An Indoor Localization System Based on Wireless Sensor Networks

by

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Abstract

Although the Global Position System (GPS) can help to navigate around the world, it cannot provide useful information in an indoor environment. I developed an indoor localization system using wireless sensor networks (WSNs). This system has two important goals: (1) to make a system that runs for long duration without changing or charging batteries, and (2) to obtain more accurate position estimates of the target nodes using received signal strength indicator (RSSI) values than other localization systems using different localization algorithms. In terms of radio frequency (RF) technology, I chose ANT radio due to its lower power consumption. According to the manufacture, ANT devices can run for one year without changing batteries. I applied a fingerprinting-based algorithm, which stored each RSSI value and its corresponding position at each location as a fingerprint, and used the parameters of the closest point to the estimated target node to calculate the final position. A local weighted k-Nearest Neighbour algorithm was proposed to estimate the position of a mobile node. I compared my system to other indoor localization systems to assess its performance.

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Acknowledgments

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Chapter 1

Introduction

With the rapid development of communication technologies, wireless sensor networks have become a viable alternative for indoor localization (i.e. the determination of a device's, and hence person's location). Imagine a scenario in a shopping mall, where the exits and elevators are not easily identifiable. Also imagine another scenario, where children are wandering around in a shopping mall or in a crowded place and have become separated from their parents. Although the GPS can provide useful location information in outdoor environments, it cannot deal with the problems in such scenarios due to the lack of line-of-sight transmission. Indoor localization can address these problems by using different approaches. If a shopping mall is deployed with sensors at each room and along corridors, customers can use an indoor localization system that can sense those sensors and show the customers' positions and then help them navigate to their destinations in a large indoor space. An indoor localization system calculates the position based on the signal strength from different sensors. Children wear sensors when they walk or play in a shopping mall, parents can locate their children's positions by using an indoor localization system that receives the signal from the sensors of the children and calculates the positions by applying different localization algorithms. In this way, it is convenient for parents to monitor their children's locations in real time in case their children go lost.

Indoor localization refers to tracking of objects in an indoor environment, and instead of using satellites, it relies on the deployed anchor nodes that receive signals from sensors [5]. Indoor localization techniques are classified into two categories: range-based and range-free [33]. Range-based schemes use angle of arrival (AoA), time of arrival (ToA), time of flight (ToF), time difference of arrival (TDoA) and received signal strength indicator (RSSI) techniques for localization [28, 45]. Thus, range-based techniques are based on measuring transmission angle, time and signal strength in order to calculate the positions of sensors. Range-free methods utilize signal strength to calculate the proximity information between nodes instead of measuring and refining angles or distances [33]. Range-free methods do not calculate an actual estimate of the distance between the anchors and the target node. In contrast, they just rely on the relative ordering to geometrically define an area in the localization place, The centroid of the area is treated as the estimated location of the target node. Some range-free schemes overlap the nearby neighbouring areas with theoretical formulas to to estimate the position of a mobile node [30, 33]. However, in areas with big obstacles, range-free schemes cannot estimate the position information of nodes as accurately as range-based schemes can [66].

I developed a range-based indoor localization technique using RSSI measurements. RSSI [25] is the power strength of radio frequency in a wireless environment, and can be used to calculate the distance between a fixed node and a mobile object. I used ANT technology [2] for my localization system. ANT radios consume low energy and have flexible topologies, so the whole system is energy-efficient and can operate for a long duration. I considered two environments for my indoor localization system: a small area (e.g., a single room), and a large area (e.g., two rooms and a corridor). I developed an algorithm based on the fingerprinting technique [26] to locate a mobile node in these two environments. I also developed another algorithm based on the RSSI and distance equation [56] and the k-Nearest Neighbour algorithm (kNN) [35] for the small area and large area. During my system evaluation, I tested the influence of various elements, such as obstacles, as well as environmental factors, such as the temperature. I also compared my work with other RSSI-based schemes, such as the *k-Nearest Neighbour* algorithm [26] and the *MinMax* algorithm [43]. In the small area, the estimated error results showed that my fingerprinting reference point (FRP) algorithm performed the best, followed by my local weighted k-Nearest Neighbour (LW-kNN) algorithm. The MinMax provided larger estimated position errors than the LW-kNN algorithm, but in some cases, its performance was better. Although the kNN algorithm performed the worst among the four algorithms, it was still a good localization approach. Although the factors including the temperature and obstacles might influence the accuracy of the estimated position errors, my results showed that the average increased errors were within 0.2m in a $5m \times 5m$ room when the environments were changed. As the change in an indoor place was slight, the error results did not show large differences. The LW-kNN algorithm and the MinMax algorithm were evaluated in the large area scenario. The LW-kNN algorithm provided better results and its average error was only 1.59m. The average accuracy rate of the LW-kNN algorithm was over 75% and the highest accuracy rate of the Room1 reaches to 86.63%, which guaranteed that this localization system could be applied in a large area.

1.1 Motivation and Problem Description

Although the GPS is widely used and can provide reliable outdoor location information, unfortunately, the characteristic of line-of-sight transmission renders that the GPS unusable for in-building location-based services. Also, the localization error around 10m makes the GPS not applicable in a small indoor space where greater accuracy is needed. However, it is also important for individuals to locate and navigate in a big building. For instance, I can find the exits or elevators simply in a big shopping center by using the indoor localization technology. This technology can be also applied to locate patients in a big hospital. As indoor localization works in smaller scale environments, it needs different techniques compared to the GPS, such as the use of wireless sensor networks. There has been numerous literature presenting various localization systems, but most of the systems are not energy and cost efficient. Some indoor localization applications can only run for several hours, which can not be applied in a place where the power outlets are limited or not conveniently placed. As deployed sensors need batteries to work continuously, making the indoor localization system run for a long time without changing batteries frequently is a challenge, especially in a place where alternative power is limited, such as a warehouse. It is also difficult to measure accurate RSSI values due to environmental factors, such as temperature and humidity. A number of localization algorithms are applied in the indoor localization. Some of them can not provide good results stably, while some can provide more accurate position estimation, but much more anchor nodes are needed. I focus on improving localization algorithms to decrease deviations of RSSI values and better estimate distance using ANT radio based wireless sensor networks. Also, I consider scalability and cost factors in my research.

1.2 Contributions

Generally, ZigBee and Bluetooth occupy the main part of the wireless sensor network research area, so a large number of research works including tutorials and papers can be accessed. For the indoor localization research domain, people also apply these two technologies as the transmission protocols. As ANT is a new wireless radio technology, it is not widely used in research yet. The tutorial and papers about it are so limited, only in the health care and sports research area. As ANT technology consumes low energy and the applications that utilize it can run for a long time, I first utilized it in the indoor localization research to make contribution to this radio technology. In order to improve the accuracy of the position estimation of the target node, I explored two localization algorithms: FRP algorithm that is based on fingerprinting technique and the nearest neighbour's parameters; LW-kNN algorithm that is based on kNN algorithm. My algorithms provided more accurate results than other widely used algorithms: kNN algorithm and MinMax algorithm. This system not only run for a long duration without changing batteries (at least one year), while other Zigbee supported devices could only run for several days or tens of hours. My indoor localization system has been tested in a small area and also extended to a large area including two rooms and a corridor to provide good performance. I also tested some factors, including size of the deployment area, number of anchor nodes, obstacles and temperature, to study the influence of them on the accuracy of indoor localization.

1.3 Thesis Outline

The next chapter introduces the background and related work. It first describes different wireless sensor network categories and applications. Next, I introduce some popular wireless radio technologies, including Zigbee, Bluetooth and ANT. Then, localization algorithms including fingerprinting, kNN, trilateration and MinMax are presented, several widely used localization methods are described and compared. In Chapter three, I introduce my two localization test scenarios: a small area and a large area (two rooms and a corridor), where I implement my two algorithms, FRP and LW-kNN. The accuracy of my algorithms and two other algorithms (kNN and MinMax) are evaluated and compared in the next chapter. I set different environments and conditions to test the influence on four factors, namely deployment area size, number of anchor nodes, obstacles and temperature. Then, in the final chapter, I make a conclusion and suggest my future work.

Chapter 2

Background and Related Work

2.1 Wireless Sensor Networks

A wireless sensor network (WSN) [19] refers to a number of sensors linked wirelessly to typically collect data about environmental conditions, such as humidity and temperature. These sensors communicate with each other by using different wireless communication protocols. A small WSN can be expanded by dynamically organizing the nodes into network topologies, such as star and tree. WSNs hold the promise of numerous new applications in the area of monitoring and control. Also they combine sensing, processing and communication to provide comprehensive and powerful applications in different domains.

As WSNs are widely used, they can be parts of systems such as battlefield surveillance and micro-climate control in buildings and environmental monitoring [19]. Also they have been applied in target tracking, wildlife habitat monitoring and disaster management. In military target tracking and surveillance, a WSN can be used to detect intrusion and identification. The following sections give an overview of different types of sensor networks and WSN applications.

2.1.1 Types of Sensor Networks

Current WSNs are widely used on land, underwater and underground. The types of WSNs are classified into the following: terrestrial WSNs, underground WSNs, underwater WSNs, multi-media WSNs, and mobile WSNs [63].

Terrestrial WSNs [18] are generally deployed with hundreds or thousands of cheap sensors in an area on the ground. These sensors are often randomly dropped from a plane or helicopter to the target place. In a terrestrial WSN, a reliable and energy-efficient communication between sensor nodes and the base station must be maintained. As the power of batteries is limited and cell batteries cannot be charged, some terrestrial sensors are equipped with additional solar batteries to guarantee continuous power supply. In order to make a terrestrial WSN run longer, an optimal multi-hop protocol is implemented between sensors in general to conserve energy [19]. This type of WSN is mainly used for environmental monitoring and natural disasters detection on the ground.

Environmental monitoring underground is also important, as a couple of security factors, such as gas, temperature and oxygen must be monitored in real-time. Similar to terrestrial WSNs, underground WSNs also consist of numerous sensors but now deployed in the underground environment, such as caves and mines. The difference between underground and terrestrial WSNs is that sensors deployed in underground WSNs are more expensive, because extra powerful hardware devices are needed to maintain a reliable and effective communication between sensors and the base station, especially when the signals must pass through rocks, oil and water [17]. Besides, due to the high cost of sensors and the deployment, underground sensors are generally deployed sparsely while terrestrial sensors are deployed densely in a specific area [42]. Energy is also an important concern in underground WSNs. Similar to terrestrial WSN, underground sensor nodes are generally equipped with a limited battery power. It is hard to replace the batteries underground, so once the sensors are deployed, efficient communication protocol has to be implemented on these sensor to conserve energy. The locations to deploy sensors are limited, because the space in a cave or mine is narrow.

Underwater WSNs [17] normally consist of a variety of sensors and vehicles that are deployed to perform collaborative and continuous monitoring tasks over a given area underwater. Underwater WSNs enable information to be transmitted in a lake, river, sea or ocean. Applications of underwater sensing vary from aquaculture to the oil industry, and include environmental monitoring, pollution monitoring and control, climate monitoring and prediction as well as the study of marine life [34]. Different from the above WSNs, acoustic transmission technology is mostly utilized in underwater WSNs, because the common transmission techniques, such as radio frequency, can only maintain short range coverage. A significant disadvantage of underwater WSNs is that the acoustic wave transmits in water less than 1500m/s, which causes high communication delay between sensors [17]. In addition, the sensors utilized in underwater WSNs are expensive, because the sensors must be waterproof, and they also suffer high pressure in deep underwater, especially when performing a task in an ocean. Also, the deep water environment is harsh and dangerous, once the sensors are deployed, they can not be replaced. The underwater environment draws numerous researchers' attention, as the change of underwater environment can lead to a great change of the environment on the ground, such as an earth quake. As only small part of the underwater world is discovered and studied by researchers, the underwater WSNs have a great potential on deep water environment research.

In a multimedia WSN, sensors equipped with cameras and microphones are deployed to monitor and track events [16]. The sizes of data collected by sensors are large, so the data needs to be compressed before being delivered. It is necessary that the sensors possess strong data compression capability which requires significant computation and is large draw on battery power. Multi-media data such as a video stream requires high bandwidth to be delivered to other sensors or base stations. As multimedia WSNs require high bandwidth, which leads to higher power consumption than other WSNs.

Sensors that can move and collect data from the environment are applied in Mobile WSNs. These sensors can not only implement the tasks that static sensors can do, but they can also move their positions in the network [63]. The collected information from a mobile node can be transmitted to another mobile node as long as they are within range of each other. Due to mobile sensors' mobility and flexibility, they can spread out to areas where individuals cannot or feel difficult to access, such as cliffs, deserts or other hazardous areas. Mobile WSN applications are not only limited to environment monitoring, they are also widely used in target locating and real-time monitoring of enemies. Compared to static sensor nodes, mobile sensor nodes can achieve a higher degree of coverage and connectivity but at a greater expense in terms of power consumption. Another difference is that the routing protocol used in the mobile WSNs is dynamic routing while static WSNs apply fixed routing or flooding. They can also be applied into military field to extend more coverage hopefully without being detected.

2.1.2 WSN Application Categories

Shown in Figure 2.1, various WSN applications are classified into two main categories: monitoring and tracking [63]. The monitoring category includes military surveillance, environmental monitoring, health monitoring, industrial monitoring and animal behaviour mon-

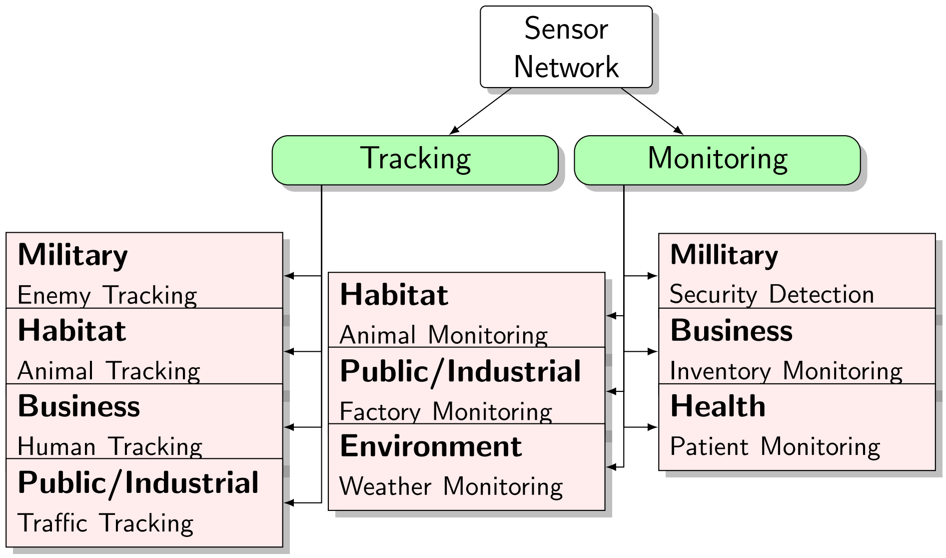

Figure 2.1: WSN Application Categories [63]

itoring. The tracking category contains tracking on military, animals, human and traffic. I now briefly review some example WSN applications.

