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Multiple SSID Framework for RSS-Fingerprint Based Indoor Positioning Systems

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MULTIPLE SSID FRAMEWORK FOR RSS-FINGERPRINT BASED INDOOR POSITIONING SYSTEMS

by

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DEDICATION

This work is dedicated to the souls of my mother and father who passed away before it was finished. May their souls rest in peace.

Ahmed Kareem Abed

ACKNOWLEDGMENTS

First, I thank God for providing me with the strength and patience to reach this point in my life.

Second, I would like to thank my country (IRAQ) to provide me the opportunity to complete my study.

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Location-Based Indoor positioning systems significance stems from the bloom of recent applications in various fields such as in tracking services for an elder or a patient within large living communities, mobile robot localization, and several other security applications. Currently, Global Positioning Systems (GPS) are the most widely used location-sensing technique. However, satellite-based GPS signals require line of sight (LOS) to work correctly, which is something cannot be achieved inside buildings. Fortunately, wireless LAN can be employed in indoor positioning systems (IPS), and since all large buildings such as malls, hospitals, airports, schools, and museums have hundreds of Wi-Fi access points, it can provide accurate IPS without any additional infrastructure. Of special significance, the Wi-Fi fingerprinting-based techniques that offer a much less complex when compared to other methods such as the angle of arrival (AOA) and time difference of arrival (TDOA). Wi-Fi fingerprinting-based techniques use the received signal strength (RSS) to build radio maps. However, RSS value is a function of the distance between the Mobile System (MS) and Access Point (AP), which varies due to the multipath propagation phenomenon and human body blockage. Furthermore, fingerprinting approaches have several disadvantages such as labor, computational cost, and diversity (in signals and environment). In this dissertation, a novel approach that uses Multiple Service Set Identifiers (MSSID) to tackle these challenges is presented. MSSID means each AP can be configured to transmit N signals instead of one signal, to serve different clients' categories simultaneously. IPS MSSID-based framework using three different realizations is proposed, implemented, and verified

inside the College of Engineering and Applied Sciences (CEAS) building at Western Michigan University.

First, a MSSID Probabilistic Neural Network (PNN)-based multi-classifier is proposed with a spatial voting scheme as a tool to determine the location of the user. Spatial voting is designed specifically to tackle the negative impact of multi-path propagation. The performance of the proposed system compared to some of the conventional methods such as K-Nearest Neighbors (K-NN) and multi-class support vector machine (SVM). Experimental results show that spatial voting of three PNN classifiers can significantly mitigate the adverse effects of RSS variation. The precision of the proposed system for PNN and K-NN at distance error of 2m is 90% and 85%, respectively. As a comparison to the proposed systems, the precision of the traditional techniques for PNN and K-NN is 82% and 78%, respectively. In addition, the experimental results show that the average distance error for PNN-based proposed system is less than 0.73 m when the length of AP (L) is 18. Furthermore, the distance error of proposed system shows high stability where it has lowest standard deviation as compared with other traditional techniques.

Second, an MSSID-based adaptive K-nearest neighbor (K-NN) is proposed to tackle the challenges associated with static K-NN based-systems. The K-nearest neighbors (KNN) is selected for its significant performance with ease of realization. However, the static nature of K-NN, that is, in using a constant number of the nearest neighbors, leads to a serious shortcoming in its accuracy. In addition, the nature of the RSS-IPS challenges such as fading due to the multipath of electromagnetic waves inside buildings would mislead the solution of nearest neighbors. These reasons often result in lower perform than expected because of the increase in the distant neighbors' biasing error. In this part, we address these challenges by proposing a new method based on multiple services set identifiers (MSSID) to select adaptively the appropriate nearest neighbors, and reject undesired ones. The ensemble technique is utilized to enhance the performance by combining the outputs of three adaptive K-NN estimators. The experimental results demonstrate the superiority of the adaptive K-NN based-proposed system over static K-NN. The results show that the precision of the proposed system for the adaptive K-NN at distance error of 2m is 73%, and the average distance error is less than 1.3 m. As a comparison to the proposed systems, the precision of the traditional K-NN at distance error of 2m is 61%, and the average distance error is 1.85 m.

Third, an MSSID- based particle swarm optimization (PSO) system is proposed. PSO technique is designed to select the most informative APs at each clustered area and combined with the K-means clustering method to confine location of the user into a smaller area and thus enhance positioning accuracy. WLAN-fingerprint based methods require recording RSS data of the surrounding APs, which results in including much more than the needed number of APs. Therefore, eliminating redundant or non-informative APs not only reduces the computational cost but also improves performance accuracy. At each cluster, PSO is applied to select the best joint combination of APs decided by the minimum mean of distance error. The results show that the proposed system outperforms other commonly proposed selection methods such as random, strongest APs, and Fisher criterion. Moreover, with reduction of 68% AP vector's length (L=11), the results report that the proposed system achieves a positioning accuracy of 0.85 m over 3000 m2, with an accumulative density function (CDF) of 88% with a distance error of 2 m.

The use of the multiple SSID technique supports IPS classifiers and produces higher precision than with single SSID. The proposed algorithms show a notable improvement over its counterpart with single SSID along with the distance error and reduction of RSS-vector's length.

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1. INTRODUCTION

1.1 Background and General Overview

Location-Based Systems (LBS) for indoor positioning have earned the attention of a large number of researchers in the last decade. The significance of these systems comes from their applications in various fields such as tracking services for elderly people or patients within large living communities, mobile robot localization, and several security purposes[1]. Global Positioning Systems (GPS) and other Global Navigation Satellite Systems (GNSS) can satisfy people's demand for outdoor location services in which Line of Sight (LOS) is dedicated for location services, and at least three satellites are required.[2]. Due to obstacles inside buildings, GPS does not work correctly within an indoor environment. As a result, a new technique has been developed to be a GPS equivalent technology for use indoors. Various techniques have been proposed for indoor localization from a signaling perspective. These techniques are classified into two categories: (1) non-radio-based techniques, and (2) radio-based techniques[3]. The first category utilizes infrared (IR)[4], ultra-sonic and sound techniques[5], visible light[6], inertia system[7], and magnetic field exploitation for indoor positioning[8]. The second category utilizes radio frequency for indoor positioning systems (IPS) such as Radio Frequency Identification (RFID), Ultra-Wideband (UWB) methods[9], Bluetooth-base methods[10], Zig Bee-based methods[11], Frequency Modulation (FM)-based methods[12], and Wireless Local Area Networks (WLAN) based on IEEE802.11 standardization. Many of the techniques mentioned above require massive transceiver and infrastructure deployments that leads to high maintenance costs.

All large buildings such as malls, hospitals, airports, schools, and museums have hundreds of Wi-Fi access points which are installed to provide WLAN infrastructure services[13]–[17]. Wi-Fi signal-based positioning techniques exploit existing WLAN devices to provide accurate indoor positioning without any additional hardware. The received signal strength (RSS) of Access Points (AP) is used as a data feature to distinguish the location inside the building. RSS-based methods can be exploited in a WLAN environment to achieve indoor localization without adding external hardware while other techniques such as Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Angle of Arrival (AOA) require additional hardware to work as IPS.

Many researchers, for three reasons, have adopted WLAN fingerprinting-based techniques. To begin, WLAN services are already available in most large buildings as an infrastructure for wireless network coverage, so additional hardware and costs are not required when they are used for an Indoor Positioning System (IPS). Second, the majority of mobiles and wireless receivers contain Networking Interface Cards (NIC), which can measure RSS values. Third, the path loss model-based approach does not work correctly inside buildings because of a multi-path fading issue which occurs because the propagation of a signal in an indoor environment is extremely complex, and the intensity of RSS signals at a given location usually varies with time and environment[18]. There are two phases of the WLAN fingerprinting-based method: off-line and online. In the offline phase, the mobile device detects Wi-Fi RSS signals from surrounding APs and collects location fingerprints to create a Radio Map (RM). In the online phase, the mobile device obtains a vector of RSS for the unknown position, which is then compared with the RM to estimate the unknown position[19].

In this dissertation, a wireless local area network (WLAN)-based indoor positioning framework is investigated. Specifically, RSS fingerprinting-based localization algorithms and techniques are proposed.

1.2 Motivation

The wide use of smart devices such as notebooks, iPads, and PDAs in our lives has caused Location-based Services (LBS) to become increasingly popular. Indoor LBSs are currently in high demand and drive the growth of location computing technologies[20]. The industry for navigation systems and indoor positioning markets has grown rapidly in recent times due to the increased prevalence of smart devices and structures. A survey estimated that LBSs would generate annual revenues of approximately $25.0 billion by 2022, as shown in Figure 1-1 [21]. In a practical sense, indoor localization will significantly improve network management, healthcare monitoring, emergency personnel navigation, and security [22], [23]. Many indoor positioning techniques, such as WLAN, Ultrasound, Lighting, RFID, and Bluetooth, have been promoted. Most of the techniques mentioned above require massive transceiver and infrastructure deployments that leads to high maintenance costs. However, many researchers have adopted WLAN fingerprinting-based techniques for three reasons. First, WLAN services, which work at a 2.4GHz Industrial, Scientific, and Medical (ISM) band within a range of 50-100 m, are already available in most large buildings as an infrastructure for wireless network coverage, so additional hardware and costs are not required when it is used for an Indoor Positioning System (IPS). Second, most mobiles and wireless receivers contain Networking Interface Cards (NIC), which can measure RSS values. Third, the path loss model-based approach does not work properly inside buildings because of a multi-path fading issue. This problem is due to the fact that propagation of a signal in indoor environments extremely complex, and the intensity of RSS signals at a given location usually vary with time and environment.

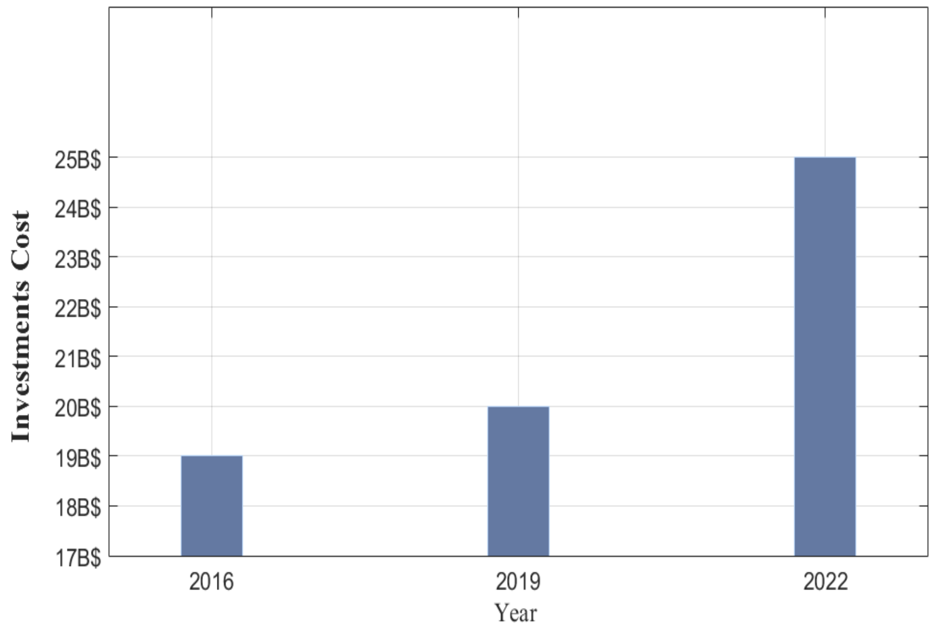


Figure 1-1: The growth of indoor positioning and navigation systems.

1.3 WLAN Positioning Systems Design Challenges

WLAN-based indoor localization systems are promising techniques and potential candidates to be the indoor counterpart of GPS. Figure 1-2 shows the use of WLAN fingerprinting-based technique inside a building. The RSS value, which is received by the mobile unit, can be used to estimate the distance between the AP and MU (Mobile Unit). However, localization is not the main functionality for WLAN, which is also used for wireless network services. Thus, some challenges will arise when using a WLAN infrastructure as IPS. These challenges are illustrated as follows:

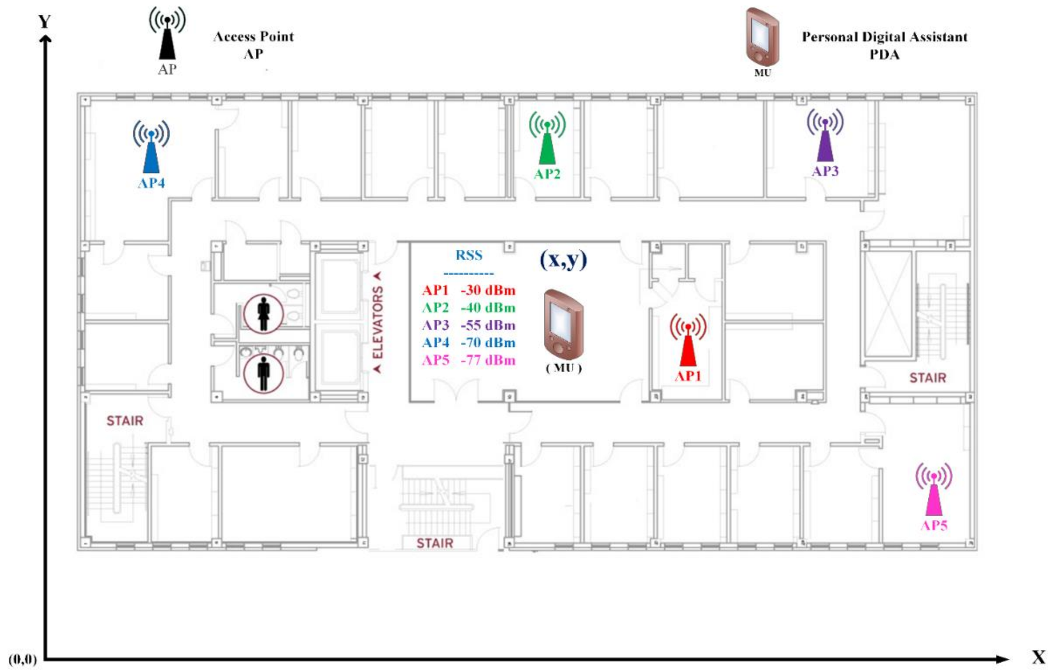


Figure 1-2: Fingerprinting-based Indoor positioning using APs' signals.

1.3.1 Temporal variation of RSS

RSS measurements are usually corrupted by environmental noise that leads to fluctuation of RSS values even at the same location. This environmental noise comes from NLoS conditions and dynamic variations of indoor environment characteristics. The condition of NLoS is considered the main source of localization errors in which the measured RSS at a specific point on a physical locations map is affected by constructive or destructive interference from multipath propagation of RF waves [24]. The waves travel through a multipath channel and arrive at a single point where their magnitudes and phases will be added. On the other hand, dynamic environment variations arise because objects move, such as people and furniture. Therefore, the multipath pattern cannot be predicted and compensated stochastically.

1.3.2 Interference

The frequency band of Wi-Fi signals operates on the radio frequency of 2.4GHz, on an unlicensed band. Thus, many electronic devices, such as Bluetooth, microwave ovens, and cordless phones, work on the same frequency band. The working of these electronic devices is considered a big challenge for WLAN-based IPSs when these devices are nearby and in operation [25].

1.3.3 Latency and throughput

A mobile device takes some time to scan RSS of AP. The main purpose of the scan is to update/confirm available Wi-Fi SSID (Services Set Identifiers) listed around the user's device. This time is considered a source of latency when determining the location of the user and becomes crucial if there are many user-positioning requests. In addition, the continuous scanning process which happens in cases in which the user is moving leads to data flow interruptions, which in turn can result in a degraded throughput [26].

1.3.4 Diversity

Most of the existing research assumes that the collecting of fingerprints of radio map and online measurements are achieved in the same device. Practically, this assumption is not true because the training device, which is used to build the radio-map during the offline phase, may be different from the positioning device used during the online phase. This results in different signal strength patterns across the devices, which could degrade the accuracy of the positioning system[27]. Hence, the problem of signal pattern variation across diverse devices should be considered when designing positioning systems. A simple solution to this issue is to measure a new radio-map for each device in order to maintain positioning accuracy. However, such a solution is infeasible due to a large number of different devices are available in the market.

1.3.5 Big data and labor cost

In an indoor location system, eliminating redundant APs not only reduces the computational cost of fingerprinting processing but also can improve positioning accuracy. The WLAN-based fingerprinting technique has built RM for Area of Interest (AOI) where each vector in the RM comes from measuring RSS of multiple APs, which are deployed in AOI. Most large buildings are equipped with a large number of APs to provide wireless network services. Nevertheless, all these APs contribute positively to positioning accuracy, where the majority are redundant. Therefore, including all detected APs in fingerprinting vectors leads to confusing IPS [20]. In addition, the resources, which are equipped on MS, are limited even in cases where the IPS uses a server's assistance to find the user's location. Due to the dynamic and unpredictable nature of RSS, RM should be rebuilt to localize Wi-Fi device precisely. Moreover, the fingerprints of RM may need to be updated if the number or the power of Wi-Fi access points in the environment changes significantly. This may increase labor time during offline calibration.

1.4 Problem Statement

There are many challenges and problems for WLAN fingerprinting-based IPS. However, there are two important problems stated in this dissertation. The first problem for the WLAN fingerprinting-based method is the effect of variation of RSS on the accuracy of IPS due to reflection, diffraction, and diffusion on various indoor walls. Consequently, the changing of the RSS value in the online phase leads to a degradation of accuracy in IPS. This change is difficult to replace with a channel equalizer due to the randomness of channel state and time dependency. The second problem, which faces the fingerprinting-based method, is the big data size of RM where each fingerprint sample on the radio map consists of the RSS of surrounding APs. Due to the wide proliferation of Wi-Fi networks, it is very common to observe a large number of APs. However, most of the APs, which are detected, are non-informative and redundant APs. Some of them might even have weak signals due to the long distance between user and APs that leads to non-trivial inconsistency on the RM. This inconsistency leads to increasing computational cost during the online phase. The classification process, which relies on a big database, becomes infeasible when it is working as a real-time system. Therefore, computational cost reduction is required to reduce the time delay and memory resources of real-time systems.

1.5 The Objectives of the Work

Most of the research literature overlook the functionality of the access points; that is, they assume each access point is transmitting one signal. In this work, we propose a new technique through by changing the setup of access points themselves and designing a framework that allows for multiple signals at the same time from each access point by setting up multiple SSID. The proposed framework shows a remarkable improvement in IPS accuracy performance. The following points review the main contributions for this dissertation:

- Study the characteristics of multiple SSIDs' RSS-signals in time and spatial domains. These characteristics help IPS designers to design an appropriate classifier to narrow down and to mitigate positioning errors.
- Design a new indoor positioning system using multiple services set identifier-based fingerprints. This system exploits multiple SSID-based spatial voting techniques to enhance the accuracy of IPS.
- Design an adaptive K-NN based on multiple SSID for IPS with an Ensemble Approach. In this contribution, we propose a new method based on multiple SSID to select adaptively the appropriate nearest neighbors and reject undesired ones. The

ensemble technique is also used to enhance performance by combining the outputs of three adaptive K-NN estimators.

- A new RSS-fingerprint dimensionality reduction method is proposed for multiple services set identifiers-based IPS. The contribution of this work is to reduce the effect of the multipath phenomenon and computational cost as well by fusing and clustering the MSSID-based fingerprinting. We investigated various kinds of selection APs such as Fisher, strongest APs, and random selection. All these techniques are tested with K-means clustering technique.
- A new AP selection technique based on Particle Swarm Optimization (PSO) is proposed to reduce calculation time and increase the accuracy of IPS as well.
- All these proposed systems are evaluated using real RSS data, which are recorded from the College of Engineering and Waldo Library at Western Michigan University.

1.6 The Scope and Outlines of the Dissertation

The works presented in this dissertation aim to solve the RSS-variation problem and reduce computational cost to be more compatible with real-time systems. This work proposes multiple services set identifier techniques to solve these problems. We propose two techniques to handle the uncertainty of samples: multiple SSID-based voting and adaptive K-NN techniques. Furthermore, we propose a new method based on the fusion technique and particle swarm optimization to reduce the computational cost of the positioning system device and to enhance the accuracy of IPS simultaneously.

The outline of the proposed dissertation is organized as follows:

- **Chapter 1**: a brief introduction to the problem, the significance, and challenges of this research field, as well as the objective and contribution of this dissertation, are presented in this chapter.
- **Chapter 2**: relevant background materials for indoor localization techniques are reviewed. Also, the computational cost reduction techniques for IPS are presented in this chapter.
- **Chapter 3**: in this chapter, the definition of multiple SSID and the characteristics of multiple SSID signals are illustrated.
- **Chapter 4:** this chapter presents detail on the proposed systems and a literature survey for mitigating the effect of the multipath issue by using the spatial voting technique.
- **Chapter 5:** this chapter presents detail on the proposed systems and a literature survey for mitigating the effect of the multipath issue by using adaptive K-NN techniques
- **Chapter 6:** this chapter presents detail on the proposed systems and a literature survey for reducing the complexity of IPS and redundancy of RSS data by using clustering-based MSSID and PSO-based AP selection techniques.
- **Chapter 7:** the final chapter is designated as a conclusion and future work.

2. INDOOR POSITIONING SYSTEM TECHNIQUES

2.1 Introduction

Demands on smartphone-based services are increasing rapidly. Location-Based Services (LBSs) such as in Indoor Positioning System (IPS) is one of those services. Various techniques have been proposed for indoor localization. Figure 2-1and Figure 2-2 show the graphical overview in dependance of accuracy with coverage and carrier wavelength, respectively [28]. From a signaling perspective, these techniques are classified into two categories: (1) non-radio-based techniques, and (2) radio-based techniques [3]. Table 2-1 summarizes the main RF techniques that are utilized in indoor localization.

Table 2-1: RF-based indoor position techniques.

Technique	Advantage	Disadvantage
Cell of origin	Base stations are available and never move	Highly inaccurate
Angle of Arrival	High accuracy	Required additional hardware such as directional antennas
Angel difference of arrival	High accuracy doesn’t require knowledge of orientation	Required additional hardware
Time of arrival	High accuracy	Required additional hardware synchronization issue
Time difference of arrival	High accuracy	Required additional hardware synchronization issues
Fingerprinting- based location	High accuracy	Computational cost Lobar cost

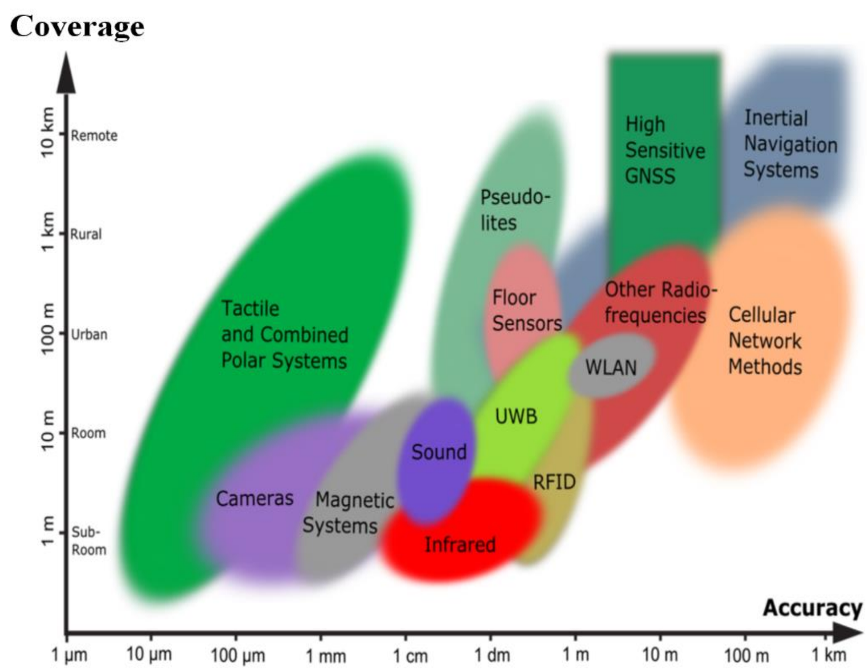


Figure 2-1: Overview of indoor technologies depend on accuracy and coverage.

