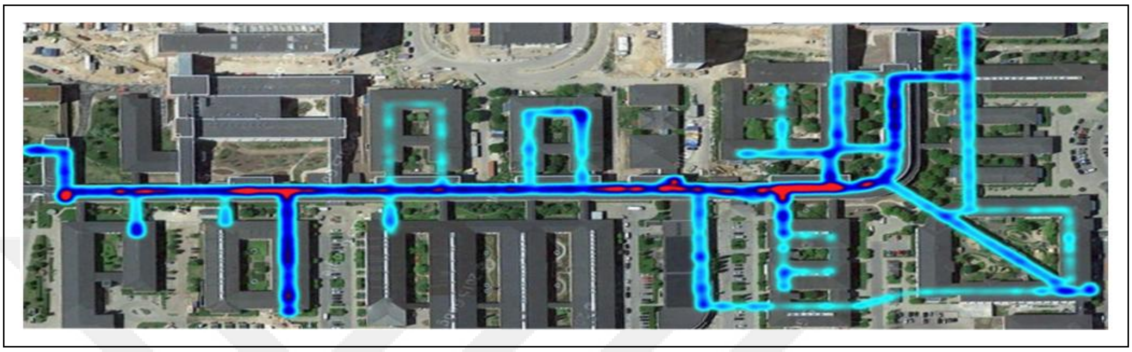


Figure 2.4. Heat map of position estimation error [34]

With the recent proliferation of smartphones with Bluetooth low energy (BLE) beacons that can communicate with other devices and with other affordable off-the-shelf signal-emitting sensors, the dominance of Wi-Fi use for indoor location sensing is greatly challenged. Because of their low-cost, small size, and long life which can be achieved using small batteries, beacons have been one of the most popular gizmos used for location estimation [35, 36].

Following suit, Wu et al. [37] used BLE signals and iBeacons for indoor location estimation. The system is designed for open areas where there are not that many objects that could affect Bluetooth signal. In the proposed system, the distance between iBeacons and user's smartphone is calculated by the use of the Received Signal Strength (RSS) Indicator. The location estimation is performed using the trilateration method and the implemented prototype is tested in an 1800 m^2 library using an iPhone 6 smartphone. Their findings indicate that their results, when compared with similar studies, outperform and provide more precise location estimation.

With the recent technological shift, sensors and single-board controllers/computers are easily accessible and available at a very low cost. As a result, tracking movements and changes in an environment get reasonably easier by embedding and scattering sensors to every corner and object. Accordingly, researchers have utilized multiple magnetometers, accelerometers, and even cameras to sense the changes in the environment. Using the same analogy, Fentaw and Kim [38] created an indoor localization system using the magnetic field measurements. Since every location in a given building is believed to have its own unique magnetic field which is the result of both natural and manmade sources like steel structures and other electronic appliances [39], changes in these can be used to track any movement in the environment. However, the use of these magnetic field fluctuations as the only distinguishing feature is not adequate since magnetic field values might not be as diversified as needed for location estimation.

Kawaji et al. [40] proposed an image-based indoor positioning system for Railway Museum of Japan. In this system, a database is created to reflect the map of the environment using omnidirectional panoramic images with location information tags. Images in the server are taken from various angles and heights. After the database is created, the users can take pictures in different locations and upload them on the server, which compiles the received images together and compares it with the panoramic images in the database with the panoramic images to estimate user’s location.

Bearing in mind all the previous work described above, the following section will detail the methodologies that can be used to design, implement and evaluate a server-based positioning system.

3. METHODOLOGY

This section details the methodology used to design and implement and comparatively evaluate a server-based location detection system.

3.1. DISTANCE DETERMINATION

Determining the distance between two points is the first step of location detection. One of these points has a fixed location with known coordinates and, generally the other one is a mobile device whose location will be determined. There are several methods that can be used to determine the distance. Such as time of arrival (ToA), time difference of arrival (TDoA), angle of arrival (AoA) and received signal strength indicator (RSSI). These methods utilize radio signals and their propagation characteristics in free space.

3.1.1. Time of Arrival (ToA)

Time of arrival is a method where distance between user and transmitter is calculated by the transmission time of the signal (Figure 3.1). The clocks of all transmitters and receivers should be synchronized for this method to work properly otherwise location finding results will be incorrect. The synchronization requirement is the major drawback of this method.

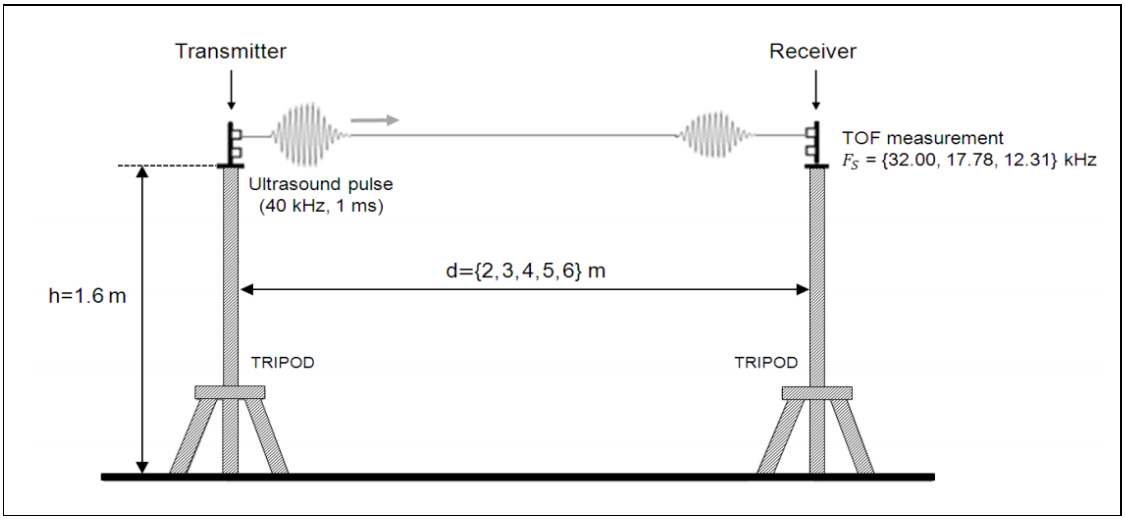


Figure 3.1. Time of arrival [41]

The technique works by sending a signal from the transmitter to the receiver. The speed of the signal is limited by the physical qualities of the medium, which at most can be equal to the speed of light. Assuming that the clocks at both ends are synchronized, the distance can be calculated using the time passed during transmission multiplied by the speed of the signal.

3.1.2. Time Difference of Arrival (TDoA)

Time difference of arrival is a method that uses time measurements at different base nodes when a signal arrives from a source node. Similar to ToA, the position of these base nodes must be known and they must be separated enough for this technique to work. However, in this technique, the time synchronization of source is not needed because only the time differences at the received base nodes are used in position calculation. The technique utilizes the signal propagation in free space (Eq. 3.1), where the signal arrives in different times due to distance difference from the source.

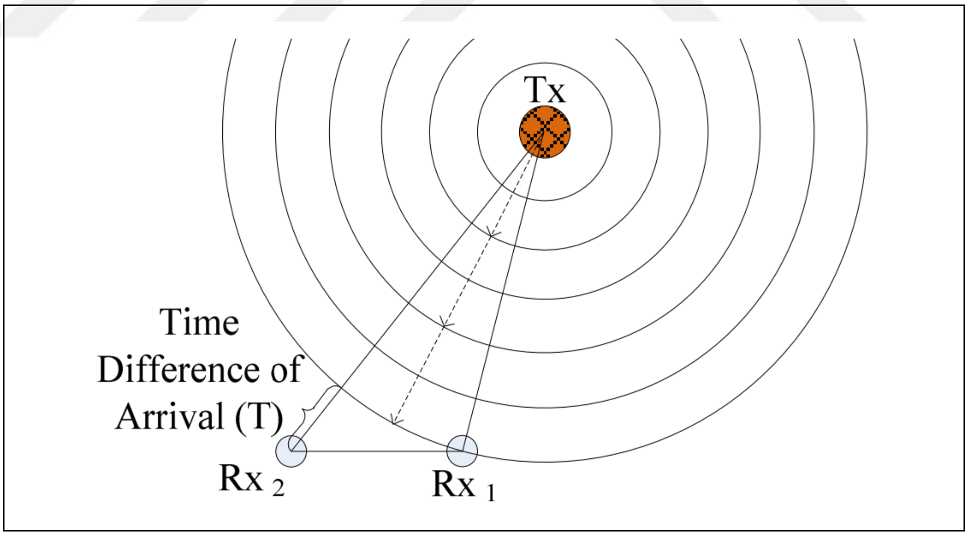


Figure 3.2. Time difference of arrival [42]

The time of arrival differences at the base nodes are represented by an hyperbola, which is defined by the figure formed when distance differences from two fixed points in space is constant. In 2D space, at least three base nodes are needed to form two hyperbolas, thus their point of intersection denotes the estimated position of the source node.

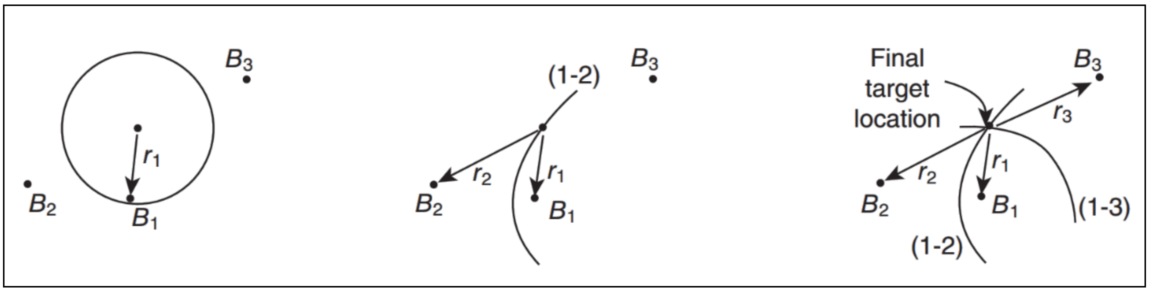


Figure 3.3. Time difference of arrival [43]

TDoA eliminates the need for source node clock synchronization, as long as the base node clocks are synchronized the error from source node will be equal at all base nodes. Since, the technique relies on time differences, the possible source time error will be mitigated.

3.1.3. Angle of Arrival (AoA)

Angle of arrival technique utilizes the incoming direction of the signal, which is also known as direction of arrival (DoA). The direction of signal determined by the incident angle it makes when it is captured by a receiver.

In general AoA systems require high complexity and high cost components such as antenna arrays with RF modules to measure the angle of incoming signal. These antenna arrays consists of multiple antenna elements spaced in half of wavelength of the signal to minimize measurement error. Also, the synchronization is very important in the antenna array, because the system utilizes time differences of arrival and signal phases detected at multiple elements. The angle is then determined by these TDoA and phase information. AoA systems are susceptible to multipath interference, the technique works best when the signal propagates in direct line-of-sight.

Regarding the necessities of AoA systems, the complexity and cost factor plays an important role in positioning system design and choice. Thus, despite its favorable accuracy, the AoA systems are not as widespread as other RSSI-based systems [43].

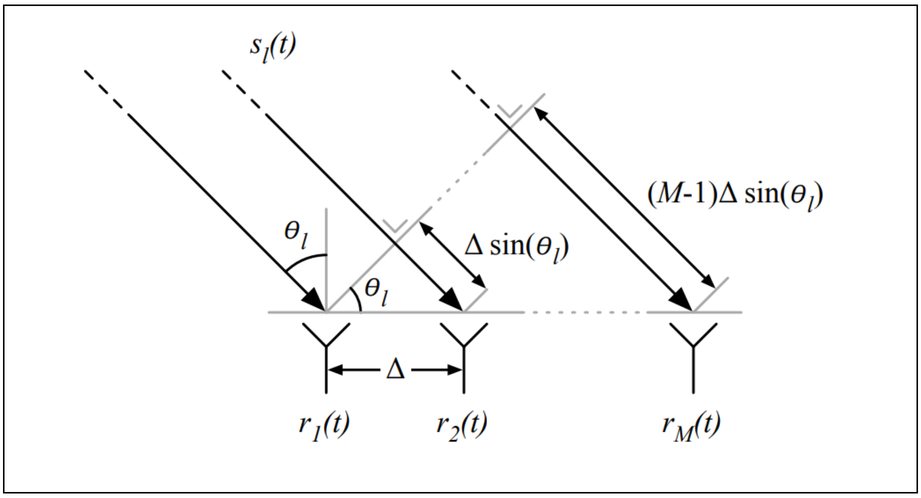


Figure 3.4. Angle of arrival [44]

3.1.4. Received Signal Strength Indicator (RSSI)

Most of the techniques discussed above require line-of-sight (LOS) operation. However, indoor environments seldom have direct LOS, which degrades the value of the time and the angle information extracted from the received signal due to multipath effect [45]. On the other hand, RSSI method performs well both in LOS and non-LOS environments, changing with respect to the distance from the transmitter. RSSI distance determination mainly uses IEEE 802.11 wireless local networking standard, with wide availability in many consumer handsets and extensive deployment in many urban areas.

IEEE 802.11 is a popular networking standard, having many variants that use different coding schemes and RF utilization with ever increasing data link rates. IEEE 802.11b/g/n variant operates at 2.4 GHz with 13 overlapping channels (only 3 non-overlapping), whereas 802.11a/n/ac operates at 5 GHz of wireless spectrum having as many as 23 non-overlapping channels with an option for increased bandwidth by channel bonding [46]. Although these properties of 5 GHz spectrum make it less crowded and less prone to co-channel interference with higher chance of throughput, limited wireless coverage and dead spots are one of the main problems of 5 GHz band. Moreover, regional restrictions, and limitations such as, weather radar operation on central 5 GHz frequencies and requirement of Dynamic Frequency Selection (DFS) on certain channels make 5 GHz band deployment less preferable.

On the other hand, 2.4 GHz band is more standardized and has rather consistent regional restrictions across different regulatory domains, but have high interference problems. Many unlicensed consumer products such as devices using Bluetooth, cordless phones, wireless mouse and keyboard solutions as well as microwave ovens work in this frequency spectrum.

Consequently, regardless of its channel scarcity, and highly probable interference, the 2.4 GHz band is still the dominant wireless band in wireless local area network deployments. Therefore, RSSI is proven for being an effective, cost-efficient and simple method and IEEE 802.11n WLAN technology at 2.4 GHz frequency spectrum is utilized as the infrastructure. RSSI is a good option for determining the distance between devices because of the attenuation property of radio signals when the distance between the receiver and the transmitter increase. Also, it is an easier method to implement and it does not have the complexities of the other methods. Using the RSSI method, the distances between two points of measurements in terms of signal propagation can be calculated using the Euclidean distance theorem (Equation 3.1).

$$d = \sqrt{\sum_{i=0}^{n} (q_i - p_i)^2} \tag{3.1}$$

3.2. TRILATERATION

Trilateration is a method for location estimation that requires at least three transmitters with known locations. For each transmitter, the distance between the user and transmitter can be calculated using the aforementioned RSS readings. Therefore, by knowing the signal strength parameters for three known transmitters an estimated location can be calculated using points of intersection [47].

Trilateration method is also used with satellites in GPS and GLONASS. In these systems, the location of the satellites is ever changing around the globe, but their location is calculated and sent to the user to update its satellite location database. A user device that knows the absolute position of the satellites at any given time, can then calculate its distance to them and from there using the three of the distances can estimate its current location on earth [48].

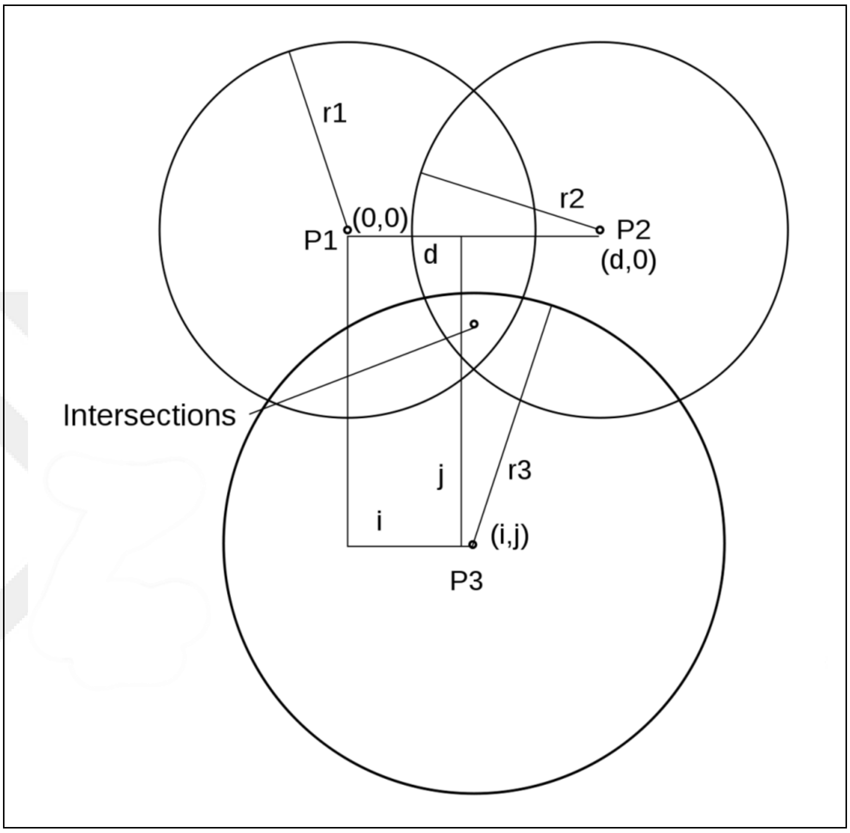


Figure 3.5. Trilateration [49]

3.3. TRIANGULATION

Triangulation method is a similar method to trilateration, utilizing at least three transmitters with known locations. In this method, rather than utilizing distances to these known locations, the angles within the triangle formed by these three transmitters are utilized. The distances to the transmitters can be calculated using trigonometry, thus the position of the mobile unit can be estimated.