WSNs are useful for the environmental monitoring of forests. Tolle et al. [57] present a case study of a WSN that records data of redwood trees in Sonoma, California for a long period. They distribute sensor nodes in different gradients of the redwood trees. Each node measures air temperature, relative humidity, and photosynthetically active solar radiation. The variations of the temperature and humidity of from top to bottom of the redwood trees are captured. As well, the dynamics of the micro-climate in different sections of the redwood trees are recorded in detail. This study is useful to plant biologists to analyse the influence of complex environmental factors affecting these redwood trees and the surrounding plants.

WSN technologies also can be used to enable the early-warning of natural disasters. Werner et al. [59] introduce a volcano monitoring sensor-network architecture deployed on Valcan Reventador in northern Ecuador. This network consists of 16 sensor nodes. Each node is embedded with a microphone and seismometer, which collect seismic and acoustic data on volcanic activity on real-time. Sensor nodes are placed 200m to 400m between each other. Nodes transmit data via a multi-hop network to a gateway node, providing radio connectivity with a laptop at the observatory. During process of operation, each sensor node receives seismic acoustic wave data at 100 Hz. The data is captured and stored in local flash memory of each sensor. When an event occurs, the node sends a message to the base station. If multiple nodes report the event in a short time interval, the laptop starts data collection that operates in a round-robin fashion. The laptop downloads the data from sensors at between 30s to 60s intervals by using a protocol that guarantees the data can be retrieved from the buffer. After data collection process is finished, the nodes return to sampling and storing sensor data. The study lasted for 19 days and achieved a good performance. During these days, 230 eruptions were detected and nearly 107 MB of data was logged. The volcanic eruption is well evaluated, which is beneficial to the study of the volcanic eruption patten in order to provide early warning to local people.

WSNs can be applied on animals to track their migration. Zhang et al. [65] introduce a system called ZebraNet which is a mobile WSN used to track how wild zebras migrate. The ZebraNet consists of a 16 bit TI microcontroller, 4 Mbits off-chip flash memory, a 900 MHz radio and a GPS unit. Zhang et al. deploy a total number of 6-10 sensor nodes on zebras' collars at a 100 km^2 field in Kenya. In order to maintain the connectivity in such a sparse ZebraNet, the radio range is designed to be 1000m. The cost is that the energy consumption dramatically increases compared to the regular short range type of transmission. After deployment, the biologists observed and concluded that the collared zebras were easily influenced by the collars. Those zebras with sensors on their collars were still affected during the first week. For instance, those zebras shake heads more frequently than other zebras. After a week, the collared zebras perform the same as the uncollared zebras. A set of movement data was also collected during the several months. As the radio range is 1000m, the zebras could be monitored far from the researchers. In this way, the migration route of the zebras was not influenced by humans, so the migration route was natural and real. This study was of great importance for the biologists to understand the path that wild zebra migrate.

Compared to traditional wired sensor networks, WSNs provide more benefits, such as lower cost, easier deployment and higher quality of measurements [55]. Due to the absence of wires, wireless sensor networks can be installed in a remote environment, where the installation of traditional networks is not possible. In addition, the cost of deployment and operation of wireless sensor networks is lowered by eliminating the cost of numerous wires. However, the constraints of WSN are shorter communication range, lower bandwidth and limited data storage space [63]. Further, the WSN nodes have limited power.

2.1.3 Indoor WSN Applications

WSNs are not only applied outdoor, but also used in indoor places in different domains, such as healthcare and localization.

Healthcare and medical research greatly benefit from WSNs. Wireless sensing and tracking have the great potential for applications in medical area. The care of elderly people is a key issue, as some of them are affected by disease and can not maintain a normal life. For instance, if old people fall on the floor and nobody is there to help, then that is a big trouble and it sometimes may lead to death. A WSN can monitor the elder and help them in their daily life. By using smart phones, the elder can be reminded about their meals or medicine so that their routines can be well organized. Based on these concerns, Malan et al. [44] introduced a wireless infrastructure called CodeBlue that includes wireless sensors, PC and

PDAs. The wireless wearable sensors are Berkeley MICA motes including micro-controllers and small amount memory, which collect heart rate and oxygen saturation from each patient and send the collected data as a packet over wireless network with a range around 20m to a PDA or PC. The TinyOS operating system runs on each MICA mote to implement the resource management and data communication. Specifically, the sensors can be used to capture vital signs from patients in real-time and deliver the data to PCs used by medical personnels. The motes are also capable of storing patient data, such as identification, history of treatment records, so the back-end storage system is not necessary. These sensors can be tracked at meter-level accuracy by using ultrasound ranging or RF localization technology so that the patient equipped with a MICA mote can be located in an indoor place in real-time.

Virone et al. [58] propose a system for smart healthcare based on an advanced WSN. This medical sensor network system integrates heterogeneous devices: some of them are wearable on the patient and some are placed inside the living space. Data is collected, processed, stored and acted upon using a number of sensors and devices in the architecture. This system provides continuous, reliable and remote healthcare monitoring, so some degenerative diseases like Parkinson's, can be detected in real-time.

Localization is also a hot topic, a number of applications are developed to provide location information of individuals and objects. The following section describes the applications of localization in different times and environment.

2.2 Localization Applications

To locate a person's or an object's position is of great importance in some situations. For instance, some tourists might be trapped on a mountain and they cannot find the way back, if a rescue team know the tourists' positions, then the rescue team can find and help them in a short time. Localization is a process of finding the location of an object or person, which is always combined and applied with navigation. The basic localization or navigation appeared long time ago. As at that time the communication technology was slow and covered only small areas, the localization technology was more important than now. A couple of notable tools were invented several hundreds of years ago, such as compass, astrolabe, crosstaff and sextant. Theses tools are used to find the direction, the altitude of the sun or other stars as well as the angle between the horizon and the sun or a star to know the latitude [8]. With the use of these tools, sailors navigated on the seas without losing theirs locations. As the ancient localization and navigations tools highly depend on the weather, when it comes to storms, my ancestors cannot even figure out directions, which is really dangerous.

In the last century, for military purposes, the U.S. Department of Defense began developing a satellite-based localization system, which finally evolved into the well-known Global Positioning System (GPS) [46]. GPS is a powerful system that is widely used in a large number of scientific, civil and U.S. Military applications. GPS is mainly used as a satellite positioning or system around the world, which can track people, vehicles and other objects in real-time. GPS is based on a time-difference-of-arrival (TDoA) technique that utilizes on-board clocks and the position of the satellite to generate navigation information, which is constantly transmitted from each GPS satellite to GPS receivers. Then the GPS receiver then predicts the receiver location based on the satellite measurements. The TDoA technique will be introduced in detail later.

GPS provides world-wide localization, but those cheap and small devices whose energy and cost are constraints prevent the use of GPS on the large networks which are formed by these devices. In order to solve the problem of locating these devices in an outdoor space, Bulusu et al. [24] introduce a system based on radio transmission and proximity information of nodes. Specifically, a large number of reference nodes are deployed in a large space and the positions of the reference nodes are known. The positions of the target nodes are based on the nearby reference nodes. As there are a couple of reference nodes in the sensing coverage of the target nodes, the target nodes localize themselves to the approximate center of their nearby reference nodes. The accuracy of the target nodes are highly depended on the distance between reference nodes as well as the sensing coverage of the target nodes. Bulusu et al's final results show that 90% of the errors are within one-third of the distances between two close reference nodes.

Localization not only includes outdoor applications, such as those implemented using GPS, but also includes indoor applications. Indoor localization is important to a range of applications, attracting a number of researchers in the past years. Some 2D indoor localization systems are proposed to provide room-level localization services, such as locating whether a person is in a classroom or a corridor. Yang et al. [61] introduce a system called LiFS based on the WiFi infrastructure and smart mobile phones. LiFS was deployed in an office building with the space of over $1600m^2$. The process of building the radio map is simple and rapid to implement as little human intervention is needed. This localization system constructs a radio strength map which contains a number of fingerprints of a floor. The fingerprint map is built based on the previous fingerprints and human motions. Each fingerprint contains the radio strength value and its corresponding position information. There is no need to know the actual positions of access points (APs), as human motions can be utilized to connect previous fingerprints by using some special methods. Their experimental results show that LiFS still achieves good and comparable location estimation accuracy to other localization approaches even without doing a site survey. The average error of LiFS is

5.8 meters and the room-level accuracy, while 80% of the errors are under 9m and 60% of the errors are under 6m.

Indoor localization can also be expanded to 3-D. Bal et al. [22] use the ZigBee protocol as the radio technology. A target node's position is depended on its neighbour reference nodes. The biggest difference is that the height position of each reference node is recorded, so this system gives a better view compared to the 2-D indoor localization system, but the accuracy is affected as there are more factors to be considered, for example, the RSSI values received from anchors in different heights give large errors.

Indoor localization attracts a number of researchers, more specific indoor localization techniques, algorithms and applications are introduced after the Radio Technologies section.

Radio technologies play an important role in localization research. The following section introduces some popular radio technologies, such as ZigBee and Bluetooth. Another radio technology called ANT is also introduced in detail, which is used in my experiments.

2.3 Radio Technologies

As the memory of each sensor is limited, and the places to deploy sensors are difficult to access, radio technologies are implemented to permit communication and data exchange between sensors and a base station [63]. WSN technologies with Bluetooth [32] and ZigBee [35], as popular RF media, are used in indoor localization.

As IEEE 802.15.4 standard, ZigBee is widely used because of its advantages, such as low power consumption. It especially provides useful parameters for location estimation, i.e. RSSI, which is defined by equation 2.13.

Bluetooth [54] enables short range wireless communication between devices. Bluetooth is not targeted for a specific application, so it has been adopted by various devices, including computers, cell phones, headsets and cars. As Bluetooth also provides RSSI, it is applied in some localization systems.

Bluetooth Smart [10], also known as the Bluetooth Low Energy (BLE), is the new and powerful version of Bluetooth wireless technology. Bluetooth Smart retains the use of Bluetooth wireless technology to devices that are powered by cell batteries. It also supports other devices such as sports devices, fitness devices, health care devices, keyboards and mice, beacons and wearables. Most Bluetooth devices on the current market support the basic 10 meter range of the Bluetooth radio, but the range of Bluetooth Smartis not limited to only 10 meters. With Bluetooth Smart, the radio range can be extended to 200 feet, especially for indoor wireless sensor applications where longer range is a key condition [14].

A Canadian RF technology called ANT [2] has been developed and is an attractive alternative, because it has lower power consumption and a simpler application development cycle. It is a practical wireless sensor network radio technology running in the 2.4 GHz band and designed for ultra-low power, ease of use and scalability. ANT supports different topologies including: peer-to-peer, star and tree topologies. ANT provides data communications and flexible network operation. In addition, it maintains adequate, fast and reliable user control while reducing heavy computational burden in providing an efficient wireless networking solution. ANT [1] is supported in many mobile devices by leading manufacturers, such as Samsung, Sony and HTC. ANT technology is dominant in sports and fitness domains. This radio technology is supported by various fitness and health sensors such as: heart beat sensor, step count sensor, speed sensor, muscle oxygen sensor, glucose sensor and blood pressure sensor. ANT is becoming more and more popular, but the research papers on it are still limited. As no one has applied ANT technology in the tracking or navigation research area, ANT technology is first used in my experiments to implement a low-energy cost indoor localization system.

Another important aspect of localization is accuracy. The following section introduces some popular localization algorithms and explains how these algorithms work. The algorithms are quite different from each other, but they all combine with the radio technologies to implement localization.

2.4 Localization Strategies

This section presents four existing important localization algorithms including fingerprinting, k-Nearest Neighbour, trilateration and MinMax. Fingerprinting and k-Nearest Neighbour calculate the locations based on fingerprints stored in the database. Trilateration applies a RSSI and distance equation 2.13 and draws a circle at each beacon node. The radius of each circle is the distance calculated by the equation 2.13 and RSSI values from each beacon node. The final position of the target node is the crossing point of the circles. MinMax also calculates the distance based on RSSI values, and then draws a square boundary based on the calculated distances for each anchor node that sends signal at a fixed position. Then I choose the maximum point of the minimum points of each square boundary and the minimum point of the maximum points of each square boundary, and average the coordinates of the two points calculated to achieve the final location.

2.4.1 Fingerprinting

Fingerprinting [26, 31, 62] is a localization technique which deals with the RSSI values between a target mobile node and the anchors sending signals at fixed positions. A location

Fingerprint Locations	**Fingerprint RSSI**
$L_1 = (x_1, y_1)$	$(r_{L_1,1}), (r_{L_1,2}) \ldots (r_{L_1,n})$
$L_2 = (x_2, y_2)$	$(r_{L_2,1}), (r_{L_2,2}) \ldots (r_{L_2,n})$
$\ldots$	$\ldots$
$L_{n-1} = (x_{n-1}, y_{n-1})$	$(r_{L_{n-1},1}), (r_{L_{n-1},2}) \ldots (r_{L_{n-1},n})$
$L_n = (x_n, y_n)$	$(r_{L_n,1}), (r_{L_n,2}) \ldots (r_{L_n,n})$

Table 2.1: Fingerprint Training Data

fingerprinting method is used as it can give good estimates of the user's locations for indoor environments. The fingerprinting technique is based on a radio map (Table 2.1), which is a collection of fingerprints at different positions. A fingerprint set is a group of radio signals measured at a specific location from the devices transmitting radio signals.

The fingerprinting technique has two phases: the training (off-line) phase and the localization (on-line) phase [31]. In the training phase, the RSSI values (signatures) from anchor nodes at selected locations (typically points on a grid) and their coordinates are recorded to the database. In the localization phase, pattern matching techniques are used to calculate the target node's location by comparing the current RSSI values to the recorded signatures. Techniques using this method differ in their ways to select signatures.

The accuracy of the estimated position of the user depends highly on the number of points collected in the fingerprint database. If there are more points, then the radio map has a finer resolution and thus a better estimation is performed. In addition, since the RSSI values vary over time, collecting more time samples of RSSI readings at the same measuring point can improve the accuracy of position estimation. Therefore, the whole fingerprint database collection process is generally time-consuming.

Another disadvantage of fingerprinting approaches is maintaining their databases. Since the RSSI propagation signals vary with time, the accuracy of using the database degenerates over time, because the current received RSSI readings slowly deviate from the readings in the database [64]. The database may even be considered useless, if the environment changes significantly. While the environmental parameters, such as temperature and humidity in an indoor place are generally stable, environmental factors in an outdoor place vary sharply. This requires the fingerprint database to be rebuilt periodically, in order to guarantee the accuracy of the localization system. Although there are limitations to location fingerprinting, it is a relatively simple and convenient method to be used by indoor localization systems. My thesis also uses a fingerprinting based approach to estimate the user's location.