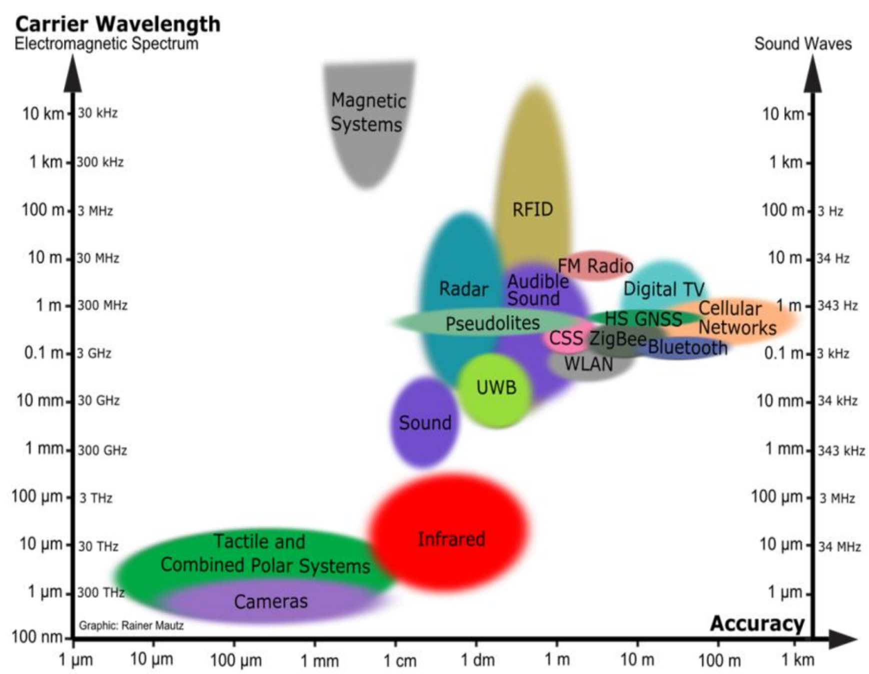


Figure 2-2: Indoor technologies depend on accuracy and carrier wavelength.

2.2 System Performance Metric

Although the accuracy of positioning systems is the most important criterion to measure system's performance, the researchers have established other criteria by which the overall performance of such systems can be evaluated and compared against each other [29]. The following criterion can be listed below:

- Accuracy: The accuracy of a positioning system is usually given by the distance error between the estimated and true position. This performance metric is highly desirable, but it is typically acquired at the expense of other metrics.
- Precision: It is a description of random errors, and it measures the coherence and consistency of the output of the system. The distance error standard deviation is the most popular way to describe precision. Small standard deviation indicates high precision, while the large standard deviation indicates low precision. In addition, Cumulative Density Function (CDF) of distance error is the best metric to measure the precision of the indoor positioning systems.
- Complexity: The complexity of the system can be investigated in terms of hardware and software. In this dissertation, only software complexity is considered, which translates into the computational complexity of the positioning algorithm. This metric is important, especially when the computations are performed on a mobile device, where the processing capability and the power supply are limited. Unlike previous metrics, there is no specific method to measure the complexity of the system. Fortunately, it can be attributed to the computational time of the algorithm. Hence, the system that takes less time (less computational processes) to complete the computations is considered of lower complexity.

- Robustness: Robustness is the ability of the system to resume functioning under perturbations. That is in the case of a node failure or the addition of a node to the system. The system is preferred to be persistent under unusual circumstances.
- Scalability: Scalability, in principle, is similar to robustness, but it deals with positioning scope changes. Such changes can be on a geographical scale or a density scale. The first scope of change is associated with the changes in the system coverage area, whereas the second is related to the changes in the number of positioning units per area. It is very often that the accuracy of the system degrades when the distance between the locator and the target is increased. The same applies when the number of units (positioning nodes) per area is reduced. The positioning system must ensure enough number of localization units to accommodate for increasing the space domain, provided that, the number of units does not exceed the required quantity. Otherwise, increasing the number of units/area will result in communication channels' congestion, more complex computations, and obviously higher cost.
- Cost: Many underlying factors other than the financial cost govern the overall cost of the positioning system. These include time, space, and energy costs. The space cost is related to the density of units per area, as explained previously. The time cost is related to the time needed for installation and maintenance. Finally, the systems energy consumption is also classified as a cost, and it is required to be fair, especially for mobile devices.

2.3 Positioning Sensor Technology

The sensor technologies for localization can be classified into RF, light wave, acoustic wave, magnetic field, and image processing, which are categorized in Figure 2-3. Radio waves-based IPS technique is recently exploited for ubiquitous computing by using Wireless Local Area

Network (WLAN). In most of the large indoor environments, WLANs are available as an infrastructure [30]. The received signal strength (RSS) of Access Point (AP) is used as a data feature to distinguish the location inside the building. The RSS-based methods can be exploited in WLAN environment to achieve indoor localization without adding external hardware while other techniques such as Time of Arrival (TOA), Time Difference of Arrival (TDOA), and Angle of Arrival (AOA) require additional hardware to work as IPS. Since the dissertation aims to study indoor localization approaches based on the WLAN RSSI (RF), an overview of the localization solutions based on this technology is emphasized.

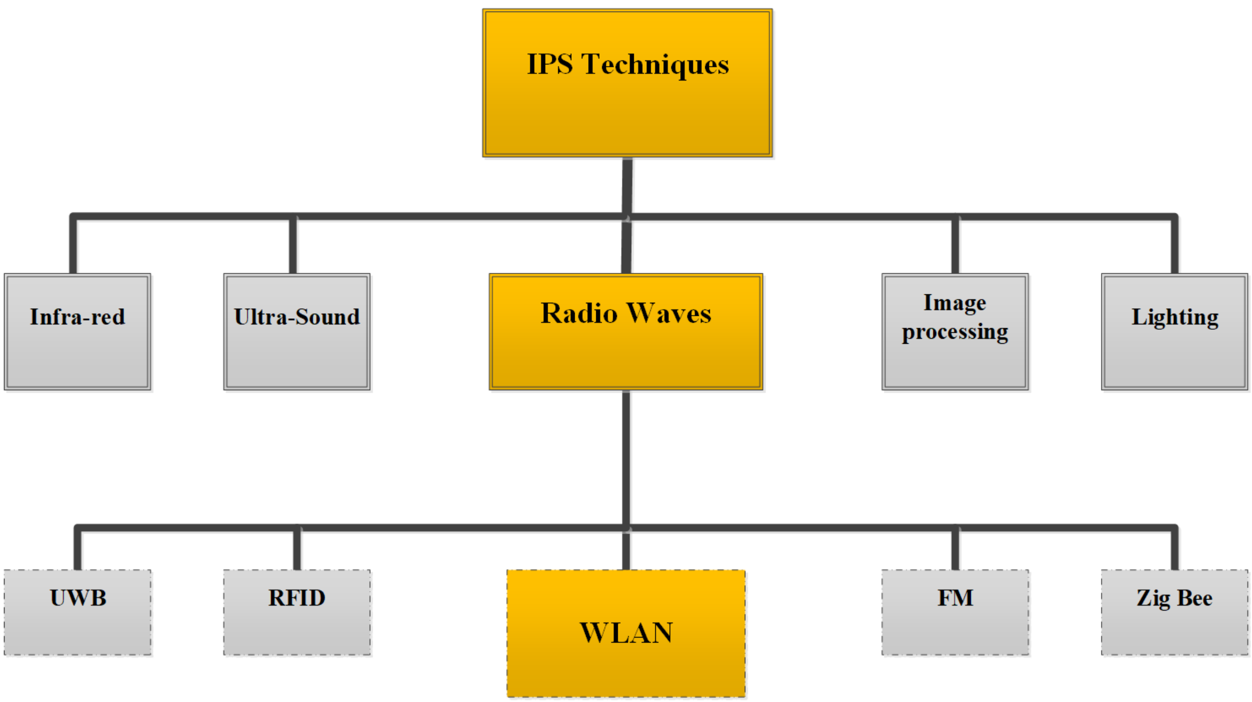


Figure 2-3: The categories of the main technologies for indoor positioning.

2.3.1 Image processing

An image processing-based technique has used the camera as the main sensor. Users can use a mobile phone to localize themselves by taking a picture for the surrounding indoor environment and comparing with a dataset of images, which are taken in advance. This technique is low cost and does not require additional hardware. The pipeline of the image-based technique is shown in Figure 2-4 . This technique involves two phases: creating a structured image databased (off-line phase) and localizing by pre-matching with image databased (on-line phase).

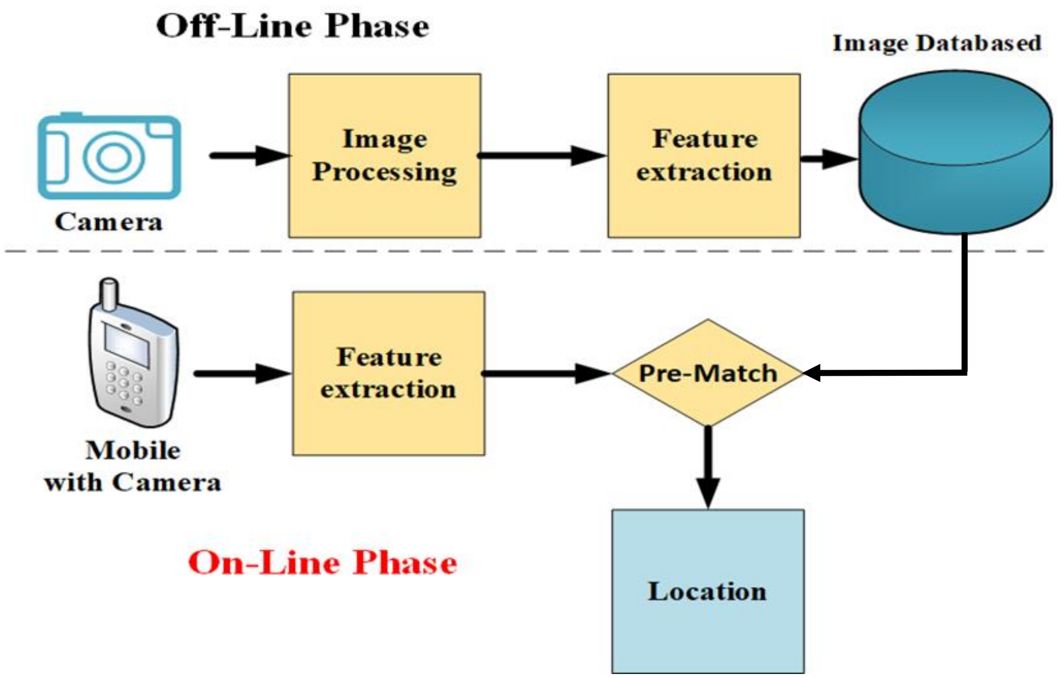


Figure 2-4: The framework of image-based technique.

The image database is stored in off-line phase with various reference style: 1) Reference from 3D building models, this technique relies on detection of objects in images and matching these with a database which contains positioning information of the building [31]. 2) Reference from images, it relies on sequences of images which are taken beforehand by the camera along the routes in the building. The current view is compared with these sequences to find the estimated location. For this technique, the main challenge is the limitation of real-time systems [32]. 3) Reference from deployed coded targets, this technique uses coded targets to identify the location inside the building. The common coded markers include concentric rings, barcodes, or patterns of colored dots [33]. 4) Reference from projected targets, this technique uses infrared light or a laser rig to find the location of the user where some applications mounting of reference markers is undesirable or not feasible. The main disadvantage of this technique that camera and light require a direct view on the same surface [34]. 5) A system without reference, this technique does not require reference points to find the location of the user. It observes position changes of objects directly by using a single or multiple static cameras with high frame rates in real-time [35], [36].

2.3.2 Sound

The sound is a mechanical variation that travels through the air or another medium. The sound is divided into two types: ultrasound and audible sound. Most of the sound-based positioning systems use ultrasound, which covers wavelength from 100um to 10mm. The relative distance or range between the transmitter, which emits ultrasound pulses, and receiver can be estimated from Time of Arrival TOA measurements, taking into account the propagation speed of sound. The ultrasound signal has several advantages such as a slow propagation speed, a negligible penetration in walls and a low cost of the transducers. The characteristics of the ultrasound signal are interesting for using in indoor positioning systems (IPS), where the achieved accuracy by ultrasound is typical of a few centimeters. The synchronization between nodes can be achieved easily by electrical pulses in systems with a wired connection. However, the wired connection leads to additional cost and makes the system more complicated. Therefore, the synchronization problem in wireless sensor networks (WSNs) is usually addressed by using radio frequency signals [37].

2.3.3 Lighting system

Optical wireless networks take a significant role in our life due to high transmission capacities. Visible light communication (VLC) using light-emitting diodes (LEDs) has become a hot topic in wireless communication. The white LED lighting becomes the next generation for indoor lighting because it has many advantages such as high luminous efficiency (up to 1100 m/W), long-time service life (up to 50000 hours), and high speed (up to 10MHz). The LED is switched to different intensity levels at a very fast rate, which is unrecognizable by human eyes. Hence, the LEDs can provide illumination and communication as well. There are two important features, which make lights available for indoor positioning:

- The light strength can be detected by light sensors, which embedded in commercial devices (e.g., smartphone, smart glass, and smartwatch).
- The light strength is stable along the time of day that leads to avoiding site survey and database maintenance.

Also, VLC is an essential communication tool, and it has the following advantages:

- Cost efficiency: The VLC uses the infrastructure of building to communicate, which means the system can be deployed with a few additional hardware.
- Broad bandwidth: the VLC is located in the frequency range from 385THz to 800THz. Therefore, the capacity to carry data is very high as compared with RF techniques.
- Energy efficiency: Most of the LED energy is used for illumination. Therefore, the VLC system is energy efficient.
- Communication security: The VLC uses a line of sight (LoS) for communication. Therefore, the communication links can be kept confidential.

Indoor positioning systems using VLC have gained a lot of researchers' attention due to the reasons, which are explained above. Many VLC-based IPSs have been proposed with positioning accuracy up to a few centimeters [38]–[42]. There are three factors should be considered when VLC is used for indoor localization: LED technology, modulation method, and type of receivers.

LEDs are expected to be the next generation device for illumination because of the advantages of a longer lifetime and low power consumption. The LED luminaire is a crucial part of VLC-based IPS, so it should not be affected by communication. The VLC-based IPS utilizes a different technique for modulation: On-Off Keying (OOK), Pulse Position Modulation (PPM), Orthogonal Frequency Division Multiplexing (OFDM), Color Shift Keying (CSK), and Carrier-less Amplitude and Phase (CAP) [43]. Visual light communication (VLC) uses two kinds of receivers which determine the position of the target [44]. The first kind utilizes photodiodes to receive light from the tracking target, and the position can be computed based on which detectors can see the emitted light. This technique does not allow the target to know its position without adding extra hardware. The second kind utilizes a camera sensor as a detector on the target together with stationary emitters which send a unique ID, allowing the target to compute its position based on the angle to each individual emitter [38]. This method is very accurate and allows an almost unlimited number of targets. However, the cameras are expensive and heavy cost image processing to detect the emitters and decode the information, which transmitted from them. The main issue with any form of VLC-based IPS is that it requires LoS. Therefore, the accuracy of localization is poor for dynamic environments.

2.3.4 Magnetic-field-based system

Magnetic positioning systems have been used for indoor localization due to its multipath phenomena robustness, and it does not require LoS to work properly inside the buildings[45]. There are two techniques, which are used for indoor localization: the first technique depends on the earth's magnetic field, and the other technique depends on the artificially generated magnetic field. The first technique uses the earth's magnetic field as a fingerprint to discriminate the position of the user. While the other technique measures the strength of magnetic fields which are generated through coils (beacons) to estimate the position of the user according to the beacons' position [46]. In this section, the second technique is reviewed because it is used in most of the magnetic indoor local positioning systems (MILPS). By examining the Biot-Savart law, the distance from the center of an electromagnetic coil can be estimated. This law is utilized to calculate the magnetic field, which is created by an exciting circular loop of wire.

$$dB = \frac{\mu_o I \, dl \times \hat{r}}{4\pi \, r^2} \qquad 2.1$$

Prigge [47] derived the following equation from Biot-Savart law, which describes the vector of the magnetic field at a given point in space:

$$B = \frac{\mu_o \, N \, I \, a}{4\pi r^3} \qquad 2.2$$

Where $\mu_o = 4\pi \times 10^{-7} \frac{V.S}{A.m}$

N: is the number of turns in the coil.

I: is a current, which passes through the coil.

$a = \pi r_o^2$, where r_o is the coil's loop radius.

The magnetic-field-based IPS contains a set of reference stations of electrical coils (Beacons) where each reference station generates a periodic magnetic field which is detected by a mobile magnetic field sensor [48], [49]. The magnetic field sensor measures the field strength of at least three reference coils, and then the position of the user can be estimated by using trilateration.

The magnetic-field-based IPS has many advantages:

- High accuracy on the order of a few centimeters. When the Eddy field noise and ferromagnetic distortion are considered in the account, the accuracy will be high.

- No LoS is required for position estimation where most of the obstacles inside the building won't be affected by a magnetic field.
- No FCC restrictions where the frequencies which are used for generating a magnetic field, are below the FCC regulations[47].

The magnetic-field-based IPS has many advantages, which mentioned above. However, the magnetic positioning systems have two fundamental challenges: short-range and sensitivity to certain materials[47]. According to Eq. 2.28, the strength of B is decreased rapidly when the distance ***r*** is increased. Therefore, many beacons are required to cover the entire building. The second challenge is represented by the nature of materials and how it reacts with a magnetic field. Eddy field noise can be created when the magnetic field comes into contact with conductive materials. These currents create their own magnetic field, thus introducing errors into the position estimation.

2.3.5 Radio frequency

RF has widely used technologies for indoor localization, including broadcast Wireless Local Area Networks (WLAN), Cellar, Global Positioning Systems, ZigBee, Bluetooth, RFID tags, and Ultra Wide Band.

2.3.5.1 Cellular-based system

The cellular network is a wireless communication network that serves geographical areas to provide communication services for mobile units. The geographical areas are divided into small regions, which are called cells. Each cell is served by one or two base stations as Figure 2-5. The cellular network tracks callers through base stations, which are closet to the users. A Mobile Switching Center (MSC) handovers channels when the users move from cell to another[50]. Therefore, the user of the cellular network can be located by using the cell-ID and geographical sector. The estimated location will be the center of the cell. This technique is called proximity, and it is discussed further in section 2.5.4.1.2. This service is available right now in all mobile phones to find mobile location. However, this technique is very poor accuracy due to the coverage area diameter of cell range from 2Km to 20Km [29]. The cellular-based system is proposed to enhance GPS performance in areas which does not have GPS such as urban areas [51].

Figure 2-5: The cellular network system.

2.3.5.2 GPS

In the 1970s, the Global Position System (GPS) was proposed by the USA Department of Defense. GPS consists of three parts: Space, Control station, and user. The space part is a constellation of 24 satellites which are distributed on 6 orbital planners surrounding the earth. This structure allows at least 4 satellites to be visible anywhere at any time on the earth. The second part consists of a control station on the ground to control and monitor the satellite's movements, and satellites clocks as well. The user part is a receiver for visible satellites signals which are used to determine the location of use by using the concept of signal time of arrival (ToA) [51] . The position of the user can be estimated by using the distances between user to visible satellites, and the visible satellites' longitude, latitude, and altitude. The user's location is estimated by using

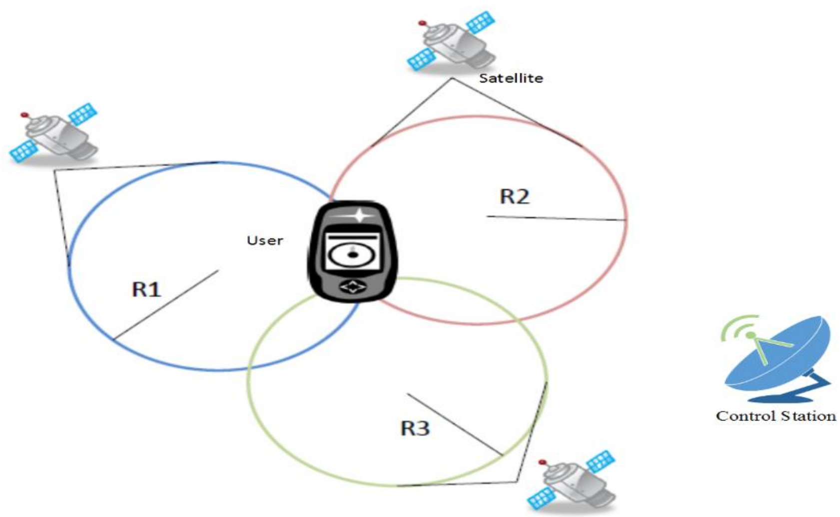


Figure 2-6: The GPS system.

literation where the point of intersection of the satellites signals propagation spheres as shown in Figure 2-6. Therefore, the positioning calculation needs at least four satellites, three for location, and one for time synchronization [52]. For outdoor positioning systems, the accuracy of GPS is acceptable with 10m distance error. However, GPS does not work inside the buildings because GPS requires LoS to work properly in an indoor environment.

2.3.5.3 ZigBee-based system

The ZigBee is operating on top of the IEEE 802.15.4 specification, which provides network, security, and application support services [53]. It is a short distance and low rate wireless personal area network [28] . It consists of a microcontroller and a multi-channel two-way radio on one piece of silicon. ZigBee is designed for applications that require low power consumption and low data throughput. There are two kinds of the physical device which is used for ZigBee nodes: full function device (FFD), and a reduced function device (RFD). The ZigBee-based technique achieves positioning by communicating with neighbored nodes. RSS values are usually utilized to estimate a distance between ZigBee nodes and user. Recently, phase shift measurement is a new approach that was proposed to ranging the nodes in a ZigBee network. Due to the time delay between the user and the ZigBee node, the phase shift of the reflected signal from the user node is used to measure the distance between them. A basic ZigBee node is small and has low complexity and cost. However, the use of ZigBee as indoor localization requires to install additional equipment to perform localization.

2.3.5.4 Bluetooth

Bluetooth is a wireless technology; Ericson Company invented it. Bluetooth is an Ad-hoc network, which uses 2.4GHz Industrial, Scientific, and Medical (ISM) band. This technology uses IEEE802.15 standards, which belongs to wireless personal area networks (WPAN). The range of Bluetooth is 10m to 15m, so its functionality covers only a room or hall level. The main function of Bluetooth technology is to connect different devices wirelessly to exchange the information with a bit rate of 1Mbps [50]. Positioning can be achieved by using Bluetooth tags, which are small transceivers with a unique signature ID. In addition, the strength of Bluetooth can be used to find the position of a Bluetooth enabled device relative to another.

2.3.5.5 UWB

The Federal Communications Commission (FCC) defines Ultra-Wide-Band or UWB as an RF signal covering a portion of the frequency spectrum, which is greater than 20% of the center carrier frequency. It has the bandwidth, which is greater than 500MHz, it is originally utilized for wireless communication, and later it is utilized to perform 2D and 3D indoor positioning. Because UWB signals can easily penetrate through obstacles with low power consumption, UWB becomes a good option for positioning with low accuracy in centimeters scale[53]. UWB-based positioning systems provide high accuracy due to the high time resolution (large bandwidth) of UWB signals. The new IEEE 802.15.4a standard has permitted to reduce the cost of UWB chips. However, the use of UWB as indoor localization requires to install additional equipment to perform localization. That is the important shortcoming of UWB-based technique. In addition, it has a short transmitting distance, similar to Bluetooth.

2.3.5.6 WLAN-based technique

In June 1997, the IEEE 802.11 WLAN standard was ratified. This technique is a standard protocol to interconnect data communication equipment each other via the air by using multiple access with collision avoidance medium sharing mechanism[53]. In the infrastructure topology, Mobile System (MS) is connected wirelessly to an Access Point (AP) that is connected to the wired network; this setup forms a WLAN. The protocol of connections between MS and AP goes through three steps: probing, authentication, and association. In probing step, the MS either can listen passively to AP signals and automatically attempts to join the AP or can actively request to join an AP. Next is the authentication step, the AP using some authentication mechanisms authenticates the MS. After successfully authenticating, the MS will send an association request to the AP, when it is approved, the AP adds the MS to its table of associated wireless devices. The AP can associate many MSs, but an MS can be associated with one AP only at a time. The most popular standard amongst this family is the 802.11b which operates on 2.4 GHz with a data rate of 11 Mbps, depending on the standard [54]. Figure 2-7 shows the three phases in WLANs whose sequence begins from top to bottom.