Triangulation is also closely related to the AoA method. It utilizes the incoming incident angle of the radio signal, which can be obtained using the position and the estimated distance of the signal source.

3.4. FINGERPRINTING

Fingerprinting is a technique that is evolved to in-crease the positioning accuracy in non-LOS indoor environments by constructing a radio map at pre-determined target locations. It is performed by sampling more than one RSS measurement over time in each target reference point to better map the environment. Once the signal map of the environment is con-structed, the location detection can be achieved by com-paring the real-time signal information with the signal map and calculating the position using a subset of signal information contained in the map.

To utilize this technique, location detection procedure is broken down into two distinct phases – offline and online phase.

3.4.1. Offline Phase

This phase can also be called learning phase, implying that the necessary signal characteristics of the environment is constructed for the real localization.

Firstly, the indoor environment is evaluated and the locations for signal sampling are determined. These locations are called reference points (RP), with each point having a distinct x and y coordinate and an array of average signal values. As the RSSI value collection and signal map generation can be a time-consuming process, an offline phase tool is needed to help the collection of acquirable signal strengths of access points (AP) at RPs.

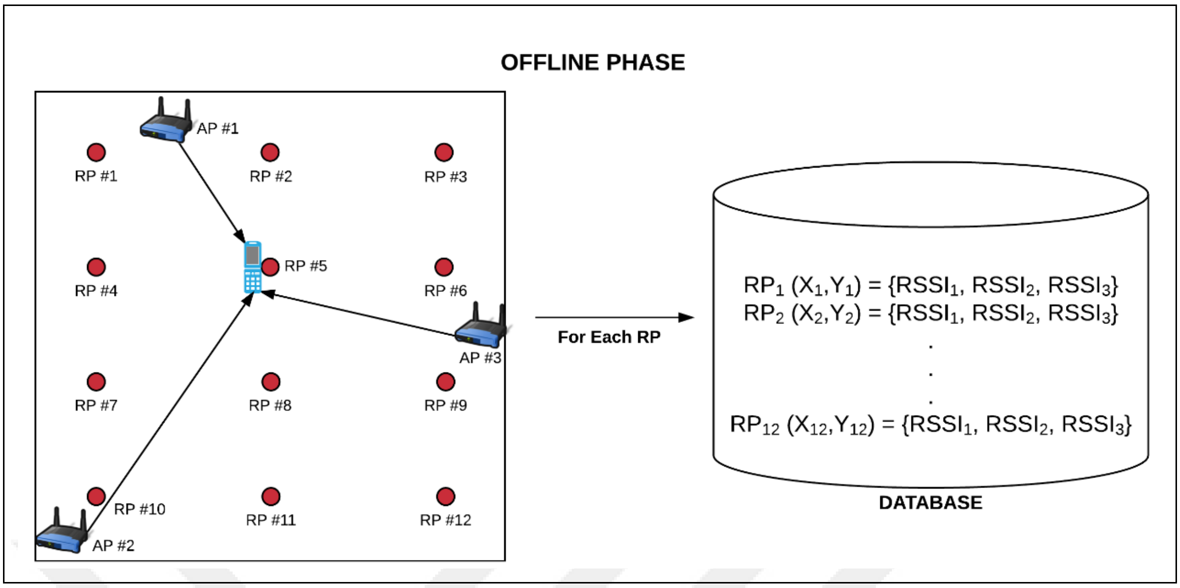


Figure 3.6. Offline phase of fingerprinting technique

As depicted in Figure 3.6, the idea is to move the mobile device through the RPs one by one, collecting RSSI samples at each RP. For a single RP, the mobile device collects a pre-determined number of RSSI values for each AP received from each accessible AP, and stores the average of these AP-specific RSSI values in signal map database. The average of RSSI samples measured at every RP is inserted into the database, as RP Data (RPD) vector in the form {ID, S_1, S_2, S_3} where ID identifies the reference point, whereas S_i denotes the signal strength received from the AP_i at a specific RP.

3.4.2. Online Phase

In this phase, the real-time localization operation is performed. Accordingly, the mobile device initiates the collection of RSSI values from each available AP at the point where the location is to be determined. Euclidean distances are calculated by using the collected RSSI of the available APs and signal map retrieved from the database. Since the signal map contains signal measurements done at each RP in the environment, the Euclidean distance calculation is performed for each RP present in the signal map. Thus, for every RP in the signal map, the distances between MU and each RP is obtained. After this step, K-Nearest Neighbor (KNN) algorithm is used to calculate location of the MU by selecting the closest RPs. The steps of this operation are given in detail below.

- For a given test point (TP), make at most 10 observations per each available AP using mobile device and store them in the observation set (OS). Here OS_i denotes observation stack of i^{th} AP. $OS_i = \{O_1, O_2, ... O_{10}\}$
- For each AP, calculate the average of all observations in OS, and generate the average signal strength (SS) vector of MU. $SS = \{s_1, s_2, \dots s_n\}$ (Here n represents the number of available APs at the location of mobile device)
- For each RP calculate the Euclidean distance between the RP and TP using the RPD and SS vector.
- Perform KNN algorithm for the closest k neighbors (RPs). The weighted average of the x and y coordinates of the candidate RPs are the estimated MU location.

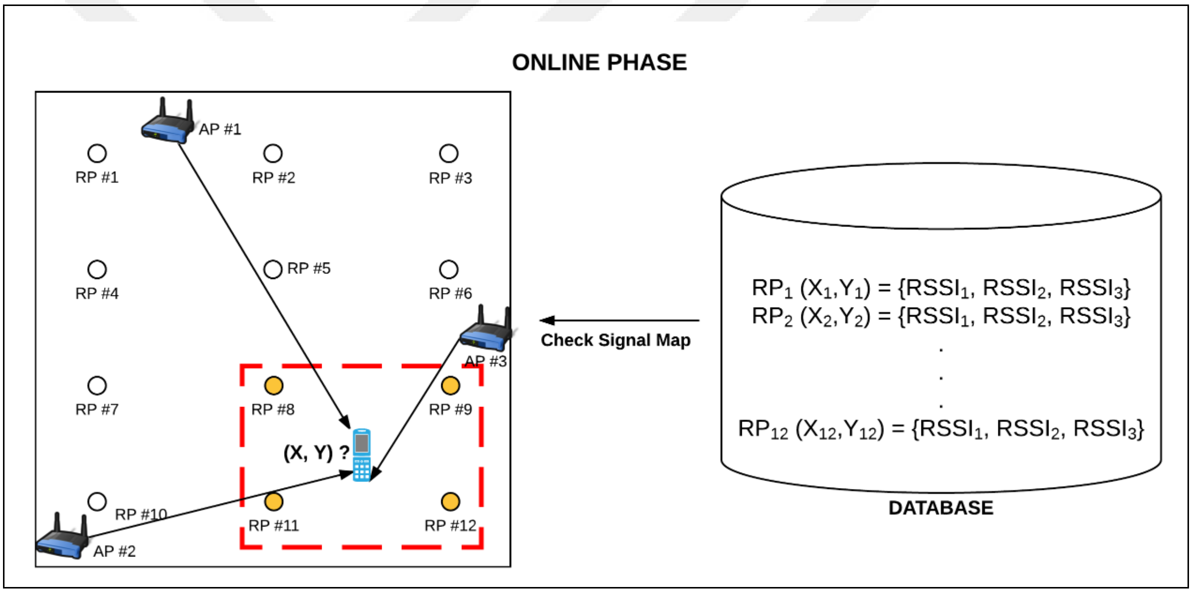


Figure 3.7. Online phase of fingerprinting technique

3.5. ULTRA-LOW BAND (UWB) TECHNOLOGY

Ultra-wide band is a radio technology that utilizes a wide spectrum of frequency bands with very low power over a short distance. According to the FCC [50], the UWB is described as technology utilizing the frequency spectrum greater than 500 MHz, having around -40 dBm/MHz spectral density in the range 3 to 10 GHz. Originally it has been used for radio communication but recently it is being utilized for indoor positioning.

UWB works by generating a series of ultra-short duration of pulses with very large bandwidth which can overcome multipath effects with high time resolution, resulting in better positioning accuracy. Also, although having a low power of transmission, the UWB can penetrate walls much easily, allowing a way for radar based device-free surveillance and localization. Thus, UWB can achieve high positioning accuracy at centimeter scale.

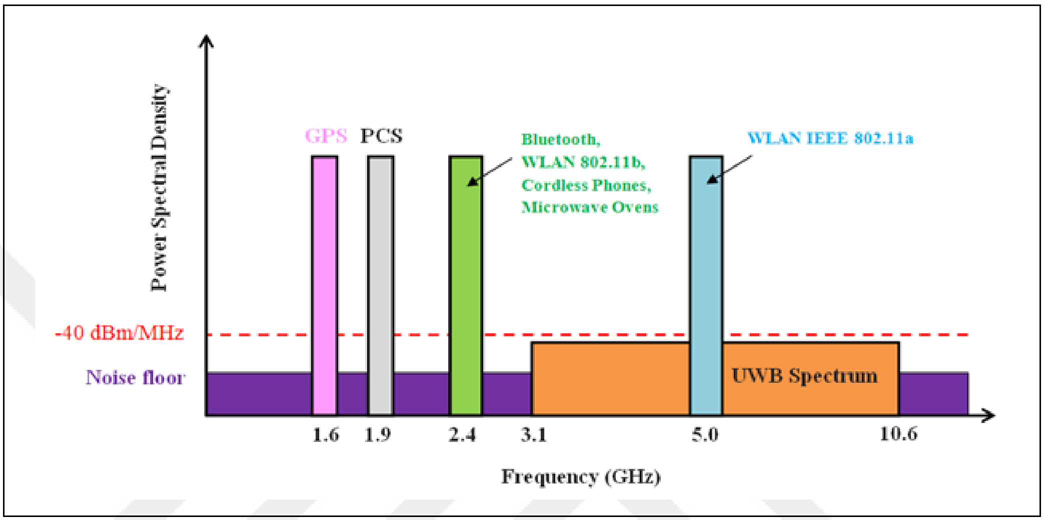


Figure 3.8. UWB among frequency spectrum [51]

Many of the positioning techniques can be used in UWB scenario. Fingerprinting and other geometric methods such as ToA, TDoA, AoA and RSSI can be utilized using UWB technology. Although UWB has aforementioned advantages, RSSI method does not benefit from ultra-wide bandwidth. Furthermore, complex and costly UWB antenna arrays are required to implement the AoA method [52]. Also, considering UWB's high time resolution due to wide bandwidth, ToA and TDoA based positioning approaches are much more suitable for UWB-based systems.

3.6. PEDESTRIAN DEAD RECKONING

Dead reckoning is a technique where the last position of an entity is calculated by using their previous position information. More specifically, the position is calculated by incorporating the previous position, the estimated speed, and the direction of an entity. In pedestrian dead reckoning (PDR) approach, instead of signal transmitting sources – such as access points or Bluetooth devices – a user is tracked from a known point using sensor data obtained from built-in sensors such as accelerometer, compass, and gyroscope.

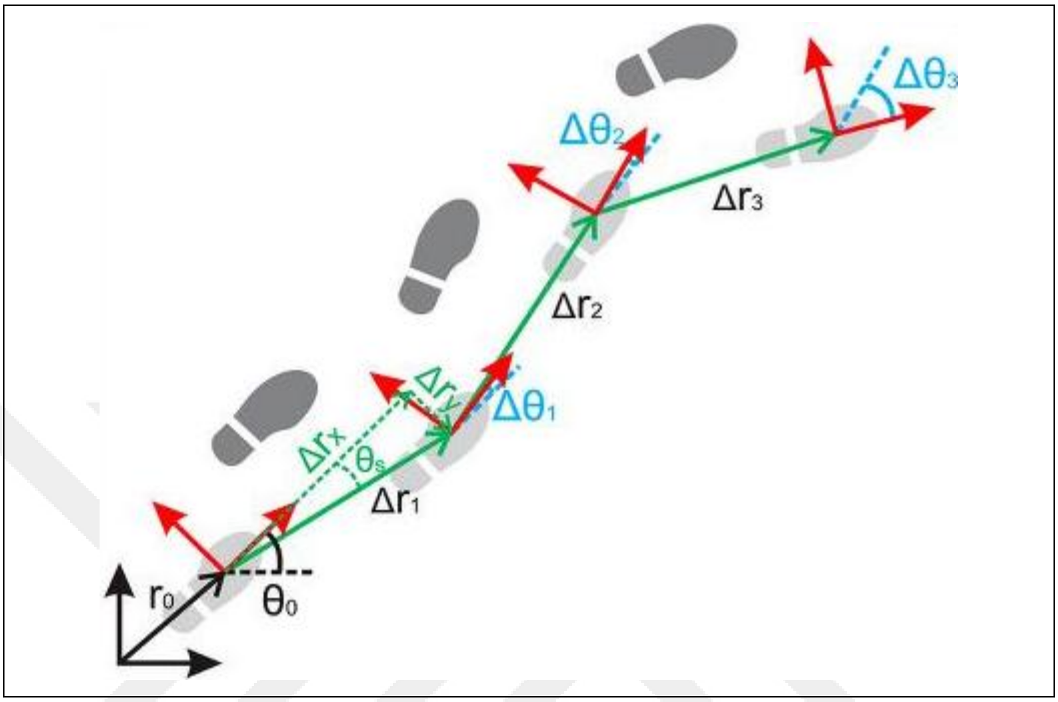


Figure 3.9. Pedestrian dead reckoning [53]

In the PDR algorithm (3.2), the previous position of the user is taken into consideration to calculate his/her next position. Because of this requirement, the user should always start from a known location. Sensor-based techniques can be used to estimate the direction the user is moving. Movement in the x, y and z-direction is calculated and total movement is added in the previous location

$$s(j) = \sqrt{s_x^2(j) + s_y^2(j) + s_z^2(j)} \tag{3.2}$$

In order to implement the pedestrian dead reckoning method, a step detection algorithm and a pedometer must be developed. On a mobile device an internal accelerometer can be used for step detection. Also, a threshold can be set to differentiate steps and other movements. Consequently, length of movement can be used to calculate the number of steps.

3.7. ALGORITHMS AND TECHNIQUES

This section details the algorithms and techniques involved in positioning systems such as KNN and K-Means Clustering algorithm.

3.7.1. K-Nearest Neighbor (KNN) Algorithm

K-nearest neighbor algorithm is a very simple classification and regression machine learning algorithm. It involves k-nearest training data to classify or determine value of a object by measuring its distance to that of the training data. K is a pre-determined number, which can be selected to optimally represent the class or value of an object.

In order to determine the closest training data, distance must be measured. One way to measure the distance between the object and training data is to use Euclidean distances. This distance value can also be used to improve regression based KNN, in which case the algorithm evolves in to weighted k-nearest neighbor (WKNN) algorithm. The weight can be taken as the inverse of the distance *1/d*, to improve the weight of the closer training data during calculation.

KNN is a very convenient algorithm to use especially in fingerprinting technique. During the online phase in fingerprinting, the position of the user is determined using the signal map generated earlier using the reference points and their known locations. Thus, the position can be calculated using a k-nearest candidate reference points. The localization accuracy can be further improved by using WKNN, in such case that the weights are taken using the complementary neighbors.

$$x = \frac{\sum_{i=1}^{4}(x_i * d_{4-i})}{\sum_{i=1}^{4} d_i} \qquad y = \frac{\sum_{i=1}^{4}(y_i * d_{4-i})}{\sum_{i=1}^{4} d_i} \tag{3.3}$$

In Equation 3.3, x_i denotes the x-coordinate of RP_i, y_i denotes the y-coordinate of RP_i and d_i denotes the measured distance between the user position and RP_i. By multiplying x_i and y_i with d_{4-i}, the weight can be incorporated in to the algorithm.

