ENHANCEMENT OF WIFI INDOOR POSITIONING SYSTEM

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ENHANCEMENT OF WIFI INDOOR POSITIONING SYSTEM

by

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DECLARATION

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LIST OF ABBREVIATIONS

2D	Two Dimensions
3D	Three Dimensions
AoA	Angle of Arrival
API	Application Programming Interface
ATT	American Telephone and Telegraph
BSSID	Basic Service Set Identifier
CMU-PM	Carnegie Mellon University Pattern Matching
FCC	Federal Communications Commission
GHz	Giga Hertz
GPS	Global Positioning System
IEEE	Institute of Electrical and Electronics Engineers
IPS	Indoor Positioning System
IPSUW	Indoor Positioning System Using WiFi
IR	Infrared
KHz	Kilo Hertz
K-NN	K-Nearest Neighbors
LAN	Local Area Network
LBS	Location Based System

LSA	Least Square Algorithm
LSE	Least Square Estimation
MAC	Media Access Control
MWAPI	Managed WiFi API
NAv6	National Advanced IPv6
NIC	Network Infrastructure
NLOS	Non-Line-of-Sight
PDA	Personal Digital Assistant
RAM	Random Access Memory
RF	Radio Frequency
RSS	Received Signal Strength
RSSI	Received Signal Strength Indication
RTLS	Real Time Location System
RTT	Round Trip Time
SDS-TWR	Symmetrical Double Sided Two Way Ranging
SQL	Structured Query Language
TDoA	Time Difference of Arrival
ToA	Time of Arrival
ToF	Time of Flight
USM	Universiti Sains Malaysia

UWB	Ultra-wideband
WBI	WiFi Based Indoor Positioning System
WEF	Wall Effect Factor
WiFi	Wireless Fidelity
WIPS	Wireless Indoor Positioning System

LIST OF SYMBOLS

$\sum$	Summation
Δ_{Th}	Threshold value Limits the amount of distance correction
O	Big Oh notation for complexity
$\|\cdot\|$	Euclidean norm used in Euclidean Distance

LIST OF ALGORITHMS

PENAMBAH-BAIKKAN KE ATAS SISTEM KEDUDUKAN SALAMAN BERDASARKAN WIFI

ABSTRAK

Terdapat banyak Sistem Berasaskan Lokasi yang telah dilaksanakan dalam persekitaran dalam bangunan, menggunakan berbagai-bagai teknologi tanpa wayar, walaupun sistem-sistem ini mempunyai daya anggaran yang kurang tepat dan kos infrastruktur perkakasan dan pemasangannya tinggi. Dengan ini, keperluan kepada satu sistem kedudukan dalam bangunan yang menggunakan infrastruktur tanpa wayar yang sedia ada (WiFi) dalam bangunan tersebut dan keperluan untuk mencapai ketepatan tinggi adalah diperlukan.

Dalam kajian ini, satu algoritma baru (WBI) telah dicadangkan, berdasarkan kepada teknologi Kekuatan Signal Penerimaan WiFi (RSS) beserta dengan metodologi trilaterasi (tiga pihak). Algoritma berkenaan menganggarkan jarak dari RSSs yang terkumpul di sekitar kawasan, dan memeriksa kejadian kesalahan yang mungin ada setelah anggaran lokasi dikira. Anggaran lokasi dikira sekiranya ia berada di dalam kotak sempadan yang terbina oleh algoritma Min-Max. Sekiranya begitu, satu mekanisme pembetulan kesilapan digunakan, menggunaan model penyaring Kalman yang memperbetulkan jarak yang jatuh di bawah keadaan bukan-mengikut pandangan (yang menyebabkan kesilapan itu), dan selepas itu, anggaran lokasi dihitung sekali lagi menggunakan jarak-jarak yang sudak diperbetulkan.

Beberapa ujikaji telah dijalankan di Fakulti Sains Komputer di Universiti Sains Malaysia sebagai tambahan kepada pelaksanaan algoritma yang telh disarankan. Eksperimen-eksperimen ini termasuk menentukan dan mengira faktor-faktor yang digunakan dalam menganggarkan jarak dan kesan penembusan dinding. Algoritma yang dicadangkan dalam kajian ini telah men-

capai purata ketepatan $2.6m$ ke atas pergerakan mudah-alih maksimum pada kelajuan $0.80m/s$, dan telah dinilai dengan dua lagi algoritma trilaterasi yang telah menunjukkan purata ketepatan masing-masing, iaitu $34.32m$ dan $218.35m$.

ENHANCEMENT OF WIFI INDOOR POSITIONING SYSTEM

ABSTRACT

There are many Location-Based Systems (LBS) that have been implemented in indoor environments using different wireless technologies, although they lacks the estimation accuracy and their hardware infrastructure and their setup costs are very high. The need for an indoor positioning system that uses the existing infrastructure (WiFi) of a building and achieves a high accuracy positioning is therefore, required.

In this research, a new algorithm named (WBI) is proposed, based on the WiFi Received Signal Strength (RSS) technology. The algorithm calculates the distances from the RSSs collected around the area, and checks for an error occurrence after the location estimation is calculated with Least Square Algorithm (LSA). The estimated location is checked wether it is inside the bounding box constructed by the Min-Max algorithm, if so, a Kalman filter is applied which in turn fixes the distance that falls under non-line-of-sight condition (that caused the error), and after that, the estimated location is recalculated with the corrected distances using LSA.

Some experiments were performed in the School of Computer Sciences in Universiti Sains Malaysia before implementing the proposed algorithm. These experiments include determining and calculating the factors used for distance estimation and the wall penetration effect. The proposed algorithm has achieved an average accuracy of 2.6m for maximum mobility movement speed of 0.80m/s, and has been evaluated against other two trilateration algorithms (LSA Corrected and LSA No Correction) which have archived the average accuracy of 34.32m and 218.35m respectively.

CHAPTER 1
INTRODUCTION

1.1 Overview

The rapid evolution of wireless network technology along with portable devices technology in the past few years have encouraged the development of location tracking applications using the standards 802.11 or 802.15 from the Institute of Electrical and Electronics Engineers (IEEE) which based on low power specification and low cost conception. Global Positioning System (GPS) helps us to locate and navigate places while we are driving, hiking, boating, and flying. The GPS system uses the orbiting satellite to locate specified position coordinates as it uses the satellite signal to navigate outdoor areas. However this system is a 'bootlicker' to determine position coordinates inside a building, where the satellite signals are not strong enough to determine the coordinates inside the indoor environments (Djuknic and Richton, 2001). There are several approaches of wireless communication adopted for Indoor Positioning System (IPS); however, these systems have drawbacks because their signals are weak when interfering with metallic or dielectric surfaces such as walls and human bodies.

