Real time Indoor and Outdoor Positioning System

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Abstract

Positioning system has been widely used in many industries to locate the target object position. One of the approach is to use the Global Positioning System (GPS). It is a prominent technology for object positioning. Although, there is a limitation on the GPS technology. GPS device relies upon the signal received from satellites, hence, the problems can occur when the signal is obstructed by buildings, walls, etc. For the outdoor positioning, the GPS is adequate for locating an object. However, once the object is inside the building, the GPS becomes inaccurate or cannot locate the object altogether. Therefore, this thesis proposes a system that use both GPS and Bluetooth Low Energy (BLE) technology to accomplish the indoor and outdoor positioning respectively. In the indoor positioning process, this thesis tries to improve the accuracy of BLE indoor positioning by predicting the environment (n) variable from a Pathloss equation based on its relation with vertical angle orientation of the BLE device. However, it does not succeed due to the fact that there are too many environment factors that can affect the accuracy. Ultimately, during the indoor positioning process, the thesis proposes a logic condition method after trilateration which achieve the highest precision score of 0.91 ,the lowest precision score of 0.47, and the average precision score of 0.73.

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Chapter 1
Introduction

1.1 Motivation

The interest in positioning system has been around for many years, especially after the success of Global Positioning System (GPS). The GPS is a satellite-based navigation technology enable the outdoor positioning with less than one-meter deviation in accuracy [22]. With the achievement of GPS in outdoor positioning, the next issue to be focused on is the indoor positioning. There has been a research on indoor positioning using multiple technologies, such as Wireless Local Area Network (WLAN), Camera positioning, Ultrasound wave, etc. along with many techniques, such as fingerprinting, triangulation, trilateration and many more. However, it is believed that there is still room for improvement in terms of accuracy for indoor positioning which will complement the full positioning (indoor and outdoor) system along with the use of GPS to achieve the outdoor positioning. Our thesis proposed a real-time indoor and outdoor positioning system with an improvement in accuracy of Bluetooth Low Energy (BLE)-based indoor positioning. The aforementioned positioning system tends to result in low accuracy positioning due to BLE nature of low power consumption and the fact that other surrounding signals such as WiFi [23] and environmental factors can cause an error in signal strength measurement. Therefore, the author believed that by knowing the equation of environment variable during the process of distance estimation before executing trilateration will help improve the accuracy.

1.2 Problem description

Performance of indoor positioning system using BLE can be improveing by predicting environment variable(n). Likewise, the indoor and outdoor positioning can be achieved by combining GPS and BLEtechnology into one system

1.3 Objective

The aim of this thesis is to implement a real-time indoor and outdoor positioning system on a mobile device and discover a method to increase the accuracy of BLE-based indoor positioning. The indoor positioning demonstration will be displayed on a 2-D map of a specified floor.

- Explore the techniques that can improve the accuracy of BLE-based indoor positioning.
- Mobile Application to show the result of indoor positioning by BLE and outdoor positioning by GPS.

1.4 Scope of work

The scope of our project regarding indoor positioning only applies to an unobstructed or free space environment and the accuracy improvement methods we propose are for BLE-based indoor positioning. Our indoor positioning system provides a 2-D position of the target.

1.5 Report structure

The rest of the thesis is structured as follows:

- Chapter 2 describes related work.
- Chapter 3 provides the background knowledge about indoor positioning.
- Chapter 4 describes the process of the system.
- Chapter 5 describes the implementation of the system.
- Chapter 6 describes the different experiments procedure and their results.
- Chapter 7 provides the conclusion of the thesis.

Chapter 2
Background Knowledge

There are various kinds of studies and researches that are related to this project. This mainly involve Bluetooth Low Energy.

There have been multiple proposed methods and multiple technologies for indoors localization. However, most of them use the Bluetooth low energy (BLE) and WiFi technology in the research. Moreover, the Received Signal Strength (RSSI) is one of the most popular and common way to estimate the position. Thus, in this chapter, we present the related work that use BLE and RSSI with these techniques: solely RSSI in distance estimation, Triangulation, Fingerprint-based method, and Trilateration.

Since GPS performs poorly in a building, different indoor positioning systems (IPSs) and technologies are studied in order to solve indoor positioning problems. Researches are carried out on different indoor localization methods and different technologies employed in indoor positioning systems. This section will describe several existing technologies used in the system to locate an indoor object. Gu and Lo's survey [14] divides IPSs into six categories according to the technologies employed.

2.1 Infrared Signal

Infrared signal (IR) [3] is electromagnetic wave with longer wavelengths than visible light, therefore, infrared is invisible to the human eyes. Infrared is generally used in commercial goods such as television, and air conditioner. Infrared that utilized for locating the object is called IR-base IPS. An example of IR-base IPS is use IR-base on incident angles of infrared emitters [6]. There are three infrared emitters on fixed known positions. An incident angle sensor measures the angle differences between each two emitters. Measured angle differences determine a position. The main disadvantage of IR-base IPS is the infrared as light wave cannot pass through opaque objects. From this problem, the object and emitters must be placed with no obstacles blocking the infrared signal.

2.2 Radio Frequency

Radio frequency (RF) refers to an oscillation rate of electromagnetic radio waves. Radio frequency is used in various technologies such as communication, detection, or even researching. In term of indoor positioning system, technology types of radio frequency that utilized for detect the object are called RF-base IPS. The main feature of RF-base IPS is it passes through most of obstacles. Therefore, RF-base IPS can solve a line of sight propagation.

2.2.1 Radio Frequency Identification

Radio Frequency Identification (RFID) [5] consist of tags and reader devices. This system is divided in two major type: active and passive. The RFID active system has a tag with battery inside, on the other hand, RFID passive does not. RFID enables identification from a distance, it does so without requiring a line of sight. The tags activated by reader device and return the information, such as product id, temperature. Using the RFID in term of indoor positioning is for tracking object or human, such as tracking patient in hospital, tracking product in supermarket.

2.2.2 Ultra-wideband

Ultra-wideband (UWB) [2] is a RF technology that can use a very low energy level for high-frequency and short-range communications over a large portion of the radio spectrum. Ultra-wideband (UWB) uses broad frequency bands to allow transmission using high-energy pulses while limiting the interference with other RF equipment operating within the same frequencies. In term of IPS, UWB-based systems usually rely on time-based methods such as Angle of Arrival (AOA), Received Signal Strength (RSS) [8] to determine the position between reference node (UWB receiver) and the target node (UWB transmitter).

2.2.3 Wireless local area network

Wireless Local Area Network (WLAN) [3] is a network in which a wireless router communicates with several WLAN compatible devices such as smart phone, laptop, which mean no need unique additional devices. Using in the indoor positioning, WLAN-base IPS use RF signal for communication, therefore, the RSSI can be used in the same way as with RFID to get the distance to a user from an access point. It can also be implemented on top of existing Wi-Fi infrastructure. The problem of WLAN-base

IPS is that the accuracy is very limited, thus it needs extra algorithms or hardware to compensate to ensure the good performance.

2.2.4 Bluetooth

Bluetooth is wireless technology widely used in local positioning system (LPS). It works in short range and lower data transfer rate. Bluetooth Low Energy (BLE) provides portable battery-powered beacon at low cost and consume less energy. BLE is used in range-based indoor positioning system [15][16], location fingerprinting [17]. Due to its ultra-low power consumption the localization using BLE can have an error rate up to 5 meters. The Topaz local positioning system [18] is the newer generation of BLE-based IPS. It provides room wise accuracy of 2 meters. The further enhancement of Topaz system is to integrate it with infrared and other transducers, with the Bluetooth positioning capability.

Received signal strength indicator (RSSI) is used to estimate the indoor position in [10]. The observation in this research is done in a 10.5 meters x 15.6 meters room with 22 beacons installed around the room. The system determines the location by measuring which beacon has the highest RSSI value. The experiment achieved the correct estimation rate of 96.6 percent.

In [11], the authors introduced the three-dimensional positioning system using three-dimensional coordinates triangulation to calculate the position of each node and RSSI to measure the distance among beacons. The error rate from estimation is reduced by 27 percent from existed two-dimensional positioning system.

Fingerprint-based method is another technique used in positioning system. In [12], the authors explored the use of BLE beacons for fingerprint positioning. The research was conducted using 19 beacons distributed around the approximately 600 square meters room. They achieve the tracking accuracies with 95 percent of the time containing an error less than 2.6 meters using dense beacon distribution (one beacon per 30 square meters) and less than 4.8 meters for lower density distribution (one beacon per 100 square meters) compared to the accuracy of error less than 8.5 meters achieved from the WiFi technology using the same method in the same environment.

In [13], the authors presented two post-processing filters (accuracy function and correction function) after applying the trilateration method to enhance the estimated result. The mean and standard deviation of the estimation are minimized after the post-processing filters are added, thus, they concluded that the trilateration method can be used in indoors localization and the post-processing filters are recommended to make the estimation more accurate.

Reference	Method/Technique	Accuracy/Result
[10]	RSSI	Accuracy rate is 96.6%
[11]	3-D Triangulation	Error rate is reduced by 27% from 2-D Triangulation
[12]	Fingerprint	Error rates in distance are less than 2.6 m (dense beacon distribution) and less than 4.8 (lower dense beacon distribution)
[13]	Trilateration, Accuracy function, Correction function	Trilateration can be used to do indoors localization and the accuracy can be improved using post processing filters.

2.2.5 Wireless Sensor Networks

Wireless sensor network (WSN) is a group of sensors spatially dispersed for monitoring recording of environment and organizing the collected data at a central location. Each sensor node contains transducer, microcomputer, transceiver, and power source. The transducer generates electrical signals. Then the microcomputer processes and stores the output. The transceiver receives commands from a central computer and transmits data to it. WSN can be constructed using star, tree, or mesh topologies. It can be applied to many topics such as, open source API, iOS, and Android [19], and WSN-based localization system using trilateration and fingerprint method [20]. Both of the methods yield result with error less than 1.2 meters.

2.3 Geomagnetic-field

Geomagnetic-field from earth is often used as navigator. The compass uses geomagnetic-field to find directions. There has been studies of indoor localization using magnetic field [21]. The geomagnetic-field based indoor localization suffers from a lot of fluctuation due to structure of the building which include steel, concrete, etc. These can make the data fluctuate. Assuming the anomalies inside the building is static, the magnetic fingerprint can be utilized in localization. In addition, the Monte Carlo localization has been proposed. Monte Carlo localization (MCL), is an algorithm for robots to localize using a particle filter. Given a map, the algorithm calculates the position of the robots as it moves. The research concludes that the deviation of magnetic field can be used in self-localization and that the ambient magnetic field may remain stable for longer periods of time.

2.4 Ultrasound Wave

Ultrasound wave is a type of inaudible sound wave that can travel through air and solid materials. The use of ultrasound wave can be seen in bats. Bats emit ultrasound on an object and rely on the echo to navigate them in the darkness. Similar mechanism is used for indoor localization called the active bat system [4], equipped with matrix of fixed reference nodes that act as ultrasound receivers on the ceiling. The tag worn by a person will emit ultrasound signal then the signals are captured by the receivers on the ceiling. The location of the person is then calculated by applying the time-based trilateration method. Unlike infrared light wave, ultrasound wave does not require line-of-sight propagation, so it can locate hidden objects.