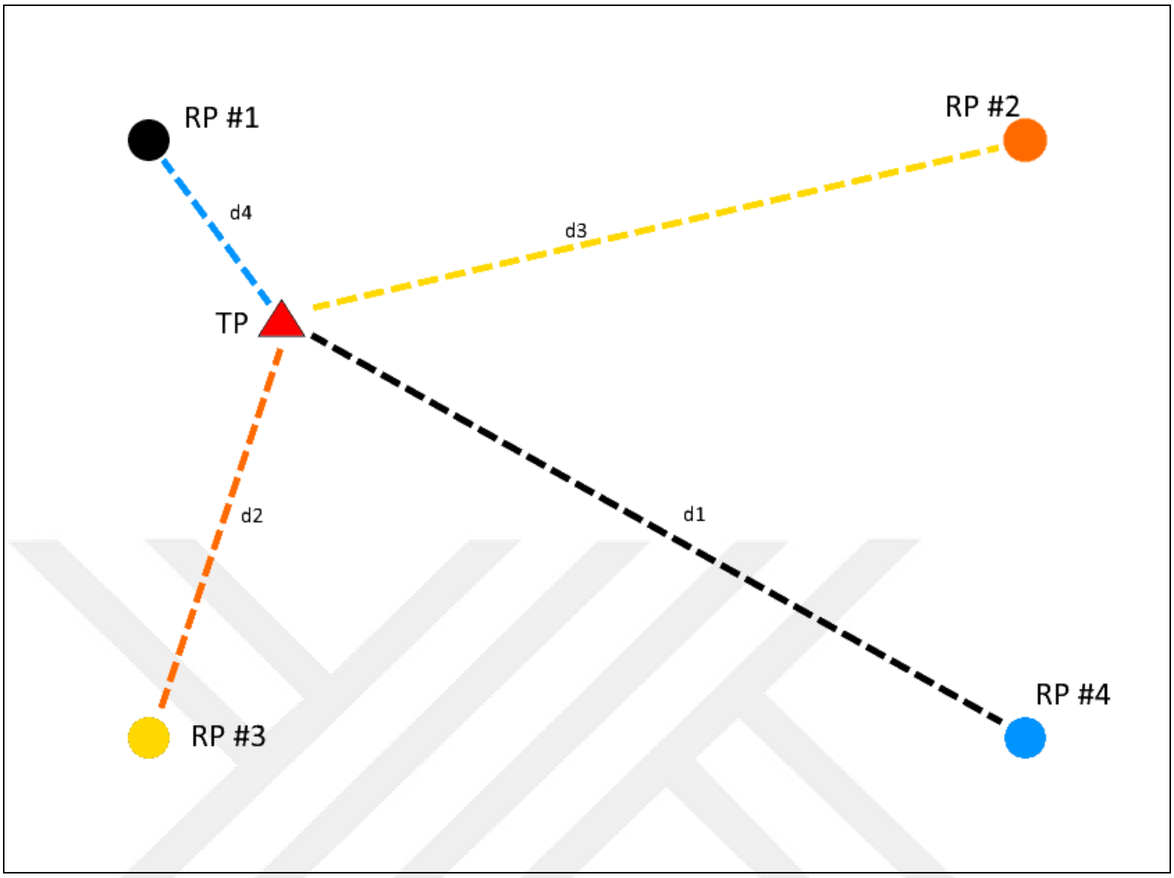


Figure 3.10. WKNN in fingerprinting

3.7.2. K-Means Clustering

K-means clustering is simple learning algorithm to partition a number of training data in to k clusters, where each training data belongs to a cluster with nearest mean. The algorithm proceeds by computing center point for each cluster by reducing the distance between cluster center and cluster members. Therefore, it aims to assign each data to the cluster with the nearest mean. When the mean values don’t change, the algorithm is said to be converged. The algorithm resembles KNN, but the latter doesn’t compute means to reclassify each training data.

K-means clustering algorithm is very sensitive to initial replacement of center points and the number of clusters, thus it may not give optimal results in every single time. Thus it benefits from dynamic center point replacement and if necessary multiple runs of algorithm until an expected result it achieved.

Algorithm 3.1. K-means clustering

1. Choose K initial center points that represent each cluster
2. Calculate the distances between each training data and center points
3. Assign each training data to a cluster that has the nearest center point
4. Recalculate each center point after each training data is assigned to a cluster
5. Repeat steps 2, 3, and 4 until there is no further change

In positioning systems, it is generally used in line with fingerprinting technique, to rule out unwanted reference point selections due to the intermediate radio signal effects such as scattering or reflections. Due these problems, an RP can be selected as among close candidates, although it can be really far away and cannot be used to represent the user location. In order to overcome this problem, more than necessary number of RPs can be selected and k-means clustering can be utilized to rule out unwanted RPs in a cluster. Thus only the cluster containing the optimal candidates of RPs can be achieved. Afterwards, among the members of the optimal cluster, KNN algorithm can be run to estimate the user's location.

The following four sections will detail the systems designed and implemented for comparative study of server-based and client-based systems.

4. BLUETOOTH LOW ENERGY POSITIONING

This section details the design and implementation of Bluetooth Low Energy based positioning system and its comparison to the Wi-Fi based system.

4.1. ANALYSIS AND DESIGN

Similarly to Wi-Fi positioning systems, Bluetooth positioning systems require at least three APs. The system (Figure 4.1) consists of three or more APs and the mobile device.

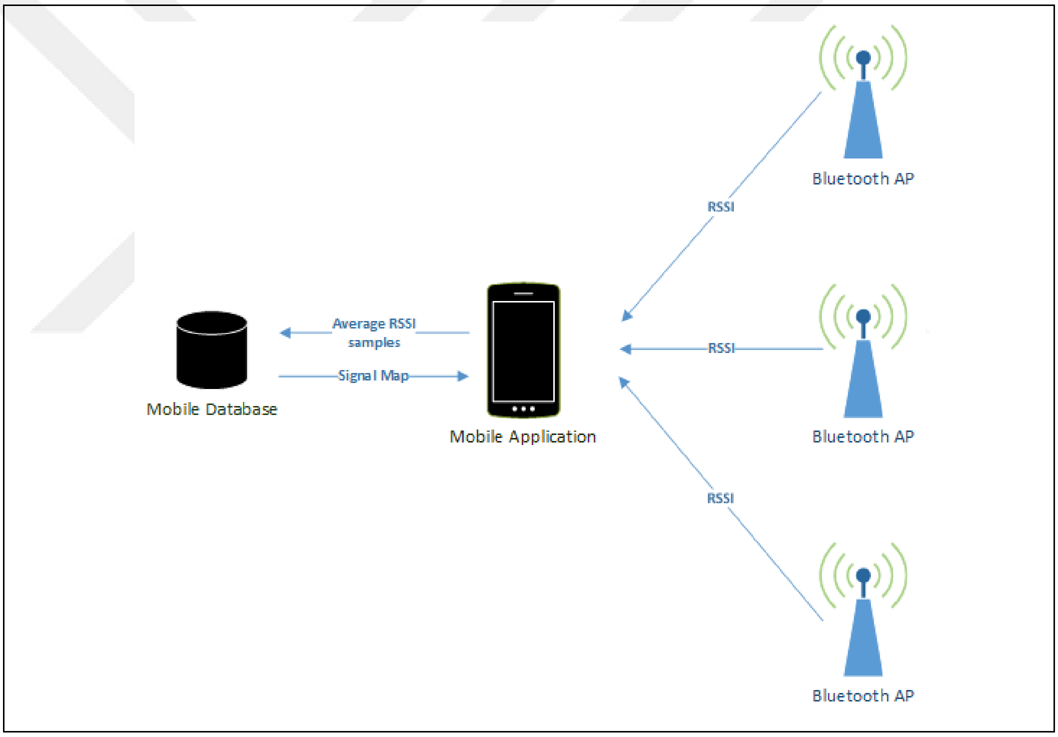


Figure 4.1. Architecture of BLE positioning system

First step for location detection is to determine distances between the mobile device and the APs. Bluetooth Low Energy has a profile called as proximate profile (PXP). This profile uses link loss service, immediate alert service and Tx power service in order to determine the distance. However, the mobile device has to be paired with the AP and connected to it before reading data from proximate profile. According to a study conducted in Nokia [54], Bluetooth scanning interval time is ranging from 20 ms to 10.24 s to discover other Bluetooth Low Energy devices. If the interval time is shorter, the energy consumption is bigger. Therefore, most of Bluetooth Low Energy devices have longer interval time. Due to long interval time, determining the distance can take couple of seconds for each AP. Connecting to three or more APs takes more time. It is very likely that the mobile device will move another location in the meantime. Therefore, proximate profile per se, is not useful for positioning.

Instead of using all features of proximate profile, only using the RSSI is a better choice. In about one second, a mobile device can read RSSI values for all surrounding Bluetooth Low Energy APs. Furthermore, reading RSSI does not require pairing or connection between devices.

4.1.1. Offline Phase Design

First step of offline phase is choosing reference points (RP). Points are selected in the signal space where they are spaced evenly to fully represent the environment. These points are used for comparison of RSSI values in online phase.

In order to collect RSSI data, the mobile device is moved to any reference point. A number of RSSI samples are read from each AP. After that, average of samples is stored for each AP. Using median value is a better option than calculating average but Bluetooth Low Energy has longer scanning interval than its predecessors, so reading many samples takes a long time. Due to small number of samples, this positioning system designed for using average of samples. Each RSSI value is stored with an ID of measured reference point and the MAC address of the AP which transmitted the received signal.

This process must be repeated for each reference point. After this process, collected data is stored on a database, which as a result would be the signal map of the area. Unless there a major change in the setting, which may cause the change of signal characteristics of the environment, it is enough to create this database once. Otherwise, the RSSI data must be collected again to create a new signal map.

4.1.2. Online Phase Design

Second phase of positioning is the online phase. In this phase, the mobile device tries to estimate its location, therefore it is repeated for each location request. Nearest neighbor in signal space (NNSS) algorithm is used to calculate location.

Firstly, the device collects RSSI of all accessible Bluetooth APs. In order to eliminate signal reading variations, average of a few RSSI can be calculated. Since reading more samples requires much more time, either the sample size must be selected carefully or to have fast estimation response only one sample must be processed. Therefore, instead of calculating the average, the system uses value of one sample for each positioning request. Then, RSSI values are retrieved from the database for each reference point and AP. Euclidean distances are calculated using collected data and the data which is retrieved from database.

Four of shortest Euclidean distances are chosen for calculation. These four reference points are nearest points which have known position. Then the distances of four nearest neighbors are used for position estimation.

4.2. IMPLEMENTATION

The system consists of two phases; offline phase and online phase. For each of the phases a mobile application is implemented on Android OS to perform the necessary operations.

4.2.1. Offline Phase

First application is designed to collect the average RSSI of every visible AP at predefined reference points. RPs are identified by an ID, which is entered on the control panel of the application. Also the number of samples to be collected at a RP can be set on this control panel. The more samples are collected; the more complete signal map of the environment is generated. However, collecting many samples makes the sample collection process longer. The user can decide to collect smaller number of samples if time is a restraint.

Otherwise, the user can increase the number of samples to create a much more complete signal map.

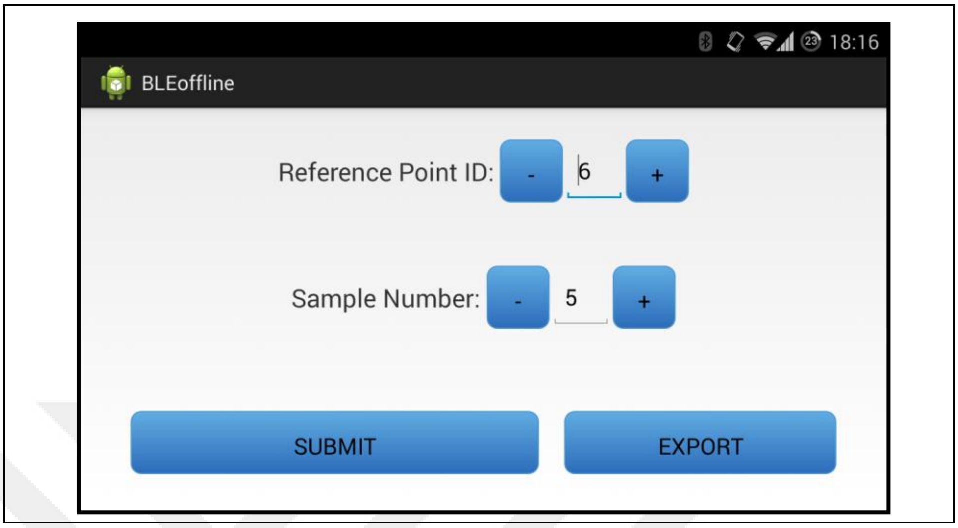


Figure 4.2. Offline phase collector

When all RPs are traversed, the signal map is completed and the user can export the SQLite database to use it in online phase.

4.2.2. Online Phase

Second application is designed to determine the position of the mobile device. Firstly, the signal map generated from the offline phase is imported to the second tool. In this application, when the user touches on the screen, it starts to calculate the location until another touch is detected. In the meantime, the application calculates the location for each newly received signal from the AP. Each calculation is stored in the database to test and debug. The debugging data include last measured RSSI for each APs, ID of selected test point and distance between calculated location and actual coordinates of selected test point.

In order to avoid signals from unknown APs, MAC addresses of the APs stored in a static data structure. If MAC address of retrieved packets is not in the array, the application ignores this signal.

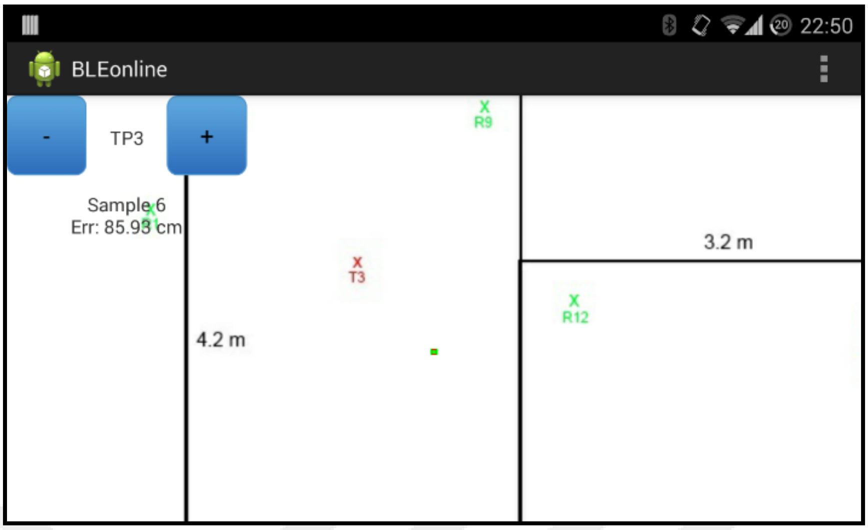


Figure 4.3. Online phase application

Additionally, the coordinates of the reference points are implemented in the application. Since the location of the mobile device is determined with respect to coordinates of reference points, the coordinates of the APs themselves are unnecessary. Though, if the positions of the APs change after the signal map is created, the signal map must be re-calculated.

4.3. TEST AND RESULTS

In Figure 4.4, the minimum and the maximum error rates and in Figure 4.5, the average error rates are shown for the implemented Bluetooth and Wi-Fi positioning systems. It can be seen in the figures that although both of them utilize the same fingerprinting algorithm, using Bluetooth Low Energy reduces the error and it has better accuracy than Wi-Fi.

Accordingly, the findings indicate that the maximum error-rate of Wi-Fi positioning system is 421.07 cm, whereas Bluetooth Low Energy system error-rate is found to be 357.91 cm. The minimum error-rate is also in favor of the Bluetooth-based system. In this field, Bluetooth-based system has an error-rate of 46.86 cm, whereas the Wi-Fi positioning system has an error-rate of 90.2 cm, nearly double of the Bluetooth-based system.

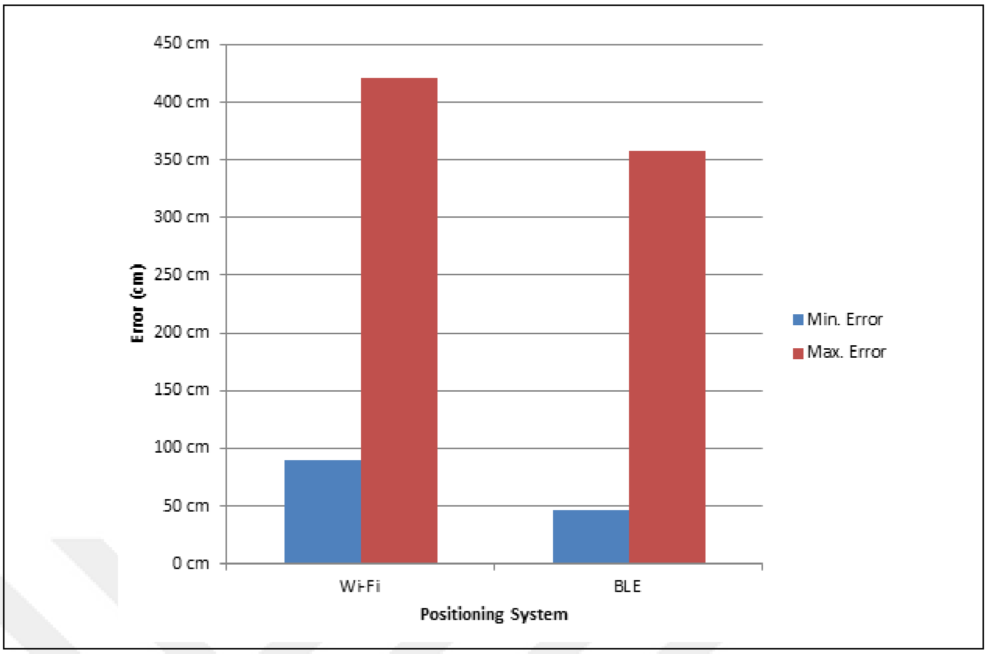


Figure 4.4. Minimum and maximum error-rate for BLE & Wi-Fi

Average error-rate of Wi-Fi system is calculated to be 233.07 cm, and Bluetooth Low Energy positioning system has an average error-rate of 176.20 cm. It can be deduced that for all conditions, BLE system performed better with higher accuracy.