WLAN can be used to estimate the location of a mobile device within this network. Since WLAN infrastructure is widespread in many indoor environments, according to the increase in demand for wireless communications, this approach is widely used for indoor localization. For this reason, one

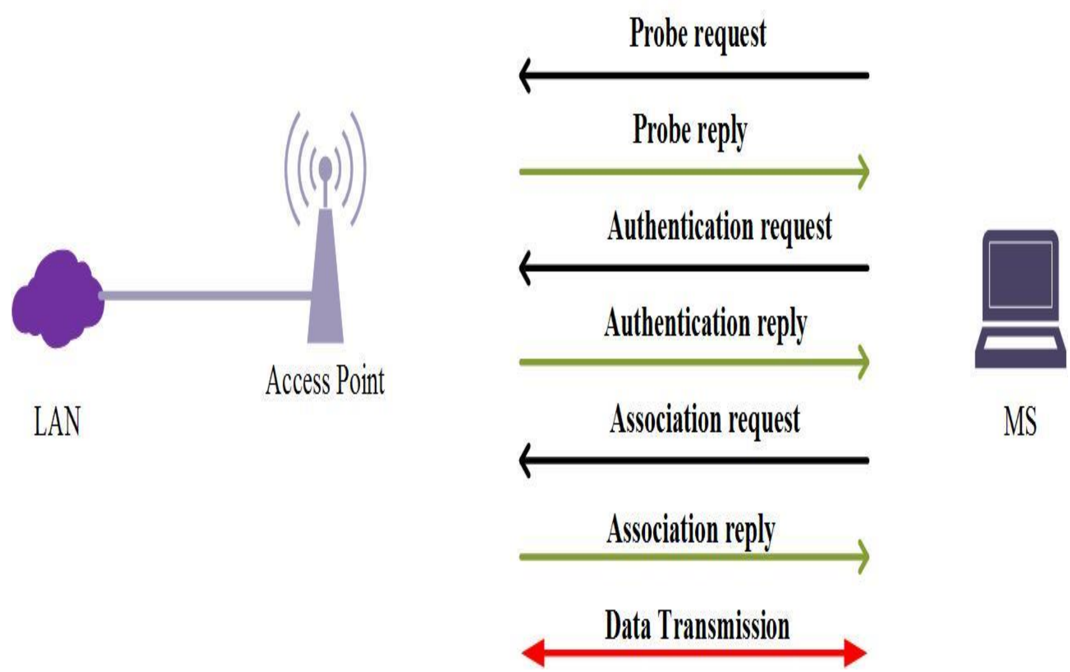


Figure 2-7: The sequence of WLAN connection protocol between MS and AP.

of the main advantages of using Wi-Fi localization technique is its cost-effectiveness due to the possibility to localize the position of almost every Wi-Fi compatible device without installing extra software and hardware. Another advantage of using WLAN is that LoS is not required. The most popular WLAN positioning method is to make use of a Received Signal Strength Indicator (RSSI), which are easy to extract in IEEE 802.11 networks. The positioning system architecture consists of the following units:

- Network: the underlying wireless network, IEEE 802.11, uses RF signals to establish communications between MS and network APs [55]. Each AP has a unique MAC address with a known fixed location. Every 100 ms, the network APs transmit beacon packets that contain data and information system. Any device works with the IEEE 802.11 protocol can receive beacon packets because beacon packets are not encrypted. Therefore, any IEEE 802.11 network can be used for indoor localization.
- Communication medium: The IEEE 802.11, which works in the ISM band, transmits over 14 channels with center frequency 2.4GHz. There are three non-overlapping channels are occupied at the same time in the same geographical area as Figure 2-8.
- Mobile System: It is the user terminal. It can receive the beacon packets because it contains a Network Interface Card (NIC). Therefore, the MS can measure all RSS values from all hearable APs at the location of MS[56].

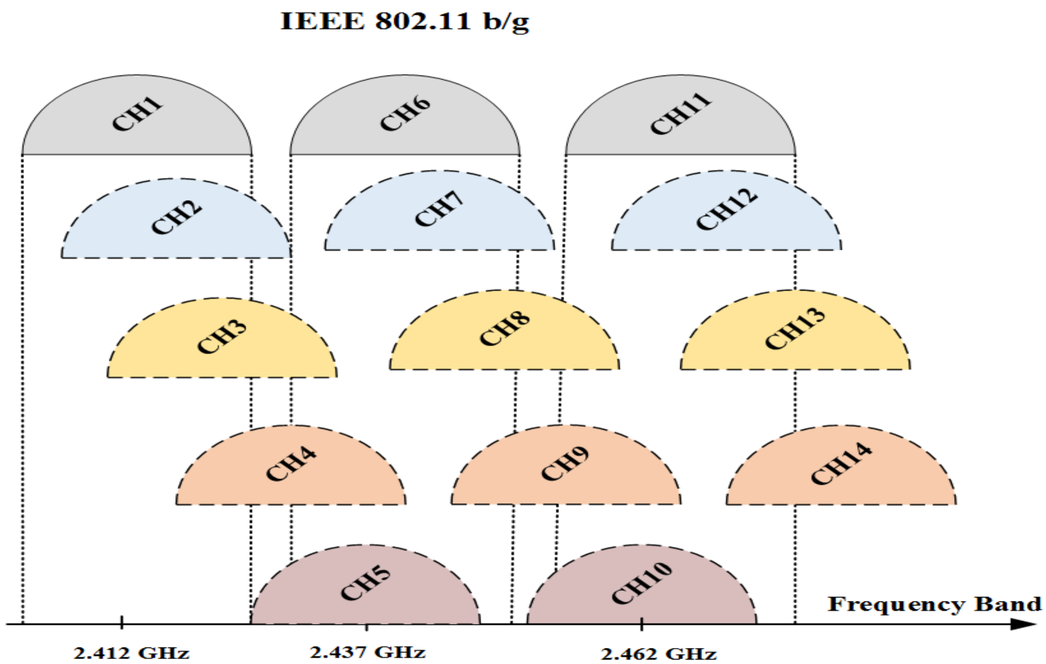


Figure 2-8: The channels of IEEE 802.11b/g WLAN.

- Server: usually, the MS achieves all steps, which are used to estimate the location of MS. However, the server is used to assist MS in estimating the location of MS because of the limitation of MS's resources such as a central processor, and memory. The location information is transmitted through a TCP/IP link to a central unit (server). The server will estimate the user's location according to the used algorithm and returns the estimated position to MS.

2.4 Radio Wave Transmission

The radio signals generally have the capability to travel through the objects. The line of sight (LoS) is a crucial condition to obtain better result when a radio signal is used for indoor localization. Unfortunately, LoS is not usually available over a long distance in the indoor environment due to the materials of obstacles such as concrete, wood, and steel. Also, the density of people moving inside a building, which is changed rapidly. However, the is no absolute needing for LoS between transmitter and receiver in an indoor environment to obtain acceptable results[57].

2.4.1 Reflection and refraction

Reflection is a physical phenomenon that happened when the sharp change in the direction of wave propagation that strikes the boundary between two different media. As shown in Figure 2-9, the incident wave is divided into two components: reflected and refracted component. Assuming the incident wave makes θ_i with the normal of a plane tangent to the boundary. The reflected wave makes an angle θ_r with the normal line and lies with the same plane with the incident wave line and the normal. On the other hand, refraction is the change in direction and speed when the wave passes in a different medium.

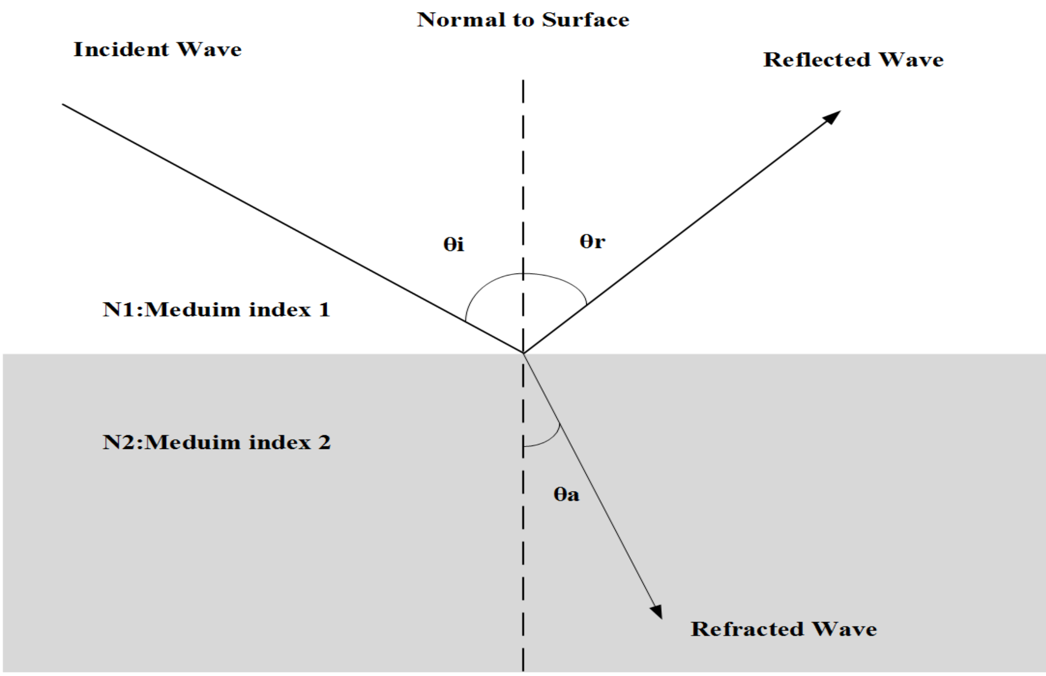


Figure 2-9: The reflection and refraction of the incident wave.

2.4.2 Diffraction

It refers to various phenomena when the wave encounters an obstacle. The group of waves will have a change in the intensities and direction after passing by obstacle or aperture whose size is close to the wavelength of the wave's size, as shown in Figure 2-10.

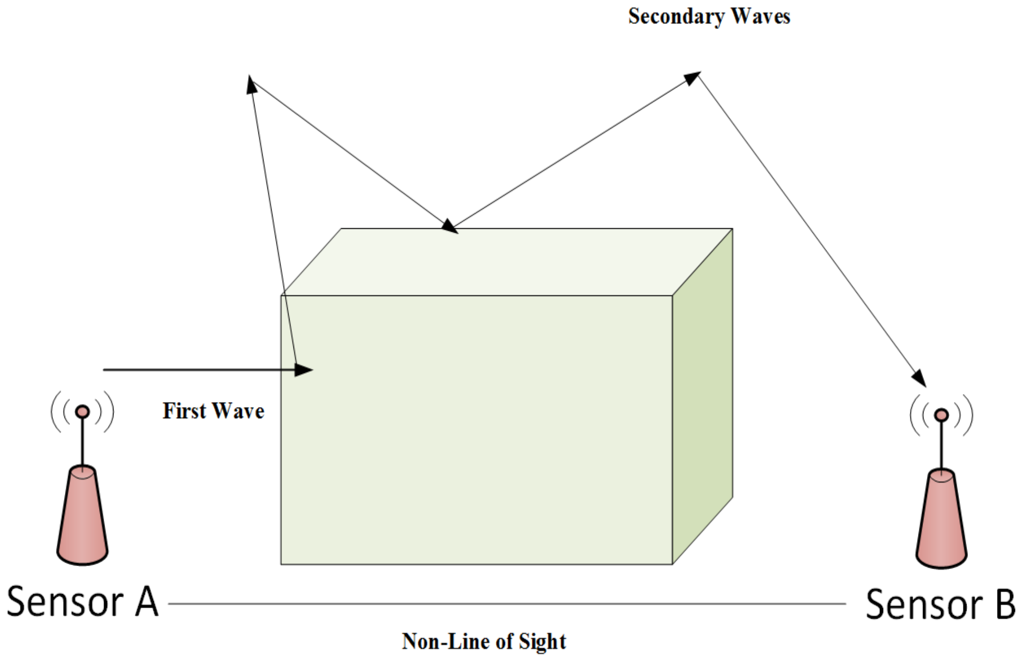


Figure 2-10: The diffraction of the radio wave.

2.4.3 Scattering

When the electromagnetic EM waves hit an object whose size is almost or greater than the wavelength of the EM wave, the energy of EM waves scattered to a different direction, as shown in Figure 2-11.

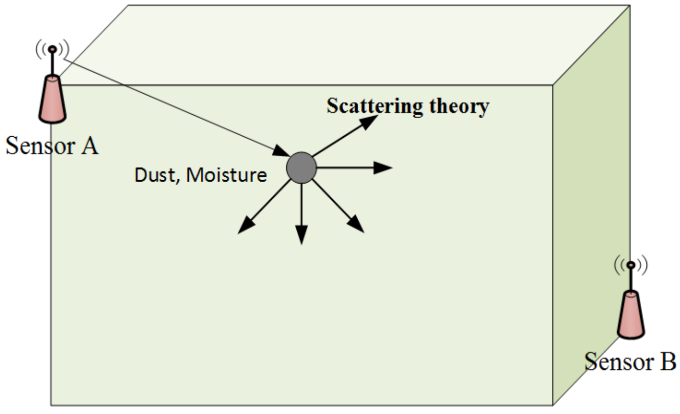


Figure 2-11: The scattering of the radio wave.

2.4.4 Multipath fading issue

Multipath is a propagation phenomenon that happened when radio signals are reaching to receiver's antenna by two or more paths, as shown in Figure 2-12. There are many reasons for multipath: reflection, refraction, diffraction, scattering, and movement of people inside the building [58]. The effects of multipath involve destructive and constructive interference. The indoor multipath situation must be taken into account because it is different from an outdoors environment. Most of the algorithms were proposed for outdoor usage. It generally assumes that the line of sight (LOS) signal is always present, and no more than three secondary paths exist in the channel [59]. However, in the indoor environment, this situation is rare because of reflections/ diffractions, and distances between objects are smaller. Thus, there are more secondary paths present in the channel. For an instant, the LOS signal that arrives through a concrete wall will be attenuated by 12-43 dB [60], while a secondary path reflected from some object and arrived through the window will be attenuated by only 1-4 dB. Therefore, the multipath issue can be considered as an important challenge to describe the indoor environment by a mathematical model. So it is difficult to calculate path loss for the indoor environment because of the variety of indoor environment. Recently, the most common method to reduce the multipath effect is using multi-antenna at the receiving end to receive the signal, but this will increase the cost and take up more volume.

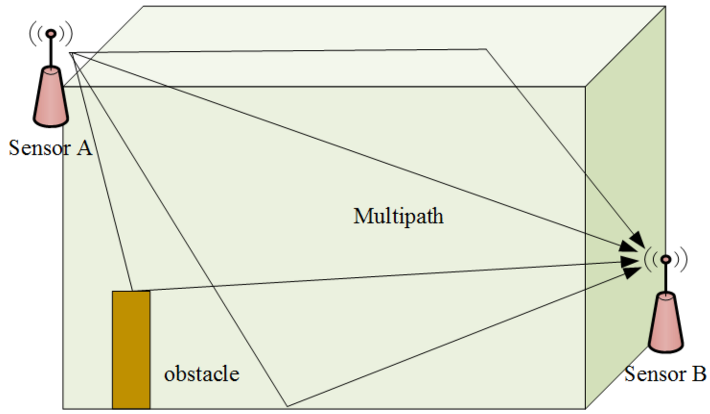


Figure 2-12: The multipath of the radio wave.

2.4.5 RSS propagation models

One of the important characteristics of wireless signal transmission is that the signal intensity decreases with the increase of distance. The principle of RSSI distance measurement is to transform the attenuation of signal intensity into the distance of signal propagation. The measured RSS at a specific point on a physical locations map is affected by constructive or destructive interference from the multipath propagation of RF waves [19]. The waves; which travel through a multipath channel; reach a single point where their magnitudes and phases will be added. Lognormal shadow model is a more general propagation model [61]. It is suitable for both indoor and outdoor environments. The model provides various parameters that can be set up according to different environments. The calculation formula is as follows:

$$RSS(d) = RSS(d_o) - 10N_p log_{10}\left(\frac{d}{d_o}\right) + X_\sigma \qquad 2.3$$

Where

RSS (d): is the estimated value of RSS at a specific distance d.

d: is the distance between the specific location and the RP location.

RSS (d_o): is RSS at a reference distance d_o.

N_p : is a path loss constant, and X_σ is a random variable which describes the variation of RSS level due to the multipath feature, and it is assumed to have a Gaussian distribution with zero mean [24]. The effects of X_σ can be mitigated by recording several values of RSS and averaging which is similar to what happens in off-line phase during fingerprint creation. However, during the on-line phase, we cannot take a large number of RSS measurements since it consumes more time than one

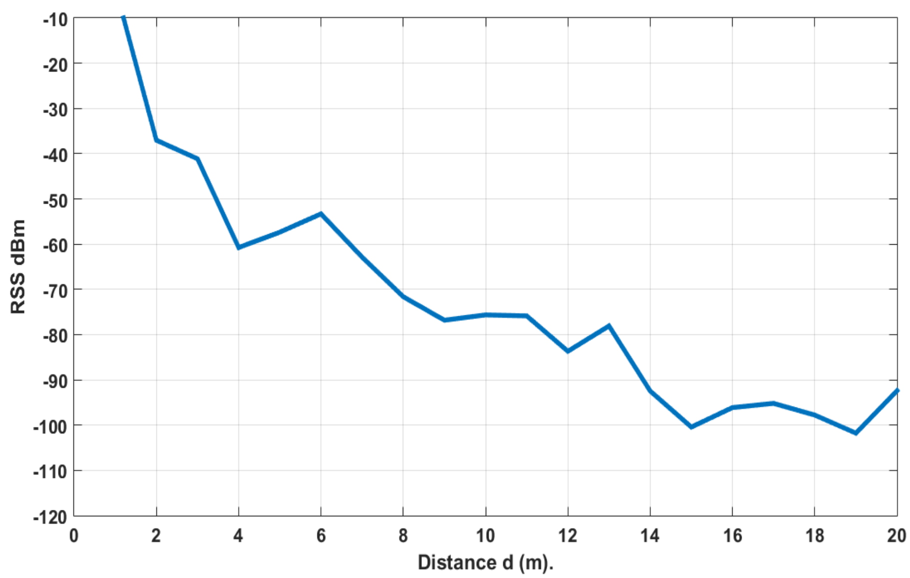


Figure 2-13. The variation RSSI versus distance d.

should allow for a real-time system. Figure 2-13 shows the decreasing of RSS power with increasing of distance *d* for the following parameters: $RSS(d_o) = -20dBm$, $N_p = 2.5$, $d_o = 2m$, and X_σ is a normal random variable with $\overline{X_\sigma} = 0\ dBm\ and\ \sigma = \sqrt{5}$.

2.5 Algorithms for Location Determination

2.5.1 TOA

Time of Arrival method, which is called sometimes Time of Flight (ToF), is a propagation time delay between the transmitter and one or more receivers. Figure 2-14 shows the principle of

ToA where the propagation time delay is calculated by using $T_d = t_1 - t_o$. After all receivers in range havethe the calculated its ToA, the ToA values are converted into the distance by multiplying the propagation time delay T_d with the propagation signal speed. Then, the distance values are being utilized for trilateration. Trilateration requires data from at least three receivers to work.

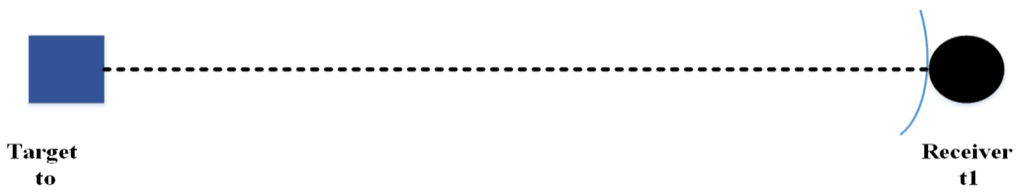


Figure 2-14: The Time of Arrival (ToA) method.

2.5.2 TDOA

Time Difference of Arrival (TDoA) is a time difference between the arrived signals to various receivers from singer transmitter (Target) as shown in Figure 2-15. In order to find the difference in arrival times, each receiver records the arrival time of the signal. These times are transmitted to the locating engine that calculates the time difference. The approximate distance from each tag can be calculated through an algorithm to find the estimated position of the target. The position of the target could be seen on the intersection of three hyperbolas in a 2D plane, and the intersection of 3 hyperboloids in a 3D space [62]. Since the localization engine compares the difference of the time of arrival for each receiver, it is very important that all the receiver clocks be synchronized. Therefore, TDoA is an appropriate method for outdoor positioning and tracking because it requires LoS and time synchronization.

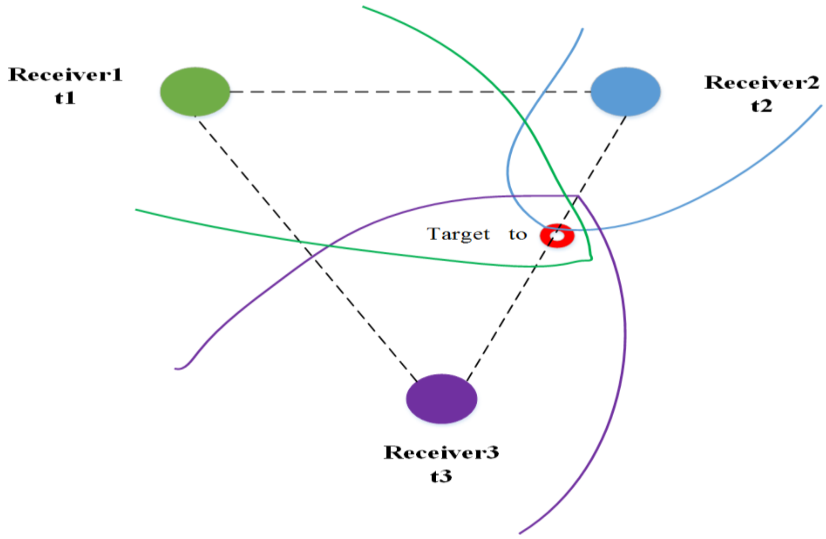


Figure 2-15: The Time Difference of Arrival (TDoA) method.

2.5.3 AOA

The Angle of Arrival (AOA) method has used the direction of the transmitted RF signal from Tag (Target) at two receivers to determine the location of the target, as shown in Figure 2-16. It measures the angle between the received signals and a pre-defined direction (e.g., north, east, west, south). This is possible when the receiver is provided direction sensitive antennas.

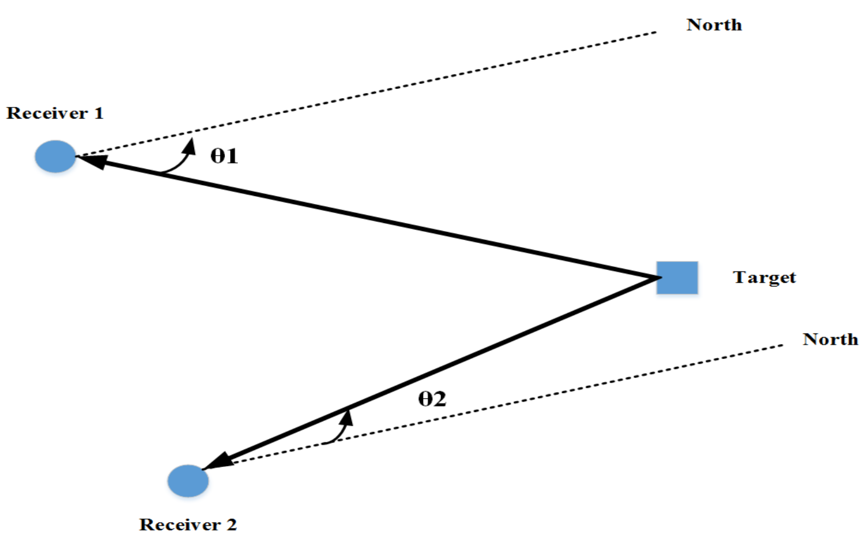


Figure 2-16: The Angle of Arrival (AoA) technique.

2.5.4 RSS-based WLAN positioning system

The traditional RSS-based indoor positioning algorithms can be classified into three categories: triangulation, proximity, and scene analysis algorithm.

2.5.4.1.1 Triangulation

An alternative approach is to estimate the distance of the mobile unit from some set of measuring units, using the attenuation of emitted signal strength. Signal attenuation-based methods attempt to calculate the signal path loss due to propagation. Theoretical and empirical models are used to translate the difference between the transmitted signal strength and the received signal strength into a range estimate, as shown in Figure 2-17 . Due to severe multipath fading and shadowing present in the indoor environment, path-loss models do not always hold. The parameters employed in these models are site-specific. The accuracy of this method can be improved by utilizing the premeasured RSS contours centered at the receiver [7] or multiple measurements at several base stations. A fuzzy logic algorithm shown in [8] is able to significantly improve the location accuracy using RSS measurement.

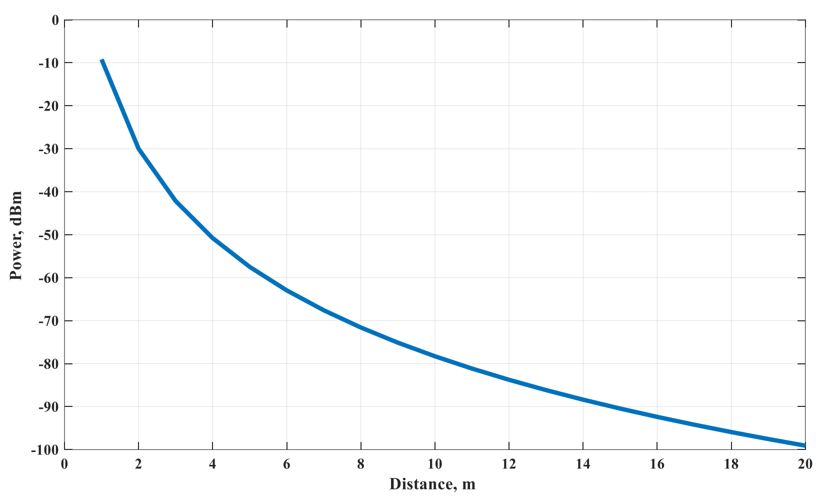


Figure 2-17: The theoretical change of RSS power of AP versus distance d (m).