2.4.2 *k*-Nearest Neighbour

A common approach in signature selection is the *k*-Nearest Neighbour algorithm [21], where the RSSI values from anchor nodes are collected at different sampling points to obtain an RSSI signature map. This approach calculates the Euclidean distance between the received signal and each fingerprint record in the database. Given a mobile (target) node's RSSI values from the anchors, the algorithm searches the training data set to find the k nearest matching data records to calculate the mobile target node's location. The average value of the positions associated with these k data records, gives the approximate location of the mobile target node. A drawback of this algorithm is the fact that all k neighbours have the same vote, which is not related to the distance between the neighbour node and the target node.

2.4.3 Trilateration

To localize a target node in a 2D plane, three anchors are sufficient. Also the distances between the target node and anchors are required. Based on this, trilateration [36, 55] is a simple method that is popularly used in localization, generally combined with other techniques. It is used to determine the unknown coordinate of a target using several anchors with known coordinates.

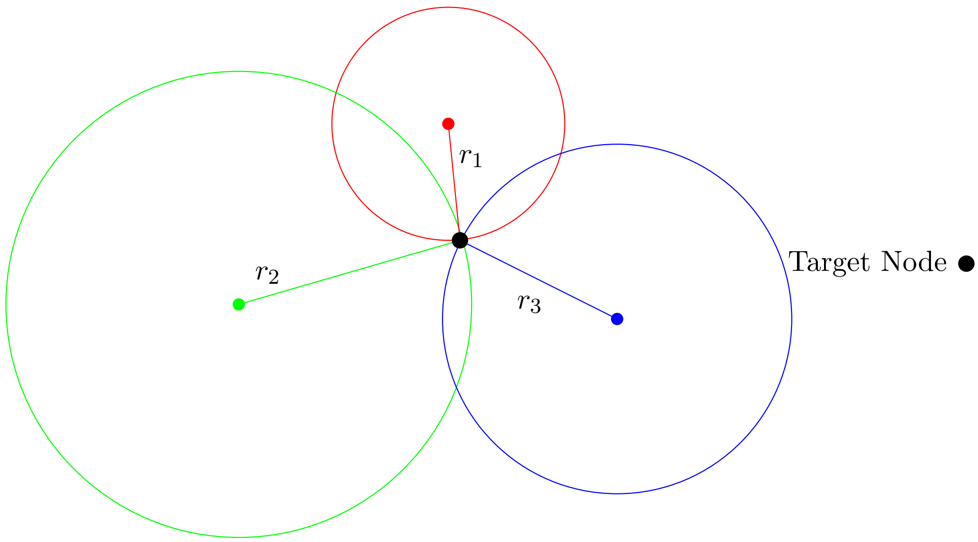

Figure 2.2: Trilateration

In Figure 2.2, I assume that the positions of three anchors are known with the coordinates of $(x_i, y_i), i = 1, 2, 3$. The unknown position of the target node is (x_t, y_t). The following equation is given by using the Pythagorean theorem [9].

$$r_i = \sqrt{(x_i - x_t)^2 + (y_i - y_t)^2} \qquad i = 1, ..., 3. \tag{2.1}$$

It is convenient to write linear equation 2.3 instead of equation 2.1, which can be created by subtracting the third equation from the above equations.

$$\begin{cases} (x_1 - x_t)^2 - (x_3 - x_t)^2 + (y_1 - y_t)^2 - (y_3 - y_t)^2 = {r_1}^2 - {r_3}^2 \\ (x_2 - x_t)^2 - (x_3 - x_t)^2 + (y_2 - y_t)^2 - (y_3 - y_t)^2 = {r_2}^2 - {r_3}^2 \end{cases} \tag{2.2}$$

Equation 2.3 can be arranged as:

$$\begin{cases} 2(x_3 - x_1)x_t + 2(y_3 - y_1)y_t = ({r_1}^2 + {r_3}^2) - ({x_1}^2 - {x_3}^2) - ({y_1}^2 - {y_3}^2) \\ 2(x_3 - x_2)x_t + 2(y_3 - y_2)y_t = ({r_2}^2 + {r_3}^2) - ({x_2}^2 - {x_3}^2) - ({y_2}^2 - {y_3}^2) \end{cases} \tag{2.3}$$

This also can be treated as a linear matrix:

$$2 \times \begin{pmatrix} x_3 - x_1 & y_3 - y_1 \\ x_3 - x_2 & y_3 - y_2 \end{pmatrix} \begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} ({r_1}^2 - {r_3}^2) - ({x_1}^2 - {x_3}^2) - ({y_1}^2 - {y_3}^2) \\ ({r_2}^2 - {r_3}^2) - ({x_2}^2 - {x_3}^2) - ({y_2}^2 - {y_3}^2) \end{pmatrix} \tag{2.4}$$

Generally, distance measurements are not perfect. Thus, the measured distances are smaller or larger than the real distance, resulting in the three circles shown in Figure 2.2 that might not intersect at the same point in some cases. The solution is to use more than three anchors to decrease errors, which turns the above equations into an overdetermined system:

$$2 \times \begin{pmatrix} x_n - x_1 & y_n - y_1 \\ x_n - x_2 & y_n - y_2 \\ \vdots & \vdots \\ x_n - x_{n-1} & y_n - y_{n-1} \end{pmatrix} \begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} ({r_1}^2 - {r_n}^2) - ({x_1}^2 - {x_n}^2) - ({y_1}^2 - {y_n}^2) \\ ({r_2}^2 - {r_n}^2) - ({x_2}^2 - {x_n}^2) - ({y_2}^2 - {y_n}^2) \\ \vdots \\ ({r_{n-1}}^2 - {r_n}^2) - ({x_{n-1}}^2 - {x_n}^2) - ({y_{n-1}}^2 - {y_n}^2) \end{pmatrix} \tag{2.5}$$

The goal in a solution of this overdetermined system is to minimize the mean square error of $\|Ax - b\|^2$, where 0.5A represents the leftmost matrix, (x_t, y_t) is the position of the target node and b represents the right $\|Ax-b\|^2$ matrix.

$$\|Ax-b\|^2 = (Ax-b)^{\mathrm{T}}(Ax-b) = x^{\mathrm{T}}A^{\mathrm{T}}Ax - 2x^{\mathrm{T}}A^{\mathrm{T}}b + b^{\mathrm{T}}b \tag{2.6}$$

In order to minimize the equation, equation 2.6 is treated as a function of x^{T} and the gradient should be set to zero [37], which results in equation 2.7:

$$2A^{\mathrm{T}}Ax - 2A^{\mathrm{T}}b = 0 \tag{2.7}$$

The final solution is calculated by equation 2.8:

$$x = (A^{\mathrm{T}}A)^{-1}A^{\mathrm{T}}b \tag{2.8}$$

2.4.4 MinMax

In the MinMax technique, each anchor node measures the RSSI value from the target node and calculates its distance d in meters to the target node using the RSSI value based on the path-loss model 2.13. Then a square with width of $2d$ is drawn around the anchor node [39]. The target node lies within the overlapping area of all of the squares drawn around all beacon nodes. This technique is simple to implement, but may have increase error of position estimation as the technique uses a bounding box instead of circle, giving a larger area measured from each anchor node.

In Figure 2.3, the bounding box of the anchor A is created by adding and subtracting the estimated distance d from the anchor position. The minimum point is $(x_1 - d_1, y_1 - d_1)$ and the maximum point is $(x_1 + d_1, y_1 + d_1)$. The most overlapped bounding box is computed by choosing the maximum of all minimum points and the minimum of all maximum points.

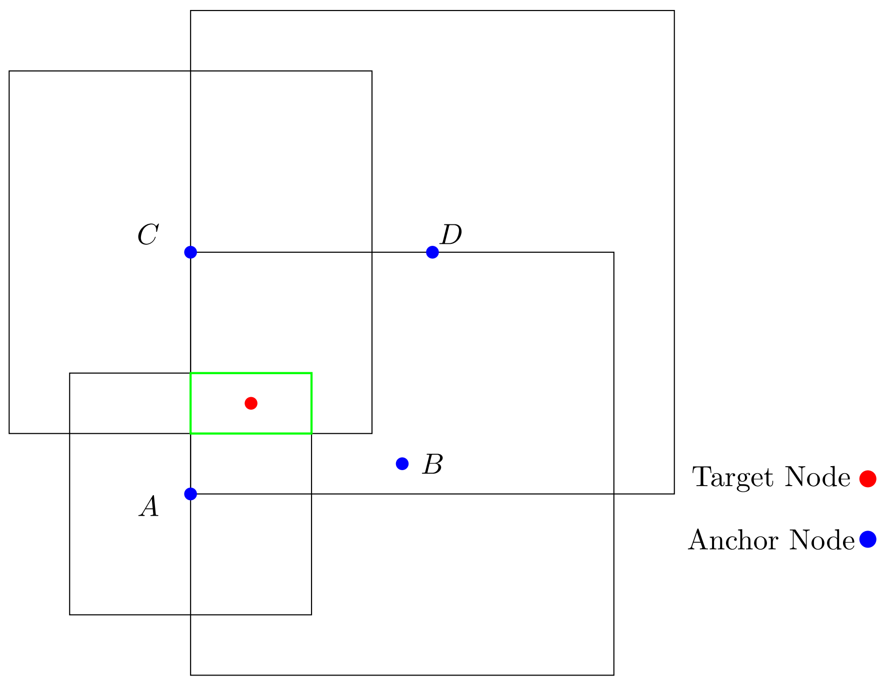

Figure 2.3: MinMax Algorithm

The minimum point is $(x_i - d_i, y_i - d_i)$ and the maximum point is $(x_j + d_j, y_j + d_j)$. Thus, the final position is the average value of these two corner points.

The above four techniques are applied in a number of research works. Apart from these techniques, there are other techniques that achieve high accuracy of the position estimation. These techniques are classified into different categories. The following section categorizes different localization technologies and presents some specific techniques from the literature.

2.5 Localization Algorithms from the Literature

GPS is widely used in localization and can provide accurate information in outdoor locations, but it cannot provide useful information in indoor locations due to its lack of line-of-sight transmission [35]. Besides, the accuracy of GPS devices can not satisfy the requirements of all indoor localization systems. Generally, the accuracy of GPS devices is about 10m [27]. The following sub-sections present an overview of the main methods for indoor node localization, as well as the algorithms that implement these methods.

2.5.1 Range-free Techniques

In range-free methods, measurements, such as signal strength values or arriving angles are not used to directly calculate distances and positions [33]. The location information of an unknown node is depended on close nodes' information. RSSI values are only used to define a proximity level between different sensor nodes, which is applied in methods that are based on proximity information of sensors. Nodes receiving higher strength signals are closer to the target device compared to nodes with lower strength signals. This information is used to define a relative ordering of nodes based on perceived proximity to the target node. Range-free methods do not calculate an actual estimate of the distance between the anchors and the target node. In contrast, they just rely on the relative ordering to geometrically define an area in the localization place, the centroid of the area is then treated as the estimated location of the target node.

Niculescu et al. [49] propose a method called DV-Hop. In their method, each unknown node asks its neighbouring anchor nodes to provide their estimated hop counts, and then estimates the distances to its neighbour beacon nodes by the hop counts to them. Through this mechanism, all nodes in the network obtain the shortest distance, in hops, to each anchor. The unknown nodes then estimate their positions based on the estimated hop distances to the neighbour beacon nodes. The system converts the hop count into the physical distance by calculating the average distance per hop without using range-based techniques. This converting process is calculated by obtaining locations of anchors and hop counts from the target node to anchors inside the network. The average single hop distance is calculated by the following equation 2.9, where (x_j, y_j) is the location of anchor j, and h_j is the distance in hops from anchor j to anchor i. Anchors propagate the estimated hop counts information to nearby nodes. This system is simple to implement, but the disadvantage is that it only works in an isotropic network where the properties of the graph are not changed in each direction, so that hop counts respond to reasonable physical distances.

$$s_i = \frac{\sum \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum h_j} \tag{2.9}$$

Cota et al. [30] present a distributed and formula-based algorithm. In their scheme, each node uses the estimated distance to beacons to solve a set of circle-circle intersection (CCI) problems through a purely geometric formulation. The resulting CCIs are processed to pick those that cluster together, and the most overlapping area is used to estimate a target node's location.

He et al. [33] present a novel range-free localization algorithm called APIT (Figure 2.4). APIT applies a novel area-based approach to locate a target by isolating the environment into a number of small triangular regions between beaconing nodes. The area where a target node resides can be narrowed gradually by distinguishing whether this node is inside or outside of these triangular regions.

The method used to reduce the estimated area is called the Point-In-Triangulation Test (PIT). In this method, the target node chooses three anchors that it is listening to and then tests whether this node is inside the range formed by connecting the three anchors. This process is repeated until there are no more new anchor combinations or required accuracy is achieved. By using combinations of anchor positions, the estimated area in which a node

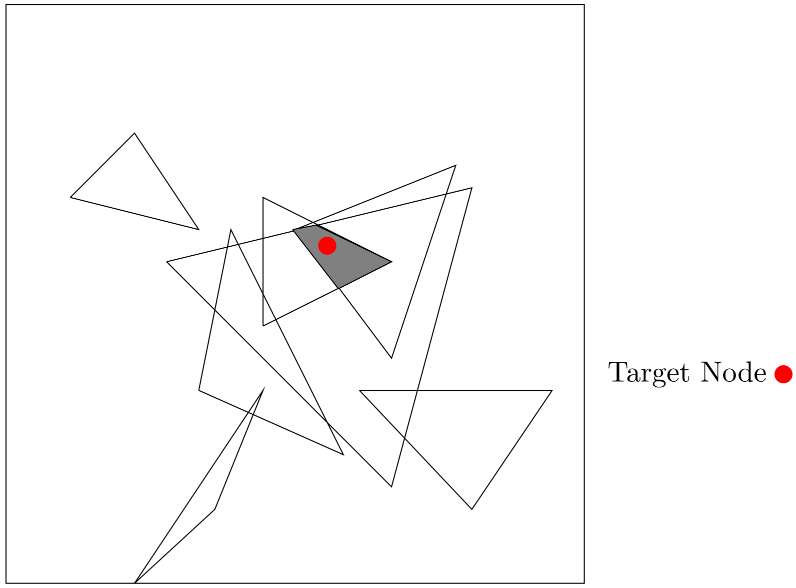

Figure 2.4: APIT Algorithm Example [33]

resides can be reduced. Then APIT calculates the center of gravity (CoG) of the intersection of all of the triangles that the target node is inside to determine the node's final position. APIT scheme performs well when an irregular radio pattern and random node placement are considered.

