# Map-assisted Indoor Positioning Utilizing Ubiquitous WiFi Signals

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I would like to dedicate this thesis to my loving parents ...

# Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other University. This dissertation is the result of my work and includes nothing which is the outcome of work done in collaboration, except where explicitly indicated in the text. This dissertation contains less than 80,000 words including appendices, bibliography, footnotes, tables and equations and has less than 150 figures.

Xuan Du

February 2018

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# Abstract

The demand of indoor positioning solution is on the increase dramatically, and WiFi-based indoor positioning is known as a very promising approach because of the ubiquitous WiFi signals and WiFi-compatible mobile devices. Improving the positioning accuracy is the primary target of most recent works, while the excessive deployment overhead is also a challenging problem behind.

In this thesis, the author is investigating the indoor positioning problem from the aspects of indoor map information and the ubiquity of WiFi signals. This thesis proposes a set of novel WiFi positioning schemes to improve the accuracy and efficiency. Firstly, considering the access point (AP) placement is the first step to deploy indoor positioning system using WiFi, an AP placement algorithm is provided to generate the placement of APs in a given indoor environment. The AP placement algorithm utilises the floor plan information from the indoor map, in which the placement of APs is optimised to benefit the fingerprinting-based positioning. Secondly, the patterns of WiFi signals are observed and deeply analysed from sibling and spatial aspects in conjunction with pathway map from indoor map to address the problem of inconsistent WiFi signal observations. The sibling and spatial signal patterns are used to improve both positioning accuracy and efficiency. Thirdly, an AP-centred architecture is proposed by moving the positioning modules from mobile handheld to APs to facilitate the applications where mobile handheld doesn't directly participate positioning. Meanwhile, the fingerprint technique is adopted into the AP-centred architecture to maintain comparable positioning accuracy. All the proposed works in this thesis are adequately designed, implemented and evaluated in the real-world environment and show improved performance.

**Key words**: indoor positioning, WiFi signal, indoor map, fingerprinting, access point, AP placement, enterprise WiFi, received signal strength, signal pattern, location-based service, deployment efficiency, energy efficiency

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# Symbols and Abbreviations

### Roman Symbols

$\mathbf{S}_i$ RSS values observed from $e_i$

$\mathbf{T}_i$ Observation timestamps from $e_i$

$d_0$ Reference distance in log-distance path loss model

$e$ A path segment

$G$ Pathway map

$L_0$ RSS at reference distance in log-distance path loss model

$M$ Number of APs selected as beacons for positioning

$N$ Number of RPs in the interesting area

$n$ Path-loss exponent in log-distance path loss model

### Greek Symbols

$\beta$ Signal's angle of arrival relative to wall

$\lambda$ Inertia weight of existing velocity in PSO

$\mu$ Scaling factor in heuristic placement scheme

$\omega$ Attenuation factor per wall thickness unit

$\phi_0$ Real-time vector of RSS at unknown location

$\phi_i$ Vector of RSS of pre-selected APs at $RP_i$

$\Psi$ Radio map consisting of RSS of all APs at all RPs

$\psi_{k,i}$ RSS of $AP_k$ at $RP_i$

$\rho$ Coverage overlap ratio

$\varphi$ Signal strength attenuation caused by walls

**Acronyms / Abbreviations**

AOA Angle Of Arrival

AP Access Point

API Application Programming Interface

AR Acoustic Ranging

BSSID Basic Service Set Identifier

CDF Cumulative Distribution Function

CSI Channel State Information

FP Fingerprint

GPS Global Positioning System

IMU Inertial Measurement Unit

IoT Internet of Things

JPS Joint Positioning Server

KNN K-Nearest Neighbours

LBS Location-based Services

LoS Line-of-Sight

MAC Media Access Control

MH Mobile Handheld

NIC Network Interface Card

OFDM Orthogonal Frequency-Division Multiplexing

PoI Point of Interest

PSO Particle Swarm Optimisation

PST Path Segments Traversal

QoE Quality of Experience

RF Radio Frequency

RFID Radio Frequency Identification

RP Reference Point

RSS Received Signal Strength

RTOF Round-trip Time Of Flight

SCC Signal Coverage Constraint

SNR Signal-to-Noise Ratio

SSID Service Set Identifier

SSP Sibling Signal Patterns

SVG Scalable Vector Graphics

TDOA Time Difference Of Arrival

TSP Temporal Signal Pattern

UI User Interface

UWB Ultra-Wideband

VAP Virtual Access Point

WLAN Wireless Local Area Networks

# Chapter 1

# Introduction

In a wide range of systems with context-aware computing, including the Internet of Things (IoT), wireless sensor networks, mobile social networks and mobile peer-to-peer computing, the indoor location is one of the essential contexts. The enabling technology for them is an accurate and reliable indoor positioning solution. Indoor positioning attracted many research efforts from both academia and industry in the past decade, and it has been well studied from various aspects.

In this chapter, the background knowledge of indoor positioning is briefly introduced, including the use cases (i.e., application scenarios), technologies which can be used for indoor positioning and the positioning techniques based on different technologies. Then the ubiquity of WiFi signals and importance of indoor map are highlighted, which motivated this research work. Next, the problems and challenges of indoor positioning are discussed from the aspects of insufficient positioning accuracy and inefficient system deployment. Finally, the contributions of this thesis towards map-assisted indoor positioning utilising ubiquitous WiFi signals are identified.

## 1.1 Background

The services based on the context of location information are called location-based services (LBS) and the key enabling technology of LBS is location sensing or positioning (i.e., the solution to estimate the location of an object or person in a room, building or in the world) [1]. Based on the fact that human beings spend 90% of their time indoors, with the advance of mobile devices and great impact of mobile applications (apps) over mobile phones, the LBS for indoor environments is highly desired. However, the very mature satellite-based positioning technology such as Global Positioning System (GPS) cannot work indoors since the signals from the satellite cannot penetrate well in the indoor environment (i.e., GPS need direct visibility to satellite) and the positioning accuracy of GPS is not refined enough for indoor scenarios [2]. As a result, an accurate and reliable indoor positioning solution is so desired to fill the shortage of GPS and is expected to provide the same functionality as the GPS (i.e., provide the location of an object device in real time) [3].

Nowadays with the surge of the IoT systems and its broad applications in real life, the indoor location is an important context to achieve various services. The primary function of positioning is to find a steady location of a stationary or moving device, which is used in the applications requiring one-off location information, such as mobile social networking or location-targeted advertisement. Meanwhile tracking a mobile device instead of obtaining a device's steady location is also on demand [4]. Tracking is a continuous process of computing a sequence of locations, rather than repeatedly locating the single steady location. Indoor location tracking is a sub-category of indoor positioning and requires typically higher positioning accuracy [4, 5].

The application scenarios of indoor positioning can be summarised as follows.

- Indoor Navigation for visitors in the large-scale indoor environment, e.g. shopping mall, exhibition centre and even car park [6, 7].
- Smart Home and Ambient Assisted Living, e.g. location-based automated heating or lighting control [8].
- Context Awareness Services, e.g. location-based social networking.
- E-Health Care, e.g. tracking and monitoring the movement of patients [9].

- Retail Industry, e.g. mobility analysis of customers and targeted retail advertisement in shopping malls.

In the last decade, indoor LBS has attracted much research efforts from both academia and industry [10]. Recent years have seen the emergence of various solutions for indoor positioning using different technologies and techniques. The technologies range from Radio Frequency (RF) signals such as WiFi [11], Bluetooth [12], UWB (Ultra-Wide Band) [13] and RFID (Radio-Frequency Identification) [14–16] to IMU (Inertial Measurement Unit) [17][18], sound [19, 20], visible light [21][22] and magnetic field [23][24], as shown in Fig. 1.1. Meanwhile, many hybrid solutions using multiple technologies are proposed [25]. The inertial sensors are commonly used with other technologies to provide prediction or correction.

There are various positioning techniques used for indoor location estimation. The widely used approaches can be classified into two categories: **range measurement** and **fingerprinting** [26]. Range measurement techniques obtain the distance between object device and reference beacons (i.e., devices deployed as the infrastructure of positioning system) based on the propagation model, such as distance to time of flight model or distance to signal strength loss model. The location of object device can be worked out using the measured distance to multiple reference beacons whose locations are known. Fingerprinting technique consists of two stages: offline site survey and online positioning, as illustrated in Fig. 2.4. Fingerprinting is a common positioning technique used by most received signal strength (RSS)-based positioning systems. RSS is the measurement of the power observed in a radio signal received. The fingerprint is defined as an RSS vector from multiple signal transmitters and collected at a location in site survey phase. Successively, the fingerprints at multiple pre-selected locations are collected to construct the fingerprint database. In the positioning phase, given an RSS vector observed at an unknown location, which is compared with the fingerprints in the fingerprint database, the associated location of the best-matched fingerprint is estimated as the location of the observed RSS vector [27–29]. The more detailed description of WiFi-based positioning and approaches to estimating indoor location are provided in Chapter 2.

## 1.2 Motivation and Objectives

Among existing technologies, the use of WiFi is a popular approach to bring indoor positioning into practice, because WiFi access points (AP) are already deployed extensively in most public places like hospital and shopping mall and most off-the-shelf mobile devices are already equipped with WiFi communication modules [30, 31]. In the WiFi-based positioning, the APs act as the natural beacons for positioning and the off-the-shelf mobile devices are the targeted positioning object. The wide deployment of WiFi infrastructure and the ubiquity of WiFi-integrated mobile devices have provided a massive opportunity for indoor LBS.