2.5.4.1.2 Proximity

Proximity algorithms provide symbolic relative location information. Usually, it relies upon a dense grid of antennas, each having a well-known position. When a mobile target is detected by a single antenna, it is considered to be collocated with it. When more than one antenna detects the mobile target, it is considered to be collocated with the one that receives the strongest signal. This method is relatively simple to implement. It can be implemented over different types of physical media. In particular, the systems using infrared radiation (IR) and radio frequency identification (RFID) are often based on this method. Another example is the cell identification (Cell-ID) or cell of origin (COO) method. This method relies on the fact that mobile cellular networks can identify the approximate position of a mobile handset by knowing which cell site the device is using at a given time. The main benefit of Cell-ID is that it is already in use today and can be supported by all mobile handsets.

2.5.4.1.3 Scene analysis

RF-based scene analysis refers to the type of algorithms that first collect features (fingerprints) of a scene and then estimate the location of an object by matching online measurements with the closest a priori location fingerprints. RSS-based location fingerprinting is commonly used in scene analysis. Location fingerprinting refers to techniques that match the fingerprint of some characteristic of a signal that is location dependent. There are two stages for location fingerprinting: offline stage and online stage (or run-time stage). During the offline stage, a site survey is performed in an environment. The location coordinates/labels and respective signal strengths from nearby base stations/measuring units are collected. During the online stage, a location positioning technique uses the currently observed signal strengths and previously collected information to figure out an estimated location. The main challenge to the techniques based on location fingerprinting is that the received signal strength could be affected by diffraction, reflection, and scattering in the propagation of indoor environments. There are at least five location fingerprinting-based positioning algorithms using pattern recognition technique so far: probabilistic methods, k-nearest-neighbor (KNN), neural networks, support vector machine (SVM) [63], and smallest M-vertex polygon (SMP) .

2.6 Fingerprinting Localization Algorithm

There are two approaches based on RSS values: the deterministic and probabilistic method. The deterministic approach uses only the average of the RSS time samples to find the location of the user. On the other hand, the probabilistic approach incorporates all the RSS time samples for the computation of the user's position inside the building.

2.6.1 Deterministic algorithm

In WLAN fingerprinting technique, the use of the nearest neighbor NN technique is quite common. Essentially, the core concept is to calculate the distances in signal space between unknown position vector, which is combined from the RSS of APs at an unknown location, and the known position vectors in the radio map (RM). Then, find the closest RP, which is corresponding to the shortest distance between the unknown position vector and RP vector. To create RM for any an indoor map, first, the area of interested (AOI) is divided virtually into grid points, the distance between these points depends on how much accuracy is required [14]. At each reference point, the RSS value reading from different APs, which are available in AOI, is measured. The collected fingerprints database at a reference point RPi is denoted as the set { $\varphi_i(1), \dots\dots, \varphi_i(Nt)$; i=1,2, …, M} where M represents the number of reference points in the AOI, and Nt is the total number of time samples at a reference point. $\varphi_i(t_o) = [\varphi_{i,1}(t_o), \dots\dots\dots, \varphi_{i,L}(t_o)]^T$ is the RSS data vector for the ith RP at a certain time t_o from the different L access points (AP_1, …, AP_L). Then, the average of the RSS time samples is computed and stored in a database, known as the RM. Where $\Psi_{i,j} = \frac{1}{q}\sum_{\tau=1}^{q} \varphi_{i,j}(\tau)$ is the average of RSS readings (in dBm scale) over time domain from AP_i at RP_j with different orientation {0^o , 90^o , 180^o , and 270^o }, for i = 1, 2, ..., L, and j = 1, 2, ..., M. The averaging procedure overcomes the human body and the antenna's orientation of the measuring device during the RSS sampling [15]. The RM can be written as:

$$\Psi = \begin{bmatrix} \Psi_{1,1} & \cdots & \Psi_{1,M} \\ \vdots & \ddots & \vdots \\ \Psi_{L,1} & \cdots & \Psi_{L,M} \end{bmatrix} \qquad 2.4$$

Where the i^{th} row represents the RSS values of i^{th} AP for M RPs, and the j^{th} column represents the fingerprint of j^{th} RP points for L APs. In on-line phase, the unknown position vector V= [RSS_1, RSS_2,…….., RSS_L] is pre-matched with RM which is stored in the off-line phase to find the estimated user location as shown in Figure 2-18.

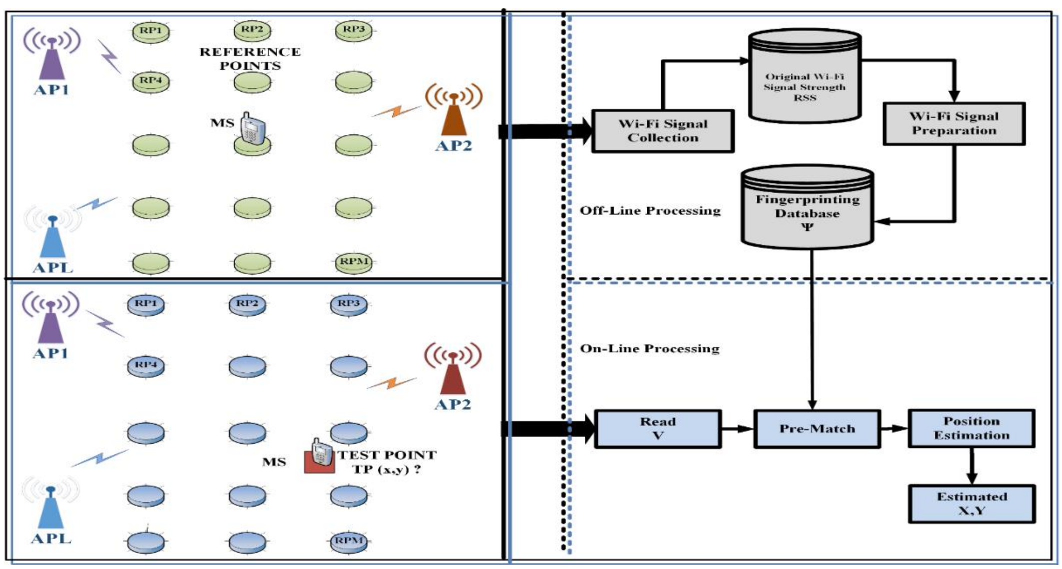


Figure 2-18: The fingerprinting-based technique.

2.6.1.1 Distance Measures

Measuring similarity or distance between two vectors in space is essential to solving many pattern recognition problems such as K-NN and clustering, etc. There are various measurements can be used for similarity, which is depending on the nature of data. The current subsection briefly introduces nine categories, which is reviewed by [64]. This dissertation is based on the Euclidean distance, which is represented in Eq.2.5 where P and Q refer to the two vectors which we need to find the similarity between them and L is the length of vectors (number of AP in this case).

$$distance_{Euclidean}\,(P,Q) = \sqrt[2]{\sum_{i=1}^{L} |P_i - Q_i|^2} \qquad 2.5$$

2.6.1.1.1 The Minkowski family

The Minkowski family measures, Lp, include the Euclidean distance (L2); the City Block distance (also known as Manhattan or Taxicab distances) (L1); the Minkowski distance (Lp); and the Chebyshev distance (L∞). The Minkowski distance, see Eq. 2.6, is the generalized formula for this family.

$$distance_{L_p}\,(P,Q) = \sqrt[p]{\sum_{i=1}^{L} |P_i - Q_i|^p},\ \forall p\ \in\ N^+ \qquad 2.6$$

2.6.1.1.2 The L1 family

The L_1 family measures are based on the City Block distance (L_1), and this family includes Sørensen distance, Gower distance, Soergel distance, Kulczynski distance, Canberra distance, and Lorentzian distance. In distance-based methods, such as k-NN, Gower distance (see Eq.2.7) and the original City Block (see Eq.2.6 with p = 1) distances are equivalent since the distance provided by Gower is the City Block value divided by a constant (the number of features).

$$distance_{gower}\,(P,Q) = \frac{1}{L} \times \sum_{i=1}^{L} |P_i - Q_i| = \frac{1}{L} \times distance_{L1}(P,Q) \qquad 2.7$$

Although the distance value provided by the other L1 family measures are not proportional to the values provided by the original L1 measure, most of them include the following term: $\sum_{i=1}^{L}|P_i - Q_i|$. For instance, Eq. 2.8 shows the Sørensen distance.

$$distance_{Sorensen}\ (P,Q) = \frac{\sum_{i=1}^{L}|P_i - Q_i|}{\sum_{i=1}^{L}(P_i + Q_i)} \qquad 2.8$$

2.6.1.1.3 The intersection family

The Intersection family contains Intersection distance, Wave Hedges distance, Czekanowski distance, Motyka distance, Kulczynski similarity, Ruzicka similarity, and Tanimoto distance. In distance-based methods, such as k-NN, some distances are equivalent. This is the case of Soergel, Tanimoto, and Ruzicka. Moreover, both Kulczynski measures are inversely proportional.

It is worth mentioning that some family 3 measures resemble the L_1 family since they include the $|P_i - Q_i|$ term. In fact, Czekanowski and Sorensen are the same measures (note that Sørensen distance was cataloged as L_1 family) see Eq.2.9 . This is also the case of Intersection distance (see Eq.2.10) which is proportional to Gower distance as denoted with $\propto$ a symbol.

$$distance_{czekanowski}\ (P,Q) = 1 - similarity_{Czekanowski}$$

$$distance_{czekanowski}\ (P,Q) = \frac{\sum_{i=1}^{L}|P_i - Q_i|}{\sum_{i=1}^{L}(P_i + Q_i)}$$

$$distance_{czekanowski}\ (P,Q) = distance_{Sorensen}\ (P,Q) \qquad 2.9$$

$$distance_{intersection}\ (P,Q) = \frac{1}{2}\sum_{i=1}^{L}|P_i - Q_i| \propto distance_{gower}\ (P,Q) \qquad 2.10$$

2.6.1.1.4 The squared L2 family

The Squared L_2 family or $\chi 2$ family is based on the Euclidean distance and includes the following distance measures: Squared Euclidean; Pearson $\chi 2$; Neyman $\chi 2$; Squared $\chi 2$; Probabilistic

Symmetric χ2; Divergence; Clark; and Additive Symmetric χ2. All of these contain the squared of Euclidean distance term,$(P_i - Q_i)^2$, weighted by different factors. For instance, the Neyman χ2 distance is shown in Eq. 2.11:

$$distance_{\text{neyman}}\ (P,Q) = \sum_{i=1}^{L} \frac{(P_i - Q_i)^2}{P_i} \qquad 2.11$$

2.6.1.1.5 The Inner Product family

The Inner Product family radically differs from the previous families and introduces the scalar product of two vectors. This product provides a scalar value and, according to Cha (2007), it corresponds to the number of matches if it is used for binary vectors. As stated by Cha, most of this family measures are frequently used in information retrieval and biological taxonomy for the binary feature vector comparison. In this family, the measures are not proportional among them, and they are Inner Product similarity in Eq.2.12; Harmonic mean similarity; Cosine similarity; Kumar–Hassebrook similarity; Jaccard distance; and Dice distance. Eq. 2.12 shows the Inner Product distance as an example of this family.

$$similarity_{interproduct}(P,Q) = P.Q = \sum_{i=1}^{L} (P_i.Q_i) \qquad 2.12$$

2.6.1.1.6 The Fidelity family

The sixth family is the Fidelity family or Squared-chord family, and it includes Fidelity similarity (see Eq.2.13), Bhattacharyya distance, Hellinger distance, Matusita distance, and Squared-chord distance. This family resembles the measures introduced in the Inner Product family, but the square root is applied to the vector values.

$$similarity_{fidelity}(P,Q) = \sum_{i=1}^{L} (\sqrt{P_i \times Q_i}) \qquad 2.13$$

2.6.1.1.7 Shannon's Entropy family

Shannon's Entropy family contains those distance measures based on Shannon's concept of probabilistic uncertainty: Kullback Leibler (see Eq. 2.14), Jeffreys, K divergence, Topsøe, Jensen–Shannon, and Jensen difference. Jensen–Shannon distance corresponds to Topsøe divided by 2.

$$distance_{\text{Kullback-Leibler}}\,(P,Q) = \sum_{i=1}^{L}(P_i \times \log\frac{P_i}{Q_i}) \qquad 2.14$$

2.6.1.1.8 The Combinations family

Combinations family contains all those distance measures which combine different approaches: Taneja; Kumar–Johnson; and Avg(L_1, L_∞). In fact, Avg(L_1, L_∞) see Eq.2.15, corresponds to the mean value provided by City Block (L_1) and Chebyshev (L_∞) distances.

$$distance_{\text{avg}(L_1-L_\infty)}\,(P,Q) = \frac{distance_{L_1}(P,Q) + distance_{L_\infty}(P,Q)}{2} \qquad 2.15$$

2.6.1.1.9 The Vicissitude family

Additionally, Cha (2007) included six distances, which were not in the literature. They have grouped into the Vicissitude family: VicisWave Hedges; Vicis-Symmetric χ2 (with three different variants); minSymmetric χ2; and max-Symmetric χ2. As stated by Cha, a large number of new distance/similarity measures can be relayed by studying the syntactic relations and may be useful in some applications. For instance, the equation for the third version of the Vicis-Symmetric is given by Eq. 2.16;

$$distance_{\text{Vicissymmetric3}}\,(P,Q) = \sum_{i=1}^{L}\frac{(P_i - Q_i)^2}{\max(P_i, Q_i)} \qquad 2.16$$

2.6.1.2 K-nearest neighbor

The K-NN method is a deterministic and non-parametric approach that is used to find the nearest K- neighbors to the user's position. The K-NN-fingerprinting-based IPS consists of two phases; these are the off-line phase and the on-line phase. In the off-line phase, the RM for the AOI will

$$D_i = \|r - \Psi\| \qquad 2.17$$

be created by measuring the values of RSS from different APs at each reference point. In the on-line phase, the measured RSS vector at the unknown position will pre-matched with RM vectors ψ by using Euclidean distance approach to find distance-vector Di as shown by Eq.2.17.

Where: r = $[r_1, \ldots, r_L]^T$ is the on-line measurement vector. The distances between the *r* vector and all RPs at the RM will be calculated. Then, the distances are stored in ascending order, and the K RPs that have the smallest distances are chosen as KNN. The estimated position $\hat{p}$ can be calculated by using Eq. 2.18.

$$\hat{p} = \frac{1}{K}\sum_{i=1}^{K} p_i \qquad 2.18$$

Eq. 2.18 represents the average K-NN. If the distances are used as weights in a weighted WK-NN to calculate an estimated position $\hat{p}$, then Eq. 2.19 should be used.

$$\hat{p} = \frac{\sum_{i=1}^{K}\frac{1}{D_i}p_i}{\sum_{i=1}^{K}\frac{1}{D_i}} \qquad 2.19$$

2.6.2 Probabilistic approach

The probabilistic models, as shown in Figure 2-19 can solve the location estimation problem[15], [65], [66]. The core concept of this method is to find the posterior distribution of the location, which is the conditional probability$p(p_i|r)$. By using the Maximum A posteriori (MAP) estimator, the conditional probability can be estimated. The MAP estimator is derived from Bayes rule. That is:

$$\hat{P}_{MAP} = \arg max_{pi} f(p_i|r) = arg\ max_{pi} \frac{f(r|p_i)f(p_i)}{\sum_{i=1}^{N} f(r|p_i)f(p_i)} \qquad 2.20$$

Where $f(p_i|r)$ and $f(r|p_i)$ are the conditional probability density function. The eq. 2.20 can be simplified into Eq.2.20 where the $f(p_i)$ is uniform distribution because there is no prior knowledge of the device's location.

$$\hat{P}_{MAP} = arg\,max_{pi} f(r|p_i) \qquad 2.21$$

The likelihood densities are included as the weight for the K RPs with the highest likelihood densities, namely:

$$\hat{P}_{MAP+weight} = \sum_{i=1}^{K} w_i p_i \qquad 2.22$$

$$w_i = \frac{f(r|p_i)}{\sum_{i=1}^{K} f(r|p_i)} \qquad 2.23$$

There are several methods to estimate the density function$f(r|p_i)$, $i = 1, 2, \ldots\ldots$, N from database of fingerprint. The two common methods are Histtheogram and Kernel-based approach. They assume that the RSS-values of different APs are uncorrelated and independent so that the density function can be simplified to be:

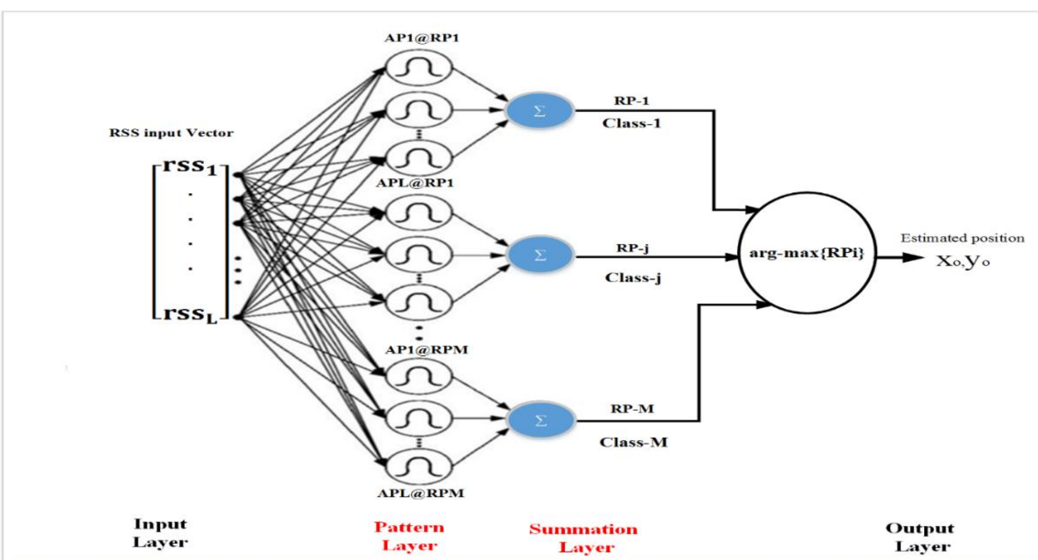


Figure 2-19: The framework of the PNN technique.

$$f(r|p_i) = \prod_{k=1}^{L} f(r_k|p_i) \quad 2.24$$

2.6.3 Histogram-based method

The histogram method can estimate the likelihood density function. Two parameters should be available to generate a histogram of RSS time samples, which are collected from different AP at each RP[15]. The first parameter is the number of bins, which are sets of non-overlapping intervals that cover the completely possible RSS range. The second parameter is the origin of bins, which is necessary for determining the boundary of bins. Then, the RSS likelihood density can be obtained as the relative frequency of bin.

There are several shortcomings in this method. First, a large number of RSS samples for each RP is required to obtain a reliable histogram. Second, the likelihood density function depends heavily on the choice of the width and origin of bin [15].

2.6.3.1 Kernel-based method

The Kernel-density estimator is the second technique to estimate the likelihood density function [65]. The density function can be estimated as follows:

$$\hat{f}(r|p_i) = \frac{1}{T}\sum_{t=1}^{T} K(r;\varphi_i) \quad 2.25$$

Where $K(r;\varphi_i)$ is the kernel function. The Gaussian Kernel is a common choice of the kernel function. By assuming that RSS-signals from different APs are independent and uncorrelated, we can define the Gaussian kernel function as follows:

$$K(r;\varphi_i) = \frac{1}{(\sqrt{2\pi\sigma_i^*})^L}\exp(-\frac{\|r-\varphi_i\|^2}{2(\sigma_i^*)^2}) \quad 2.26$$

Where σ_i^* is the kernel bandwidth. The drawback of this method that it takes all the RSS time samples which are collected at each RP into account for estimating the likelihood function, so the computational time is much larger than the KNN method [65].

2.7 Fingerprinting computational complexity reduction

In an indoor location system, eliminating redundant APs does not only reduce the computational cost of fingerprinting processing but also it can improve the positioning accuracy as well. The WLAN-based fingerprinting technique has built an RM for AOI where each vector in the RM comes from measuring RSS of multiple APs, which are deployed in AOI. Since most large buildings are equipped with a large number of APs to provide wireless network services. Nerveless, all these APs contribute positively the positioning accuracy where the majority are redundant. Therefore, including all detected APs in fingerprinting vectors leads to confusing IPS [20]. In addition, the resources, which are equipped on MS, are limited even the IPS uses the server's assistance to find the user's location. There are many techniques to reduce the computational cost for an IPS:

2.7.1 Clustering

The computation time for finding a position is directly proportioned to the number of RPs. Therefore, a coarse localization is introduced in the on-line phase to confine the positioning process within a small area. The clustering process is achieved in an off-line phase where the RPs of AOI are classified into small groups, which are named clusters. Each cluster has a representative, which is called exemplar to represent RPs subset of the cluster in the on-line phase. In this work, K-means and fuzzy C-means are discussed in detail.

2.7.1.1 K-means

In general, the K-means clustering algorithm aims to find the center point of a cluster by minimizing the signal distance between the exemplar Cj and members of the same clusters.

Given a set of input pattern $X = \{x_1, \dots, x_j, \dots., x_M\}$, where M represents Number of FP, $and\ x_j = (x_{j1}, \dots \dots, x_{jL}) \in R^L$ so, we have $C = \{C_1, \dots \dots., C_k\}\ K \leq M$ exemplars for AOI.

By minimizing an objective function J, in this case, a squared error function. The objective function:

$$J = \sum_{j=1}^{K} \sum_{i=1}^{M} \left\| r_i^j - C_j \right\|^2 \qquad 2.27$$

Where $\left\| r_i^j - C_j \right\|$ is a measured distance between data points r_i^j and exemplar of cluster C_j, it is an indicator of the distance of the n data points from their respective cluster centers. Figure 2-20 shows the distribution of FPs on K clusters C = [C_1, ……., C_k]. The algorithm can be summarized in Table 2-2.

Table 2-2: Algorithm of K-means clustering

K-Means Clustering Algorithm

Input:

RPs of AOI (RM), **K** (number of clusters)

output

Exemplars vectors **$C=[C_1, \ldots\ldots., C_k]$**, Assign each RP to a certain cluster

K-means Mechanism

1- Initialize K centroid points which represent initial group center point (centroid)
2- Calculate the distances between RPs and centroids.
3- Assign each RP to a cluster that has the closest centroid.
4- When all RPs are assigned, calculate the cluster centroid again.
5- Repeat step 2, 3, and 4 until there is no change for each cluster.

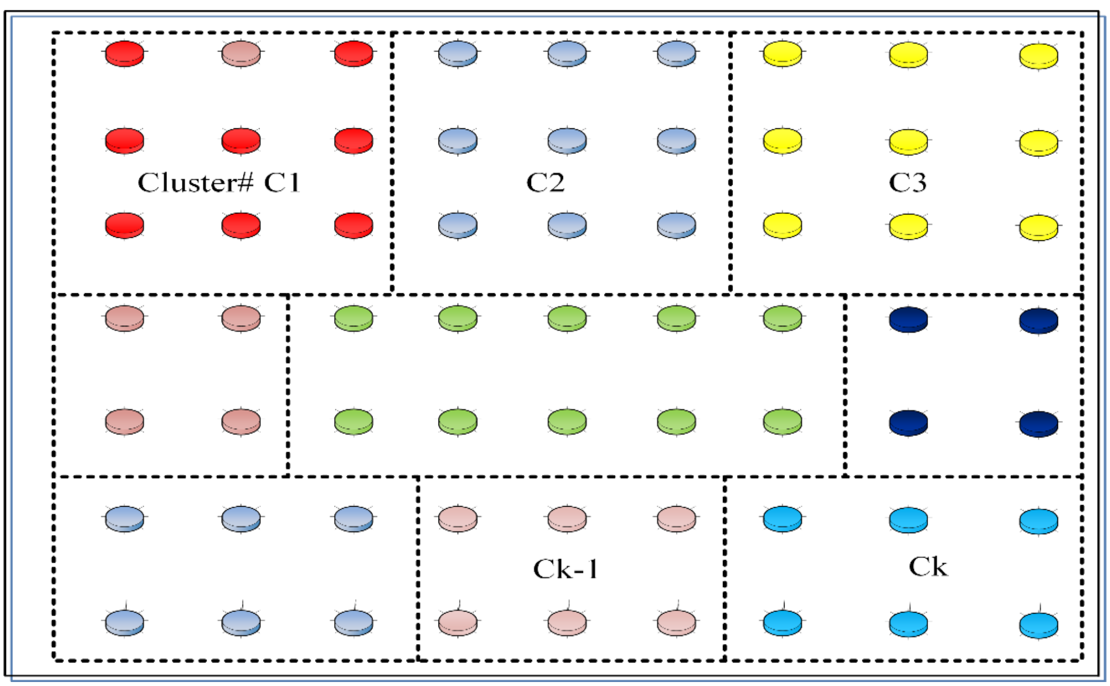


Figure 2-20: K-means clustering technique.