There are many services that could use this tracking system in their indoor environments to increase their services. For example, multimedia appliances which are considered as smart home applications that act as a median to forward the multimedia (i.e. video) to the closest video screen- this could be done using the home positioning system (Ramani et al., 2003). Robotics in robotic fields use the indoor positioning system to navigate in the building by itself (Ladd et al., 2002). The location information granularity uses the location determination applications such as in large public libraries, where it functions to guide the readers to the books they choose. In hospitals, this facility keeps track of patients who need care, detects the whereabouts of the doctors and nurses, and keep an eye on expensive devices.

This chapter starts with reviewing the background of the indoor positioning systems, demonstrates some advantages and drawbacks of some indoor positioning systems, and identifies the scope of indoor positioning systems using Wireless Fidelity (WiFi) networks, and then moves on to show the problem statement, the objective of study, the scope of research, and contribution of this research.

1.2 Background and Motivation

Outdoor positioning applications based on the successfulness of the GPS have become motivation for the researcher to develop efficient indoor positioning systems. Since decades of years, the GPS systems have been relying on the satellites that estimate the location of the receiver. The indoor positioning systems in the other side cannot rely on the direct signal from GPS satellites; they require alternative methods and techniques to detect the receiver locations.

Many technologies have been used for location estimation in indoor environment such as Infrared (IR), the Radio Frequency (RF), and ultrasound signal which are considered as the major technologies. However these technologies are affected on intensive multi-path effects and are very sensitive on the building objects' thickness propagation effect. Therefore, the environment for indoor positioning areas unlike outdoor positioning areas, requires an in-depth understanding of radio propagation in order to obtain an efficient deployment (Tadakamadla, 2006).

There are three major properties that usually manage to get the estimated location of a mobile with a wireless device that have the low power radio feature; they are the radio connectivity existence, the radio signal attenuation with distance, and the packet time of arrival. The use of RSSI in most radios does not required any additional hardware and eliminates the wireless mobile devices' hardware but it is affected with power consumption, size and cost. In a specified building (Tauber, 2002), the radio propagation of a given radio model could be used for locating the mobile position. Nevertheless, the given radio model requires more details of RF propagation, considering the change in wireless devices' (receiver) sensitivity and orientation (Mazuelas et al., 2009; Randell and Muller, 2001).

Nowadays, several methods and technologies other than RSSI have proposed that depending on the mentioned properties, they are used for the indoor positioning system to locate mobile nodes in 2D or 3D places (Ward et al., 2002) which use the Time of Flight (ToF) technology; As plus point, these technologies improve the positioning estimation accuracy and reduce the complexity and cost. Some of these methods are listed bellow:

(i) Angle of Arrival (AoA).

(ii) Time of Arrival (ToA).

(iii) Time Difference of Arrival (TDoA).

(iv) Received Signal Strength (RSS) (Mazuelas et al., 2009).

(v) Time of Flight (ToF).

(vi) Symmetrical Double Sided Two Way Ranging (SDS-TWR) (Kong et al., 2010).

1.3 Problem Description

Since the GPS signal is weak through indoor buildings and cannot propagate through metallic or dielectric surfaces (e.g. walls), the indoor positioning system using GPS signal ends to be ineffective. Moreover, most of existing indoor positioning systems can determine user's location inside the building within few meters and in actuality, would lack location accuracy. Furthermore, they require a complex or an expensive hardware (Djuknic and Richton, 2001).

The processes used to estimate the coordinates for a moving object (i.e. user) inside the building is called the position estimation, , where this process depends on a predefined space by a set of referential nodes. A system deployed to determine the location or to use the position estimation process is called the "position location system" or "positioning system". Therefore, a Wireless IPS which uses the existing network infrastructure of a building is needed to determine the location information requested by any end-user (Mao et al., 2007).

1.4 Objectives

This research aims to develop a Real Time Location System (RTLS) based on WiFi in the school of Computer Science - Universiti Sains Malaysia (USM). Put in other words, it focuses on implementing an indoor positioning system using the WiFi network infrastructure separated over the school building to eliminate the needs of extra hardware and to make use of the existing wireless network to achieve a real time positioning system through the following objectives:

(i) To enhance algorithms to detect the current location of a user who carries a WiFi enabled mobile device.

(ii) To implement an indoor positioning system using the enhanced algorithms.

1.5 Scope of Research

The research scope is restricted to determine the user's accurate position coordinates inside a building as the following would suggest:

(i) Algorithms for indoor positioning are based on WiFi technology.

(ii) Assuming that the device is a laptop equipped with a WiFi card.

(iii) School of Computer Sciences building to be made as the referred location (test bed).

1.6 Contribution of Research

This research proposes an algorithm for location estimation using WiFi signals of an existing infrastructure that improves the estimation accuracy, and evaluates the proposed algorithm against the existing trilateration algorithms for location estimation in the school of Computer Sciences building in USM.

1.7 Outline of Research

This research is organized into six chapters. Chapter 1 has briefly outlined the background of the indoor positioning system, motivation, problem description, objectives, research scope, and contribution of research. Chapter 2 covers the literature review of location based system technologies and techniques, and discusses the advantage and disadvantage of each. Chapter 3 explains the proposed design used as WiFi based indoor positioning system (WBI). Chapter 4 reviews the experiments setup and implementation of the WBI. Chapter 5 presents the experimental results and their analysis. Chapter 6 discusses the conclusions of this research and recommendation for future works.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter discusses and reviews the literature review of the indoor positioning systems. First, it describes the major component of a typical indoor positioning system, and then reviews the taxonomy of indoor positioning from different prospective by identifying different sensing technologies and demonstrating most of the methodologies and measurements that used for location estimation, at the end, describes the well-known application for indoor positioning system.

2.2 Indoor Positioning System Common Components

The common component of indoor positioning is the mobile nodes that the end user carries; the mobile node (mobile station) might be a mobile device, an infrared badge, RF badge or even a laptop with wireless card. Another major component that indoor positioning relies on is the reference nodes (receiver) which are the wireless devices that propagate the signal over the building as the wireless infrastructure (Gu et al., 2009). Some location system relies on external hardware called *location server* which used to provide statistical information on different times and conditions about the user's location in order to enhance the accuracy (Papapostolou and Chaouchi, 2009; Savvides et al., 2001).

In typical IPS, the mobile station propagates the packet to the reference nodes using a sensing technology signal; the reference nodes that are in the range receive the signal (packet) and send it back to the mobile station. The mobile station receives the packet from one or more than one reference nodes, and then a measurement technique applied to estimate the mobile accurate position. Some IPS uses helping factor that increase the estimation accuracy (e.g. light and scene analysis (Gu et al., 2009; Parthornratt and Techakittiroj, 2006)). Figure 2.1, represents a basic indoor positioning system scheme.