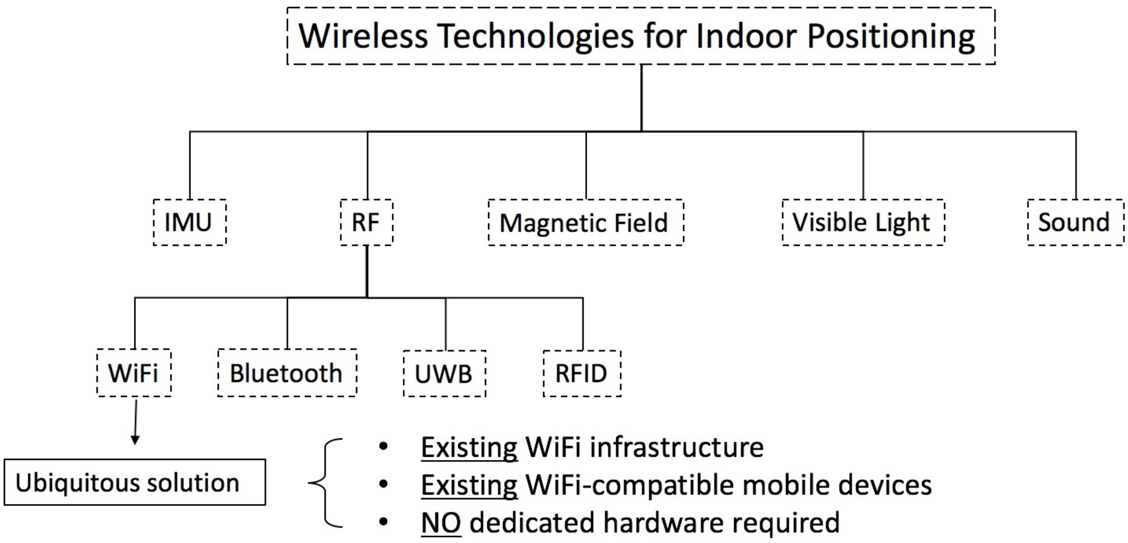



Fig. 1.1 Wireless technologies for indoor positioning

The positioning systems and LBS need to clarify the following questions: how to express locations, how to obtain a location and then how to display a location in the user interface (UI). For the outdoor environment, location can be expressed by latitude and longitude of the geographic coordinate system and map platforms such as Google Map and Open Street Map can provide mature graphical presentation interface and sufficient geographic data to indicate the required outdoor locations [32–34]. While for the multiple-storey indoor space, neither the geographic coordinate system nor graphical map platform exists. Thus, an appropriate setup of indoor coordinate system and presentation of the indoor environment, e.g. indoor location and indoor map, are essential for indoor positioning systems.

We believe the indoor map will become pervasive and will be a crucial component to bring indoor positioning into practice. Firstly, the widely-used Google Map was just launched in 2005 to provide the mapping of the outdoor environment, and nowadays almost all the location-based services are based on Google Map or similar platforms [32]. With the development of the Internet of Things, Smart Cities, Ambient Assisted Living and so on, the indoor location information is becoming an important context and mapping of indoor space is on demand [4, 8, 9]. Therefore, we believe the indoor map will be developed promptly, and a giant platform like Google Map but for the indoor environment may appear very soon. Some indoor map systems have been available in the market, but the functionality is still limited. Secondly, in the last decade, researchers proposed many indoor positioning solutions by obtaining and fusing various data, including different RF signals, the inertial sensor, acoustic data, vision data and indoor map. Among those data, apart from the indoor map the availability and quality of them are dependent on the positioning technology. However, the indoor map is always available and can work with any positioning technology [27]. Thirdly, to support tracking or navigation services, the map is an essential prerequisite and has been commonly used in outdoor in-car navigation [35].

Thus, the ubiquity of WiFi and the critical role of the indoor map for indoor positioning motivate this thesis to investigate the indoor positioning problem through the usage of the ubiquitous WiFi signals and information from the indoor map. The objective of this thesis is to improve the positioning accuracy and deployment efficiency of indoor positioning system from three aspects, which is summarised as follows.

1. Investigate the data structure to describe the information available in the indoor environment and the approach to implement it as an indoor map.

2. Investigate the ubiquitous WiFi signals and its opportunities to improve the performance of indoor positioning, especially in conjunction with information obtained from the indoor map.

3. Investigate the role access point plays in WiFi-based indoor positioning and its opportunities to assist positioning.

## 1.3 Problems and Challenges

The essential and inevitable problem for indoor positioning is the complex indoor environment, characterised by non-line-of-sight (LoS) and signal fluctuation caused by dynamic environmental changes such as people and furniture. For positioning system based on range measurement, to predict the distance between reference beacon and target device accurately, the essential condition is modelling the radio propagation correctly. However, it is very difficult to model the signal propagation in the indoor environment due to a variety of interference. Most importantly, the low availability of LoS path is one critical obstacle, which makes it difficult to find a LoS channel between the signal transmitter and receiver. The reason why GPS performs poorly indoors is also the missing LoS between the mobile device and the satellites. Due to non-line-of-sight in the indoor environment, fingerprinting becomes a popular technique for positioning by using RSS of WiFi signals. However, because of the reflecting surface in indoor space, the signal is affected by the multi-path fading and shows significant fluctuation, which leads to inconsistent RSS observation and eventually mismatched fingerprint, so that the accuracy of positioning is decreased directly [36–39]. Despite such complex indoor environment, highly accurate indoor location information is still highly expected to be provided by indoor positioning solutions.

In the existing fingerprint-based positioning systems using WiFi, some of them can achieve location error of fewer than two meters. This level of accuracy is sufficient to identify a room-level location and can satisfy most indoor positioning scenarios that don't require higher granularity of location information [30, 40, 41]. However, along with accuracy, another significant problem behind is deployment overhead. For fingerprint-based positioning system, no matter whatever method is used to estimate location, the site survey to create radio map is inevitable. The technique that most systems adopt is the explicit and designated offline manual survey, in which every accessible location of the interesting area needs to be surveyed by manpower before the online positioning work. For example, the COMPASS [42] system need spend more than 4 hours to survey a small building floor of 125 m2. Another problem with the offline survey is that the site survey work needs to be repeated fully or partially when there are environmental changes, such as removal or adding of AP. Thus, the fingerprint-based system need manually profiling the space, which typically is exceptionally time-consuming, labour-intensive and intrusive.

Moreover, the energy consumption is also a major concern. While the positioning modules running on mobile devices often require fast WiFi scanning and computation-intensive processing, the computing resources and battery capacity of mobile devices are quite limited, which leads to a significant drain of battery in short time. For fingerprint-based positioning, typically the fingerprint database contains a large number of RSS data, and a sophisticated algorithm is utilised to improve positioning accuracy, which makes the energy consumption problem even worse. To reduce the energy consumption of mobile device some server-based positioning systems are proposed by offloading the computation-intensive of positioning to a remote server, but the data communication between mobile device and server can still cause energy consumption [43]. Also, the network connection to server needs to be considered to prevent the downtime of positioning service [44].

Therefore, the latest challenge is how to exploit the synergy of existing technologies to improve the accuracy and optimise the deployment process to be more efficient, rather than developing new technology for indoor positioning [45–48]. The problems and challenges can be summarised as follows.

- Insufficient positioning accuracy caused by
  - Signal fluctuation caused by multi-path fading and shadowing
  - Dynamic changes of complex indoor environment
  - Heterogeneous mobile devices of users
- Inefficient system deployment including
  - Time-consuming and laborious site survey
  - Complex follow-up works to calibrate radio map
  - Energy consumption of mobile device

# 1.4 Contributions

In this thesis, the contributions of indoor positioning are provided in three directions (i.e., AP placement algorithm, positioning using signal patterns and AP-centred architecture) to improve the positioning accuracy and system efficiency. An indoor map system is proposed to provide the information that can be utilised to assist indoor positioning. The main contributions are summarised in detail as follows.

## 1.4.1 Map-assisted Access Point Placement for Positioning

This thesis presents an indoor map system that provides a geographic coordinate system and graphic presentation, where the detailed map information such as walls can be explicitly expressed. The author studies the problem of optimising the AP placement to achieve better performance for fingerprint-based positioning, in which the walls in the indoor map are used to assist the AP placement algorithm. In this work, AP placement is formulated into an optimisation problem in which the sum of the Euclidean distance of fingerprints among all the reference points is maximised. The fingerprint at each reference point is predicted by an indoor radio propagation model which considers the attenuation of walls with the assistance from our indoor map. The optimisation problem is solved by Particle Swarm Optimisation (PSO). The effectiveness and efficiency of the proposed AP placement algorithm are measured via the accuracy of positioning in the real-world positioning system, where k-nearest neighbours (KNN) is adopted as the positioning algorithm. The experimental results show that our map-assisted AP placement can provide higher positioning accuracy.

## 1.4.2 Positioning using Signal Patterns and Pathway Map

To identify the opportunity for indoor positioning using ubiquitous WiFi signals, the WiFi signals under modern enterprise WiFi infrastructure are analysed firstly. Then the signal patterns between coexisting access points and signals' correlation with indoor pathway map are investigated to address the problem of inconsistent WiFi signal observations. The sibling signal patterns (SSP) are defined for the first time and processed to generate Beacon

APs which have higher confidence in positioning. The spatial signal patterns are used to bring the estimated location into a limited area through signal coverage constraint (SCC). The positioning schemes using Beacon APs and SCC are proposed and shows improved positioning accuracy. The proposed schemes are adequately designed, implemented and evaluated in a real-world environment, revealing its effectiveness and efficiency.

### 1.4.3 AP-centred Positioning with Fingerprint Technique

An AP-centred indoor positioning system is proposed to address some common concerns in the conventional MH (Mobile Handheld)-based positioning system, such as passive positioning and excessive involvement of MH, in particular for scenarios of positioning multiple MHs simultaneously. Meanwhile, the popularly-used fingerprint technique is combined into the AP-centred architecture to achieve higher positioning accuracy. The proposed system is entirely designed, implemented and tested in a real-world deployment. In the environment covered by the APs running the proposed system, the location of the WiFi-enabled MHs appearing in this environment can be computed by a positioning server without disturbing MHs. The accuracy of positioning result obtained from the AP-centred positioning system is evaluated in comparison with a traditional MH-based system in the real experiments. The proposed AP-centred system shows not only the feasibility of AP-centred positioning but also better performance on positioning accuracy and energy consumption of MH.

## 1.5 Structure of the Thesis

The rest of this thesis is organised as follows. Fig. 1.2 shows the structure of this thesis.