2.5 Geomagnetic-field

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2.6 Audible Sound

Audible Sound is sound wave that typically generated by human. Basically, it can travel through air, and solid object, medium is necessary for its travel. Audible sound wave can be emitted by every mobile devices such as mobile phones and laptops. The study of an indoor location system that senses audible sound state that sound is sensitive to noise, so the localization process that uses audible sound will be degraded by noise interference. A possible solution is to operate audible sound-based IPS in a small, quiet environment.

2.7 Camera Positioning

The use of camera and computer vision technology for indoor localization is known as vision-based IPS [1]. In the studied, the micro-flyer equipped with two cameras take pictures of the special texture on the wall. By analyzing the distortion of the captured texture, the system can estimate its relative locations from the walls. The UAV (Unmanned Aerial Vehicle) [7] shots laser beams to the surrounding. By capturing and analyzing the position of the laser points on the walls and ground, the UAV can predict its distance from ground and walls. However, vision based localization consumes significant amount of power and computing resources that are used to analyze the captured image. Furthermore, the use of camera will increase the cost of the system results in low scalability

Chapter 3
Background Knowledge

Before describing our positioning model, it is important to understand the different properties of indoor and outdoor positioning system and study several existing solutions to positioning problems. This chapter present topologies of indoor and positioning system structure, and positioing methods.

3.1 Topology of Indoor Positioning System

The Indoor Positioning Systems could be classified into four categories which are self positioning, remote positioning, indirect self positioning and indirect remote positioning systems.[11]

3.1.1 Remote Positioning

The general concept of remote positioning is tracker device (Transmitter) will send the signal and receiver will receive the sent signal from the transmitter. After receiving the signal, the whole data will be transferred to the server. The server will compute the location of mobile device from the collected data. The overview of remote positioning system is depicted in Figure 3.1

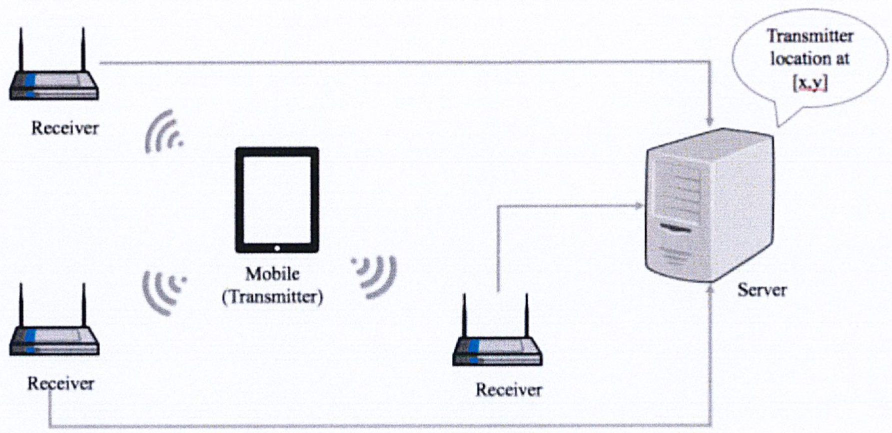


Figure 3.1: Remote Positioning

3.1.2 Self Positioning

The mobile device will receive the signal from all transmitters. However, the location of all transmitters must be fixed and the mobile device must know where is the all transmitters are located. After receiving the signal, the mobile device will act like the center station to calculates its positioning according to the location of transmitters. The overview of self positioning system is shown in Figure 3.2

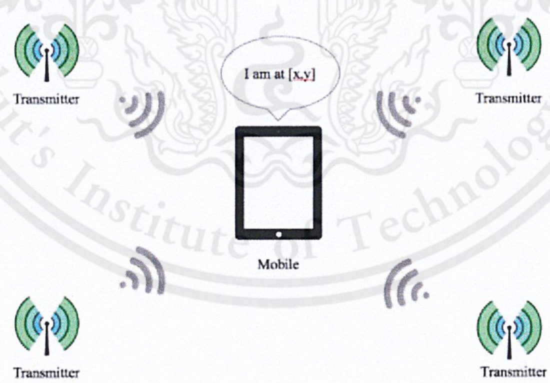


Figure 3.2: Self Positioning

3.1.3 Indirect Remote Positioning

In an indirect remote positioning, signals will be collected at receiver in the mobile device and send to central server the same ways as in the remote positioning but in this topology the measurement result from the receiver will be sent back to the mobile device. In short, it is a remote positioning system transmitting mobile device's position to the mobile device. The overview of indirect remote positioning system show in Figure 3.3

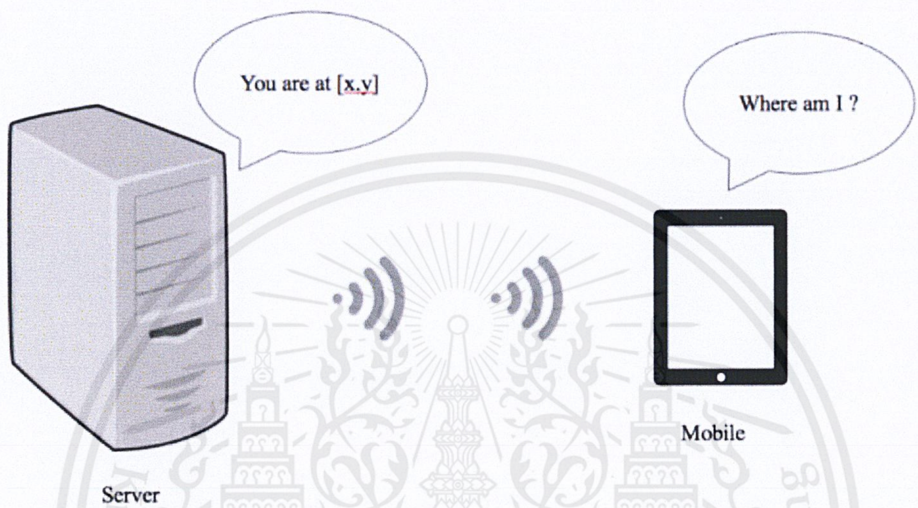


Figure 3.3: Indirect Remote Positioning

3.1.4 Indirect Self Positioning

In this topology, mobile device will receive the signals from several transmitters in known locations as same as the self position topology. Then the mobile device will calculate the location and send result to the central server. In short, it is a self-positioning system that sends position data to the central server. Figure 3.4 depicts the overview of indirect self positioning system.

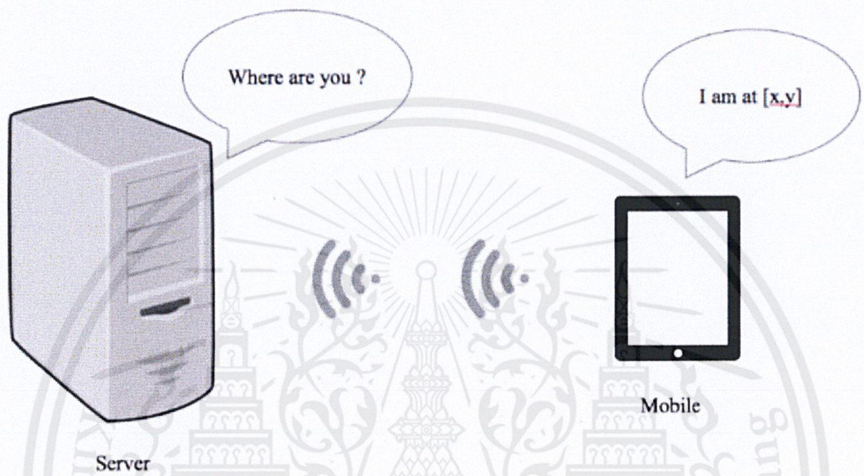


Figure 3.4: Indirect Self Positioning

3.2 Technologies of Outdoor positioning

The Outdoor Positioning Systems could be classified into two categories which are Global Positioning System (GPS), and cellular network

3.2.1 Global Positioning System (GPS)

GPS is a satellite-based radio-navigation system. It is a global navigation satellite system that provides geolocation and time information to a GPS receiver anywhere on the Earth where there is an unobstructed line of sight to four or more GPS satellites. Obstacles such as mountains and buildings block the relatively weak GPS signals. The GPS does not require the user to transmit any data, and it operates independently of any telephonic or internet reception, though these technologies can enhance the usefulness of the GPS positioning information. The GPS provides critical positioning capabilities to military, civil, and commercial users around the world. The United States government created the system, maintains it, and makes it freely accessible to anyone with a GPS receiver.

3.2.2 Cellular network

Mobile communication systems such as GSM (Global Standard for Mobile Communications) or UMTS (Universal Mobile Telecommunication System) are based on a set of cellular networks. Since some years location-based services (LBS) are delivered by these cellular approaches. LBSs are made possible through a suitable relationship between the cellular service provider, cellular networks and mobile user's terminals, which work in sync, to locate the user (mobile terminal), and then transfer the position data either upon the request or as a continuous stream. The major issue is to locate the user with a required accuracy and limited latency

3.3 Positioning Methods

There are many methods have been researched for indoor and outdoor positioning. In this section, it can divided method into three positioning methods; triangulation, trilateration, and fingerprint-based method. In additional, those locate objects by measuring signals. The main type of signal used in indoor positioning are infrared(IR) and radio frequency(RF) signal and this thesis will focus on using Bluetooth signal which is one type of RF signal.

3.3.1 Triangulation

Triangulation estimation is a trigonometric approach of determining an unknown location based on two angles and a distance between them. Two or more fixed nodes are required for location estimate by receiving mobile signal (Bluetooth signals) from the signal-transmitting device. Furthermore, Angle of Arrival(AoA) is a technique used in triangulation, this technique determines the angle of arrival of the mobile signal sent from the signal-transmitting device at which it is received by multiple receivers. From Figure 3.5, the location of the target node T1 is determined by measuring the angles of incidence ($\theta 1$, $\theta 2$) at which signals are sent from T1 and arrive at the receiving nodes R1 and R2. Geometric relationships can be used to calculate the coordinate (X,Y) of the target node.