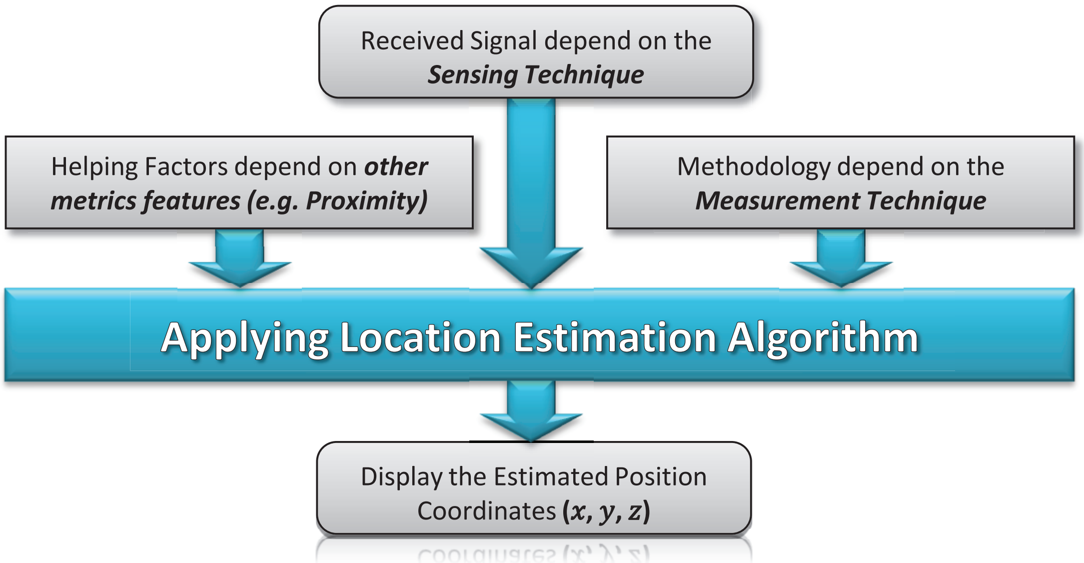

Figure 2.1: Typical indoor positioning system scheme (Kaemarungsi, 2005)

2.3 Indoor Positioning Taxonomy

Typically, wireless reference nodes separated over a building or an office room. At least one or more reference node or mobile node signals will fall under the interfering with metallic or dielectric surface such as walls, which weeks the signals strength and delays the signals time of arrival. The mobile node gets incorrect and confused signals from the reference nodes or vice versa which cause incorrect analysis and then inaccurate position estimation (Hightower and Borriello, 2001). The problem persist on how to make use of these received signals to get an accurate location of the mobile node and how to know that one or more signals hit an object and need a correction. There are many researches conduct with regards to this problem and achieve a very good positioning accuracy. In this section, the taxonomy of indoor positioning is presented from two prospective categories. The first category is indoor positioning sensing technologies and the second category is indoor positioning methodologies.

2.3.1 Indoor Positioning Sensing Technologies

There are many systems used as the sensing technologies for indoor positioning, the characteristics and limitation of a positioning system depend on what sensing technology is used. The wireless signal is the medium of the thesis implementation, therefor, non-wireless technologies that used for indoor positioning are not considered. IR, RF, ultrasound, and ultra-wideband are the common wireless sensing technologies and demonstrated in this proposal as follows: (Tauber, 2002)

2.3.1(a) Infrared

Active Badge is the system that uses the infrared technology and deployed at the Olivetti Research Laboratory (AT&T Cambridge), it requires line-of-sight vision and affected by walls or obstructions because, its signal has the properties of visible light and could be affected by indoor lightening interfaces. Its propagation speed is approximately the speed of light; however, it also has a small range of signal transmission about 5 meters which is another limitation that makes it less effective in indoor environment (Want et al., 1992).

2.3.1(b) Radio Frequency

RADAR system uses IEEE 802.11 which is the standard based on RF for indoor location system (Bahl and Padmanabhan, 2000; NI et al., 2003). The RF signal is better than IR signal in terms of propagation, bandwidth and cost; it could pass through common building materials. It uses the infrastructure of wireless networking, and does not required complex installation steps, and only few base stations are accepted to make it works. However, the mobile node must have a wave Local Area Network (LAN) Network Infrastructure (NIC) of higher frequency

(2.4GHz), which might be impractical; furthermore, up to 3 - 4.3 meters of accuracy achieved for RADAR implementation (Hightower and Borriello, 2001).

2.3.1(c) Ultrasound

Ultrasound technology propagates low frequency signal approximately (43.3 KHz) (Ward et al., 2002), the speed of the signal propagation is slow ($343 m/s$) compared to others. The hardware required to achieve highly effective and accurate system is expensive, and inaccessible to most users. Furthermore, the ultrasound signal propagation cannot pass through the wall and ranged around 3 - 10 meters and it can determine position for probability of 95% within the range ($9 cm$ of the actual position as in Active Bat location system. (Harter et al., 1999).

2.3.1(d) Ultra-wideband

IEEE 802.15.3 is the standard based on Ultra-wideband (UWB) signal. The allowed signal range for UWB is 3.1GHz - 10.6GHz with a transmit power of (-41 dBm/MHz) which limits signal propagation range up to 10 meters. UWB transfers a very large data rates in a very low power; also, it is robust to fading and interference. However, UWB receiver requires more complex architectures using digital signal processing techniques and its signal affected by the multipath reflections (Wilson, 2002).

2.3.2 Indoor Positioning Methodologies

The indoor positioning methodologies use the measurement techniques of location estimation to get the mobile station location. Measurement techniques are another way to categorize the indoor positioning systems; they could be *lateration*, *angulation*, *location pattern*, *fingerprint*, or any combination of them. The *lateration* technique based on the distance and the *angulation* technique based on the angle. *Lateration* and *angulation* are subcategories of *triangulation* (Hightower and Borriello, 2001). There are other metrics such as proximity, scene analysis, and non-geometry features (light level or temperature) that help in location measurement (Tauber, 2002). The distance measurement is the key or the metric for indoor positioning. Single strength attenuation based on path loss and the signal time delays based on speed are the two ways for calculating the distance. AoA, TDoA, RSSI, and SDS-TWR are the well-known methods used to calculate the distance. Some well-known methodologies for location based system are described in the following paragraphs:

Angle of arrival **(AoA)** method requires special hardware; it uses sensitive antennas that can detect the direction, this antenna should be placed on the receiver. When the signal arrived, by calculating the angle between a line from the mobile station to the receiver and a line from a predefined direction to the receiver, the mobile station (transmitter) direction is obtained. However, a set of antennas ranged (4 - 12) are required and should be placed in a horizontal line, therefore, the accuracy depend on the number of antennas, also it is affected by the multipath propagation. Figure 2.2 illustrates the AoA method (Rong and Sichitiu, 2006).