In Chapter 2, a detailed survey on WiFi-based indoor positioning is performed. It first discusses the RF technologies which are similar to WiFi and used for indoor positioning. Next, the approaches to estimate locations in the indoor environment, especially the fingerprinting technique are reviewed, followed by the related works from peers to solve the problems of

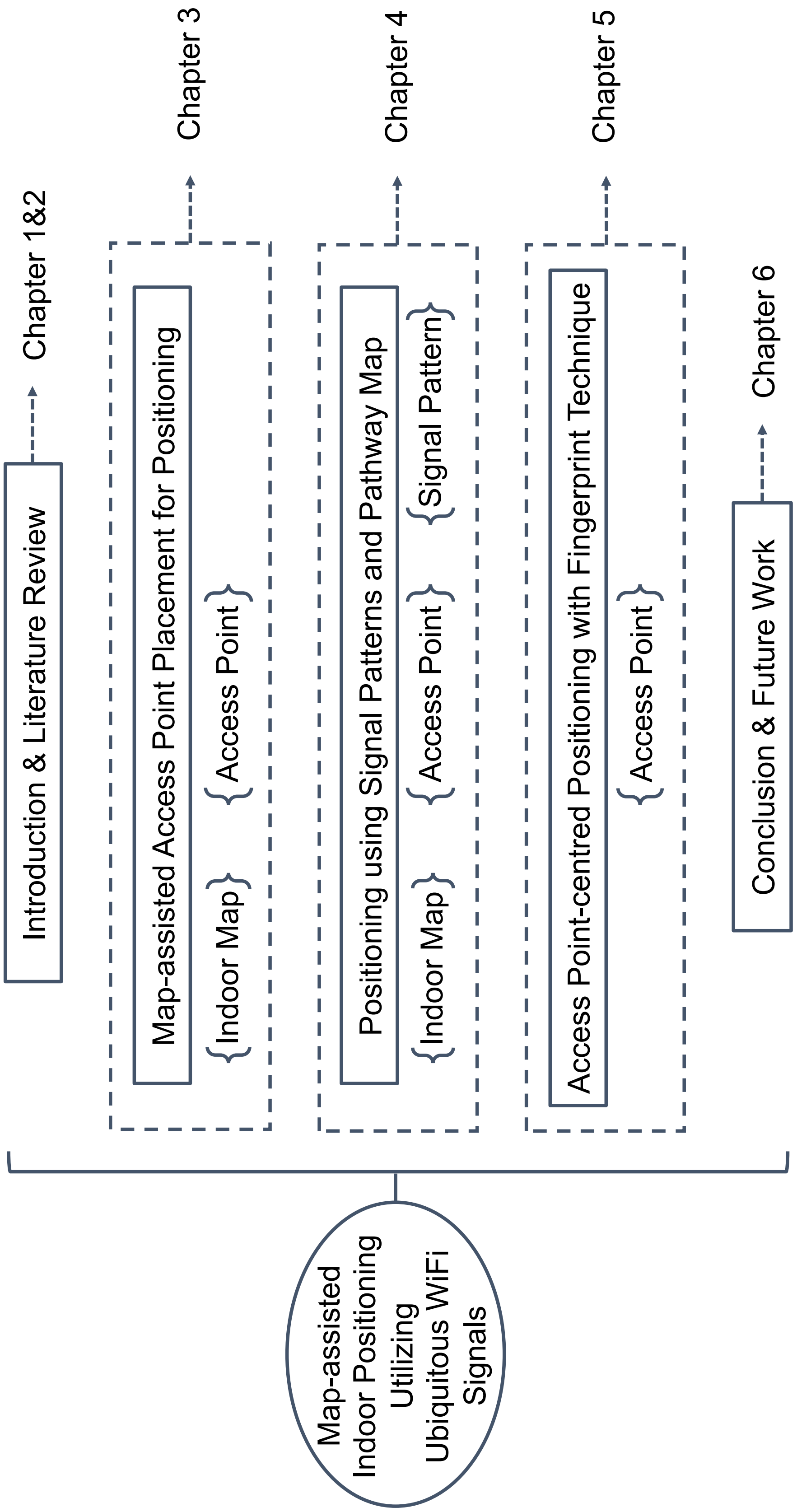



Fig. 1.2 The structure of this thesis

insufficient accuracy and inefficient deployment. Finally, the existing approaches to express indoor location and map for indoor positioning are presented.

In Chapter 3, a map-assisted AP placement algorithm is presented, which considers the signal attenuation caused by walls in the indoor environment. An indoor map system adopting vector graphic technology is first introduced. Then an optimisation model for AP placement in fingerprint-based indoor positioning system is presented, where the wall information of the indoor map is utilised thoroughly. A kNN-based positioning system has verified the effectiveness of it in experiments and the accuracy has been analysed.

In Chapter 4, the WiFi signals under modern enterprise WiFi infrastructure, signal patterns between coexisting access points and signals' correlation with indoor pathway map are investigated to address the problem of inconsistent WiFi signal observations. Some positioning scheme using the signal patterns are proposed and shows improved positioning accuracy. The proposed scheme is fully designed, implemented and evaluated in a real-world environment, revealing its effectiveness and efficiency

In Chapter 5, an AP-based indoor positioning architecture with fingerprint technique is proposed, which can infer mobile device's location without having to install any additional software on the mobile device. To achieve passive positioning, the whole positioning service (RSS scan and location estimation) moves from mobile phone to a remote cloud, which relieves the mobile device's participation in the positioning process.

In Chapter 6, the achievements of the thesis are summarised, and some future research directions are identified.

# Chapter 2

# Literature Review

Indoor positioning is a well-known problem and attracts a lot of research efforts in the last decade. The literature review of this thesis mainly focuses on RF technologies similar to WiFi that enable indoor positioning, the approaches to estimate locations in an indoor environment, especially the fingerprinting technique, various solutions to improve positioning accuracy and deployment efficiency, and indoor location and map used for the indoor positioning system.

## 2.1 Comparison of RF Technologies for Positioning

The indoor positioning system is typically consisting of location-known beacons and mobile target devices. The beacons and target devices are communicating with each other using a specific type of wireless technology to determine the distance between them. Radio Frequency (RF) is the frequency that the radio signals are carried and transmitted from the antenna. In this work only RF technologies are considered and these existing technologies include WiFi [11], Bluetooth [12], Ultra-Wide Band (UWB) [13] and radio-frequency identification (RFID) [14] and etc. [30, 49]. The features and peers' work of these conventional RF technologies used for indoor positioning are discussed as follows.

### 2.1.1 WiFi

In recent years the wireless local area networks (WLAN) have been deployed in the most indoor environment especially the public areas, such as universities, hospitals, airport, etc. Currently, WiFi (IEEE 802.11) has been the representative technology for WLAN. In addition to broadband data transmission, WiFi networks also provide a good alternative to indoor positioning beacons. The WiFi's key advantage over other wireless technologies is that the existing WiFi infrastructure and WiFi-enabled devices like smartphones can be reused for positioning directly, which therefore makes the hardware cost for positioning zero. The received signal strength of WiFi acts as a common metric for channel quality and is widely used to infer propagation distance. Most WiFi-based positioning systems use the RSS as the metric to estimate location.

There have been numerous WiFi-based positioning systems and the accuracy of them is approximately 1 to 5 meters. RADAR [11] is an earlier famous system using WiFi for indoor positioning and achieved around 2.37-2.65 meters in 50 percentile and 5.93-5.97 meters in 90 percentile. Youssef [50] using probabilistic method acquires the accuracy of more than 90% to within 2.1 meters, and some other systems revealed that neural networks technique could increase the accuracy to 1 meter with 72% probability. Because of the popularity of WiFi devices and the ubiquitous deployment of WiFi networks, people are continuously attempting to make use of the WiFi signals to achieve indoor positioning. The WiFi signals also suffer from multi-path fading. In addition, the various WiFi chips equipped with mobile devices lead to the problem of device heterogeneity.

### 2.1.2 Radio Frequency Identification

The radio frequency identification (RFID) is a means of storing and retrieving data through the electromagnetic transmission to an RF compatible integrated circuit. An RFID system consists of RFID readers and RFID tags. The RFID reader can read data emitted from RFID tags. RFID readers and tags use a defined radio frequency and protocol to transmit and receive data. The coverage range of RFID signal could be up to 50 meters and even hundreds of meters with special antenna [31]. In the indoor positioning systems using RFID technology, the RFID tag is attached to the target object, and the RFID readers are mounted on the ceiling with known locations. The RFID reader can measure the distance to the object by analysing the radio signal strength information [51].

A system called LANDMARC [15] is a prototype indoor location sensing system using RFID technology, and it could achieve the accuracy of 1 meter in average and 2 meters in the worst case. The LANDMARC reveals that the non-line-of-sight nature of RFID is a significant advantage and the radio transmission range is enough for indoor positioning. However, there is a tradeoff between the accuracy and the density of reference tags. The installation and maintenance of numerous infrastructure components in the positioning area are time-consuming and not cost-effective. As a result, whether RFID can be used as the enabling technology depends on the application scenarios and accuracy requirement.

### 2.1.3 Ultra-Wideband

Ultra-Wideband (UWB) is a kind of radio technology in which the pulses are ultra-short (typically one ns). UWB transmits a signal over multiple bands of frequencies simultaneously, from 3.1 to 10.6 GHz [31]. The short duration pulses are easy to be distinguished from the reflected signals caused by the multi-path effect. The multi-path distortion of radio signals in the indoor environment is the major obstacle of the positioning systems using conventional radio signals. UWB technology improves the positioning accuracy significantly by overcoming multi-path propagation. Furthermore, because of high penetration ability of UWB, the accuracy of the UWB-based positioning system could achieve about tens of centimetres.

Ubisense is an indoor positioning system based on UWB technology to estimate the location using triangulation technique. The *time difference of arrival* (TDOA) and *angle of arrival* (AOA) techniques are employed to compute distance by measuring the difference in arrival times and signal angles. In the Ubisense system, there are networked sensors fixed in the known locations and moving tags that transmit UWB signals to the fixed sensors. The data detected by the multiple sensors is gathered to a central server to estimate the location of the moving tag. The sensors in Ubisense are deployed as cells with at least four sensors in each cell, and all the sensors throughout buildings can be networked together in a manner similar to cellular phone networks so that the coverage range and scalability are not problems.

### 2.1.4 Bluetooth

Bluetooth is a short-range (typically 10-15 m) wireless technology that was developed to provide low-cost and low-bandwidth communication scenarios [12]. Bluetooth has been widely used in various types of devices like mobile phone, laptops, media players etc. and Bluetooth chipsets are low cost. Thus Bluetooth has a great market potential for indoor positioning. In Bluetooth based positioning system, the Bluetooth tags are required to be deployed in the positioning area as the positioning infrastructure. The earlier Bluetooth-based positioning systems using old Bluetooth standard (before version 2.1), such as Topaz [31], need to spend around 20 seconds to discover the RSS due to the time-consuming pre-connection, which makes it impossible for real-time positioning. The latest Bluetooth-integrated devices such as Android smartphones could provide Application Programming Interface (API) to access Bluetooth resources and most of today's Bluetooth chipsets have been equipped with the new Bluetooth standard that can provide RSS reading easily and quickly. Another feature of Bluetooth chip is the low power consumption, which is a significant advantage for the battery-limited systems.

### 2.1.5 Summary of Comparison

The comparison of these RF technologies from several different aspects is illustrated in Table 2.1. Among these RF technologies, WiFi is the most promising option for generic indoor positioning which is easy to deploy, low cost and could provide sufficient accuracy for most application scenarios. The existing WiFi access points (APs) can be used as positioning beacons, and commodity smartphones are the targeted mobile devices, so dedicated hardware is not required for the positioning purpose.