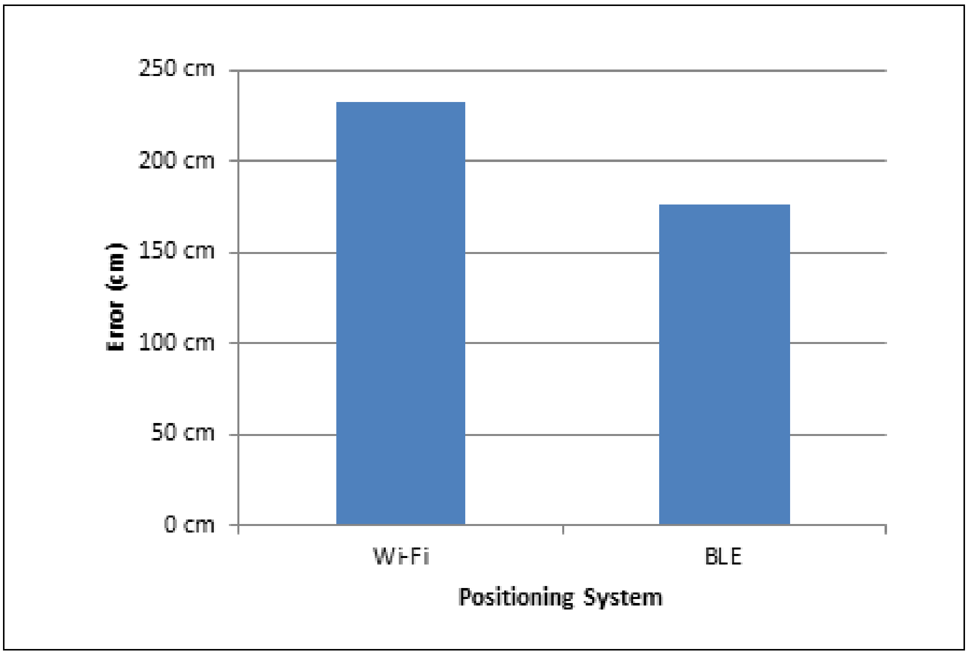


Figure 4.5. Average error-rate for BLE & Wi-Fi

5. WI-FI BASED LARGE INDOOR AREA POSITIONING

There are various studies that utilize fingerprinting method with numerous algorithmic approaches, most of these studies typically are undertaken in a controlled laboratory environment or comparably less crowded indoor faculty floors where the radio signal propagation and fluctuation are in near-ideal conditions, while some others only rely on simulations that simulated crowded environments.

In this system, our aim is to evaluate the capabilities and performance of fingerprinting approach in a real world setting, where radio signals are prone to fluctuation and the environment is far from being ideal, having lots of objects and obstacles that obstruct the healthy propagation of radio signals.

For this purpose, a local branch of a well-known supermarket chain is selected. The proposed evaluation area is 2300 square meters and all of the stages of localization are performed in work hours, where there is a guaranteed constant human traffic and a dynamic environment. A generic implementation of fingerprinting technique is selected, with k-nearest neighbor (KNN) algorithm for location determination. Various tests on density of RPs and transmit power of APs are performed to see the effects of different parameters on localization accuracy.

5.1. IMPLEMENTATION

The following section will discuss the system architecture and implementation details of the proposed positioning system.

5.1.1. System Architecture and Test Bed

The architecture of the proposed system can be found in Figure 5.1. Accordingly, the system is composed of wireless access points and a mobile device such as a tablet, which is used in both signal map creation and localization steps. The database where the signal map is going to be stored is placed on the tablet as an internal database file for simplicity.

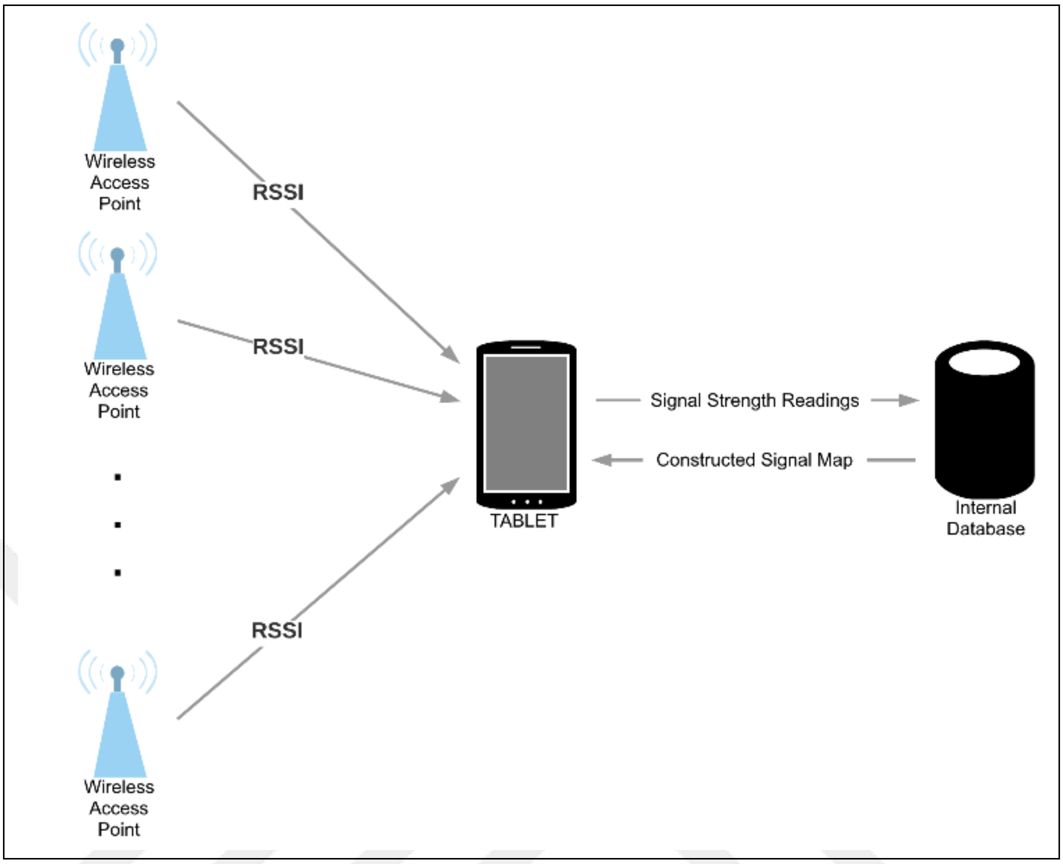


Figure 5.1. System design

As the access point, TP-Link WA901ND is selected, which can be seen in Figure 5.2a. This is a 802.11n device transmitting at 2.4 GHz and supporting 3 spatial streams with up to 450 Mbps theoretical link rate. It also has 3 5dBi omni-directional detachable antennas, which is important for both high coverage and to be able to capture even the weak client-side signals.

In this scenario, WLAN RSSI readings had to be acquired in various locations, hence, a mobile device which can easily perform wireless networking task and acquire RSSI data was needed. For this purpose, an Android-based tablet is chosen because of its widely established open-source API, which enables flexible low-level networking and RSSI data collection. The tablet is an Asus Eee Pad Transformer (Figure 5.2b) running Android OS 4.0 which also supports IEEE 802.11n standard at 2.4 GHz.

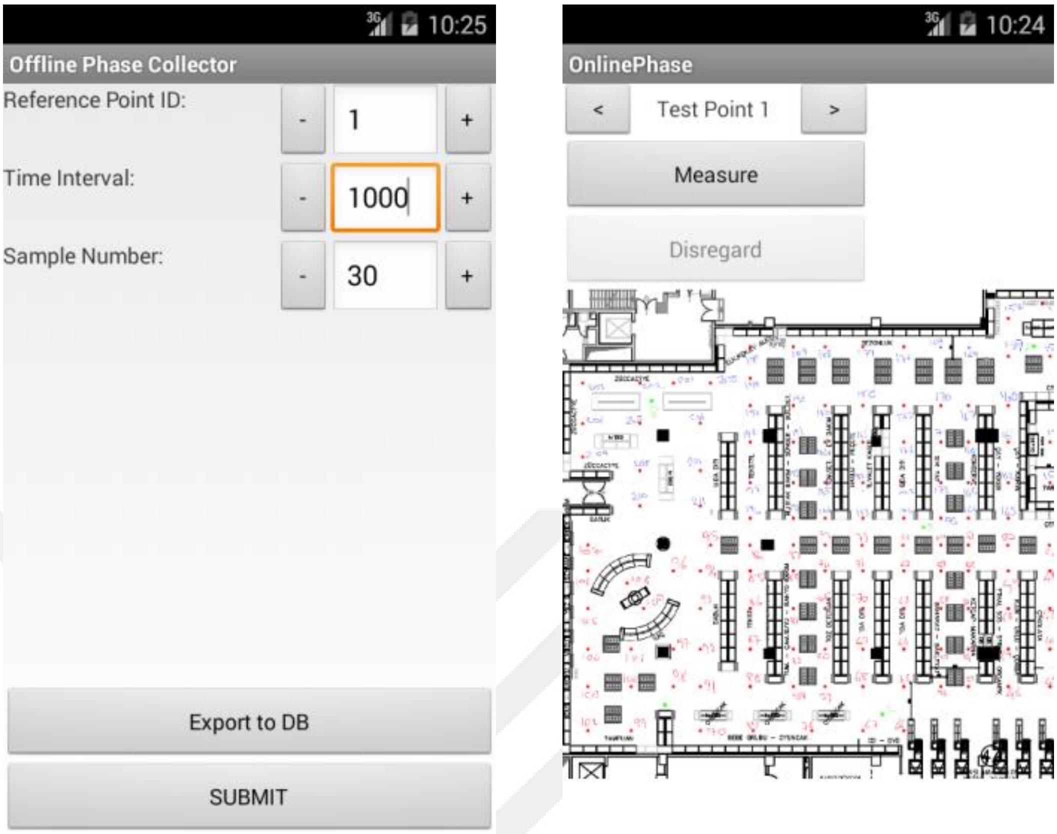
(a) (b)

Figure 5.2. (a) TP-Link WA901ND, (b) Asus Eee Pad Transformer

In order to evaluate the proposed system, a local branch of a supermarket chain is selected. It has been decided to evaluate and test the localization system in real-world scenario, where the environment and its objects would inhibit and stress the capabilities of the proposed system and also to have a real constant human traffic and interaction which would simulate a real usage pattern. For this purpose to cover the entire test bed area of 2300 square-meters, 10 of the aforementioned APs are installed in uniform manner to the ceiling trays of the supermarket. All of these APs are configured with default access point settings with same wireless configurations, except unique SSIDs for identification purposes.

5.1.2. Android Applications

To perform the necessary fingerprinting phases and access the generated signal map of the medium two distinct mobile applications are developed. The offline phase data creation tool is used to generate the signal map of the environment by the collecting RSSI samples at given RPs. An online phase localization tool was developed and used to sample real time RSSI readings and compare them against the signal map that is stored in the internal database. Then the comparison results were used to estimate the location of the mobile unit.



(a) (b)

Figure 5.3. (a) Offline phase collector, (b) Online phase application

The offline phase RSSI data collector application is written to perform the first stage of the fingerprinting technique, which is the offline phase. The application helps to simplify the signal collection process which involves moving through a large number of reference points and collecting an adequate number of samples. The interface consists of an ID field to identify the RP, an interval field to determine the interval in milliseconds between each sample, a sample count field to determine how many samples should the application collect, and a button to initiate the scan. Collected samples are stored in an internal database as a signal map of the test environment.

The online phase location estimation tool was utilized as part of the second stage of the fingerprinting technique. Accordingly this tool collected a number of samples at a given indoor point and access the database that is constructed during the offline phase. With the real time data in hand, the application run the KNN positioning algorithm to estimate the location of the device with the help of RP data. The application interface consisted of an ID field which identified the test point (the real ground position was hardcoded in the application for instant error estimation), and a button to initiate the location estimation process.

5.2. EXPERIMENT AND EVALUATION

In this study, our aim was to evaluate the positioning system in a real-life setting. Therefore, for this very purpose, a local store chain is selected and partnered with and the proposed system will be tested in one of their branches. The building housing this particular branch of the store has an area of 2300 m^2. In order to cover the entire test bed, 10 access points are installed on the ceiling by the store's personnel. The positions of these APs are calculated and noted to be used in evaluation.

The transmit power of the access points played an important role in the experiments due to the highly specific characteristics of the environment. As it can be seen in Figure 5.3b, the supermarket has a distinct inner environment, where the goods available for purchase is divided by counters stationed in parallel to each other in two rows. Throughout the experiments, this placement of the inner environment proved to be a real problem because one should expect to measure signal strengths close to noise floor from the far side of the market. On the contrary, because there is a direct line of sight due to the parallel corridors, increasing signal strengths of the distant APs are encountered when these conditions are met. To minimize this effect, lower transmit power tests are included to our evaluations as it can be inferred from the Friis transmission equation in Eq.4.1, the received signal power P_r is directly proportional to the transmit power P_t.

$$P_r = P_t G_t G_r \left(\frac{\lambda}{4\pi R}\right)^2 \tag{5.1}$$

Two RP density configurations are tested with 61 and 211 RPs and for each one the signal transmit powers of APs are changed accordingly to evaluate their effect in wide indoor environments such as this market branch.

5.2.1. 61 RP Configuration

For this test, RP location to collect signal readings and their coordinates are determined. Utilizing the same RP configuration, two distinct positioning tests are performed. Firstly, the offline and online phases of fingerprinting algorithm are performed with APs configured to transmit with low power, then the same procedure is repeated with high transmit power. For this purpose, the settings for each AP is adjusted so that it corresponds to 25 mW for low and 100 mW for high. In the low transmit power configuration, an average of 6.19 meters of error-rate is achieved whereas, with high transmit power, the error-rate increased to 6.29 meters. The lowest and highest readings for each configuration is listed in Table 5.1.

Table 5.1. 61 RP configuration

Signal Strength (mW)	Lowest (cm)	Highest (cm)	Average (cm)
25	5.02	1515.53	619.43
100	160.47	1443.17	628.77

5.2.2. 211 RP Configuration

Bearing in mind the assumption that the positioning accuracy of the system can be increased by increasing the number of RPs so that they better represent the radio signal characteristics of the environment.

Similar with the previous configuration, new RP positions with a denser pattern are selected with pre-determined coordinates and two new signal maps are constructed to measure the positioning errors using 211 RP configuration.

Utilizing the newly identified 211-RP map the performance of the system is evaluated. For low transmit power, an average of 5.94 meters of error-rate is achieved, whereas the error-rate increased to 6.51 meters in high transmit power mode. The results indicate that high transmit power of 100 mW resulted with higher errors-rate, which may be due to high refraction and reflection of radio signals in a densely populated environments, such as our second test bed. The lowest and highest readings for each transmit power configuration can be found on Table 5.2.

Table 5.2. 211 RP configuration

Signal Strength (mW)	Lowest (cm)	Highest (cm)	Average (cm)
25	107.98	1264.81	593.54
100	66.01	1723.64	651.03

5.2.3. Comparison of RP Configurations

Due to the large size of the test bed with complex inner structure, it has been expected to achieve better accuracy with the denser 211 RP configuration. This assumption is based on the fact that the signal map would better represent the radio propagation characteristics of the environment. Indeed, the findings support our assumption and indicate that a higher 211 RP configuration yield better results at least with low (25 mW) transmit power setting. If a comparison made between 61 RP low transmit power and 211 RP low transmit power, can clearly be seen that the average positioning error-rate is decreased by approximately 26 cm.

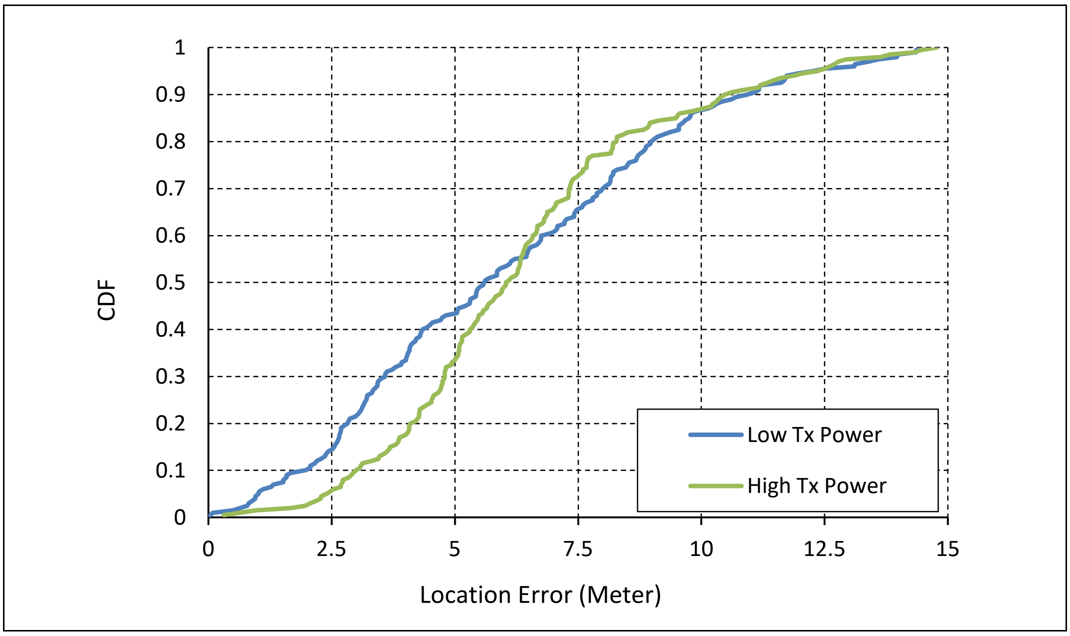


Figure 5.4. CDF of low and high transmit power for 61 RP

The cumulative distribution function shown (CDF) Fig 5.4 represents the 61 RP configuration cumulative error distribution, which indicate that 90 percent of errors are below 10.47 and 10.84 meters for low and high transmit powers respectively. Whereas, Fig. 5.5 showing the 211 RP configuration, show that 90 percent of errors are below 9.78 and 11.37 meters respectively. Although with a denser RP placement the positioning error is increased for high transmit power, for low transmit power a noticeable improvement in positioning accuracy can be seen. This finding proves the argument of the role of inner environment in signal propagation and reflection.