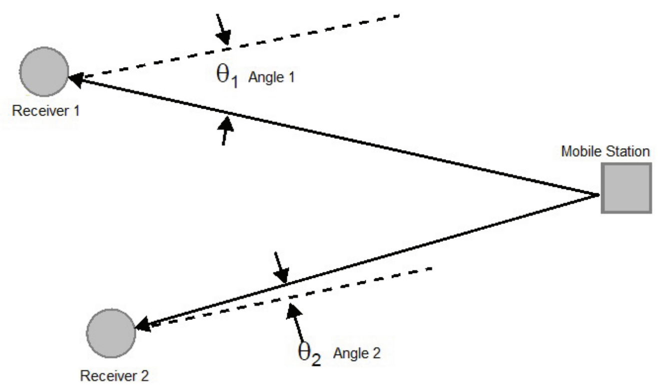

Figure 2.2: Determining mobile station position using AoA (Nanotron, 2007)

Time of arrival (ToA) method calculates the propagation time of the signal traveled from the mobile station to the receiver. At least three receivers required to do the estimation. The distance calculated by multiplying the propagation delay or ToF by the propagation speed for each receiver and then applying a triangulation method. However, this technique needs a synchronization mechanism between the mobile station and the receiver. A nanosecond scale difference between the nodes causes on large distance error, therefore, a precise nanosecond needed to achieve a high accuracy positioning which has high cost in term of time, hardware, and effort (Zeimpekis et al., 2003).

Time difference of arrival **(TDoA)** method uses the delay time, or it uses the elapsed time when the signal received by the mobile station from the time when the signal sent from the transmitters. The mobile station sends the signal to all known-fixed-position receivers at the same time, therefore, each receiver record the time when the signal arrived. The mobile station should be in the intersection of the hyperbolas of each receiver. However this method requires a synchronized clock between the receivers and mobile station, the precision of position accuracy depend on how accurate the clock synchronization between the receivers, moreover, each receivers has a complex structure since the location estimation engine inside it (Nanotron, 2007; Zeimpekis et al., 2003). An example that uses the TDoA is Active Bat (Harter et al., 1999). Figure 2.3 shows the TDoA concept.

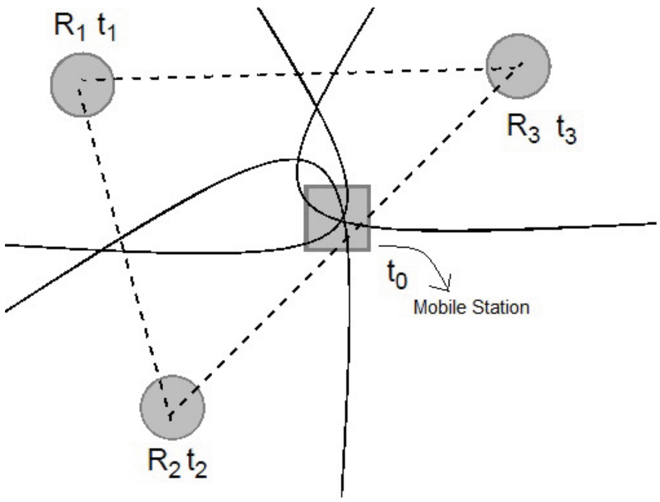

Figure 2.3: Determining mobile station using TDoA (Nanotron, 2007)

Received signal strength indication **(RSSI)** method based on path loss, by converting the signal strength power value along with the path loss into a distance. In other words, the distance is calculated using the signal attenuation. A location server that holds the receivers information (i.e location coordinates) is required for location estimation. The estimation algorithm is one of the algorithms applied in ToA method and could be placed in the server. However, RSSI affected in non-stationary and non-line-of-sight environment (Brunato and Battiti, 2005); therefore, it requires a proper metrics that increase the accuracy such as fingerprint (Papapostolou and Chaouchi, 2009) which maps all the RF in offline phase. Figure 2.4 illustrates the RSSI method.

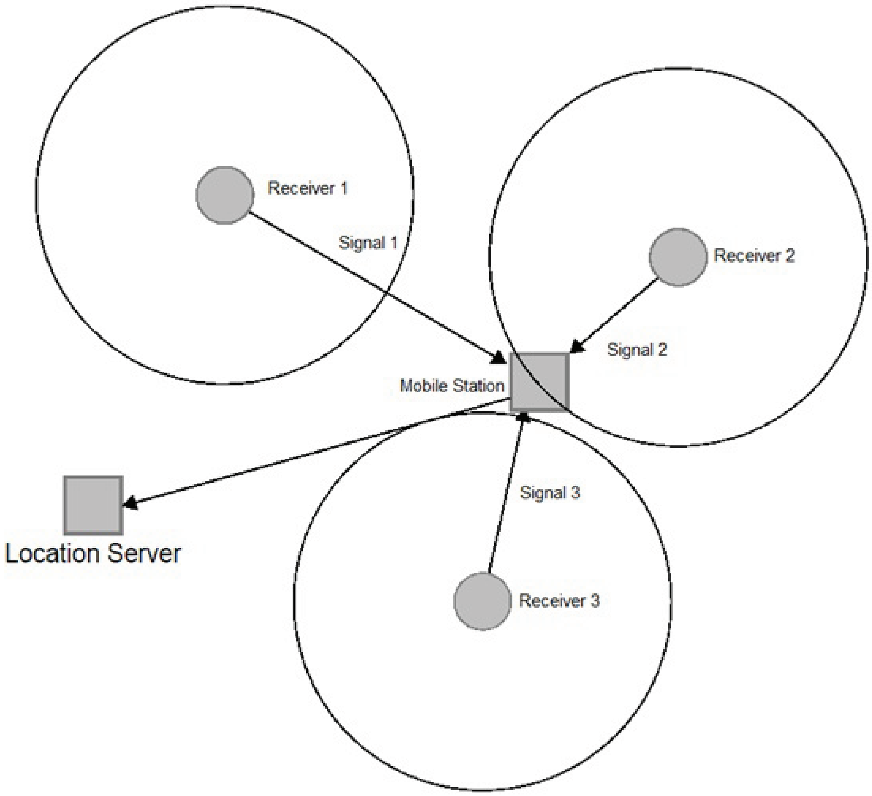

Figure 2.4: Determining mobile station using RSSI (Nanotron, 2007)

Symmetric double sided two way ranging **(SDS-TWR)** technique is an extended of ToF method in which ToF suffer from the problem of clock synchronization, therefore, a Round Trip Time (RTT) method applied to the ToF method by sending a signal and waiting for an acknowledgement. SDS-TWR provides protection against multipath propagation; this methodology is commonly used in the ultra-wideband technology with. However, this method suffers from the licensed issue since the ultra-wideband is only allowed for indoor positioning which first happen in 2002 by the Federal Communications Commission (FCC) in United States. IEEE 802.15 use SDS-TWR for RTLS as in the product of Nanotron Company (Nanotron, 2007). (Kong et al., 2010) is an example that uses SDS-TWR method for indoor positioning.