Table 2.1 Comparison of RF technologies used for indoor positioning

| | Coverage | Cost | Deployment | Accuracy |
|---|---|---|---|---|
| RFID | Moderate | Moderate | Hard | 1-2 m |
| UWB | Short | Expensive | Hard | tens of centimeters |
| Bluetooth | Short | Low | Moderate | 1-3 m |
| WiFi | Moderate | Low | Easy | 1-5 m |

## 2.2 Location Estimation Approaches

The location estimation approaches and its fundamental principles are presented in this section for readers to understand the problems of the field. The widely used approaches for WiFi-based positioning can be classified into two categories, range measurement and fingerprinting[26]. Both methods are facing numerous challenges to achieve their expected performance for indoor positioning [41]. In the two approaches mentioned above, they require the targeted device to participate in the positioning work. There are also some other positioning approaches without the involvement of targeted device, which is named device-free passive positioning and introduced afterwards.

In the WiFi-based indoor positioning, RSS is widely used in the last decades, because RSS reflects the distance between transmitter and receiver. The RSS is also easy to obtain in most mobile devices by calling the API of the operating system. However, in typical indoor environments, wireless signals often propagate via multiple paths in a dynamic environment, which leads to unpredictable and inconsistent RSS measurements. Thus, the accuracy of RSS-based positioning is decreased mainly because of RSS fluctuation. Channel state information (CSI) is an emerging technique to replace RSS information, which is also introduced in the follows. CSI can work with either range measurement or fingerprinting technique.

### 2.2.1 Range Measurement

Range measurement techniques are used to obtain the distance based on the propagation model. Therefore range measurement techniques are also known as modelling-based approaches. A propagation model is used to describe the characteristics of radio propagation in the indoor environment. The different propagation models can be used to describe the relationship between different propagation properties, such as the relationship between propagation distance and signal strength loss, propagation distance and propagation time, etc..

Based on range measurements a traditional technique to estimate the location is triangulation, which uses the geometric properties of triangles to estimate the location of an object by measuring its distances from multiple reference points (RPs) [52]. In triangulation method, with at least three reference points, the location of the object in a two-dimensional environment will be able to be estimated through calculating the intersection of the ranges between the object and each reference points, as shown in Fig. 2.1. The position of the reference points must be known prior to the positioning process, and the location information must contain physical coordinates, rather than just semantic information, such as room number or name. In the positioning approaches based on range measurements, the positioning accuracy depends on the measurement precision directly.

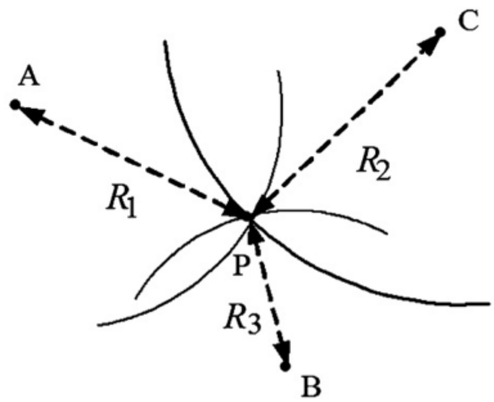



Fig. 2.1 Illustration of triangulation, a typical geometric positioning technique based on range measurement.

#### 2.2.1.1 Propagation Loss Model

Propagation loss model is a conventional model used to measure the distance using received signal strength (RSS), which can be called path loss model as well [53, 54]. The signal propagation loss models can be theoretical or empirical to estimate the propagation distance by measuring the difference of received signal strengths in the propagation path. The Fig. 2.2 illustrates the log-distance path loss model, which is an empirical model to predict the path loss of a signal and has empirical coefficient parameters. The empirical coefficient values are depending on the frequency of signal and transmission environment. The meaning of the parameters shown in Fig. 2.2 is introduced in Eq. (3.11) in Section 3.3.1. The theoretical model tends to be more flexible than the empirical model. The model is constructed based on the fact that wireless signals travelling through a certain environment undergo specific types of signal loss, which can be modelled using well-known radio propagation and path loss theories to build up the relationship with propagation distance. Path loss model suffers from similar problems as propagation time model, and multi-path fading and shadowing are the major issues for it [55]. The best-known systems using range measurement technique based on propagation loss model can achieve a median accuracy of around 2-4 meters [11, 56]. These systems are easy to deploy because RSS values are easily available on most mobile devices.

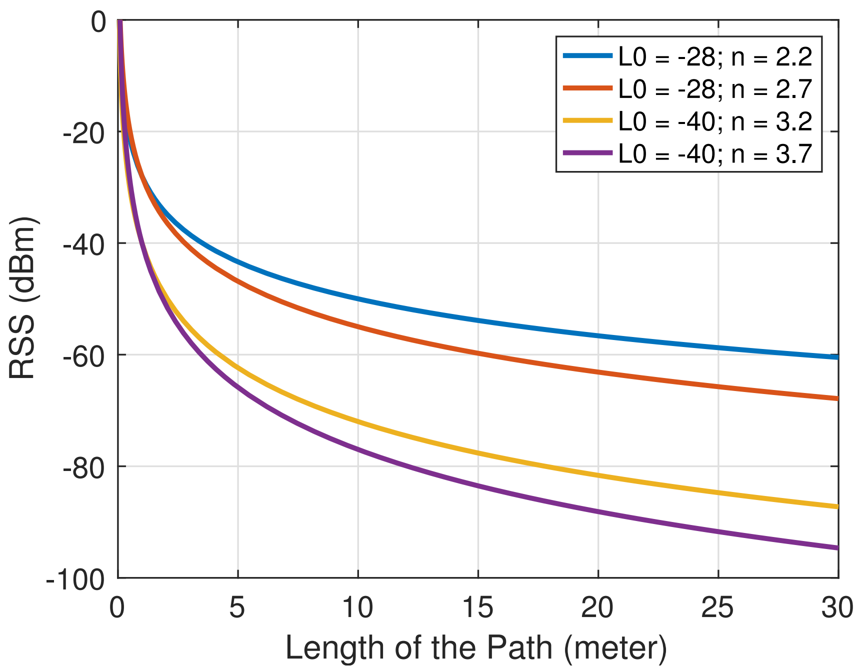



Fig. 2.2 Plot of Log-distance Path Loss Model.

#### 2.2.1.2 Propagation Time Model

Propagation time model describes the radio propagation characteristic that the propagation distance is directly proportional to the propagation time. There are numerous techniques based on propagation time model to measure the distance between the object and reference points. Time of arrival (TOA) is one straightforward method based on propagation time model to estimate the propagation distance, which can be computed by multiplying the radio signal velocity and time of flight. To measure the one-way propagation time, the positioning system must meet a necessary condition that all distributed transmitters and receivers need to be precisely synchronised and timestamp must be labelled with the signal sent from the transmitter. Round-trip time of flight (RTOF) works in a similar way like TOA, which also uses absolute travel time to calculate distance. The signal transmitter acts as the signal receiver to measure the round-trip travel time of the signal, and the receiver in TOA becomes a transporter to send the signal back to the transmitter. In the RTOF method, the delay caused by transporter is the major problem that leads to incorrect measurements. Time difference of arrival (TDOA) is to measure the difference in time when the multiple receivers received the signal from the transmitter, in which the multiple receivers (measuring units) share a synchronised time but the signal transmitter (target object) doesn't need to participate any synchronisation process with receivers. TDOA also brings another benefit that the signal propagation noise and delay can be taken into computing. The best-known systems using propagation time model achieve a median accuracy of 2 meters. However, these methods usually need hardware/firmware modification and time synchronisation in commodity WiFi infrastructure.

### 2.2.2 Fingerprinting

Fingerprinting is a significant positioning technique used by most RSS-based positioning systems. Fingerprint-based positioning system consists of two stages: offline site survey and online positioning, as illustrated in Fig. 2.4.

It is a common practice that some locations in the interesting area are chosen as reference points (RPs) in the site survey stage, as the illustration in Fig. 2.3. The granularity of the reference points usually is about one to two meters. For example in the system using WiFi, the site survey is conducted by the WiFi-compatible mobile device to collect the WiFi fingerprint at every reference point in the interesting area. The fingerprint is defined as a record of received signal strength (e.g., a set of RSS from surrounding reachable APs, which is also named RSS vectors) collected at a reference point. The fingerprints obtained at all the reference points constitute a fingerprint database of this area to serve the positioning process.

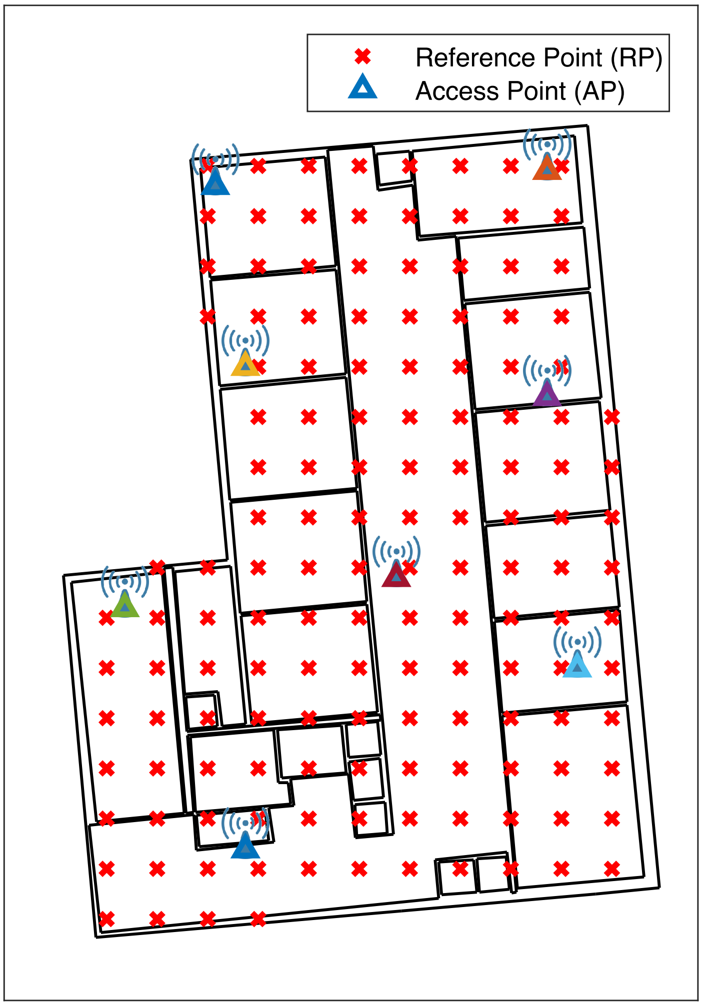



Fig. 2.3 Illustration of reference points and access points over indoor map.

In the positioning stage, the real-time RSS of surrounding WiFi signals received by a user with a WiFi-compatible device is compared with the records in the pre-collected fingerprint database to find the best-matched fingerprint, which is conducted by the major positioning algorithm. The corresponding location information of the best-matched fingerprint is returned to user as the positioning result [27–29][30].