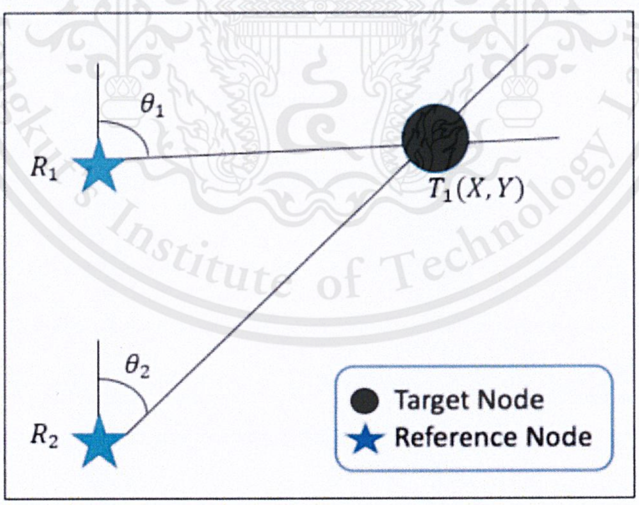


Figure 3.5: Angle of Arrival

3.3.2 Trilateration Method

Trilateration is a method to compute the unknown position of a node. At least three reference nodes with known positions are required in this method. Besides, the distances between these nodes and the mobile node are required to be known as well. Theoretically, each reference node forms a circle around itself with the radius of the distance to the mobile node. The position of the unknown node corresponds with the intersection of these three circles. Figure 3.6, where the coordinate of the target object (X,Y) can be estimated using the coordinates of the receivers ((X1,Y1), (X2,Y2) and (X3,Y3)) and the distances (d1, d2 and d3).

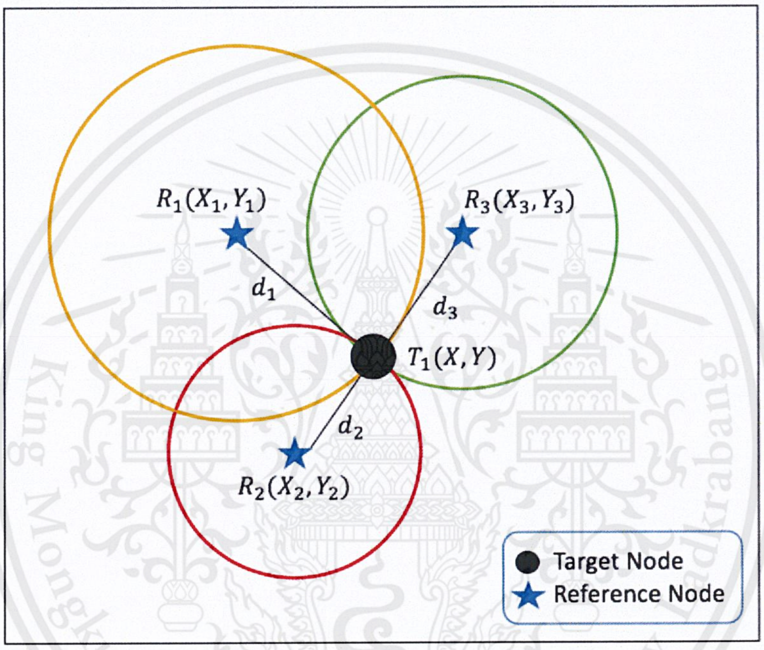


Figure 3.6: Trilateration

3.3.3 Fingerprint-Based Method

Fingerprint-Based method is one of the techniques for indoor positioning. The process of the fingerprint method consist of two main phases: training phase and classification phase. During the training phase we have to collect the RSSI data from transmitter device in specific area such as open area room and map the data into a classification model. After that, we train our system with the model we previously created. Next we go to the classification phase. In this phase the system will receive an input, which will be a RSSI sent from the transmitter device, then it will classify the location of the transmitter device via the model that it had learned. The fingerprint method can be a very accurate method with the use of a massive amount of data in the training phase. With that come a major disadvantage: it requires a lot of set up during the training phase. We need to collect large amount of data in order to just tell which area the device is in. To be able to track the device location with more precision the setup will be too impractical to be beneficial. And also the model that we use to train the system have to be proprietary to each location.

Chapter 4
Proposed Method

4.1 System Architecture

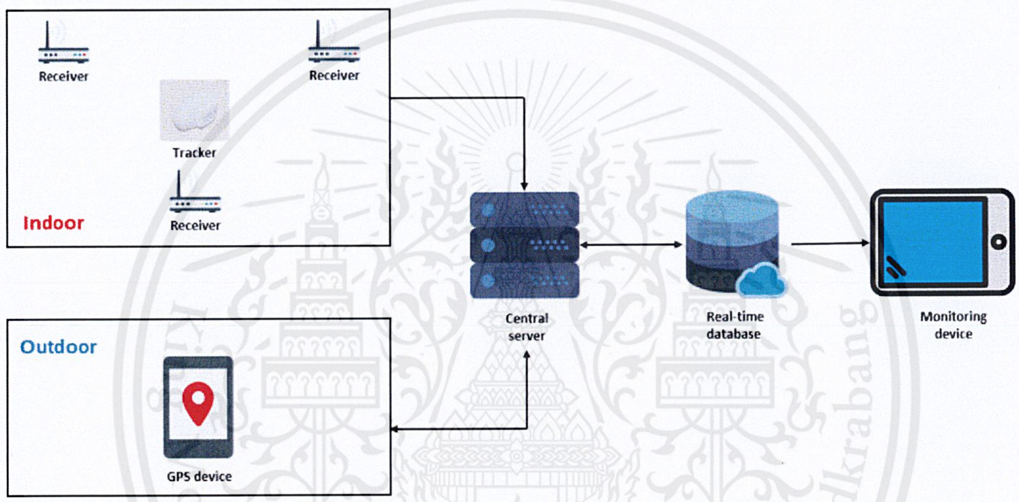
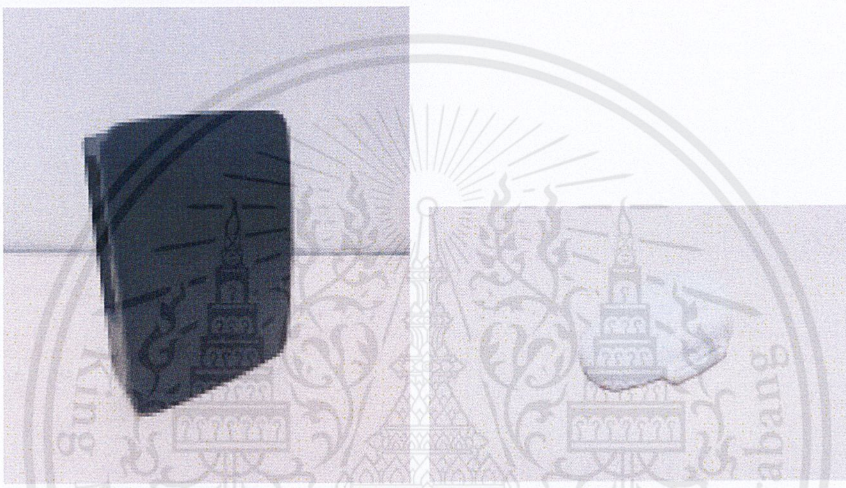


Figure 4.1: System Architecture

Our research employs architecture shown in Figure 4.1. The system contains two main parts: indoor positioning and outdoor positioning that are working together. For indoor positioning, the system comprises of three main components: Tracker, Receiver, and Server. Tracker sends Bluetooth signal to the receiver. Then the receiver reads RSSI (Received Signal Strength Indicator) from received signal and sends it to the server. Afterwards, the central server preprocesses the RSSI data and then calculate the position of the tracker. The preprocessing techniques used in our research are moving average and channel separation by K-means clustering method. After the data is preprocessed, it is fed into the path loss model in order to obtain the distance between the tracker and the receiver. Lastly, the trilateration method is used to acquire the position of the tracker. After getting the result, the position will be updated to the real-time database.

The tracker and receiver that we use are BLE (Bluetooth Low Energy) device and Raspberry Pi 3 respectively. The BLE device is used to transmit the Bluetooth signal at the sampling rate of 10 Hertz. The Raspberry Pi 3 is used for receiving the Bluetooth signal from the BLE device in form of RSSI (Received Signal Strength Indication). The RSSI is computed in decibel unit. Figure 4.2 shows the devices that we use to collect the RSSI data. For outdoor positioning, the GPS (Global Positioning System) in gps device will be enabled when the tracker is no longer in the building, i.e. when the receiver does not receive any signal from the tracker. Figure 4.2a and 4.2b depict the device that we use to receiver The RSSI data and Tracker which send the RSSI data respectively. After getting outdoor position, it will be update to real-time database.



(a) Receiver(RaspberryPi). (b) Tracker(Air-Node).

Figure 4.2: Component Deivices.

4.2 Software Architecture

Our software architecture comprises of four components: mobile application for displaying the target object position in 2D map, a real-time NoSql database that it is Firebase's real-time database for storing the position of the target object in real time, central server that receives the data from receivers for calculating the position of target object, and GPS device for outdoor positioning that will be enabled when the target object is outside of the building. The central server and GPS device send the position data to real-time NoSql database. Then the mobile application retrieves both indoor and outdoor position data from real-time database and renders it on 2D map.

4.3 System Process

For system process, the author focus on the indoor positioning process that is BLE indoor positioning system. The flow of methodology is as depicted in Figure 4.3. The general processes of the system are divided into two main sections which are "Finding Path Loss Model" and "Finding Object Location." The "Finding Path Loss Model" section consists of three processes: Data Collection, Preprocessing and Environmental Characterization. The Data Collection process is the collection of a huge set of RSSI data in a free-space environment at multiple known distances and different angle of rotation of the tracker as a training set by having the receivers receiving RSSI transmitted from the target object. In the Preprocessing process, the raw RSSI data is being preprocessed through methods such as moving average, and channel separation. In the Environmental Characterization process, a method called curve fitting is performed on the cleaned set of RSSI data to get the log-distance path loss model, in which the model is used to find the distance between the tracker and each receiver. Next in the "Finding Object Location" section, RSSI values are being measured continuously by the receivers. This section consists of two processes: RSSI-Distance Conversion and Trilateration. In the RSSI-Distance Conversion process, the measured RSSI values are preprocessed by the aforementioned methods and substituted into the corresponding log-distance path loss model to convert RSSI to distance. After this conversion, we are able to obtain the distances between the target object and the receivers. Finally in the Trilateration process, the trilateration equation is applied to determine the exact location of the target object.

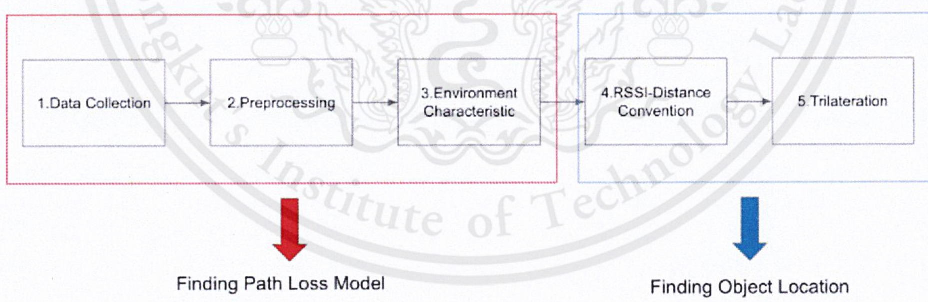


Figure 4.3: System topology

4.3.1 Data Collection

The first process of this section is data collection. In our system, the tracker attached to the target object send out the Bluetooth signal (BLE). Then the receivers receive the signal from tracker, extract the RSSI data from it, and send that data to the server for further calculation. In the data collection process, the receiver and the tracker are placed on stands with a height of 1 meter. The receiver is placed on a fixed location while the BLE tracker is placed at different distances away from the receiver. At each distance, the tracker is rotated in eight different angles of rotation: 0, 45, 90, 135, 180, 225, 270 and 315 degrees. The reason of setting eight device angles of rotation is to attempt to cover possible device orientation and increase the set of RSSI data.