2.4 Related WiFi based Indoor Positioning Systems

There are many WiFi based indoor positioning system, some of them are based on the mathematical expression, others uses geographical information or adds probabilistic mechanisms. Figure 2.4 demonstrate the taxonomy of some WiFi based indoor positioning systems

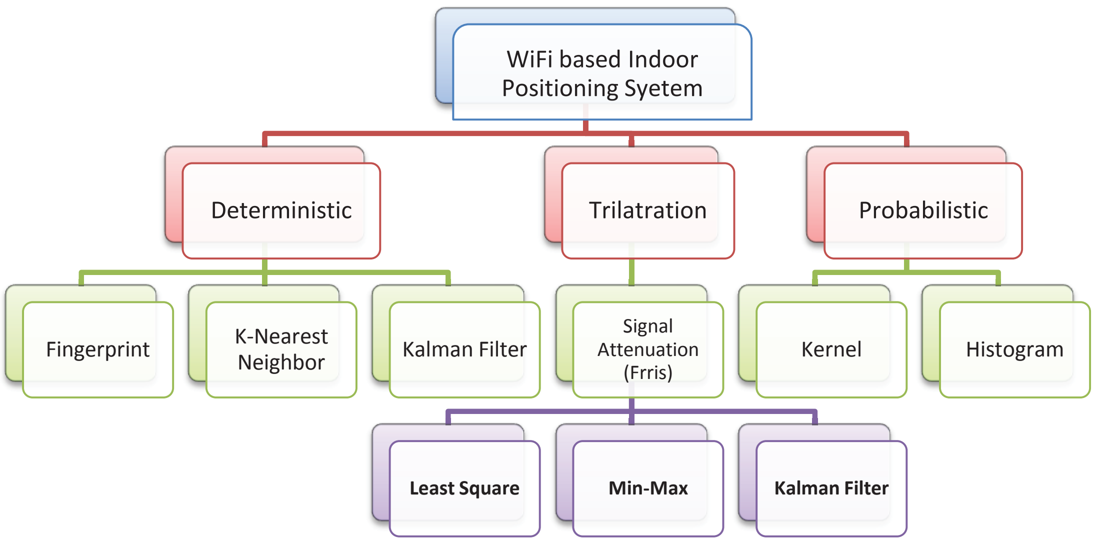

Figure 2.5: Taxonomy of some WiFi based indoor positioning systems

2.4.1 Deterministic Techniques

2.4.1(a) Fingerprint

Transparent location fingerprinting (Brunato and Kallo, 2002) is a *deterministic* technique, it uses map of environment (database) that has a sequence of pairs; the first part represents a set of radio signal strengths and the second part represents the corresponding physical coordinates in the map. A matching algorithm is applied during runtime by selecting the nearest reference nodes in the map to the new signal strength such matching is Bayesian or Nearest Neighbor, after that the weighted average of their coordinates is used as the final estimated position, therefore, *Euclidian distance* is used to calculate the distance of each selected reference nodes in order to calculate the weighted average (Brunato and Kallo, 2002). However, the average positioning error is about 1.87 meters, moreover, sometimes up to 10 meters of errors show up. The more reference nodes selected to calculate the average weight the lowest average of error is returned. Another determinsitc technique such as (Ali-Loytty et al., 2009) uses fingerprinting along with Kalman filter to enhance the positioning accuracy.

2.4.1(b) Kalman Filter with K-Nearest Neighbor

Yim et al. (2010) proposes a Kalman filters based positioning as an extended of a Bluetooth based Kalman-Filter tracking method. The author proposes an improvement on Kalman filter by taking the six parameters as the inputs of the Kalman model; these parameters are the Three Dimensions (3D) position coordinates with their errors. Kalman filter is applied after the K-Nearest Neighbors (K-NN) estimation. The accuracy achieved in this method is $2.11m$. However, it requires knowing the appropriate parameters for the environment, moreover, an offline phase should be conducted to record the Received Signal Strength (RSS)s which in turn will be used for K-NN estimation on the run-time phase.

2.4.2 Probabilistic Techniques

2.4.2(a) Histogram and Kernel

A *probabilistic* technique as in (Roos et al., 2002) uses the signal strength probability associated for each reference node instead of using the mean value that used in *deterministic*. Two method are used to match the signal strengths stored in the database; the first method is called *kernel* which assigning to a kernel a probability around each of the observations in the training data. *Histogram* is the second method that discretizes continuous values to discrete ones, in other way, it is a method that groups the observation data into distinct values. The average positioning error for one observation is ($2.57m$) for *Kernel method* and ($2.76m$) for *histogram method*, they are both less than average error in *deterministic* technique ($3.71m$). Whereby, the average error positioning for 20 observation are ($1.69m$) for *kernel method*, ($1.56m$) for *histogram method*, and ($1.67m$) for *deterministic* technique.

2.4.2(b) CMU-PM

There are other systems such as Carnegie Mellon University Pattern Matching (CMU-PM) (Smailagic et al., 2001) and (Youssef and Agrawala, 2005) that combine the signal strength attenuation along with *probabilistic* algorithm to get better positioning accuracy. Both gather the signal strengths between the mobile station and reference nodes which in turn produce a sufficiently dense table of pattern. The advantage of this system is that it could detect the mobile station within 1.52 meters. The disadvantage is the requirement of large amount of training to get sufficient table pattern.

2.4.3 Trilateration Techniques

2.4.3(a) Least Square Algorithm (Dynamic Loss Exponents)

Mazuelas et al. (2009) proposed a trilateration least square algorithm based on the signal strength attenuation. Using Friis formula the distances are estimated. The estimation algorithm calculates the path loss exponents which best fit different channel environments between the access points and mobile station. This algorithm could estimate location accurately in dynamic environment by calculating the distance path loss of an access point in real-time, and it could achieve $3.97m$, however, the more access points used in estimation the more error in accuracy achieved, that is because it uses a heuristic reasonings to maximize the compatibility function of the path loss exponent. The advantage of this algorithm that it does not need offline setting (calibration stage) or any mapping technique that helps in achieving high accuracy, furthermore, it has a low complexity since the path loss exponent is determined dynamically using real-time RSSs values. Figure 2.6 shows the least square estimation approach.