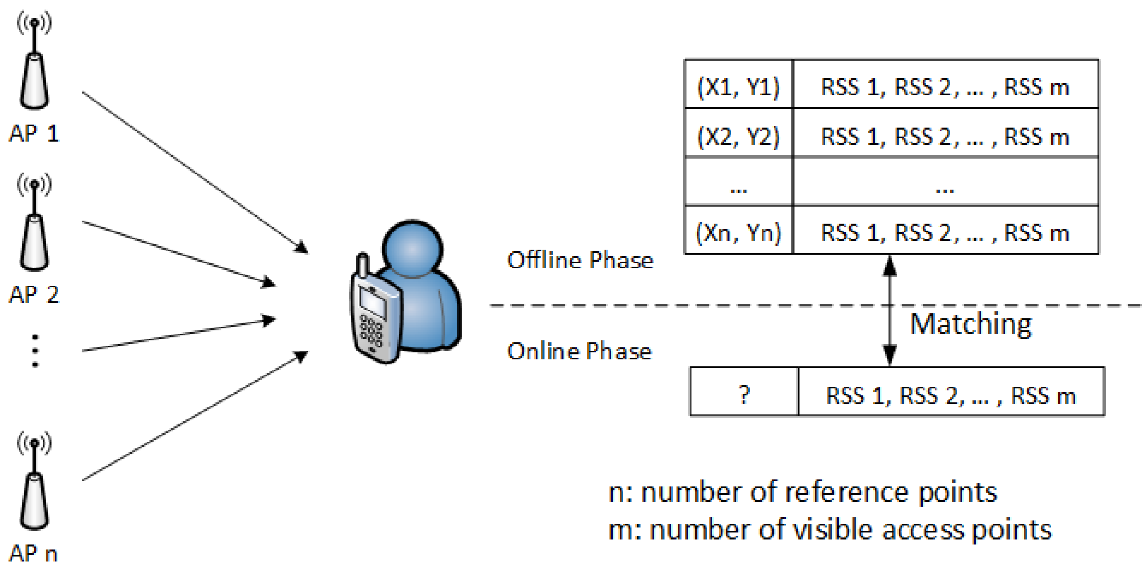



Fig. 2.4 Principle of fingerprinting-based positioning

Fingerprint-based positioning is also named pattern matching-based approach or scene analysis approach [57]. The primary reason to present the idea of the fingerprint is that the severe multi-path effect of radio propagation suffered by modelling-based positioning approaches. In fingerprinting-based positioning, the multi-path characteristics in different indoor locations are considered as the unique pattern to each location, so that the problems caused by multi-path propagation in conventional modelling-based positioning are avoided and become as a unique metric to distinguish different locations. Meanwhile, it brings another benefit that the location of the reference points are not necessary to be known because it is not based on range measurements to estimate location. The best-known systems using fingerprinting technique can provide around 0.6 meters of median accuracy [45, 58].

However, there are also several disadvantages of fingerprinting technique. First and foremost, employing the fingerprinting technique means the system need to conduct the offline site survey to build up the fingerprint database, which is time-consuming and labour-intensive. To avoid the decrease of accuracy due to the environmental changes, regular updates (i.e., repeat or partially redo the site survey) are required to adapt to the changes, so that the system can maintain the up to date fingerprint database. In addition, with the rapid evolution of mobile devices, the device heterogeneity is another significant issue need to be addressed, which can affect the performance of indoor positioning largely. Finally, because fingerprinting techniques typically require frequent WiFi scan and complex fingerprint matching algorithm, the battery energy of mobile device is a concern as well and will be more outstanding when the system is vastly deployed in mobile devices.

### 2.2.3 Device-free Passive Positioning

A physical device attached to the person is typically the targeted device of positioning and usually required to participate actively in the positioning process. Thus, several works are proposed to enable detecting, tracking and identifying entities without requiring any attached devices and active participation in positioning. The work in [59] utilises the installed wireless data networks (i.e., WiFi networks) to detect the changes in the environment and hence identify the location of entities passively. Their work relies on the fact that RF signals are affected by changes in the environment, such as people and furniture. When the signals are sent with the same power every time, the temporal variability of the signal remains the same. Because of multi-path effect, the signals' RSS measurement or time of flight can be varied if there is obstacle sitting between the transmitter and receiver. The entities such as people can easily affect the signal at the 2.4GHz frequency range. In their work, the APs and monitoring stations (i.e., any device capable of receiving WiFi signal) are deployed to continuously monitor and process the changes of RSS measurements, which are then used to detect the changes in the environment and analyse the correlation to the locations of entities. Their experiment is conducted in a testbed consisting of APs and monitoring stations running 802.11b protocol at the 2.4GHz frequency. APs broadcast beacons every 100ms and RSS value can be extracted from the header of the link-layer frame (MAC layer). Their results show that the system can detect the appearance of entities correctly in 100% probability and identify the location of entities with more than 86% accuracy, which establishes the proof of the feasibility of device-free passive positioning.

### 2.2.4 Channel State Information

RSS is only a single-value MAC layer information offered by the wireless network adaptor. RSS value is a packet-level estimator, i.e., the average value of the signal power over a packet, which is easily varied by multipath. Thus, recent efforts have dived into the PHY (Physical) layer to obtain richer information which can represent the multi-path propagation. The OFDM (Orthogonal frequency-division multiplexing) system is commonly used in the physical layer of today's WLAN (i.e., IEEE 802.11 a/g/n) to provide high throughput. In OFDM a channel is orthogonally divided into multiple sub channels, namely subcarriers. The data is modulated and transmitted in parallel on multiple subcarriers at different frequencies. The OFDM system offers channel measurement at the subcarrier level, which is called channel state information (CSI) [60]. CSI is a fine-grained metric full of frequency domain information, which describes how a signal propagates from the transmitter to the receiver and reveals the effect of multipath [61–63]. Thus, compared with RSS, more robust and reliable signal features can be extracted from CSI.

FILA [64] explores the fine-grained CSI measurements by processing the CSI of multiple subcarriers in a single packet. A refined radio propagation model using processed CSI information is proposed to compute the distance between AP and target device, then the simplest trilateration method is used to obtain the location. FILA achieves up to 10 times accuracy gain over the corresponding RSS-based propagation model. Meanwhile, FILA also introduces a CSI-based fingerprinting approach, which uses the frequency diversity attribute of CSI to manifest a location uniquely. Their evaluation shows the CSI-based fingerprinting can achieve the median accuracy of 0.65 m, which outperforms the similar RSS-based approach by about 0.2 m.

SpotFi [65] provides a positioning service using commercial off-the-shelf WiFi NICs (Network Interface Cards) with three antennas, which achieves a comparable accuracy to the systems with large antenna arrays which are not available in commodity WiFi infrastructure.

The key technique of SpotFi is super-resolution algorithm to compute the angle of arrival (AoA) of the package through the CSI measurements, which forms a sensor matrix from 30 OFDM subcarriers and 3 antennas. The AoA and RSS measurement from different APs are combined together to estimate the location of the targeted device through triangulation.

## 2.3 Improving Positioning Accuracy

In this section, the solutions to improve the positioning accuracy in state of the art are introduced. Most of the solutions are proposed explicitly for the positioning system using WiFi technology and fingerprint technique. The improvements can be achieved from different aspects, including the AP placement, usage of signal patterns and assistance from other signals.

### 2.3.1 Optimisation of AP Placement

The WiFi APs are used as the beacons for WiFi-compatible mobile devices to work out their locations. The accuracy of indoor positioning using WiFi can be substantially enhanced by appropriate AP placement strategies, i.e., in a given indoor environment to deploy the APs at the locations where the mobile devices can work out their location more precisely.

The majority of the work addresses the AP placement problem from the angle of providing data services, namely, how to place APs to increase the WLAN performance [66]. Issues concerned here consist of reducing interference, increasing coverage and data rate and eventually providing better QoE (quality of experience) to end users [67–73]. However, in the WiFi-based indoor positioning, its performance can be affected by AP deployment, so that the AP placement problem can also be studied for improving the performance of indoor positioning [74][75]. Therefore, the following discussions focus on this angle.

The fingerprint at each RP is stored in a database at the site survey stage. Then at the positioning stage, the fingerprint records in the database are compared with the real-time RSS vector to compute the location of a mobile device. As a result, the goal of all these studies in the literature is to maximise the differential and diversity of the fingerprints or minimise the number of similar fingerprints.

In [76], an optimisation model is proposed to maximise the sum of the Euclidean distance of RSS vector among RPs within a limited area. A Differential Evolution algorithm is used to solve the optimisation model. The experimental results show that the APs are better to be scattered asymmetrically and the increase of the number of APs placed in the positioning area does not always obtain improvement of positioning performance. A similar technique as above is proposed in [77], which aims to maximise the minimum Euclidean distance of RSS vector between different RPs. The work in [78] defines a threshold called Similar Fingerprint (SF) and aims to minimise the total number of SFs among all the RPs by Simulated Annealing algorithm. In [79], on top of positioning, wireless coverage is also considered when carrying out AP placement. The minimum number of AP and locations of APs to achieve the desired coverage scope is determined in the first stage. In the second stage, the locations of APs are further adjusted to increase the fingerprint difference without compromising the coverage requirement. The fingerprint difference here is also defined as the Euclidean distance of RSS vector. Their result shows their approach cannot only guarantee radio coverage but also improve the positioning accuracy significantly. In [80], one approach inspired by the signal-to-noise ratio (SNR) is presented to find the most beneficial placement by maximising the numerator signal and minimising the denominator noise simultaneously. This work regards the location discriminant information as signal and the degree of unstable measurements of RSS as noise. The placement based on maximising SNR techniques shows considerable improvement of positioning precision and the best placement of APs is extremely asymmetric.

The approaches to describing and indicating the area to place APs of most of the other works are limited and inefficient. For example, in [78], their experimental area of 195 $m^2$ is partitioned into a grid of 3 $m$ x 3.5 $m$ for placing the APs, so there are a total of 18 possible locations where an AP can be placed. In this approach, the area to place APs is dramatically reduced to 18 single points from a space of almost 200 $m^2$, so that the probability to obtain the most-effective placement is reduced as well. Apart from using grid [76], defining the area by dimensions of a rectangle is the most common approach to specify the placement space [79, 80]. The searching space is an open rectangle space without any limitation, and the AP can be placed anywhere inside the rectangle. If grid or rectangle is used to represent a searching space, the interference caused by obstructions in the indoor environment is ignored, so that the fitness of the optimised placement is affected as well.