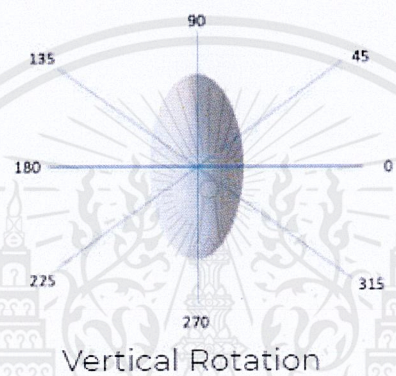


Figure 4.4: Device angle rotation

4.3.2 Preprocess

After collecting the raw RSSI data from data collection process, data preprocessing techniques are used for removing unnecessary data and smoothing the noisy data. Two different data preprocessing techniques are applied on the RSSI data of a specific tracker orientation, namely, moving average and channel separation.

Moving Average

Moving average or moving mean is a method to smooth out short-term fluctuations and highlight longer-term trends or cycles by creating series of averages of subset of the whole data set.

$$y'_1 = \frac{y_1 + y_2 + y_3 + ... + y_(w + 1) - 1}{w} \tag{4.1}$$

$$y'_2 = \frac{y_2 + y_3 + y_4 + ... + y_(w+2) - 1}{w} \tag{4.2}$$

Where y'_n is the data in the filtered data set, y_n is the data from the original set and w is the window size. Since we are including the overlapped data, $y_n$will also include the original data at $y_2...y_(w+1)$ - 1in the calculation even though $y_2...y_(w+1) - 1$ is already included in the calculation of Eq. 4.1. After the process is done we will get a filtered data set y which has a significantly less standard deviation than the original data set y .thus, having less noise.

Chanel Separation

The BLE has 40 physical channels, three of which are used for broadcasting its advertising packets. Due to this nature of BLE, a channel separation preprocessing technique is used. The collected data is separated into three clusters for each advertising channel. K-means clustering is performed to distinguish which of the three channels the data belongs to. The top cluster represents channel 1 containing a set of highest RSSI values, the middle cluster for channel 2 and the bottom cluster for channel 3. For each channel, moving average is applied to smooth the series of data. In the end, we get 3 sets of filtered data (one from each channel).

4.3.3 Environmental Characterization

The objective of this method is to find the value of n that constructs a curve that has the lowest total sum of squared error (SSE) or curve fitting process in Eq 4.3, meaning the best fit to the series of data points. SSE measures the deviation between the expected data point and the predicted data point produced by the curve fitting method. After obtaining the result of n, and then use n to substitute in Eq. 4.3 for create Path-loss model.

$$RSSI_d = RSSI_{d0} - 10n\log_{10}\frac{d}{d0} \tag{4.3}$$

4.3.4 RSSI-Distance Conversion(Distance Estimation)

In this process, the RSSI value is collected continuously by at least three receivers. The collected RSSI data is preprocessed by the two preprocessing techniques and substituted into the corresponding path loss model to determine the distance between the target object and each receiver. The equation of the path loss model can be rearranged from Eq. (4.3) to solve for the d (distance between the target object and each receiver) as in Eq. (4.4).

$$d = d_0 10 \frac{RSSI_d - RSSI_{d0} - X_\sigma}{-10n} \tag{4.4}$$

The $RSSId_0$ (RSSI value at reference distance d_0, d_0 = 1) and n is specific to each path loss model (determined in the previous process), while the $RSSI_d$ (RSSI value at target distance) is obtained from either the mean or median of the preprocessed test set (e.g. mean of data preprocessed by moving average and channel separation, median of data preprocessed by moving median).

4.3.5 Trilateration

Once we obtain the distances between the target object and each reference node as seen in Figure 3.2, trilateration method can be applied to determine the exact location of the target object. Referring to Figure 3.6, Eq. (4.5), Eq. (4.6) and Eq. (4.7) can be constructed according to the Euclidean distance formula.

$$d_1^2 = (x - x_1)^2 + (y - y_1)^2 \tag{4.5}$$

$$d_2^2 = (x - x_2)^2 + (y - y_3)^2 \tag{4.6}$$

$$d_3^2 = (x - x_3)^2 + (y - y_3)^2 \tag{4.7}$$

Simplifying the above equations through several mathematical operations produce the following Eq. (4.8) and Eq. (4.9), where Eq. (4.8) is used to find the x coordinate of the target object and Eq. (4.9) is for the y coordinate.

$$A = -2x_1 + 2x_2$$

$$B = -2y_1 + 2y_2$$

$$C = d_1^2 - d_1^2 - x_1^2 + x_2^2 - y_1^2 + y_2^2$$

$$D = -2x_2 + 2x_3$$

$$E = -2x_2 + 2x_3$$

$$F = d_2^2 - d_3^2 - x_2^2 + x_3^2 - y_2^2 + y_3^2$$

$$X = \frac{CE - FB}{EA - BD} \tag{4.8}$$

$$Y = \frac{CD - AF}{BD - AE} \tag{4.9}$$

Knowing the coordinates of the three reference nodes (i.e. (X1, Y1), (X2, Y2), (X3, Y3)) and the distances between the target node and the reference nodes (i.e. d1, d2, d3), these known values can be substituted into the equation to obtain the x and y coordinate of the target node.

Chapter 5
Implementation

5.1 Library

5.1.1 Websockets

Websocket is a library for building WebSocket servers and clients in Python with a focus on correctness and simplicity.

5.1.2 Bluepy

Bluepy is a Python module which allows communication with Bluetooth Low Energy devices.

5.1.3 Numpy

Numpy is the fundamental package for scientific computing with Python

5.1.4 Scipy

NumPy is a Python extension module that provides efficient operation on arrays of homogeneous data. It allows python to serve as a high-level language for manipulating numerical data, much like IDL, MATLAB, or Yorick.

5.1.5 Sklearn

It features various classification, regression and clustering algorithms including support vector machines, random forests, gradient boosting, k-means and DBSCAN, and is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy.

5.2 Development Tools

5.2.1 React native

Our system need to run on both iOS and Android. Thus, cross platform framework is solution. React native is the framework of Javascript that created by Facebook for rendering mobile application. It's based on React but instead of targeting the browser, it targets mobile platforms React Native uses the same fundamental UI building blocks as regular iOS and Android apps. Therefore, React Native makes it easy to develop and render in both Android and iOS, so it called Cross-platform framework. The author use this framework to develop position monitoring demonstrate application.

5.2.2 Node.js

Node.js is server technology to run our backend system ,it is the library of Javascript that execute the code outside of a web browser. Usually, JavaScript is used for client-side scripting, in which scripts written in JavaScript are embedded in a webpage's HTML and run client-side by a JavaScript engine in the user's web browser. Node.js lets developers use JavaScript to write command line tools and for server-side scripting, running scripts server-side to produce dynamic web page content before the page is sent to the user's web browser. The author use this framework to be a central server for calculating the indoor position and controlling both indoor and outdoor position system.

5.2.3 Firebase Real Time Database

To keep data in cloud server, and need minimum response time to access. Firebase Real Time Database can provides a realtime database. The service provides application developers an API that allows application data to be synchronized across clients and stored on Firebase's cloud. The author use this real-time database to store indoor and outdoor position in real time.

5.2.4 GitHub

GitHub is a web-based version-control and collaboration platform for software developers. GitHub is used to store the source code for a project and track the complete history of all changes to that code. It allows developers to collaborate on a project more effectively by providing tools for managing possibly conflicting changes from multiple developers. In this thesis, the author use GitHub to store the calculating indoor position and position monitoring demonstrate application source code.

5.3 Setup

5.3.1 Pre-processing

Moving Average

Algorithm 1,describes the preprocessing process using moving average function. It requires a list of number (*rssi*) that the moving average will be applied to and a window size (*num*). It finds the average or mean of subset of the *rssi* list starting from first element in the list. The size of subset is *num*. After finding the mean of first subset, it will substitute that mean value into the *filtered* list and move to the next element and continue finding the mean of that subset. It will repeat this step until it reaches the end of the *rssi* list.

Algorithm 1 Moving Average

procedure Moving Average($rssi$, num)
    $n \leftarrow$ size of $rssi$
    $filtered \leftarrow$ an empty list
    for $i \leftarrow 1$ to n **do**
        $new \leftarrow$rssi start from i to $i + num$
        $average \leftarrow$ mean of new
        $filtered \leftarrow$ append $average$
    return filtered

5.3.2 Environmental Characterization

Algorithm 2,describes path loss function which require *dataStat* or filtered RSSI data from previous process and list of distances. The pathloss equation is assigned to the *fitType*. After curvefitting, the result will be kept in the [*fitresult, gof*]. Gof or Goodness-of-fit is a statistics obtained from the curvefitting function. The *n* can also be obtained from the *fitresult*.

Algorithm 2 Environmental Characterization

procedure PathLoss($dataStat$,$distance$)
    $x - axis \leftarrow$ list of distance
    $dataList \leftarrow$ use mean value from dataStat
    $fitType \leftarrow$ assign path loss model formula
    $[x - data, y - data] \leftarrow$ assign x-axis data from dataList
    $option \leftarrow$ set graph mode to non linear graph
    $option - display \leftarrow$ set to off mode
    $[fitresult, gof] \leftarrow$ get the result of curve-fitting method
    $n \leftarrow$ get n value from fitresult

5.3.3 RSSI-Distance Conversion(DistanceEstimation)

Algorithm 3,describes procedure of RSSI-Distance conversion.when the author know the $rssiMean$ and $nMean$, the author can transform path loss function of determine environment characteristic(n variable) to find $distanceMean$.

Algorithm 3 DistanceEstimation

procedure getDistance($buffer$,$rssiRefMean$,$nMean$)
    for each l in enumerate($kmeans\_model$) **do**
        $rssiMean \leftarrow$ get mean value from buffer(i)
        $distanceMean \leftarrow 10^{(}(rssiMean - (rssiRefMean))/(-10^{n}Mean))$
    return distanceMean

5.3.4 Trilateration

Algorithm 4 describes procedure of trilateration, first it need to setup by define coordinate of x-axis and y-axis to $x1$,$y1$,$x2$,$y2$,$x3$,and $y3$. For instance, $x1$ equal to 0 and $y1$ equal to 4, those need to define because it to make function know the exactly position of at least three points. In additional, $r1$,$r2$,and $r3$ is the distance that get between object and three points. After that pass those to formular and simplify itself to get the position of object.

