

# **Wi-Fi Based Indoor Positioning System Using Smartphones**

A thesis submitted in fulfilment of the requirements for the degree of  
Master of Applied Science

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November 2013

## **Declaration**

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

Bin Hu

November 2013

## **Acknowledgments**

I would like to express my sincere gratitude and appreciation to my senior supervisor - Professor Kefei Zhang for his continuous support of my research and for his guidance, patience, encouragement, enthusiasm, and immense knowledge. I would also like to thank my second supervisor Dr. Suqin Wu, who gives valuable opinions for this research and huge help for reviewing and revising my thesis.

I am grateful to Mr. Yuntian Bai, whom I have been working with throughout the period of my study over the indoor positioning project. His unselfish support and valuable advice is highly appreciated. I would also like to thank all my lab mates for being very cooperative and helpful.

I would like to thank Associate Professor Allison Kealy from the University of Melbourne for providing the commercial version of Ekahau system. I would also like to thank Dr. Thomas Gallagher from New South Wales University, who gives some technical supports for the Ekahau system.

Finally, I am indebted deeply to my parents and my wife for their strong moral supports, sacrifice and encouragement. All these make my study possible.

## **Abstract**

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With the rapid development of smartphone industry, various positioning-enabled sensors such as GPS receivers, accelerometers, gyroscopes, digital compasses, cameras, Wi-Fi and Bluetooth have been built in smartphones for communication, entertainment and location-based services. Smartphone users can get their locations fixed according to the function of GPS receiver. This is the primary reason why the huge demand for real-time location information of mobile users has been unprecedented in recent years. However, the GPS receiver is often not effective in indoor environments due to the signal attenuation and multipath effects, although it as the major positioning devices have a powerful accuracy for outdoor positioning. This research investigates other built-in sensors and develops methods for improving the accuracy of indoor positioning. Combination with the wireless network, it can be a viable alternative solution for the indoor positioning purposes of the smartphone users. The main advantage of this solution is that it can be deployed with a minimal cost, as no specialized hardware is necessary for setting up the system. However, challenges remain for this solution due to complex indoor environment involved and extensive calibration data overhead.

In this thesis, fingerprinting based indoor positioning methods are studied and developed. Field experiments using smartphones and a commercial indoor positioning system (i.e. Ekahau) are carried out in the newly established RMIT indoor positioning laboratory. Then a new indoor positioning system using matching algorithms is designed, developed and tested. Results show that the RMS accuracy achieved using the new system is 2m when 2m spacing resolution is used. The accuracy achieved of the commercial system (i.e. Ekahau RTLS) under an exactly identical environment is 2.79m. The advantages of our system in comparison with the off-the-shelf commercial system are its expendability in further development and easy modification/upgrading of the software system.

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## Abbreviations

3G	Third generation mobile telecommunication
A-GPS	Assisted GPS (see GPS)
AOA	Angle of Arrival
AP	Access Point
API	Application Programming Interface
BSSID	Basic Service Set Identifier, same as MAC in value
Cell-ID	Cell Identification
COO	Cell of Origin
dBm	Decibel miliwatt
GPS	Global Positioning System
IEEE	Institute of Electrical and Electronics Engineers
IEEE 802.11	See WLAN
INS	Inertial Navigation System
KNN	K-Nearest-Neighbor
LAN	Local Area Network
LOS	Line of Sight
MAC	Medium/Media Access Control, same as SSID in value
NN	Nearest Neighbor
RFID	Radio Frequency Identifier
RSS	Received Signal Strength
RP	Reference Point
RTLS	Real-Time Location System
SQL	Structured Query Language
SSID	Service Set Identifier
TOA	Time of Arrival
TDOA	Time Difference of Arrival
UWB	Ultra Wide Band
Wi-Fi	Wireless Fidelity
WLAN	Wireless LAN (see LAN)
XML	eXtensible Markup Language

# Chapter 1 Introduction

## 1.1 Background

Driven by increasing demand for high-end smartphones from developed countries and unprecedented popularity for low-cost products from emerging economies, smartphones are expected to account for the majority (up to 52%) of global cell phone sales in 2013—two years earlier than previously predicted (LAM, 2012). With the rapid development of smartphone technologies, deeper personalised engagement and frequent important personal assistance from phones are a necessary requirement. Most people are dependent on their phones as the sole source of telecommunication and a key element of entertainment, as well as an important way to connect each other via social media and emails. This means that application and operating system developers need to fulfil a hefty order, which makes smartphones an integral part of our daily life. This huge market potential triggers strong interest from developers, innovators and researchers. Figure 1.1 below shows the world market share of mobile handsets.

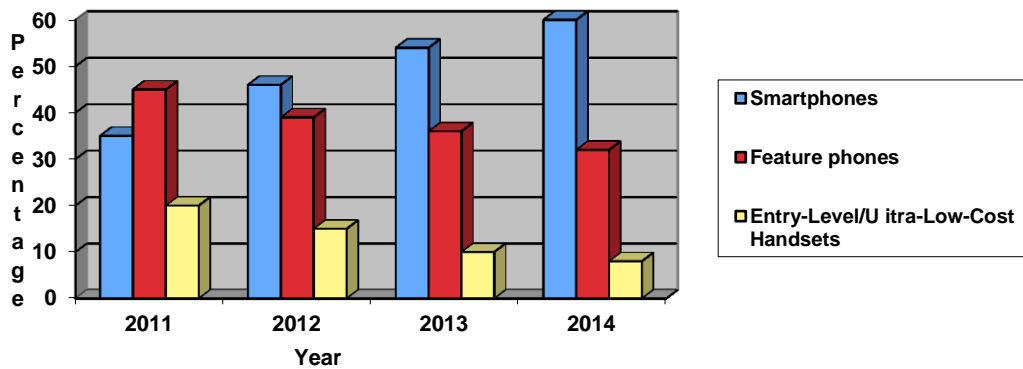


Figure 1.1 Worldwide market shares of mobile handsets  
(source: IHS iSuppli Research, August 2012)

Wi-Fi has been a default feature for several years at the very high end of the smartphone market, whether it is the Apple iPhone, Samsung Galaxy or the Nokia Lumia. Indeed, such a feature is an important characteristics of Wi-Fi to the overall experience of a smartphone that there is now strong evidence that handset manufacturers are seeking to differentiate through the Wi-Fi capabilities of their devices. As a result, wireless local area networks (WLAN) technology experiences

significant development due to the rapid demand of smartphone industry. For example, the WLAN world market grew more than 20 percents in 2012, topping \$4 billion in annual revenue (Machowinski, 2013). This growth includes enterprise access points, WLAN controllers and Wi-Fi enabled phones. As shown in Figure 1.2 below, the market for Wi-Fi enabled equipment is expected to grow to \$6 billion by 2017.

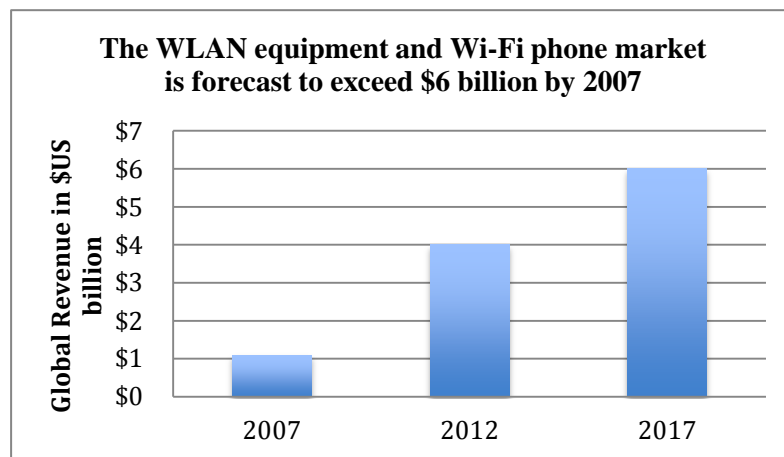


Figure 1.2 The global revenue of WLAN equipment and Wi-Fi phone market

Smartphones become more and more sophisticated due to their ever increasing functionalities through incorporating various types of sensors such as Global Positioning System (GPS) receivers, accelerometers, gyroscopes, digital compasses, cameras, Wi-Fi, and Bluetooth etc. These sensors have been used for not only communications, but also entertainment and location-based services (LBS). Among these sensors, the GPS is used predominantly for positioning in open areas since GPS receivers do not work well in difficult environments e.g. indoor environments and/or inadequate satellite signal coverage areas. This leads to recent significant international efforts of research and development in indoor positioning through exploring other built-in sensors, especially Wi-Fi although these sensors were originally designed primarily for entertainment and/or telecommunications. In the past few years, WLANs have been widely deployed and people can easily connect to a Wi-Fi network using his/her smartphone. This opens a new avenue for indoor positioning using WLAN and smartphones. Recently, locating mobile devices in indoor environments using wireless signal strength has gained a strong interest in the international community. The main reasons driving WLAN as an alternative indoor positioning tool are due to the fact that

GPS cannot be used in indoor environments for positioning purposes and the availability of 802.11 Wi-Fi networks.

## **1.2 Problem Statement and Technical Challenges**

In the past few years, GPS has been widely used in outdoor positioning and tracking in our daily life (e.g. GPS in-car navigation systems). However, for indoor environments, it is well known that GPS does not work well since walls, floors and other construction objects can greatly attenuate or even block satellite signals. Several alternative techniques such as Assisted-GPS (A-GPS), Bluetooth, WLAN, Zigbee and Radio Frequency Identifier (RFID) etc. have been proposed for indoor positioning and tracking. In this research, an efficient indoor positioning system based on the IEEE 802.11 wireless technique will be investigated (802.11TM, 2013). The Received Signal Strength (RSS) fingerprinting method in particular will be studied and smartphones, which have low-quality WLAN antenna requirements and limited power, memory and computation capabilities, will be used as a mobile device.

There are several technical challenges in designing and deploying an RSS fingerprinting indoor positioning system using smartphones as a mobile platform. The highly unstable feature of RSS in indoor environments is the major challenge for RSS-based WLAN positioning systems. There are four main reasons that lead to the high level of RSS variations. The first reason is the structure of the indoor environment and the presence of different obstacles, such as walls, doors and metal furniture etc. The WLAN signals experience severe multipath and fading effects and the RSS varies over time even at the same location. Secondly, the IEEE802.11 WLAN frequency range is in the 2.4 GHz public bands, which is shared with many other devices such as microwave ovens, smartphones, laptops and other wireless signal transmitters. In the calibration phase, which is used for collecting the RSS data and storing the corresponding location information in a database, these devices will likely lead to radio interference and make the wireless signal strength fluctuate. It is, therefore, not suitable for collecting stable signal strength and setting up a RSS database. Furthermore, normal human body can also affect the WLAN signal strength since the 2.4 GHz Wi-Fi signal strength could be greatly attenuated through human bodies, which consists of

70% water. Therefore, when signal strengths are collected using a smartphone, the RSS values on the straight line between the smartphone and an access point (AP) will be influenced by the body of the person. Finally, the orientation of the measuring devices also affects the RSS, as the orientation of the antenna affects the antenna gain and the signal is not isotropic in indoor environments. All of the above make it extremely difficult to model the relationship of the RSS and the position. To overcome the problems, the fingerprinting method is often used to characterise the relationship between the RSS and the position.

Another main challenge is the computational capabilities of the mobile devices. In order to achieve a high accuracy position solution, the fingerprinting method needs a good quality database where dense RSS samplings are required. In addition, limited computation speed and memory space of smartphones will make the on-the-fly storage of the database and direct computation in smartphone difficult. Table 1.1 displays a comparison of the processor speed and memory equipped between a Samsung smartphone which is used in this research to evaluate the performance of the proposed positioning system, and a standard laptop which is also used in this research. It shows that the smartphone has very limited computation speed and memory capacity in comparison to the laptop. Thus, the computational complexity and the use of memory must be taken into consideration when deciding which device is better suitable for the positioning server.

Table 1.1 Comparison of the smartphone and laptop used in this research

Device	Processor Speed	RAM
Samsung i9300	1433 MHz	1 GB
HP Elite Book 2560p	2.7 GHz	8 GB

### 1.3 Research Aim and Objectives

The aim of this research is to design an indoor positioning system with good performance. The main objectives of this thesis are:

- To study and evaluate a typical commercially available indoor real-time location system (i.e. Ekahau Real Time Location System) as a case study.

The performance of the probabilistic algorithm used in Ekahau RTLS is analysed, and its position capability is used as a reference for comparisons and validation of our new system;

- To identify an optimal approach to enhance position estimate accuracy for indoor environments;
- To develop a client side application based on Android platform for collecting signal strength in the calibration phase and obtaining the position in the positioning phase;
- To develop a server side positioning system for establishing a signal strength database and algorithm; and
- To compare the performance of the new system in terms of accuracy, stability, implementation and integration against the commercial system.

The proposed positioning system is primarily a software implementation and thus no additional specific hardware is required. The client side application is coded in Java language running on an Android platform (Android, 2013) and a SQL database (Microsoft, 2013) is used to support the server side applications. A number of experiments are conducted in the RMIT SPACE Research Centre lab, which is located in level 4, building 100 (Design Hub) of RMIT University.

## **1.4 Thesis Outline**

This thesis is composed of 5 chapters. The first chapter describes the current development and market trend of smartphones and WLAN industry and the reasons for integrating smartphones and WLAN network for indoor positioning. Apart from the problem statements, it sets the aim and objectives of this research. Chapter 2 presents a brief introduction of various positioning technologies and the main challenges for indoor environments are discussed with the conclusion that the smartphones and fingerprinting technique is the best solution for indoor positioning. Then an overview of smartphone technologies is presented and followed by a description of typical localization algorithms. In Chapter 3, the commercial real-time location system Ekahau is introduced and a field experiment using smartphones and Ekahau RTLS is presented in details including estimation approach and algorithm analysis, environmental setup and

performance evaluation of the case study. Chapter 4 discusses a new positioning system using smartphones and an existing Wi-Fi network. The client side Android application and the server side positioning system are described. The performance of the new system is assessed through comparing with the Ekahau system. Chapter 5 concludes the thesis and the future works are recommended.

## **Chapter 2 Overview of Positioning Technologies**

Nowadays, numerous positioning technologies or systems can be used to determine the position of people or mobile objects. Different levels of accuracy are obtained for different applications. The most widely used positioning system is the GPS, which offers both high accuracy (cm level) and low accuracy (meter level) positioning capabilities depending on how the system is used (i.e. receiver types and positioning methods). Satisfactory performance in outdoor environments is relatively easy to be achieved. However, the applicability of GPS positioning in indoor environments is constrained most of the time since GPS signals are obstructed. Alternative positioning systems, such as the assisted GPS (A-GPS) system, Wi-Fi based positioning system and inertial navigation system (INS), are used due to their specific characteristics. For example, Wi-Fi based positioning systems have gained increasing popularity in indoor environments, even though it still has some challenges.

This chapter overviews a number of typical positioning technologies from fundamentals, system requirements, pros & cons and positioning performance. It is organised as follows. Section 2.1 introduces various positioning technologies and section 2.2 summarises the main challenges of Wi-Fi based positioning systems in indoor environments. With the rapid development of smartphone technologies, positioning using a mobile platform has become a future trend. Therefore smartphone-based positioning technologies are examined in section 2.3. In section 2.4, four typical positioning measurements, namely Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA) and RSS-based positioning techniques, are introduced. Position estimation methods of trilateration and fingerprinting are discussed in section 2.5. Two types of Wi-Fi based fingerprinting algorithms including deterministic and probabilistic algorithms are summarised in section 2.6.

### **2.1 Typical Positioning Techniques**

Many positioning techniques are used to estimate the position or location of a mobile device in both outdoor and indoor environments. Again, for outdoor open space environments the most commonly used system is GPS due to its high accuracy, all time

availability and relatively easy to use. However, the critical drawback of the system is its incapability indoor due to the obstruction of GPS signals in indoor environments. Therefore, alternative techniques need to be explored to achieve positioning capabilities ubiquitously. Several commonly used positioning or location techniques and/or systems are introduced below.

### **2.1.1 GPS**

GPS is a US satellite-based radio navigation system with a nominal constellation of 24 satellites. It was originally intended for military navigation applications, but in the early 1980s, the system was made available for civilian use. Since then GPS has been widely used for navigation and positioning, and various types of GPS receivers for different positioning accuracies have been available. For example, for high accuracy positioning such as geodetic surveying and engineering surveys where millimetre- or centimetre-level of accuracies is required, GPS is a superb choice due to its many advantages compared to most of other positioning techniques. Nowadays, GPS is regarded as a popular tool/positioning utility to locate mobile objects that need basic position and navigation services. For example, GPS chips embedded smartphones become a standard component for the acquisition of its location information. For the determination of 2D position e.g. latitude and longitude (or easting and northing), a GPS receiver needs to track GPS signals from at least three satellites. With four or more satellites in view, the receiver can determine the 3D position (latitude, longitude and altitude) of the user. Once the user's location has been determined, the GPS-enabled smartphone unit can provide navigation and some other information, e.g. the user's current speed, bearing, track, trip distance, distance to destination, sunrise and sunset time. One of the advantages of the GPS system is its 24-hour availability. Figure 2.1 is a snapshot of GPS satellites' visibility in Melbourne on 3<sup>rd</sup> July 2013.

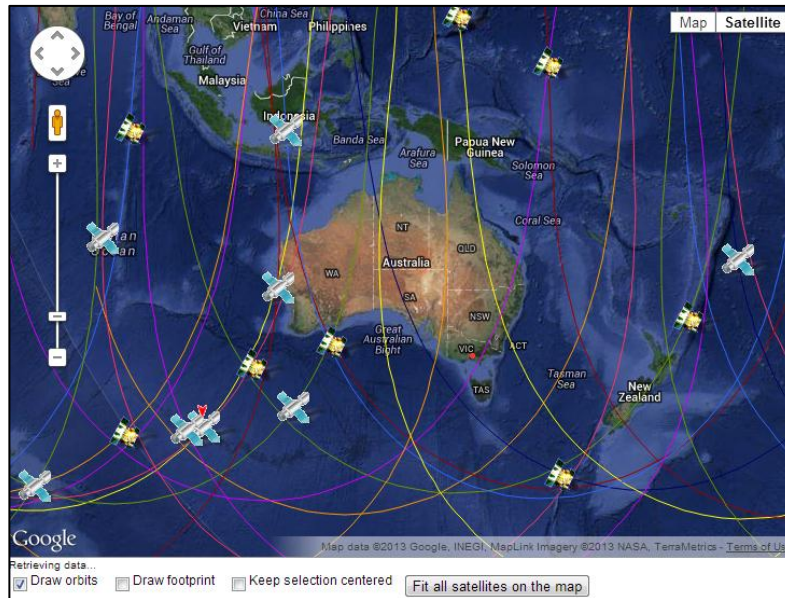


Figure 2.1 GPS satellites' visibility in Melbourne on 3 July 2013  
 (Source from <http://www.n2yo.com/>)

### 2.1.2 A-GPS System

A-GPS or AGPS can enhance the performance of standard GPS positioning using a cellular network as a complementary information source (Diggelen, 2009). It improves the location accuracy of cell phones (and other associated devices) in the following two ways:

1. To enhance the speed of the "time to first fix" (TTFF), A-GPS acquires and stores location information of the satellites (i.e. GPS almanac) via a cellular network so the location information does not need to be downloaded via satellites.
2. To assist positioning a smartphone when GPS signals are weak or not available. GPS signals may be impeded by tall buildings and cannot penetrate building walls. A-GPS uses proximity cellular towers to help calculate position.

### 2.1.3 Wi-Fi based Systems

Wi-Fi is now a widely acknowledged and used technology for positioning. Positions can be determined with a good accuracy in an indoor environment when Wi-Fi infrastructure is available. Most positioning approaches using a Wi-Fi system are similar to the Cell ID approach. Signal strength fingerprinting methods are used for most advanced Wi-Fi positioning systems (Beom-Ju et al., 2010), in which Wi-Fi signal strengths are observed from various APs in the area of interest. Then the observations are stored in a database

before the user implements real positioning tasks in the area using smartphone Wi-Fi sensors. This is in fact a calibration phase. In the real implementation of a positioning task, the user determines his/her location by matching his/her Wi-Fi signal strength observation with the RSS values in the database. The best matching one is taken as the location estimate. The APs are also termed reference points, locations of which are known.