2.4.3(b) Least Square Algorithm (Wall Effect Factor)

Wang et al. (2003) propose a positioning system based on the RSSI technique. It calculates the distance between the mobile station and the receiver using the signal strength attenuation, and then applying mathematical expression to present the polynomial regression of third degree which in turn estimates the mobile station position. Since this system based on the signal strength attenuation, it is very fast to detect the positioning in comparison with the *probabilistic* and *deterministic* systems. It achieved 1-3 meters of positioning accuracy. However, it is not fully dynamic since a off-line phase is required.

2.4.3(c) Min-Max Algorithm

A quantitative study of indoor positioning localization by Langendoen and Reijers (2003) describes the several methods used for distance measurement and location estimation. In this study, Min-Max algorithm is presented; it is used for location estimation by constructing two points for a bounding box where its average considered the final location estimation.

The study conducted an experiment for Min-Max and proved that it is not very sensitive to bias error especially for a positive range bias. However, Min-Max estimation is not accurate for location estimation. The author combine Min-Max with DV-hop (stands for Distance Vector - Hop) in an experiment the average accuracy degrades from 43% to 77% when the nodes are randomly distributed which considered significant when compared with trilateration that has degrades only from 42% to 54%. The advantage of Min-Max it is less sensitive to bias error, however, it is not an effective method for location estimation but it is useful when it is combined with other estimation algorithm. Figure 2.6 shows the least square trilateration with Min-Max approaches.

Another research by Cypriani et al. (2009) uses Min-Max to select the nearest point to the calculated distance circles. The algorithm is a hybrid model of trilateration of the propagation model and the cryptography technique.

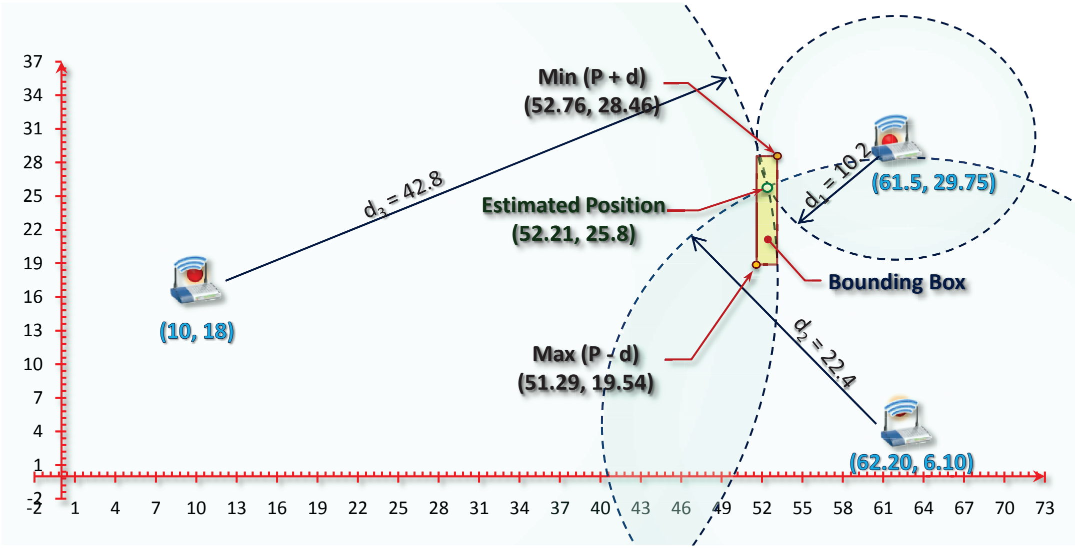

Figure 2.6: Least square trilateration with Min-Max approaches Langendoen and Reijers (2003)

2.5 Critical Analysis

Brunato and Kallo (2002) conducted a positioning system that estimate the location using deterministic technique where its system should have two phases. The first phase maps the area with some values that identify the specific part of position in the area into a database; the second phase is the run-time process where the system looks for the nearest value in the database. However, Roos et al. (2002) criticized this technique because the accuracy of the systems that use such technique is often inadequate. The author provides a probabilistic technique that depends on the signal strength probability that would be associated to the access point instead of using the mean value that used in the first phase of the deterministic technique.

Wang et al. (2003) proposed an indoor positioning system based on wireless LAN infrastructure. The system does not need a calibration phase as in the *deterministic* and *probabilistic* technique, it calculates the ranging distance using signal strength attenuation and then a location estimation method is applied. The distance is calculated using the free space formula of Friis where the signal attenuation is determined by the fixed path gain slope value. However, Mazuelas et al. (2009) criticized the used of fixed path gains slope for dynamic environment such as presence/absence of people and the orientation of the mobile station. Mazuelas proposed dynamic models that best fit the propagation of signal even if there is a dynamic change in the environment. The models calculate the path gain slope at that particular time of estimation and used it for distance calculation after that a location estimation algorithm is applied to get the final estimation.

Yim et al. (2010) criticized the use of simple mathematical expression to determine the location estimation by representing the signal strength and distance as a relationship between the sender and receiver as Wang et al. (2003) and Mazuelas et al. (2009). They found out that radio frequency propagation loss model based on distance calculation and mathematical expression is less accurate in terms of positioning accuracy than the fingerprinting model that has a calibration and run-time phases. They proposed a method based on fingerprinting model using K-NN enhanced by using Kalman filter.

Meanwhile, the proposed design in this thesis does not require an offline phase to calibrate the data. Besides, it does not require any probabilistic statistics or any complex procedure. However, it depends on existing infrastructure of a building, and an error detection mechanism based on a location estimation method along with a correction mechanism based on Kalman filter model. Moreover, it needs some of the environment parameters that used on the distance calculation.

The environment parameters can be obtained by making small experiments on the environment. Hence, this study could provide better estimation accuracy. Table 2.1 summarizes the researches discussion in the previous section.