Algorithm 4 Trilateration

procedure CalculatePosition(x_1,x_2,x_3,y_1,y_2,y_3,$r1$,$r2$,$r3$)

  $a \leftarrow (-2 * x1) + (2 * x2)$

  $b \leftarrow (-2 * y1) + (2 * y2)$

  $c \leftarrow (r1)^2 + (r2)^2 - x_1 + x_2 - y_1 + y_2$

  $d \leftarrow (-2 * x_2) + (2 * x_3)$

  $e \leftarrow (-2 * y_2) + (2 * y_3)$

  $posX \leftarrow \dfrac{(c * e) - (f * b)}{(e * a) - (b * d)}$

  $posY \leftarrow \dfrac{(c * e) - (a * f)}{(b * d) - (a * e)}$

  $position \leftarrow$ [posX,posY]

  return position

5.4 Proposed System Development

The system is developed using mobile application to show the location of both indoor and outdoor positioning in 2-D map.

5.4.1 Mobile Application Development

To develop the demonstrate mobile application in order to monitor the object position in the indoor and outdoor, we select React Native framework which is created for developing mobile application in both Android and IOS platform. We also use real time database from Firebase that integrated with the application to display all object position in real time. To illustrate more clearly, we choose the hospital's patient tracking system as a demonstration application. Below are some of the user interface of the mobile application with Figure 5-1 as patients indoor position tracking page. It displays all patients that in the hospital area.

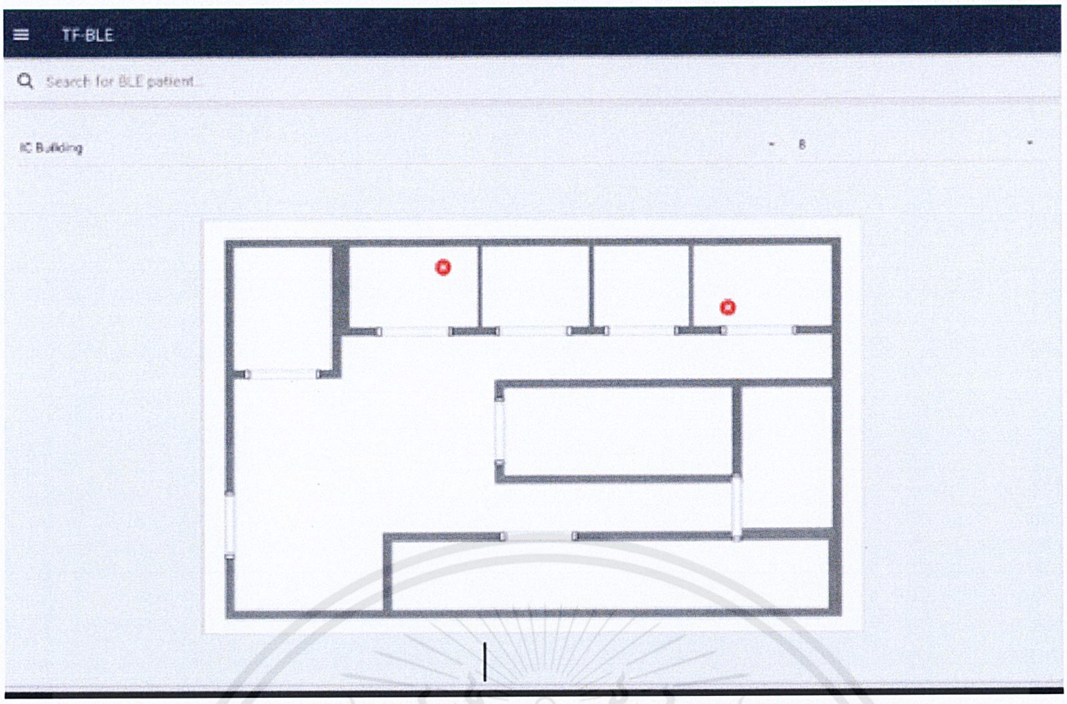


Figure 5.1: Screen-shot of indoor positioning mode (BLE)

In additional, it can track a wanted object (patient) by press a search bar from Figure 5.1 and then it will show the list of objects (patients) in Figure 5.2. Admin can input the word to filter the list and select object and then it will display in Figure 5.3

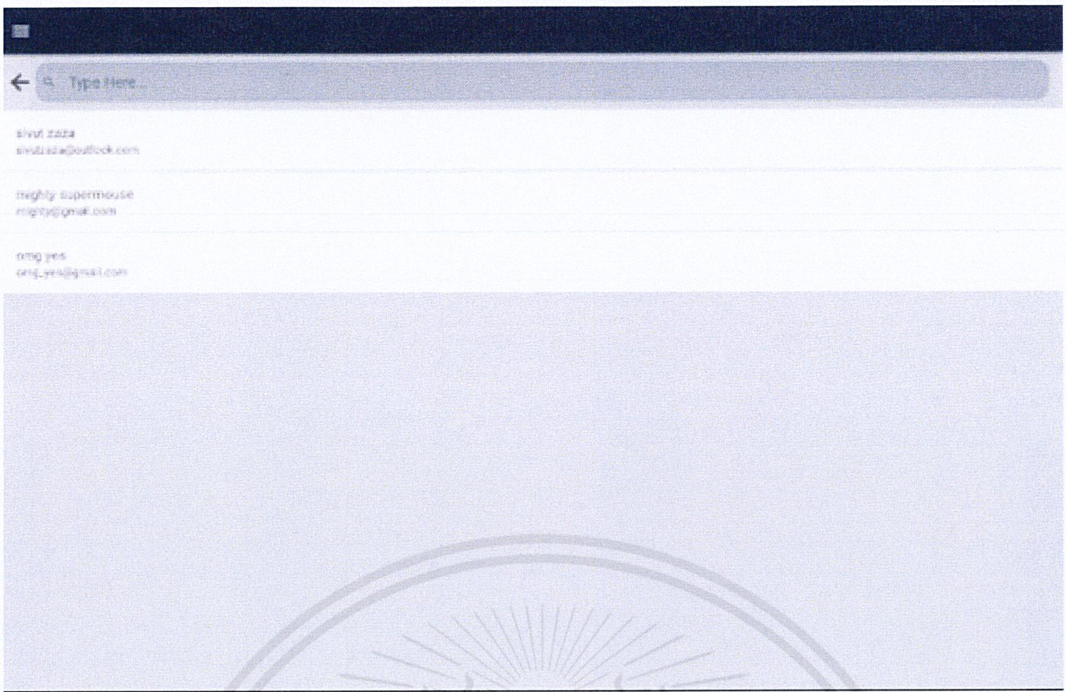


Figure 5.2: Screen-shot of search page

In outdoor position tracking page, it works same as an indoor position page. It displays all objects (patients) that already outside the receivers area (hospital area). Below are some of the user interface of the outdoor position tracking page as Figure 5.4 . Moreover, it can track wanted object (patient) by press a search bar in Figure 5.4 and then it will show the lists of outside objects same as indoor positioning mode in Figure 5.2. After select wanted object, it will display in Figure 5.5

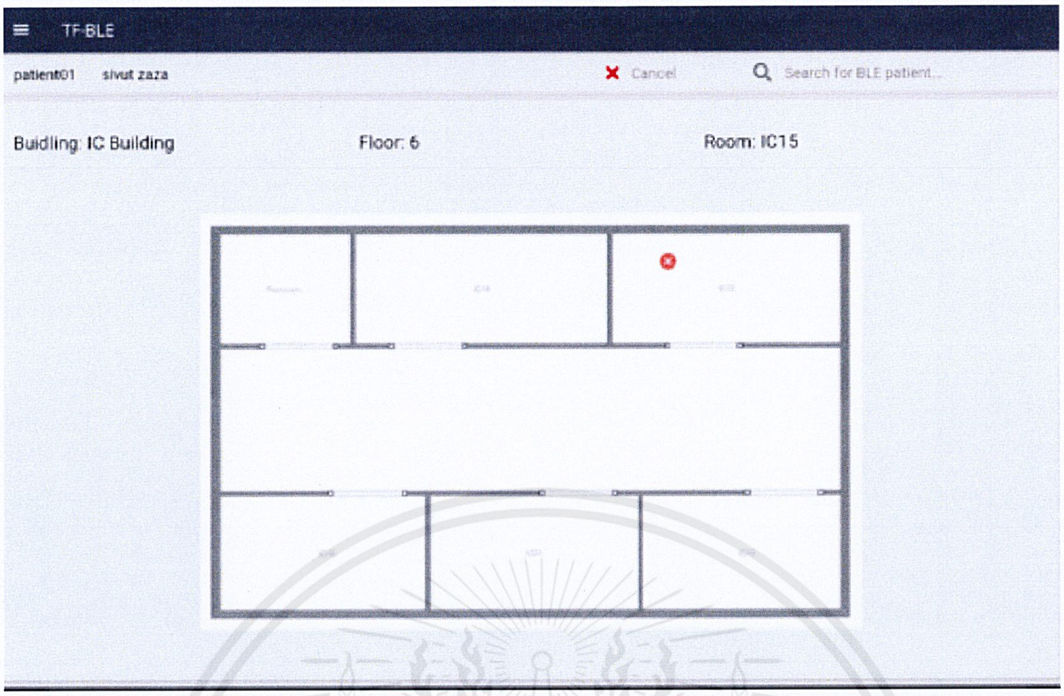


Figure 5.3: Screen-shot of tracked object in indoor positioning mode

Figure 5.4: Screen-shot of outdoor positioning mode (GPS)

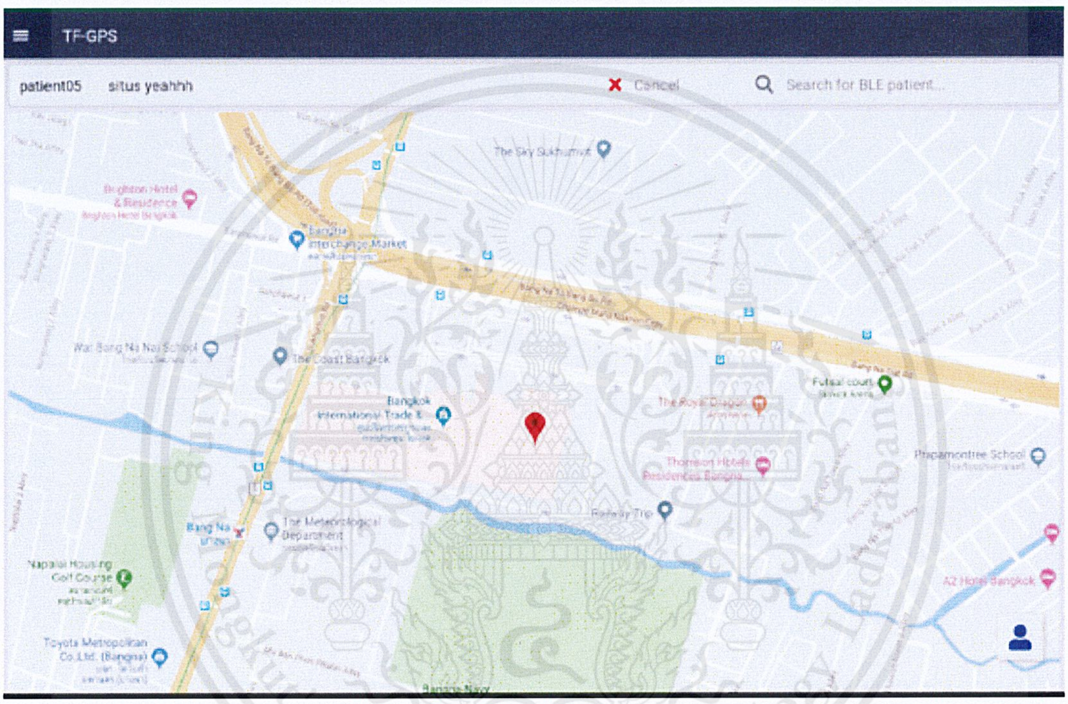


Figure 5.5: Screen-shot of tracked object in outdoor positioning mode

Chapter 6
Experiment & Result

Data preprocessing and n variable in Path Loss Model can affect the accueacy of distance estimation. In this section, the author show the result after preprocessing technique and the soulution to predict n variable.