#### **2.1.4 Inertial Navigation System (INS)**

The INS is a self-contained navigation technique in which measurements provided by accelerometers, gyroscopes and/or compasses are used to calculate the position and orientation of an object relative to a known starting point, orientation and velocity (Woodman, 2007). Low-cost MEMS gyroscopes and accelerometers are often considered as potential supplemental tools for indoor navigation. However, INS usually can only provide an accurate solution for a short period of time because the sensors' measurement errors (e.g. bias and drifting) rapidly change over time and thus it is difficult to separate or mitigate them from navigation signals (Hide, 2003). Inertial measurement units (IMUs) typically contain three orthogonal gyroscopes and three orthogonal accelerometers, measuring angular velocity and linear acceleration respectively.

#### **2.1.5 Other Systems**

A number of other systems, such as Bluetooth, Radio Frequency Identification (RFID), infrared and ultrasonic have been also investigated for their potential use and capability of positioning. Bluetooth is a technology commonly used for short-range wireless communications with low power consumption (Zandbergen, 2009). RFID is a generic term to describe a system that uses radio waves to transmit the identity (in the form of a unique serial number) of an object or person wirelessly. Infrared is electromagnetic radiation with long wavelengths, which is often used in short-range communication between infrared embedded devices. Infrared communications are useful for indoor environments; however, infrared cannot penetrate walls which makes it very difficult to be used between rooms. Bluetooth, RFID and infrared have been already used in some modern smartphones. Ultrasonic is an oscillating sound pressure wave with a frequency greater than the upper limit of the human hearing range. Ultrasonic devices can be used

to detect objects and measure distances. All the above systems can only operate in short-range measurements.

### 2.1.6 Comparison of Different Positioning Techniques

The accuracy, key characteristics, main advantages and disadvantages of the aforementioned various positioning techniques used in mobile devices are compared (see Table 2.1). GPS with a high accuracy has emerged as the leading technique to provide location information. The GPS technique adopted in most mobile devices employs a server-side component for the processing of GPS signals and is referred to as A-GPS. Both GPS and A-GPS techniques need the signal from the GPS/A-GPS satellite to unobstructedly propagate to the receiver, which is so-called line of sight (LoS), to support high accuracy positioning. Wi-Fi positioning and INS can provide medium accuracy without LoS, thus they are more suitable to be used in indoor environments. However, high cost for infrastructure and limited coverage is a major issue for Wi-Fi positioning, while INS also has some issues since it is prone to rapid accumulative errors.

Table 2.1 Comparisons of various position techniques (Zandbergen, 2009, Barbeau, 2011, Allychevalier, 2010)

Technique	Accuracy Level	Advantage/Disadvantage
GPS	High (10 m)	Good accuracy Line of Signal (LoS) is needed
A-GPS	High (10 m)	Assisted GPS Network interaction is required and only effectively used for locating a particular place in a small area
Wi-Fi positioning	Medium (10-100 m)	Good accuracy for indoor environments and no need LoS High cost for infrastructure and limited coverage
INS	Medium (accumulative error)	Cheap Bias and drifting are a concern
Cellular network positions	Low-medium (1 km)	No requirement for infrastructure Problematic in low signal conditions

## 2.2 Positioning Using Smartphone Technology

Smartphone technology is discussed in details in this section since smartphone positioning is the focus of this research. Smartphones are those mobile phones using a mobile operating system with advanced computing capability and connectivity. They are considered as miniaturised portable computers since they are similar to laptops and desktop computers in many ways. Various built-in sensors in smartphones, which are originally designed for communications and entertainment, have been adopted for LBS nowadays, and the use of smartphones for indoor positioning is especially important. Currently, GPS technology has been well integrated into smartphones and its positioning performance is good for outdoor environments. However, it cannot work properly in indoor environments due to the attenuation and multipath effects of GPS signals. In order to address this issue, other built-in sensors are expected to play an important role in indoor positioning with sound quality and satisfaction.

### 2.2.1 Development History of Smartphones

Smartphones first appeared nearly 20 years ago, even though they were not formally called smartphones back then. The popularity and range of smartphones have been exploded only in recent years. The development history of typical smartphones is summarised in Figure 2.2 (Smartphone-Guide, 2011).



Figure 2.2 Major milestones of smartphone development history

### 2.2.2 Advanced Functionalities of Smartphones

The first generation smartphones mainly combined the functionalities of a personal digital assistant (PDA) and a mobile phone. A PDA is a handheld mobile device that functions as a personal information manager. Today, more and more advanced functionalities in smartphones are available and they are listed in Table 2.2

Table 2.2 Key advanced functionalities of contemporary smartphones

Functionality	Key features
3G	3G is a high speed mobile network designed to handle the increased data transfer of smartphones and their mobile Internet functions.
Email	The ability to connect to POP3 or IMAP-based email servers, just as you can do on a desktop computer.
Wi-Fi	A hidden Wi-Fi antenna within the handset allows users to connect to the Internet via a wireless router or Wi-Fi hotspot.
Web Browser	The ability to display full HTML versions of websites, not just the WAP or simplified mobile version.
Video Camera	The ability to capture high quality photographs and video footages, often HD videos. Many high-end devices now have two separate cameras.
Apps	The ability to add additional software including games to a smartphone. There are hundreds of thousands of apps available for downloading.
File Storage	Due to their ability to play media files and have new software (apps) installed, smartphones will have more internal storage space than feature phones. There is also usually a slot for a Micro SD card
GPS	Very few smartphones do not have the ability to use GPS combined with a map application for navigation
Touch-Screen	A large multi-touch screen is another very common feature of smartphones. The Blackberry range handsets are one of the few exceptions
Media Player	The ability to play back different types of media, including audio and video files, is another common feature of many mobile devices
Standard Feature	The ability to make normal calls and send SMS/MMS messages, add appointments to a calendar, transfer files using Bluetooth, choose different ringtones and wallpapers, and create contact lists etc.

### 2.2.3 Smartphone Operating System

The operating system (OS) used in a particular phone is one of the most important features for many users. The OS controls how the phone behaves and what the user can do with it, as well as what application software package can be installed. It is therefore finding an OS that works best for the user can bring lots of benefits and convenience. The main smartphone OSs available in the current market include Apple iOS, Android, Windows Mobile, Blackberry OS and Nokia Symbian. Due to the separation of the OS of a smartphone from its hardware, the OS can be updated without the need for a new device. All of the major OSs are regularly updated for adding new features or improving

their functionalities. This means that it is possible for a smartphone to remain up-to-date far longer than a basic feature phone would. Figure 2.3 shows the market share of different mobile OSs from 2008 to 2011 (Nita, 2010, Pingdom, 2010, Corporation, 2011).

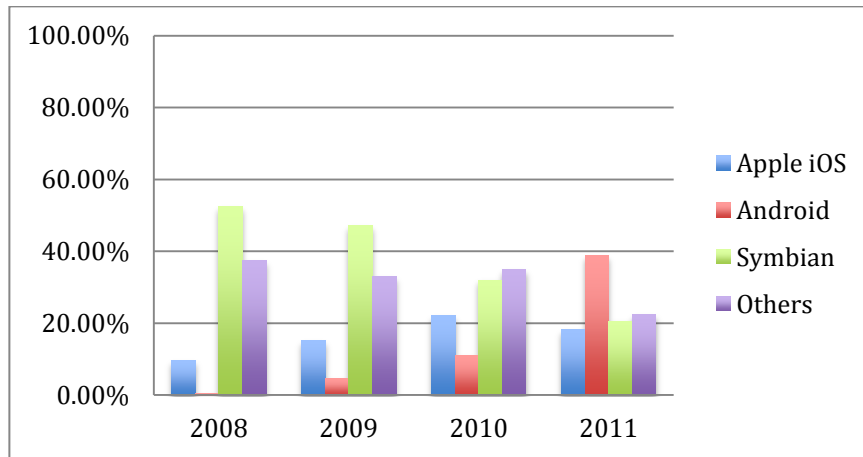


Figure 2.3 The market share of smartphone OS

#### 2.2.4 Typical Types of Sensors in Smartphones for Positioning

Nowadays, smartphones are increasingly embedded with various types of sensors such as GPS receivers, accelerometers, digital compasses, gyroscopes, Bluetooth and Wi-Fi technology. Use of various combinations of these sensors is very useful and effective for seamless positioning. In this section, different types of positioning-enabled sensors and related positioning techniques are briefly discussed.

##### *GPS receivers*

Currently, most smartphones are equipped with a high-sensitivity GPS module for positioning purposes. For example, Samsung i9100, which is an Android smartphone, carries a CSR's SiRFstarIV GPS receiver, which provides tracking capability of -160 dBm to -163 dBm and can maintain its -160 dBm acquisition sensitivity without any network assistance. Along with low-power location awareness capabilities, the SiRFstarIV receiver includes active jammer removal technology that can dynamically detect, track and actively block up to eight separate sources of interference in the GPS frequency band, which would otherwise affect GPS performance (World, 2011). This feature enables it to coexist in close quarters with other noisy components without much

extra effort. Features such as Bluetooth, Wi-Fi and 3G mobile radios, as well as large LCD screens employed in smartphones are often sources of this kind of interference.

### ***Wireless and cellular network-based sensors***

Generally, all contemporary smartphones support cellular networks, WLANs and Bluetooth networks. A cellular network is an asymmetric radio network making up of fixed transceivers (or nodes), which maintain tracking the signal while the mobile transceiver, which uses the network, is in the vicinity of the node. A WLAN is the one in which a mobile user can connect to a local area network (LAN) through a wireless (radio) connection. A Bluetooth network is a short-range wireless communication network with short wavelength radio transmissions in the radio band ranging from 2.4 Hz to 2.48 Hz, creating personal area networks with a high level of security (Chittoor Sundaramurthy, 2010). All of these three types of networks can be used for prominent localization methods like the signal strength fingerprinting method.

### ***Inertial sensors***

Inertial sensors include accelerometers and gyroscopes. An accelerometer measures the acceleration of an object. A gyroscope measures the angular rate and is commonly used for measuring or maintaining the orientation of an object (Maenaka, 2008). An IMU is an electronic device that measures and reports velocity, orientation and gravitational forces of an object using a combination of accelerometers, gyroscopes and sometimes also including magnetometers. Over the last few years, with the rapid development of micro-electro mechanical systems (MEMS), an increasing number of micro-electro sensors have been embedded into smartphones. In contrast to traditional inertial sensors, MEMS provides with a smaller size, lower power consumption and lower cost but higher reliability (Ioan et al., 2011). A Samsung i9100, for example, contains an AKM8975 three-axis digital compass, a ST LIS331DLH three-axis accelerometer and a ST L3G4200D three-axis Gyroscope sensor to provide nine degrees of freedom.

With the development of microsensor technology, new generation sensors used in smartphones have better performance. Using smartphones as a tracking device for indoor positioning has become a mainstream research direction in the industry and research community.

### 2.3 Main Challenges for Indoor Positioning

For indoor positioning, Wi-Fi based positioning has been recently regarded as a favorable choice due to its widely availability. However, this technology still poses significant challenges and limitations due to the complexity and dynamics of indoor environments. It is adversely affected by many unpredictable factors including the movement of people, changes of environmental settings, radio interference and signal propagation loss caused by different building materials. In addition, wireless cards from different vendors can be also another factor affecting the RSS measurements. These pose a big challenge for developing a reliable and effective indoor positioning system.

A normal human body consists of about 70% water. The 2.4 GHz Wi-Fi signal strength, which is the same frequency as IEEE 802.11 standard can be greatly attenuated through water since water can absorb the resonance frequency at the 2.4 GHz signal strength level. This implies that in some cases, people located physically between the APs and the mobile devices can typically block the Wi-Fi signals. Figure 2.4 presents a RSS variability comparison of the signal strengths measured at the same location, where is in the room 33 level 10 Building 12 in RMIT University (the layout seeing Figure 2.5), from the same AP with different numbers of human bodies. It shows that the more the number of people blocks the signal, the weaker the RSS measured.

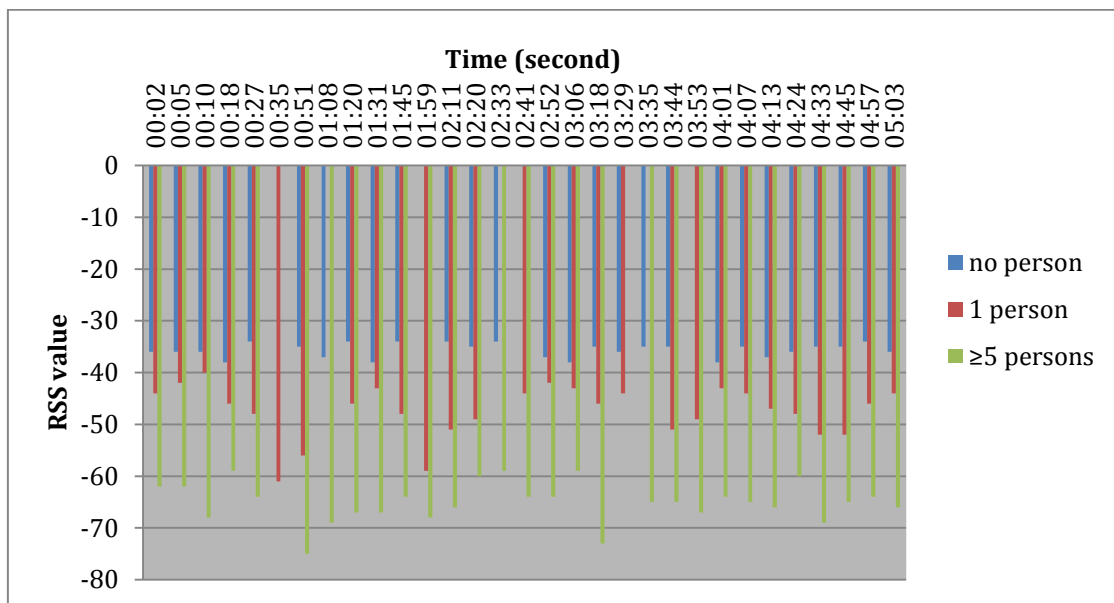


Figure 2.4 Effects of different numbers of human bodies on RSS measurements conducted in the room 33, level 10 building 12 in RMIT

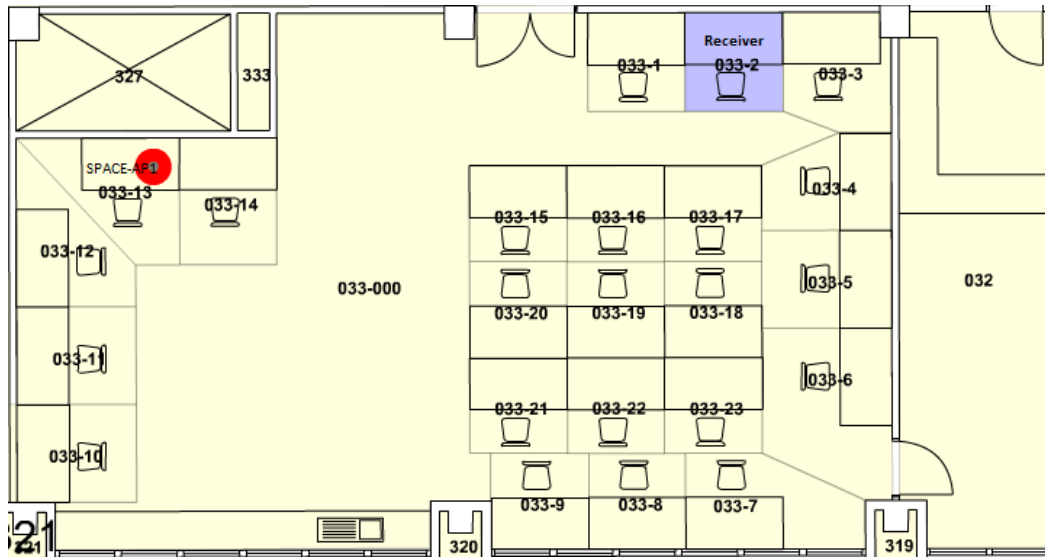


Figure 2.5 The layout of the room 33 level 10 building 12 in RMIT University

Radio interference in an indoor environment is another very important factor that needs to be considered. All wireless networks such as cellular telephone networks and WLANs rely on broadcasting stations to transmit signals. Large cellular antenna towers as well as small wireless Internet routers are used in these stations to transmit signals at particular radio frequencies. Unfortunately, users of wireless device may be affected by signals at the same frequency from other interference sources nearby, making the wireless signals difficult to flow smoothly. Sometimes, significant signal disruptions are also expected and this phenomenon is known as interference. The devices that could cause interference include, for example, microwave ovens, baby monitors and garage door openers.

Different wireless cards also have different effects on signal strength because different vendors use different methods to measure RF energy, although these methods all comply with the IEEE 802.11 standard, which defines RF measurement values as a number between 0 and 255 (J.Bardwell, 2002). Table 2.3 lists the measurable RSS ranges by different types of wireless cards available from various vendors.

Table 2.3 Measurable RSS ranges of various types of wireless cards (Kaemarungsi, 2005)

Vendor	Model	Standard	Max RSS (dBm)	Min RSS (dBm)	Range (dBm)
Lucent	Orinoco Gold	802.11b	-10	-102	92
Lucent	WaveLAN Silver	802.11b	-10	-94	84
Cisco	Aironet 350 Series	802.11b	-10	-117	107
Proxim	*Orinoco Gold	802.11a/b/g	-11	-93	82
SMC	*EZ Connect SMC2635W	802.11b	-14	-82	68
D-Link	*AirPlus DWL-650+	802.11b	-50	-100	50

\* denotes the card with Cardbus 32-bit interface.

For a wireless network in an office, obstructions such as walls, furniture, and people can affect the propagation of signals enormously. The signal strength attenuation is introduced first and the factors contribute to the variability are analysed which includes the type and structure of the various articles/furniture in the building. Different types of building materials cause different degrees of losses. In a multi-storey building, signal losses between adjacent floors also occur and a loss of approximately 6 dB is usually experienced between adjacent floors. Table 2.4 shows typical attenuations caused by different building materials at 2.4GHz, which is in the signal strength of 802.11n WLAN (Rackley, 2007).

Table 2.4 Attenuation of signal strength caused by different building materials at 2.4 GHz

Range	Material	Loss (dB)
Low	Non-tinted glass, wooden door, cinder block wall, plaster	2–4
Medium	Brick wall, marble, wire mesh, metal-tinted glass	5–8
High	Concrete wall, paper, ceramic bullet-proof glass	10–15
Very high	Metal, silvering (mirror)	>15

## 2.4 Estimation Methods for Indoor Positioning

Trilateration and fingerprinting are two main estimation methods often used for estimating the location of indoor mobile objects with Wi-Fi networks.

### 2.4.1 Cell of Origin (COO)

COO is a mobile positioning method for locating a mobile device. This method relies on the fact that cellular networks can identify the approximate position of a mobile handset, e.g. in which cell the device is at a given time (Liu et al., 2007). The accuracy of this method depends on the size of the cells of the network. In a large urban network, the size of the cells can be from 100 to 1000 metres, which indicates the approximate accuracy of the COO positioning.

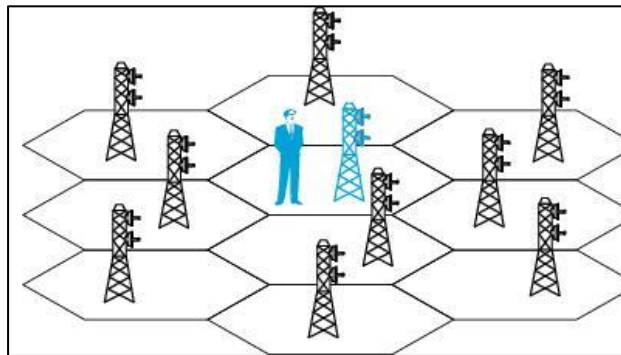


Figure 2.6 The COO method for positioning (Cisco System, 2008)

The concept of COO can be useful for indoor positioning. When applied in the Wi-Fi 802.11 systems, this technique tracks the cell (or “associated access point” in the Wi-Fi 802.11 systems) to which a mobile device is associated. The primary advantage of this technique is easy implementation since it does not require complex algorithms, which makes position estimation very fast. Almost all cell-based WLANs and other cellular-based RF systems can be easily and cost-effectively adapted to provide COO positioning capability. However, the overwhelming drawback of pure COO positioning approaches is coarse granularity. For various reasons, mobile devices can be associated to those cells that are not in a close physical proximity, despite the fact that other nearby cells should be better candidates (Cisco System, 2008).