2.5.2 Range-based Techniques

Range-based methods are generally defined by protocols that use point-to-point Euclidean distance estimates or angle estimates to calculate locations. Range-based systems utilize angle-based, timing-based or signal-strength-based techniques for distance estimation. Range-based methods are widely used in indoor localization, but some of them require additional hardware components.

ToA Technique

The time difference of arrival (ToA) technique is used as a way of obtaining range information via signal propagation time. It involves measuring the time it takes a signal to travel from the transmitter to the base station [45]. This method generally provides good performance in an empty testing place, but error may rise when there are certain obstacles, such as individuals or walls. Imagine that the distance between two nodes P and Q needs to be measured. Node P sends a message to node Q at time t_0. At time t_1, node Q receives the message, and then at time t_2, node Q sends another message to node P. The second message is received by node P at time t_3. As I know the propagation speed of the signal v, the distance d between nodes P 0and Q can be calculated by the equation below (Equation 2.10).

$$d = \frac{v((t_3 - t_0) - (t_2 - t_1))}{2} \tag{2.10}$$

Correal et al. [29] describe a ToA-based Ultra Wideband (UWB) location system using relative location principles to provide enhanced location performance in wireless networks. However, this performance requires a direct transmitting path between different sensors, giving a limitation similar to the need for line-of-sight. also, ultrasonic waves cannot propagate through a wall easily, so it is generally used with other techniques, such as radio technology [38].

TDoA Technique

The time difference of arrival (TDoA) technique is similar to the ToA, but it applies different propagation signals: a fast signal, generally radio signal, and a slow signal, usually ultrasonic signal [55]. I assume that node P and node Q are sender and receiver. Node P sends a radio signal at t_0, and then node Q receives the radio signal at t_1. After that, node P sends an ultrasonic signal to node Q at t_2. Finally, node Q receives the ultrasonic signal at t_3. The propagation speeds of radio and ultrasonic are v_r and v_u respectively. The distance between node P and Q is calculated as the following (Equation 2.11):

$$d = ((t_3 - t_1) - (t_2 - t_0))\frac{v_r v_u}{v_r - v_u} \tag{2.11}$$

Addlesee et al. [15] propose a TDoA-based fine-grained indoor positioning system called the Bat. In this system, the radio frequency (RF) base sends messages to all the receiver nodes and the Bat node. When the Bat receives that signal, it transmits ultrasonic pulses to other nodes. Then this system uses the time intervals between the ultrasonic pulses and RF messages to calculate the distances between the active Bat and other receiver nodes. Although this system offers a high accuracy, it needs many receiver nodes and these nodes should always be turned on. Priyantha et al. [52] propose a better TDoA-based system called the Cricket. It also uses the RF and ultrasonic techniques, but it does not have a RF base station for central control. Therefore, it is simpler and can protect user privacy because a user does not have to communicate with the base station, but it is sensitive to multi-fading, which means the signal propagates in multi-path and reflects from objects, resulting in the inaccurate received signal strengths.

AoA Technique

To localize a target node in 2D, it is sufficient to know two angles towards it from two different known positions [50]. Specifically, angles are measured by getting the signal direction sent by the adjacent nodes through the combination of array antenna and multiple receivers. However, the angle of arrival (AoA) technique is difficult to use for WSN applications, because it requires additional hardware to measure angles. Thus, compared to other range-based method, AoA is less cost efficient.

RSSI Technique

The principle of the radio signal strength indicator (RSSI) ranging technique describes the relationship between the received power, transmitted power of wireless signals and the distance among wireless sensor nodes. This relation is shown in equation (Equation 2.12). P_r is the received power of wireless signals. P_t refers to the transmitted power of wireless signals, d is the distance between the sending nodes and the receiving nodes, n represents the transmission factor whose values depend on the environment of propagation (indoor and outdoor) [60].

$$P_r = P_t \times (\frac{1}{d})^n \tag{2.12}$$

The relationship between RSSI and distance is defined by equation 2.13 [56]:

$$RSSI(dBm) = A - [10n \lg(d/d_0)] \tag{2.13}$$

where n is the path loss exponent and its value is typically between 2 and 6 for indoor locations [53]. The path loss exponent value is related to the experimental environment. A is the received signal strength at 1 meter distance in dBm, d is the distance from a transmitter to a receiver in meters and d_0 is a reference distance, typically 1 meter.

Cherntanomwong et al. [26] propose an efficient approach which uses ZigBee as a communication radio to maintain the connection between devices. The ZigBee radio is cost-efficient and has low complexity as well as power consumption advantages, but it transmits at a low data rate [2]. They apply a location fingerprint-based algorithm which divides the experimental area into a number of equal and small areas, and then stores the RSSI value and the coordinate at each crossing point as a fingerprint. After that, they use the current received signal strength to match the fingerprints and calculate the final position of the mobile node. This algorithm provides good performance in a small testing area. They also compare the performance between using four anchors and six anchors. The results show that more anchors give more accurate estimated positions, but the increase of position estimation accuracy is slight, as the four nodes are sufficient for the size of the experimental area.

Huang et al. [35] propose a system also based on ZigBee protocol and the k-Nearest Neighbour algorithm that calculates the position of a target node based on the locations of the target node's k nearest neighbours. They classify the RSSI values into four classes according to the RSSI ranges they belong to. The received signal is adjusted by different ratios based on the distance coverage of its class and is referred to as weighted RSSI. The weighted RSSI can improve accuracy when choosing the nearest neighbour nodes.

OnkarPathak et al. [51] propose a trilateration-based approach using RSSI data from WiFi access points to estimate locations on a large floor including laboratories, staff cabin and classrooms. Results show that the average positioning error of this system is around 2.5 m. The accuracy of this system can be improved if more access points are deployed.

Lau et al. [40] propose a low complexity RSSI smoothing algorithm to minimize the fluctuation of the radio signal received from each fixed reference node when the target node is moving. However, in their method, the current positions are based on the previous locations and the mobile node should move in a fixed route, which means the node cannot move arbitrarily. In addition, if the calculated position of the current measuring point gives a large error, it will affect the following points to be measured.

Luo et al. [43] compare four RSSI-based localization algorithms: MinMax, Maximum Likelihood, Ring Overlapping Circle RSSI and k-Nearest Neighbour. They apply cumulative distribution function (CDF) of localization error as well as basic statistical metrics (average value and median value) of localization error to measure the localization performance. The CDF model is defined as:

$$F(e) = \int_0^e f(x)dx \qquad x \geq 0 \tag{2.14}$$

where e is a random value on x-axis and $f(x)$ is the probability of each x value less than e. The CDF model describes the cumulative probability of a value less than or equal to e. From the CDF of localization error, it is simple to observe the localization error at a given confidence level, such as 60%. Their results show that the MinMax has better performance than other algorithms. The MinMax algorithm is easier to implement and the running time and data storage are linear in the number of anchors. Although the k-Nearest Neighbour algorithm provides good accuracy in some cases, it is sensitive to the positions of the nodes.

Lee et al. [41] propose a WSN based 3-D system for multiple user tracking. As the RSSI is easily affected by multipath fading, they use a refined algorithm to filter out the noise transmitted in the RSSI signals. Only a few solutions focus on a 3-D model, so this is their advantage.

Anagnostopoulos et al. [20] propose a weighted average method, combined with the selection of the closest beacons and then averaging the estimated distances which correspond to the latest received RSSI measurements from each anchor. They use a new device called iBeacon [6] as an anchor node that employs the Bluetooth Low Energy (BLE) technology.

2.6 Summary

In this chapter, different types of wireless sensor networks were first presented. Then, WSN applications categories were introduced. After that, I introduced some indoor WSN applications including healthcare monitoring and localization. In the next section, four popular radio technologies including ZigBee, Bluetooth, BLE and ANT were presented. ANT radio technology is new and becoming popular in the fitness area. It was applied in my experiment to implement my indoor localization system due to its low power consumption characteristic. The following section mainly described four localization approaches including fingerprinting, k-Nearest Neighbour, trilateration and MinMax. Among these approaches, the MinMax generally provided more accurate position estimations than the other approaches. In addition, two localization method categories including range-based and range-free methods were introduced. Range-based methods including techniques based on measuring transmission angle, time and distance were also reviewed. Among these techniques, AoA, ToA, TDoA and RSSI were dominant and provided better performance than other techniques in terms of position estimation accuracy. In contrast, range-free methods only utilized signal strength to calculate the proximity information between nodes instead of using and refining angles or distances. Range-free techniques also required many more devices than range-based techniques.

My indoor localization system is range-based and it applies RSSI information to calculate the distances and then the locations of the target nodes. Previous research mainly focused on ZigBee and Bluetooth protocols, but I use the ANT technology as the RF base for communication between sensors. The following chapter introduces my indoor localization system in detail, which includes two experimental scenarios: a small area and a large area (two rooms and a corridor).

Chapter 3

Localization Scenarios

Keeping the localization system energy-efficient is a key component to make sure that the whole system can run for a long period, such as a couple of weeks. The ANT technology was used in my indoor localization system. It is widely used in the fitness and sports domain, and also has the advantages of low power consumption and flexible network deployment. Based on this technology, I considered two scenarios to test my indoor localization system: a small area and a large area. I developed two algorithms for the small area. The first algorithm was based on the fingerprinting technique [26] and the nearest reference point parameters (n and A in Equation 2.13) to calculate the position of the mobile node. The other algorithm was based on the RSSI measurements and the k-Nearest Neighbour algorithm [21]. The large area consisted of a corridor and a second room, in addition to the single room of the small area. In the large area, I applied new devices (WASPs/WASP-PoEs) [13] (will be introduced in detail later) as anchors instead of Garmin Chirps [2] in the small area. The information collected from the WASP/WASP-PoEs were transmitted to the server in the same local area network. The localization operation was also performed at the server. I used the second algorithm in the small area as the localization algorithm in the large area. The following algorithm 1 briefly explains the training phase and position estimation phase of the first algorithm: fingerprinting reference point (FRP) algorithm.

Algorithm 1: Fingerprinting Reference Point

Phase FINGERPRINT TRAINING

```
begin
    Initialize the database (quad-tuple values);
    foreach reference point on the grid do
        Collect multiple RSSI readings from anchor nodes;
        foreach RSSI reading do
            Eliminate noise from the raw RSSI readings with a 1-D median filter;
            Find and store the average RSSI set into the database;
        end
    end
end
```

Phase POSITION ESTIMATION

```
begin
    Read the RSSI values sent from the anchors to the mobile node;
    Eliminate noise from the raw RSSI readings with a 1-D median filter;
    Search for the node's nearest neighbour in the database and calculate A and n, using equations
    3.4 and 3.3;
    Calculate final coordinate by using A and n from the previous step and current received RSSI
    values;
end
```

3.1 Small Area Scenario

My experimental tools in the small area include several Garmin Chirps [2] as anchor nodes that use ANT radios and send RSSI values every 1.5 to 2 seconds. The size of a Garmin Chirp is only ($3.3cm \times 2.3cm \times 0.7cm$) and the weight is 28 grams, so it is convenient to carry. In addition, the communication range is around 10 meters, which is sufficient for a small area coverage.

A Garmin Chirp can run for at least one year on a single coin battery [4]. As a comparison,

Figure 3.1: A Garmin Chirp [3]

a TelosB can only run about 150 hours on two AA batteries [48]. I also use an ANT equipped USB dongle attached to my laptop as the mobile (target) node and all the calculation is executed on this laptop.

The small area consists of a $5m \times 5m$ grid with 1m steps (Figure 3.2). The Garmin Chirps are placed at the four corners as the anchor nodes. Another deployment area of $2.5m \times 2.5m$ is also applied in this experiment as a comparison to the $5m \times 5m$. This is used to test whether the position estimation accuracy is influenced dramatically when the node deployment area is changed while the number of anchors is the same.

3.1.1 Fingerprinting Reference Point Calculations

Consider Figure 3.3, where the upper left corner, point A, is the coordinate (0,0). The mobile (target) node O receives RSSI values -40, -24, -42, -36, from anchors A, B, C, and D, respectively. A larger RSSI values means the corresponding anchor nearer to the target node. Now consider Table 3.1 with the partial fingerprint readings of the neighbouring nodes in the database. The algorithm selects the second entry (of reference point q) from

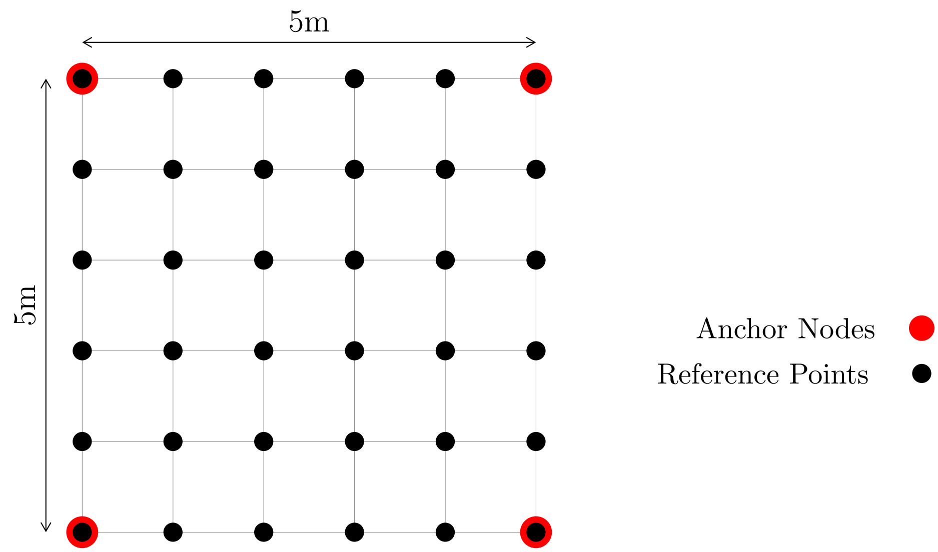

Figure 3.2: Small Area Layout

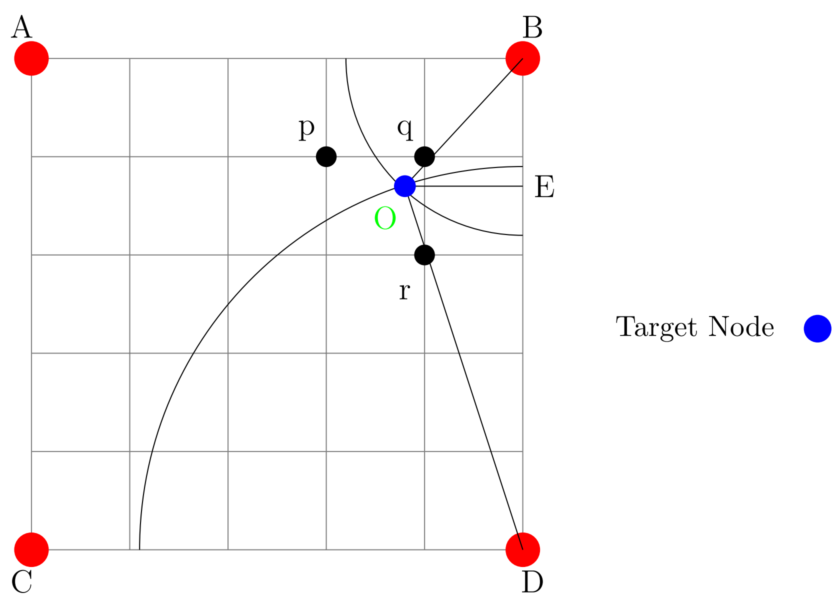

Figure 3.3: Location Estimation

the table, because it has the minimum difference to mobile node O. At this step, compared to the traditional selecting way (simply adding the RSSI difference from each anchors), different weight is assigned to different anchors to guarantee that anchors with higher RSSI values can

Coordinates	**RSSI** (r_1, r_2, r_3, r_4)
...	
(3,1)	(-38.3, -29.7, -44.9, -39.2)
(4,1)	(-40.6, -21.8, -43.2, -32.1)
...	
(4,2)	(-42.2, -30.5, -40.6, -29.6)
...	