6.1 Dataset

To investigate how angle are effect to preprocessing technique and environment characteristic. All dataset in our experiment are collected in an open area with no obstacle between tracker and receiver inside the 6th floor of the International College building in King Mongkut's Institute of Technology Ladkrabang (KMITL) at eight different angle of rotations of the tracker: angle 0, angle 45, angle 90, angle 135, angle 180, angle 225, angle 270, and angle 315.

Training Sets

Following is the list of all datasets we collected using Raspberry Pi 3 Receive and BLE tracker.

1. Dataset 1: 200 samples at 12 distances, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, and 6 meters collected on October 17, 2018.
2. Dataset 2: 200 samples at 12 distances, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, and 6 meters collected on November 12, 2018.
3. Dataset 3: 200 samples at 12 distances, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, and 6 meters collected on November 21, 2018.
4. Dataset 4: 200 samples at 12 distances, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, and 6 meters collected on December 04, 2018.
5. Dataset 5: 200 samples at 12 distances, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, and 6 meters collected on February 20, 2019.

6. Dataset 6: 200 samples at 12 distances, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, and 6 meters collected on March 1, 2019.

6.2 Measure

There are two main statistical measure that we use to evaluate the performance of our system, the first one is the minimum absolute error (RMSE), and the second is precision score the reason why the author uses two measure because in trilateration experiment, there are two experiments and each of them give the different type of result.

6.2.1 Root Mean Squared Eror(RMSE)

One of our experiment, the result is the regression line data points. Thus, The Root Mean Square Squared Error (EMSE) is tool for measuring the absolute difference between the expected and the actual result. RMSE basically measures the average of the differences between the expected and the actual results, calculated by Eq 6.1

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6.1}$$

where n is the number of predictions, y is the vector of expected values and $\hat{y}$ is the vector of actual values being predicted.

6.2.2 Precision Score

The precision score is ratio of correctness,it is a metric for multi-label classification of how many selected items are relevant

$$PrecisionScore = \frac{TP}{TP + FP} \tag{6.2}$$

where tp is the number of true positives and fp the number of false positives. The precision is intuitively the ability of the classifier not to label as positive a sample that is negative. The best value is 1 and the worst value is 0.

6.3 Experiment

There are four experiments on all of our datasets to study the nature of the data and formulate hypotheses. In this section, the author explore the factors that related to the performance of the system. It consist of Preprocessing technique, and environment variable in Path loss model.

6.3.1 Experiment1: Preprocessing by Moving Average

Objective

This experiment explains the effectiveness of RSSI after reducing the noise of data by using moving average and visualize the path loss model from the moving average of RSSI data.

Experimental Procedure

The raw RSSI set is filtered by moving average with a windows size of 20, using Matlab on test set for all 8 angles of vertical rotation to smooth the RSSI readings before the curve fitting is performed on the means of the filtered data to obtain the path loss model. The data from dataset 4 at angle 0 is taken as an example to showcase the result after applying moving average filter.

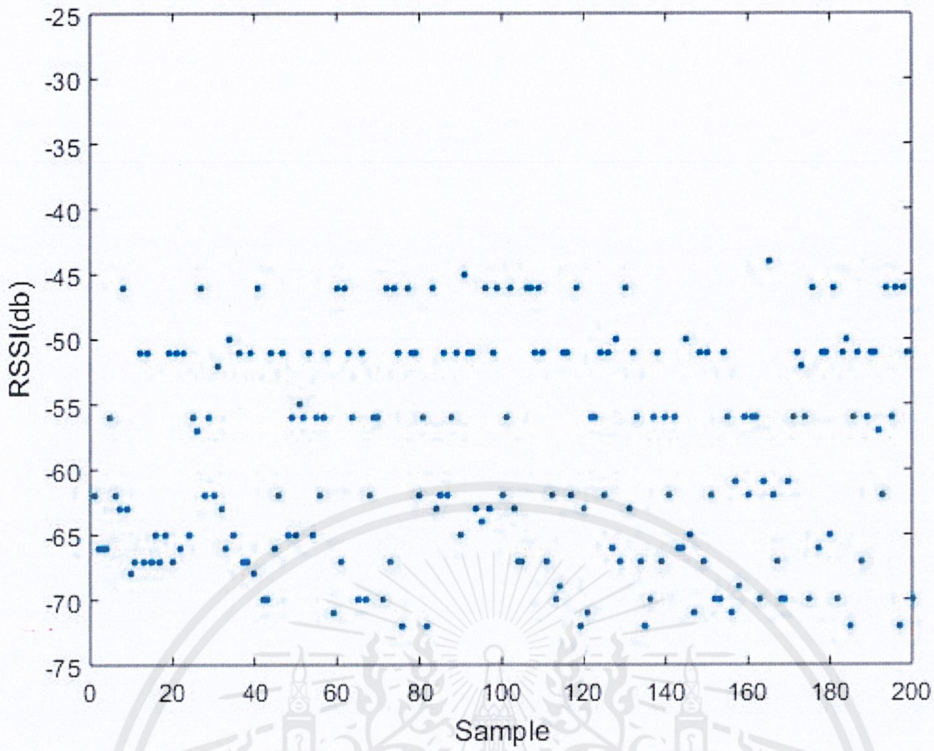


Figure 6.1: Scatter plot of raw data from dataset 4 at angle 0

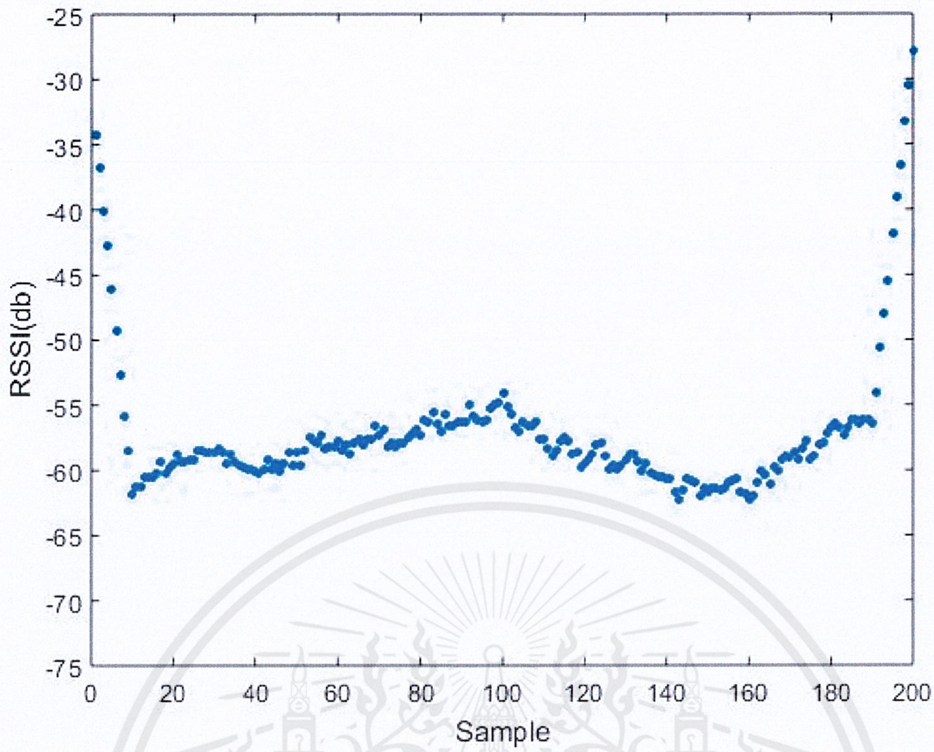


Figure 6.2: Scatter plot of data from dataset 4 at angle 0 after applying moving average

Result

When the data is less scatter and smoother after applying the moving average, it means that we can remove the noisy data or resolve the inconsistencies in the data and transform it to an understandable format,The data before applying the moving average is shown in Fig.6.1 and the data after applying the moving average is shown in Fig.6.2.

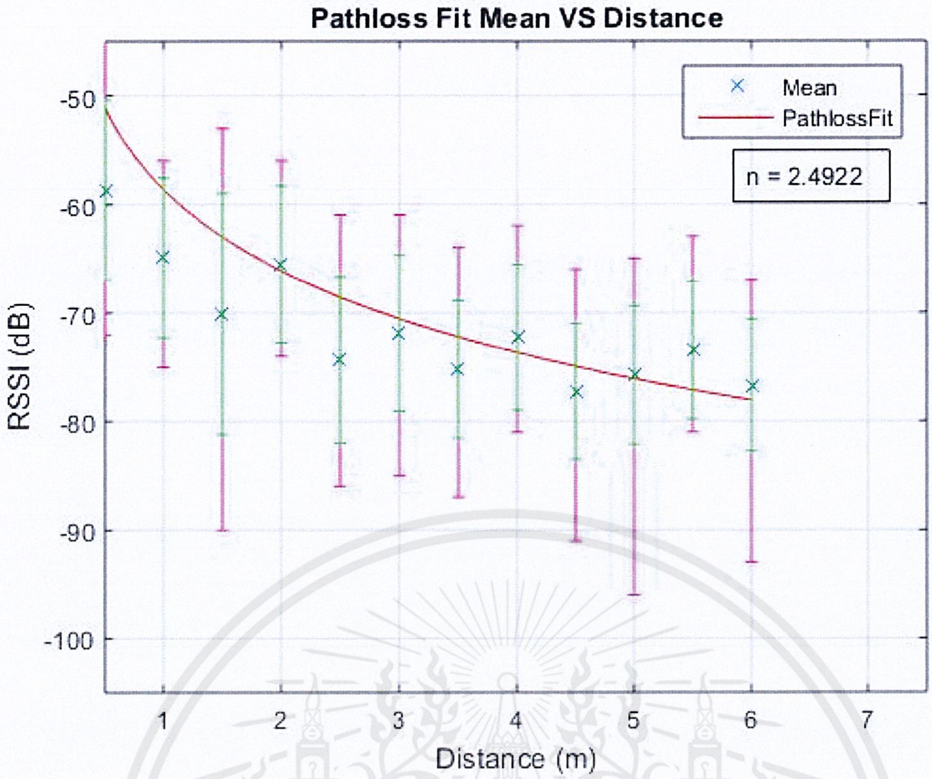


Figure 6.3: Example curve fitting of Dataset 4 at angle 0

Fig.6.3 shows the example result of curve fitting to pathloss model of raw Dataset 4 at device orientation angle 0. The pink bar at each point indicates its min-max error bar, while the green bar indicates its standard deviation.