Table 2.1: Summary of WiFi based indoor positioning systems

System	Method	Environment & Accuracy	Advantage	Disadvantage
Deterministic (Fingerprinting)	K-NN	$625m^2$ area. 1.87*m* accuracy, sometimes up to 10*m*.	Less computation	Require calibration phase. Accuracy depends on the number of calibrations and access points. Weak in dynamic environments.
Probabilistic	Kernal and Histogram	Floor (16*m* x 40*m*). 10 APs. Accuracy: - 1 observation Kernel: 2.57*m* & Histogram: 2.76*m*. - 20 observations Kernel: 1.69*m* & Histogram: 1.56*m*.	Good accuracy. Less computation	Require calibration phase. The estimation accuracy depends on the number of observations.
CMU-PM	Probabilistic and Signal Attenuation	Floor. 5 APs	Good accuracy. Less computation	Require calibration phase and a large amount of training to get sufficient pattern
Horus	Probabilistic and Signal Attenuation	1^{st} Test bed (68.2*m* x 25.9*m*), 6 APs, accuracy (4.2*m*). 2^{nd} Test bed (11.8*m* x 35.9*m*), 4 APs, accuracy (6.4*m*).	Good accuracy with respect to the environment. Less computation.	Require calibration phase. Weak in dynamic environment.
Trilateration	LSA - Signal Attenuation	Several environments Mean Error (3.97*m*) with different path slope.	Deal with dynamic change of environment (RSS Path slope). Does not require calibration phase.	Complex algorithm. High computation process. Require initialization state
Trilateration	Min-Max	When combining Min-Max with DV-hop, accuracy degrades from 43% to 77%.	Less affected by distance bias error.	Bad accuracy. Must be combined with other estimation algorithm to improve the accuracy.
Trilateration (Correction)	Signal Attenuation with Wall Penetration Loss	Floor (17.5*m* x 84*m*). 6 APs. Accuracy range from 1*m* to 3*m*.	Considered wall penetration loss (Fix error caused by wall)	Complex algorithm. High computation process. Require experiment to define the wall penetration loss. Weak in dynamic environment
Deterministic (Correction)	K-NN with Extended Kalman Filter (EKF)	Floor. 8 APs. Accuracy (2.11*m*).	Good accuracy. Smooth positioning. Error Correction (Kalman Filter)	Required calibration phase, and knowing the appropriate parameters for the environment.

2.6 Summary

This section summarizes the related indoor positioning systems based on different methodologies. The research only covered the wireless indoor positioning systems which are roughly divided into methodologies that employ different technologies 802.11 RADAR, 802.15 ultra-wideband, ultrasonic and IR. These technologies are all propagate different ranges of signal frequencies, and they are all have different characteristics in terms of propagation, time, and cost. The methodologies are briefly described within their systems such as RSS, TDoA, AoA, probabilistic, fingerprint and others. However, their key problem is the inaccuracies of the location that could possibly caused by multipath interferences, huge amount of data training, environment condition, and clock synchronization. The drawbacks of the systems have been addressed though showing the accuracy resolution of each system; they are all having different range of positing accuracy and different condition requirement such as hardware.

RSSI methods are powerful and fast, it requires low power consumption but it is very weak when it comes to interfering with objects. RSSI needs additional methods to support such as location information as in *fingerprint* or *probabilistic* methods in order to achieve a better positioning accuracy. The ToF methods are powerful and bring high estimation accuracy of mobile station but it needs high cost hardware. It cannot be implemented in WiFi that employs IEEE 802.11 because it is only supported with standards IEEE 802.15.

In addition, probabilistic could achieve good positioning accuracy; however, it requires a large amount of training in order to get the proper data pattern whereby the deterministic could achieve a better positioning accuracy if more signal strength received from more reference nodes. The combination of them produces much better positioning accuracy. However, it shares the combination of their drawbacks.

CHAPTER 3
PROPOSED DESIGN

3.1 Proposed Design

In this section, the proposed design is described. As in figure 3.1, the proposed algorithm has the following procedures: First, the mobile station propagates a request packet to the reference nodes nearby the signal range. Then, each reference node received the packet, sends back the same packet to the mobile station. The mobile station gathers the signal strengths along with reference node IDs and sends them to the server which is responsible for location estimation. The reason of putting the algorithm execution in the server side because the mobile station processor is slow for this continues computing and searching especially if it is a mobile phone. Furthermore, the access points configuration database is inside the server which in turn will speed up the computation time.

The server applies a several steps for calculating and estimating the location. At the beginning, it receives the signal strengths of the reference nodes from the mobile station. Then, it calculates the distances between the mobile station and each reference node using Friis transmission formula. The mobile station locations are calculated based on the distances using trilateration along with Least Square Estimation (LSE) algorithm (Mazuelas et al., 2009; Mao et al., 2007). The proposed algorithm detects location error by applying Min-Max algorithm for the estimated location (Langendoen and Reijers, 2003; Kong et al., 2010). If the location error detected, then an error correction is applied using Kalman filter. In fact, this location error could be caused due to Non-Line-of-Sight (NLOS) communication link between the mobile station and one or more of the reference nodes (Le et al., 2003).