It is possible that the inconsistent outcome that is evident in Fig. 5.4 is the result of the testing done with 61 reference points in 2300 m^2 indoor environment. This shows that inadequate number of reference points is the problem and its inability to accurately map the environment in question.

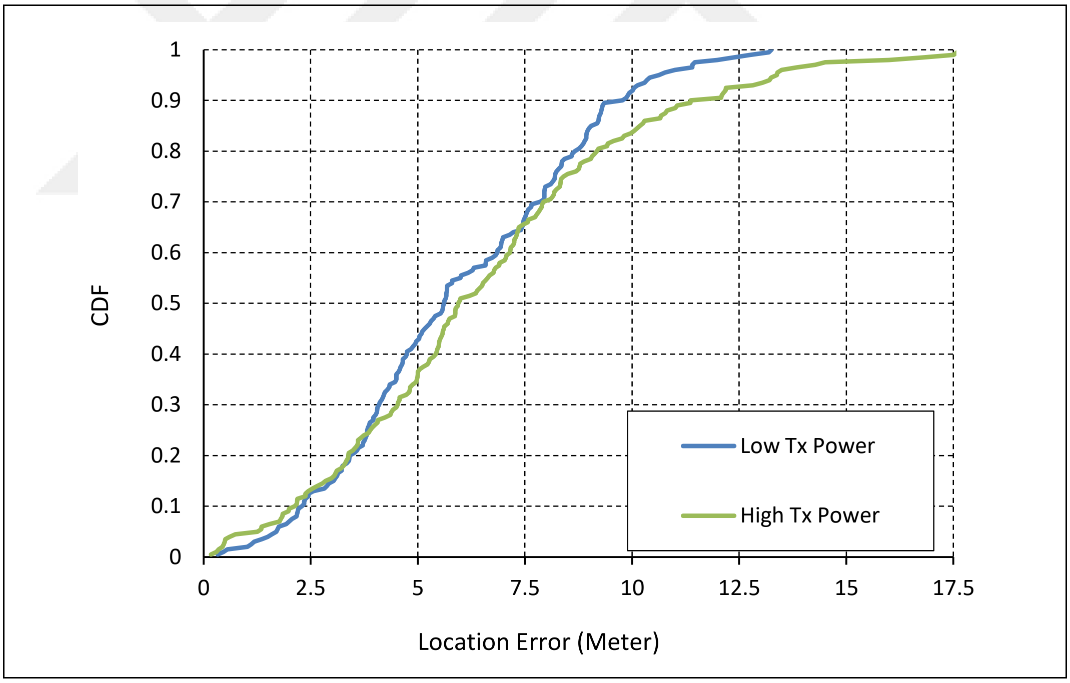


Figure 5.5. CDF of low and high transmit power for 211 RP

6. PDR-BASED LOCATION DETECTION

In this study, a PDR based positioning system coupled with BLE technology is designed and implemented. The proposed system aims to assess the positioning systems that are reliant on on-device sensors and their usability within supermarket context from administrator and user perspectives.

6.1. ANALYSIS AND DESIGN

This section analyses and discusses the requirements that need to be addressed to successfully achieve PDR positioning system.

6.1.1. Step Detection

An accelerometer as a sensor provides three values: roll (x), yaw (y) and pitch (z), where each component denotes three-dimensional values of the acceleration vector. The readings from the accelerometer sensor can be fluctuating and include the effect of gravity. Thus, in order to remove these unwanted effects, a high pass filter is used, and a pre-determined threshold is selected for registering a step. The threshold can be increased or decreased to accommodate different walking patterns.

However, not all movements are steps. The users turn corners or tilt the device, which should not be considered as steps. Hence, the system must detect non-step movements that are created by sideway accelerations or movements. The approached described the next section is used to identify these shifts and movements as rotations or changes in the user’s orientation and differentiate from a step movement by the user.

6.1.2. Rotation Estimation

Rotation estimation can be a cumbersome task on smartphones. Nowadays, there are built-in orientation sensors and magnetometers embedded on almost every smartphone. However, the presence of electromagnetic interference in indoor environments can introduce fluctuations in the sensor readings. These variances can be extremely severe, leading to extremely inaccurate data around electronic appliances such as computers and televisions.

To prevent the problems mentioned above, orientation values (x, y, and z) for different directions in an indoor environment can be recorded, simply to create an orientation value map of the environment. Since to make pedestrian dead reckoning to work, the user should be starting from a known point in the indoor environment, at that very time orientation database – saved in smartphone's memory - and the current device reading could be compared. As a result of this comparison process, user's device can calculate which direction it is heading (Figure 6.1).

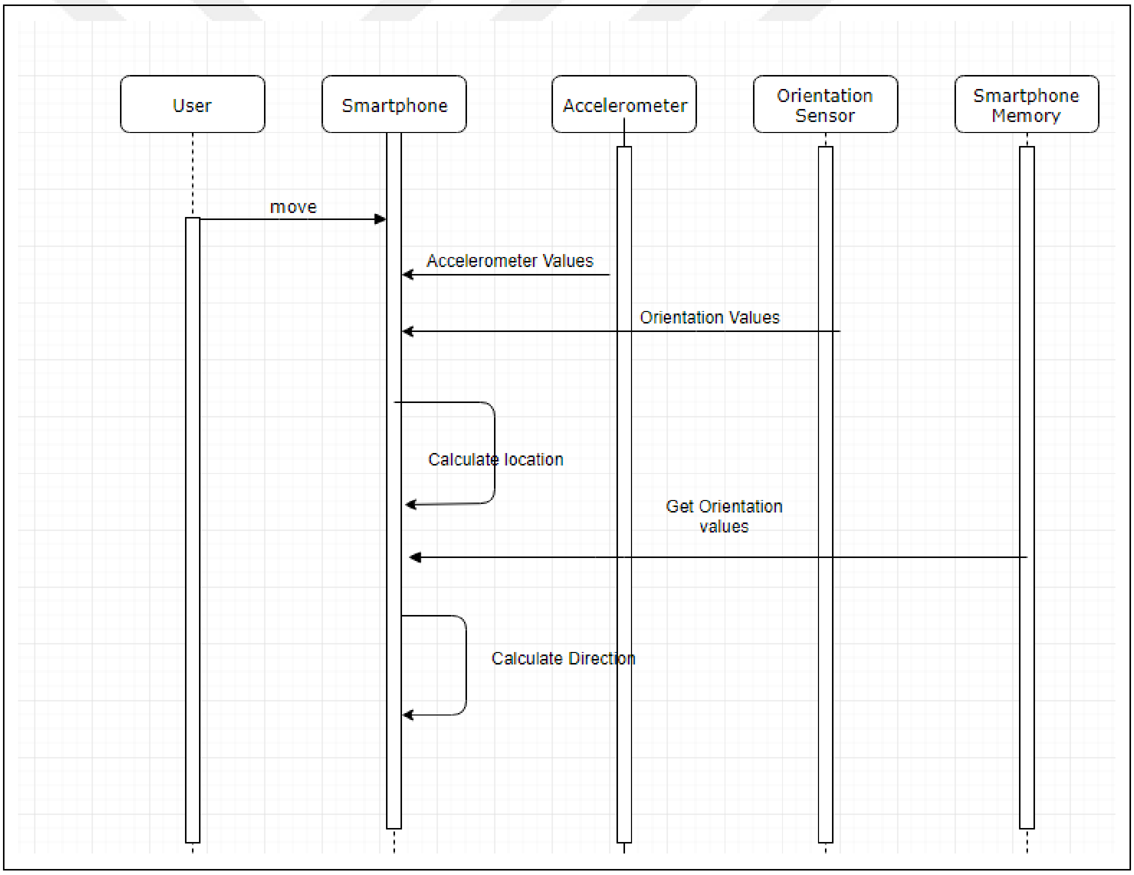


Figure 6.1. Sequence diagram of direction estimation

6.1.3. Pedestrian Dead Reckoning

After obtaining direction, the new position of the user can be calculated as shown in the Equation (6.1).

$$\begin{aligned} x_n &= x_p + l_s \sin(a) \\ y_n &= y_p + l_s \cos(a) \end{aligned} \tag{6.1}$$

In Equation 6.1, x_n and y_n are the new coordinates values, x_p and y_p are the previous coordinate values, α is the rotation degree and finally, l_s is the calibrated step length. The calibrated step length (l_s) is the average distance taken in a single step.

6.1.4. Hybrid Approach

The first and upmost important difficulty of user tracking with Pedestrian Dead Reckoning method is the need for a known starting point. Furthermore, since the sensors involved in step detection aren't that reliable, depending on the threshold values a step can be registered twice or not at all. Due to the fluctuation of sensor data and the need of previous location data to calculate the next location, if an erroneous reading or calculation is made then this error can extrapolate and result with a very inaccurate location estimation.

In order to lessen the impact of error accumulation, Bluetooth Low Energy (BLE) beacons can be used at key locations. BLE devices transmit beacons continuously; therefore, these beacons' RSSI value can be used to infer proximity and refine the device location. Assuming the location of the BLE device is known, the user's location can be updated when the RSSI value from the BLE device exceeds a pre-determined threshold. The working principle of this process is given in a sequence diagram in Figure 6.2.

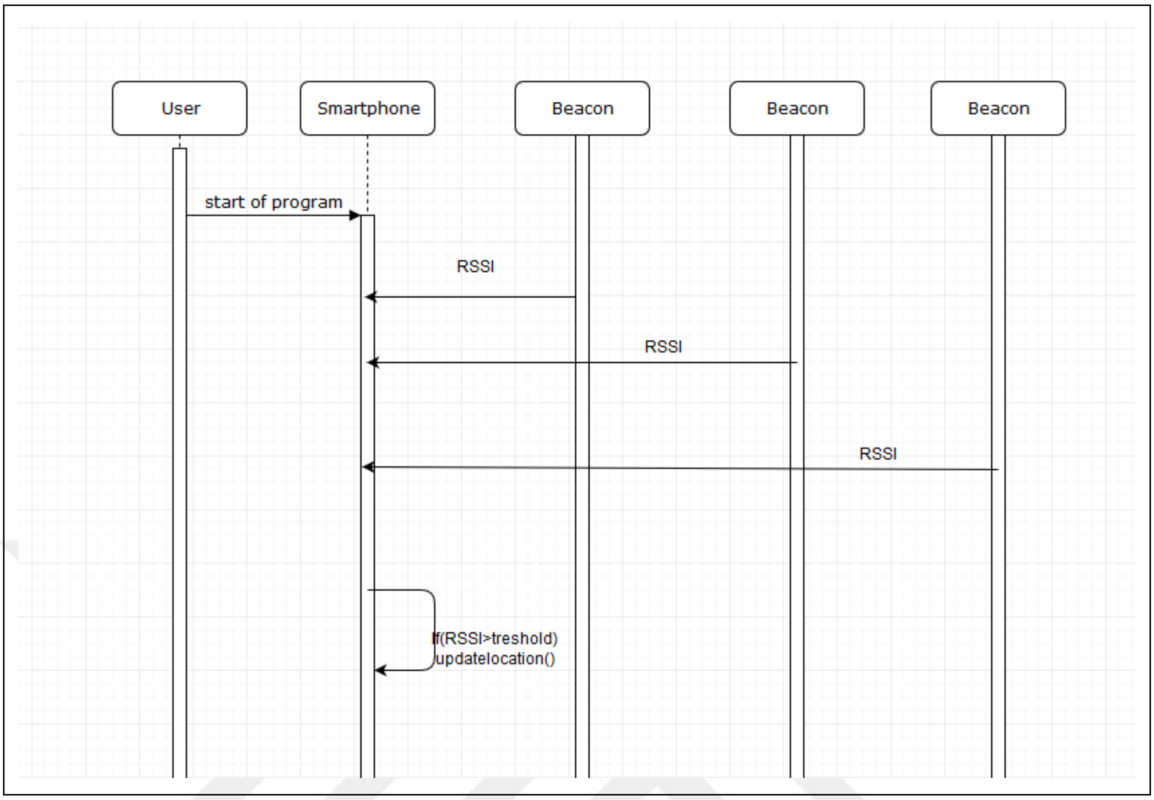


Figure 6.2. Sequence diagram of location correction

6.2. IMPLEMENTATION

Following section details the steps taken to implement the proposed solution and describes the two interfaces for the two user tiers of the system – administrator and shopper. Furthermore, it describes the functionality of these two separate applications by walking through their graphical user interface.

The proposed system consists of administration and user components. The administration component is on a server that runs a web service implemented by HTML, JavaScript, PHP languages and a MySQL database. The user component is the customer or end-user facing application that is implemented on Android platform using Java programming language.

6.2.1. System Implementation

The user application must be executed on a tablet or a smartphone that has accelerometer and orientation sensors since it is responsibility of sensor-based calculations. Due to the library requirements, the Android device is needed to support Application Programming Interface (API) level 19 (code name KitKat) and above.

The sensor-based calculations are the most crucial pieces of the system. One of these pieces is the step detection, which utilizes the built-in accelerometer. The real-time acceleration value taken from the accelerometer consists of three vector components. These are namely x, y, and z, which return the acceleration of the device in the respective planes. The step detection is gauged by calculating the change in each vector component and then adding the changes in x and z components of the acceleration vector. In order to prevent false step detections, the y component is subtracted from the addition vector. If the resulting vector calculation is above a threshold value, the step is considered to be taken and the user position is updated accordingly.

Another sensor-based segment is rotation estimation, which is used in conjunction with step detection to estimate the direction user is walking. Unfortunately, the magnetometer, which is used for orientation, can be unreliable in environments where there is high magnetic interference. A survey is done to eliminate this problem on the test bed. During this survey, compass values for four major directions (north, south, west and east) of the environment are recorded and their range is obtained to easily determine the orientation of the device.

Unfortunately, only sensor-based implementation is not enough if a reasonable level of accuracy is expected from a tracking system. In solutions that utilize dead reckoning, false positive detections or location changes can be missed due to higher thresholds and can add up to huge error rates in the long run. As mentioned before, the problem arises from the ever-increasing distance made from the starting point based on an erroneous data, which extrapolates the location estimation error due time. As proposed in the design section with the hybrid approach, the concept of a starting point with its known location can be applied to various points in the indoor environment where the device itself can make autocalibrations using BLE sensors. Thus, the location reported can be corrected to a great extent to provide an error-free position indicator.

Accordingly, a solution to this can be deploying Bluetooth Low Energy beacons with their low cost and long durability to tricky locations wherever calibration is required. Then, whenever the user comes to the proximity of a BLE device his/her location can be updated with the location of the pre-set BLE device. Thus, the system can reset its counter and start detecting steps from fresh and error-free. By deploying such devices in pre-determined locations, the system error rate can be reduced substantially. The proximity to a BLE device can be detected using an RSSI threshold value. If the measured RSSI value exceeds the expected threshold, the device location can update itself to detected BLE beacons location.

Any modern web browser can be used to access the administration panel and perform system management tasks through the web service. Accordingly, XAMPP web server bundle is used and an interactive HTML page (Figure 6.3) is created as an interface. To run SQL queries in the database, a PHP script is written and executed when web service is loaded on a browser. In the XAMPP web server bundle Apache web server is used, and a web service is served using PHP on this web server. The administrator can add the required item by drag and drop using this web service on the HTML page. Each action of the administrator is reflected in a MySQL database where the inventory is stored. The changes are reflected in the mobile application by web service which pushes the necessary data.

6.2.2. System Walkthrough

The administration panel (Figure 6.3) is a web page that includes the item placement and inventory management. The administrator panel enable administrators to manipulate the location and size of the items in the HTML page by simply dragging and dropping the required item. The item selection interface is divided into 4 rows and 8 columns, which represents the aisles of a supermarket. The location of every item is stored in the database by its name, row, column, and alignment.