2.7.1.2 Fuzzy C-means clustering algorithm

Unlike the K-means clustering technique, the membership of each RP is not crisp in the fuzzy C-means clustering approach [67]. As shown in Figure 2-21, fuzzy C-means clustering can divide the AOI into K subsets with clustering centers C = [C_1, …, C_k] $\epsilon\ R^M$ that verify the minimum cost function, which is a sum of squared error between the RP's fingerprint and the clustering center. Its formula is as follows:

$$J_m = \sum_{i=1}^{M}\sum_{j=1}^{K} u_{ij}^{m} d_{ij}^{2} \quad ,1 \le m < \infty \qquad 2.28$$

Where **m** is greater than 1, and u_{ij} is the degree of membership of RP_i in the cluster j, and $\sum_{i=1}^{K} u_{ij} = 1$. The $d_{ij} = \left\|x_i - c_j\right\|^2$ represents the Euclidean distance between the PR_i fingerprint and the vector of cluster center C_j. The value of $u_{ij}$is randomly chosen between [0-1]. Fuzzy partition is achieved through an iterative optimization of 2.28. In order to find u_{ij} and C_j, the following equation should be applied:

$$u_{ij} = \frac{1}{\sum_{k=1}^{K}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}} \qquad 2.29$$

$$c_j = \frac{\sum_{i=1}^{M} u_{ij}^{m} . x_i}{\sum_{i=1}^{M} u_{ij}^{m}} \qquad 2.30$$

The iteration will be stopped when $max_{ij} = \left\{\left|u_{ij}{}^{(k+1)} - u_{ij}{}^{(k)}\right|\right\} < \varepsilon$, where ε is a criterion value falls in between [0 -1], and k is the iteration steps.

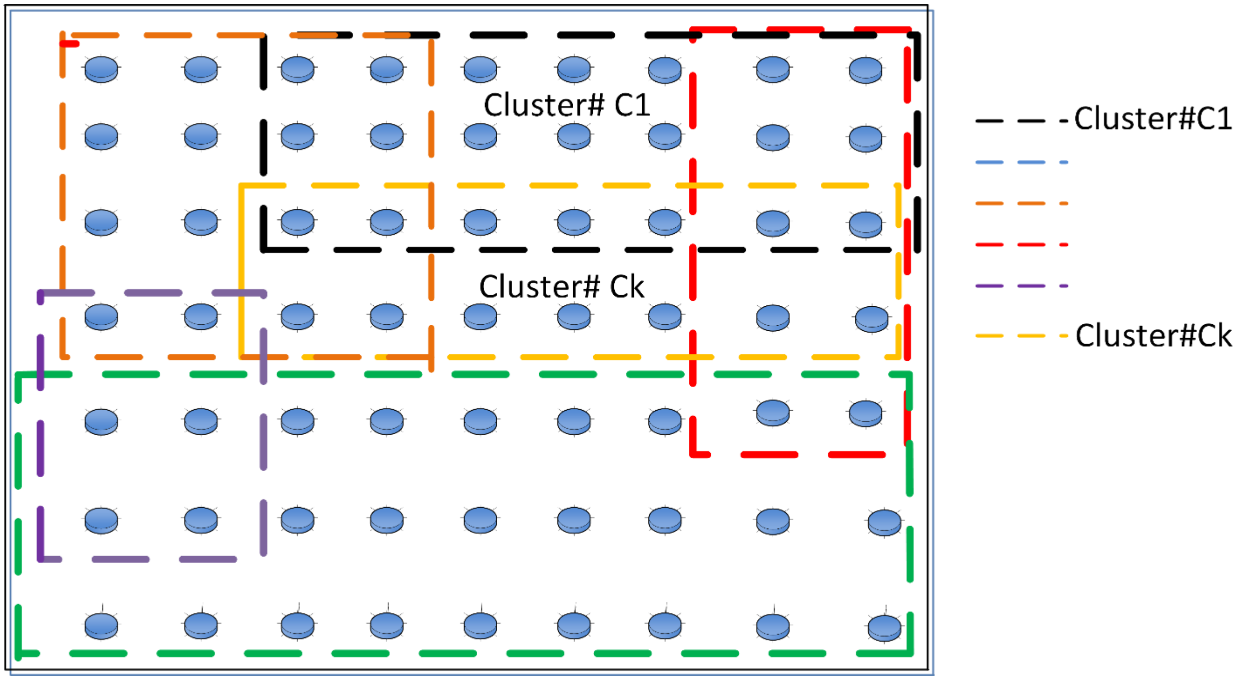


Figure 2-21: The distribution of RPs on the fuzzy C-mean clustering.

2.7.2 AP selection methods

To ensure high WLAN services quality, a large number of AP provides most large buildings. This number L is often much greater than that required for indoor positioning. These extra APs lead to excessive cost computations and possible biased estimation in case of some APs are unreliable. So choosing an informative subset of L APs is sufficient for positioning. In this work, we apply a different kind of AP selection such as strongest APs, random APs, and stable APs.

2.7.2.1 Random AP

Unlike the above methods, which choose appropriate APs according to different criteria, random combination scheme does not consider the behavior of AP in time or spatial domain. The method chooses K APs randomly from L APs, and RM has changed accordingly to the indices of the RSS-measured vector. Therefore, it has less computation complexity during the on-line phase, and it does not require a large number of RSS time samples.

2.7.2.2 Strongest AP

The strongest approach based on selecting the subset of L APs with highest RSS readings from online RSS measurement vector. The strongest APs provide a high probability of coverage over time. The subset of APs can be obtained by sorting the on-line vector V in descending order, and selecting K APs in the upper of the sorted vector with highest RSS values where K < L. The indices of fingerprints on RM are sorted accordingly when an unknown location is estimated.

2.7.2.3 Stable AP

This metric is based on the behavior of APs in the time domain. The APs with the highest time variance over AOI are excluded. In the off-line phase, K APs with low time variance over the AOI is selected from L APs. In the on-line phase, the measured vector V is sorted accordingly to estimate the user's location. The stability of APs ζ^i can be calculated as (2.31).

$$\zeta^i = \frac{1}{T-1}\sum_{l=1}^{T}\sum_{j=1}^{M}(r_j^i(t_l) - \psi_j^i)^2 \qquad 2.31$$

In the literature, we can find another technique for selection of APs such as Bhattacharyya distance, Information Potential (IP), Information Gain (InfoGain), Entropy Maximization, and Group Discrimination (GD) [68].

2.7.2.4 Fisher criterion

During the off-line phase, Fisher criterion exploits the statistical properties of RM fingerprints to select informative APs for positioning. The ability of discrimination of each AP across RPs is calculated and sorted in descending order. The highest K discriminative APs with the highest stability are chosen as informative APs. A score is assigned for each AP separately as:

$$\zeta^i = \frac{\sum_{j=1}^{M}(\psi_j^i - \bar{\psi}^i)^2}{\frac{1}{T-1}\sum_{l=1}^{T}\sum_{j=1}^{M}(r_j^i(t_l) - \psi_j^i)^2}, \quad i = 1,2,\dots\dots,L \qquad 2.32$$

Where $\overline{\psi}^i = \frac{1}{M}\sum_{j=1}^{M}\psi_j^i$, M is a number of RPs in the radio map, r is an instantaneous vector at each RP, and T is a number of time samples at each reference point.

2.8 Existing Systems

There are several commercial techniques, which are used for indoor location-based services [29]. In this section, two different techniques will be reviewed: RADAR system, and HUROS system. The RADAR system is used deterministic method while HORUS system is used the probabilistic method. Both techniques use RSS of WLAN without additional hardware and cost.

2.8.1 RADAR-based system

RADAR is the first Wi-Fi-based indoor positioning system in the world, which is invented by Microsoft company [69], [70]. It has used the deterministic methodology, which is based on RF fingerprinting algorithm and propagation modeling to determine a user and machine location inside buildings. This technique has used K-NN method and signal propagation modeling to find the estimated position of the user. Wall attenuation factor (WAF) and floor attenuation factor (FAF) propagation model is used, instead of the Rayleigh fading model and Rician distribution model, which are used in the outdoor situation. WAF takes into consideration the number of walls (obstructions). Infrastructure-based wireless RF LANs have traditionally been used for data connectivity only. However, Microsoft company researchers have instead developed algorithms that let you use these networks for tracking and locating mobile users as well. Their technique is to average the received samples and use the average value in the k-nearest neighborhood algorithm with propagation modeling to determine the best location estimate. The RADAR system is able to estimate and track the user’s location within a few meters of his/her actual location.

2.8.2 HORUS-based system

Horus system lies in the category of probabilistic techniques[55], [71]. Its goal is to identify the noise characteristics of the wireless channel and to develop techniques to handle them. It uses a joint clustering technique to reduce the calculation time. Each candidate location coordinate is regarded as a class or category. In order to minimize the distance error, location L_i is chosen while its likelihood is the highest. For instance, if the system averages n samples, the system needs to calculate the probability of the average value using the distribution of the average of n original distributions. Obtaining this distribution is not trivial if the samples are not independent. The experiment results show that this technique can acquire accuracy of more than 90% to within 2.1 m. Increasing the number of samples at each sampling location could improve its accuracy because increasing the number of samples would improve the estimation for means and standard deviations of Gaussian distribution [71].

3. CHARACTERISTICS OF MSSID RSS-SIGNALS

3.1 Introduction

Indoor positioning systems that use RSS-fingerprints of WLAN is often used instead of the radio propagation model due to the variation of RSS inside the buildings. Therefore, understanding the statistical properties of RSS-signals is very important for IPS designers. The statistical properties of RSS-signals study the nature of RSS signals and the effect of the environment changing on the RSS-variation inside the building due to pedestrian moving, or furniture changing. The statistical information can provide insights into how many APs are necessary to uniquely identify a location with given accuracy and precision [72]. In addition, it can provide knowledge about how preprocessing the RSS-data to obtain high accuracy by neglecting non-informative data and selecting an informative one. The distribution of RSS-signals, standard deviation, mean, maximum, minimum, median, correlation, and (in) dependence of RSS from multiple APs are important factors for understanding and modeling the fingerprinting-based IPS.

The statistical analysis of RSS-signals has been studied in [69], [73]. Bahl et al. studied the effect of orientation of the user on the mean of RSS. The study shows that the user's orientation affects the value of RSS by 5dBm maximum. Therefore, the usage of orientation data will improve the accuracy of IPS. In [73], the quality of hardware and number of received RSS samples are studied to figure out the effect of these parameters of the accuracy of IPS. Ahmad et al. [74] present the analysis of RSS variation and the effect of RSS absence on the accuracy of IPS due to channel degradation. In [75], the detailed analysis of RSS measurements is taken to investigate the effect of WLAN card, time, duration of measurement, interference, and building environment on the accuracy of IPS.

Most researchers, who studied the statistical properties of RSS signals, supposed that each AP advertises one service set identifier (SSID). The SSID is a unique identifier that is used to set up and maintain the connectivity with wireless devices. In the large building, there is various kind of clients, and each client requires different network features such as keys, speed, bandwidth, security, and privacy. Therefore, the using of separated APs for each wireless network is infeasible. In order to address this issue, multiple SSID are set up on the single AP to advertise various wireless networks (SSID) at the same time. Fortunately, most of the APs, which are used in malls, hospitals, and universities, can work with multiple SSID setting. This feature is used with virtual LAN (VLAN), where the AP allows different users to connect with different networks simultaneously [76].

This chapter presents a fundamental of MSSID configuration and statistical analysis of RSS signals of MSSID in an indoor environment. The analysis includes the time correlation, and spatial correlation between multiple SSID signals, mean, and standard deviation. Moreover, the chapter illustrates the heat map of the MSSID RSS-signals over AOI.

3.2 Fundamental of MSSID

Figure 3-1 shows AP, which is configured to work as MSSID. The AP advertises various kind of SSID where each SSID requires a specific network feature to work with it. Each SSID is

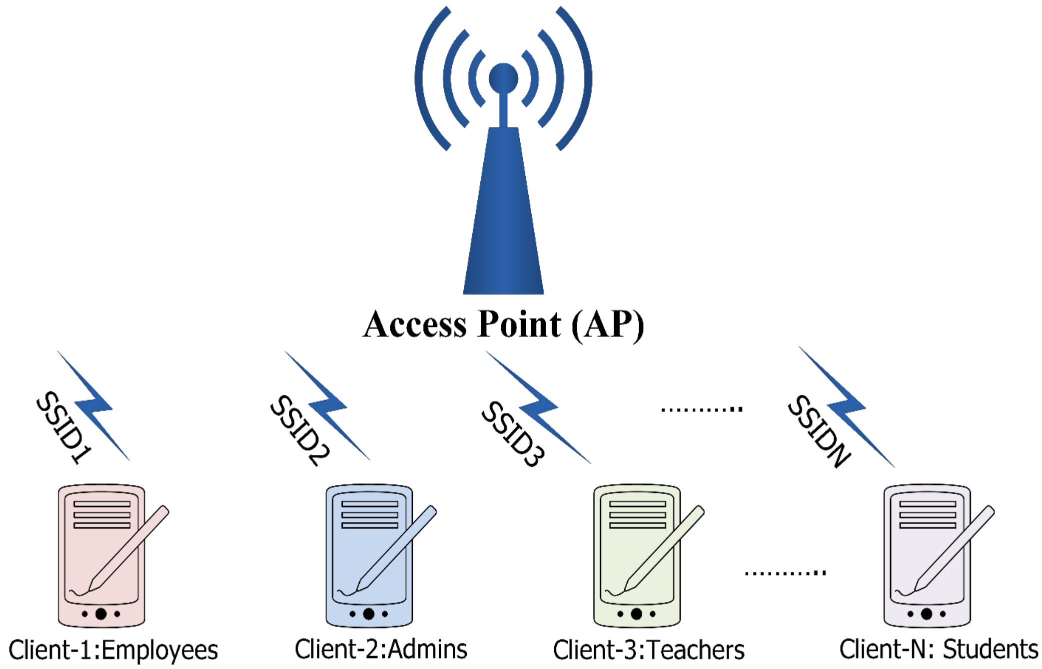


Figure 3-1: AP configuration as multiple SSID.

advertised on the same channel frequency. In order to prevent colliding between two signals, which are transmitted on the same channel, 802.11devices use Clear Channel Assessment (CCA) protocol to compromise this issue [77]. This technique checks the status of a channel by listing to see if another SSID is actively transmitting on the channel before attempting to send its own frames. Each SSID frame is transmitted every 100ms to advertise SSID to the clients.

3.3 Mean and Standard Deviation of MSSID Signals

AP transmits multiple signals (MSSID) at the same time by using CCA technique, which is mentioned above. Table 3-1 summarizes the statistical values of MSSID at two locations: near and far location from the location of AP. The distance L1 (near) is around 2m from AP while L2 (far) is around 20m from AP under the line-of-sight condition. The table illustrates that the values of the mean and standard deviation of MSSID of each AP are similar at both locations L1 and L2.

Table 3-1: The statistical values for MSSID in near and far position.

Statistical Value	**Location L1 (Near)**			**Location L2 (Far)**		
	SSID1	**SSID2**	**SSID3**	**SSID1**	**SSID2**	**SSID3**
Mean	-33dBm	-31dBm	-33dBm	-69 dBm	-71dBm	-73 dBm
St.D	5.2	4.6	5.5	2.2	2.4	2.1

3.4 Time Samples of MSSID Signals

RSS-based fingerprinting approaches have been widely used for indoor localization. The RSS signal plays a very crucial role in determining the nature and characteristics of location fingerprints, which are stored in RM. The power of RSS signal is a function of the distance between the AP and user's device, which is affected by multi-path issue [24]. Figure 3-2 shows the time behavior of MSSID signals where the AP is configured to transmit 5 SSID (SSID1, SSID2… SSID5) at the same physical AP.

The measurements are taken with 5,000 samples at a specific position; the sample rate is one sample per second and under the line-of-sight condition. In Figure 3-3, it clearly shows the multi-path on the MSSID signals. MSSID utilize the same channels that the physical AP is set up. As mentioned before, to avoid a collision or frame loss, the MSSID technique uses Clear Channel Assessment (CCA) protocol to investigate the case of channel whether it is exploited by another SSID. If the channel is clear after a check, the device can use the channel and send data. Therefore, the probability of all SSID signals that are affected by fading, as shown in Figure 3-4.

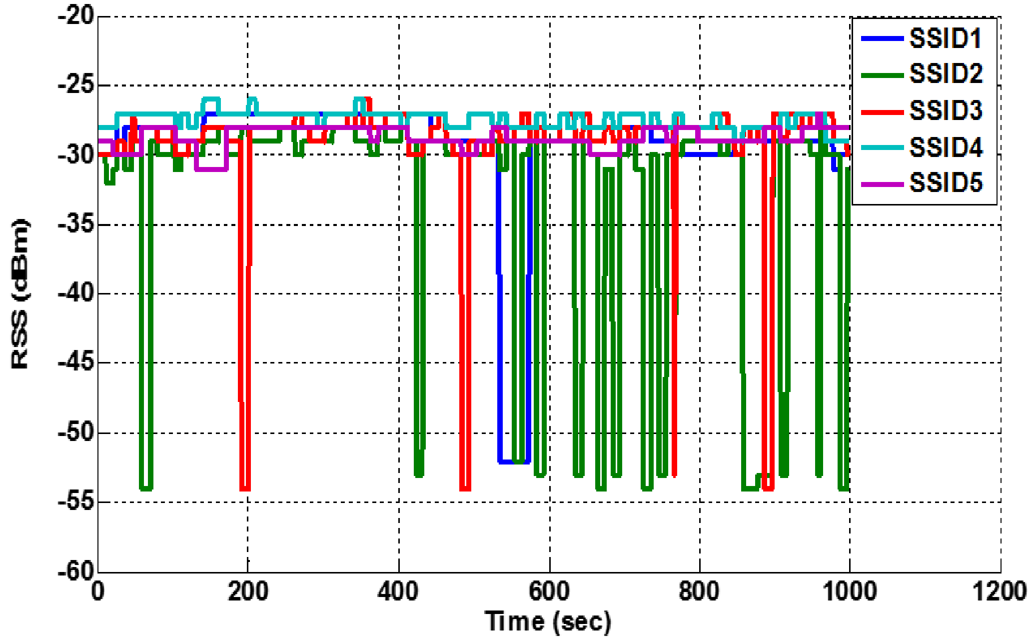


Figure 3-2: The time behavior of MSSID's RSS-signals.

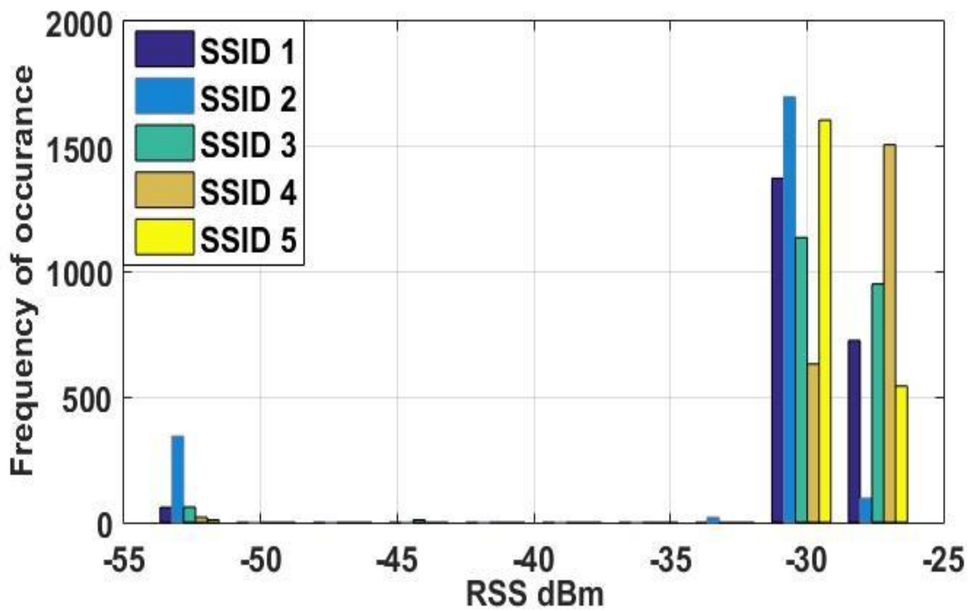


Figure 3-3: The histogram of multiple SSID.

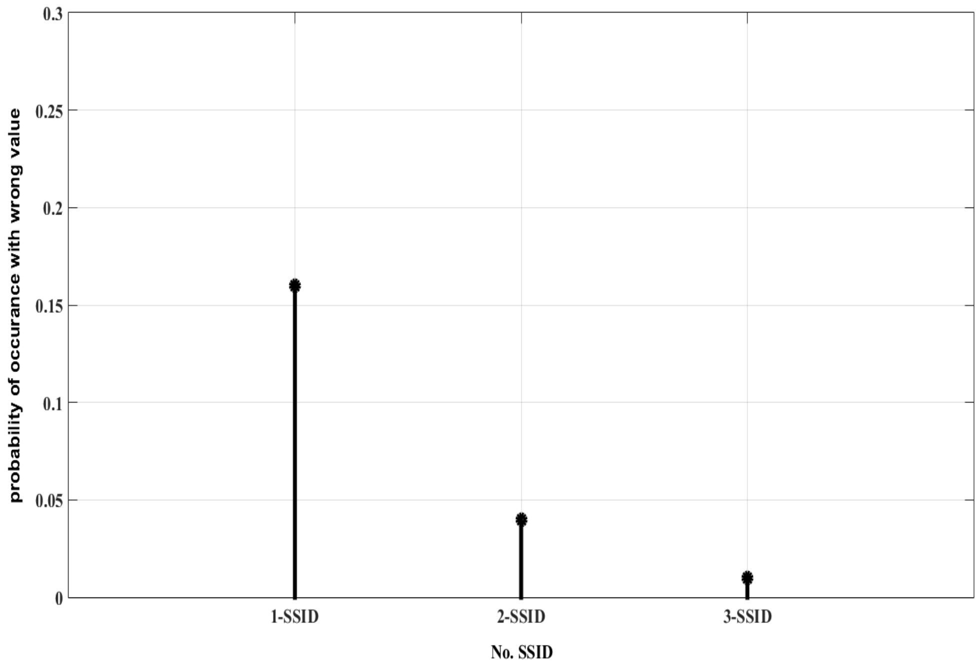


Figure 3-4: The likelihood of occurrence with different wrong RSS value for SSID.

3.5 Time and Spatial Correlation Coefficients of MSSIDs' Signals

The behavior of N SSIDs' signals on the same physical AP is nearly identical to deploy N individual APs. In order to investigate independence of these signals and the similarity over the AOI, Table 3-2 and Table 3-3 illustrate the correlation coefficients of SSIDs' signals at a specific location, and the spatial correlation coefficients over the AOI, respectively.

Table 3-2: The correlation coefficient between multiple SSID signals at a certain point.

SSID	**$SSID_1$**	**$SSID_2$**	**$SSID_3$**	**$SSID_4$**
$SSID_2$	0.021	-	-	-
$SSID_3$	0.000	0.013	-	-
$SSID_4$	0.012	-0.01	0.045	-
$SSID_5$	-0.012	0.007	0.029	0.012

Table 3-3: The spatial correlation coefficient between multiple SSID signals over AOI.