### 2.4.2 Trilateration

Trilateration uses the distances of an object from three known points, which are usually fixed points with known coordinates to determine the position of an object. This method has been widely used in conventional surveying and GPS positioning. GPS receivers use the trilateration method to determine the user’s position, speed and elevation etc. In indoor positioning, the coordinates of APs are held as fixed nodes, and a database for

storing accurate location of the APs needs to be established beforehand. This includes both accurate coordinates of the APs and the unique Media Access Control (MAC) address for each of the APs. During active measurements for a mobile device, the average signal strengths for all visible APs are measured and trilateration can be used to estimate the location of the device.

It is very difficult to estimate accurate distances based on RSS measurements due to signal attenuation. Walls, floors, microwave ovens, cordless phones and Bluetooth devices all cause signal attenuation since the same frequency (2.4 GHz band) is used in the 802.11b protocol and its related devices. The orientation of the antenna and the movement of people inside the building are all other factors affecting the signal strength. This signal attenuation makes the accuracy of the distance estimation based on RSS measurement degraded, which in turn makes the positioning results of the trilateration method degraded accordingly. For example, the position errors from pure Wi-Fi signals excess 6–8 meters (Rizos et al., 2007).

### **2.4.3 Fingerprinting**

The fingerprinting technique has been used for indoor positioning for several years. Its main advantage is that it can use existing WLAN infrastructures or other network environments. Compared with other techniques like TOA and AOA, this technique is more suitable for indoor environments as it can handle the non-LOS and multipath problem (Parmanathan, 2006). Apart from this, it is relatively simple to be deployed. If there are no specific hardware requirements at the mobile device, any existing WLAN infrastructure can be used for positioning. When used with Wi-Fi systems, the fingerprinting method can be typically divided into two phases, calibration phase and positioning phase. As shown in Figure 2.7, the calibration phase is for establishing a database storing locations of reference points (RPs) in the area of interest. In this phase, signal strengths from all the RPs are measured first, then the mean values of the RSS at each of the RPs are calculated, along with other information including the coordinates, the orientation and MAC address etc. In the positioning phase, the signal strengths from the APs are measured at the mobile side and compared with all the records in the database to identify the most probable location of the mobile object using either the deterministic or probabilistic algorithms (G.Dempster, 2012). The workflow of the positioning phase is shown in Figure 2.8.

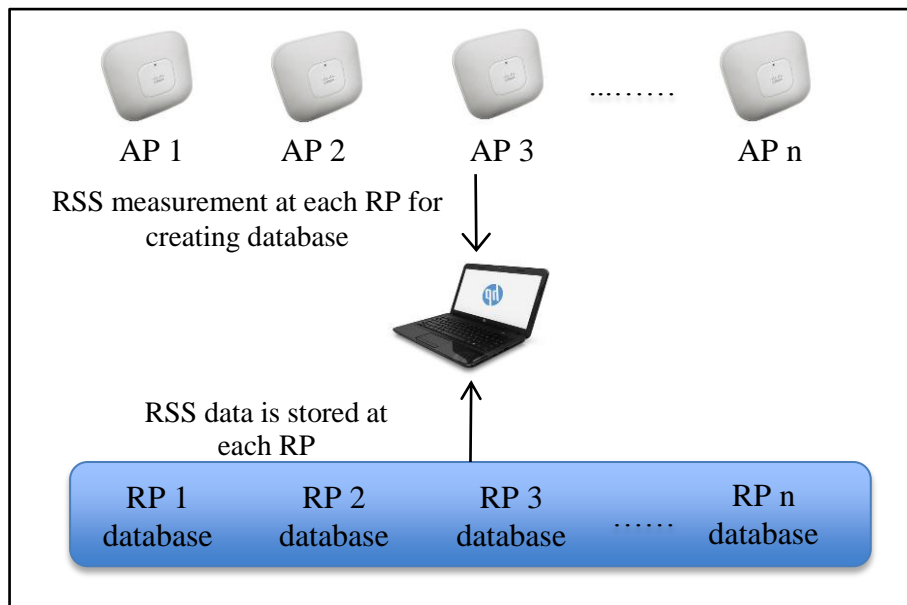


Figure 2.7 Calibration phase of fingerprinting method

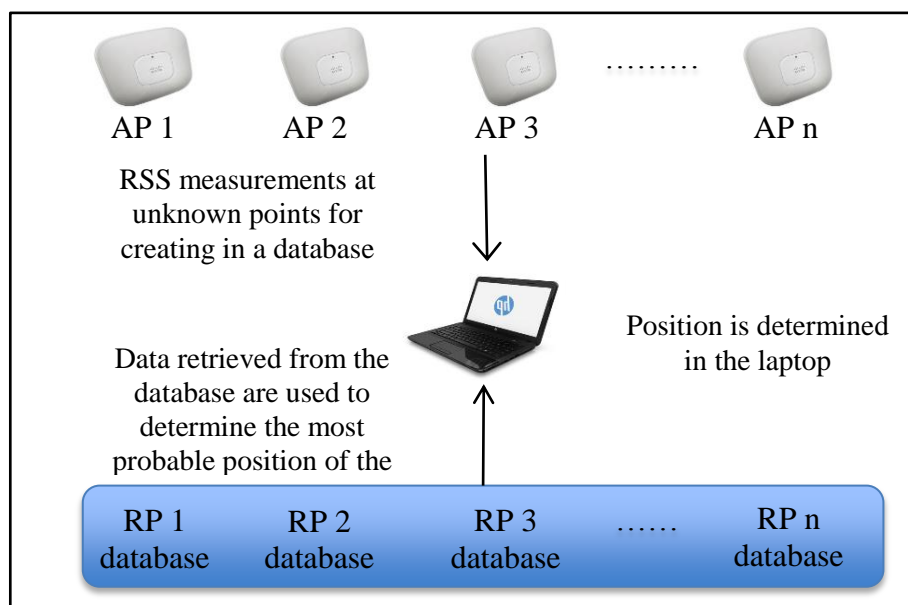


Figure 2.8 Positioning phase of the fingerprinting method

#### 2.4.4 Comparisons of Typical Positioning Methods

The table below compares the above mentioned three typical positioning methods, COO, trilateration and fingerprinting. For indoor positioning, due to the advantage of continuous positioning and environmental effects having been considered in the

calibration phase, the fingerprinting method is more suitable for indoor positioning and thus it is selected for our experiments.

Table 2.5 Comparisons of the three typical positioning methods

Method	Accuracy	Advantage	Disadvantage
COO	Low to medium	Simple algorithm	Discrete positions; accuracy depends on the size of cells; a large number of devices are required
Trilateration	Medium	Continuous positioning; no training phase required	At least three receivers are required; poor positioning accuracy may occur, caused by environmental effects
Fingerprinting	High	Continuous positioning; environmental effects are considered in the training phase	Poor positioning accuracy in dynamic environments

## 2.5 Measurements for Indoor Positioning

Various types of measurements can be used to determine the position of a mobile device and the following four types of measurements or models are commonly used.

### 2.5.1 Time of Arrival (TOA)

An electromagnetic signal has a constant propagation speed. If the time of the signal propagation between a base station and a mobile station can be measured, the distance from the base station to the mobile station can be estimated using the trilateration method. The 2D position of the mobile station can be estimated using more than two such distances. In indoor wireless environments, this method can be used to locate smartphones using Wi-Fi routers. Figure 2.9 shows how the trilateration method using TOA-derived distances works.

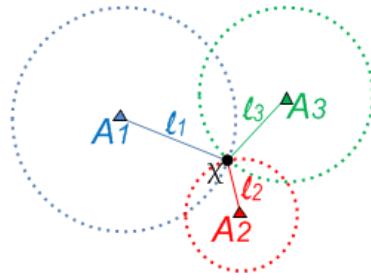


Figure 2.9 TOA measurements for positioning

Assume  $X$  is the position of the smartphone user to be estimated,  $A_1$ ,  $A_2$  and  $A_3$  are three Wi-Fi routers with known positions, and  $l_1$ ,  $l_2$  and  $l_3$  are the distances measured from  $X$  to the three routers, then the distances can be calculated by

$$l = C \cdot t \quad (2.1)$$

where  $c$  is the speed of the signal propagation and  $t$  is the signal's transmission time.

The TOA measurements have limitations. It requires accurate synchronisation of time among all the base stations and the mobile station. A small time error will lead to a large error in the distance calculated. Furthermore, the signal must be labeled with a time stamp in order to allow the base node/station to determine the time at which the signal was emitted. This additional time stamp increases the complexity of the signal propagation and may lead to an additional error.

### 2.5.2 Time Difference of Arrival (TDOA)

The aforementioned TOA uses the absolute time of signal transmission to calculate the distance the signal travels. TDOA uses difference between the propagation times arrived from different base stations. When a mobile station sends a signal, its strength will be received by at least three base stations, the position of the mobile station can be estimated using the trilateration algorithm.

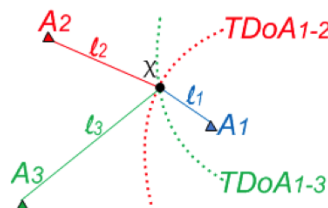


Figure 2.10 TDOA measurements for positioning

Figure 2.10 shows the positioning principle using TDOA measurements.  $X$  is the position of the smartphone user,  $A_1$ ,  $A_2$  and  $A_3$  are three Wi-Fi routers,  $l_1$ ,  $l_2$  and  $l_3$  are the three distances from  $X$  to the three routers, and  $TDOA_{A_1-2}$  and  $TDOA_{A_1-3}$  are two hyperbolic curves with a constant range difference. The following formula can be used for the hyperboloid

$$TDOA_{A_1-n} = |t_1 - t_n| = k_{1n} \quad (2.2)$$

$$|l_1 - l_n| = C \cdot k_{1n} \quad (2.3)$$

Where,  $n$  is the number of a Wi-Fi router,  $t$  is the signal transmission time and  $k$  is a parameter that stands for TDOA.

The TDOA positioning method also has limitations. It requires an accurate clock and is affected by multipath errors of the signal propagation, noise, and interference. In addition, it involves a high cost for additional antenna and location equipment at each cell site.

### 2.5.3 Angle of Arrival (AOA)

An AOA is defined as the angle between the propagation direction and its reference direction. The reference direction is known as orientation which is the fixed direction against which the AOAs are measured (Rong and Sichitiu, 2006). As shown in Figure 2.11, AOA method uses angular measurements ( $\theta_1$  and  $\theta_2$ ) of signals that arrive at a pair of base stations  $A_1$  and  $A_2$  with Wi-Fi routers to determine the location of the mobile device  $X$ . Due to multiple base stations receiving the signal of the mobile device, the base stations need additional equipment for determining the compass direction from which the user's signal is arriving. Information from each of the base stations is sent to the mobile switch for analysis and generation of an approximate latitude and longitude, for the mobile device.

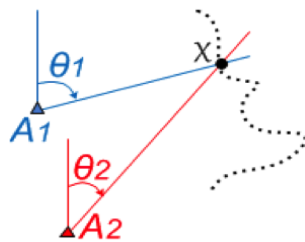


Figure 2.11 The basic principle of AOA measurements

The formula for the calculation of the user's location is

$$\tan(\theta_1) = \frac{x-x_1}{y-y_1} \quad (2.4)$$

$$\tan(\theta_2) = \frac{x-x_2}{y-y_2} \quad (2.5)$$

When using the AOA measurements for positioning, at least two angle measurements from two base points (i.e. reference stations) are required. This method is sensitive to multi paths and it is assumed that the angle of the received signal is known and can be measured via a directional antenna and antenna arrays. Therefore, additional hardware is required to estimate arrival angles and hence indirectly increases the cost. The more the number of antennas, the better the accuracy. This is the main limitation that makes this method not very viable.

#### 2.5.4 RSS-based Positioning Technique

Each type of the above mentioned measurements has some drawbacks. In an indoor environment, it is difficult to find a LOS channel between the transmitter and the receiver and radio propagation more likely suffers from multipath effects. Multipath effects would affect the time and angle of arrival of a signal. As a result, the accuracy of the position estimate could be degraded (Chen, 2012). The RSS-based technique has become an alternative approach for positioning due to its simplicity and low complexity. It can be easily implemented in modern wireless devices such as laptops and PDAs, and acquire signal strength from various types of networks that support the 802.11 protocol. In addition, it does not need complex data processing for accurate clock synchronization and data exchange. The following three formulas are used to express the RSS measurement equation (Di et al., 2009).

$$PL = PL_{1metre} + 10\log(d^n) + s \quad (2.6)$$

where  $PL$  is the path loss (in dB) of the signal,  $PL_{1metre}$  is the 1-metre reference path loss (dB),  $d$  is the distance between the transmitter and the receiver (in m),  $n$  is the path loss exponent and  $s$  is the shadow fading (dB).

$$RX_{PWR} = TX_{PWR} - Loss_{TX} + Gain_{TX} - PL + Gain_{RX} - Loss_{RX} \quad (2.7)$$

$$d = 10^{\frac{RX_{PWR} - TX_{PWR} - Loss_{TX} + Gain_{TX} + Gain_{RX} - Loss_{RX} - PL_{1metre} - s}{10n}} \quad (2.8)$$

where  $RX_{PWR}$  is the detected RSS (dB),  $TX_{PWR}$  is the transmitter's output power (dB),  $Loss_{TX}$  and  $Loss_{RX}$  are the transmitter and receiver cable and connector losses (dB) respectively,  $Gain_{TX}$  and  $Gain_{RX}$  are the transmitter and receiver antenna gains (dB) respectively.

### 2.5.5 Characteristics of the Four Measurement Models

Each of the aforementioned four measurement types or models has its own characteristics. TOA, TDOA and AOA measurements are often used for outdoor positioning because they require the condition of LOS between the transmitter and the receiver. However, in indoor environments, this condition can be hardly satisfied due to the obstruction, interference and multipath effects etc. Moreover, a mobile device needs to measure at least three APs for positioning using trilateration. This is the reason that these three measurement models are not so commonly used in indoor environments. The RSS-based technique does not need LOS, complex clock synchronization and data exchange as the distance is obtained from the signal attenuation during transmission. Furthermore, RSS values can be recorded in various networks that support the 802.11 protocols. As a result, RSS-based measurements have wide applications. The main characteristics of the four measurement models are compared in Table 2.6 below.

Table 2.6 Comparisons of different measurement models

Measurement method	Time synchronisation	LOS requirement	Accuracy	Other features
TOA	Mobile object and all receivers	Yes	High	$\geq 3$ receivers
TDOA	All receivers	Yes	High	$\geq 2$ receivers
AOA	Not required	Yes	Medium	Antenna array
RSS	Not required	No	Medium	$\geq 3$ receivers

## 2.6 Fingerprinting Algorithm

The fingerprinting technique is based on the relationship between a given location and its corresponding radio signature. Every fingerprint has the RF information or RSS information of each AP and the fingerprint from the given location has a unique combination when compared to all the fingerprints in the map (Kaemarungsi and

Krishnamurthy, 2004). In terms of fingerprinting algorithms, it can be classified into two basic groups, deterministic and probabilistic algorithm (Honkavirta et al., 2009, Li et al., 2006).

1. *Deterministic algorithm.* It attempts to find the minimum statistical signal distance between the detected RSSI location vector and the location vectors of various calibration reference points. This may or may not be equal to the minimum physical distance between the actual mobile device's physical location and the recorded location of the calibration sample. The sample point with the minimum statistical signal distance between itself and the detected location vector is generally regarded as the best raw location estimate contained in the calibration database. Examples of deterministic algorithms like nearest neighbor are those based on the computation of the Euclidean or Manhattan distances (Brunato and Battiti, 2005).

2. *Probabilistic algorithm.* It uses probability inferences to determine the likelihood of a particular location given that a particular location vector array has already been detected (Youssef and Agrawala, 2005, Kushki, 2008). The calibration database itself is considered as the a priori conditional probability distribution by the algorithm to determine the likelihood of the occurrence of the particular location. Examples of such approaches include those using Bayesian probability inferences (Roos et al., 2002, Youssef et al., 2003).

### **2.6.1 Nearest Neighbor (NN) Algorithm**

The earliest and simplest deterministic algorithm is the NN algorithm used in RADAR, which is an in-building RF-based user locationing and tracking system (Bahl and Padmanabhan, 2000). The idea of this algorithm is to calculate the Euclidean distance between the current RSS at an unknown location and the signal strength mean values from each AP recorded in a database, and then find the closest neighbor (the minimum Euclidean distance), which is taken as the coordinate estimates of the unknown location (Zhou, 2006). Assume  $S_m = \{S_{m1}, S_{m2}, \dots, S_{mn}\}$  is the array of real-time signal strength mean values measured at an unknown location and  $n$  is the number of APs;  $S_{m1} \dots S_{mn}$  are the signal strength mean values from  $AP_1$ ,  $AP_2$  and  $AP_n$  respectively.  $S_i = \{S_{i1}, S_{i2}, \dots, S_{in}\}$  is the array of signal strength mean values of all the RPs in the database, where  $S_{i1}$  is the signal strength mean value from  $AP_1$  and  $S_{in}$  is the signal

strength mean value from  $AP_n$  respectively, The Euclidean distance can be then defined as:

$$d = \sqrt{(S_{m1} - S_{i1})^2 + (S_{m2} - S_{i2})^2 + \dots + (S_{mn} - S_{in})^2} \quad (2.9)$$

### 2.6.2 K-Nearest-Neighbor (KNN) Algorithm

The KNN algorithm is an extension of the NN algorithm introduced above.  $k$  is the number of the minimum Euclidean distance between each RP and the location of the mobile device (Li et al., 2005). When  $k$  ( $k \geq 2$ ) nearest neighbors are first identified from the fingerprint database according to the calculated Euclidean distances between the signal strength of each RP and the one got at the location of the mobile device, then the best location estimated is determined by the average of the coordinates (x, y) of all the  $k$  nearest neighbors. If  $k=1$ , KNN turns to NN. Assume the Euclidian distance and the signal strength vector of the mobile user is  $\{RSS_{i1}, RSS_{i2}, \dots, RSS_{in}\}$ , where  $RSS_{in}$  refers to the RSS of  $AP_n$  at  $RP_i$ , then the Euclidean distance can be calculated by the following formula:

$$d_i = \sqrt{\sum_{k=1}^n (RSS_{ik} - RSS_k)^2} \quad (2.10)$$

Since the signal attenuation in the 802.11 wireless networks is influenced by many factors, it is possible that the RSS values obtained at two different locations are almost the same. Generally, NN algorithm, which only considers the RP with the nearest RSS value, often obtains an estimated location far from the actual location. However, KNN considers more nearby neighbors and better results can be obtained (Jun et al., 2008).

### 2.6.3 Weighted K-Nearest Neighbors Algorithm

Similar to the KNN algorithm, the weighted k nearest neighbors method generates the final result through weighted mean of the  $k$  positions that have  $k$  minimum Euclidean distances. Assume  $S_m = \{S_{m1}, S_{m2}, \dots, S_{mn}\}$  is the array of real-time signal strength mean values at unknown locations and  $n$  is the number of Aps;  $S_j = \{S_{j1}, S_{j2}, \dots, S_{jn}\}$  have the minimum Euclidean distances to  $S_m$ ,  $L_j$  is the location corresponding to  $S_j$ ,  $j=1 \dots k$ . The estimated location (EL) can be calculated by (Zhou, 2005):

$$EL = \sum_{j=1}^k \frac{1}{d(S_j, S_m)} * L_j / \sum_{j=1}^k \frac{1}{d(S_j, S_m)} \quad (2.11)$$

The deterministic algorithms provide reasonable positioning accuracy, however, the performance of these algorithms is usually related to the size of the database, and thus building a large database is the basic assurance of high accuracy. Furthermore, the variation of the signal strength measured at each point is large, thus the average of the signal strengths, rather than an individual measurement, is used to estimate locations.