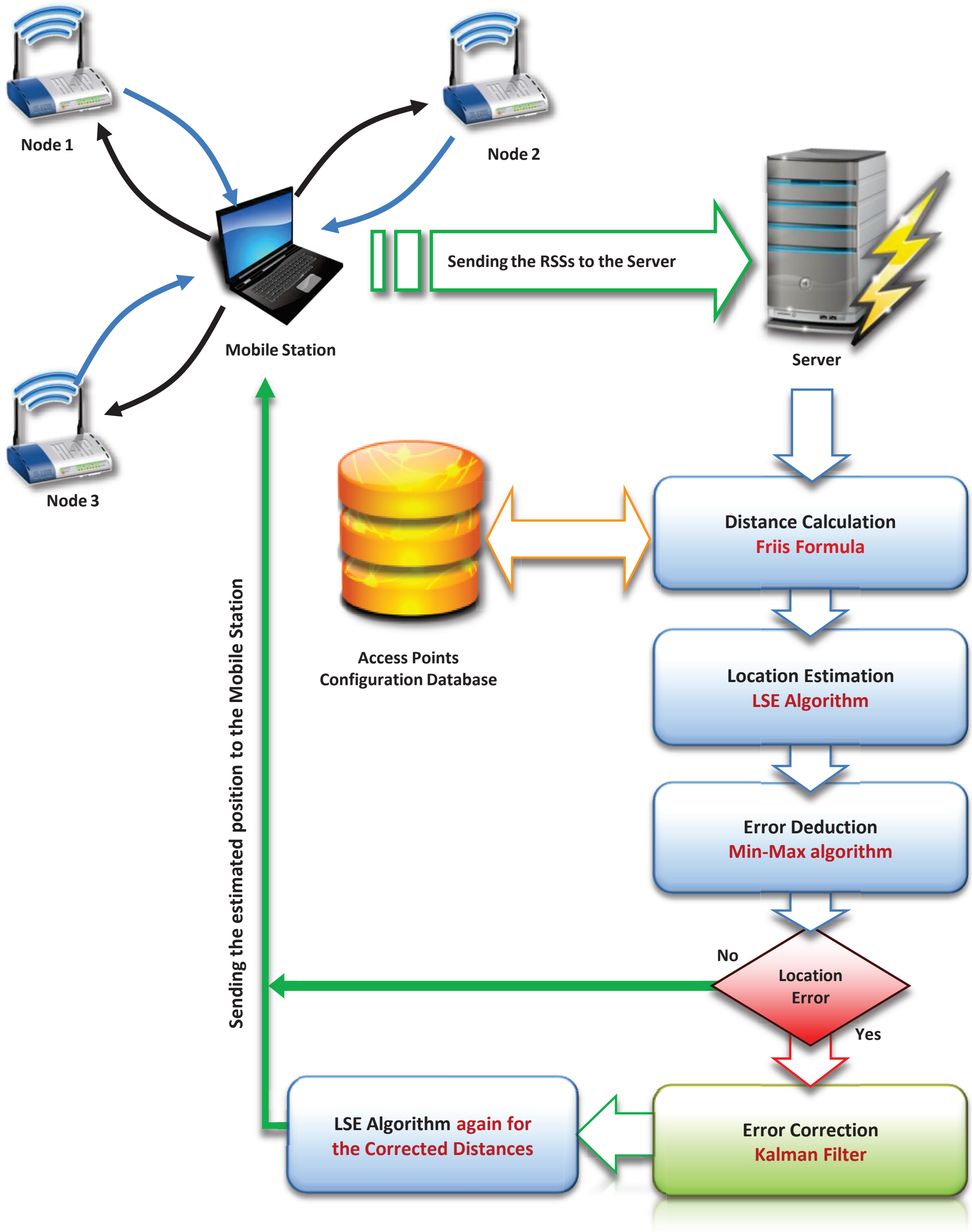

Figure 3.1: The proposed design procedures

Kalman filter is the model used to estimate the amount of error and uses it for correction (Yim et al., 2010; Guvenc, 2003). Figure 3.1 Shows the proposed system implemented by the following modules:

3.1.1 Distance Calculation

Suppose we have n nodes along with a mobile station as object being tracked. The mobile station will start to scan for the nearby signals that are in range and then record their signal strengths. After that, the mobile station sends n information to the servers. The information consists of n signal strengths SS_n. The signal strength vector of the reference nodes for the mobile station defines $S = (SS_{dB1}, SS_{dB2}, SS_{dB3} \cdots SS_{dBn})$. Considering that each reference node has a known fixed position then each node assumed to have a predefined signal strength PG_{dBn} of a known distance d_0, where $j \in (1, n)$. The distance of received signal strength could be defined by:

$$SS_{dBj} = -PG_{dBj} - 10\hat{n}\log_{10}\left(\frac{d_j}{d_0}\right) \tag{3.1}$$

Where d_j is the distance between the mobile station and the j^{th} reference node, $j \in (1, n)$, and $\hat{n}$ is the path gain slope.

3.1.2 Location Estimation

After that, the LSE algorithm is used for location estimation (Mazuelas et al., 2009; Mao et al., 2007), the basic input of this algorithm is the distances d_j. A trilateration is applied using those distances of n nodes, and it is reordered as a linear equation in the form $A\hat{x} = b$, where

$$A = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) \\ 2(x_2 - x_n) & 2(y_2 - y_n) \\ \vdots & \vdots \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) \end{bmatrix}, and \quad b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ x_2^2 - x_n^2 + y_2^2 - y_n^2 + d_n^2 - d_2^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_n^2 - d_{n-1}^2 \end{bmatrix}.$$

The estimated location of a mobile station is then solved using standard least square equation given by:

$$\hat{x} = (A^T A)^{-1} A^T b \tag{3.2}$$

Where $\hat{x}$ is a matrix $[\,x \;\; y\,]^T$ that holds the estimated coordinates. One estimation is chosen from changing the order of the distances in the matrices and this estimation determined by:

$$\hat{p} = arg\min_{x} \sum_{j=1}^{n} (\|\hat{x} - p_j\| - d_j|)^2 \tag{3.3}$$

Where $\hat{p}$ is the estimated location of the mobile station, n is the number of reference nodes, and p_j is the location of the j^{th} reference node $j \in (1,n)$ and $\|\hat{x} - p_j\|$ is the Euclidean norm (Rong and Sichitiu, 2006).

3.1.3 Error Detection

The error detection mechanism is applied for the estimated location using Min-Max algorithm (Langendoen and Reijers, 2003; Kong et al., 2010), the server checks whether the estimated location calculated using LSE is out of the Min-Max boundary box or not. The coordinates for the Min-Max bounds are constructed for each reference node using its location p_j and the estimated distance d_j. The bounding box for the Min-Max method defined as:

$$\max(p_j - d_j) \leq \hat{p} \leq \min(p_j + d_j) \tag{3.4}$$

Once the location error detected, the server calculates the distance $\hat{d_j}$ from the center of the bounding box to each reference node j to determine which link has fall under the NLOS condition. The large difference calculated from the two distances $\hat{d_j}$ and d_j for each reference node j indicates that the reference node j has fall under the NLOS condition. The condition of NLOS can be written as:

$$\begin{aligned} H_0 &: \|\hat{d_j} - d_j\| \leq \Delta_{Th} \\ H_1 &: \|\hat{d_j} - d_j\| > \Delta_{Th} \end{aligned} \tag{3.5}$$

Where Δ_{Th} is the threshold value for the location error detection. In figure 3.2, $node2$ and the mobile station S have a location error due to the corruption caused by NLOS, as in the figure the estimated location S' is out of the Min-Max boundary. Therefore, the difference between the distances $\hat{d}_j(S, node2)$ and $d_j(S, node2)$ is above the threshold value Δ_{Th} which in turn indicates that the link between S and $node2$ is under NLOS condition and needs to be correct.

Figure 3.2: The Min-Max boundary with location error (Kong et al., 2010)

3.1.4 Error Correction

In order to correct the error caused by NLOS, Kalman filter is used in the proposed work when the Min-Max method detects a location error. The Kalman filter is adopted from (Yim et al., 2010; Guvenc, 2003) modified to fit the proposed algorithm. Figure 3.3 shows the location error correction concept using Kalman filter. The system state model of Kalman filter is as follows:

$$\hat{x}'_k = \hat{x}_{k-1} + w_{k-1} \tag{3.6}$$

Where $\hat{x}'_k$ is the system state value at a time k, it is the expected distance taken from the previous prediction $\hat{x}_{k-1}$. w_{k-1} is a zero-mean white process noise. The measurement model described as follows:

$$z_k = \hat{x}'_k + v_k \tag{3.7}$$