SSID	$SSID_1$	$SSID_2$	$SSID_3$	$SSID_4$
$SSID_2$	0.98	-	-	-
$SSID_3$	0.95	0.98	-	-
$SSID_4$	0.94	0.98	0.95	-
$SSID_5$	0.97	0.96	0.97	0.94

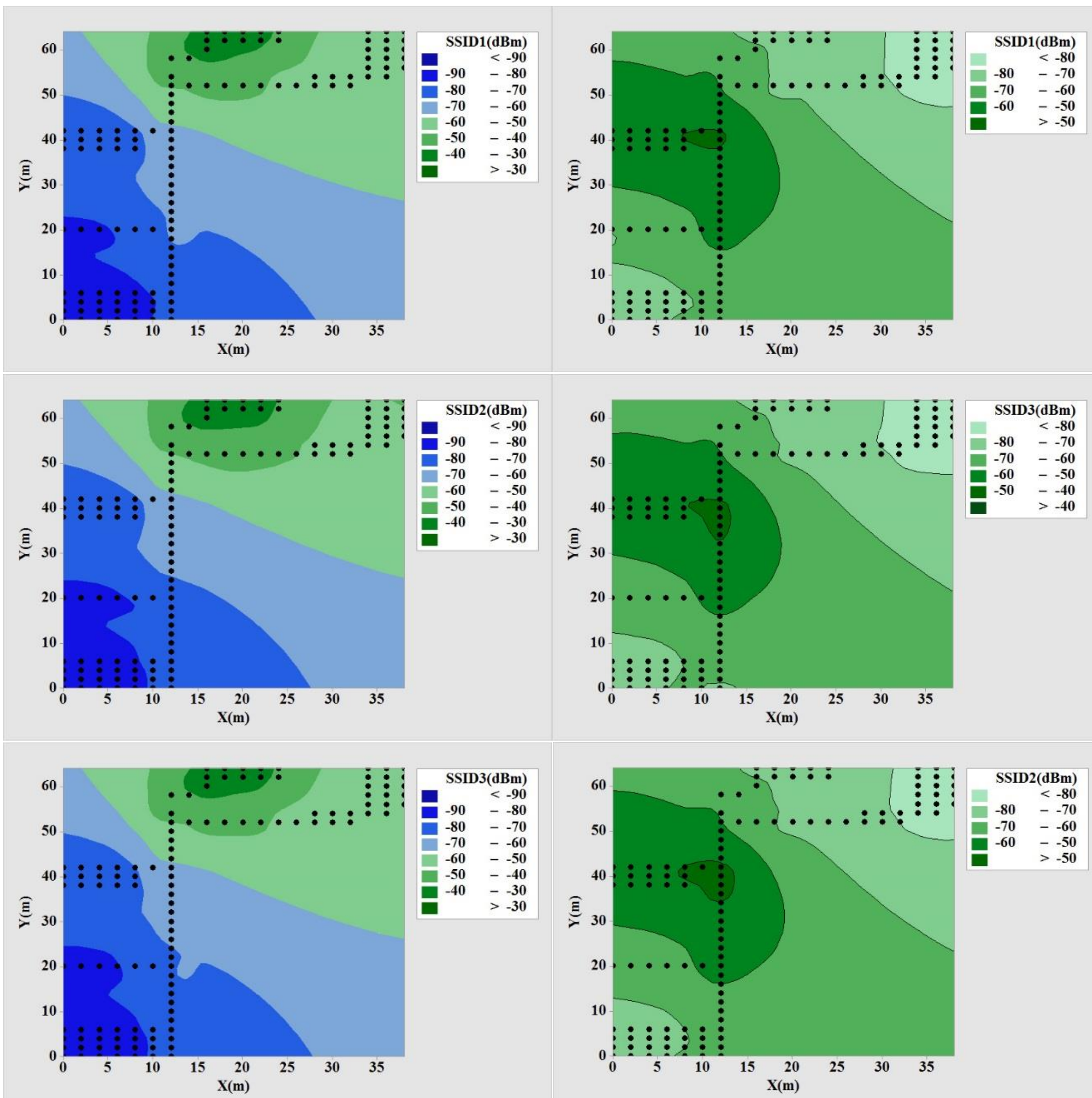


Figure 3-5: The contour map of two APs each one is configured with three SSID.

The correlation coefficients are $|Cij| < 0.05$ that means all these signals are independent and its behaviors as similar to the behavior of five separated APs. Table 3-3 shows the spatial correlation coefficient over the AOI. We can see that these values over the AOI are close to 1 that means all SSID signals, which are deployed on the same AP, have a similar spatial power distribution. Furthermore, Figure 3-5 shows the counter map for two APs, each one with three SSID in a different location on AOI. Therefore, the using of MSSID within the same fingerprint leads to an increase in the computational cost of IPS and degrade the IPS' accuracy. Most of the researchers consider each signal comes from a certain AP where they deal with unique MAC as single, separated AP. This work tries to fill up this gap by study the behavior of these signals and then design a classification engine to enhance the performance of IPS, which deploys MSSID.

3.6 Path Loss of MSSID RSS-Signals

The RSS signal value decreases with distance *d* according to the function of logarithm-distance path loss model [30]. Figure 3-6 shows the behavior of MSSID signals and the mean of these signals versus distance d. The behavior of the mean of MSSID is close to path loss model with path loss exponent (n=3.5). The fusion of MSSID signals by averaging them contributes to mitigating the effect of the multipath issue. Table 3-4 illustrates that the standard deviation of the RSS signal decreases with distance d. In addition, the standard deviation of the mean of MSSID is less than individual signals of MSSID.

Table 3-4: The standard deviation of MSSID signals versus distance (m).

SSID No.	L_1=2m	L_2=10m	L_3=20m
SSID1	5.1	3	2.2
SSID2	5.5	2.8	2.4
SSID3	4.6	2.7	2.1
Mean of MSSID	2.6	1.5	1.4

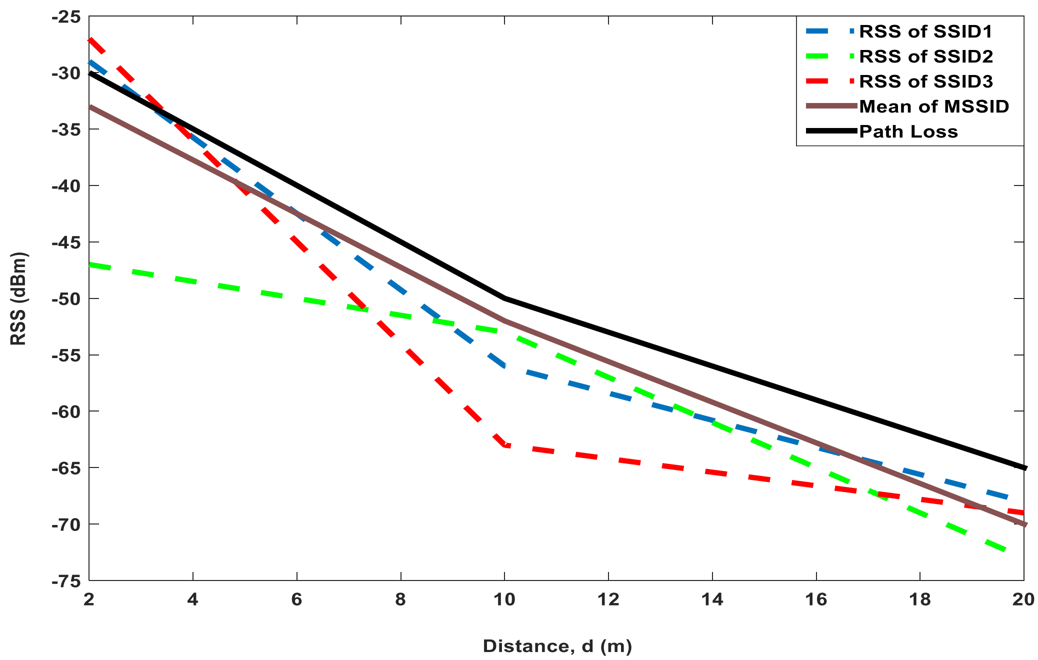


Figure 3-6: The change of RSS signals of MSSID versus distance d (m).

4. MSSID-BASED SPATIAL VOTING TECHNIQUE

4.1 Introduction

All large buildings such as malls, hospitals, airports, schools, and museums have hundreds of Wi-Fi access points, which are installed to provide WLAN infrastructure service [13], [14], [16]. Wi-Fi signals-based positioning techniques exploit the existing WLANs devices to provide accurate indoor positioning without any additional hardware. For indoor environments, it is quite difficult to make use of the well-known GPS. Positioning with GPS can only be achieved by receiving signals from at least three to four GPS satellites at the same time. This is usually not available inside a building and makes the GPS useless and inefficient. The Wi-Fi-based fingerprinting technique is a simple method to deploy inside the buildings compared to other techniques such as angle of arrival (AOA) and time difference of arrival (TDOA). Instead of relying on these systems, which require additional hardware to estimate the location, fingerprinting-based location systems use RSS features to compute the mobile system (MS) position without any additional infrastructure. However, the big issue for WLAN fingerprinting-based method is the variation of RSS due to reflection, diffraction, and diffusion on the indoor scattering walls. Wi-Fi received signal strength (RSS) fluctuations over time introduce incorrect positioning. To minimize the fluctuation of RSS, we developed a new technique, which uses the general framework that is based on fingerprinting of multiple services set identifiers (SSID) configured on the same access point.

4.2 Related Work

Many types of research are trying to figure out the relationship between these measures and the performance of IPS with different hypothesizes. Research in WLAN fingerprinting indoor localization has been mainly focusing on how to improve the collection of RSS fingerprints and how to enhance the accuracy of IPS. Some of these efforts are reviewed as follow:

Mora-Becerra [78] introduced a multiple communication channel RSS as a frequency diversity method to mitigate multipath propagation effects. Three methods for RSS fingerprinting have been used and implemented on a smartwatch to improve the accuracy of IPS; they are KNN, Neural Networks model, and Particle Filter. The results show that the performance of the particle filter is the best as compared to other methods.

A. Bardella et al. [79] proposed a new algorithm to improve the reliability of RSSI, averaging samples collected at different frequencies by a CC2420 radio, which implements the IEEE 802.15.4 standard, both in real indoor and outdoor scenarios. In order to do that, a simple communication protocol is introduced to coordinate data exchange between nodes. This protocol exploits multichannel transmission in order to mitigate the multipath issue, which arises in an indoor environment.

A. Yazici et al. [80] proposed an algorithm to enhance the performance of indoor positioning systems via the integration of different classifiers where each classifier follows different measured feature with a different algorithm. For this purpose, firstly Wi-Fi Received Signal and magnetic field sensor values are combined to construct a hybrid fingerprint map. Then, the selected classifiers, including decision tree, multi-layer perceptron, and Bayesian network, are integrated using majority voting method. The test results demonstrate that the ensemble of sensor measurements and classifiers outperform the other individual classification algorithms in terms of classification accuracy. The proposed approach yielded the average distance error of 1.23 meter approximately.

R. Ma et al. [81] proposed an algorithm, which is based on traditional location fingerprinting algorithms and consists of two stages: offline acquisition and online positioning. The offline acquisition process selects optimal parameters to complete the signal acquisition, and it forms a database of fingerprints by error classification and handling. To further improve the accuracy of positioning, the online positioning process first uses a pre-match method to select the candidate fingerprints to shorten the positioning time. After that, it uses the improved Euclidean distance and the improved joint probability to calculate two intermediate results and further calculates the final result from these two intermediate results by weighted fusion. The improved Euclidean distance introduces the standard deviation of WiFi signal strength to smooth the WiFi signal fluctuation, and the improved joint probability introduces the logarithmic calculation to reduce the difference between probability values. Comparing the proposed algorithm, the Euclidean distance-based WKNN algorithm, and the joint probability algorithm; the experimental results indicate that the proposed algorithm has higher positioning accuracy.

Generally, the aforementioned research works overlook the functionality of the access points, that is, they assume as if each access point is transmitting one signal. In this work, we propose a new technique through changing the setup of access points itself and designing a framework that allows for multiple signals at the same time from each access point by setting up multiple SSID.

4.3 MSSID-based Proposed System

This research aims to use multiple SSID on the same access point to increase the performance of IPS. Mathematically, N FP vectors can represent each point, where N is the number of SSID on each AP, which are deployed in the AOI. Accordingly, N RMs (Ψ_1, Ψ_2… and Ψ_N) are generated as in equations (4.1 - 4.N):

$$\Psi_1 = \begin{bmatrix} SSID_{1,1,1} & SSID_{1,2,1} & \cdots & SSID_{1,M,1} \\ SSID_{2,1,1} & SSID_{2,2,1} & & SSID_{2,M,1} \\ \vdots & & \ddots & \vdots \\ SSID_{L,1,1} & SSID_{L,2,1} & \cdots & SSID_{L,M,1} \end{bmatrix} \quad 4.1$$

$$\Psi_2 = \begin{bmatrix} SSID_{1,1,2} & SSID_{1,2,2} & \cdots & SSID_{1,M,2} \\ SSID_{2,1,2} & SSID_{2,2,2} & & SSID_{2,M,2} \\ \vdots & & \ddots & \vdots \\ SSID_{L,1,2} & SSID_{L,2,2} & \cdots & SSID_{L,M,2} \end{bmatrix} \quad 4.2$$

$$\vdots$$

$$\Psi_N = \begin{bmatrix} SSID_{1,1,N} & SSID_{1,2,N} & \cdots & SSID_{1,M,N} \\ SSID_{2,1,N} & SSID_{2,2,N} & & SSID_{2,M,N} \\ \vdots & & \ddots & \vdots \\ SSID_{L,1,N} & SSID_{L,2,N} & \cdots & SSID_{L,M,N} \end{bmatrix} \quad 4.N$$

Where L is the number of APs in the AOI, M is the number of the fingerprints in the radio map, and N is the number of SSID on the AP. In order to verify voting, N should be an odd number. The IPS proposed framework is presented in the block diagram in Figure 4-1.

In this proposed system, Multiple SSID are utilized on the same AP to mitigate the effect of the fading issue on the IPS performance. The proposed multiple PNN classifiers-based IPS using multiple SSID technique is shown in Figure 4-2. The proposed system has two phases: offline phase and on-line phase. In the offline phase, the variance and mean of RSS values on the selected reference points will be collected and stored in the database. The mean at each reference point will be calculated by taking the average of RSS time samples for all APs in different directions (0^0, 90^0, 180^0, and 270^0).

In the online phase, each TP will be represented by N-vectors V_1, V_2, ..., V_N according to N SSID (this paper uses N=3) for each AP. The spatial voting scenario will be applied to select the most appropriate location for the location of the user. The spatial voting scenario includes omitting of outlier-location that comes as a result of the effect of the multi-path fading due to the change in the indoor environment. In other words, if d_{ij} represents the spatial distance between the three estimated locations L_1 (x_1,y_1), L_2 (x_2,y_2), and L_3 (x_3,y_3), where i, j=1, 2, or 3 and $i \neq j$, then L_i or L_j whose summation output has the maximum respect to its RM, is selected to be the most probable location of the mobile device.

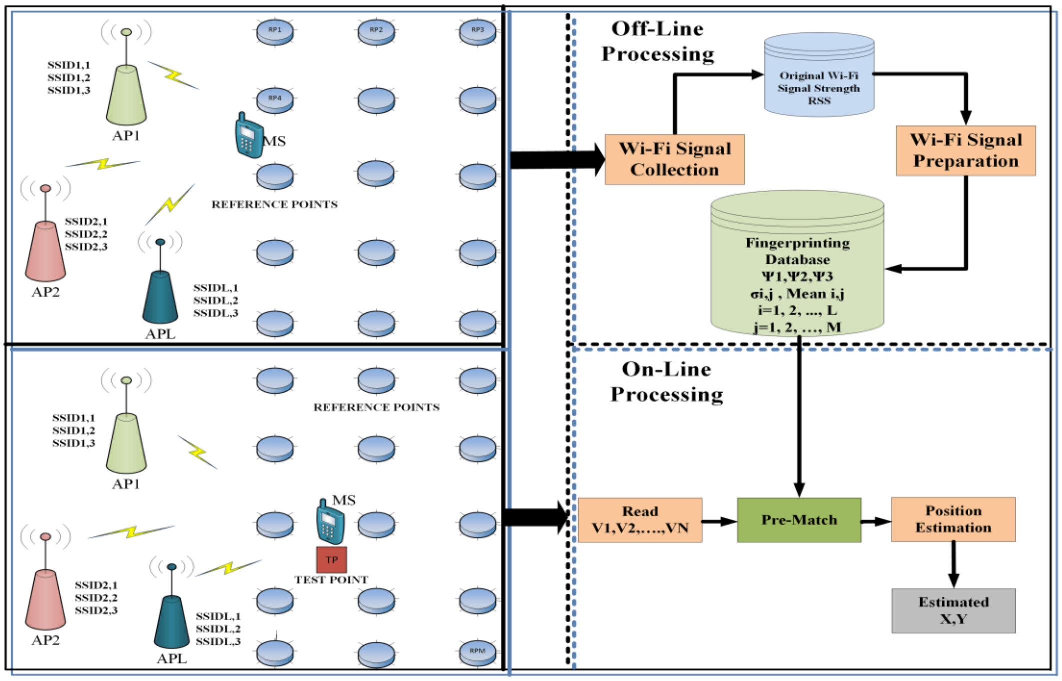


Figure 4-1: The proposed system for IPS with multiple SSID.

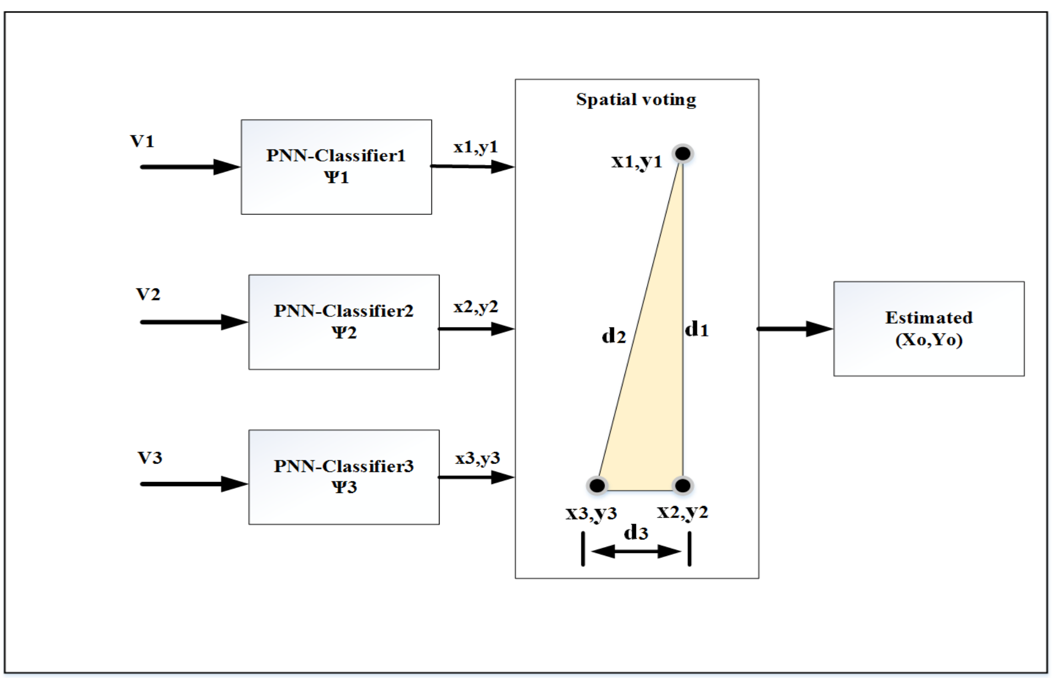
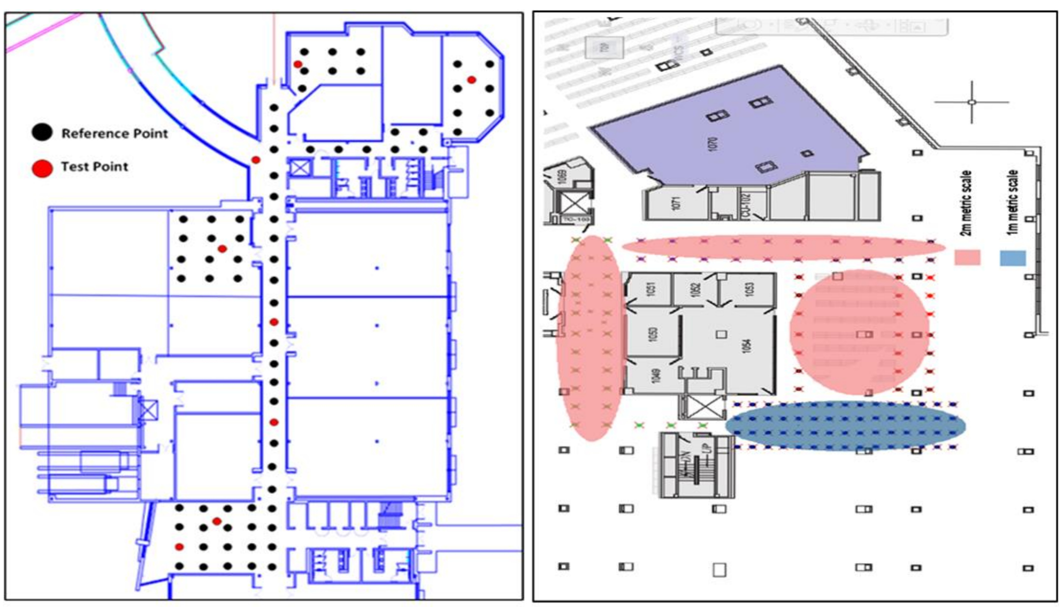


Figure 4-2: The mechanism of the proposed system.

4.4 The Experimental Work & Measurement Site

In order to evaluate the behavior of the proposed systems which are mentioned in this chapter and the next two chapters, real data are recorded from the College of Engineering and Applies Science (CEAS) at Western Michigan University and Waldo Library. The CEAS comprises three rooms, a large study lounge, and long corridors; while Waldo library comprises big halls and long corridors with a total area for each one is 3000m^2 as shown in Figure 4-3. For CEAS, the AOI is divided virtually into 117-grid points as RPs with a spacing of (2m×2m). Cartesian coordinate (x_i, y_i) represents each RP_i on the map. The number of APs, which are deployed in this area, is L=34 APs where all APs are working with the 2.4GHz band. Wireless NetView program is installed on Toshiba Satellite E45t-A4300, which has Intel wireless-N7260 adapter to collect the vector of RSS from different APs with a 1-second period. Each RP_i is created from 200 RSS time samples, 50 samples for each direction (0^o, 90^o, 180^o, and 270^o). In the online phase, we used 20,000 TPs, which are selected randomly on the AOI to verify the validation of the proposed system.



A) CEAS at Western Michigan University. B) Waldo library at Western Michigan University.

Figure 4-3: The AOI for the proposed systems.

4.5 Experimental Results

A MATLAB program is used to verify the behavior of the proposed system. The measurements of RSS signals are taken from real WLAN which are deployed at the CEAS building, WMU. The APs are placed in the CEAS building according to the following factors: the basis of coverage, WLAN bandwidth, and channel reuse. 18 different access points are used in the AOI, and each access point is configured with three SSID. The total SSID is 54, and each AP transmits at different non-overlap standard channels (1, 6, and 11). The distance error (DE) is a tool to measure the distance error by using the difference in spatial distance between the estimated location and the real user location. The DE between the estimated position according to the FP at the i^{th} TP; (x_o, y_o); and the i^{th} TP actual spatial location (x_i, y_i) is:

$$DE_i = \sqrt[2]{(x_i - x_o)^2 + (y_i - y_o)^2} \qquad 4.3$$

So, the average distance error can be determined as:

$$ADE = \frac{1}{n}\sum_{i=1}^{n} DE_i \qquad 4.4$$

Where n represents the number of RSS test vectors.

Both K-NN and PNN techniques are used to be as a classifier in the proposed system. In Figure 4-4, we present the CDF (Cumulative Density Function) of Distance Error for the proposed system. The performance of the proposed system is compared with traditional (single SSID) K-NN, PNN, and multi-class SVM techniques. The performance of the proposed system in both technique exhibits outperform as compared with the performance of traditional K-NN, PNN, and multi-class SVM technique. Table 4-1shows that the precision of the proposed system for PNN and K-NN at distance error of 2m is 90% and 85%, respectively. While the traditional technique PNN and K-NN is 82% and 78%, respectively. Furthermore, the proposed system shows high stability, where it has the lowest standard deviation as compared with other traditional technique. In Figure 4-5, we present the average of Distance Error for the proposed system and the traditional techniques. Clearly, the results show that the average error is highly affected by the number of APs. The average of distance error for PNN-based proposed system is less than 0.73 m when AP=18. The total virtual AP which can be scanned in the AOI is 54 SSID (18AP *3 SSID for each one), so in order to get a fair comparison, we put all SSID in the fingerprint vector to represent any point in the AOI. Figure 4-6 shows a fair comparison between the proposed system with PNN and traditional PNN. As we can see in the traditional PNN, the redundancy in SSID leads to increasing distance error and computational cost as well.

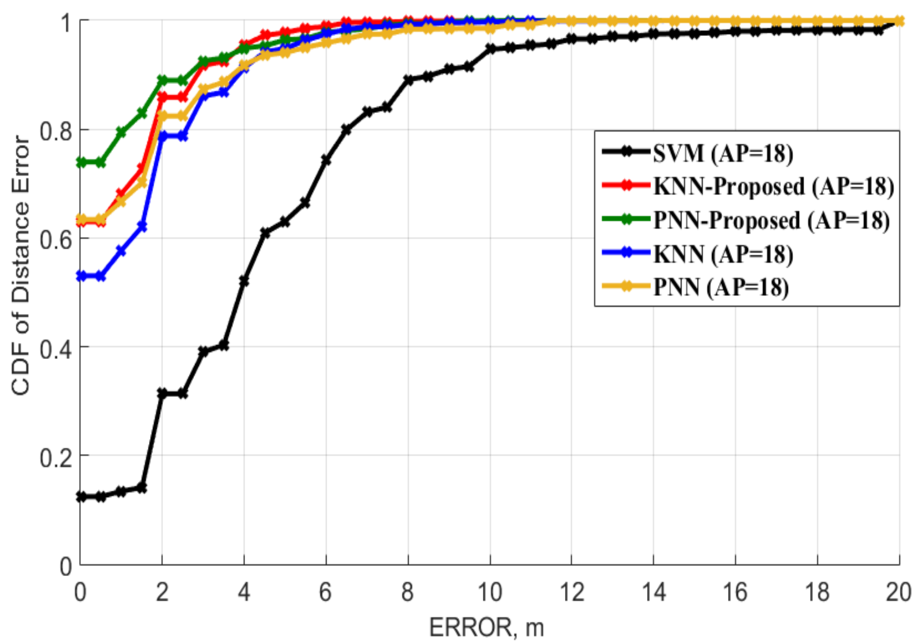


Figure 4-4: The CDF of distance error for the proposed system.