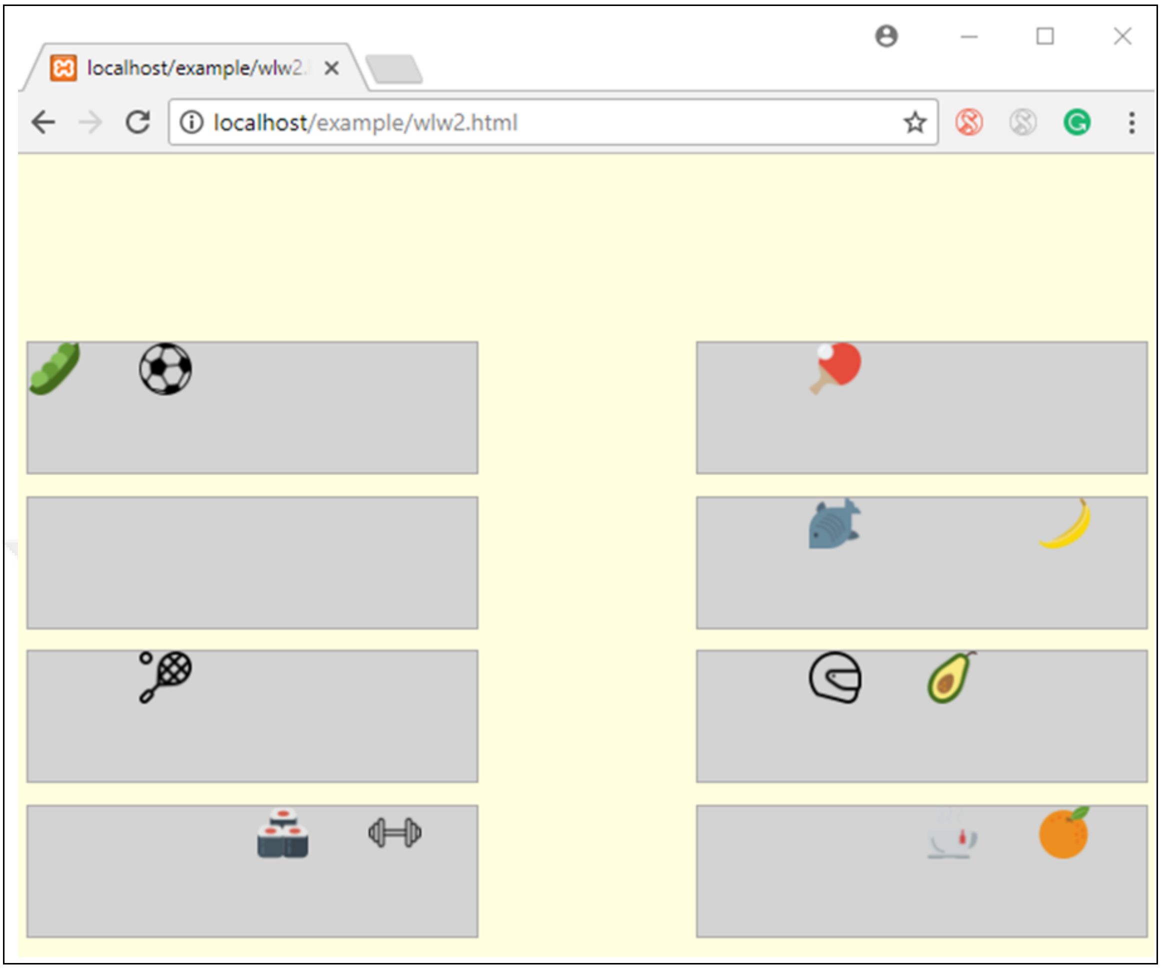


Figure 6.3. Web service user interface

The user-tier application (Figure 6.4) is executed on the Android operating system. The application connects to the web service, which downloads the latest item map of the supermarket in real-time. The user interface is designed to be simple and user-friendly. It represents the supermarket aisle layout with rows and columns and indicates where the items are. The user's location and his/her direction are indicated with a blue arrow, which is updated in line with data provided by the PDR algorithm.

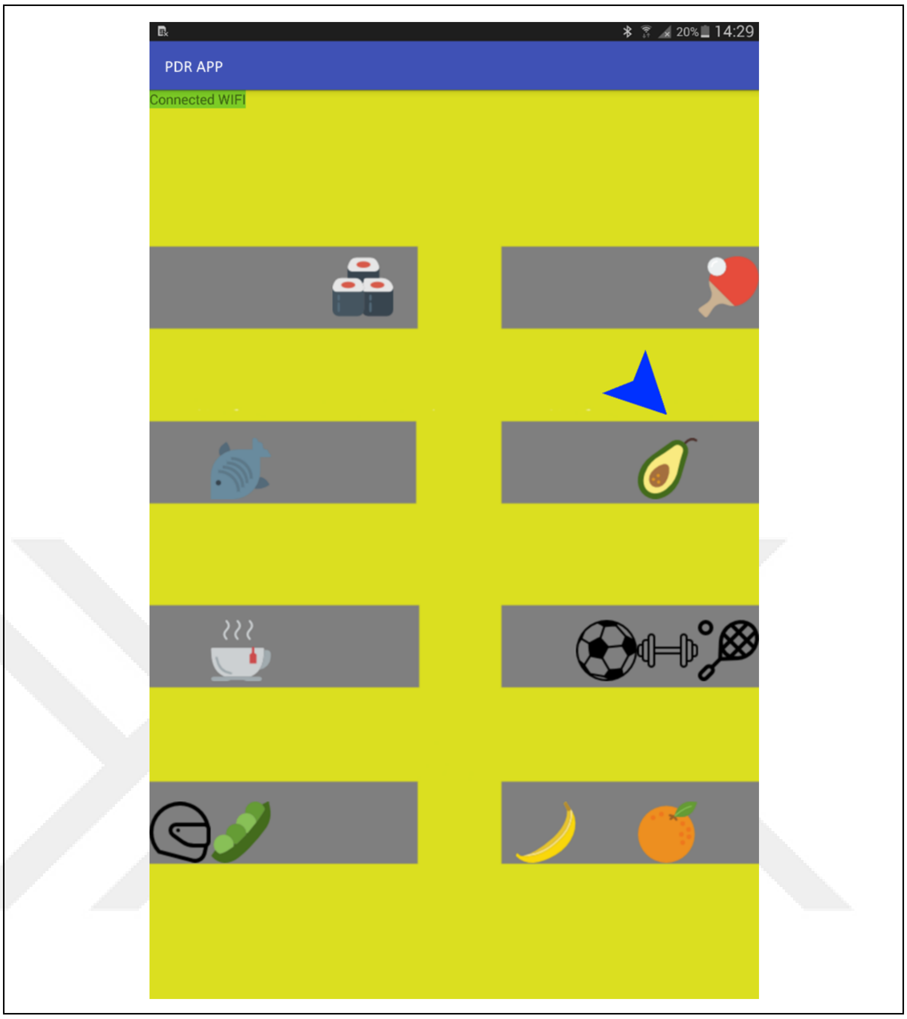


Figure 6.4. Android application

6.3. TESTING AND EVALUATION

This section describes the tests conducted to evaluate the prototype and presents its results. Initially, testing setting and devices are described in detail. Secondly, the findings of both subjective and objective test are discussed and analyzed.

Throughout the evaluation of the prototype, a Samsung Galaxy Note 10.1 2014 tablet is used as the user device. The tablet has Android 4.4.2 as operating system with API level 19. It also has a built-in accelerometer and orientation sensor suitable for step and rotation detection. The device is also equipped with IEEE 802.11n Wi-Fi and Bluetooth 4.0, which are required to connect to the network and access BLE beacons.

Figure 6.5. Texas Instruments SensorTag CC2650STK

As BLE beacons, Texas Instruments SensorTag CC2650STK (Figure 6.5) with Bluetooth Low Energy are used throughout the evaluations. The CC2650STK beacons have multiple built-in sensors, such as temperature and motion, but in the framework of this study, they were only utilized as Bluetooth signal emitters.

As the testing environment, a 47 square-meter Pervasive Systems Laboratory in the first floor of Engineering Faculty at Yeditepe University is used. Five BLE beacons are placed at intersection points of aisles as well as at the starting point, which is the entrance of the laboratory. The intersections are selected for error-correction of PDR and to reduce the user’s probability of entering to the wrong aisle.

For subjective testing purposes, the evaluators were selected from various backgrounds with diverse competency in information technologies. They were divided into two groups. The first group was selected as administrators. They were asked to use and evaluate the administration side of the system by using the web interface via their browser to add and store items in the inventory. Then, they are all asked to make some pre-defined changes on the administration web service. The second group was selected as supermarket customer users of the system. They used the Android application that utilized the PDR algorithm to locate the items in the supermarket. The supermarket customers group participants were given some tasks and products to find in the supermarket using the application. The supermarket customer group performed their given tasks twice – one without the support of BLE beacons and one with the support of the BLE beacons. as a result of this, the difference in location estimation precision can be measured and the error-rates between with the BLE supported and without can be compared.

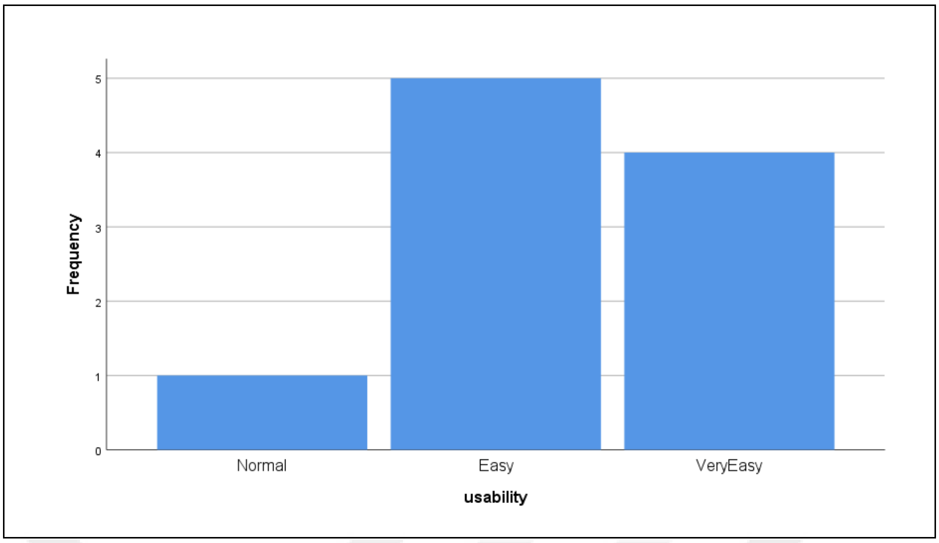


Figure 6.6. Administration usability tests

The results of the administration usability tests (Figure 6.6) showed that none of the participants found the service hard to use. Especially, the simple drag and drop interface proved to be very user-friendly. On this specific matter the participant opinions ranged between easy and very easy.

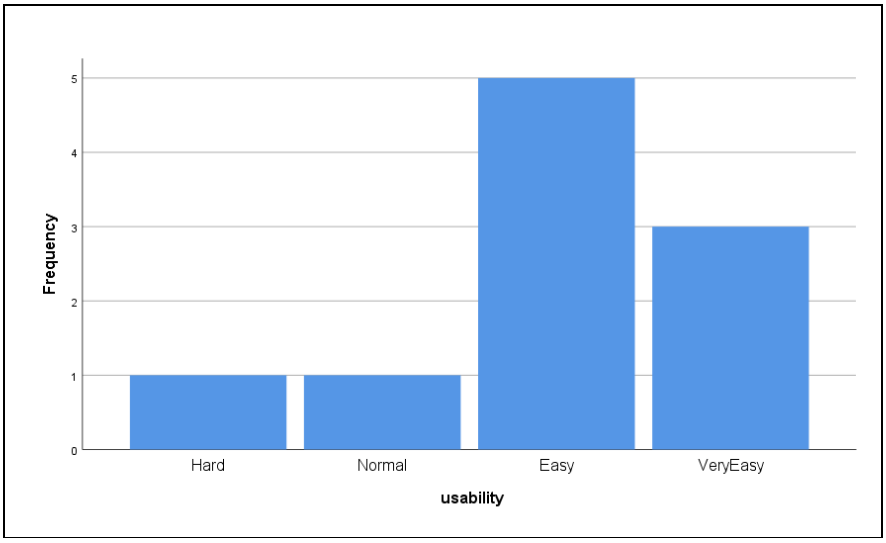


Figure 6.7. Mobile application usability tests

Mobile application usability tests (Figure 6.7) showed that most participants found the application is easy to use except for a single one participant. It is believed that the one person who found hard to use the system was due to BLE correction issues, which sometimes changed location of the blue user marker abruptly. This kind of behavior can be corrected if the positioning algorithm is improved and the need for BLE-based correction becomes less obvious.

Figure 6.8. Localization tests

The results of the localization tests (Figure 6.8) show that the error rates in PDR without location correction are increasing linearly. Indeed, This was an expected behavior from the regular PDR algorithm. These errors are caused by the propagation of erroneous readings and accumulation of errors in the long run. Hence, if the user required to be tracked for a long period of the time this approach would not be very feasible. However, with the use of beacon-based location correction, long-term error accumulation effect can be decreased and location estimation error rate increase can be reduced. The participants utilizing the corrected PDR were able to locate the items that they were asked to find with an error rate of 55 centimeters on average.

7. SERVER-BASED INDOOR LOCATION DETECTION

Following section details the design and implementation of the server-based positioning system. Furthermore, it elaborates on the results and the findings of the proposed location estimation model.

7.1. ANALYSIS AND DESIGN

In recent releases of mobile operating systems many low level functionalities are progressively being disabled or becoming harder to access due to security concerns. As a result of these changes, in some operating systems some operations are becoming more cumbersome and/or harder to implement, which causes backward compatibility issues between versions of the same operating system. Furthermore, from location sensing perspective, if client-based approached is followed the same solution should be implemented for each and every OS platform. Also when a need of an update raises, it requires to be implemented for each and every one of these platform, which as a result depending to the number of platforms supported might double or triple the workload.

Thus in order to overcome this problem, a centralized (infrastructure-based) positioning system, which uses sniffer devices to gather mobile unit signal data, can be developed. To create the signal map as part of the offline phase, the mobile unit's signal strength can be collected at known reference points. As a result, when the mobile unit queries for position detection, sniffer devices collect signals emitted from the requesting device and compare it with the signal map created in the offline phase. The KNN algorithm is run on the server where it has access to the signal map database. The calculated position information is then sent to the mobile. The entire signal determination and position calculation is done on the server. Hence, utilizing this server model, the proposed system can determine location of a mobile device independent of its operating system.

The system architecture of the proposed system can be seen in Figure 7.1. This location detection solution is composed of a server and at least three wireless sniffer devices, where each device is connected to the server via Ethernet connection. The server hosts database where the signal map of the environment and sniffer device information is stored. By making use of this architecture adding additional sniffer devices for increased coverage becomes very easy and affordable.

In this scenario, sniffer devices are required to capture 802.11 frames over the air, and filter them according to the MAC addresses of the mobile device that needs its position estimated. In order for this scenario to work, the mobile device is required to be connected to a wireless infrastructure to initiate server registration for its MAC address, and also to generate wireless traffic for the sniffers to capture. This wireless traffic between the MU and the wireless network is essential because the system exploits the packets captured from this traffic to determine the position of the user. Therefore, in order to make this system work, an additional access point is needed for the mobile device to connect and communicate.

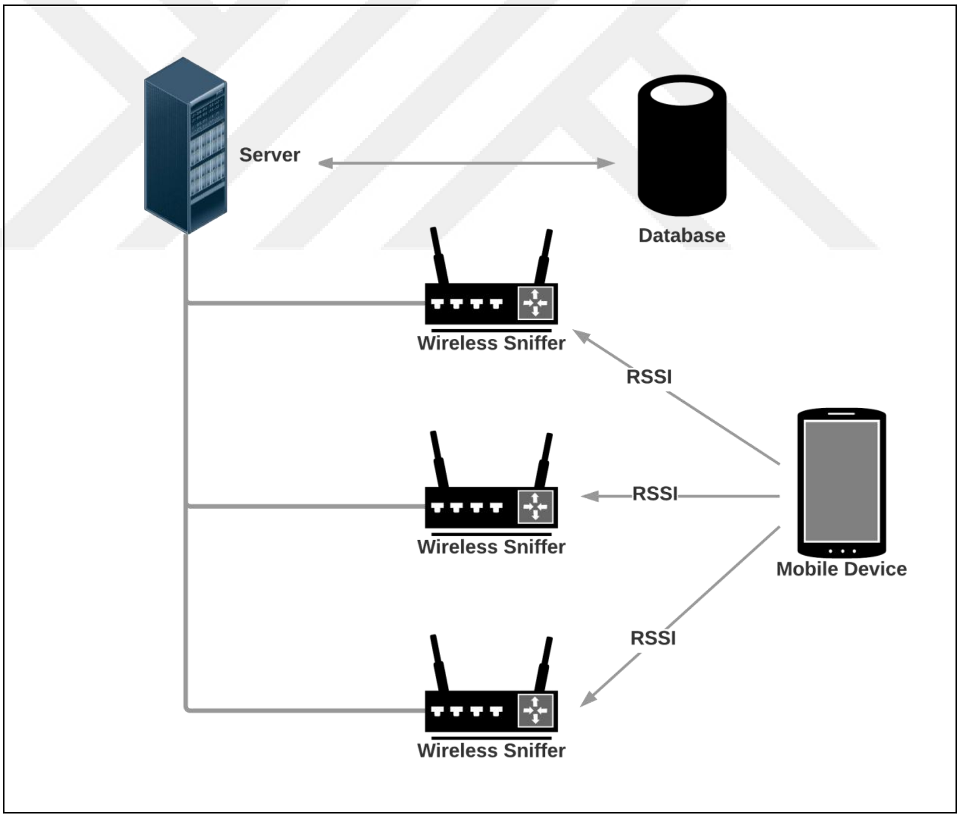


Figure 7.1. Server-oriented system architecture

Accordingly, the infrastructure requirements of the proposed system is as follows; the server platform should be capable of performing the necessary calculations in a short amount of time and handle large number of consecutive requests of position estimations.

Also, since the mobile devices runs on battery and have limited resources, the mobile application must be relatively simple and straightforward to minimize battery consumption. Therefore, the system should follow the thin client and thick server model. Considering, the size of the location detection area cloud systems can be used. However, in our proof of concept, the server should be able to handle requests sent from a single device within medium-sized room.