#### 2.6.4 Bayesian Algorithm

In order to achieve more accurate results, probabilistic algorithms have been developed. In probabilistic algorithms, the Bayesian algorithm is a basic probabilistic algorithm and it uses the Bayesian inference to determine the most likely location of the mobile device. During the training stage signal strength profiles are measured on a grid of location. A statistical distribution of the RSS at different locations is expressed by an empirical model. For example, assuming Gaussian measurement distribution, one can estimate mean and variance at each grid point using multiple observations. A statistical distribution is designed for all the points in the grid. Alternatively different observation sets can be combined as a sum of several equally weighted Gaussian kernel functions at locations L. A conditional probability and Bayesian inference can be used to estimate the location (Gunturu, 2008). For positioning, the Bayesian algorithm can be written as:

$$p(l_x | o_x) = \frac{p(l_x) \cdot p(o_x | l_x)}{\sum_{i=1}^m p(l_i) \cdot p(o_x | l_i)} \quad (2.12)$$

where  $l_x$  is the unknown location to be estimated,  $o_x$  is the currently RSS at unknown location x,  $l_i$  stands for the calibration location i, m is the number of calibration locations,  $p(l_x)$  is the prior probability of location x, and  $p(o_x | l_x)$  is a likelihood function in Bayesian terms that refers to the probability of signal strength obtained at x. During positioning process, the conditional probability at location x is calculated for fingerprints and the location corresponding to the maximal probability is taken as the best location estimate of the mobile device.

## **2.7 Summary**

In this chapter, an overview of mainstream positioning technologies including GPS, A-GPS, Wi-Fi and INS etc. are given. According to comparisons with other positioning systems, Wi-Fi based positioning systems are more favoured for indoor environments. The main challenges using Wi-Fi positioning systems for indoor environments are also discussed and an overview of smartphone technologies is presented.

Four types of measurements (i.e. TOA, TDOA, AOA and RSS) for positioning are elaborated and three most commonly used estimation methods for indoor positioning are introduced and inter-compared. Four fingerprinting algorithms including NN, KNN, Weight-KNN and Bayesian algorithms are introduced and their specific characteristics are examined.

## **Chapter 3: Field Experiments Using Smartphone and Ekahau — A Case Study**

Currently, a number of Wi-Fi based commercial real time location system (RTLS) has been developed and this includes Aer Scout, WhereNet, Newbury and Ekahau (Aer Scout, 2013, WhereNet, 2013, Newbury, 2013, Ekahau, 2013). Ekahau is a software-based system using Wi-Fi technology for location estimation that is used for this research. It provides different software packages to help in tracking Wi-Fi enabled mobile devices such as laptops, smartphones and Wi-Fi tags. Ekahau has been deployed in many commercial areas including hospitals, corporate offices, shopping malls and some industry sites. Compared with other systems, Ekahau is the only system that has the client software whereas the Aer Scout, WhereNet and Newbury do not have any client software (Bhaumik, 2010). Ekahau is also very cost effective in terms of hardware, as it does not require any proprietary hardware. However, most other systems including Aer Scout, WhereNet and Newbury require proprietary hardware. Therefore, Ekahau was selected as a main research platform and Ekahau RTLS is used for our case studies.

### **3.1 Introduction**

The Ekahau RTLS is the only Wi-Fi based tracking system that can operate over any brand or generation of Wi-Fi networks while offering sub room-, room-, floor- and building-level accuracy. As a Wi-Fi software system based on 802.11 a/b/g/n standard, the Ekahau RTLS does not require readers, new cabling, choke points or excitors. It operates over existing Wi-Fi infrastructure and uses a statistical probability algorithm to estimate the location of the object being tracked. Figure 3.1 shows how the Ekahau RTLS works (Ekahau, 2012).

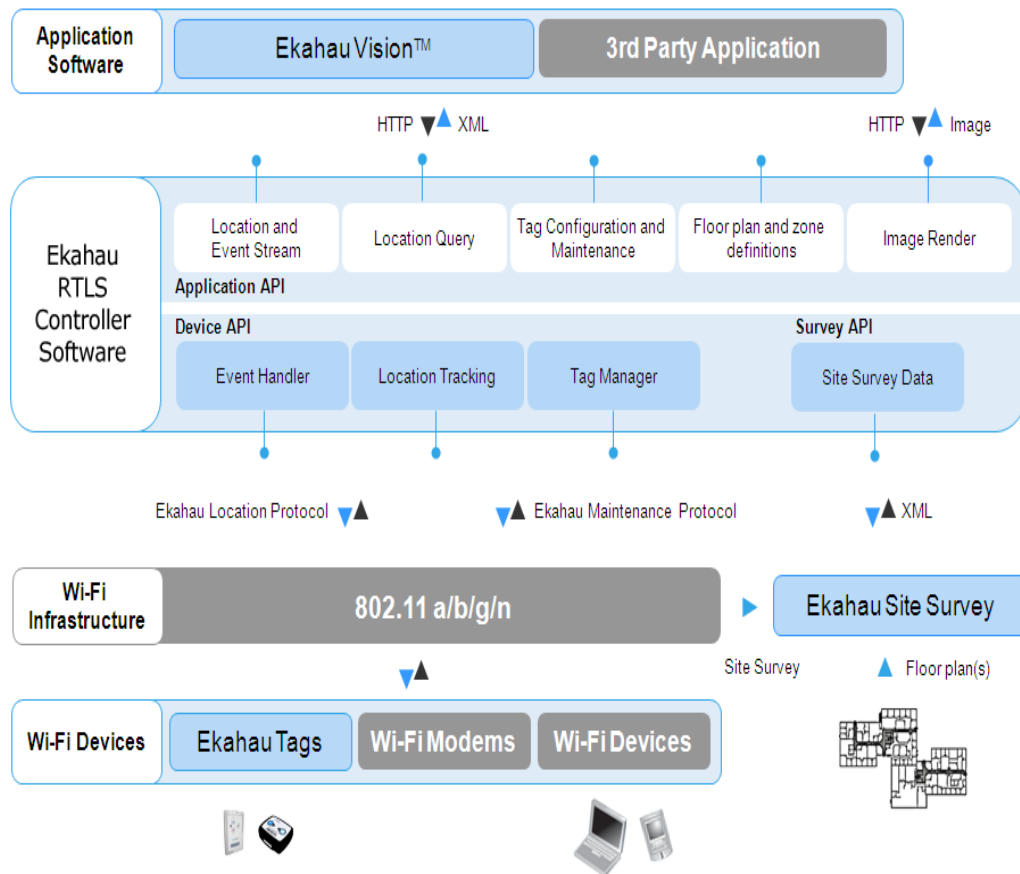


Figure 3.1 Architecture and work flow of the Ekahau RTLS

Typically, an RTLS consists of a wireless data network, tags, server software and end-user application software. The Ekahau RTLS uses RSS measurements from existing Wi-Fi APs for location estimation and tracking, thus it leads to lower cost. As a whole tracking solution for asset and people tracking, the Ekahau RTLS usually consists of five components called, RTLS Controller server software and its API, Ekahau Site Survey, Ekahau Wi-Fi Tags, Ekahau Vision Application and Ekahau Positioning Client. Ekahau Wi-Fi tags are not introduced below since they are not used for building Ekahau RTLS solutions in our case study.

### Ekahau RTLS Controller (ERC)

The ERC is the core of the Ekahau RTLS. It is a web service that runs on a dedicated Windows® server. The ERC has an easy-to-use web browser user interface and provides the following five features:

- Tag management and deployment activities;

- Accurate location estimation;
- Event handler;
- Systems and devices management; and
- Open application APIs for integrating 3<sup>rd</sup> party applications.

For application developers, the ERC is a web service. The location information is available for applications through an open HTTP request and XML response based interface. The developers do not have to understand how the Wi-Fi devices are configured and how the location algorithm works. They can concentrate their application design and development efforts on translating location update events into valuable information. Figure 3.2 displays the requests from an application developed in the mobile device to the ERC (Ekahau, 2012).

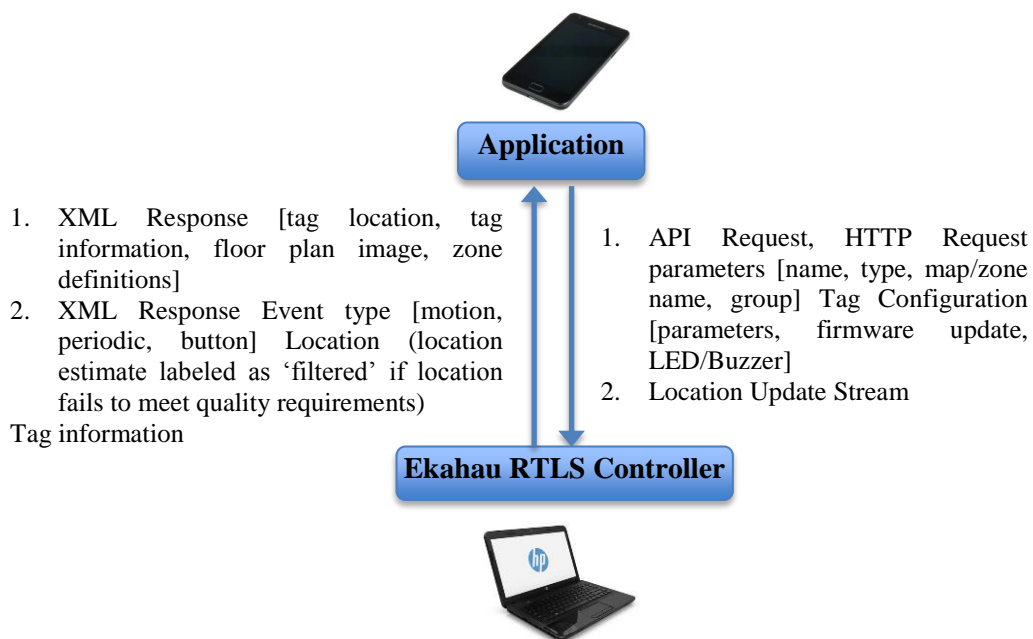


Figure 3.2 The flow chart of the request and response between the application and the ERC

### Ekahau Site Survey (ESS)

The ESS is used for creating a reference database in the calibration phase to help the ERC to calculate the location of Wi-Fi devices. It can be also used for creating the wireless networks plan, and analysing the wireless network and location accuracy. The main tasks of the ESS include:

- Recording signal measurements;

- Defining the environment such as open spaces, rails and zones;
- Analysing and optimising location accuracy;
- Tracking local Wi-Fi devices such as Wi-Fi tags, Wi-Fi routers, laptops or smartphones; and
- Saving and sending the project to the ERC.

### **Ekahau Vision**

Ekahau Vision is an end-user application for location and visualising the location of the mobile objects in real time. Monitor, measure and manage mobile objects can be performed after the Wi-Fi based location devices are activated over existing Wireless LAN by installing Vision™. Ekahau Vision receives real-time position updates from the ERC and displays whereabouts of the mobile devices; laptops or Wi-Fi tags are on the map.

### **Ekahau Positioning Client (EPC)**

The EPC is a small software tool for tracking mobile devices. It is available for laptops operating on Windows XP / 2000/ Vista / 7, mobile devices operating on Windows CE/ Mobile 5 (Pocket PC)/ Mobile 6 (Classic and Professional) and for other selected devices like the Android and Symbian platforms. The EPC works similar to Wi-Fi tags, which are used by scanning compatible Wi-Fi devices for RSS data and transmitting the data over the wireless network to the ERC server. The EPC together with the Ekahau Vision™ software may be used to track and view real-time locations of smartphones, tablets, laptops and other Wi-Fi enabled enterprise assets.

## **3.2 Estimation Approach and Algorithm**

Unlike the traditional “triangulation” method, Ekahau’s patented algorithm uses a probabilistic approach to process RF signals. More specifically, it uses a method called Multi-hypothesis tracking for location estimation. The algorithm constantly calculates multiple possible location estimates for the object being tracked and gives each possible location estimate a numerical score. For the calculation of the score, the algorithm gets input all known factors from the real world. This includes, for example, the characteristics of the environment, the mobile device, the signal history and the

movement models. The location corresponding to the highest score is taken as the location estimate.

However, the Multi-Hypothesis method was soon found to be very computationally intensive since hundreds of position scores for each mobile device being tracked need to be calculated. For large-scale deployments with tens of thousands of real-time devices tracked, further development is needed. This scalability issue is resolved well in Ekahau through introducing new concepts such as “rails”, “relevant sample points”, “open spaces” and “zones” to the topology framework of the algorithm. These technologies assist the algorithm in calculating the “legal pathways” where a mobile object is able to move in the physical world and to determine which areas are relevant based on signal measurements so that the computations are only restricted to those routes and areas.

### **Rail setting**

Rails indicate the possible paths of movement of the devices being tracked. The rails improve the accuracy of location estimates by indicating which routes will be most likely than others. For example, the rails indicate that it is much more likely for the device to walk through the doorway than to move through the walls. The rails do not force the device being tracked to be located on the rails, and they do not completely disallow the tracked device to take paths that are not indicated by the rails. Instead, the rails just indicate that some paths are more likely than others.

### **Open spaces**

In some areas, typical walking paths are unknown, and the device being tracked may reside anywhere within these areas, e.g. when the device is in a large meeting room, inside a cafeteria or a hotel lobby. These relatively large open spaces are defined as polygons and are called open spaces in the Ekahau RTLS.

### **Zones**

Zones represent areas of interest that are communicated via the ERC to the application. Zones create human-understandable names for locations on the map. For instance, one can create an alarm system on the application layer to represent restricted areas.

### 3.3 Environmental Setup

For testing and analysing the accuracy and performance of the Ekahau RTLS, an indoor positioning lab is established. Its facilities and environmental settings for our case study are introduced below.

#### System design and environmental setup

Our indoor positioning lab is established in the SPACE Research Central on level 4 Building 100 (Design Hub building), at RMIT University, Melbourne. The floor plan layout of the lab is shown in Figure 3.3. Eleven mobile desks and three low shelves are used for setting the wireless APs and increasing the complexity of the indoor environment. Linksys WAP54G wireless APs are placed at different locations as both wireless signal transmitters and receivers. HP Elite Book 2560p combined with Windows 7 professional OS are adopted as the server device. A Samsung Galaxy S3 smartphone is used as the Wi-Fi enabled mobile device to be tracked. Both the laptop and smartphone are integrated with an Intel(R) 82579 LM Gigabit Network Connection wireless card and an Intel wireless PMB9811X Gold Baseband adapter respectively. These network cards synchronise with the network and measure signal strength from the APs and mobile devices. Figure 3.4 shows these hardware devices in the SPACE lab. In this case study, the 802.11 n protocol is used.

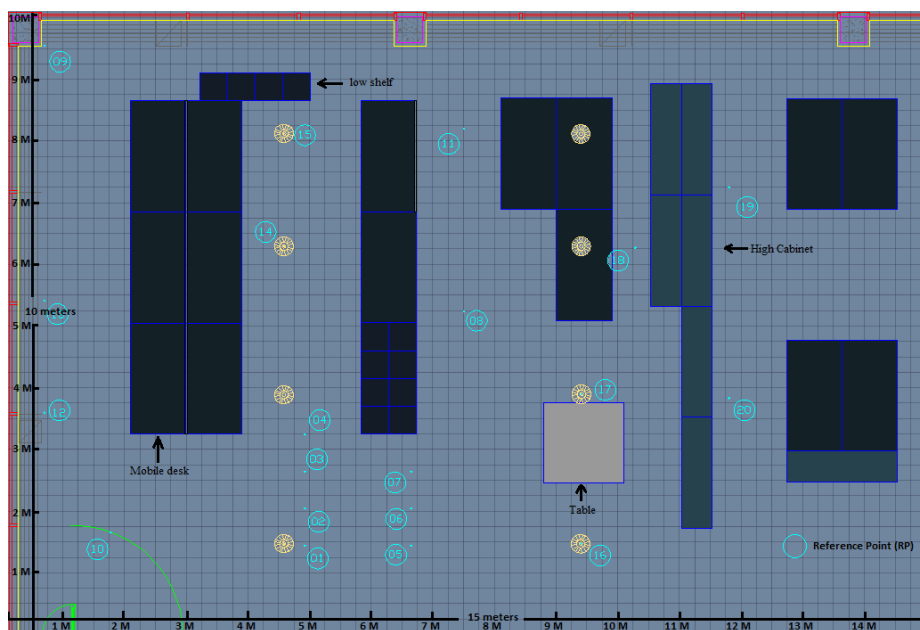


Figure 3.3 The layout of the indoor positioning lab on level 4, Building 100 at RMIT University (the Design Hub Building)



Figure 3.4 Hardware devices used in our experiment

#### *WLAN APs*

Six Linksys Wap54G APs are chosen to build the WLAN environment. It follows IEEE 802.11g, which supports data rates up to 54 Mbps. It is also backwards compatible with existing IEEE 802.11b devices. The specifications of each of the APs, including their brand, SSID, MAC address and signal transmission channel are summarised in Table 3.1.

Table 3.1 Specifications of each Cisco router

Model	SSID	MAC address	IP address	Channel
Cisco Linksys Wap54G	SPACE-AP1	00:18:F8:28:49:C8	192.168.100.11	2
Cisco Linksys Wap54G	SPACE-AP2	00:1A:70:AC:1B:97	192.168.100.12	3
Cisco Linksys Wap54G	SPACE-AP3	00:1A:70:AC:22:69	192.168.100.13	4
Cisco Linksys Wap54G	SPACE-AP4	00:1A:70:AC:22:5D	192.168.100.14	5
Cisco Linksys Wap54G	SPACE-AP5	00:1A:70:AC:1F:FD	192.168.100.15	7

#### *Laptop and Smartphone*

A HP laptop is used as a server for creating a database, calculating the position and sending the position estimate to the smartphone. The Samsung smartphone is used as the mobile device to be tracked. The specifications of the laptop and the smartphone, including the brand, CPU, OS and the WLAN adapter model are listed in Table 3.2.

Table 3.2 Specifications of the laptop and the smartphone

Brand	CPU	OS	WLAN adapter
HP Elite Book 2560p	I7	Windows 7 Pro	Intel(R) 82579 LM Gigabit Network Connection
Samsung Galaxy S3	1433MHz	Android OS 4.0	Intel wireless PMB9811X Baseband adapter

### **Design considerations of deploying the Ekahau RTLS**

Before deploying the Ekahau RTLS, several factors need to be taken into considerations at the design stage. This includes:

1. *Positioning algorithm.* The Ekahau RTLS uses the fingerprinting method and a positioning accuracy as high as 3–5 meters was reported in a case study at the King Hamad University Hospital (Report, 2012). Building a signal strength database is necessary for this tracking method and the quality of the database plays a critical role for the performance of the system.
2. *Influence of indoor furniture.* Different furniture such as mobile desks, cupboards, low shelves and chairs affects signal strength reception differently. For the fingerprinting method, a high level of variability in RSS values at different APs will benefit the positioning accuracy.
3. *The size of the testing area.* The positioning accuracy of the Ekahau RTLS is affected by many factors such as the number of RPs, the number of APs necessary to cover the service area, accurate definition of open spaces and rails, and the time necessary to collect the signal strength. Therefore, we have to select a testing area that is sufficiently covered by our five APs all the time.
4. *The number of APs.* Normally, at least three APs are needed for positioning no matter what positioning method (e.g. the triangulation or fingerprinting) is used. Using more APs can improve the precision and accuracy of location estimates; however, it may increase mathematical complexity and data processing time. In addition, it is not necessarily true that the more the number of APs, the more precise and accurate of the location estimates. In our case study, only five Aps were used. These APs need no connection to the Internet since they are made in the same layer of the network as the server. The signal strengths measured from these APs are used to create the reference database and the location detection of the device tracked.

5. *The number of RPs.* A number of RPs need to be selected from the testing area and the signal strengths measured at each RP need to be recorded in the reference database. This is implemented in the calibration phase of the fingerprint method. The number and distribution of the RPs affect the performance of the Ekahau RTLS. When selecting the RPs, it needs to ensure every RP has a sufficient number of APs visible at every point of time. In our case study, 20 RPs were selected at various locations in the testing area (see Figure 3.5).