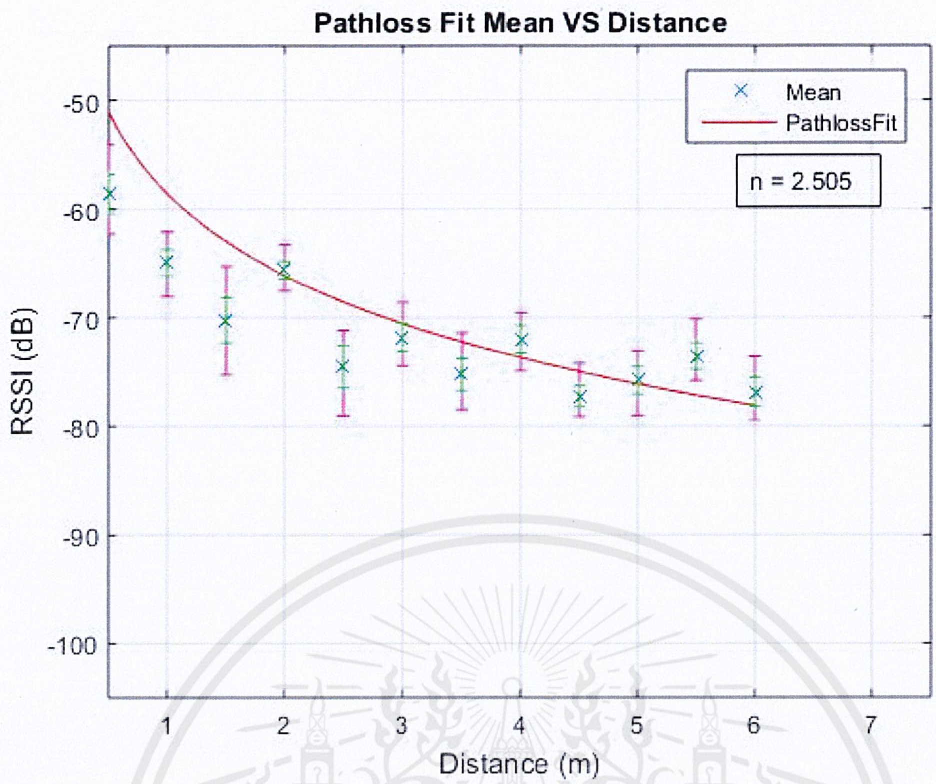


Figure 6.4: Example curve fitting of Dataset 4 at angle 0 after applying moving average

Fig.6.4 shows the example result of curve fitting to pathloss model of the Dataset4 at angle 0 after filtering with moving average. From the observation, the min-max error bar and the standard deviation in Fig.6.4 is significantly smaller comparing to the plot shown in Fig.6.3. The conclusion of statistics from before applying filter and after applying filter is shown in Fig.6.5 and Fig.6.6 respectively.

Distance(m)	Mean	Median	Mode	SD
0.5	-58.65	-57	-51	8.2345
1	-64.94	-60	-58	7.3592
1.5	-70.085	-69	-53	11.1196
2	-65.515	-65.5	-72	7.225
2.5	-74.32	-75	-79	7.6558
3	-71.89	-69.5	-69	7.1578
3.5	-75.2	-78	-79	6.3697
4	-72.235	-70	-79	6.7071
4.5	-77.24	-78	-85	6.2367
5	-75.725	-74	-82	6.3752
5.5	-73.465	-70	-68	6.353
6	-76.665	-73	-72	6.0784

Figure 6.5: Statistics details of raw Data 4 at angle 0

Distance(m)	Mean	Median	Mode	SD
0.5	-58.6006	-58.65	-57.7	1.7988
1	-64.9395	-64.8	-64.35	1.2155
1.5	-70.2345	-70.15	-71.85	2.0741
2	-65.626	-65.65	-65.65	0.8276
2.5	-74.4765	-74.05	-74	1.9573
3	-71.8113	-71.7	-73.75	1.2896
3.5	-75.2285	-75.2	-75.15	1.4782
4	-71.9768	-71.75	-73.5	1.2683
4.5	-77.2215	-77.3	-77.9	0.9633
5	-75.7768	-75.85	-76.5	1.2543
5.5	-73.5412	-73.8	-74.65	1.2131
6	-76.8376	-76.95	-76.2	1.3425

Figure 6.6: Statistics of Dataset 4 at angle 0 after applying moving average filter

6.3.2 Experiment2: Prediction of n variable in Path Loss Model

Objective

This experiment is conducted in an attempt to predict the n variable which is the environment variable that can directly affect to the accuracy of RSSI-Distance Conversion (Distance Estimation) in Eq. (4.4)

Experimental Procedure

The curve fitting to pathloss model is performed on different filtered RSSI data; Dataset 1, Dataset 2, Dataset 3, and Dataset 4 which are different in collect date. However, the author try to control the environment by collect data in the free space with out signal interference from other Bluetooth devices. After the curve fitting process and n variable is obtained, we plot the value of n from we retrieved from curve fitting at every angle and observe the trend of the graph from various datasets.

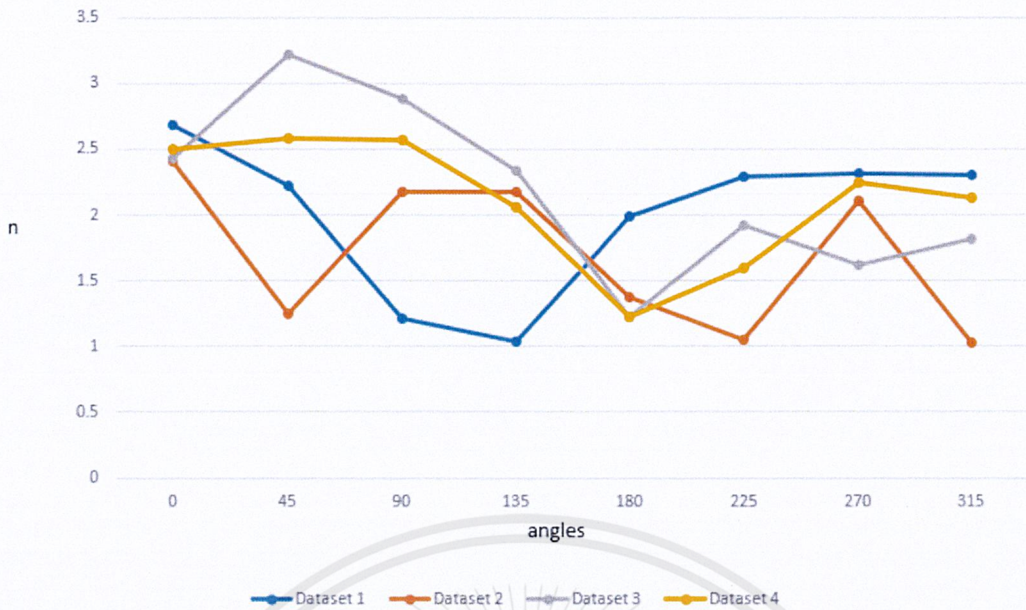


Figure 6.7: Plot of n from multiple Datasets

Result

The author expects to find the pattern of the graph which can form equation by observing the behavior of data that plot into the graph and compare it with the others. Furthermore, if it looks like to be similar or exactly be the same, it means that there is a relation among those. unfortunately, the pattern obtained from each dataset varies too much to be able to infer the overall pattern. For example, the pattern from Dataset 2 is similar to the graph of sine, though, the same cannot be said for the rest. The pattern from Dataset 3 and Dataset 4 is similar to each other as their RSSI data were collected on the same date and almost at the same time. Nevertheless, there is an inadequate information to conclude the pattern according to the graph trend.

6.3.3 Experiment 3: Trilateration

Objective

This experiment is conducted to evaluate the performance of trilateration by the path loss models of known angle (angle 0) obtained from preprocessing techniques: moving average with window size of 20 separation technique

Experimental Procedure

Our training set consists of the RSSI data of angle 0 from Dataset 5 which have 200 samples at 12 distances, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5,and 6 meters. It is preprocessed by applying a moving average filter and then curve fitted to obtain the pathloss models.

For the test set, we use the 200 samples of RSSI data that are collected real-time by each receiver. Similar to the training set, it is preprocessed by applying the moving average filter and curve fitted into the pathloss models to estimate the distance between the target object and the receiver before applying the trilateration technique to acquire the position of the target object. The three closest receivers based on the distance between receiver and tracker(target object) will be used for the trilateration. Figure 6.8 describe the overview of trilateration setup and 6.9 show the real environment on 6th Floor of IC KMITL for the trilateration experiment.