Table 4-1: The performance of the proposed algorithm.

Technique	**Avg.(m)**	**Std.Dev**	**Precision(Error<=2m)**
PNN-Based Proposed system	0.73	1.56	90%
KNN-Based Proposed system	0.97	1.55	85%
PNN	1.3	1.76	82%
KNN	1.45	1.86	78%
SVM	5	5.6	35%

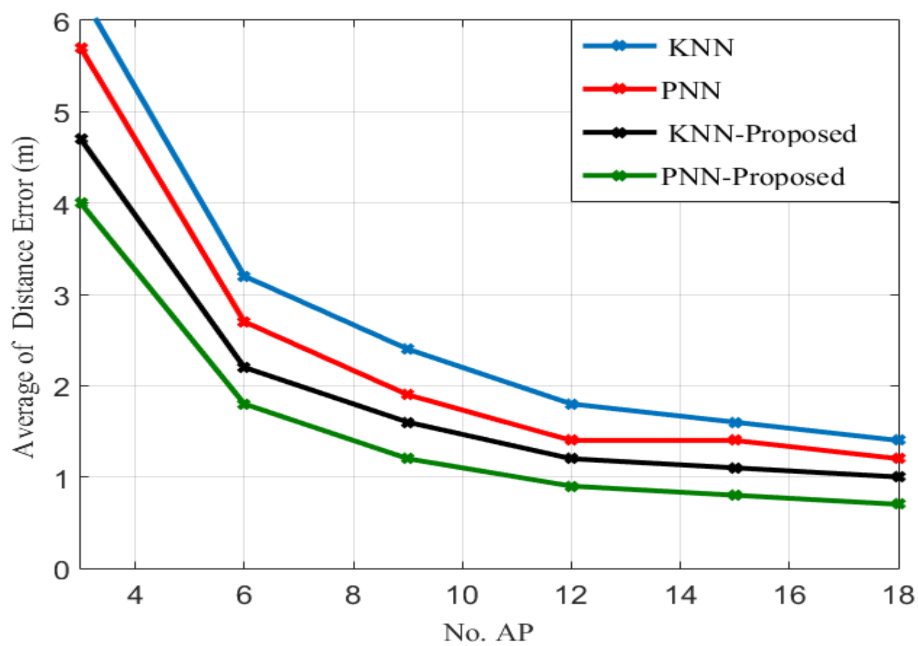


Figure 4-5: The average distance error of the different technique versus the number of AP.

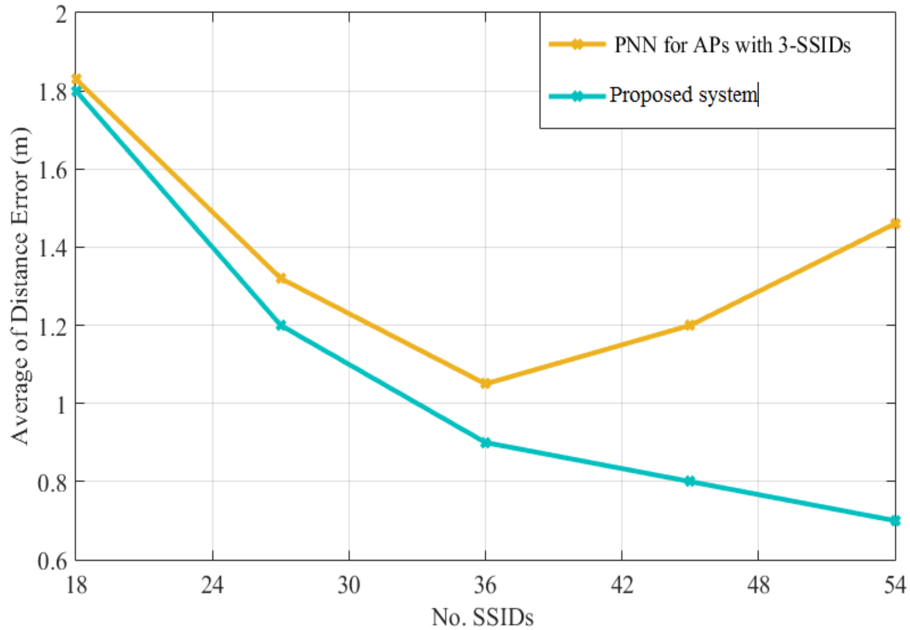


Figure 4-6: The average distance error of the proposed technique versus the number of SSID.

4.6 Summary

Indoor positioning system has become an active research area for its many applications in different fields of our daily lives such as medical, industrial, and security. WLAN Fingerprinting-based methods offer high accuracy with no need for new infrastructure. In this paper, we proposed a solution for the IPS using MSSID and PNN multi-classifier-based technique to estimate the user's position by using a spatial voting technique. The use of the multiple SSID technique supports the classifier to be working with higher precision than with single SSID. The algorithm shows a notable improvement over its counterpart with single SSID.

5. AN ADAPTIVE K-NN BASED ON MSSID FOR IPS WITH AN ENSEMBLE APPROACH

5.1 Introduction

Location-Based Systems (LBS) for indoor positioning have earned the attention of a large number of researchers in the last decade. The significance of these systems comes from their applications in various fields such as tracking service for elderly people or a patient within large living communities, mobile robot localization, and several security purposes. The Received Signal Strength (RSS)-based fingerprint method has been recognized as one of the promising techniques for Indoor Positioning Systems (IPS.) The K-nearest neighbors (K-NN) is selected for its significant performance with ease of realization. However, the static nature of K-NN, that is, in using a constant number of the nearest neighbors, leads to a serious shortcoming in its accuracy. Also, the nature of the RSS-IPS challenges such as fading due to the multipath of electromagnetic waves inside buildings would mislead the solution of nearest neighbors. These reasons often result in lower performance than expected because of the increase in the distant neighbors' biasing error.

5.2 Related Work

The K-NN method has been widely adopted and researched for its relative simplicity and adaptability. The researchers tried to make the value of K (number of nearest reference points) adaptive to improve the accuracy of IPSs. They proposed various algorithms to minimize distance error. Some of these efforts are reviewed as follow:

Jongtack et al. [82] proposed an algorithm that adapts K-value by analyzing the correlation between K and RSS values. The adaptive KNN algorithm adjusts the K value according to the Euclidean Distance ED pattern exhibited by the RPs with respect to a TP. The proposed system provides an improvement above 30% on the positioning accuracy compared to the algorithm with a fixed value.

I. Lee et al. [83] suggested a dynamic K-NN method for WLAN to improve the performance of IPS. The optimal K value changes based on the topologies and distances of its nearest neighbors. The proposed method is validated by collecting real data from the largest convention center in Seoul, Korea. The results show that both the mean of distance error and the standard deviation are reduced by using the dynamic K-NN technique.

P. Torteeka [84] proposed the Wi-Fi fingerprint-based IPS technique by incorporating the fuzzy set theory with basic K-NN to improve system accuracy. The static K-NN algorithm uses crisp theory to estimate the location of an unknown position vector in the on-line phase. In order to improve the accuracy and robustness of IPS, the fuzzy theory-based the proposed system is used to obtain the optimal weight of K. The experimental results show that the proposed system exhibits a certain level of positioning system accuracy.

J. Torres et al. [85] proposed ensembles of IPS based on fingerprinting to simplify parameters selection, and obtain robust systems. The work focused on integrating the ensemble approach to the static K-NN algorithm to obtain robust IPS in real multi-building and multi-floor environments.

M. Umair et al. [86] proposed a robust fingerprinting method for localization based on adaptive K-NN method. Their approach used the adaptive method to determine the optimal value for K. The behavior of the proposed system compared with the traditional K-NN method. The results show that the proposed method outperforms the static K-NN for a variety of access points (APs) number.

B. Shin et al. [87] proposed a novel fingerprinting algorithm. They suggested enhancement weighted K-NN method to improve the accuracy of IPS by changing the number of considered neighbors. The experimental results exhibit that the proposed algorithm gives higher accuracy when it is compared with the traditional K-NN method.

5.3 The Proposed System

The conventional K-NN is an easy method to implement, but it has two main shortcomings: first, the accuracy of the system is sensitive to the value of K; second, the accuracy might decrease when some nearest neighbors are too distant. We propose a new method for adaptive K-NN based on multiple services set identifiers (MSSID) to select nearest neighbors by selecting desired neighbors and neglecting undesired nearest neighbors.

In machine learning, ensemble techniques are commonly utilized to combine the outputs of multiple classifiers in order to improve overall accuracy [88]. A Wi-Fi-based IPS may be considered a machine learning method since it computes the position of a user by matching a fingerprint with respect to a reference database. This work also presents a framework for WLAN-IPS with ensemble approach, which permits the cooperation of multiple adaptive K-NN estimators based on MSSID in positioning procedure. This research aims to use multiple SSID on the same access point to increase the performance of the K-NN method by making the value of K adaptive. N FP vectors can represent each point, where N is the number of SSID on each AP that is available in the AOI.

The proposed IPS framework is presented in the block diagram in Figure 5-1. In this proposed system, we also have two phases; they are the offline phase and the online phase. In the offline phase, RSS-values for the selected reference points will be collected and stored in the database. The fingerprint at each reference point will be calculated by taking the mod of RSS time samples for all APs in different orientations {0^o, 90^o, 180^o, and 270^o}. The mod will choose the highest redundant value among 200 RSS-time samples at each RP. In the online phase, each TP will be represented by N-vectors V_1, V_2, ..., V_N according to N SSID (N=3 in this work) for each AP. The WK-NN approach will be applied to select the first three of the closed neighbors to the TP for ψ_i where i=1, 2, …, N. The histogram technique will be applied on the 9 NNs (three NNs at each classifier) in order to determine whether the $NN_{i,j}$ appeared three times or less. The logical weight $D_{i,j}$ =1 if the candidate neighbor appears in all classifiers within the first three closed neighbors, otherwise $D_{i,j}$= 0. The logical weight will be one regardless of the position index of $NN_{i,j}$ on the different classifiers. We have four scenarios for the value of k (0, 1, 2, and 3). In case k =0 that means no neighbor of 9 NNs appeared three times. In this case, the proposed system will use the traditional WK-NN method for each classifier, that means $D_{i,j}$=1 for $\forall$i, j (i, j=1,2,3). The weight $d_{i,j}$, which is utilized in the traditional WK-NN, is the reciprocal of the square of the distance between two vectors in the signal domain. The result of multiplication between two weights $D_{i,j}$ and $d_{i,j}$ will be the final weight ($W_{i,j}=D_{i,j} \cdot d_{i,j}$) which is used to calculate the estimated position on each classifier. The final estimated position will be aggregated by using ensemble technique for three WK-NN classifiers by using the averaging method.

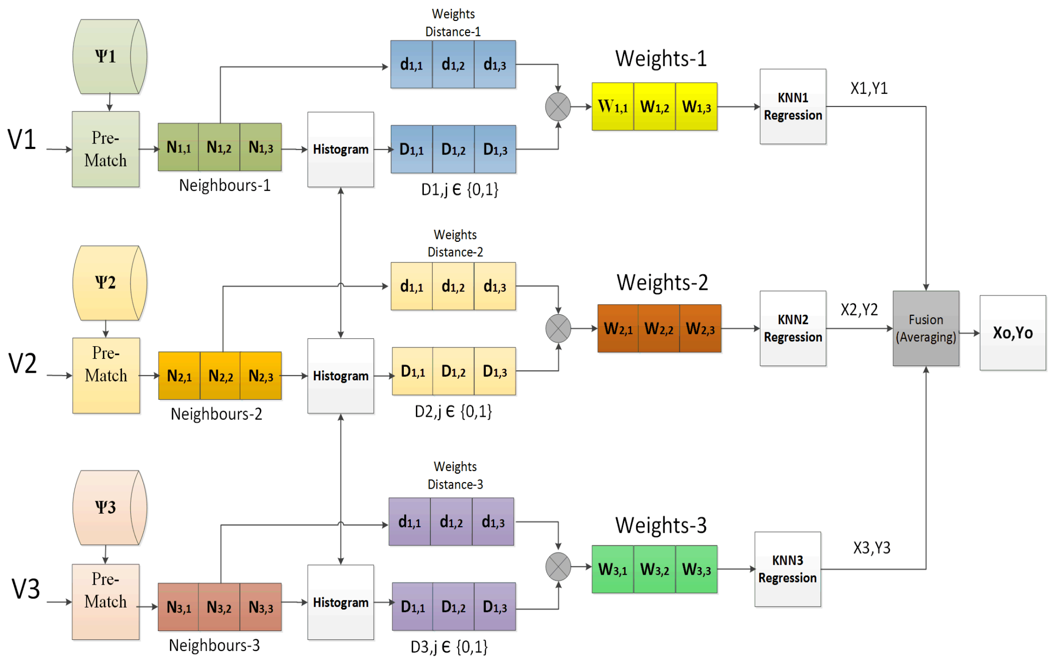


Figure 5-1: The framework of the proposed

5.4 Experimental Results

The performance of the proposed method is simulated through a MATLAB program with real-time RSS data. The measured RSS-data is collected from 32 APs (each AP is configured with N=3 SSID), which are deployed in AIO. Figure 5-2 shows the variation of distance error versus K, which represents the number of NNs. It is clear that the best performance has occurred when K=3, which is in agreement with results of other efforts [89, 90]. As expected, the error is increased when K value is increased due to biasing error. We follow our proposed system validation by comparing the performance of the proposed system with the best behavior for traditional WK-NN method with K=3. Figure 5-3A depicts the variation of K value versus the input RSS samples. The value of K is changed according to online input RSS samples with three integer values (1, 2, and 3). The histogram of K values is presented in Figure 5-3B, where 20,000 test points, (TPs) are investigated through the experiment. Figure 5-4 shows the CDF of distance error for the static WK-NN (K=3) and the proposed algorithm without and with ensemble technique. One can notice that the outperformance of the proposed algorithm with and without ensemble technique is over the performance of static WK-NN. The accuracy of the proposed system is also investigated versus the number of APs that were selected to represent the RP maps, as shown in Figure 5-5. The number of APs in the AIO affects the accuracy of the proposed framework. The distance error is decreased when the number of APs is increased.

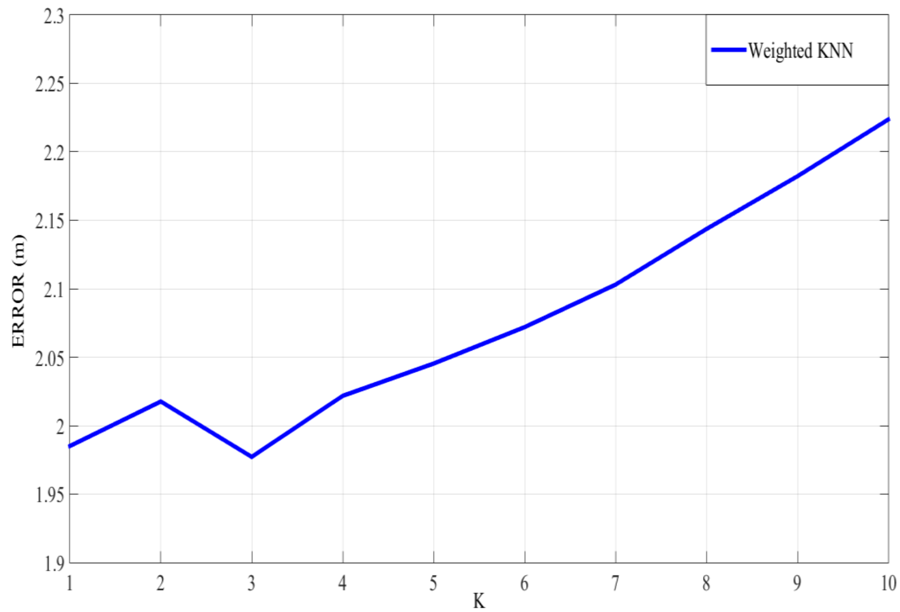


Figure 5-2: The performance of WK-NN.

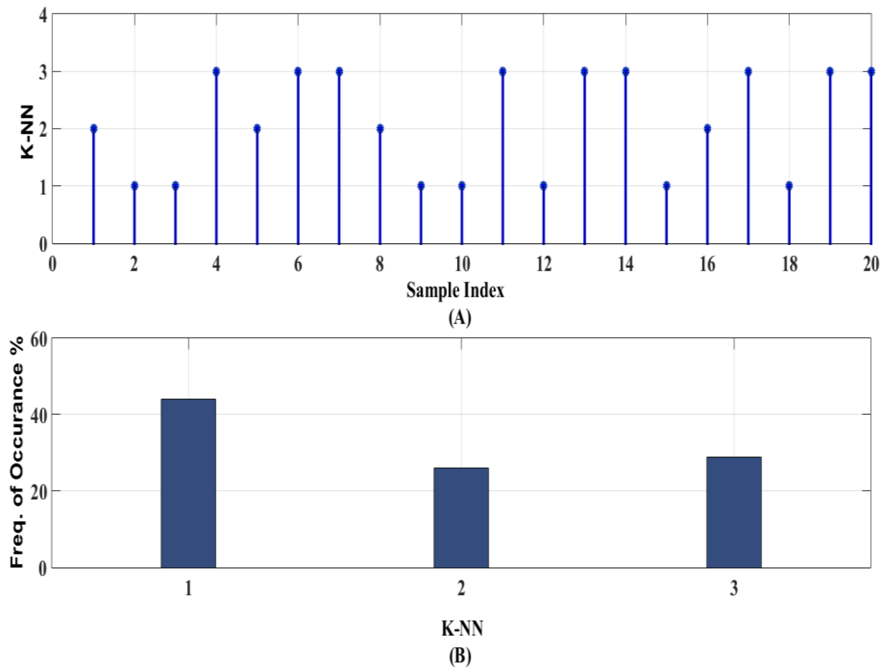


Figure 5-3: (A) The variation of K-NN value for the proposed system.

(B) The histogram of K value for the proposed system.

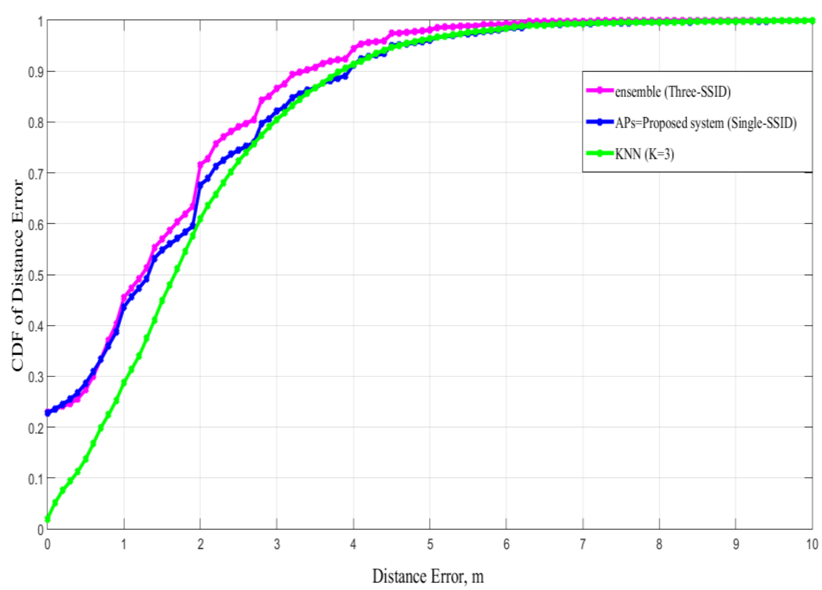


Figure 5-4: The CDF of distance error for the proposed technique.

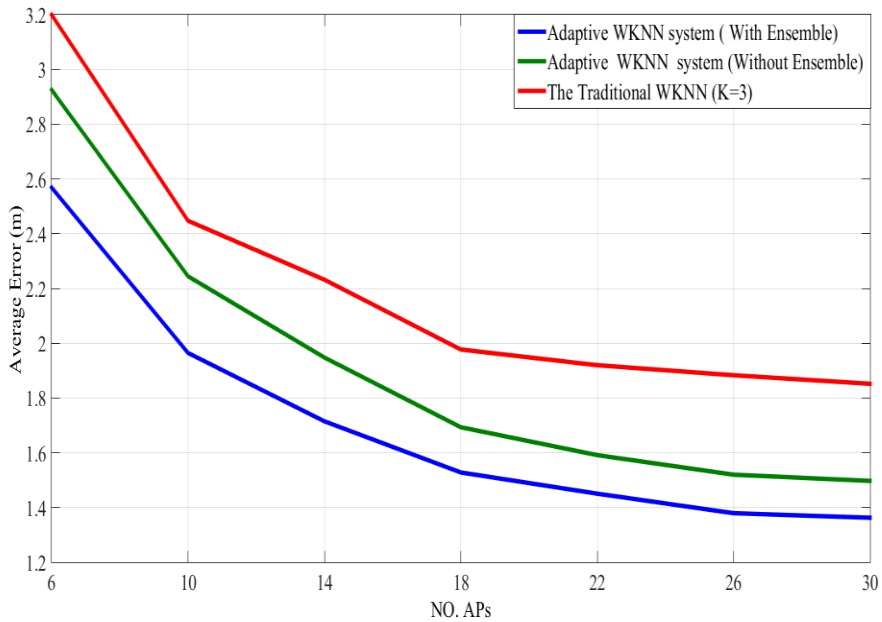


Figure 5-5: The average of distance error vs. No. of APs.

5.5 Summary

In this paper, we proposed a solution for the indoor positioning system, that is MSSID-based adaptive K-NN to estimate the user's position. The adaptive K-NN based on MSSID technique assists in selecting reliable K nearest neighbors and neglects the unreliable ones, which are an intrinsic problem due to the indoor environment variations. As shown by the results, the selection of a reliable k nearest neighbors enhances the performance of the IPS significantly. The ensemble-based technique has also reduced both the mean and the variance of the distance error. Also, using algorithms such as adaptive K-NN, simple and easily realizable, allows for true feasibility of real-time IPS.

6. RSS-FINGERPRINT DIMENSIONALITY REDUCTION FOR MSSID-BASED IPS

6.1 Introduction

The first challenge for WLAN fingerprinting-based method is the variation of RSS due to reflection, diffraction, and diffusion on the indoor scattering walls. The second challenge for the fingerprinting-based method is the big data of RM where each fingerprint sample on the radio map consists of RSS of surrounding APs. Due to the wide proliferation of Wi-Fi network, it is very common to observe a large number of APs. However, most of APs, which are detected, are non-informative APs. Some of them might have weak signals due to the long distance between the user and APs that leads to non-trivial consistency on the RM. This inconsistency leads to an increase in computational cost during the online phase. The classification process, which depends on the big database, becomes infeasible when it is working as a real-time system. Therefore, the computational cost reduction is required to reduce time delay and memory resources of real-time systems.

In this work, we proposed a new technique to reduce the computational cost of IPS. The fusion technique is utilized to reduce redundancy of MSSID signals where each AP transmits N signal simultaneously. Then, the K-means clustering technique is used to divide the Area of Interest (AOI) into K subareas, in order to confine the positioning process into a small spot instead of the whole area. The main contribution of this work that Particle Swarm optimization is chosen to select a superior pattern of joint APs at each cluster in the off-line phase to obtain the best result on the online phase. Real data is taken from the College of Engineering at Western Michigan University to evaluate the proposed system. The results of the joint selecting APs system by using PSO are compared with standard methods for individual selecting AP such as random, strongest APs, and Fisher criterion.

6.2 Related Work

Research in WLAN fingerprinting indoor localization has been mainly focusing on how to improve the collection of RSS fingerprints and how to enhance the accuracy of IPS with a less computational cost. The above goals are very crucial for any real-time IPS system[91]. Several attempts have been made by different techniques to verify the two goals. Most of the papers focused on using the traditional techniques, which utilize clustering, and APs selection [55], [92]. Also, some of them used Principal Component Analysis (PCA) and Linear Discrimination (LM) to transfer high dimensional data into a meaningful representation of reduced dimensionality [93]. However, PCA has a major drawback where it preserves the features with the maximum variance but not most discriminative ones. Therefore, PCA dimensionality reduction might be at the cost of degradation in the IPS. The following works are proposed to reduce computational cost and improve the accuracy of IPS as well.

Ayah et al. [94] proposed a new technique based on Fast Orthogonal Searching (FSO). The proposed technique is implemented to reduce the dimensionality of the radio map. They developed FOS, which is used to select more relevant APs to the positioning process. The results exhibit that the performance of the proposed system outperforms PCA, where the modified FOS provides low error as compared with PCA performance.