Table 3.1: Fingerprint Training

obtain larger weights. Thus, the RSSI value -24 from anchor B, occupies the most weight when selecting the closest neighbour from the database.

$$R_{Bq} = A - [10n \lg(d_{Bq}/d_o)] \tag{3.1}$$

$$R_{Dq} = A - [10n \lg(d_{Dq}/d_o)] \tag{3.2}$$

Since the position of the point q is known, the values of the parameters n and A can be calculated using Equations 3.1 and 3.2, where R_{Bq} and R_{Dq} are the RSSI values from anchor B and D to point q, and d_{Bq} and d_{Dq} are the distances from anchor B and D to point q. Equations 3.3 and 3.4 show how n and A are calculated.

$$n = \frac{\lg(d_{Bq}/d_{Dq})}{10(R_{Dq} - R_{Bq})} \tag{3.3}$$

$$A = \frac{d_{Bq}/d_{Dq}}{R_{Dq} - R_{Bq}} \lg(d_{Bq}/d_o) \tag{3.4}$$

As the reference point q and the mobile node O are closest, their parameter values, A and n, should be very similar. Since the RSSI values R_{BO} and R_{DO}, as well as A and n are known, the distances d_{BO} and d_{DO} can also be calculated according to Equations 3.7 and

3.8. Finally, by using the Pythagorean Theorem [9], the distances of d_{BE} and d_{OE} can be calculated by Equations 3.5 and 3.6 to obtain the coordinates of point O.

$$d_{BE} = \frac{{d_{BD}}^2 - {d_{OD}}^2 + {d_{OB}}^2}{2d_{BD}} \tag{3.5}$$

$$d_{OE} = \sqrt{{d_{BO}}^2 - (\frac{{d_{BD}}^2 - {d_{OD}}^2 + {d_{OB}}^2}{2d_{BD}})^2} \tag{3.6}$$

3.1.2 Local Weighted k-Nearest Neighbour Algorithm

The Local Weighted k-Nearest Neighbour (LW-kNN) algorithm 2 is based on the RSSI value and the k-Nearest Neighbour algorithm, described as the following:

Algorithm 2: Local Weighted k-Nearest Neighbour

```
begin
    Initialize the database (for quad-tuple values);
    foreach reference point on the grid do
        Calculate the average values of parameters A and n from Equation 2.13;
    end
    foreach RSSI reading do
        Calculate the distances between the mobile node O and the anchor nodes by using the A and
        n from the last step and Equations 3.7 and 3.8 to obtain the node O's rough position;
        Each anchor node is given a weight according to the distance between it and the node O's
        neighbour point that is closest to this beacon (Equation 3.9);
        Each anchor node's weight times its coordinate and the sum is the position of the mobile
        node (Equation 3.10);
    end
end
```

$$R_{BO} = A - [10n\lg(d_{BO}/d_o)] \tag{3.7}$$

$$R_{DO} = A - [10n\lg(d_{DO}/d_o)] \tag{3.8}$$

Similar to the FRP algorithm above, at the position estimation stage, the closest neighbour of the mobile node is selected by applying different weights to anchor nodes according to the distances between the neighbours and anchor nodes. In this way, a more accurate nearest neighbour will be selected compared to the traditional k-Nearest Neighbour algorithm. In the two equations below, W_k represents the weight of each nearest neighbour, D is the distance between node O's neighbour point and its nearest anchor node on the corner, (x_o, y_o) is the coordinate of the target node and h is the number of nearest neighbours. Equation 3.9 below gives a shorter distance assigns greater weight. Equation 3.10 explains that the final mobile node's position is calculated by summing each nearest neighbour's coordinate multiplied by its weight.

$$W_k = \frac{\frac{1}{D_k}}{\sum_{k=1}^{h} \frac{1}{D_k}} \tag{3.9}$$

$$(x_o, y_o) = \sum_{k=1}^{h} W_k (x_k, y_k) \tag{3.10}$$

3.2 Large Area Scenario

This scenario is based on the same algorithms and devices used in the small area, but I also introduce new devices called WASP-PoE and WASP [12]. A WASP is an ANT-to-WiFi bridge to connect ANT devices, such as a Garmin Chirp, to WiFi. The WASP [13] is capable of communicating with at most 8 ANT devices and designed to receive messages from multiple ANT devices. The ANT messages are reformatted and broadcast as UDP packets via WiFi. WASP provides an effective and low energy option to capture data from different sensors continuously to an Ethernet based device. A computer or other mobile devices can receive the ANT data transmitted via WASPs if all of devices are within the same local area network and the WASPs must be in the infrastructure mode, which is used as anchors to continuously transmit ANT messages to the server computer.

Figure 3.4: A WASP Device [11]

WASP-PoEs are similar to WASPS, but the difference is that WASP-PoEs communicate with PCs through a wired Ethernet network. Thus, it is easier to deploy a WASP/WASP-PoE and ANT network by using WASP-PoEs, as I just need to connect WASP-PoEs via Ethernet to the local network with the PC. WASPs need more network configurations to join the same network with the server PC. However, flexibility of WASP-PoEs decreases as they do not support WiFi. Once a connection to a network is established, a WASP opens a multicast UDP streaming connection at IP address 239.78.80.1 using port 51113. The ANT data is automatically forwarded to this address. Then other devices, such as PCs or tablets can access to the data through this multicast address if they are within the same local area network that the WASPs are connecting to. Appendix A explains how to configure and deploy WASPs/WASP-PoEs in detail. WASPs/WASP-PoEs are deployed as anchors instead of Garmin Chirps in the large area scenario. The following section introduce how WASPs/WASP-PoEs are used to locate the mobile nodes.

3.2.1 Experiment Deployment and Algorithm

The experiment deployment area is extended to a larger indoor space including a corridor and another room, which is used as a proxy to represent a location in a shopping mall, school or hospital.

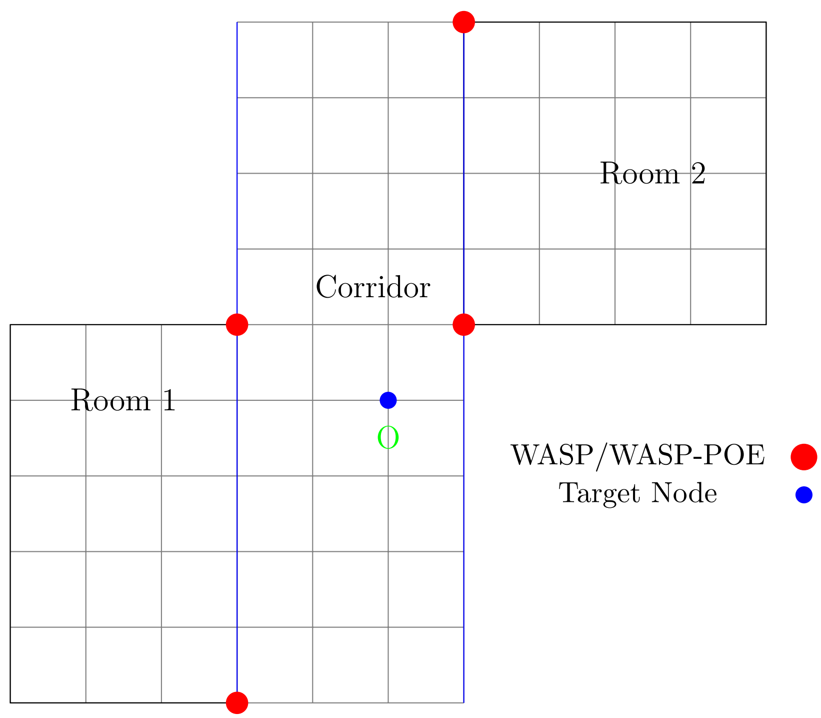

Figure 3.5: Large Area Layout

Figure 3.5 shows the layout and the placement of WASP/WASP-PoEs in the large area. Similar to the small area, the deployment area is also divided into grids ($1m \times 1m$). A person wears a Garmin Chirp sending RSSI values to WASPs/WASP-PoEs. This time, the WASPs/WASP-PoEs are anchor nodes located at the red dot positions while Garmin Chirps are mobile target nodes. After the WASP/WASP-PoEs receive the ANT data from the Garmin Chirps, the data is transmitted to a server PC via WiFi or Ethernet. Each time the received data contains the Garmin Chirp ID, the WASP/WASP-PoE IP address and the RSSI values from a Garmin Chirp to a WASP/WASP-PoE. Then, the locations of users are calculated and shown on the server PC.

The large area scenario also applies the algorithms in the the small area. In the fingerprint training phase, I use the fingerprinting algorithm [26] to collect the raw RSSI values and the 1D median filter [31] to eliminate the signal noise. Next, I apply the mode technique in [47], using the RSSI value that has the highest frequency at a specific position instead of the mean RSSI value, to obtain the RSSI value at each coordinate as my training fingerprint data. As there are walls between rooms and the corridor, the ANT signal attenuates sharply when transmitting through the walls between rooms and the corridor. The fingerprint database that I built can deal with this issue, because it has recorded the attenuate signals if there are barriers between Garmin Chirps and WASPs/WASP-PoEs. In the location estimation phase, the local weighted k-Nearest Neighbour algorithm is used to estimate the positions of the mobile nodes. The transmission range of the large area scenario is extended by WASPs/WASP-PoEs, so the server does not need to be moved as long as it is within the same local area network. This scenario can be expanded to a larger area, such as a hospital or gym.

In the large area, as the size of deployment area is much larger than that of the small area scenario, greater errors than those of the small area are acceptable as long as whether a person with a sensor is in a room or in the corridor can be distinguished. The localization accuracy of large area scenario is at room-level. The position close to the wall between two rooms is difficult to distinguish. My goal is to deploy these devices in a wide indoor environment efficiently and provide an accurate estimated position.

3.3 Summary

My indoor localization system was deployed under two testing scenarios: a small area and a large area. The ANT technology was chosen as the communication radio between ANT supported devices, such as Garmin Chirps and WASPs/WASP-PoEs, due to its advantages of low energy cost. Two algorithms: the FRP algorithm and the LW-kNN algorithm were proposed in this section. The FRP algorithm was based on the fingerprinting algorithm and then it searched and calculates the estimated nearest point's parameters (A and n) of the mobile node. The final position of the mobile node was then calculated by using the current received RSSI values and calculated parameters of the nearest point. The LW-kNN algorithm assigned different weights to the mobile node's neighbour points according to the distances between the mobile node and them. The final coordinate was calculated by summing each node's coordinate multiplying its weight. In the large area scenario, the testing area was extended to a place including two rooms and a corridor. WASPs/WASP-PoEs were treated as anchors to receive RSSI values from a Garmin Chirp (mobile node), and then to calculate the mobile node's position by using the algorithms in the small area scenario. The accuracy of these localization algorithms is evaluated in the next chapter. Also, the k-Nearest Neighbour (kNN) and MinMax algorithms are compared with the two algorithms above under different environments.

Chapter 4

Experimental Evaluation

In my experiments, RSSI values from fixed nodes are important because all the calculations of distances are based on these values. This evaluation part was tested on 4 aspects: deployment area size, number of anchors, obstacles and temperature. Four localization algorithms including: fingerprinting reference point (FRP), local weighted k-Nearest Neighbour (LW-kNN), MinMax and k-Nearest Neighbour (kNN) were tested under different environments. The goal of this part was to evaluate my hypothesis tests:

- As the deployment area size decreases with the number of anchor nodes unchanged, the accuracy of estimation position will increase significantly,
- Increase in the number of anchor nodes will increase the position estimation accuracy,
- Static or mobile obstacles lead to less accurate estimated positions,
- The temperature of the environment affects the position estimation accuracy.

4.1 Small Area Evaluation

4.1.1 Experiment 1: Impact of Size of Deployment Area

Deployment area is a parameter which influences the accuracy of position estimation. In order to test this, the experiment is deployed in two environments of different sizes: $5m \times 5m$ and $2.5m \times 2.5m$. In both environments, the numbers of anchor nodes are four and all of these nodes are placed at the corners. No big obstacles are placed in these areas, so the signal can transmit smoothly.

The goal of this this experiment to test whether the position error of the target node changes significantly if the deployment area is decreased. Also, my algorithms are tested to show if they can provide more accurate performance than other algorithms in different deployment area sizes. At the fingerprint training phase, I first use the 1D median filter in [31] to eliminate signal noise, then calculate the average value at each point, after that, store the positions and the RSSI values. In the position estimation stage, the kNN algorithm[21] is compared to my algorithms. The MinMax algorithm [43] generally performs better than other three algorithms: *Maximum Likelihood*, *Ring Overlapping Circle RSSI* and *k-Nearest Neighbour*, so it is also an important comparison of my algorithms.

Table 4.1 summaries the average and median errors of four algorithms in $5m \times 5m$ (in meter). It demonstrates that my FRP algorithm performs better than the other algorithms in each error category (average error is 1.13m, median error is 1.18m) while the kNN algorithm gives the largest errors not only in average error (1.36m), but also in median error (1.48m). The LW-kNN and the MinMax algorithm rank in the middle, but the LW-kNN algorithm performs slightly better than the MinMax algorithm.