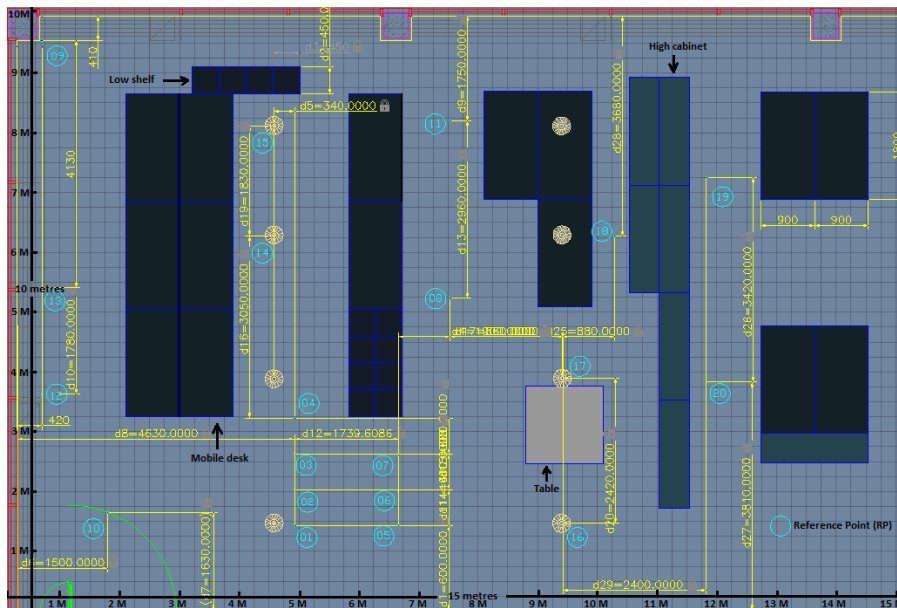


Figure 3.5 Location of 20 RPs in the testing area (RMIT SPACE Indoor Lab)

### **Installation of ERC in the laptop as a remote server**

The ERC is installed in the HP Elite Book 2560p laptop. It can be easily used through the IE browser of the laptop. Basically, it is used for location tracking and Wi-Fi device's configuration and management. Figure 3.6 displays the interface and some configuration of the ERC.

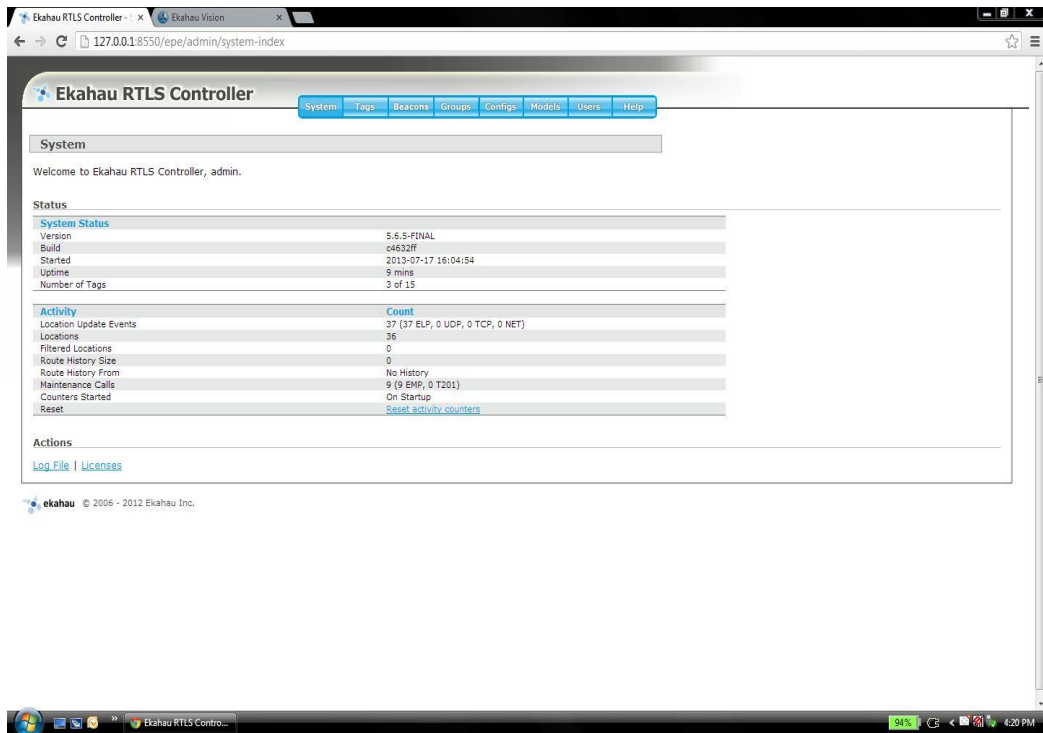


Figure 3.6 The interface of the ERC

### Deploying RTLS using ESS

The ESS is used for creating the wireless network plan and analysing the signal strength of our wireless network. As shown in Figure 3.7, we start walking from the g2 AP, which is on the outside of the door and then walked across the RPs one by one, and ended at RP 20. The whole data collection time is about 10 minutes. The ESS automatically create a RSS database based on the walking path when the site survey is finished. Theoretically, we could improve the accuracy of the Ekahau RTLS by repeating site survey in different walking paths. In this case study, only a RSS database for our test environment is created. Figure 3.7 shows the walking path of our tests. The SSID and MAC address of testing five APs are displayed under the left Access Points categories. The signal strengths of the APs in the experimental area are measured by the Ekahau RTLS after site survey is conducted (see Figure 3.8), from which we can find that the signal strengths of our indoor environment are relatively well distributed and their values are between -20 dBm and -60 dBm. The strongest signal strength is close to the AP and it is found that some positions do not necessarily have signal strength attenuation. The poor signal strengths are all around the door and some metal furniture.

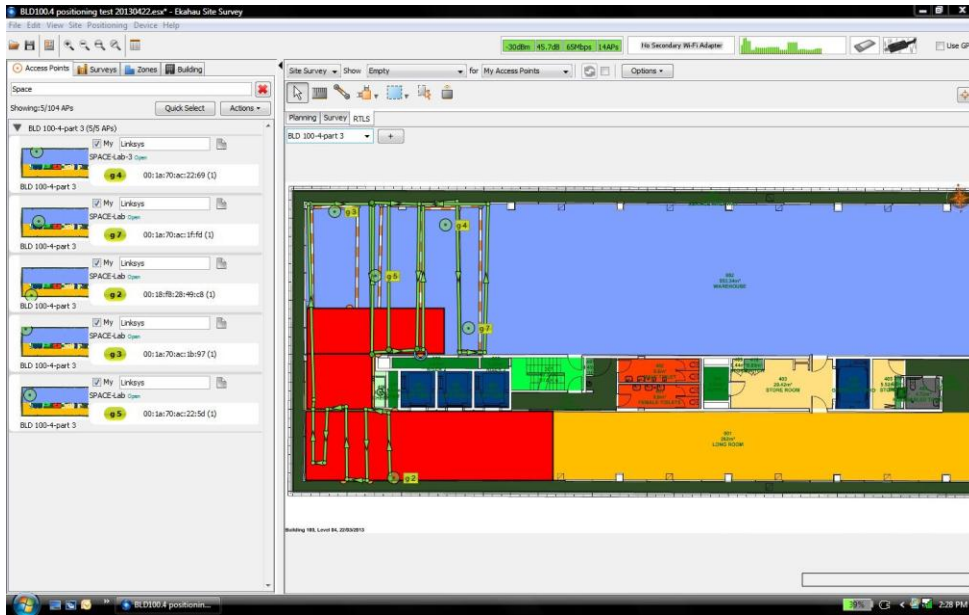


Figure 3.7 Walking path of the Ekahau tests

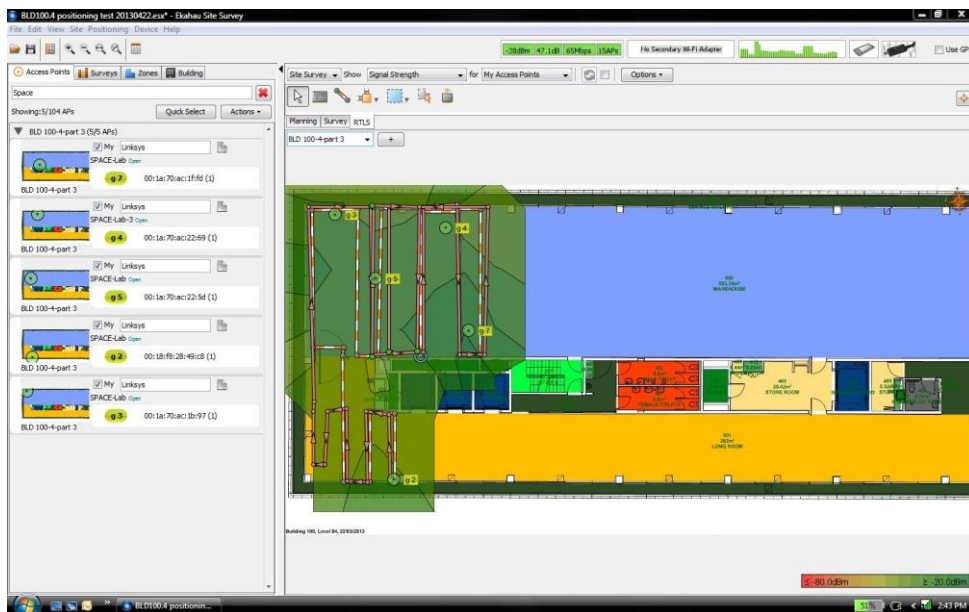


Figure 3.8 The signal strength distribution in the experimental area

### Installation of the EPC on the smartphone

The EPC application is downloaded from the Ekahau website and installed on the Android Samsung Galaxy S3 smartphone for our tests. The interface of this application is displayed in Figure 3.9.

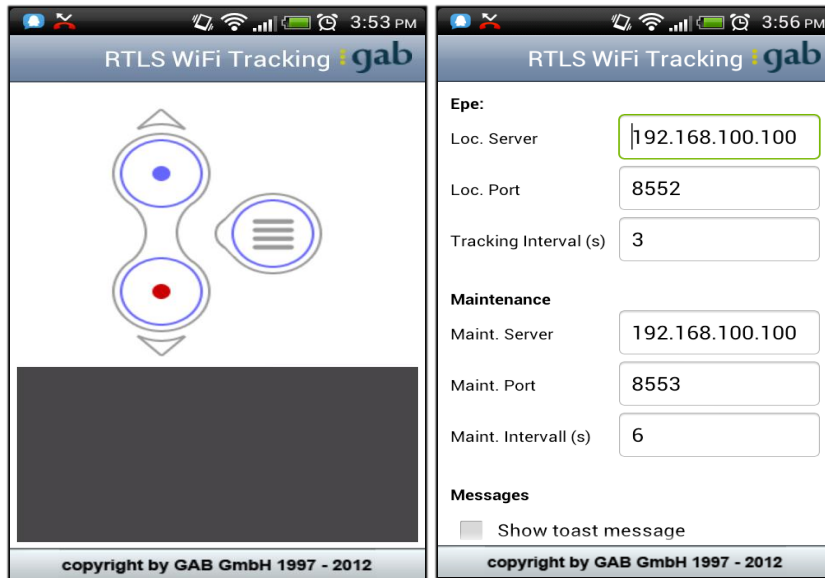


Figure 3.9 The interface and configuration of the EPC

According to the configuration of the IP address of the EPC, it is located in the same IP segment as the ERC. Both ERC and the EPC can be easily identified with the help of their IP address and hence they can communicate with each other.

The ERC is the core of the entire setup. The ESS is used to perform the site survey of the experimental environment and establish a positioning model. According to the normalised RSS values obtained from various network adapters or different network adapter cards, the ESS can build a positioning model following the common network standard the ERC can read. Then the positioning model is transferred to the ERC and used as a reference database for further position estimation of real positioning tasks. When the smartphone running the EPC application moves around in the test environment, the EPC will obtain the surrounding RSS values and then transmit them to the ERC. Then the ERC uses the Ekahau position-detecting algorithm to compare the obtained RSS values to the RSS values stored on the ERC before. Finally, an approximate position estimate will be calculated and sent to the smartphone using the XML format. The smartphone updates its position by transmitting the RSS values to the nearest AP. The updated position will be calculated at the server site (ERC) and sent to the smartphone. Meanwhile, this position data is sent to the Ekahau Vision for monitoring the smartphone. The entire setup of our field experiment is described in Figure 3.10.

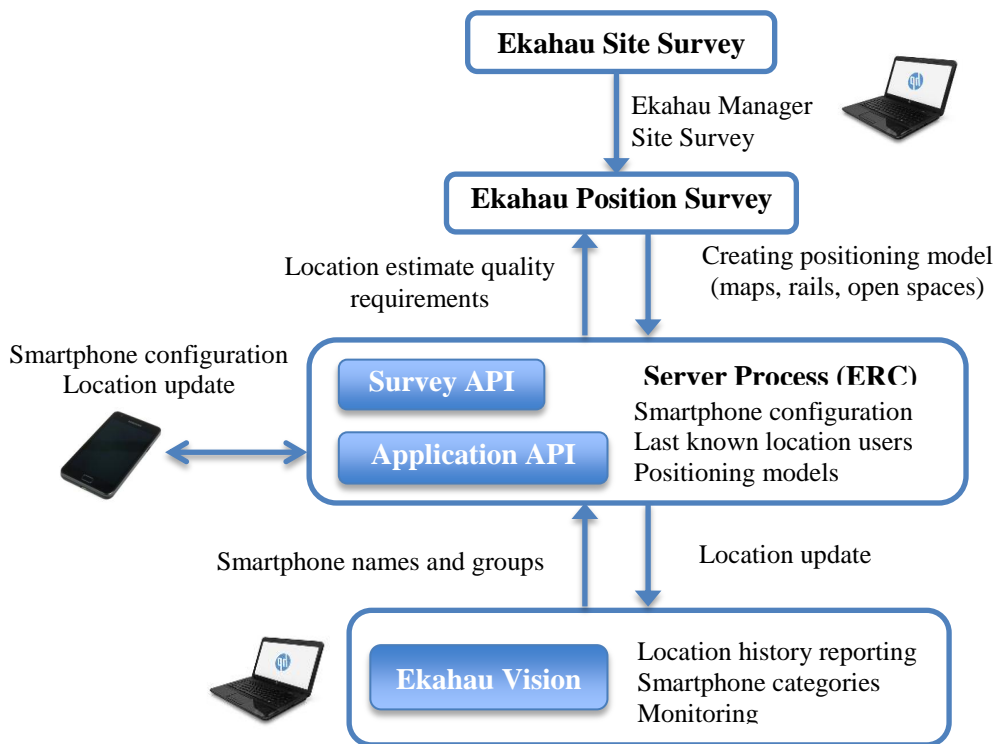


Figure 3.10 The diagrammatic representation of the Ekahau RTLS in our field experiment

### 3.4 Performance Evaluation

In this section the performance of the Ekahau RTLS is evaluated using the smartphone introduced above as a tracking device. The main focus of the performance assessment is on the accuracy, precision and stability of the position estimates can be achieved by using the Ekahau RTLS testing system. Various factors that affect the performance of position estimates including the indoor environment, response time, the settings of the Ekahau RTLS, and the effects of the number of APs are analysed in this section.

#### *Accuracy*

Accuracy (or location error) is the most important requirement of positioning systems. Usually, mean distance error is adopted as the performance metric, which is the average Euclidean distance between the estimated location and the true location. As aforementioned, 20 RPs at different positions are set up in our experiment. In order to analyse the accuracy of this Ekahau RTLS, a java-based application using the Ekahau developer SDK is developed to obtain 20 estimated location samples at each RP from Ekahau RTLS. Figure 3.11 displays the 20 estimated location samples recorded at RP 1. Table 3.3 lists the results of the estimated location of each RP in comparison with their

associated reference values recorded in the Ekahau RTLS database. The difference between the two datasets indicates the accuracy of the location estimates.

	A	B	C	D
1	Data Collection Time	MAC address	X	Y
2	17/04/2013 12:06:34	18:87:96:51:CE:69	428	200
3	17/04/2013 12:06:37	18:87:96:51:CE:69	428	199
4	17/04/2013 12:06:40	18:87:96:51:CE:69	428	203
5	17/04/2013 12:06:43	18:87:96:51:CE:69	428	211
6	17/04/2013 12:06:46	18:87:96:51:CE:69	428	211
7	17/04/2013 12:06:49	18:87:96:51:CE:69	427	209
8	17/04/2013 12:06:52	18:87:96:51:CE:69	428	206
9	17/04/2013 12:06:55	18:87:96:51:CE:69	428	205
10	17/04/2013 12:06:58	18:87:96:51:CE:69	428	204
11	17/04/2013 12:07:01	18:87:96:51:CE:69	427	206
12	17/04/2013 12:07:04	18:87:96:51:CE:69	428	205
13	17/04/2013 12:07:07	18:87:96:51:CE:69	428	207
14	17/04/2013 12:07:10	18:87:96:51:CE:69	428	212
15	17/04/2013 12:07:13	18:87:96:51:CE:69	428	209
16	17/04/2013 12:07:16	18:87:96:51:CE:69	428	210
17	17/04/2013 12:07:19	18:87:96:51:CE:69	428	206
18	17/04/2013 12:07:22	18:87:96:51:CE:69	428	208
19	17/04/2013 12:07:25	18:87:96:51:CE:69	427	222
20	17/04/2013 12:07:28	18:87:96:51:CE:69	428	212
21	17/04/2013 12:07:31	18:87:96:51:CE:69	427	215

Figure 3.11 The 20 estimated locations at RP 1

Table 3.3 The accuracy of the location estimates across 20 testing points

Reference point	Reference location (cm)		Estimated location (cm)		Accuracy (cm)
	X	Y	X	Y	Distance
RP 1	463	141	428	208	75
RP 2	463	201	428	196	35
RP 3	463	261	428	199	71
RP 4	463	321	427	192	133
RP 5	637	141	427	198	217
RP 6	637	201	427	201	209
RP 7	637	261	377	242	262
RP 8	723	522	428	375	330
RP 9	42	953	193	797	217
RP 10	150	163	329	187	181
RP 11	723	818	612	618	228
RP 12	42	361	138	387	100
RP 13	42	539	136	498	103
RP 14	429	626	427	397	228
RP 15	429	809	428	579	229
RP 16	913	141	573	198	344
RP 17	913	383	622	208	339
RP 18	1001	625	871	432	232
RP 19	1153	723	1002	958	279
RP 20	1153	381	1003	604	268

### ***Precision***

Basically, the accuracy indicator only considers the value of mean distance errors. However, precision considers how consistently the system works. Usually, the cumulative probability function (CDF) of the distance error is used for measuring the precision of the positioning system. In our experiment, the precision of the Ekahau RTLS is analysed through the distribution of distance errors between the estimated and the actual physical location. Twenty RPs are used for the computation of the statistics of the Euclidean distance errors (between the estimated and the actual physical location from each RP). The following CDF graph illustrates the probability of the positioning error. The x-axis represents the distance in centimetres and the y-axis represents the probability of the error.

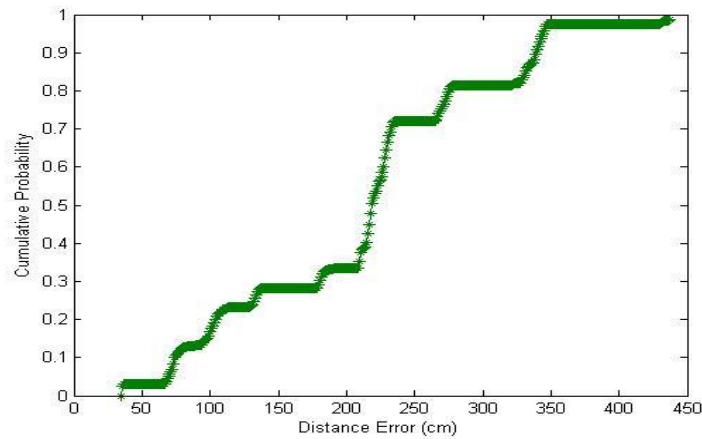


Figure 3.12 Probability of the positioning error in the field experiment

### ***Stability***

A positioning system with a high stability is not strongly affected by “abnormal” environmental information (e.g. when some RSS are not available and/or their values are outside the ranges recorded in the system). The stability of the Ekahau RTLS depends on the stability of the signal strength in the test environment. When the mobile device does not sense the signal strength of an AP or the signal strength fluctuates drastically, the Ekahau RTLS will calculate its location with a large error. In order to analyse the stability of the system, we continuously collect RSS values from the SPACE-AP1 for about one hour using the Vistumbler software (see Figure 3.13). Vistumbler is a Wi-Fi networks tool that detects for nearby wireless networks within the range of a Wi-Fi adapter and display the networks SSID, signal strength, encryption being used, mac

address, the networks channel, access point manufacturer etc. (Vistumbler, 2013). In our experiment, it is used for visualizing the variation of the signal strength. It shows that the RSS values typically vary between -28 dBm to -45 dBm and in some instances the RSS were not recorded properly at all.