In summary, the goal of all these techniques in the literature is to maximise the differential and diversity of the fingerprints or minimise the number of similar fingerprints. Most studies of the AP placement problem use the radio propagation model to predict signal strength, and most of the above works did not consider the obstacles in the positioning environment when the optimised AP placement is deployed. Furthermore, the placement results are displayed on preliminary floor plans that are usually drawn manually, e.g., using drawing software [78, 81].

### 2.3.2 Use of Signal Patterns

The main problem leading to insufficient positioning accuracy is the inconsistent WiFi signals, which is caused by signal fluctuation, changes in the indoor environment and mobile device heterogeneity. Thus, in recent years various solutions are proposed to mitigate the influence of inconsistent WiFi signals by observing the signals from a broader view to generate patterns which can help improve positioning accuracy. The discovery and usage of several signal pattern are discussed as follows.

Even though in the fingerprinting-based positioning system the RSS values are simply used as the metric of fingerprint and not used to calculate the distance between the receiver and AP, the RSS values actually still correlate with the location of APs. The APs are usually scattered in the indoor environment. Thus the remarkable RSS values measured at certain area can be used as the WiFi landmarks to identify this area uniquely. These WiFi landmarks can be discovered when the site survey is completed and the RSS measurements of the whole site are available. Inspired by such observation, people are investigating the patterns of WiFi signals from the spatial aspect, which is called **spatial signal pattern**.

Initially the spatial patterns of individual APs are investigated and used to correct or constrain the location estimation, which typically needs to work with motion information from inertial sensors and may not always be available since the APs are not densely deployed to form sufficient landmarks [82, 83]. Later on the spatial patterns of multiple APs are considered to investigate more reliable approaches. The order of RSS values from different APs is used in HALLWAY [84] as a location-dependent measurement to distinguish the rooms, which can reduce the influence of heterogeneous mobile devices and signal fluctuation. The effectiveness of the order of RSS values depends on the use scenarios and indoor floor plan, because the granularity of its location estimation is limited to a certain level and if the rooms are too small the adjacent rooms cannot be discriminated. Except for the order of RSS values, another approach to mitigating measurement uncertainty is to identify the target location using a range of RSS values rather than the absolute RSS values. Based on this observation, Sectjuntion [85] is proposed to partition the coverage of each AP to sectors according to discrete signal levels from the location where the AP shows maximum RSS value. The RSS sector calculation is conducted after the site survey is completed and takes the RSS measurements at RPs of the whole site into the calculation. The APs with a narrow range of RSS observations are filtered out of the RSS sector calculation because it discriminates fewer sectors. Then the target location is estimated using the intersection of sectors from multiple APs. The spatial signal pattern can help narrow down the search space and reduce the maximum error distance (i.e., in the positioning process to prevent the search space being a dispersed set of RPs, which are quite distant apart geographically).

In the conventional fingerprint-based positioning system, a fingerprint refers to the absolute values of RSS observed at a location (i.e., one of the RPs). As the previous statement, the movement, one-off RSS observation, device and usage diversity all could cause significant RSS variance. To minimise the influence of RSS variance, instead of looking at the one-off RSS value at one point, people are looking at the time-sequence values of RSS observed from a sequence of RPs, which is believed to be more robust than a single value.

**Temporal signal pattern** (TSP) is a sequence of WiFi signal observations during a short-term movement in the indoor environment, which is observed over time domain. Compared with approaches that use signals observed at a single time and location, the temporal signal pattern is to make use of the correlation between sequential signals and moving trajectory, which is illustrated in Fig. 2.5. The temporal signal pattern along a movement is unique to the trajectory of movement. The temporal signal patterns are mainly characterised by its trend of change, including rising, decline and peaks.

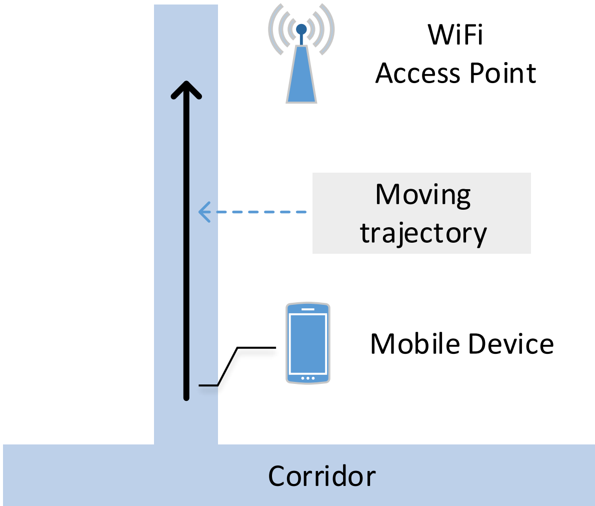



Fig. 2.5 Illustration moving trajectory.

When a mobile device is moving along a trajectory, a set of time-sequence RSS values are observed and named as a temporal signal pattern of the moving trajectory, which is illustrated by the dashed curve in Fig. 2.6. The two dashed curves are the raw value of RSS observed by mobile devices of different setups. From the dashed curves we can see that the RSS is fluctuated significantly because of the movement and the average RSS is different under different device setup. Mobile device setup is depending on device model and device placement, such as placing in hand, pocket or bag. Therefore, using a one-off observation during movement and the absolute RSS values to calculate the position could lead to crucial positioning error. If we find the linear regression model of these two signal patterns by least-square regression, which is depicted by the solid lines in Fig. 2.6, we can see that their slope is nearly the same. The slope indicates the trend of RSS changes of the signal pattern. In such approach, examining the trend of changes instead of the absolute RSS values can address the RSS variance problem effectively.

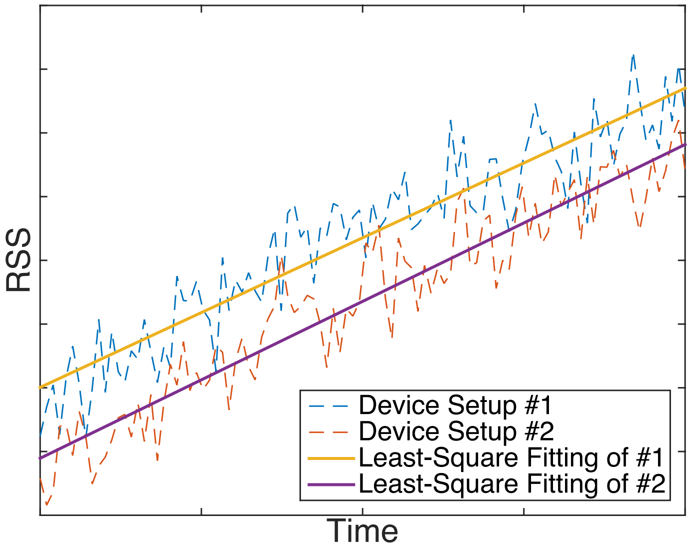



Fig. 2.6 Illustration of temporal signal pattern when moving along a trajectory with different device setup.

On the other hand, the temporal signal pattern can be used to effectively determine the direction of the mobile device when leaving a junction. When a user is approaching and leaving a junction, the fingerprints of locations around the junction are very similar and it's very difficult to predict without other information like a compass. However, the continuous observation of RSS from certain AP will show a certain temporal signal pattern which can distinguish the direction that the mobile device is heading to. As the illustration in Fig. 2.7, different trajectory options at a junction can lead to different temporal signal trend, which is unique and can be used to determine the trajectory of the mobile device.

Kim et al. [86] propose a smartphone-based pedestrian-tracking system using WiFi, which utilises both spatial and temporal signal patterns. They deeply investigate the inconsistent RSS problem and their analysis shows that fingerprint-based indoor tracking suffers significant performance degradation due to the RSS variance, while the positioning of a stationary location is more robust to the RSS variance. In their system, an approach named Peak-based WiFi Fingerprinting (PWF) is proposed to overcome the inconsistent RSS problem. In the site survey the RSS vectors at different locations are collected as the traditional fingerprinting system, then the locations with maximum RSS of each AP are selected and recorded with the maximum RSS values. In the tracking phase the peak RSS is detected from

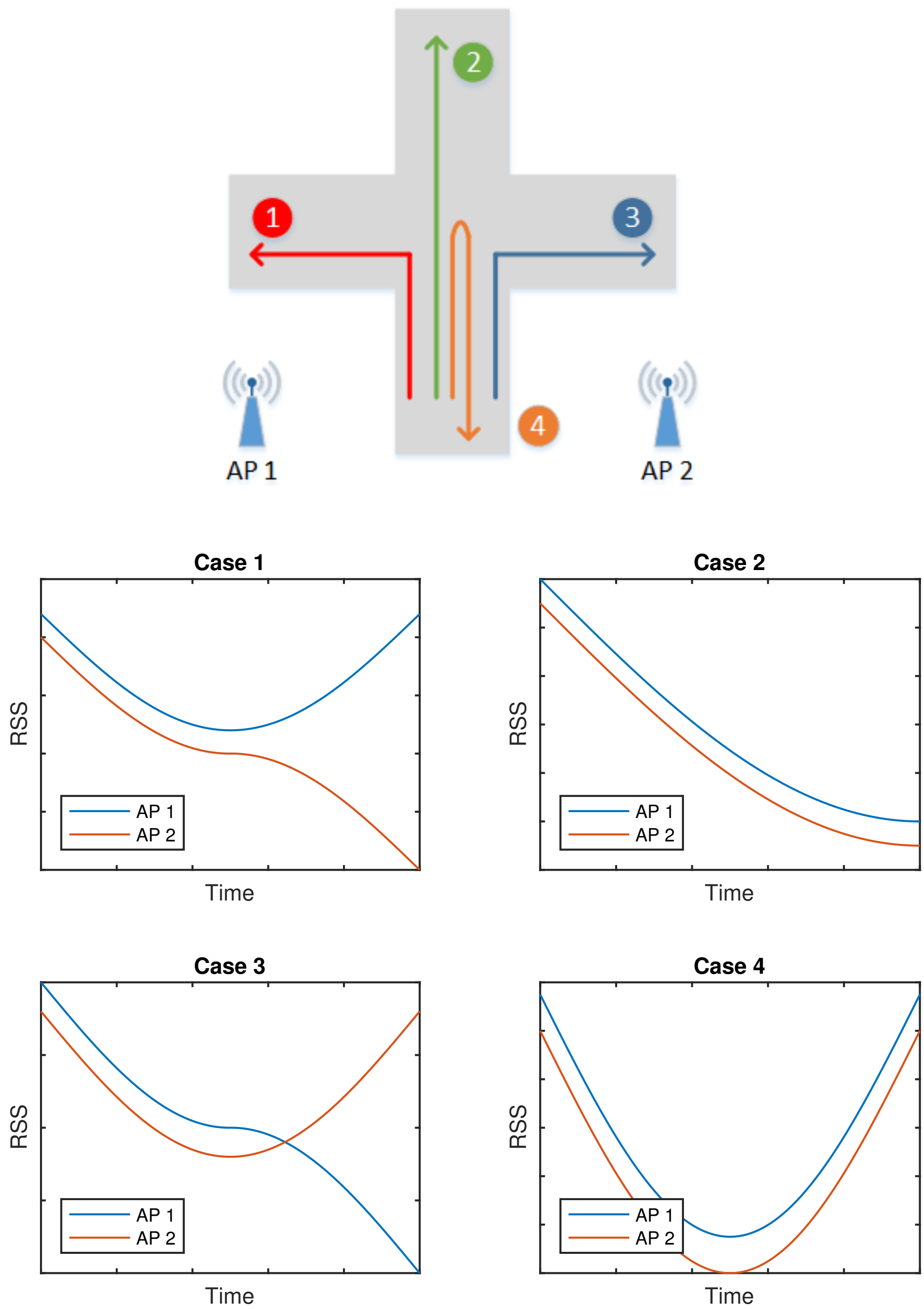



Fig. 2.7 Illustration of trajectory options at a junction and the corresponding temporal signal trend.

a sequence of observed RSS values and compared with the maximum RSS value recorded in the site survey. If the RSS value difference between the observed peak and recorded maximum value is less than a predefined threshold, the location with the observed peak is determined as the estimated location. Because RSS peak locations are limited and PWF has only about 20% occurrence ratio, other schemes such as traditional KNN method are used in the positioning of other locations. The PWF method improves the system accuracy by detecting the signal strength peak from temporal signal patterns but has the problem of potential missing scan of peak values.