As depicted in Figure 7.2, the sequence diagram of the system, once the client is connected to the AP serving internet access, the client can send the system startup command to start the positioning process. Then the server contacts to wireless sniffers to start Airodump processes for capturing 802.11 frames. Once the general system startup is accomplished, the client can send positioning request periodically, the server requests new station data from the sniffers and performs positioning algorithm to calculate user position. The server then sends the calculated user position back to the client.

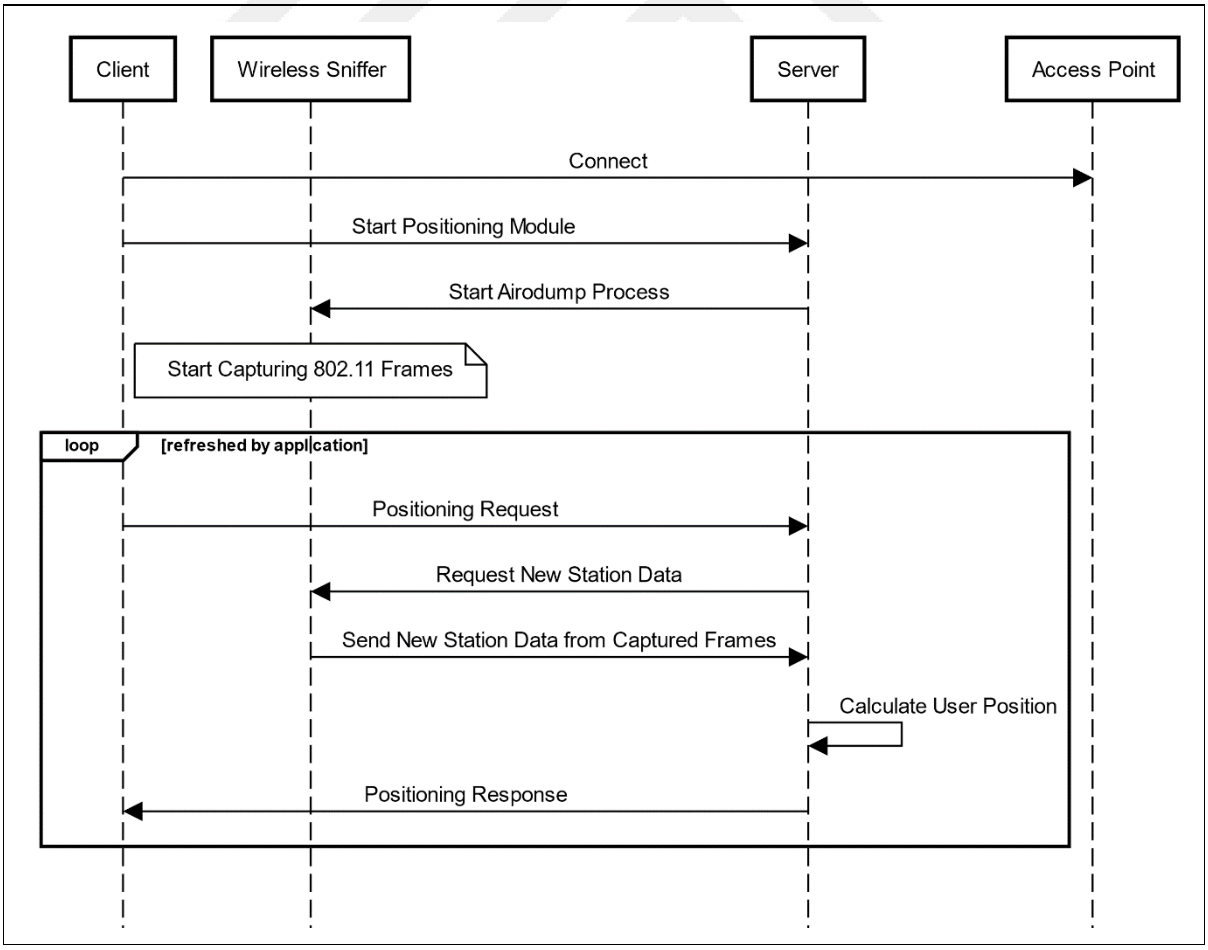


Figure 7.2. Sequence diagram of the system

7.2. SYSTEM IMPLEMENTATION

7.2.1. Wireless Sniffer Modules

As wireless sniffer devices, three Linux PCs with Ubuntu operating system are employed. These PCs are regular desktop stations with Mid ATX chassis, but in a real-life scenario these PCs can be substituted with mini-PCs.

The sniffing process is performed using a special wireless application suite called Aircrack-ng. This suite includes many wireless related applications to attack, monitor, test and crack wireless 802.11 networks [55]. From the suit member application, our study makes use of Airodump-ng application, which enables the wireless network interface adapter to sniff wireless packets in the environment.

Figure 7.3. TP-Link WL722N wireless adapter [56]

The sniffer function requires special wireless adapters which can be put into the monitoring mode. Therefore, TP-Link 802.11n wireless adapter with model number WL722N (Figure 7.3) is selected. This device is a special one with an Atheros chipset, which can easily put into monitoring mode and coupled with Airodump-ng application. The code provided in Algorithm 7.1 is used to create a monitoring interface on the machine and sniff wireless packets in the environment.

Algorithm 7.1. Creating monitoring interface

```
#!/bin/bash

output=$(ifconfig | grep -o eth0 2>&1)

if [ $output != "mon0" ]; then
    iw dev wlan0 interface add mon0 type monitor && ifconfig mon0 up
fi
```

After the monitoring interface is created, Airodump-ng process executes. Then, Airodump-ng simply uses this newly created monitoring interface and listens to all available wireless packets across all Wi-Fi channels. Collected wireless data is then used to create formatted device lists on the terminal. Since the device lists are in formatted form, they can easily be dumped to a CSV file which can later be manipulated. This data dump contains MAC address of the station, first time seen, last time seen, signal strength of the station, and information whether a station is connected to an AP, and if connected, the MAC address of this AP.

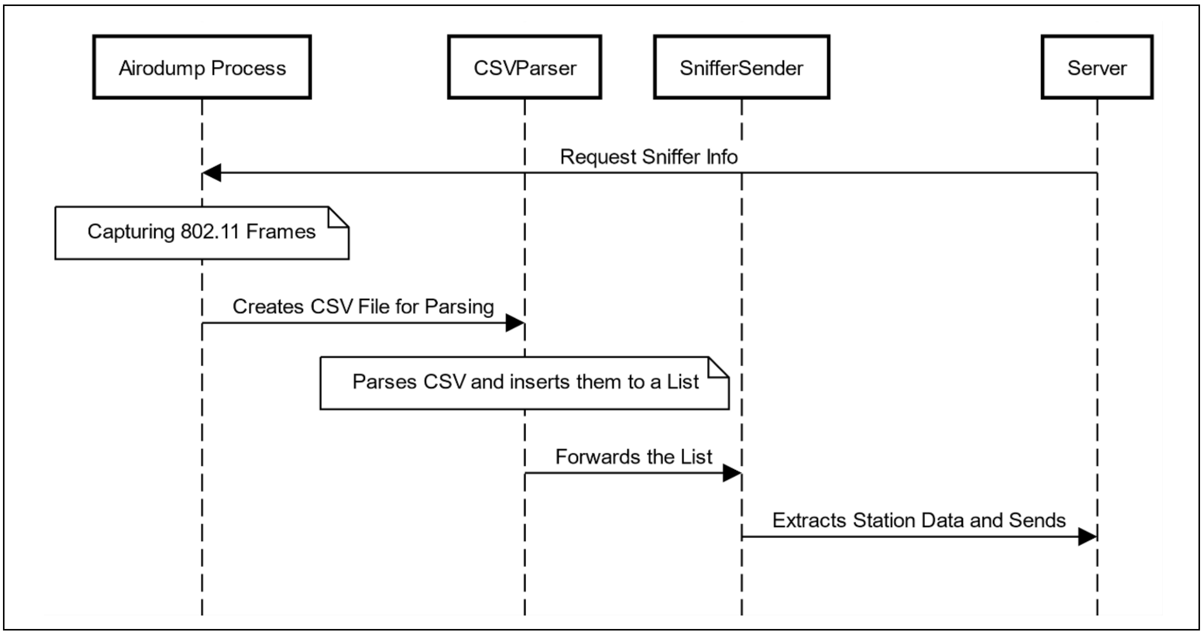


Figure 7.4. Sequence diagram of the wireless sniffer

Bearing in mind the MAC address of the device that requested position estimation, the data from CSV file can be parsed to get its signal strength. Consequently, its MAC address along with its signal strength values are send to the server every time a sniffer captures 802.11 frames containing this MAC address. The procedure of this operation is detailed in Figure 7.4.

7.2.2. Server Program Implementation

Server side application is written in Java programming language along with a JDBC database. The server has separate components for configuring and running the positioning system. Namely these components (Figure 7.5) are; offline phase calibration, online phase localization, sniffer registration, and database management. Sniffer registration module accepts the addition of new sniffer modules for later expandability, in our case three sniffer modules are generated. Offline phase calibration is responsible for creating the signal map by the help of sniffer modules. Online phase module is responsible for real-time localization and mobile device connection management. Database module is responsible for database connection and management.

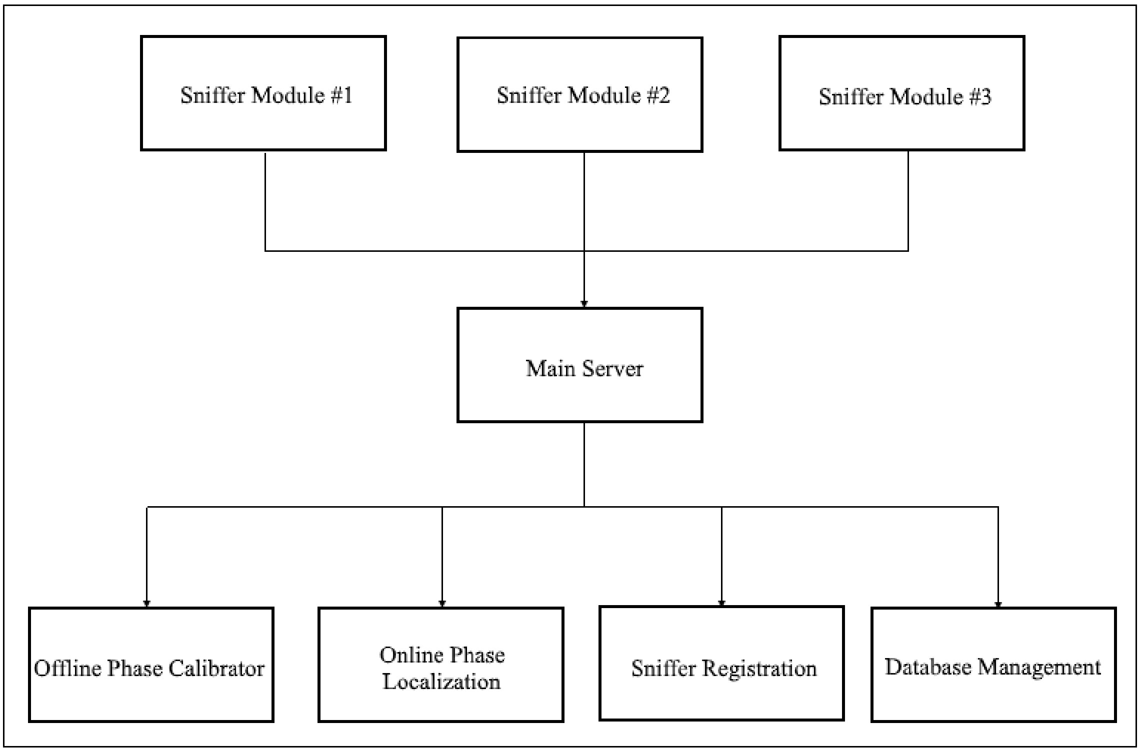


Figure 7.5. Server components

In the case of a positioning request from the mobile device, the server contacts the sniffer module and requests the most recent signal data for the device in question. Since sniffing and the signal strength collection is a continuous process, the online phase module extracts the required data from the database via the help of the database management module and performs necessary positioning calculation. The result of this calculation is written to the database continuously and updated in every few seconds when necessary data is gathered for another location update. For the online phase localization WKNN algorithm is chosen and deployed in the server. The k value in the WKNN algorithm is chosen to be four, which gives the best results in the test environment the system is implemented.

7.3. TESTS AND RESULTS

7.3.1. Test Environment

The proposed system is implemented and evaluated in the Pervasive System Laboratory in the Engineering Faculty. The test environment was the whole of the laboratory, which is approximately 47 m^2. In order to cover the entire test environment, the sniffer PCs are sporadically spread around the laboratory so they were as far away from each other as possible. On the other hand, 15 RP locations are selected and each one of them are distributed with 1.4 meter intervals. Furthermore, 10 test points are selected at random locations to estimate the location and calculate the error-rate. The coordinates of each sniffer PC, RP and TP is calculated in reference to the test bed and implemented on the database to be used in location determination.

A detailed depiction of the test environment is provided in Figure 7.6, where the RPs are marked with “X”s, sniffer PCs with an antenna, and the TPs with their TP numbers. In order to measure the error-rate of the proposed solution, a number of measurements are conducted on 10 test points by utilizing the fingerprinting and finding how they compared with the actual coordinates within the test environment.

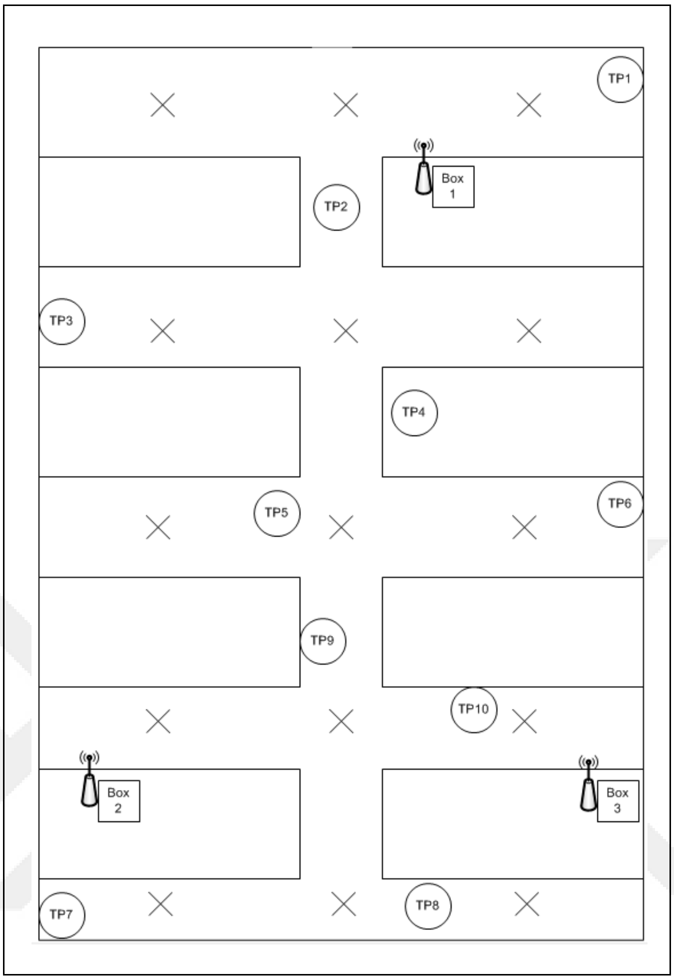


Figure 7.6. Test environment

7.3.2. Results of the System

In order to evaluate the proposed system for its performance, 10 pre-determined test points were set. At each of these test locations, the system tried to capture 20 airborne packets that were transmitted from the mobile device and by making use of the collected packet information to perform the location estimation. According to the CDF for location estimation error-rate in Figure 7.7, the systems performs within 3 meter positioning error-rate 70 per cent of the time.

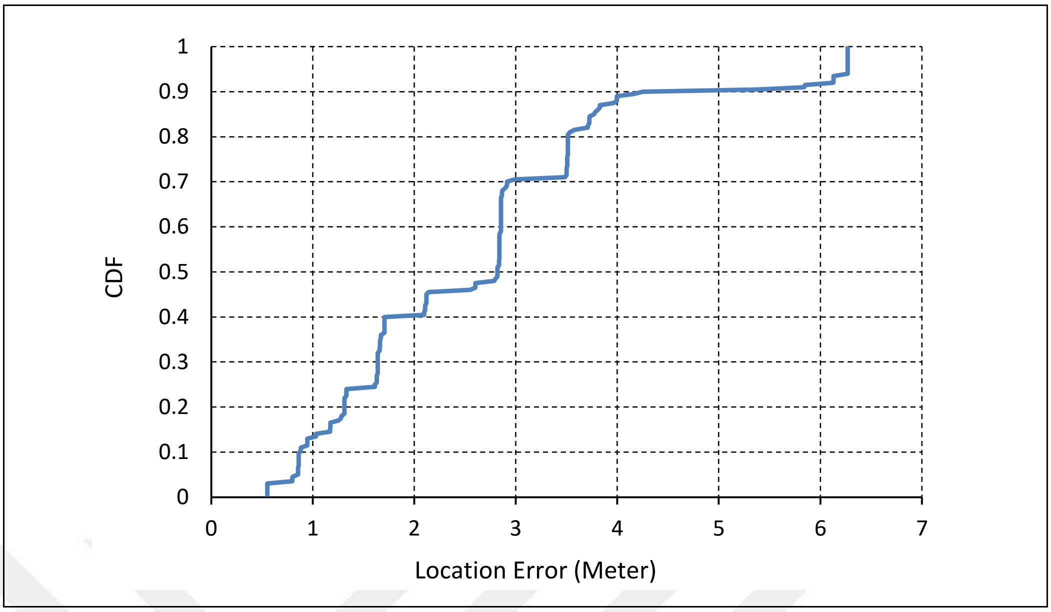


Figure 7.7. CDF of location estimation error-rate

As it can be seen from Table 7.1, where the results are given in centimeters and N is the sample size for each TP, the mean system location estimation error-rate ranged between 105.85 cm and 615.15 cm. Overall mean of location estimation error-rate of this solution was 266.15 cm and standard deviation was 38.77 cm. To elaborate more on the single test results, it can be seen that 5th test point has the lowest error with 55.44 cm. Whereas, 1st test point has the greatest error with 626.99 cm.