X. Hu et al. [95] proposed an improved Wi-Fi fingerprinting positioning algorithm, which is called WKNNSAP. The proposed algorithm uses a similarity coefficient of APs to combine RSS fingerprints that are used to measure fingerprint distance. The semi-supervised affinity propagation-clustering algorithm is used to gain a more reasonable clustering result and eliminate the outliers. The results show the ability of the proposed system as a comparison with existing systems.

B. Altintas et al. [96] proposed enhanced IPS system based on K-means clustering technique. K-means clusters groups the nearest neighbors according to their distance to the mobile user. The evaluation results show that the performance of clustered KNN is closely tied to the number of nearest neighbors to be clustered, the number of clusters, and initiation of the center point in the K-means algorithm.

Zhou et al. [97] utilized fuzzy C-mean off-line clustering to mitigate the online computational cost. The system is evaluated on the testbed of underground parking. The results exhibit a slight enhancement in the accuracy of the proposed system compared with traditional methods.

Ran et al. [98] proposed an indoor localization system using an ordered sequence of APs based on RSS without survey. RM is constructed by cutting the layouts of the AOI into small regions with knowledge of the position of APs. K-means is used to cluster the AOI into a group of clusters. An ordered sequence APs is chosen for each cluster as a signature to discriminate each other. The results show that the proposed system based on AP selection can obtain a localization accuracy 5m with an accumulative density function (CDF) of 50% to 60%. Furthermore, the results exhibit that the increasing number of APs leads to degrading the accuracy of IPS.

Daisuke Taniuchi et al. [88] proposed a new algorithm for enhancing the accuracy of IPS by using ensemble-learning techniques. The proposed technique consists of multiple weak estimators; each estimator utilizes a set of randomly selected APs to estimate the position of the user. Furthermore, they give a certain weight for each pattern of APs based on the usefulness of weak estimator. The results outperform the existing methods.

Feng et al. [99] proposed Compressive Sensing (CS) technique-based IPS. The proposed algorithm consists of two stages: coarse positioning, which is achieved by affinity propagation clustering, and fine positioning, which used CS theory to recover user position. In order to apply the CS theory; i.e., satisfy the sparsity and incoherence conditions; certain scenarios have been used to select APs; they are strongest APs and Fisher criterion. Experimental results show that CS theory is very effective with IPS due to the sparsity of the positioning problem.

6.3 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) as a novel computational intelligence technique is a population-based stochastic optimization technique, which was developed by Kennedy and Eberhart in 1995 [100]. The PSO is initialized with a population of random solutions and searches for an optimal solution by updating the position of particles for each step (iteration). Each particle represents a potential solution, and its knowledge and memory are utilized to find the optimal solution in L-dimensional search space, where L is a number of APs in this work. Each particle can be represented as $x_i = [x_{i1}, \dots \dots, x_{iL}]$. The velocity of the i^{th} particle, which is the added amount to the previous particle position to be updated the position, can be represented as $v_i = [v_{i1}, \dots \dots, v_{iL}]$, and it is limited by [$V_{max}$, V_{min}] which are maximum and minimum velocity, respectively. The optimal previous position $pBest_i$ of the i^{th} particle (the position that is giving the best fitness value) is recorded and represented as $p_i = [p_{i1}, \dots \dots, p_{iL}]$. The global pBesti value is $g_i = [g_{i1}, \dots \dots, g_{iL}]$, and called gbest. At each iteration, a particle is updated according to the following equations:

$$v_{iL} = W \times v_{iL}(t) + C_1 \times rand_1 \times (pBest_{iL} - x_{iL}(t) + C_2 \times rand_2 \times (gBest_{iL} - x_{iL}(t) \qquad 6.1$$

$$x_i(t+1) = x_{iL}(t) + v_{iL}(t+1) \qquad 6.2$$

$$W(t+1) = W(t) \times 0.99 \qquad 6.3$$

Where W is the inertia weight, C1, and C2 are acceleration factors, and rand1, rand2 are random numbers. $v_{iL}(t), x_{iL}(t), v_{iL}(t+1),\ and\ x_{iL}(t+1)$ are the previous velocity, the previous position, the updated velocity, and the updated position, respectively.

6.4 PSO-Based Proposed System

As shown in Figure 6-1, the proposed system is divided into two stages: off-line and on-line stage. At the off-line stage, the first stage is to fuse the RSS signals of MSSID, which is installed on the same AP, and then the fused RM of the AOI is classified into K clusters by using a K-means clustering technique. PSO algorithm is applied to each cluster to find the best joint combination of APs, which verifies the minimum distance error at each cluster. Therefore, there is a certain combination of APs, P_i for C_i, where PSO-based technique is searching to find the best weight vector X_{iL} which is multiplied by fingerprint vector of each reference point RP_j in the cluster C_i to obtain minimum distance error. The non-informative APs are not selected, where a certain threshold is applied to neglect the low weights of these APs. The threshold Th is chosen where $x_{iL} = x_{iL}$ if $x_{iL} > Th$; otherwise $x_{iL} = 0$. K-Nearest Neighbor approach (K=3) is used to find x_{iL} at each cluster when PSO is being applied. Table 6-1 summarizes the parameters of PSO-based technique, which is utilized in this work. Figure 6-2 and Figure 6-3 show the behavior of PSO in the off-line phase for a specific reference point. We can see the approach of the best solution (estimated position) to the reference point whose coordinate (24, 62) due to changing of x_{iL} by particle swarm optimization. In the on-line phase, the instantaneous fused samples, whose location is unknown, is compared with the exemplars of RM to find the closest cluster to this sample. Accordingly, fused V is multiplied by x_{iL} to be matched with reference point vectors of cluster C_i. Finally, the estimated position of the target is calculated by using K-NN technique.

Table 6-1: The summarization of PSO parameters.

No. Particles	**100**	V_{min}	**-0.2**
No. Iteration	**1000**	V_{max}	**0.2**
Min. Position	**1**	C_1	**2**
Max.Position	**0**	C_2	**2**
W	**1**	**No. Variable (L)**	**34**

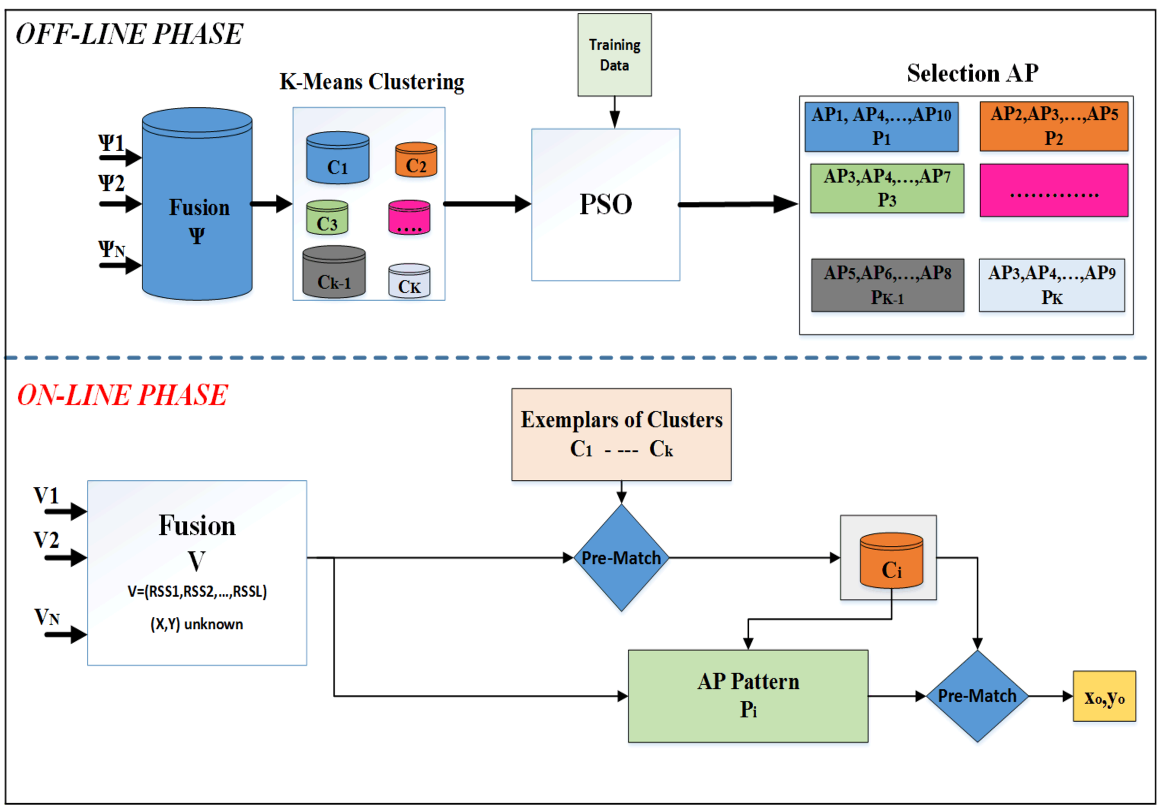


Figure 6-1: The framework of the proposed system.

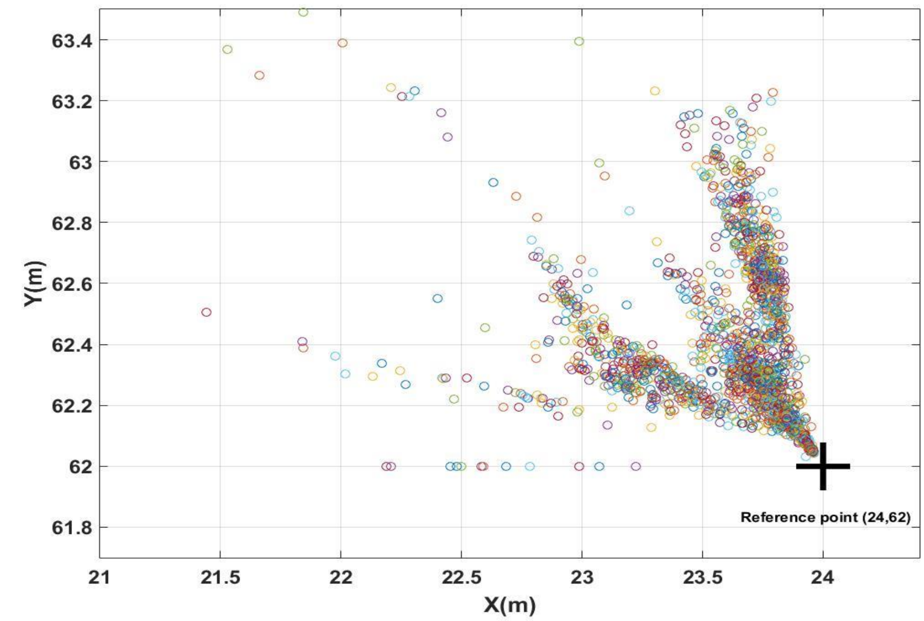


Figure 6-2: The behavior of PSO to find the best combination of APs.

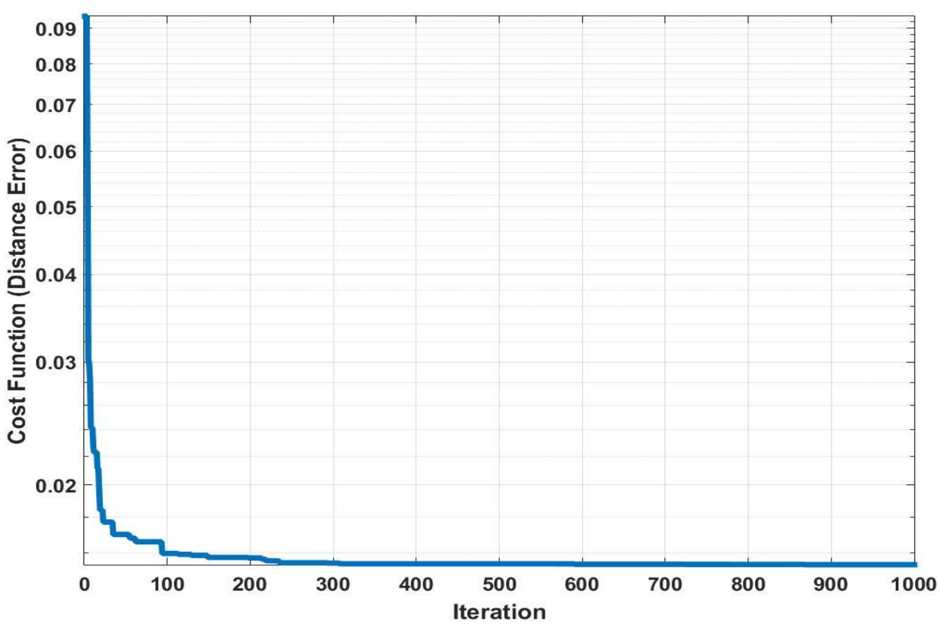


Figure 6-3: The iteration versus cost function.

6.5 Experimental results

The performance of the proposed system is simulated by using MATLAB R2015a program with real RSSI data of L=34 APs, which are deployed in the AOI. Figure 6-4 shows the CDF of distance error of PSO, Fisher, strongest AP, and random AP selection, respectively. The number of clusters is q=20, and 68% AP reduction (APs=11). As we can see, the behavior of the PSO-based proposed system outperforms the behavior of other traditional techniques. Table 6-2 summarized the average error of all investigated technique with different numbers of a cluster (q=1, 10, and 20). Figure 6-5 shows the CDF of the distance error of the PSO-based proposed system for a different number of clusters (q=1, 10, and q=20). The performance of PSO with q=20 exhibits distinction slightly as compared with q=10.The performance of PSO with q=1 (no clustering) is powerless as compared with q=20, and q=10. Interestingly, this result is related to the clustering process, where there is a correlation between the mean distance error and the number of clusters. Figure 6- shows the effect of percentage of AP reduction on the mean distance error. It is apparent from the figure that the increasing of AP reduction percentage leads to an increase in the mean distance error slightly for the PSO-based proposed system. Also, we can see that the reduction of the PSO-based proposed system outperforms the reduction of traditional AP selection methods.

Table 6-2: The mean of distance error of various techniques.

No. Clusters	**PSO-Based System**	**Random**	**Strongest**	**Fisher**
q=1	1.50m	1.78 m	1.40 m	1.70 m
q=10	1.20 m	1.65 m	1.32 m	1.30 m
q=20	1.18 m	1.60 m	1.35 m	1.32 m

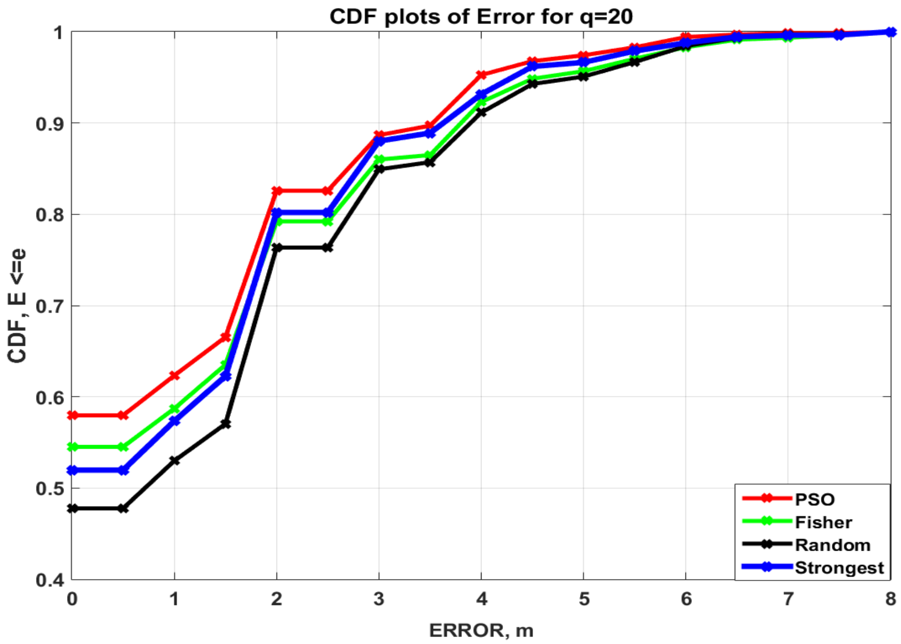


Figure 6-4: The performance comparison of the PSO-based proposed system with conventional AP selections.

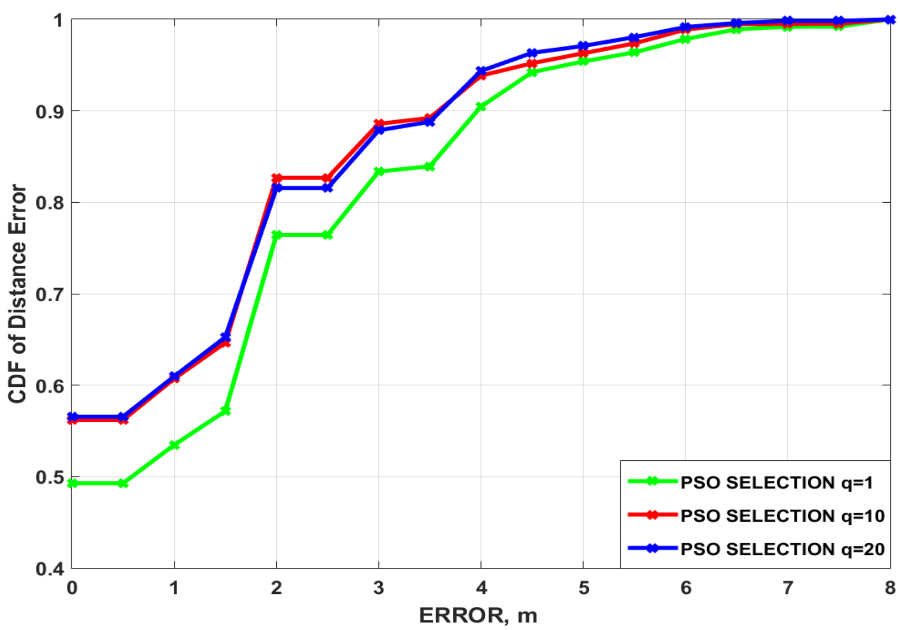


Figure 6-5: The CDF of distance error of the proposed system for different Number of clusters.

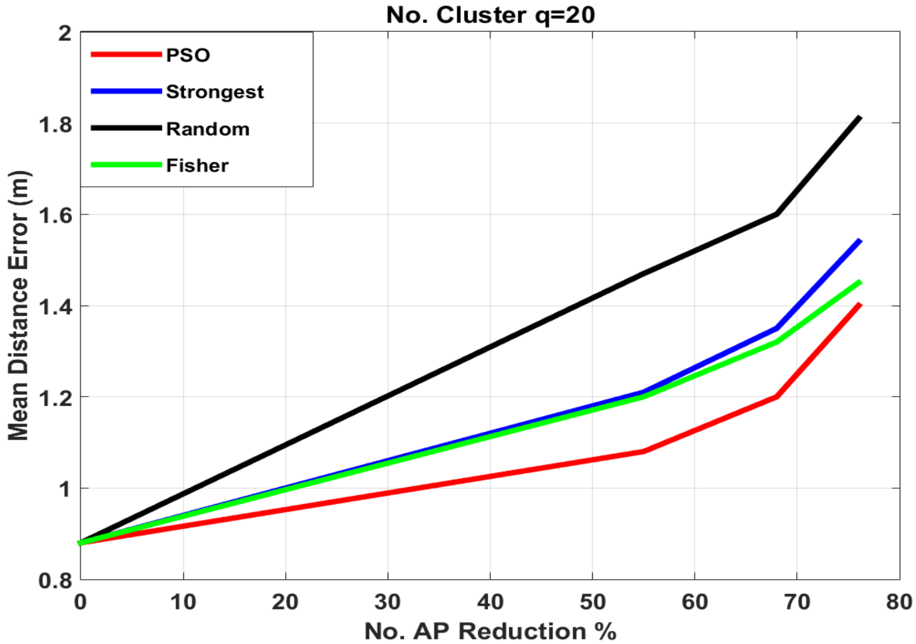


Figure 6-6: The mean distance error versus percentile of AP reduction.

6.6 Summary

This paper studies the using of PSO technique to select an appropriate pattern of APs for each cluster, which is used to reduce computational cost in an indoor positioning system. The proposed system is compared with various kind of AP selection methods such as random, Fisher, and strongest APs. Real RSSI data are token to evaluate the proposed system. The results exhibit the proposed system outperforms other techniques for higher accuracy for the same number of selected APs. In addition, the results illustrate a correlation between the number of clusters and the accuracy of IPS. Furthermore, the precision of the PSO-based proposed system is slightly affected by the percentage of the AP reduction.

7. CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

Indoor positioning is an active and noble research area for its numerous applications in many different areas of our daily lives. Tracking people and localizing objects within indoor environments have become a necessity and thus motivating many researchers to tackle the challenges of IPS. GPS does not work indoors because it requires Line of Sight (LoS) to ensure reasonable accuracy. Alternatively, WLAN Fingerprint-based methods offer high accuracy with no need for added hardware.

The main goal of this dissertation is to enhance the accuracy and reduce the computational cost of WLAN fingerprint-based systems by using Multiple Services Set Identifiers. In order to achieve this goal, three main ideas are proposals and introduced. First, we propose a new technique changing the setup of access points themselves and designing a framework that allows for multiple signals at the same time from each access point by setting up multiple SSID. A spatial voting scenario is also proposed as a tool to enhance the performance of PNN classifiers. Second, we propose a new method for adaptive K-NN based on multiple services set identifier (MSSID) by selecting desired neighbors and neglecting undesired nearest neighbors. In addition, this work presents a framework for WLAN-IPS with an ensemble approach, which permits the cooperation of multiple adaptive K-NN estimators based on MSSID. Finally, we proposed a new technique to reduce the computational cost of IPS. The K-means clustering technique is used by dividing the Area of Interest (AOI) into K subareas, to confine the positioning process into a small spot instead of a whole area. The main contribution of this work is represented at the off-line phase by selecting informative AP patterns for each cluster by using the particle swarm optimization (PSO) technique. The following points summarize the main contributions and conclusions of this dissertation:

1- Multipath fading is an inherent issue in IPS due to its changeable environment. Therefore, investigating the statistical characteristics of RSS-signals is very advantageous for IPS designers.

2- Multiple Service Set Identifiers technique is used recently to provide network services to different clients in a given building. This dissertation focuses on using multiple RSS signals on the same AP to mitigate distance error. These signals are uncorrelated at any specific point on the map. The RSS power distribution of each SSID on the same AP is corresponding in the spatial domain. In addition, we conclude that using RSS of MSSID signals in the same fingerprint leads to redundancy.

3- We propose a solution for IPS using MSSID and PNN multi-classifier-based techniques to estimate the user's position by using a spatial voting technique. The use of the multiple SSID technique supports the classifier to work with higher precision than with single SSID. The algorithm shows a notable improvement over its counterpart with single SSID.

4- A new solution was proposed for an indoor positioning system that is-based in MSSID and an adaptive K-NN model to estimate the user's position. The adaptive technique assists in selecting reliable K nearest neighbors and neglects the unreliable ones, which are an intrinsic problem due to indoor environment variations. As shown by the results, the selection of reliable k nearest neighbors enhances the performance of t IPS significantly. The ensemble-based technique has also reduced both the mean and variance of distance error. In addition, using simple and easily realizable algorithms such as adaptive K-NN allows for greater feasibility of real-time IPS.

5- The use of the PSO technique was investigated to select an appropriate pattern of APs for each cluster that was used to reduce computational cost in an indoor positioning system. The proposed system is compared with various kinds of AP selection methods such as random, Fisher, and the strongest APs. Real RSSI data are token to evaluate the proposed system. The results demonstrate that the proposed system outperforms other techniques with higher accuracy for the same number of selected APs. In addition, the results illustrate a correlation between the number of clusters and the accuracy of the IPS. Furthermore, the precision of the PSO-based proposed system is slightly affected by the percentage of AP reduction.

7.2 Future Work

Future work will include several tasks to extend the current proposed system:

1- We will study the use of MSSID with the 2.4GHz and the 5GHz bands, which are deployed on the same AP to enhance the WLAN-based IPS. The coverage area of 5GHz is smaller than 2.4 GHz. Therefore, we can use this feature of the 5GHz band to improve coarse localization by a clustering technique while the 2.4GHz band can be used for fine localization.

2- It might be possible in future investigations to study the use of 5 GHz and 2.4GHz bands together with PSO to enhance the accuracy of IPS. In addition, we can develop a new binary PSO algorithm for use in AP selection to be with a better-understood physical meaning technique (logic 1 for selecting AP and logic 0 for non-selecting AP).

3- The behavior of the mean of MSSID signals is close to path loss, as shown in Figure (3-6) because averaging MSSID signals contributes to mitigating the effect of the multipath issue. Accordingly, it might be possible to use the path loss model to determine the user's location by using the first three strongest APs. In this case, knowing the coordinates of APs in the AOI is sufficient to determine the user's location without creating a radio map, which takes more time and labor cost.

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