Figure 4.1 shows the Cumulative Probability Function (CPF) for the average estimated

Algorithms	Average Error	Median Error
k-Nearest Neighbour (kNN)	1.36	1.48
MinMax	1.35	1.39
Fingerprinting Reference Point (FRP)	1.13	1.18
Local Weighted k-Nearest Neighbour (LW-kNN)	1.33	1.35

Table 4.1: Average and Median Errors of Four Anchors in $5m \times 5m$

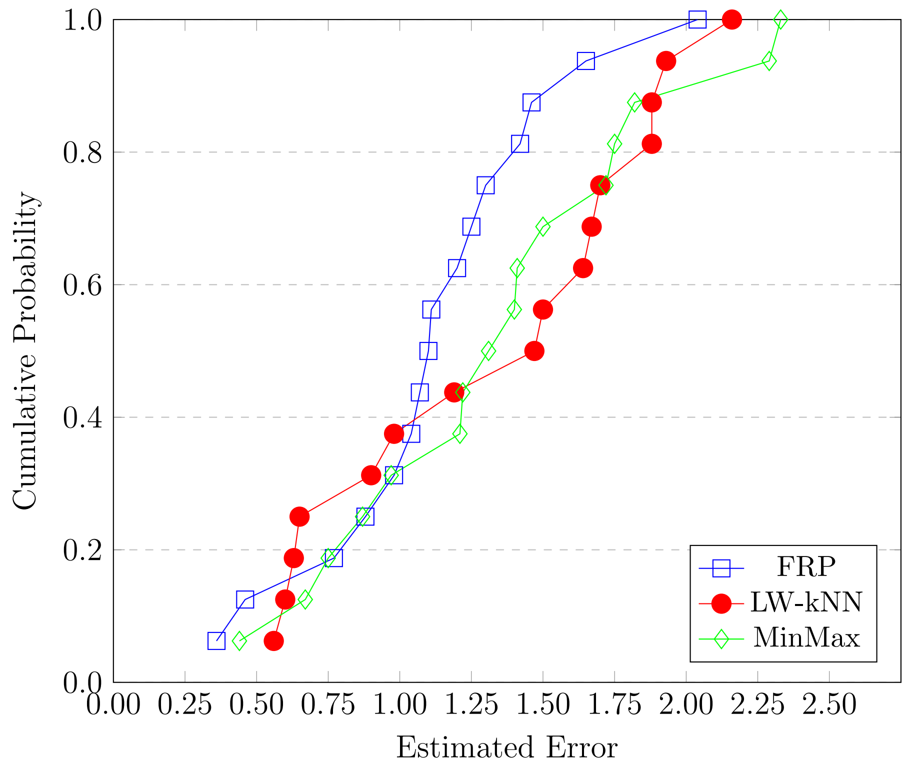

Figure 4.1: CPF of Average Errors of Four Anchors in $5m \times 5m$

position errors of the top three algorithms: FRP, LW-kNN and MinMax algorithm from Table 4.1. CPF [43] demonstrates the distribution of estimated position errors. For instance, in the range between 20% and 60% , the errors of the FRP algorithm are within 0.75m and 1.18m, while the errors of the MinMax algorithm fall into the range between 0.75m and 1.38m. The faster the trend rises, the better performance it gives. Thus, it indicates that the FRP algorithm provides the best accuracy according to the overall trend of the CPF. I also notice that there are some crossings between different algorithms. For example, the LW-kNN algorithm crosses the FRP algorithm at the point (0.62, 0.16) and (1.03, 0.38) in the figure, which means that the LW-kNN algorithm provides about 22% better position estimation errors than those of the FRP algorithm. Even though the FRP algorithm performs the best overall, the LW-kNN algorithm gives smaller errors than it on some specific measured points in the deployment area, such as (3, 3) and (3, 2). As LW-kNN can provide smaller position estimation errors than FRP at some specific points, it can be used for testing those points with smaller errors and the rest points can be tested by FRP in future research.

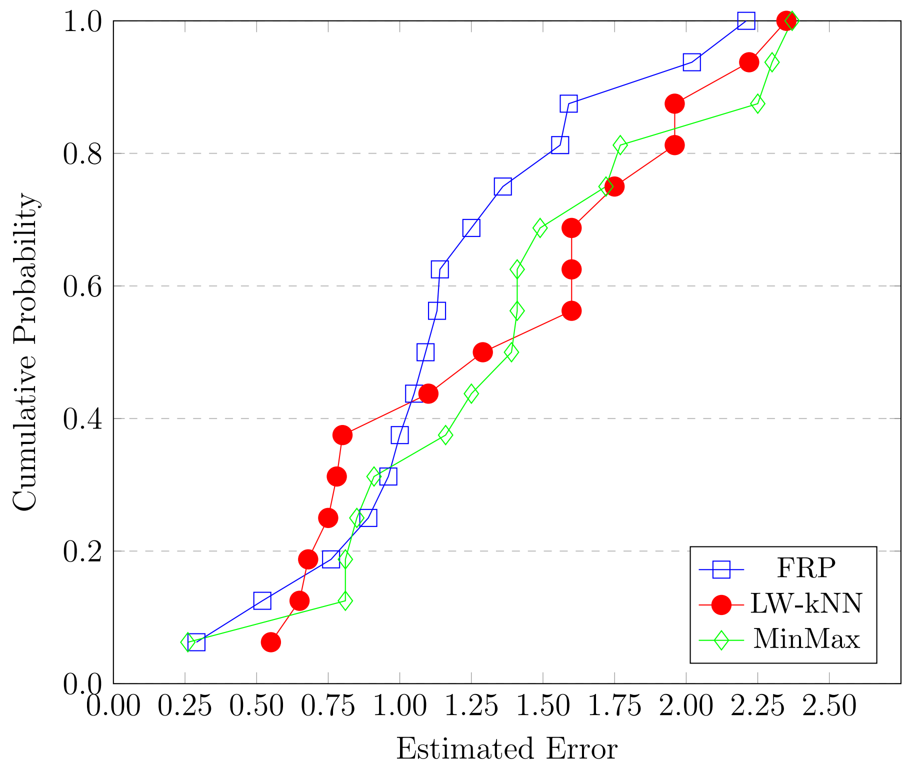

Figure 4.2: CPF of Median Errors of Four Anchors in $5m \times 5m$

Figure 4.2 shows the CPF of median errors of the three best algorithms. At each percentage level, the FRP algorithm outperforms to the other two algorithms, except between the range 18% and 43%. The trend of the FRP algorithm grows sharply before the percentage level 87%, but slows down after that, which indicates that most of the errors of FRP algorithm (around 87%) stay within the range between 0% and 87% (0.25m to 1.54m). The performance of the LW-kNN algorithm is superior to that of the MinMax algorithm between the percentage level 10% and 55%, and then after 55% their results are similar.

Table 4.2 summaries the average error and median error of the four localization algorithms in the $2.5m \times 2.5m$ test scenario (in meter). The performance of the FRP algorithm ranks the first, followed by the MinMax algorithm in both average error and median error. The LW-kNN algorithm is only superior to the kNN algorithm although it achieve good performance (the average error is 0.70m and the median error is 0.72m). I also notice that while the size of the measured area is decreased from $25m^2$ to $6.25m^2$, the estimated errors do not drop dramatically. The proportion of the average errors of $25m^2$ and $6.25m^2$ is 1.93, which is similar to the proportion of the square roots of their area sizes ($5/2.5 = 2$).

Algorithms	**Average Error**	**Median Error**
k-Nearest Neighbour (kNN)	0.74	0.83
MinMax	0.64	0.64
Fingerprinting Reference Point (FRP)	0.61	0.62
Local Weighted k-Nearest Neighbour (LW-kNN)	0.70	0.72

Table 4.2: Average and Median Errors of Four Anchors in $2.5m \times 2.5m$

Figure 4.3 shows the similar trends to those of the three algorithms in Figure 4.1. The FRP algorithm still performs the best, but the performance of the MinMax algorithm is superior to that of the LW-kNN. The errors of the FRP and LW-kNN algorithm are distributed more evenly than those of the MinMax algorithm. The MinMax algorithm performs the best between the percentage levels 22% and 68%, but its largest error (1.32m) is much larger than that of the FRP algorithm (0.85m) and LW-kNN (1.08m).

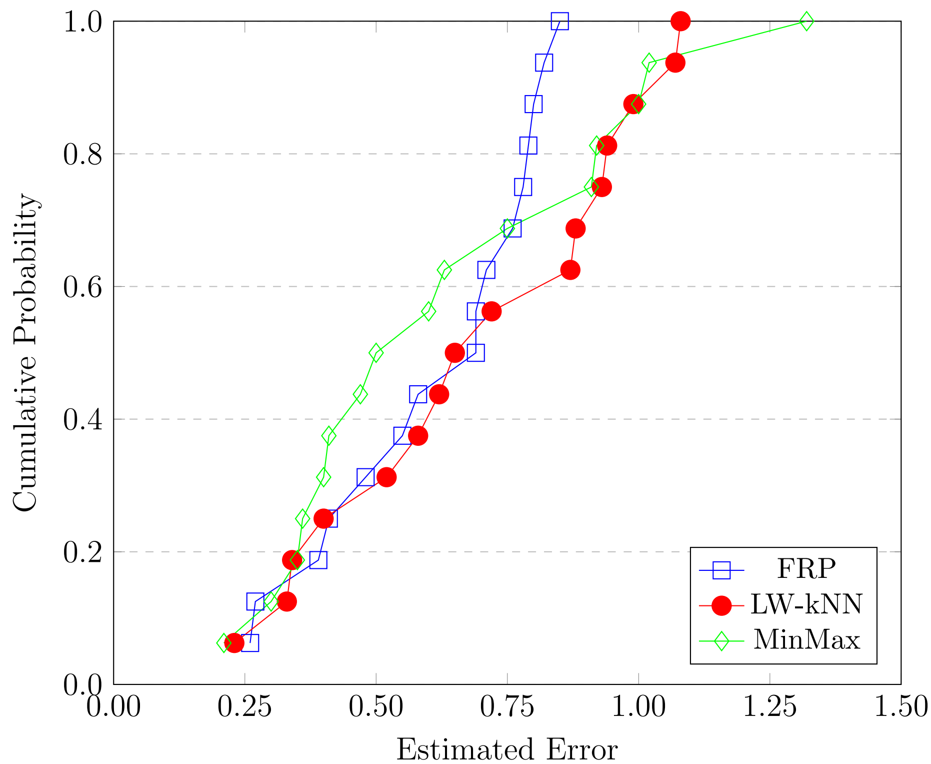

Figure 4.3: CPF of Average Errors of Four Anchors in $2.5m \times 2.5m$

4.1.2 Experiment 2: Impact of Number of Anchors

In this experiment, the number of fixed anchor nodes is varied to show the influence on the localization accuracy of the mobile node. Specifically, this experiment is deployed in the small area scenario and the numbers of anchor nodes are four and six respectively. As shown in Figure 4.4, the four green anchors represent the four-node scenario. Two new anchors are placed at the left and right side of the deployment area for the six-node scenario. The results of these two scenarios are compared between each other. Then, how many fixed nodes are sufficient for a specific area, such as a $5m \times 5m$ area will be known. Both Experiment 1 and 2 are focusing on the node density, and the experiment deployment sizes and node numbers are changed in each experiment, respectively.

In the small area, four and six fixed nodes are deployed respectively in a $5m \times 5m$ square

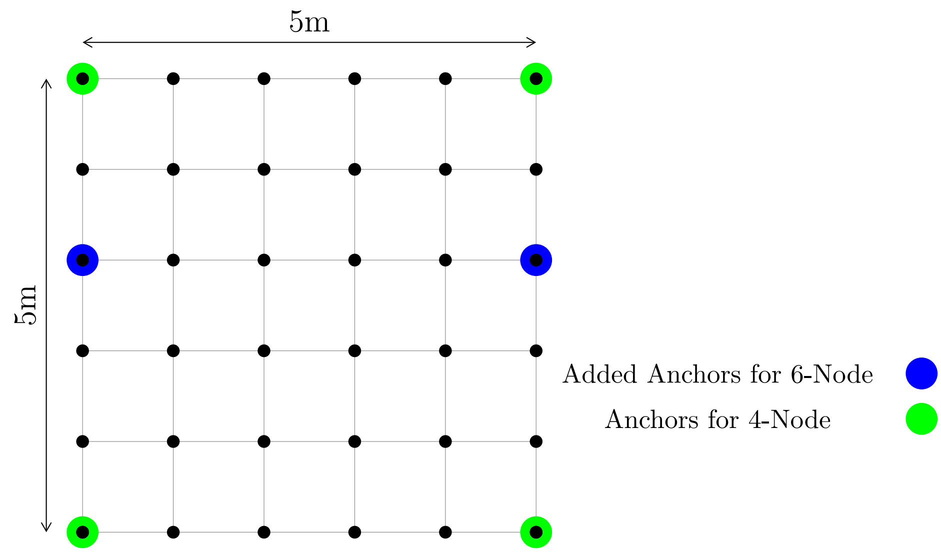

Figure 4.4: Layout of Four and Six Anchors

Algorithms	**Average Error**	**Median Error**
k-Nearest Neighbour (kNN)	1.25	1.36
MinMax	1.27	1.28
Fingerprinting Reference Point (FRP)	1.08	1.02
Local Weighted k-Nearest Neighbour (LW-kNN)	1.23	1.29

Table 4.3: Average and Median Errors of Six Anchors in $5m \times 5m$

area that is divided into 25 equal sub-parts. Table 4.3 summaries the performance of the four algorithms in a $5m \times 5m$ place with six anchors. It shows that the errors of all the algorithms decrease compared to the performance in Table 4.1 (4 anchors in 5m x 5m area), but the decreased amount is not that significant. The average decreased amount of the average errors of the four algorithm is only 0.085m, while the average value of the median errors of the four algorithms drops from 1.375m to 1.237m.

Figure 4.5 shows the effect on two algorithms when the number of nodes is increased from four to six. I find that FRP-6Node performs better than the FRP-4Node overall, except the range between 7% and 18% as well as 48% and 69%. Although FRP-6Node utilizes more nodes, it still cannot guarantee that all the points it tests can provide more accurate results compared to the FRP-4Node. However, it is clear that the largest error of the FRP-6Node is decreased from 2.04m to 1.61m. Similar to the FRP algorithm, the LW-kNN-6Node outperforms the LW-kNN-4Node except for the range between 7% and 38%. The largest errors of the LW-kNN-6Node and the LW-kNN-4Node are 1.97m and 2.16m respectively.