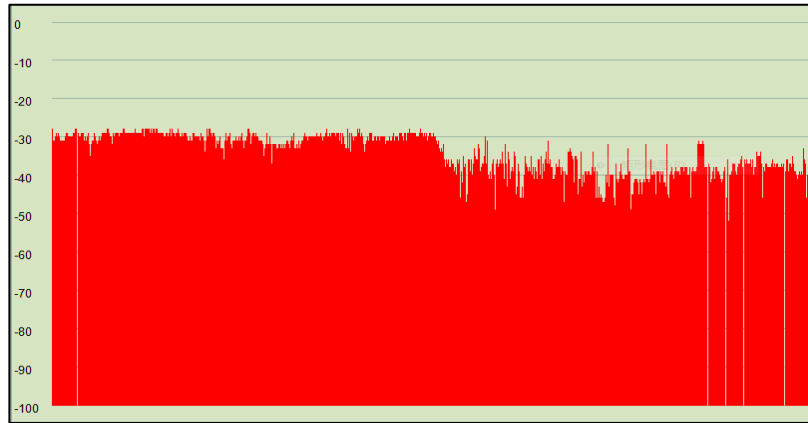


Figure 3.13 Variations in RSS values of SPACE-AP1 in one-hour period of time

The major factors that affect the accuracy, precision and the stability of the Ekahau RTLS in this test are the response time, the influence of the indoor environment and the settings of the Ekahau RTLS.

***Response time of the Ekahau RTLS***

The response time between the system and the mobile device affects the position estimate. This is a limitation caused by the data loading speed of the network and the computational capability in tracking stage. The system will usually not respond promptly when the moving direction or the moving speed of the smartphone user suddenly changes. Table 3.4 displays the response time when the user moves from one RP to another in our test.

Table 3.4 The time delay for a position change in the mobile user

Position change of the user	Response time (in seconds)
RP 1 → RP 2	3
RP 2 → RP 3	3
RP 3 → RP 4	3
RP 4 → RP 5	5
RP 5 → RP 6	3
RP 6 → RP 7	3
RP 7 → RP 8	4
RP 8 → RP 9	5

RP 9 → RP 10	4
RP 10 → RP 1	3
Mean respond time	3.6

### ***The effects of the indoor environment***

As an RSS fingerprinting based system, the Ekahau RTLS is sensitive to the variations in the signal strengths at the APs. In our case study, the indoor environment is a relatively open area, the variations of RSS values at different RPs are not very clear even though some barriers like mobile desks, chairs, and low shelves are used to “strategically” increase the complexity of the indoor environment. Therefore, according to Table 3.3, we can see that the estimated locations of some RPs are almost the same, while their actual physical locations are different.

### ***The effects of the ESS settings***

The setting of ESS also affects the accuracy of the Ekahau RTLS. In our case study, only a basic walking path is set, but not the rails and open spaces. Therefore, it will not help the ERC to identify the location of the user when the user moves following a rail or in an open space. From the analysis of Gunturu (2008), we can see that there is considerable improvement in the RSS observations if rails are used (see Figure 3.14). As discussed earlier, the Ekahau RTLS works based on the concept of the probabilistic algorithm. The probability curve for signal strengths of AP without rails is broad and wide; therefore the corresponding location is picked from a broad range of possible locations. However, the probability curve becomes steeper when rails are used. The corresponding estimated location is selected from a smaller number of possible locations. Therefore, rail setting can help to improve the accuracy of the system considerably.

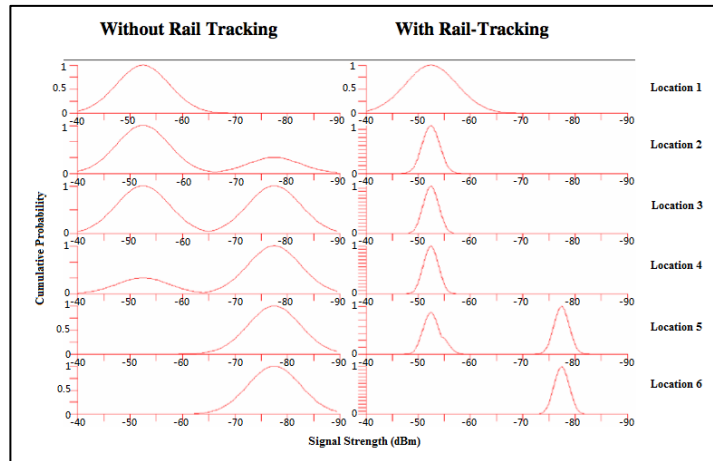


Figure 3.14 Comparison of signal strength with and without use of rails (Gunturu, 2008)

### *The effects of the number of APs*

The number of APs can also affect the accuracy of the positioning system. In this section a simple test is presented that uses the same setting and different numbers of APs. This simple test is conducted in the RMIT indoor positioning lab by increasing the number of APs to seven; the performance of the seven APs testing case outperforms the five APs case. It reduces the distance error by 0.32 m compared to the five APs case. In addition, the seven APs case also significantly reduces the maximum error from 4.98 m to 4.72 m (0.26 m). Figure 3.15 illustrates the CDF of the positioning errors against different numbers of APs. It is clearly noticed that the more the number of APs we use, the more accurately and precision the Ekahau RTLS can predict the location.

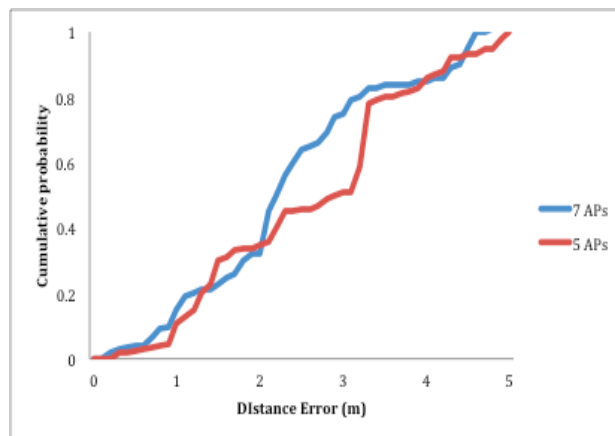


Figure 3.15 CDF of the positioning errors against different numbers of APs

### **3.5 Summary**

This chapter introduces a commercial indoor positioning system - the Ekahau RTLS. Five key aspects of the software system are presented and valuated. A field experiment using an Android smartphone and Ekahau RTLS is designed and tested through a case study. The performance of the Ekahau RTLS is evaluated in terms of: accuracy, precision and stability. Furthermore, the major factors that affect the accuracy, precision and the stability of the system are also discussed.

## **Chapter 4: New System Development Using a Smartphone and Wi-Fi**

In this chapter, a Wi-Fi based indoor positioning system is developed using an Android smartphone to receive Wi-Fi signal strength measurements. This system is easy to be implemented and low cost since only APs are required for hardware, in addition to the Android smartphone. In this system, five APs are installed at pre-selected locations to cover all the area of interest for localisation. For location estimation, the RSS-based fingerprinting method is used and a simple matching algorithm is adopted to filter the error in signal strengths.

The following sections mainly describe how our positioning system is set up and run. The testing results in our specific indoor environment are evaluated and compared with that of the Ekahau RTLS.

### **4.1 Software Platform, Tools and Development Kit**

In our indoor positioning system, the Android software platform, the Apache Tomcat web server, Microsoft SQL Server database and Android development kits for experiments are selected. A smartphone application is developed in the Android platform for the collection of Wi-Fi signal strengths and signal strength data are collected and imported into the Microsoft SQL Server database which will be called by the positioning algorithm implemented on the server. Apache Tomcat sets up a web server for connecting the client side Android application and the server side. The smartphone user uses the Android application to receive location estimates sent by the server. More details on the platform, development kits and some assistant tools used in our system are described below.

**Android platform:** Android is an open source Linux-based operating system that is designed by Google primarily for touchscreen mobile devices such as smartphones and tablet computers. It provides various device drivers and management modules, class libraries and frameworks such as lightweight database SQLite and Web kit browser. Google releases the code under the Apache License and allows the software to be freely modified and distributed by device manufacturers, wireless carriers and developers. With the rapid increase of Android smartphone market share, the Android operating system has become one of the most widely used operating systems in the smartphone industry.

In our experiment, the Samsung Galaxy I9305T with Android 4.1.2 OS is used for developing the client side application.

The Android platform is divided in four layers, which include five groups (see Figure 4.1), and the names and explanation for the five groups are given below (Android, 2013).

1. **Application:** It is the only layer used by smartphone end users. It can run multitask simultaneously and is written in Java language.
2. **Application framework:** It is used to implement the standard structure of an Android application.
3. **Libraries:** The available libraries are written in C/C++ and are called through a Java interface.
4. **Android runtime:** It consists of two components: a set of core libraries which provide most of the functionalities in the Java core libraries, and the virtual machine Dalvik, which operates like a translator between the application and the operating system.
5. **Linux kernel:** This kernel is used by Android for the management of devices, memory, process and networking.

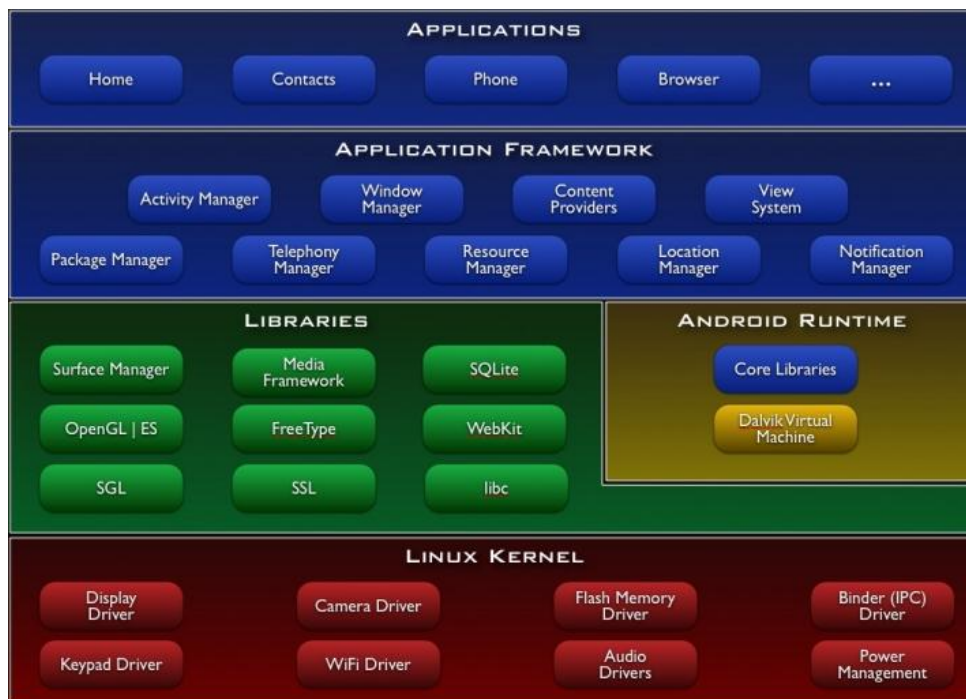


Figure 4.1 The architecture of the Android platform (Wang, 2011)

**SQL Server database:** A Microsoft SQL Server database is a relational database management system developed by Microsoft. It is normally used to store and retrieve data as requested by other software applications. Recently, lightweight database SQLite is available for all Android applications due to the limited memory space and computation speed. Android smartphones can run a SQLite database which is sufficient for applications with a small size database. However, this database cannot meet the requirements of storage capacity for a large amount of data for our experiments. Therefore, we adopt the Microsoft SQL Server database running on a remote server with a high computational speed and a large memory space for storing the signal strength data. The user needs to connect to the server database to retrieve the data and obtain location estimates from the server.

**Apache Tomcat:** Apache Tomcat is an open source software implementation of the Java Servlet and Java Server Pages technologies. The Java Servlet and Java Server Pages specifications are developed under the Java community process. Apache Tomcat includes tools for the configuration and management of web server, but can also be configured by editing XML configuration files (Tomcat, 2013). In our experiments, Apache Tomcat runs in web service for communicating with the Android smartphone and sending location estimate to it.

## 4.2 Algorithm

There are two major localization methods: trilateration and fingerprinting. The selection of which method for an application mainly depends on whether the location coordinates of APs are known. Trilateration is the most commonly known approach to calculate positions of points using distance measurements. The distance between points can be calculated from both signal propagation time and speed. Signal propagation models for converting signal strengths into distances assume an exponential attenuation model for Wi-Fi signals and use the path loss to determine the likelihood of objects' location based on the distance between the objects and the APs. In order to use this approach, for 2D location estimation, at least two APs with known coordinates are required. If we draw a circle with the centre at each AP and a radius equal to the distance from the AP to the

mobile object, the intersection of the circles from all APs gives the possible position of the mobile object. This is the basic principle of trilateration.

An exponential attenuation model of the signal propagation is usually used to express the relationship between signal strength and distance. However, this is prone to large errors due to the complexity of the indoor environments and strong time-varying characteristics of the Wi-Fi signal strengths. In contrast, the fingerprinting positioning method uses a set of signal strength observations from APs and compares these observations with all the records in the calibration database to find the set with the closest matched reference location. In an open space indoor environment, the signal strengths observed at an area near relevant APs will have little difference. This makes it difficult to identify which surrounding reference location is the best match. The complexity of the indoor environment is helpful in this regard since it will potentially cause large differences in the RSS set of the reference locations. In our experiments, the RSS fingerprinting method is used due to the complexity of the indoor environment of the lab.

Fingerprinting based algorithms mainly include two types: deterministic and probabilistic algorithms (see section 2.6). Normally, the deterministic algorithm has high computational efficiency but low accuracy. The probabilistic algorithm usually uses the Bayesian law to determine the most likely location of the mobile device. Compared with the deterministic algorithm, it has higher accuracy but requires larger amount of calculation effort. In our experiments, a simple matching algorithm is used for location determination of the smartphone user. In the calibration phase, the mean value of the RSS from all APs observed at each RP are calculated to reduce the errors from the time-varying characteristics of the Wi-Fi signal strengths. Formulae 4.1 and 4.2 are used for the calculation of distances between the test vector  $s = (s_{AP_1}, s_{AP_2}, s_{AP_3}, \dots, s_{AP_n})$  of RSS readings in the Android smartphone and the RP vector which is associated with the known location and stored in the database as  $S = (S_{AP_1}, S_{AP_2}, S_{AP_3}, \dots, S_{AP_n})$ :

$$L = \sqrt{\sum_{i=1}^n |s_i - S_i|^2} \quad (4.1)$$

$$R_L = (\bar{S}_{AP_1}, \bar{S}_{AP_2}, \dots, \bar{S}_{AP_n}) \quad (4.2)$$

where  $n$  is the number of APs;  $R_L$  is the weighted mean value of the signal strengths from  $n$ -th APs and  $\bar{S}_{AP_1}$  is the mean value of the signal strengths from  $AP_1$ .

Vectors  $s$  and  $S$  represent the average values of signal strength stored in arrays. In our experiments, the calibration database containing at least 200 samples is built and these samples are collected by the Android smartphone at each RP from all relevant APs over a period of time.

In the positioning phase, the smartphone device collects the RSS observations from different APs, then calculates the mean RSS value and finds the closest matched signal strength value stored in the calibration database for the location determination of the smartphone device. Generally speaking, the more the data collected for the database, especially from more RPs, the better the accuracy of the positioning estimates. However, large amount of data will adversely affect the position estimation speed. This has been tested and the results are shown in the sections below.

The simple match algorithm discussed above is used in our experiments. The following four steps describe how this algorithm works.

*1. Collecting signal strength for the database*

20 RPs are set up and the MAC addresses and RSS values of APs at each RP are collected over a period of time (say 10 mins). The format of the data transferred into the database is displayed in Table 4.1.

Table 4.1 The format of the MAC addresses data and RSS values observed at RP 1

BSSID	MAC address	RSS value
SPACE-AP1	00:1A:70:AC:1F:FD	-75
SPACE-AP2	00:1A:70:AC:22:5D	-44
SPACE-AP3	00:1A:70:AC:1B:97	-55
SPACE-AP4	00:1A:70:AC:22:69	-53
SPACE-AP5	00:18:F8:28:4A:B4	-69

*2. Calculating the range of RSS*

For each RSS measurement, a signal strength range is determined based on the mean RSS plus standard deviation value  $x$ , of a series of RSS values collected for a long period of time,  $[RSS-x, RSS+x]$ . It should be noted that when calculating the mean and the standard deviation values, those weak and unstable RSS values are filtered out first. For the standard deviation value, many sets of RSS values observed at various locations are

tested and the standard deviations of each set of RSS values from one observing location to one AP are calculated. Due to the fact that the standard deviation values from different sets are all within 3 dBm (see Figure 4.2) which shows some sets of results observed at one location, in this research 3 dBm is adopted for all measurements. As a result, if a RSS value measured in the positioning phase is within the range of  $RSS \pm 3$  dBm, then the RSS value will be used to find the closest matched record in the database for location determination.

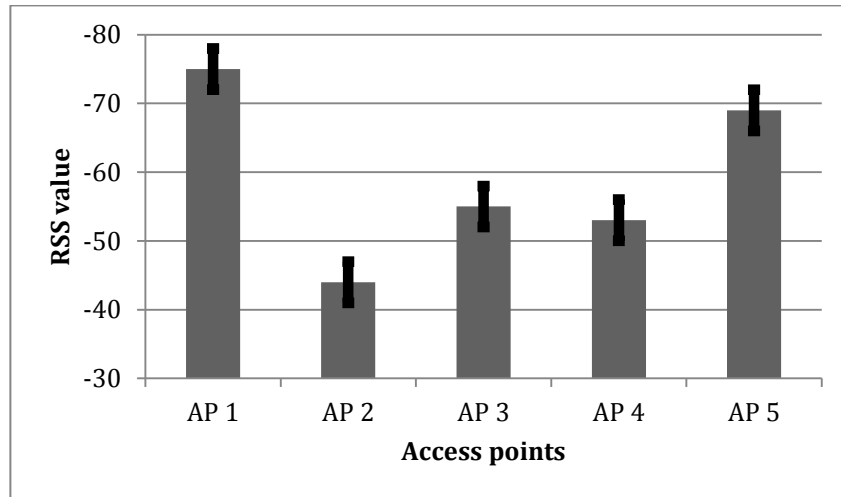


Figure 4.2 The mean RSS value and standard deviation results from one location, all the standard deviations from the five APs are about 3 dBm.

### 3. Comparing and matching observed RSS with database

After a RSS measurement is obtained, it is then compared with the database records to identify those matched candidates. For example, if a RSS measurement from AP1, all records from AP1 observed at all RPs in the database should be compared. It should be noted that the database data are in fact the mean RSS values. When we search the matched data, instead of directly using the retrieved RSS values, the retrieved RSS value  $\pm 3$  dBm is used for the comparison. If the observed RSS value is within the range of the retrieved RSS value  $\pm 3$  dBm then this database record's corresponding RP is given a weight value of 1. If the observed value is outside the data range, then the database record's corresponding RP is discarded, i.e. its weight is given a value of zero. Then the same procedure is repeated for all the other APs. The next step is to calculate the sum of all weights from each RP and all APs. The last step is to compare the summed weight values between all the RPs; the RP that has the highest weight value is regarded as the

estimated location. If more than one RPs have the same highest weight value, the location that has the strongest signal strength is taken as the estimated location. The pseudo-code of the location determination algorithm is explained in Figure 4.3 below. In this figure, L is a location to be determined; the RSS in line 3 is the observed RSS value at L; the variable RSSI is the mean RSS value stored in the database.

```

1: Initialization, For Each L Set Weight=0;
2: For Each AP
3: Select L IF  $RSS \in (RSSI-x, RSSI+x)$ 
4: n=Count (L)
5: IF L Selected, Weight=1/n
6: Else Weight=0
7: End IF
8: End For
9: Return L where max (Weight)

```

Figure 4.3 Pseudo-code of the matching algorithm for location determination

#### 4. Returning position result

As soon as the best matched database record is identified, the location result will be sent to the client application. For example, if the client side user is located at a point near RP1, the location of RP1 will be showed in the map of the client side application and the location determination process for this point has completed. The flow chart of the whole location determination process is shown in Figure 4.4 below.