Table 7.1. Detailed test results

TP #	N	Mean (cm)	Std. Deviation (cm)	Std. Error (cm)	Minimum (cm)	Maximum (cm)
1	20	615.51	22.47	5.03	538.52	626.99
2	20	184.66	67.57	15.11	117.00	372.65
3	20	321.96	57.61	12.88	255.16	425.03
4	20	105.85	21.94	4.91	85.56	131.31
5	20	126.97	51.38	11.49	55.44	170.66
6	20	293.09	23.55	5.27	285.35	371.32
7	20	350.99	0.99	0.22	348.62	353.62
8	20	257.62	102.94	23.02	133.27	399.53
9	20	121.46	36.75	8.22	79.88	167.17
10	20	283.41	2.47	0.55	278.98	291.27
Total	200	266.15	38.77	8.67	55.44	626.99

It can be noted that test points (2, 4, 5, 9, 10) that are covered within reference points has lower location estimation error, whereas test points (1, 3, 6 , 7, 8) which are not covered within the reference points and reside on the outer radius and extremities of the room has greater error-rate (Figure 7.8). This phenomenon can be the result of the WKNN algorithm itself, where the candidate location estimate is calculated using the nearest four RPs. In the case of test points that reside in the locations that are not directly covered within RPs, the WKNN algorithm cannot perform optimally, thus it increases the error-rate.

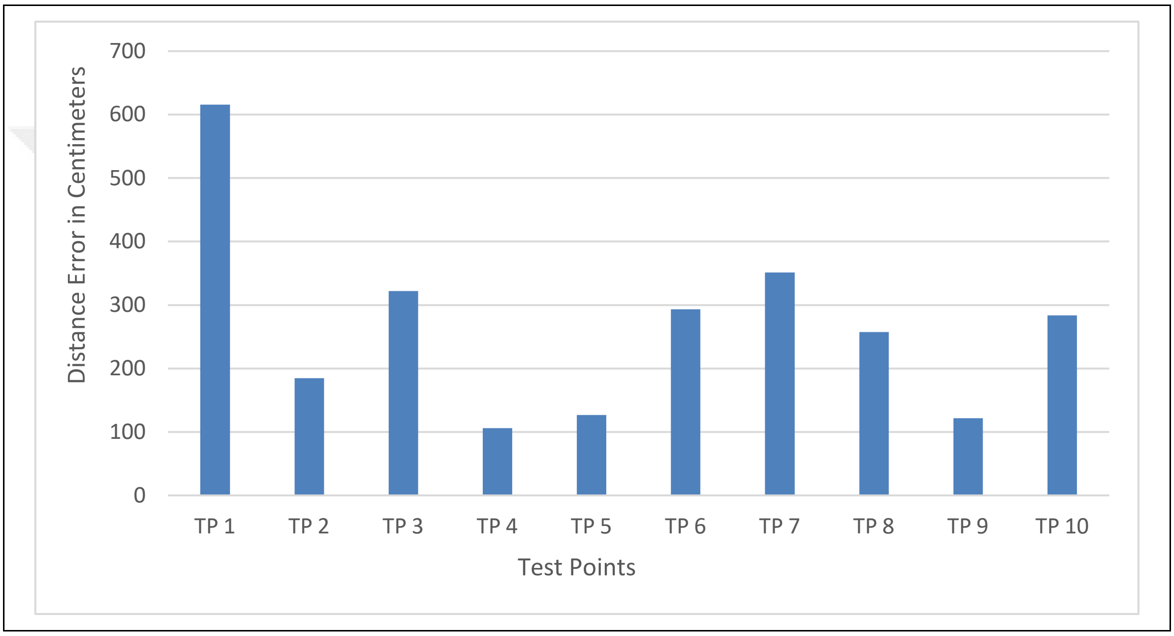


Figure 7.8. Test results per TP

8. DISCUSSION AND CONCLUSION

In this thesis, a study is undertaken to evaluate a server-based indoor positioning system with three client-based positioning systems. The client-based systems are chosen to include technologies that are popular among academia, such as Bluetooth, Wi-Fi and sensor-based PDR. Among the client-based systems designed, implemented and tested in previous sections, their positioning performance and accuracy are compared to the proposed server-based system. The proposed server-based system is suitable for large area deployment, due to its Wi-Fi sniffer modules, which can be added in additional numbers to cover the area in need. The system only utilizes airborne Wi-Fi frames generated from the device for location sensing, therefore it does not suffer from client-based systems where they need on-device apps and OS API compatibility.

BLE positioning system based on fingerprinting technique achieved an average of 176 cm positioning error-rate. Another fingerprinting-based large indoor area Wi-Fi positioning system is deployed on a supermarket branch to evaluate real-world scenario performed the worst averaging around 593 cm in its best case. The results of this system show how the positioning systems behave in complex inner environments where there is a constant human traffic. The sensor-based system which incorporates PDR algorithm achieved the best results, with an average error rate of 55 cm. However, PDR algorithm is very reliant on the initial location accuracy and orientation detection, so its performance proved to be mostly dependent on the hybrid position correction using BLE beacons. Thus, for a large area of deployment many BLE beacons must be incorporated if high accuracy is expected from PDR-based systems. Finally, server-based positioning system aimed to perform in similar performance accuracy to client-based systems albeit a more complex design process. The findings show that it performs within these expectations. The average positioning error for server-based system is 266 cm which is comparable to the tested systems.

Although BLE system and PDR sensor-based system performed better than proposed server-based system in controlled environments, real-world scenarios such as large indoor positioning system shows that complex inner structures and human presence affects the performance of positioning systems in indoors. Thus, when considered to real-world scenarios, server-based system turns out to be a desirable candidate, where the benefits from the proposed system can be utilized.

As a future work, the server-based system can be improved by adding hybrid functionality with sensor-based methods. Such system with iBeacon and PDR support, can choose the most accurate method on-the-go and cut down the positioning error-rate even in large indoor environments. Furthermore the algorithm can be improved by adding probabilistic approaches to Wi-Fi and Bluetooth techniques. Consequently the accuracy and performance of the server-based system can be tested in a large indoor environment such as the supermarket branch used in the Wi-Fi positioning system.

REFERENCES

1. Perez S. iOS 7 Eliminates MAC Address As Tracking Option, Signaling Final Push Towards Apple's Own Ad Identifier Technology. [cited 2018 5 April]. Available from: https://techcrunch.com/2013/06/14/ios-7-eliminates-mac-address-as-tracking-option-signaling-final-push-towards-apples-own-ad-identifier-technology/.

2. Dey AK. Understanding and using context. *Personal and Ubiquitous Computing*. 2001;5(1):4-7.

3. Blomberg M, Henriksson G. *Evidence for the minoan origins of stellar navigation in the aegean*: Département d'Anthropologie Historique, Institut d'Archéologie de l'Université de Varsovie; 1999.

4. Lowrie W. *Fundamentals of geophysics*. Zurich: Cambridge University Press; 1997.

5. Britten FJ. *The watch & clock makers' handbook, dictionary and guide*. London: Spon; 1896.

6. Hubert A. All You Need To Know About Celestial Navigation. 2016 [cited 2018 4 April]. Available from: https://blog.active-outside.com/sailing/all-you-need-to-know-about-celestial-navigation.

7. Howeth CLS. *History of communications-electronics in the united states navy*. Washington, D.C.: Bureau of Ships and Office of Naval History; 1963.

8. Bedwell D. Where am i? American Heritage Magazine. 2007.

9. NASA - NSSDCA - Spacecraft - Details. [cited 2018 6 April]. Available from: https://nssdc.gsfc.nasa.gov/nmc/spacecraftDisplay.do?id=1964-001C.

10. Jansky, Bailey. THE LORAN-C SYSTEM OF NAVIGATION. Washington, D. C.; 1962 [cited 2018 6 April]. Available from: http://www.loran-history.info/Loran-C/Jansky%20_%20Bailey%201962.pdf.

11. Hegarty CJ, Chatre E. Evolution of the global navigation satellite system (GNSS). *Proceedings of the IEEE*. 2008;96(12):1902-17.

12. Brain. The Global Positioning System (GPS). 2000 [cited 2018 5 April]. Available from: http://healthcybermap.org/HGeo/pg3_3.htm.

13. What is a GPS? How does it work?. [cited 2018 5 April]. Available from: http://www.loc.gov/rr/scitech/mysteries/global.html.

14. GLONASS History. [cited 2018 5 April]. Available from: https://www.glonass-iac.ru/en/guide/.

15. Zak A. Deployment of the GLONASS Constellation. [cited 2018 5 April]. Available from: http://www.russianspaceweb.com/glonass_deployment.html.

16. Reddy H, Chandra MG, Balamuralidhar P, Harihara SG, Bhattacharya K, Joseph E, editors. An improved time-of-arrival estimation for WLAN-based local positioning. *2007 2nd International Conference on Communication Systems Software & Middleware*; 2007.

17. Yamasaki R, Ogino A, Tamaki T, Uta T, Matsuzawa N, Kato T, editors. TDOA location system for IEEE 802.11b WLAN. *2005 IEEE Wireless Communications and Networking Conference*; 2005.

18. Tay B, Liu W, Zhang DH, editors. Indoor angle of arrival positioning using biased estimation. *2009 7th IEEE International Conference on Industrial Informatics*; 2009.

19. Peneda L, Azenha A, Carvalho A, editors. Trilateration for indoors positioning within the framework of wireless communications. *IECON: 2009 35th Annual Conference of IEEE Industrial Electronics, Vols 1-6*; 2009.

20. Bahl P, N. Padmanabhan V, editors. RADAR: An in-building RF-based user location and tracking system. *19th Annual Joint Conference of the IEEE Computer and Communications Societies*; 2000.

21. Caicedo D, Pandharipande A, editors. Ultrasonic array sensor for indoor presence detection. *2012 Proceedings of the 20th European Signal Processing Conference*; 2012.

22. Kemper J, Hauschildt D, editors. Passive infrared localization with a probability hypothesis density filter. *2010 7th Workshop on Positioning, Navigation and Communication*; 2010.

23. Addlesee M, Curwen R, Hodges S, Newman J, Steggles P, Ward A, et al. Implementing a sentient computing system. *IEEE Computer*. 2001;34(8):50-56.

24. Bergamo P, Mazzini G, editors. Localization in sensor networks with fading and mobility. *13th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*; 2002.

25. Castano JG, Svensson M, Ekstrom M, editors. Local positioning for wireless sensors based on Bluetooth(TM). *RAWCON: 2004 IEEE Radio and Wireless Conference, Proceedings*; 2004.

26. Sanchez D, Quintana MA, Navarro JL. WLAN location determination using probability distributions with search area reduction via trilateration. *ICWMC: 2009 5th International Conference on Wireless and Mobile Communications*. 2009.

27. Taheri A, Singh A, Agu E, editors. Location fingerprinting on infrastructure 802.11 wireless local area networks (WLANs) using Locus. *LCN 2004: 29th Annual IEEE International Conference on Local Computer Networks, Proceedings*; 2004.

28. Martin E, Vinyals O, Friedland G, Bajcsy R, editors. Precise indoor localization using smart phones. *Proceedings of the 18th ACM International Conference on Multimedia*; 2010.

29. Farshad A, Li JW, Marina MK, Garcia FJ, editors. A microscopic look at WiFi fingerprinting for indoor mobile phone localization in diverse environments. *2013 International Conference on Indoor Positioning and Indoor Navigation*; 2013.

30. Ni LM, Liu YH, Lau YC, Patil AP, editors. LANDMARC: Indoor location sensing using active RFID. *Proceedings of the First IEEE International Conference on Pervasive Computing and Communications*; 2003.

31. Yunqiang Y, Fathy AE, editors. See-through-wall imaging using ultra wideband short-pulse radar system. *2005 IEEE Antennas and Propagation Society International Symposium*; 2005.

32. Wirola L, Laine TA, Syrjarinne JI, editors. Mass-market requirements for indoor positioning and indoor navigation. *2010 International Conference on Indoor Positioning and Indoor Navigation*; 2010.

33. Li KJ, Bigham J, Bodanese EL, Tokarchuk L, editors. Location estimation in large indoor multi-floor buildings using hybrid networks. *2013 IEEE Wireless Communications and Networking Conference*; 2013.

34. Mathisen A, Sorensen SK, Stisen A, Blunck H, Gronbaek K, editors. A comparative analysis of indoor WiFi positioning at a large building complex. *2016 International Conference on Indoor Positioning and Indoor Navigation*; 2016.

35. Jeon JS, Kong Y, Nam Y, Yim K, editors. An indoor positioning system using Bluetooth RSSI with an accelerometer and a barometer on a smartphone. *2015 10th International Conference on Broadband and Wireless Computing, Communication and Applications*; 2015.

36. Joel Yves A, Hao P. RSSI-based indoor localization using RSSI-with-Angle-based localization estimation algorithm. *International Journal of Sensor Networks and Data Communications*. 2015;04(02):1000122.

37. Wu XD, Shen RF, Fu LY, Tian XH, Liu P, Wang XB. iBILL: using iBeacon and inertial sensors for accurate indoor localization in large open areas. *IEEE Access*. 2017;5:14589-99.

38. Fentaw HW, Kim TH, editors. Indoor localization using magnetic field anomalies and inertial measurement units based on Monte Carlo localization. *2017 9th International Conference on Ubiquitous and Future Networks*; 2017.

39. Robert-Lachaine X, Mecheri H, Larue C, Plamondon A. Effect of local magnetic field disturbances on inertial measurement units accuracy. *Applied Ergonomics*. 2017;63:123-32.

40. Kawaji H, Hatada K, Yamasaki T, Aizawa K, editors. An image-based indoor positioning for digital museum applications. *2010 16th International Conference on Virtual Systems and Multimedia*; 2010.

41. Medina C, Segura JC, De la Torre A. Ultrasound indoor positioning system based on a low-power wireless sensor network providing sub-centimeter accuracy. *Sensors*. 2013;13(3):3501-26.

42. Kunin V, Turqueti M, Saniie J, Oruklu E. Direction of arrival estimation and localization using acoustic sensor arrays. *Journal of Sensor Technology*. 2011;1(3):71-80.

43. Zekavat R, Buehrer RM. *Handbook of position location: Theory, Practice and Advances*. New Jersey: Wiley-IEEE Press; 2011.

44. Wielandt S, De Strycker L. Indoor multipath assisted angle of arrival localization. *MDPI Sensors*. 2017;17(11):2522.

45. Hightower J, Borriello G. Location sensing techniques. 2001.

46. Poole I. WiFi Channels | WiFi Frequency Bands List | Radio-Electronics.com. [cited 2018 10 April]. Available from: http://www.radio-electronics.com/info/wireless/wi-fi/80211-channels-number-frequencies-bandwidth.php.

47. De Blas A, Lopez-de-Ipina D, editors. Improving trilateration for indoors localization using BLE beacons. *2017 2nd International Multidisciplinary Conference on Computer and Energy Science*; 2017.

48. Bagci M, Hacizade C, editors. Performance analysis of GPS based orbit determination via numerical methods for a LEO satellite. *2015 7th International Conference on Recent Advances in Space Technologies*; 2015.

49. Trilateration Technique. [cited 2018 14 April]. Available from: https://upload.wikimedia.org/wikipedia/commons/thumb/c/c3/3spheres.svg/1200px-3spheres.svg.png.

50. FCC. In the Matter of Revision of Part 15 of the Commission's Rules Regarding Ultra-Wideband Transmission Systems. [cited 2018 12 April]. Available from: https://www.fcc.gov/document/matter-revision-part-15-commissions-rules-regarding-ultra-wideband-transmission-systems.

51. UWB. [cited 2018 16 April]. Available from: http://www.vlsiegypt.com/home/wp-content/uploads/2012/11/111912_0903_Whydoweneed4.png.

52. Gezici S, Poor HV. Position estimation via ultra-wide-band signals. *Proceedings of the IEEE*. 2009;97(2):386-403.

53. PDR Overview. [cited 2018 17 April]. Available from: http://www.eenewsanalog.com/sites/default/files/styles/inner_article/public/import/pedestriandeadreckoning440.jpg?itok=kAe42I80.

54. Liu J, Chen C, Ma Y. Modeling neighbor discovery in bluetooth low energy networks. *IEEE Communications Letters*. 2012;16(9):1439-41.

55. Aircrack-ng. [cited 2018 18 April]. Available from: https://www.aircrack-ng.org/.

56. TP-Link WN722N. [cited 2018 17 April]. Available from: https://static.tp-link.com/TL-WN722N_EU_3.0_01_large_1506586482853c.jpg.