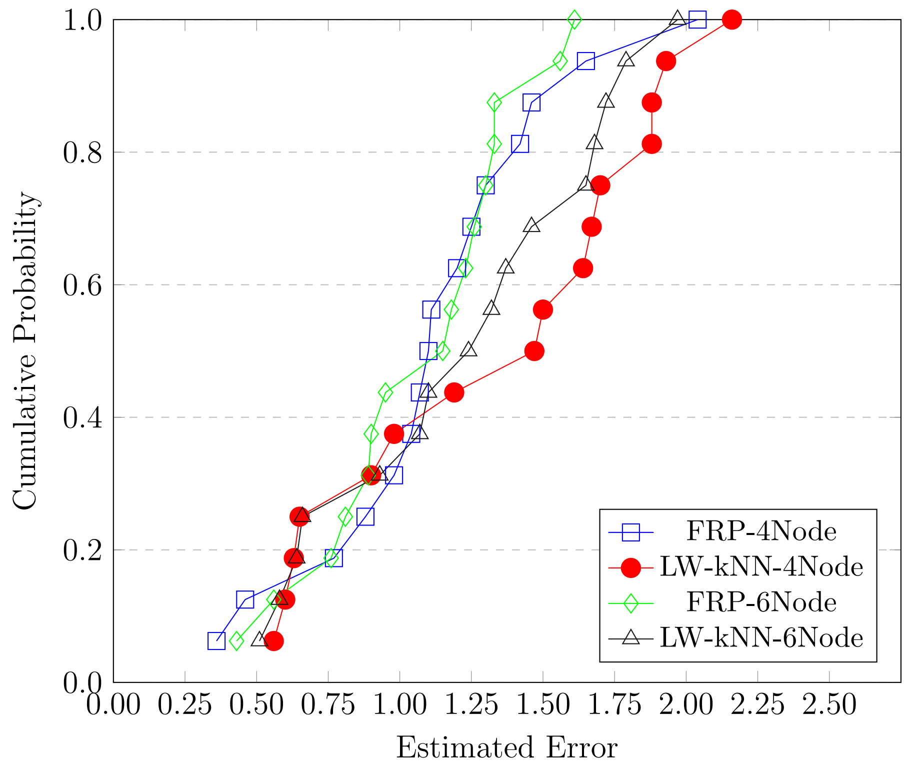

Figure 4.5: CPF of Average Errors of Four and Six Anchors in $5m \times 5m$

4.1.3 Experiment 3: Impact of Obstacles

As radio signal propagation is sensitive to obstacles, this experiment was deployed to test the influence of obstacles to the accuracy of position estimation. Specifically, static obstacles, such as tables and chairs, are placed between anchors and sensor nodes. A big white board was also placed beside one sensor, thus this environment is crowded. In addition, random mobile obstacles are introduced in this experiment: several individuals are moving within or passing the testing area randomly. In this way, a crowded situation with static and mobile obstacles is implemented. In order to evaluate the influence of obstacles, I build my experiment in a $5m \times 5m$ place and compared the performance of my two algorithms (FRP and LW-kNN) with obstacles and without obstacles. The following Figure 4.6 demonstrates the influence of obstacles on the FRP and the LW-kNN algorithm.

Algorithms	**Average Error**	**Median Error**
FRP	1.13	1.18
LW-kNN	1.33	1.35
FRP-Obstacle	1.24	1.21
LW-kNN-Obstacle	1.45	1.57

Table 4.4: Average and Median Errors using Four Anchors in $5m \times 5m$ with and without Obstacles

From Figure 4.6, I find that both the FRP and the LW-kNN are affected by obstacles. As the radio signal attenuates when passing though the obstacles, the RSSI values are affected. As a result, at the estimation stage, when I first search the rough position of the mobile node, the results are changed to some inaccurate values, leading to larger errors. It also shows that even though these two algorithms are influenced by obstacles, their accuracies do not fall down sharply. I notice that still 45% of the estimated position errors of the FRP and the LW-kNN are within 1.15m and 1.27m respectively. The biggest difference between the FRP and the FRP-Obstacle is around the 90% level. Specifically, 90% of the estimated position errors of the FRP are within 1.46m while the FRP-Obstacle's error range increases to 1.72m. The maximum difference between the LW-kNN and the LW-kNN-Obstacle is at 32% level. The error range of the LW-kNN-Obstacle increases from 0.9m to 1.24m compared to the LW-kNN, indicating that those measured points with small errors in the LW-kNN are greatly

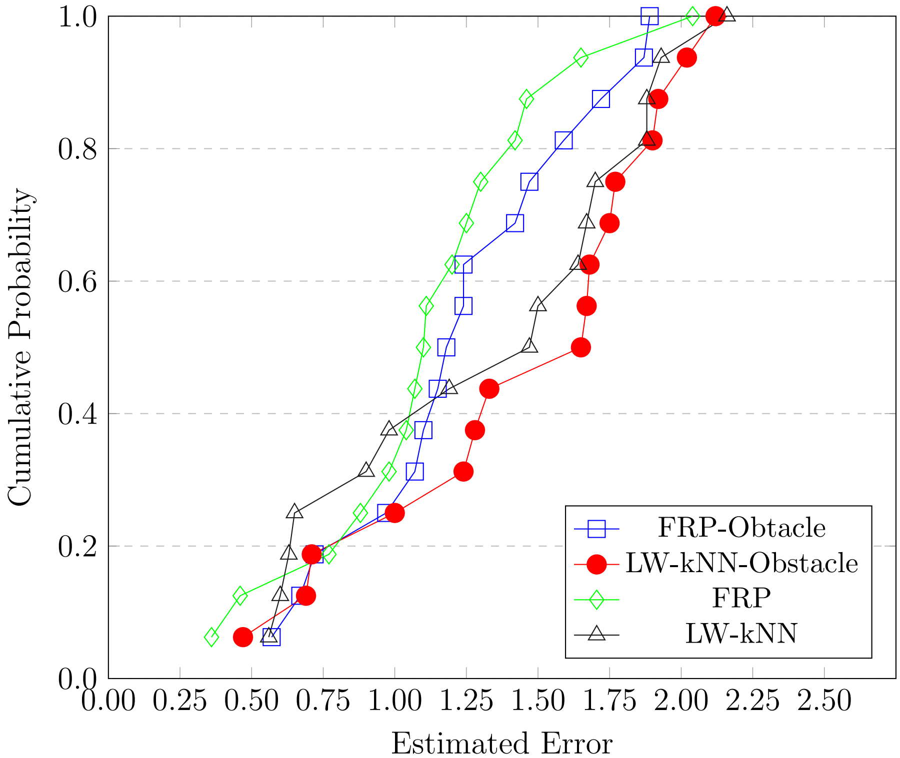

Figure 4.6: CPF of Average Errors with Four Anchors in $5m \times 5m$ with and without Obstacles

affected by obstacles. From the whole trend of the graph, I conclude that the estimated position errors of the FRP-Obstacle mostly increase by a similar amount compared to the FRP at different levels, which means the error differences between the FRP-Obstacle and the FRP grow similarly at each percentage level instead of rising significantly at a specific percentage level.

4.1.4 Experiment 4: Impact of Temperatures

Boano et al. [23] tested the influence of temperatures on RSSI readings in an outdoor place. The results show that RSSI readings drop down as the temperature rises, but the decreasing amount of RSSI readings is not big. The goal of my experiment is to evaluate the impact of temperatures on indoor localization errors. As the change of temperatures at an indoor place is slight, a temperature difference of 5°C is more than sufficient for my experiment. Hence, my experiment is deployed into two environments with different temperatures: 19°C and 24°C. Four anchor nodes are deployed in an $5m \times 5m$ place. Table 4.5 summarizes the performances of the FRP and the LW-kNN of different temperatures.

Algorithms	**Average Error**	**Median Error**
FRP-24	1.16	1.26
LW-kNN-24	1.37	1.36
FRP-19	1.13	1.18
LW-kNN-19	1.33	1.35

Table 4.5: Average and Median Errors of Four Anchors in $5m \times 5m$ with Temperatures 19°C and 24°C

Table 4.5 shows that the average and median errors of FRP-24 (FRP at 24°C) increase in a small amount (less than 0.1m) compared to FRP-19 (FRP at 19°C). I also notice that the performance of the LW-kNN-24 is almost the same as the performance of LW-kNN-19, as the differences of the average and median error are only 0.04m and 0.01m. As a result, small changes of temperatures, such as 5°C can only increase the estimated errors slightly, which is not a significant factor in an indoor localization system.

Figure 4.7 demonstrates the performance of the FRP and the LW-kNN at 19°C and 24°C in detail. The errors of FRP-24 are larger than those of FRP-19 between 12.5% and 81.25%, but the average increased errors difference is within 15cm, which is not a significant increase. The trend of the LW-kNN-19 is close to that of the LW-kNN-24, except the percentage range between 31% and 38% with the maximum difference of 0.35m.

Obviously, there are several challenges in this work. For instance, when measuring the RSSI values from fixed nodes at a specific spot, even though the mobile node remains still, it is difficult to measure constant values because slight changes of temperature, obstacle,

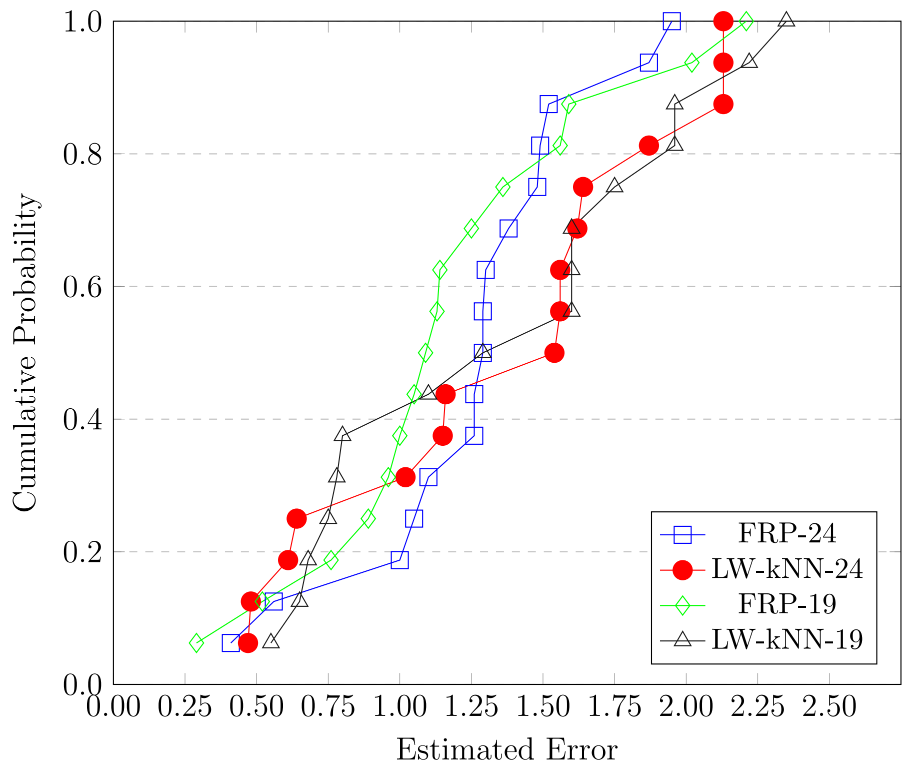

Figure 4.7: CPF of Average Errors of Four Anchors in $5m \times 5m$ with Temperatures 24 °C and 19 °C

multi-path fading may influence RSSI values and a device cannot generate stable signals all the time. These reasons influence the accuracy of the whole experiment, so I use the nearest point as the reference point of the mobile node, which is a clear advantage of my algorithm. The reason why I use the nearest point to calculate the parameters, like A and n, instead of directly using the averaged A and n is that it has the similar values of impact factors, such as temperature, humidity and multi-path fading to the mobile node.

4.2 Large Area Evaluation

In the large area, my devices are deployed in an area of a layout similar to the space in the indoor localization competition of [7]. The median error of the 22 approaches is 3.19m.

Specifically, my evaluation area includes two rooms and a corridor and the area size is $58m^2$. Figure 3.5 shows how the WASP/WASP-PoEs are placed in the large area. The algorithms in the small area scenario are also are used in the large area scenario. The 1D median filter in [31] is used to eliminate signal noise from the raw RSSI values. After that, the mode technique in [47] is applied to obtain the RSSI value at each coordinate as the final fingerprint data. In the position estimation phase, the LW-kNN algorithm is used to calculate positions. The MinMax algorithm is also evaluated in this experiment as a comparison to the LW-kNN algorithm. I am interested primarily in whether a mobile node is in the corridor or a room.

Algorithms	**Average Error**	**Median Error**
MinMax	1.69	1.76
Local Weighted k-Nearest Neighbour (LW-kNN)	1.59	1.54

Table 4.6: Estimated Errors for the Large Area Scenario

Table 4.6 summaries the average errors and median errors of the MinMax and the LW-kNN algorithm. The LW-kNN algorithm is superior to the MinMax algorithm, especially on median errors (1.76m and 1.54m). Table 4.7 shows the average errors, the median errors and the accuracy rate of the LW-kNN algorithm at each location of the large area. The three locaions provide high accuracy rate, especially for Room2 (86.63%), because the layouts of Room1 and Room 2 are different, and there are walls along the corridor. I also find that the average errors and the median errors are the smallest in Room1, but the accuracy of this location is the lowest. The accuracy rate refers to whether the measured results are within the tested location. Thus, although the measured results are close to the real tested positions, they may be in another location, such as Room2. The accuracy rate of the Corridor (72.25%) is lower than other locations. As there are more tested points close to the boundary in the Corridor, some of the points give large errors that lead to wrong location estimation.

Location	Average Error	Median Error	Accuracy Rate
Room1	1.26	1.35	74.56%
Room2	1.67	1.56	86.63%
Corridor	1.64	1.57	72.25%

Table 4.7: Errors and Accurate Rates of the LW-kNN at Each Location of the Large Area

Figure 4.8 shows the CPF of the average errors of the large area. The LW-kNN algorithm appears to provide better performance than the MinMax algorithm overall. Specifically, the performance of the LW-kNN is so close to the MinMax, and it is only superior to the MinMax between the percentage range 10.3% and 17.8%. In addition, the LW-kNN provides smaller errors on the smallest error (0.19m) and the largest error (3.50m) than the MinMax. 50% of the estimated errors in the large area scenario are under 1.55m, which is not much larger than that of the small area scenario.

Figure 4.9 shows the CPF of the median errors for the large area scenario. Similar to the results of the average error, the performance of the LW-kNN is better than that of the MinMax overall. Specifically, the MinMax is only superior to the LW-kNN within the range 10.3% to 15.4%. In addition, the largest error of the LW-kNN (4.55m) is larger than that of the MinMax (3.90m). Besides, at the percentage level 66.7%, the difference between the LW-kNN and the MinMax is the largest (1.56m and 2.50m).