### 4.3 Design of Experimental Tests

In order to evaluate the performance of our system against that of the Ekahau system, various experiments are conducted in the same indoor environment: the lab on Level four of Building 100, at RMIT University, Melbourne. The layout of the lab is shown from Figure 3.1. Unlike the Ekahau RTLS, our system does not need any site survey software to create a system plan to assist in creating a more efficient calibration database, as long as the number of RPs is sufficient and the deployment of the RPs is well enough for position determination. More details on the way how the client application and the server were designed and developed are discussed below.

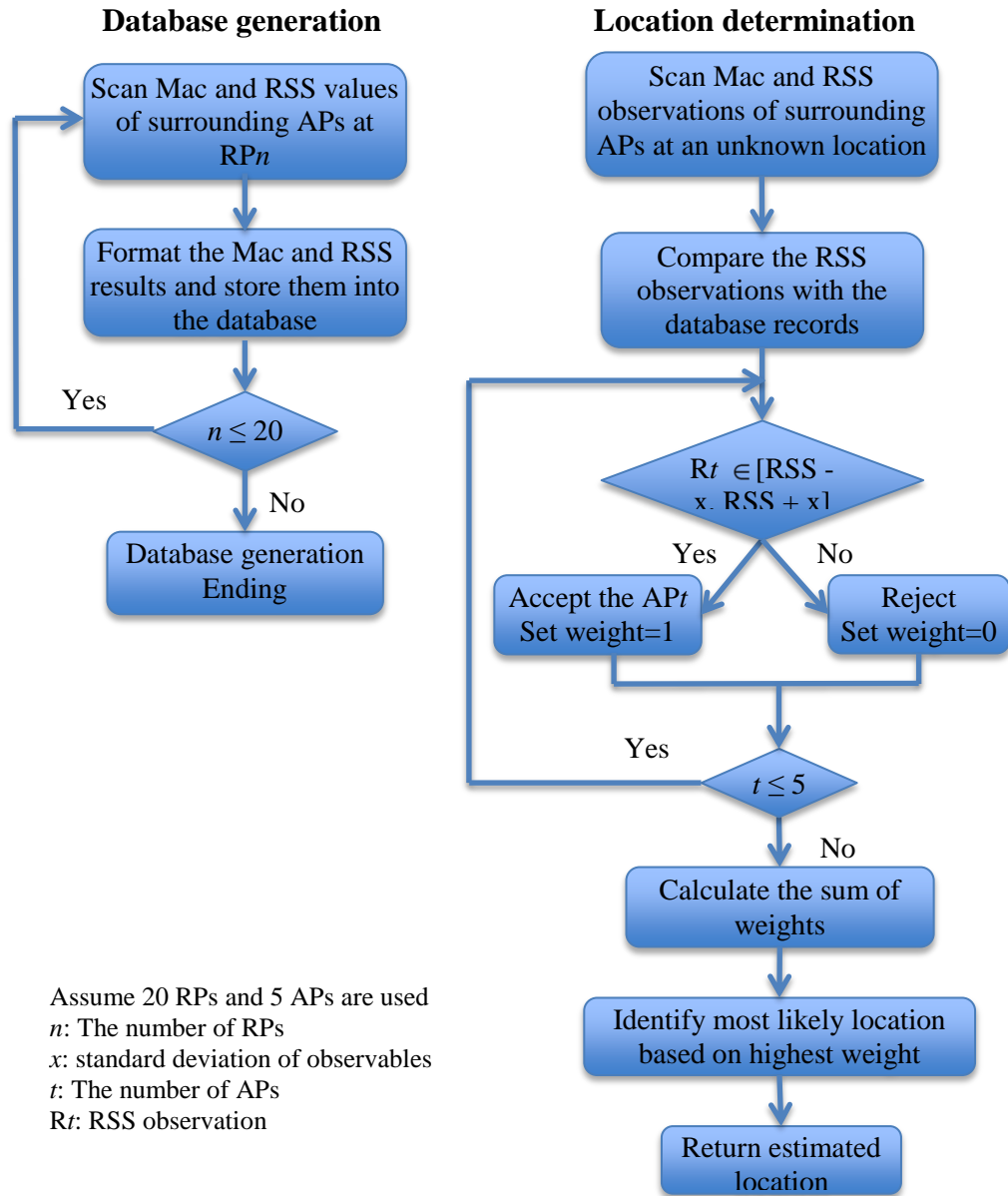


Figure 4.4 Flow chart of the location determination procedure used in our system

### 4.3.1 Client Side

The client side application is developed by the Android programming language and installed in the Android smartphone for testing. The three main functions of the client application in the calibration phase are scanning and collecting RSS at all selected RPs from surrounding APs, sending the RSS to the server side; and in the positioning phase the main function of the client application is getting the location of device tracked from the server side. The Wi-Fi module of the Android platform can easily realise these functions. The workflow of the client side application is shown in Figure 4.5.

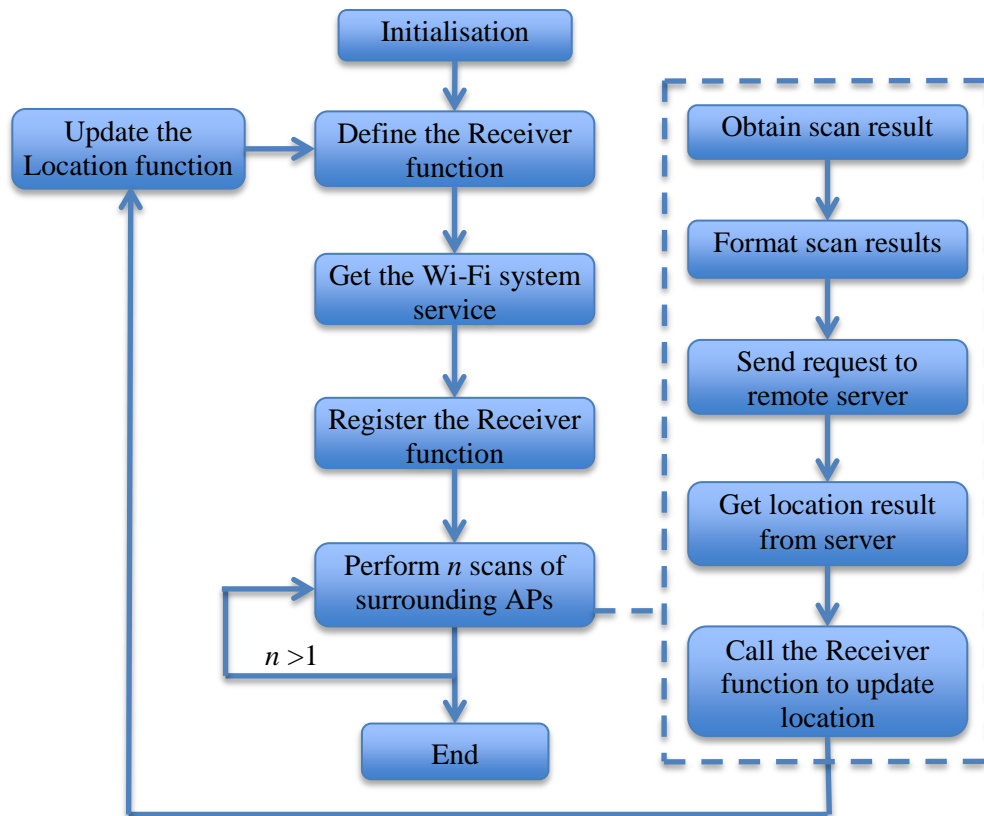


Figure 4.5 The workflow of the client side application

The source code for the aforementioned three functions of the client side application are introduced and explained below.

*Function 1: Collecting RSS from surrounding APs*

As shown in Figure 4.6, three objects (mainWifi, wifiList, receiver) of the WifiManager, List<ScanResult> and WifiReceiver classes are created. The WifiManager class provides the primary API for managing all aspects of the Wi-Fi connectivity by calling the context.getSystemService(Context.WIFI\_SERVICE) method. The receiver is registered into the Android system by calling the registerReceiver () method. Then the onReceive () method is reloaded and it will be called when the BroadcastReceiver class is receiving an Intent broadcast. After that, the StartScan () method is called to start scanning surrounding APs. Finally, the scan results of the last AP is returned by calling the getScanResults () method.

```

private WifiManager mainWifi;
private List<ScanResult> wifiList;
private WifiReceiver receiver;

public MyScanWifi(Context context)
{
    super();
    this.context = context;

    setScanWifiInterface((ScanWifiInterface) context);

    if(mainWifi==null)
        mainWifi = (WifiManager) context.getSystemService(Context.WIFI_SERVICE);
    receiver = new WifiReceiver();
    context.registerReceiver(receiver, new IntentFilter(
        WifiManager.SCAN_RESULTS_AVAILABLE_ACTION));
}

class WifiReceiver extends BroadcastReceiver
{
    public void onReceive(Context c, Intent intent)
    {
        wifiList = mainWifi.getScanResults();
    }
}

```

Figure 4.6 The snippet code of scanning and obtaining the RSS from APs

### *Functions 2&3: Communication between client application and positioning server*

According to the standard HTTP communication protocol, the client side and the server side can easily communicate with each other by connecting into the Internet. Figure 4.7 shows the Java snippet code for this communication. More specifically for our experiments, the servlet, which is a Java programming language class used to extend the capabilities of a server to respond any types of requests, is used to respond the requests of our client side application. It enables the client side application and web servers communicate based on the Java platform. The get command is used to provide the fingerprinting request by the client side and get the estimated location from the server. The URL variable contains the IP address of the server and the `getResponse ()` method is used to send the GET command/request to the server for acquiring the location estimate from the server.

```

public MyHttp()
{
    super();
    this.url = "http://192.168.100.1:8080/mylocationServlet";
    this.testmap = new HashMap<String, String>(3);
    testmap.put("name", "{pointArray[{}]}");
}

public void setUrl(String url) {}

public void settestmap(Map<String, String> testmap) {}

public HttpResponse post() {}

public String getResponse(HttpResponse httpResponse) {
    String result = null;
    if (httpResponse.getStatusLine().getStatusCode() == 200)
    {
        try {
            result = EntityUtils.toString(httpResponse
                .getEntity());
            Log.d("test", "result =" + result);
        }
        catch (ParseException e)
        {
            e.printStackTrace();
        }
        catch (IOException e)
        {
            e.printStackTrace();
        }
    }
}

```

Figure 4.7 The snippet code for communication between the client application and the server

The data sent from the client application to the positioning server are mainly the BSSID, MAC addresses and RSS values of each AP.

### 4.3.2 Server Side

The server side consists of a web server and a positioning server. The web server is used to communicate with the client application such as getting requests from the client and sending the estimated location to the client. The positioning server runs the positioning algorithm and sends the estimated location to the client side through the communication function of the web server. Figure 4.8 shows the workflow of the server side.

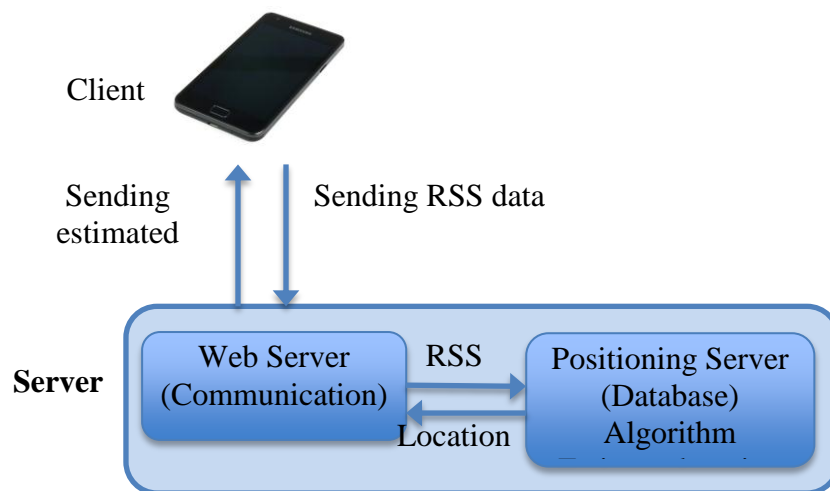


Figure 4.8 The workflow of the server side

#### *Configuration of web server*

The Apache Tomcat software is installed and run on the web server for responding positioning requests from the client application. For communication between the Android client application and the web server, configuration for the use of the Apache Tomcat software is needed. A folder named WEB-INF under the system's webapps folder, and a folder named Classes and a web.xml description file under the WEB-INF folder are created first. The Classes folder is for storing the class files of the Java projects for the client side application and the web.xml file is for defining the servlet name, servlet class and servlet mapping. The snippet code of web.xml is shown in Figure 4.9.

```

<servlet>
  <servlet-name>mylocationservlet</servlet-name>
  <servlet-class>com.hb.mylocationservlet</servlet-class>
</servlet>
<servlet-mapping>
  <servlet-name>mylocationservlet</servlet-name>
  <url-pattern>/ mylocationservlet </url-pattern>
</servlet-mapping>

```

Figure 4.9 The snippet code of the web.xml file on the web server

### Configuration of positioning server

For communication with the web server, configuration for the web.xml file on the positioning server is needed, like the web server (see Figure 4.10). Furthermore, SQL database is installed in the positioning server. Two database tables for calibration need to be created for APs and RPs. The detailed fields in the two tables are listed and explained in Tables 4.2 and 4.3 below.

```
<servlet>
  <description></description>
  <servlet-name>Algorithmservlet</servlet-name>
  <servlet-class>com.hb.algorithm.Algorithmservlet</servlet-class>
</servlet>
<servlet-mapping>
  <servlet-name>Algorithmservlet</servlet-name>
  <url-pattern>/Algorithmservlet </url-pattern>
</servlet-mapping>
```

Figure 4.10 The snippet code of the web.xml file on the positioning server

Table 4.2 Database table for Aps

Field	Type	Description
ID	Number	ID of AP
Name	Text	Name of AP
SsID	Text	SSID of AP
Mac	Text	Mac address of AP

Table 4.3 Database table for RPs

Field	Type	Description
ID	Number	Fingerprinting location ID of RP
X	Number	X coordinate of RP
Y	Number	Y coordinate of RP
AP_num	Number	Number of AP
RSS_avg	Number	Average RSS
SSID	Char	SSID of AP
Mac_add	Char	Mac address of AP
Add_info	Char	Comment

### 4.3.3 Setup of RPs and Data Collection

The experimental area in the SPACE Research Lab is 10 m by 12 m. The five Wi-Fi routers, which are in fact five APs that have the same configuration and positions as the Ekahau RTLS testing, are placed on the floor. In order to analyse the effects of the number of RPs on the accuracy of our system's performance, we conduct tests using the same configuration of APs but three different numbers of RPs. In the first scenario, 20 RPs on the floor are deployed in grids with 2 metres separation between two adjacent RPs, while for the second scenario 48 RPs in grids of 1.5 meters separation are deployed. The last scenario deployed 108 RPs in grids of 1 meters separation. The distribution of these three scenarios is shown in Figures 4.11-4.13.

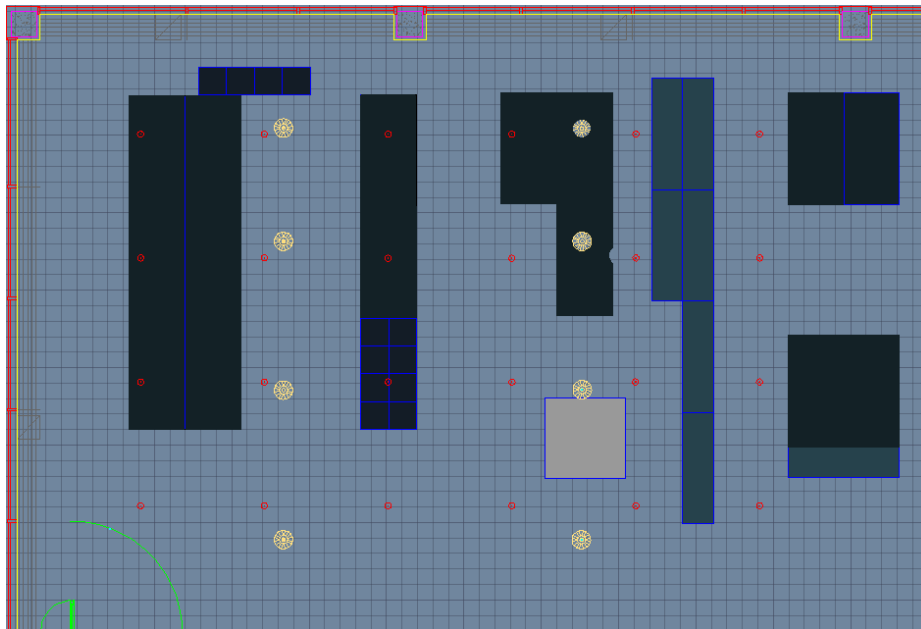


Figure 4.11 The distribution of the 20 RPs for scenario 1

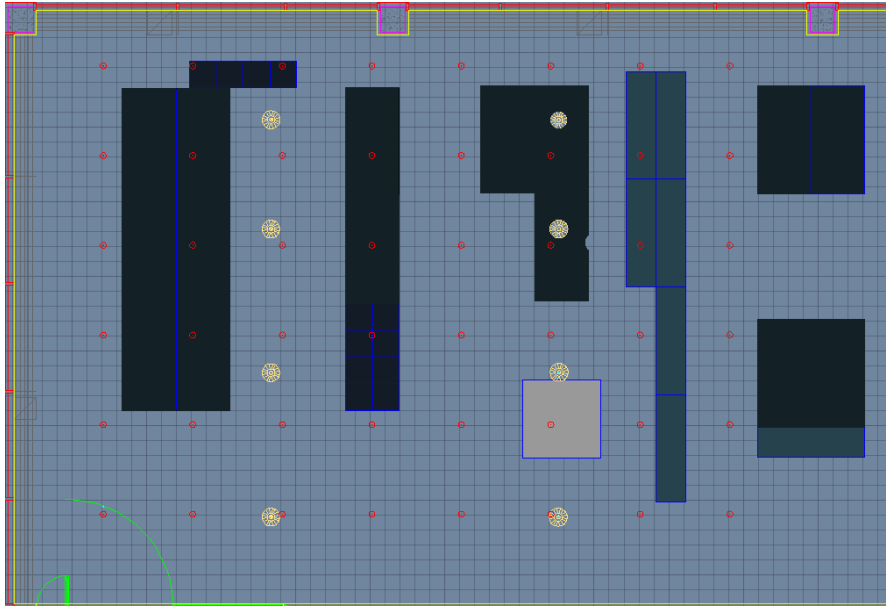


Figure 4.12 The distribution of the 48 RPs for scenario 2

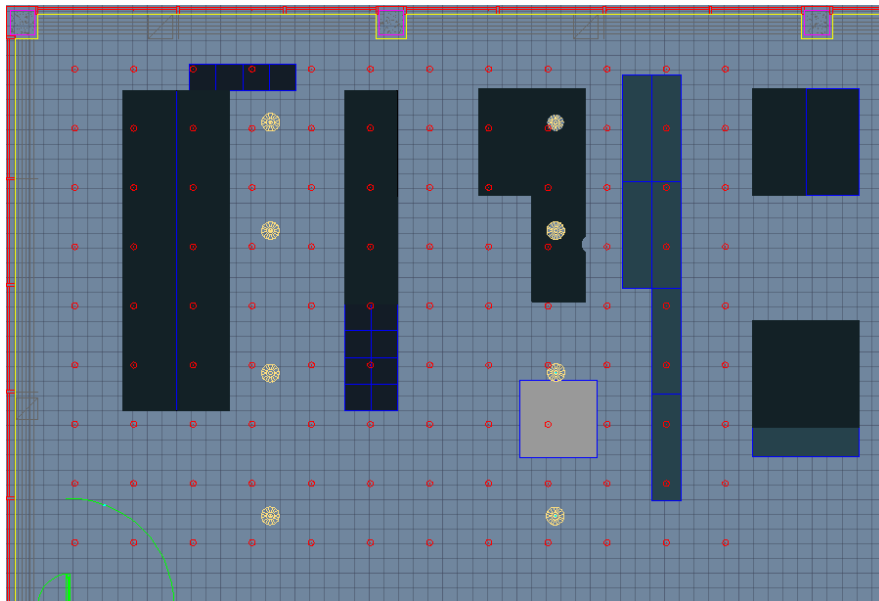


Figure 4.13 The distribution of the 108 RPs for scenario 3

To capture the RSS data, the Wi-Fi RSS collection application is installed in the Samsung Galaxy S3 smartphone with an Intel wireless PMB9811X Gold Baseband adapter embedded and used to collect the Mac address and RSS values of scenarios. At each RP 100 sampling RSS values are collected and three RSS databases are created for the performance comparison of the three scenarios.