Walkie-Markie [87] is a system that aims to generate the map of indoor pathway using the WiFi signal and IMU data crowd-sourced from multiple mobile phone users. The WiFi-defined landmark (WiFi-Mark) is introduced in Walkie-Markie to act as the anchor to merge large volume of partial trajectories and limit the drift of IMU-based tracking. WiFi-Mark is defined as a location where the trend of an AP's RSS reverses, i.e., as the user moves along a pathway, the RSS reading is changing from increasing to decreasing. This approach by examining the RSS trend instead of RSS readings turns out that no matter how the devices are different and how the user is holding the device, the WiFi-Mark occurs at the same location, which shows the effectiveness of temporal signal patterns.

### 2.3.3 Fusing with other Data Source

In order to improve the positioning accuracy, other data sources in mobile devices such as inertial sensors, microphone and camera are utilised to assist the WiFi signals, which is a hybrid technique for indoor positioning. The hybrid approach is widely used in recent years due to the advances of sensors and other input components on the commercial mobile device. The approaches relying on the inertial sensors are also named as motion-assisted schemes, in which the walking trajectory are measured by the inertial sensors to fuse with estimated location by WiFi signals to achieve higher accuracy. The challenges using measurements of other sensors are the effective and efficient fusion models and schemes to consider multiple measurements [88–92].

With the pervasive application of inertial sensors on commodity mobile devices, the motion assistance is a classical hybrid technique for positioning. The inertial sensors in commercial smartphones consist of accelerometer, gyroscope and magnetometer. An accelerometer measures the 3D linear acceleration ($m/s^2$) or G-force (gravity) of the device. A gyroscope provides the angular velocity (radian/s) and measures the orientation in principle of angular momentum. Magnetometer gives the strength and direction of magnetic fields [18]. In the motion-assisted schemes, in order to fuse the motion with WiFi signals efficiently, the data obtained from inertial sensors need to be very accurate. However, the inertial sensors in commercial off-the-shelf smartphones usually suffer from bad calibration and noisy measurement [93]. In most recent works the inertial sensors are mainly used for prediction of pedestrian's walking trajectory, which includes walking detection, step counting and stride length measurement [17, 94, 95]. Walk detection can be based on the identification of different motion states using thresholds in readings of an accelerometer. Step counting can be based on peak detection or zero crossing of acceleration readings. The walking distance can be obtained by multiplying step counts with the stride length, while in the real application the motion pattern is largely affected by users' heterogeneity. For example, the stride length depends on the step frequency and height of the user. Some advanced works utilise step models to calibrate the relationship between stride length and step frequency [96]. Some recent works propose online calibration of step counter by learning the stride length when the user is walking in the indoor environment with the information of indoor map [97]. Some more advanced works propose a calibration-free scheme which works transparently for heterogeneous devices and users [98]. In summary, the major challenges of motion-assisted positioning are calibrating and tuning the inertial sensors to minimise noisy measurements and adapting to different users' motion profiles [99, 100].

Researchers from Microsoft Research India [101] proposed a system that fuses RF and AR (Acoustic Ranging)-based positioning techniques into a single systematic framework that is based on Bayesian inference. The proposed framework is independent of the RF and AR schemes so that it allows users to adopt their preferred approaches to measure the RF and AR. Another recent work proposed a generic framework named Wi-Dist [102], which is applicable to a wide range of sensing technologies. Wi-Dist enables indoor positioning with adaptive spatial and temporal mobile sensing independent of how distance is measured. Fusing fingerprints with mutual distance information potentially improves positioning accuracy. An experimental study of Wi-Dist is implemented based on WiFi, and their results show that Wi-Dist achieves more than 40% higher accuracy than state-of-the-art schemes.

## 2.4 Improving Deployment Efficiency

The explicit survey is the very traditional approach and extremely labour-intensive. Therefore, several other schemes are introduced to reduce the site survey cost. At the very early stage in 2010, to minimise the site survey effort, researchers from Microsoft India proposed an indoor positioning system, EZ, that doesn't require explicit site survey and doesn't build any radio map [56]. In this section, a couple of approaches to site survey in the fingerprint-based positioning system are introduced.

### 2.4.1 Explicit Crowdsourcing

Explicit crowdsourcing is also known as the folksonomy-based survey. To save the offline site survey time and adapt the latest environment change, the folksonomy-based survey manner was present and Redpin is a typical example [103]. In Redpin there is no designated offline site survey before the online positioning, thus at the first time to run localisation the radio map is vacant. During online positioning phase, if the real-time fingerprint cannot find any best-match one in the radio map, the system prompts the user to indicate the current location. And if the positioning result based on the existing radio map is incorrect, the user can revise the radio map by correcting location information of the fingerprint. Luo and Chen et al. [104] presented a more complex system using a similar idea called human-centric collaborative feedback.

### 2.4.2 Implicit Survey

In the most recent two years, to reduce the site survey time and manpower to the minimum, WILL [105] removes the traditional site survey and employs an automatic survey approach in which humans are not involved in the laborious survey work directly. Unlike traditional site survey, designated and dedicated people for site survey are not required. The moving staffs in the building such as securities are carrying the collecting device to conduct the site survey when they carry out their routine work. No manual operation is required and the WiFi fingerprint is collected when moving. After they traverse the entire floor, the collected data are processed to restore the motion. WILL adopts the fingerprinting-based approach, but the users are not involved in the explicit participation to collect WiFi fingerprint and label fingerprint with corresponding location information. The idea of WILL is through a combination of independent WiFi fingerprint with user motions to construct a logical floor plan under certain semantics. Then the mapping between logical floor plan and physical floor plan will be created automatically using some algorithms. In this way WILL could achieve an average room-level accuracy of 86 percent using an automatic site survey method without human participation [25, 46, 105–111].

## 2.5 Indoor Location and Map

To achieve indoor positioning the first and foremost step is to investigate the approach of specifying and presenting indoor location. The indoor map plays an important role to enable indoor positioning in the real world. However, most works in literature didn't introduce the details of their approach, and in most cases the indoor map system is not existing or implemented using a simplified approach. In this section, the typical approaches to present indoor locations in indoor positioning systems are discussed.

### 2.5.1 Presentation of Indoor Location

For outdoor positioning, most systems will utilise the standard geographic coordinate system (latitude and longitude) to indicate a specific location. However, there is not any standard coordinates system for an indoor environment. Thus, the method to present locations is the first problem that most positioning systems need to address. The types of location information can be categorised into the physical location, symbolic location, absolute location and relative location [31]. Physical location is represented by a point on a 2D/3D (3 dimensions) map in the form of coordinates. Symbolic location is expressed in a natural-language way, such as room C201. Absolute location uses a shared reference grid to identify all objects. Relative location is expressed by the proximity to the known reference locations. The coordinate-based geometric method is still the traditional geographic approach used by most positioning system [112]. Compared with symbolic identifiers such as location name or room number, the geometric coordinate system with graphical representation is the most straightforward method to indicate indoor locations and its environmental context. This is particularly the case for the positioning systems that update the users' location frequently and display the users' movement continuously. Three typical approaches used in fingerprinting-based indoor positioning systems are discussed in this section.

#### 2.5.1.1 Reference Grid

The reference grid model is widely used to construct the radio map, as the illustration in Fig. 2.8 in which the positioning area is divided into a coordinate grid with a granularity of one to two meters. The site survey covers the reference points of the whole grid, and the radio map contains the corresponding fingerprint of every point on the grid. An obvious drawback of reference grid is that, to balance the trade-off between granularity and accuracy, the numerous reference points on the grid result in time-consuming site survey process [113].

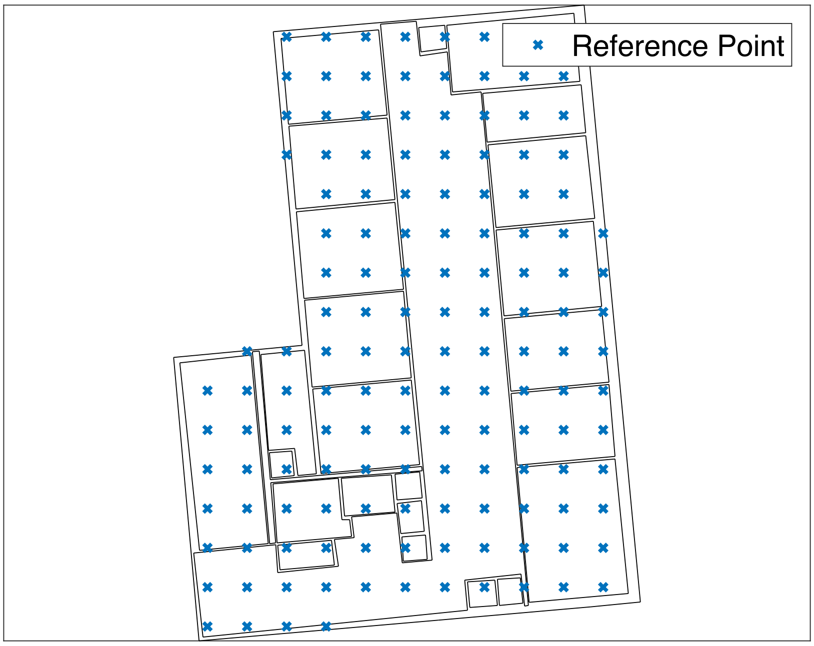



Fig. 2.8 Illustration of presenting indoor location using grid.