4.3 Summary

In this section, four algorithms: FRP, LW-kNN, MinMax and kNN were evaluated. I compared their performances (estimated errors) in different experimental areas and conditions. My FRP algorithm performs the best among these four algorithms. In most cases, LW-kNN achieved better results than MinMax and kNN. Although the kNN algorithm provided good

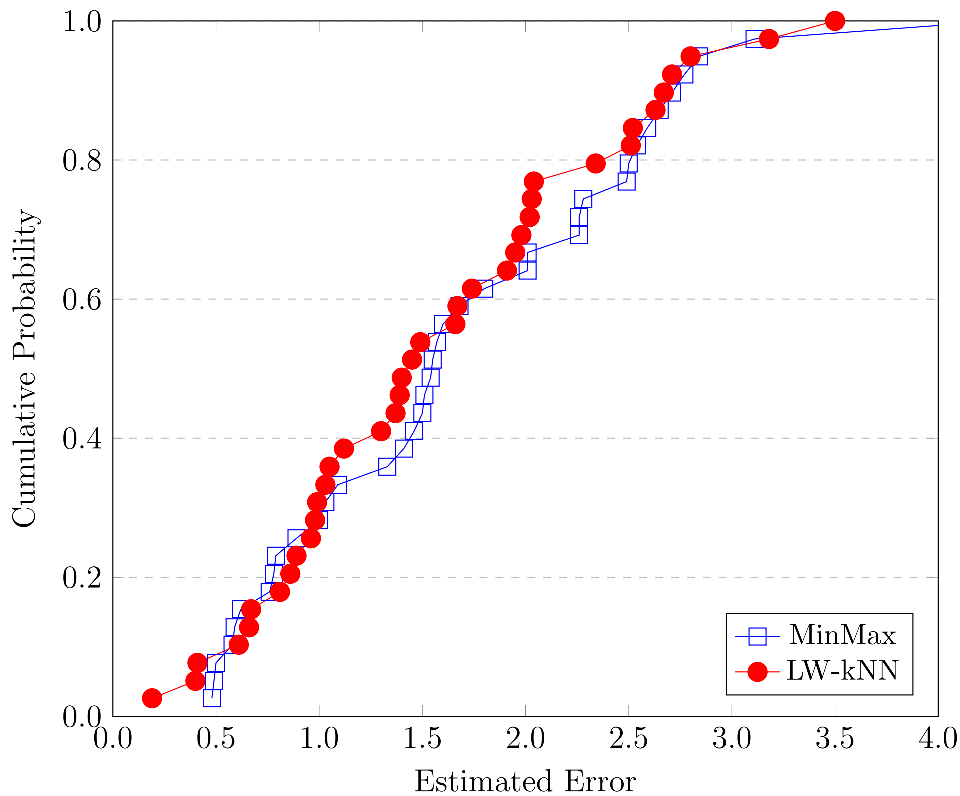

Figure 4.8: CPF of Average Errors for the Large Area Scenario

performance, it could not compete with the three other algorithms. In Experiment 1, I evaluated the impact of deployment area size. I conclude that as the area size decreased, the estimated errors dropped. The rate of decrease is almost linear to the square root of the deployment area size. In Experiment 2, the number of anchor nodes was set to four and six. I concluded that the accuracy increased as the number of anchor nodes grew, although accuracy appeared to rise slightly. As obstacles to radio transmission is also another key factor, it was evaluated in Experiment 3. I concluded that the signal was attenuated when passing through an obstacle, leading to decrease of the accuracy in the position estimation, but the decease of accuracy was not large. In Experiment 4, the impact of room temperature was evaluated. As the temperature did not change too much in an indoor place, the estimated

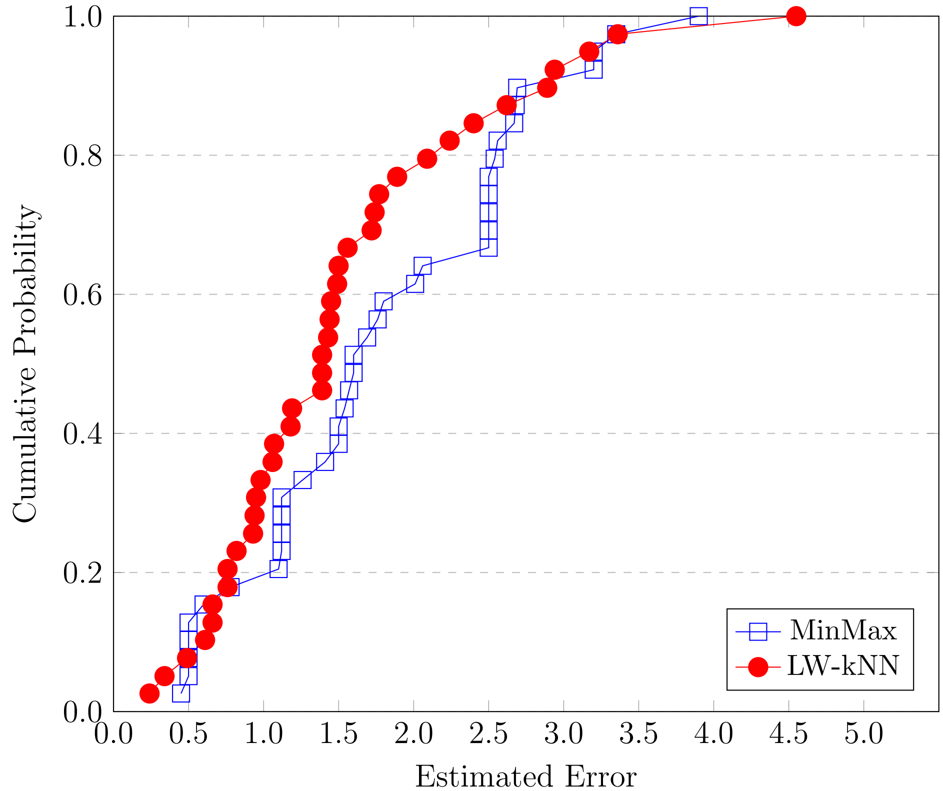

Figure 4.9: CPF of Median Errors for the Large Area Scenario

errors were affected slightly. In the large area scenario, two algorithms were also compared to test whether a person was in a room or a corridor. The LW-kNN showed a better result than the MinMax. The average error of LW-kNN was only 1.59m, and its highest accuracy rate was 86.63% in Room2.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

Node localization is a significant research area in WSNs. This research focuses on making the indoor localization system last long without changing batteries and on calculating the accurate position of a mobile node, for example, maintaining average estimation position errors within 1.6m in a large area including two rooms and a corridor. Range-based schemes are good choices to estimate the position of a mobile node. A RSSI-based scheme that belongs to range-based schemes was chosen as my indoor localization system, because it is a more accurate and less expensive scheme than other range-based approaches, such as ToA. ANT supported devices (Garmin Chirps) sending signals every 1.5 to 2 seconds were deployed in the testing area. My system can run at least one year without changing batteries, but the ZigBee supported devices using AA batteries only run 150 hours. Thus, my indoor system can run in a large area where alternating current is limited, such as a warehouse. A fingerprinting algorithm was used to store the position and RSSI value at each point, and then I used the reference point's parameters to estimate the position of the mobile node. The LW-kNN algorithm was also presented to make the location estimation more accurate. In the system evaluation part, my localization algorithms were compared to the kNN algorithm in [21] and the MinMax algorithm in [43]. The deployment area size was set to different sizes to test the influence on the accuracy of the estimated position. Other experimental factors, such as the number of nodes, obstacles and temperatures were also tested. The FRP algorithm performed the best among the four algorithms. The LW-kNN algorithm was superior to the MinMax algorithm in most of the cases. The kNN algorithm cannot provide results as good as the other three algorithms. In the large area, WASPs/WASP-PoEs were introduced to cover a larger indoor area including two rooms and a corridor and then locate whether a person wearing a Garmin Chirp was in a room or at a specific place in the corridor. The LW-kNN algorithm provided better performance than the MinMax algorithm at performing this task. The average error of the LW-kNN was only 1.59m and the accuracy rate of the Room2 of the LW-kNN algorithm reached to 86.63%.

5.2 Future Work

This research can be further explored in the following aspects:

- Apply another radio technology, such as BLE;
- Deploy experiments to a much larger place, such as the whole floor of a big building;
- Smart Patient Monitoring.

As this indoor localization system was developed by using the ANT technology, another currently popular radio technology BLE [10] can also be applied in the indoor localization system, as it is widely embedded in numerous electronic devices. In addition, the development area can be extended to a larger area including a greater number of rooms and a long corridor, for example, the whole floor in a hospital. In such case, more ANT devices would be deployed in each room and along the corridor as anchor nodes. Besides, as some ANT sensors can provide not only RSSI values, but also other information, such as heart beat, speed and falling indicator. Thus, this system can be deployed in a hospital to monitor patients' health information and locations in real-time. In some cases, for example, if a patient is detected to have fallen down in a specific area of a corridor or a room, then the nearest nurse will be immediately notified to help that patient. As each patient's location and health information can be monitored by the server side, this type of smart monitoring system would be beneficial to hospitals, especially where there exists a lack of nurses.

Appendix A

Supporting Document

A.1 WASP Configuration

Before running this indoor localization system, all the WASPs/WASP-PoEs must be connected to the same local area network where the server connects. WASP-PoEs are simple to join the network, because each of them has an Ethernet. Just guarantee to connect the Ethernet cable between a WASP-PoE and the experimental local area network. Configuring WASPs is more complex than configuring the WASP-PoEs. The following steps describe how to configure a WASP from the power off state in detail:

- Press the button for about three quarters of a second. When the green LED starts to blink, release the button immediately after a red LED flash, then it goes to the Limited AP Mode, indicated by a repeated single blink each second on the green LED. In this mode, a wasp creates a limited AP infrastructure network with a name same as its serial number on the back of each WASP, such as WA012345678.
- Use another wireless device, such as a laptop or mobile phone, to connect to the

wireless network created by the WASP. After this device is successfully connected to the network, open a browser and type *http://config.wasp.local* (if this URL does not work, then type *192.168.240.1*), then it navigates to the page that shows the current available networks for WASP to join (Figure A.1).

10		-24	WPA/WPA2 Enterprise	6	Select
11		-20	WPA/WPA2 Enterprise	6	Select
12	uofm-wpa	-24	WPA/WPA2 Enterprise	6	Select
13	uofm-guest	-24	No Security	6	Select
14	uofm-wpa	-19	WPA/WPA2 Enterprise	6	Select
15	uofm-secure	-19	WPA/WPA2 Enterprise	6	Select
16	uofm-secure	-19	WPA/WPA2 Enterprise	11	Select
17		-20	WPA/WPA2 Enterprise	11	Select
18	Penguin00G	-16	WPA/WPA2 Personal	11	Select
19	uofm-wpa	-19	WPA/WPA2 Enterprise	11	Select
20	uofm-guest	-20	No Security	11	Select
21	eduroam	-21	WPA/WPA2 Enterprise	11	Select
22	OpenWrtPDSL	-21	WPA/WPA2 Personal	11	Select

Figure A.1: WASP Setup: Select Network

- In Figure A.1, I choose the *OpenWrtPDSL* as my local area network. After clicking on the *Select* button, it jumps to the page shown in Figure A.2. Then I change the *Channel* to *All* and type the password and make sure the *Security* is setted to *WPA/WPA2* category.

- Then click on the *Next* button and it jumps to the next page shown in Figure A.3. If the information shown is correct, click on *Sava and Apply* button. Then the configuration information is stored in the WASP. After that, the red LED of the WASP blinks rapidly

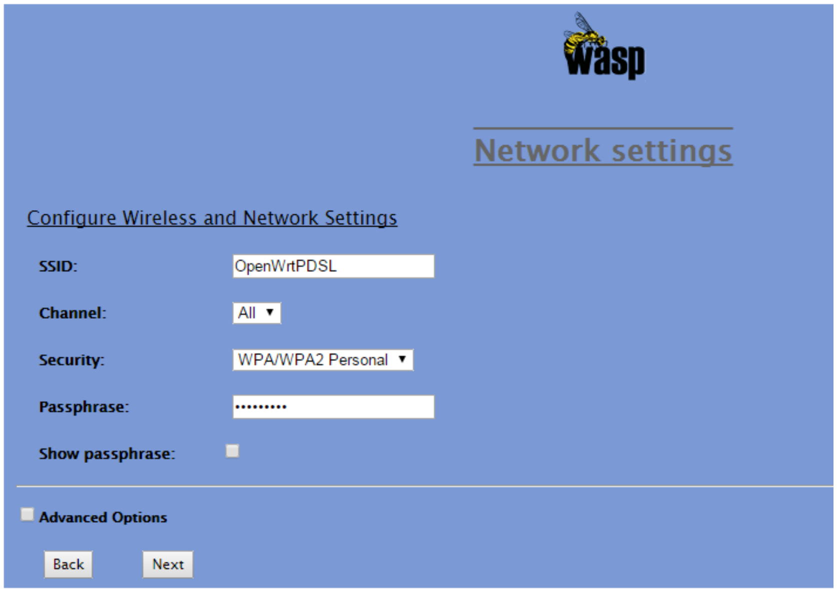

Figure A.2: WASP Setup: Configure Wireless and Network Settings

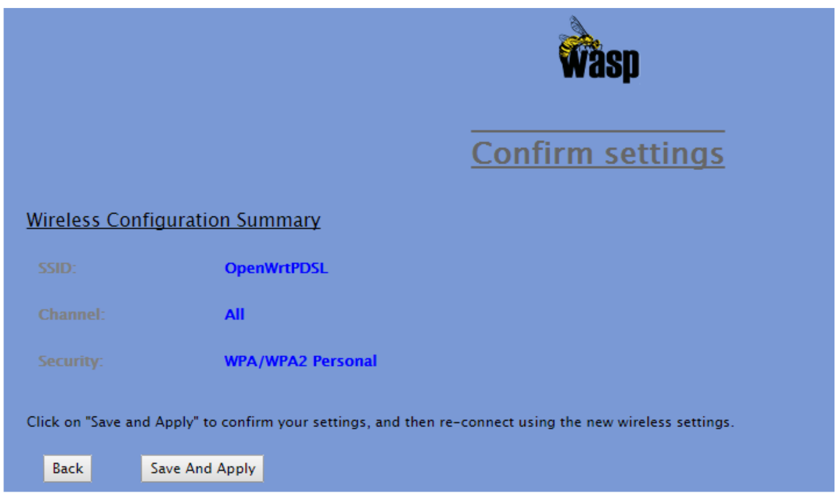

Figure A.3: WASP Setup: Configure Wireless and Network Summary

for about 3 seconds to execute the configuration. If there is still a continuous rapid flashing on the red LED, it indicates that the WASP fails to join the preconfigured network and it is still searching for its preconfigured network. The way to solve it is to do the steps above again or hold the button until the red LED and green LED blink at the same time for three times to turn it off, and then turn it on. If the red

LED stops blinking and there is a double blink each second on the green LED, then it indicates that the WASP enters to the infrastructure mode and successfully joins the preconfigured network.

Appendix B

Acronyms

AoA Angle of Arrival

BLE Bluetooth Low Energy

CDF Cumulative Distribution Function

CPF Cumulative Probability Function

CoG Center of Gravity

FRP Fingerprinting Reference Point

GPS Global Positioning System

kNN k-Nearest Neighbour

LW-kNN Local Weighted k-Nearest Neighbours

PIT Point in Triangulation

RF Radio Frequency

RSSI Radio Signal Strength Indicator

TDoA Time Difference of Arrival

ToA Time of Arrival

WSN Wireless Sensor Network

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