## 4.4 Test Results

In this section, the test results of the aforementioned three testing scenarios are presented and the performance of the new positioning system developed is evaluated and compared with the commercial Ekahau RTLS introduced in Chapter 3. As described in the above section, we setup three scenarios for testing different numbers of RPs. The performance of the results is evaluated below in terms of positioning accuracy and reliability of RSS observations.

### 4.4.1 Performance of Our System

#### *Positioning Accuracy*

Theoretically, when a matching algorithm is used to determine the mobile object's location, e.g. in our case, the best matched RP's location is taken as the location estimate of the mobile object, the accuracy of the location determined in fact depends on the resolution of the signal strengths observed at neighbouring RPs. For example, if the signal strengths observed from the same set of APs at two neighbouring RPs are the same, the two RPs' locations can be said to be irresolvable. Thus, the minimum resolvable distance of the two RPs' locations can be regarded as the accuracy of the matching algorithm. The three testing scenarios have three different spacings: 2 metres, 1.5 metres and 1 metre (see Figure 4.11-4.13). We randomly select 20 testing points in the testing area and their location estimates, i.e. the best matched RPs' locations, are shown in Tables 4.4, 4.5 and 4.6 for the three scenarios respectively.

Table 4.4 The results for test scenarios 1 (RP spacing: 2 m)

Test Point	True Location		Best Matched Location		Best Match?
	X	Y	X	Y	
1	463	141	400	200	Yes
2	463	201	400	200	Yes
3	463	261	400	200	Yes
4	463	321	400	400	Yes
5	637	141	600	200	Yes
6	637	201	600	200	Yes
7	637	261	600	200	Yes
8	723	522	600	400	Yes
9	42	953	200	800	Yes

10	151	163	200	200	Yes
11	723	818	800	800	Yes
12	42	361	200	400	Yes
13	42	539	200	600	Yes
14	429	626	400	600	Yes
15	429	809	400	800	Yes
16	913	141	800	200	No
17	913	383	800	400	No
18	1001	625	1000	600	Yes
19	1153	723	1000	800	Yes
20	1153	381	1000	400	Yes
Total best matching rate					<b>90%</b>

Table 4.5 The results for test scenarios 2 (RP spacing: 1.5 m)

Test Point	True Location		Best Matched Location		Best Match?
	X	Y	X	Y	
1	463	141	450	150	Yes
2	463	201	450	300	No
3	463	261	450	300	Yes
4	463	321	450	300	Yes
5	637	141	600	150	Yes
6	637	201	600	300	No
7	637	261	600	300	Yes
8	723	522	600	450	No
9	42	953	150	900	Yes
10	151	163	150	150	Yes
11	723	818	750	750	No
12	42	361	150	450	No
13	42	539	150	450	No
14	429	626	300	600	No
15	429	809	450	900	No
16	913	141	900	150	Yes
17	913	383	900	300	No
18	1001	625	1050	600	Yes

19	1153	723	1050	750	No
20	1153	381	1200	300	No
Total best matching rate					<b>45%</b>

Table 4.6 The results for test scenarios 3 (RP spacing: 1 m)

Test Point	True Location		Best Matched Location		Best Match?
	X	Y	X	Y	
1	463	141	400	100	No
2	463	201	400	200	No
3	463	261	400	200	No
4	463	321	400	300	No
5	637	141	600	200	No
6	637	201	600	200	Yes
7	637	261	600	200	No
8	723	522	600	500	No
9	42	953	100	900	No
10	151	163	100	200	No
11	723	818	800	800	No
12	42	361	100	300	No
13	42	539	100	600	No
14	429	626	400	600	Yes
15	429	809	400	900	No
16	913	141	900	200	No
17	913	383	900	300	No
18	1001	625	1000	600	Yes
19	1153	723	1100	700	No
20	1153	381	1100	300	No
Total best matching rate					<b>15%</b>

According to these results, scenario 3 has the worst total best match rate of 15% while scenario 1 has the best total match rate of 90%. Scenario 2 gives the total best match rate of 45%. For scenario 1 results, the reason for the failure rate of 10% is that the test point has similar distances to more than one nearby RPs, in this case the matching algorithm cannot always successfully identify the real best matched one due to the limited grid

resolution. Comparing the results among the three scenarios, we can conclude that the spacing of the RPs setup for scenario1 is reliable for our location determination in the testing indoor environment, since its success rate reaches 90% with an accuracy roughly equal to 2m spacing.

***Reliability of RSS observations***

As described in the previous chapter, the performance of a positioning system is mainly determined by both positioning algorithm and quality of observations. Different mobile devices receive different qualities of observations due to different performance of their Wi-Fi adaptors. The quality of the observations can be measured by several factors including accuracy, stability and success rate etc. In this research, the observations of the smartphone used for indoor positioning are RSS. When a time series of RSSs are received by a mobile device observed at a point under the same environmental settings, the smaller the variations in the RSSs, the more stable the RSS observations. For the success rate of the RSS observations, a mobile device may either fails to detect the RSS or receive out of range RSS values. This failure is most likely caused by the poor quality of the Wi-Fi adapter. In order to compare the quality of the RSSs received by different mobile devices, three mobile devices with different types of Wi-Fi adapters are used to collect 100 RSSs at the same RP in the RMIT Lab from the same AP. These three devices are a Samsung i9300, an Ipad mini tablet and a HP laptop. The testing results are shown in Figures 4.14-4.16.

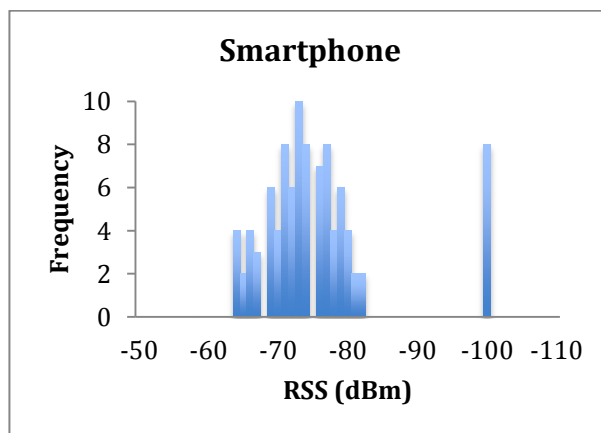


Figure 4.14 The histogram distribution of the RSSs collected by the smartphone (4 RSS failed to detect are not shown here).

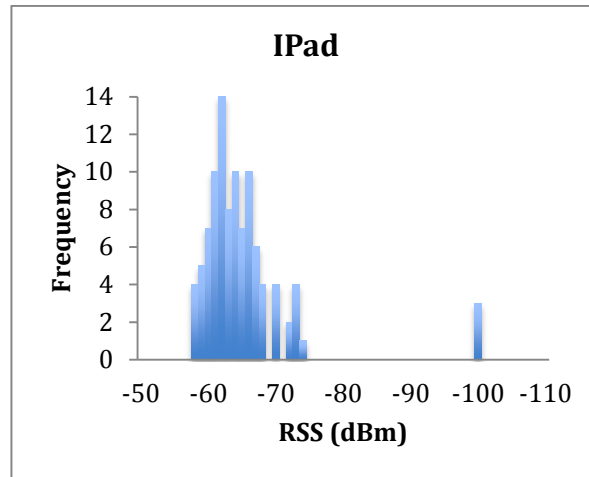


Figure 4.15 The histogram distribution of the RSSs collected by the iPad (1 RSS failed to detect are not shown here).

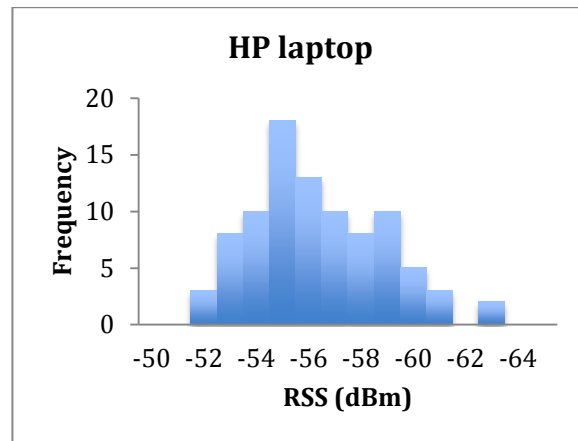


Figure 4.16 The histogram distribution of the RSSs collected by the HP laptop (10 RSS failed to detect are not shown here).

From these figures we can conclude that:

1. There are some instances during the sampling period that the three devices failed to receive RSS observations.
2. Although the RSSs collected by the HP laptop are the strongest, 10 of the RSSs failed because multiple wireless network cards are embedded and used, which affects the receiving capability of the RSSs among these cards.
3. The RSSs collected by the smartphone are significantly lower than that of the other two devices, as the quality of the device's Wi-Fi adapter is the poorest.
4. The largest variation range in the RSS observations is from the smartphone, with a value of 18 dBm (from -64 dBm to -82 dBm), while the variation range from the

iPad is 16 dBm (from -58 dBm to -74 dBm) and laptop is 11 dBm (from -52 dBm to -63 dBm). The largest variation range means the lowest reliability. The lowest reliability of the RSSs from the smartphone is anticipated since its Wi-Fi adapter has poorer quality than the other two devices.

According to these results, it is clear that a good quality Wi-Fi adapter is the determining factor for the reliability and strength of RSSs. For our positioning system, most frequencies and stable RSS values are selected for calculating the standard deviations of the RSS measurements and the result is  $\pm 3$  dBm. The reason for selecting the smartphone for the experiments is its better mobility, lighter weight and wider usage. Although the current smartphones have limitations on the Wi-Fi adapters, it is expected that proper sized Wi-Fi adapters with better quality will be used in smartphones in future.

#### 4.4.2 Comparison of Our System with Ekahau RTLS

After the positioning performance of our positioning system is analysed, the performance of our system against the Ekahau RTLS is also evaluated in terms of accuracy, position updating time and system integration.

##### *Accuracy*

The performance of the Ekahau RTLS is tested against our system using the same 20 points for the comparison of the two systems and the positioning results have been shown in Table 3.3 in Section 3.4. In this section the root mean square error (RMSE) is used to measure the overall accuracy:

$$RMSE = \sqrt{\frac{1}{n-1} \sum_{i=1}^n \|p_n(i) - \hat{p}_n(i)\|^2} \quad (4.3)$$

where  $p_n(i)$  is the reference location and  $\hat{p}_n(i)$  is the estimated location for testing point  $n$ .

The statistical result of the positioning errors of the 20 testing points is 2.79 m (the maximum error is 4.79m and the minimum is 0.58m). This is compared against the results of our system from scenario 1 (see Section 4.4.1), which has a 2 m spacing resolution of RPs, with a 90% rate of correct matching. It should be noted that although this 2 m spacing resolution is not completely the same as the accuracy of the positioning estimate of our system, using it as a measure of the positioning accuracy of our system

can be accepted, to some extent. This is because the best matching algorithm used in our system does not output direct positioning results like the Ekahau RTLS, instead, its estimation results are the best matched RP's locations. The reason for the selection of scenario 1 is for its high rate of best matching.

### ***Positioning time***

Positioning time is referred to the time taken from the start of the RSS observations to output the position estimates. It consists of two parts: time on the transmission of the RSS observations from the client side to the server, and the computation and transmission time for the position estimate. Because both positioning systems use the probabilistic approach and the RSS observations measured at a user's location from surrounding APs are used to compare against the records stored in the fingerprint database to determine the user's location. The time on location estimation is approximately proportional to the number of APs. In order to reduce the computation time, a high-speed laptop is selected as the remote server to calculate the location for both systems. In addition, the default (finest) interval of three seconds for the RSS collection using the Samsung i9300 smartphone is used due to the limitation of the quality of the smartphone Wi-Fi adapter. As a result, when the smartphone is used as a mobile device, the highest resolution of positioning estimations will be at least three seconds. In the case that the smartphone user moves in a high speed or changes direction abruptly, a continuous tracking of the user will have large errors caused by the three seconds measurement resolution. Figure 4.17 shows positioning times resulting from 20 testing points that are continuously tracked by the two systems.

Theoretically, both systems should use the same time series of observations for their performance comparison. However, due to the difficulty to implement the two positioning systems simultaneously using the same remote server on the laptop, our test results are in fact from two different time series of observations from the same set of testing points and the same speed of movement. The two time series are very close, which are taken respectively from 10:17:35 am to 10:20:15 am on 15<sup>th</sup> June 2013 and from 10:22:00 am to 10:24:40 am on 15<sup>th</sup> June 2013.

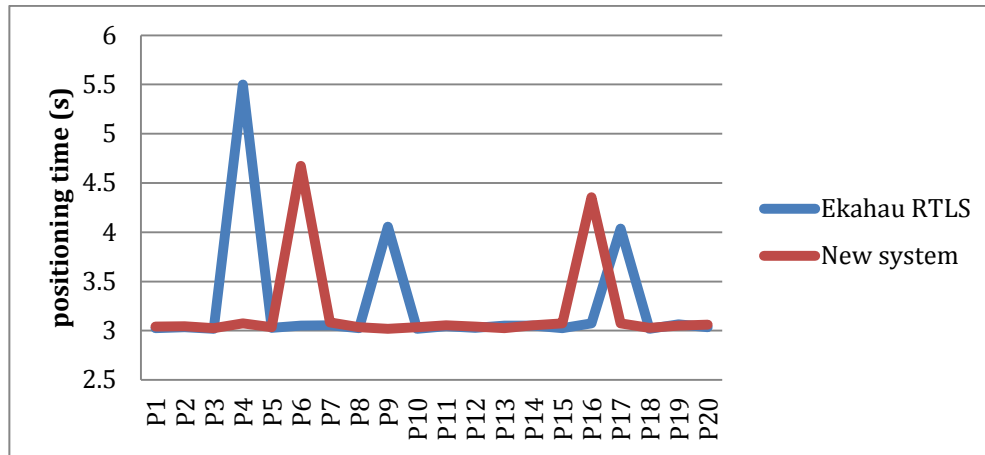


Figure 4.17 The positioning time of 20 testing points that are continuously tracked by both systems

Figure 4.17 shows that, out of the 20 testing points, the positioning times of 15 points from both systems are almost the same while the rest 5 points have large differences (see the 5 spikes). The reason of these large spikes/differences in positioning times of the two systems is most likely due to the “noisy” RSS observations.

#### *Expandability of both systems*

The expandability of a positioning system includes software and hardware. The hardware used in our positioning system and Ekahau RTLS is almost the same. Both systems can be expanded by integrating various other mobile devices such as PDA and Wi-Fi enabled tags or Wi-Fi enabled phones. For software expansion, our system is more flexible than Ekahau RTLS since Ekahau is a commercial product so its source code and the positioning algorithms are not readily available to the users, not to mention the difficulty to modify the software. Ekahau only provides a Java SDK to support users to read the device’s location (x, y, floor) and some other information. However, our systems’ software can be easily modified to incorporate new algorithms developed and the functions of the client and server.

### **4.5 Summary**

In this chapter, a new Wi-Fi based indoor positioning system using a Samsung i9300 smartphone as a positioning device is designed, developed and tested in the SPACE

Research Lab at RMIT. The main components of the system including the client and the server side applications are presented. The performance of our system and the Ekahau RTLS in terms of positioning accuracy, positioning time and system expandability are evaluated. Our new indoor positioning system presents better positioning accuracy and expandability. Both systems, however, take a similar amount of time to get the position fixed.

## **Chapter 5: Conclusion and future work**

### **5.1 Conclusion**

Since IEEE wireless protocol was released about ten years ago, Wi-Fi technical standards have been well developed and widely used due to the high speed, wireless connectivity and large coverage of the Wi-Fi technology. Nowadays the demand for real-time location information of mobile users is unprecedented. For outdoor environments, using GPS can achieve high accuracy positioning results. However, in indoor environments, due to the attenuation or obstruction of GPS signals, GPS technology cannot be used effectively. Therefore, Wi-Fi based positioning technology has been researched and developed for indoor environments.

In this thesis, the huge market potential and rapid development of smartphones technologies were briefly assessed. It is concluded that the integration of the smartphones and Wi-Fi for indoor positioning is a mainstream direction in research and industry commercialisation. The main challenges for indoor environment are discussed with the conclusion that the fingerprint technique based on RSS is the optimal solution and the smartphones is the most suitable mobile device due to its wide usage. Commonly used estimation methods and algorithms of fingerprint technique are reviewed.

We successfully implemented a Wi-Fi based indoor positioning system using a smartphone and the fingerprint-based positioning method. The performance of the system was assessed and compared with the Ekahau RTLS commercial system in the SPACE Research Lab of RMIT University. A number of case studies were designed and field experiments were conducted using various mobile platforms (i.e. smartphone, iPad and laptop) and the development and requirements of hardware and software systems were described.

The statistical result of the positioning errors of the Ekahau RTLS was 2.79 m (the maximum and minimum errors were 4.79 m and 0.58 m respectively) in the specific indoor environment. This is compared against our testing system results of 2 m, which is, more precisely, the spatial resolution of the best matching algorithm. The performances of both systems were affected by the quality of the RSS observations collected from a

smartphone. The current smartphones have limitations on the quality of Wi-Fi adapters. It is expected that better quality and proper sized Wi-Fi adapters will be available in smartphones in future. The spatial resolution of the proposed indoor positioning system can be further improved by setting up more complex indoor environment, and increasing the number of APs or combining other types of sensors into the smartphone.

The indoor positioning laboratory recently established by the SPACE Research Centre at RMIT building 100, level 4 provides a great platform for all the tests since various indoor positioning system settings can be created. It is also considered as a great testbed for multi-sensor integration related research to incorporate various indoor positioning sensor technologies such as RFID, Zigbee, magnetometers, UWB etc.

## 5.2 Future Work

This research is our first attempt during the process of the establishment of the RMIT indoor positioning laboratory. Several aspects can be further explored to enhance the performance of the proposed Wi-Fi based positioning system for future work. Three main aspects are listed as follows:

1. *Setup RSS database for different brand Wi-Fi adapters:* The proposed indoor positioning system is device-dependent, thus different brand Wi-Fi adapters with various receiving capabilities need to be tested. The fingerprinting process must be done for each type of Wi-Fi adapter. Further research needs to be carried out to investigate new methods to reduce the impact of the device-dependent errors. High stability is expected for other mobile devices rather than Samsung smartphone.
2. *Multi-sensor fusion:* most current smartphones are equipped with other types of sensors such as accelerometer, gyroscope and digital compass, in addition to the built-in Wi-Fi adapter. Data obtained from accelerometers, gyroscope and digital compass could be very useful sources of information for indoor positioning since it can provide auxiliary data such as speed and orientation of movement. The improved positioning system can therefore make best use of the observations from these sensors to improve the accuracy of the position estimates. New algorithms for the integrated system need to be developed and its performance needs to be assessed.

3. *Smartphone-based server or cloud server*: The positioning server of the proposed system is configured at a remote laptop. With the development of the CPU computation power and memory space of smartphones, we could setup both the positioning server and the RSS calibration database into a smartphone to decrease the data transmission time. This is important for the case of multiple clients. Moreover, we could also use cloud service, which has been popularly used in IT industry, as our positioning server. More research should be extended into the cloud service to enhance indoor positioning capability and performance.

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