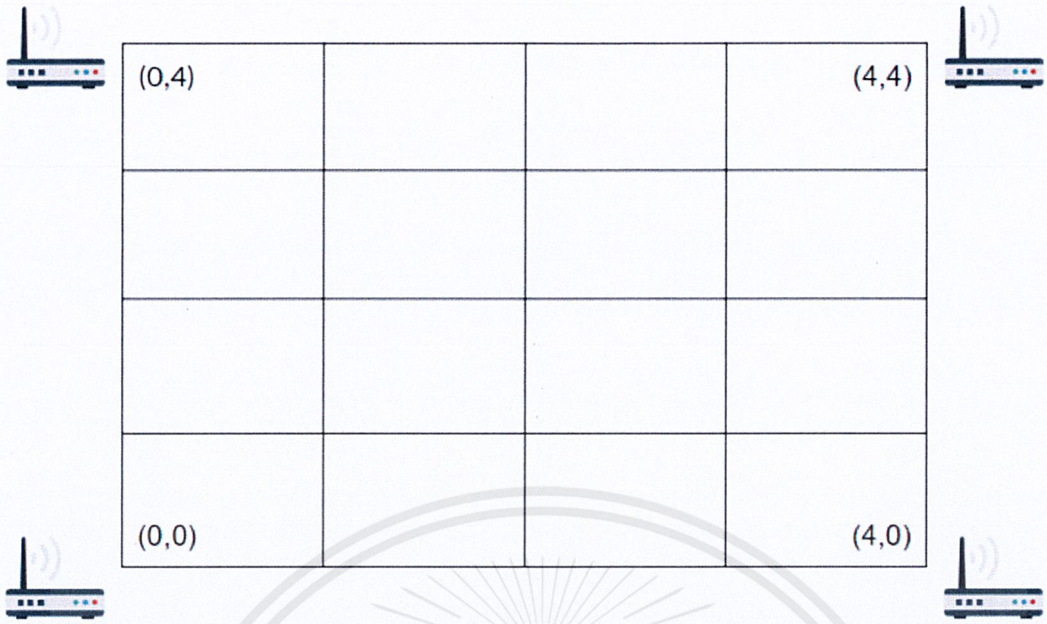


Figure 6.8: Overview of Trilateration Setup

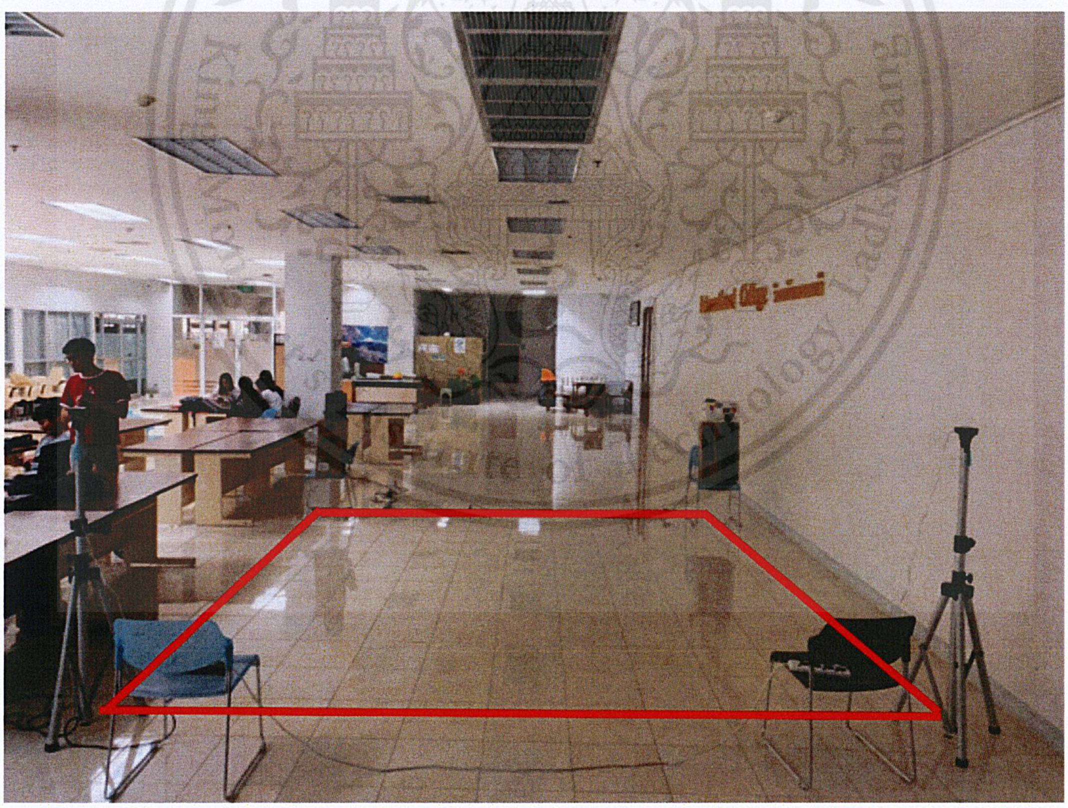


Figure 6.9: Trilateration Setup on 6th Floor of IC KMTL

	(0,0)	(1,0)	(2,1)	(3,3)	(0,4)	(4,4)
RMSE	0.86	1.19	0.62	0.82	0.83	1.1
Min Abs Error	0.14	0.04	0.48	0.16	0.13	0.14
Max Abs Error	2.40	2.6	3.1	2.56	1.7	4.25
SD	0.71	0.77	0.89	0.64	0.52	1.16

Table 6.1: Result of Trilateration

Result

From the table, it show the performance comparison of trilateration at different position. For example, (0,0) mean the position at x-axis equal 0 and y-axis equal 0 according to Figure 6.8 .Likewise, its based on Root Mean Square Error(RMSE), minimum absolute error, maximum absolute error and the standard deviation (SD) of the absolute errors. In RMSE the value that close to 0 that mean no error occur. However, it can see that the minimum and maximum, of RMSE are 0.62 and 1.19 respectively, it can conclude that are very high RMSE and illustrate there are a huge error on this experiment.

6.3.4 Experiment 4: Trilateration with grid system

Objective

This experiment tired to reduce the error in RMSE from Experiment 3 by setting grid system which is the condition rule to avoid the fluctuate result which product from tracker

Experimental Procedure

Due to the high error of RMSE that show in Experiment 3, this experiment tried to reduce error by making grid system. From 6.10, it can be obviously seen that after trilateration computing to get the coordinate position of object ex (1,3), it will sent this value to grid system process to compute. After that,system will get the grid-line representation which is result from that process. Figure 6.11 it demonstrate the grid-line representation or result from grid system when position of object is inside the range of that are set. For instance, if the position of object is (1,1.5) after pass to logic condition, the result will be "Block1"

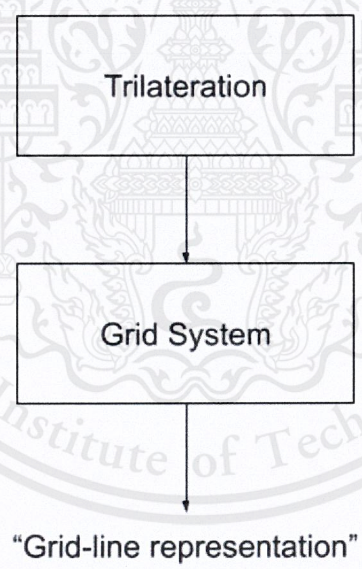


Figure 6.10: Flow of Work

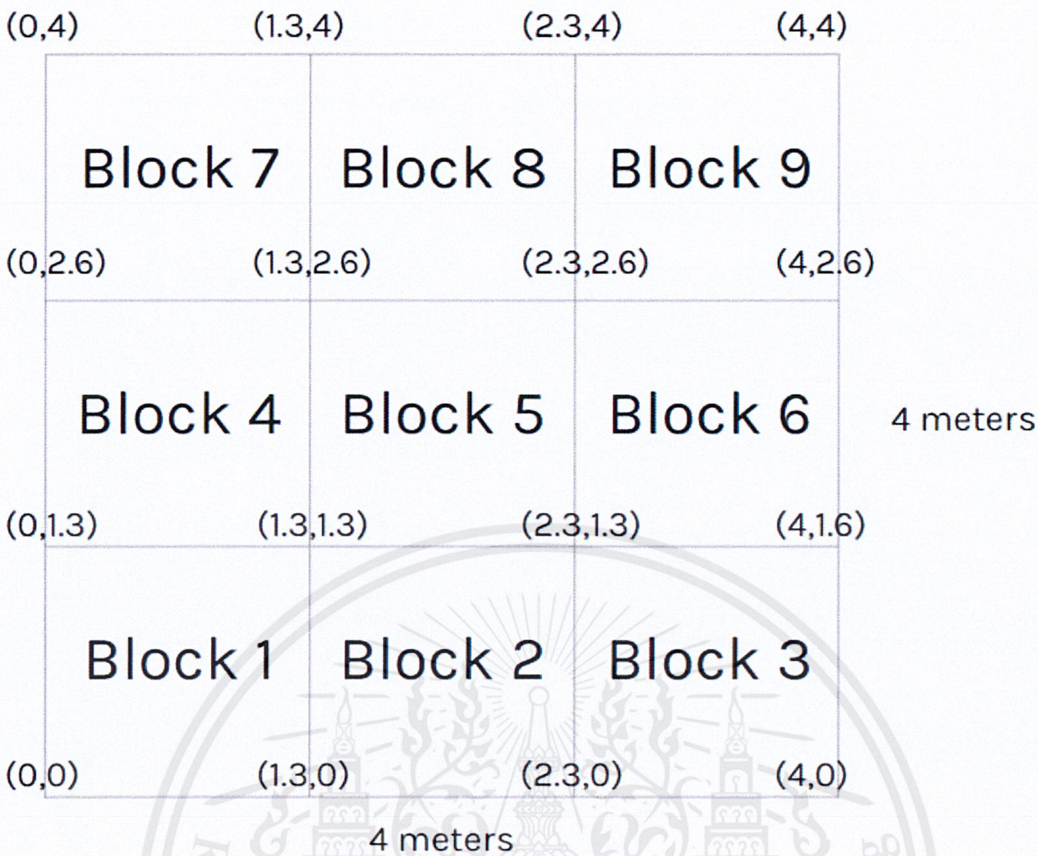


Figure 6.11: Grid System

6.3.5 Result

From table 6.2, it show the precision score of trilateration with grid system,the highest precision score is 0.88 at block9 and lowest score is 0.77. Moreover, the standard deviation is 0.053 that means that the result do not have a lot of "spread". The result in the sample don't vary much, and are very tightly clustered together.

	Block1	Block2	Block3	Block4	Block5	Block6	Block7	Block8	Block9
Precision Score	0.91	0.69	0.91	0.60	0.47	0.65	0.91	0.52	0.91
Average Precision Score	0.73								
SD	0.17								

Table 6.2: Result of trilateration with grid system

Chapter 7
Conclusion

In this thesis, the author studied the environment variable(n) which can affect distance estimation in path loss function. The point is if we know the right value of n, we can get the right distance and make system more accurate. Unfortunately, there are so many uncontrollable factors which are related to n such as, signal interference, temperature, and other things. Nevertheless ,to complete our objective, the author proposed the new solution by creating grid system after trilateration process to get the position and return a more reliability result. In the end, the authors could achieve all the objectives. The grid system, it got a high precision score of 0.91 and standard deviation of 0.17. A mobile application, it was completely created to present the result of indoor positioning by BLE and outdoor positioning by GPS.

7.1 Problem and Obstacle

7.1.1 Hardware Limitation

For Bluetooth Low Energy device 4.1, the RSSI value send from the device is very fluctuate and unreliable in sometimes. Especially, the environmental factors such as objects or people in the area could affect the BLE signal transmission which also leads to wrong distances estimation.

7.2 Future work

7.2.1 Hardware

In the future, there will be Bluetooth 5.1 which has direction-finding feature that will let Bluetooth devices pinpoint physical location to the centimeter, aiding in indoor positioning. Bluetooth 5.1 offers two different methods for determining direction, named

"Angle of Arrival" (AoA) and "Angle of Departure" (AoD). One of the two devices must have an array of multiple antennas, and the data received from those antennas can be used to identify the direction the Bluetooth signal is coming from.

If you're carrying a smartphone around and that phone has Bluetooth 5.1, a positioning system can have a good idea about your exact location. This could be used to improve navigation indoors, find your lost keys, or enable smarthome hardware to better pinpoint your location

7.2.2 Algorithm

In indoor positioning computation method, there are many solutions to improve the positioning performance For example, Indoor Positioning System with Pedestrian Dead Reckoning and BLE Inverse Fingerprinting by H. J. Bae and L. Choi [24]

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