#### 2.5.1.2 Symbolic Identifiers

Because fingerprint-based positioning is not based on the range measurements to estimate location, the coordinate-based geographic system is not necessary. A symbolic identifier is a non-geometric geographic method without coordinates to denote locations. A symbolic identifier is adopted by Redpin [103] in which the radio map is the mapping between WiFi fingerprints and symbolic identifiers like room number or name, thus the positioning result is expressed in a natural-language way rather than coordinates of conventional methods.

#### 2.5.1.3 Topological Floor Plan

The WiFi-based positioning is designed for generic location-sensing services based on off-the-shelf devices rather than high-accuracy systems using specialised hardware. Therefore room or region-level granularity of location should be able to provide sufficient context for most location-aware applications. As illustrated in Fig. 2.9, radio map based on topological floor plan is constructed using similar approach as occupancy grid, and the only difference is that the positioning area is divided into topological cells based on physical regions, such as room or corridor, rather than a point on the grid [113]. The topological floor plan will not only reduce the site survey time dramatically but also utilise the wall-penetrating effect of radio signals to make the recorded fingerprints to be distinguished in a more effective manner [46]. However, the topological floor plan is only suitable for the indoor environment consisting of dense rooms, rather than large open plan rooms.

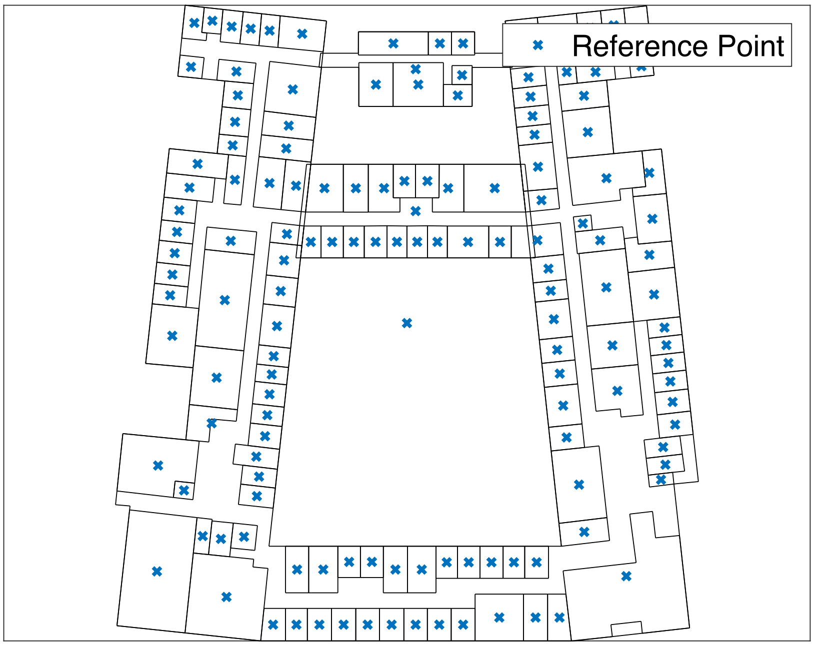



Fig. 2.9 Illustration of presenting indoor location using topological floor plan.

## 2.5.2 Solutions for Indoor Map

The majority of the indoor maps or floor plans used for indoor positioning employ raster graphics [114]. Z. Peng [115] in 2004 proposes that Scalable Vector Graphics (SVG) has the ability to produce superior quality vector maps and has enormous potential to achieve interoperability. ArrayXPath [116] is a web-based service for mapping and visualising gene-expression profiles onto biological pathway resources, in which a clear separation of the data and the visual presentation brings immense benefits. R. Kamadjeu [117] uses SVG to develop a database-driven system generating interactive district-level country immunisation coverage maps and graphs, which demonstrates the potential of SVG technology in resource-constrained settings.

There are several reasons that the vector graphics has advantages over raster graphics. Firstly, the raster graphics is fixed pixel-based static and permanent image files that cannot be modified after creation, while the vector graphics are editable and the display resolution is adjustable. Thus the vector graphics show better resolution than raster images when zooming in and out the view. Secondly, the image content in the vector graphics is objective-oriented thus the objective of the image is retrievable and with customised properties. Finally, the coordinate of an object is one default and compulsory property of each objective in vector graphics. Therefore, if using vector graphics as the indoor map, the problem of both coordinate system and map visualisation is solved.

## 2.6 Chapter Summary

In this chapter, firstly, the different RF technologies and techniques used for indoor positioning are introduced, and the advantages and drawbacks of them are analysed and compared. Secondly, the existing solutions to improve the positioning accuracy and deployment efficiency are reviewed to identify the gaps needed to be addressed. Thirdly, the indoor location and map and its usage in the indoor positioning systems are discussed.

From the existing indoor positioning systems, we can see that the indoor location referencing and presentation is the essential component. Different approaches are used in the current systems, but none of them can meet the requirements of the increasingly complicated positioning technique and LBSes. We believe the indoor map will become pervasive and will be a crucial component to bring indoor positioning into practice. Thus, this thesis investigates the data structure to describe the information available in the indoor environment and the approach to implement it as an indoor map. The proposed indoor map system is presented in both Chapter 3 and Chapter 4.

The APs play an essential role for the WiFi-based indoor positioning. The existing works on the optimisation of the AP placement illustrate that it could improve the positioning accuracy. The goal of all the techniques in the existing works is to maximise the differential and diversity of the fingerprints or minimise the number of similar fingerprints. Most studies of the AP placement problem use the radio propagation model to predict the RSS at the different location (i.e. RP). Most of the existing works did not consider the obstacles in the positioning environment when the RSS is predicted. However, the obstacles could lead to unpredictable RSS in the indoor environment because of multi-path fading and shadowing. Thus, this thesis proposes a map-assisted AP placement solution, which is presented in Chapter 3.

In the WiFi-based positioning system, the main reason for insufficient positioning accuracy is the inconsistent WiFi signals. In the existing works, some of them propose to utilise other signals to assist purely WiFi-based positioning or other metrics like measurements of channel state information instead of RSS. They have their advantages to outperform the RSS but meanwhile also involve new challenges like deployment difficulties. The primary benefit from WiFi signal is its ubiquity, which can provide easy-to-deploy and low-cost positioning solutions. Several recent works reveal that observing the signals from a broader view to generate patterns could mitigate the influence of inconsistent WiFi signals. Thus, this thesis profoundly investigates the ubiquitous WiFi signals and its opportunities to improve the performance of indoor positioning, especially in conjunction with information obtained from the indoor map. The work about positioning using signal patterns and pathway map is presented in Chapter 5. Besides, an instructed site survey is proposed to not only generate signal pattern but also improve the deployment efficiency.

Apart from the AP placement, the role AP plays in WiFi-based indoor positioning and its opportunities to assist positioning are further investigated. From the aspect of system architecture, most of today's systems are centralised on the mobile devices, which has some practical problems like excessive involvement or device variance. Also, considering the issue of energy consumption on mobile devices, the computation-intensive positioning tasks could be relocated. There are several existing device-free passive positioning solutions, but the accuracy or feasibility is still not satisfied. Therefore, in this thesis, an AP-centred positioning solution is proposed in Chapter 5, in which the fingerprinting technique is still utilised to keep the benefits from it.

# Chapter 3

# Map-assisted Access Point Placement for Positioning

To eventually fulfil indoor positioning using WiFi, the first and foremost step is AP placement, i.e., how to place WiFi APs to achieve effective positioning. In the fingerprint-based positioning using WiFi, the access points act as the beacons for WiFi-enabled mobile devices to work out their locations, so the quantity and placement of APs have significant influence for positioning performance. Several studies in the literature [76–78, 80] have revealed that the accuracy of indoor positioning using WiFi can be substantially improved by appropriate AP placement strategies. In other words, deploying the WiFi APs at the locations can help the mobile devices work out their location more precisely in a given indoor environment. If the quantity and placement of AP can be optimised and generated automatically by algorithms, it would be beneficial in real life for the deployment of WiFi-based indoor positioning systems, especially in the large-scale indoor environment.

In the literature works which optimised the AP placement for indoor positioning, most of them use the radio propagation model to predict the received signal strength and generate the optimised AP placement. Propagation loss model is a conventional model used to estimate the received signal strength at certain propagation distance. In these works, their propagation loss model does not consider the specific constraints in real scenarios such as the effect of obstacles like walls and time-varying changes due to moving people. While wireless signals often propagate via multiple paths because of the obstacles in the complex indoor environment and the obstacles can lead to loss of signal strength. Thus, without considering the obstacles in the indoor environment, the propagation loss model cannot provide correct RSS estimation.

To consider the obstacles in the indoor environment when optimising the AP placement, the dynamic objects like moving people won't be considered because the influence of them is not consistent. Among the stationary obstacles, the walls of the building are the main obstacle causing multi-path propagation and loss of signal strength when the signal is passing through, which have been observed when using WiFi router in our home. The main reason that the previous works failed to consider indoor obstacles is the nonexistence of indoor map that can present indoor environmental information such as walls, corridors and so on. In contrast, in this thesis, the work adopts advanced vector graphic technology where detailed map information such as walls and corridors can be explicitly expressed and thus the wall-penetrating effect of signals is taken into consideration for optimisation of AP placement to achieve more precise indoor positioning.

## 3.1 Introduction of Indoor Map

In this work the location of indoor obstacles like walls need to be considered when placing the APs, so the geometrical information of floor plan is required to assist the system. As a result, the best approach to search the indoor multi-floor environmental context is building up a set of digital maps. Based on the digital map, it is convenient to indicate every location on every floor, which is the essential ability of every positioning system. Moreover, floor plans could provide a visualised approach to present the indoor environment, which could help the users to be clear about their exact location during both site survey and positioning phases. Finally, a significant role of the digital floor plans can assist the location estimation and tracking by considering the environmental context.

The indoor map is implemented using SVG as the vector image format. The indoor map is processed and generated following the procedure illustrated in Fig. 3.1. Firstly the raw

SVG file is produced either by drawing using Adobe Illustrator (AI) or similar SVG drawing software or by converting from other file formats, such as the most common Computer-aided Design (CAD) format used in construction design. Secondly, the raw SVG file of the indoor map is processed manually or automatically depending on file source. The goal of the process is to extract the useful data from raw SVG file and then save it to a new SVG file based on our format and data structure. Upon now the SVG file can provide a graphic representation of indoor map as Fig. 3.2. Finally, to make the indoor map accessible as data for AP placement or positioning algorithm, the data in the SVG file is retrieved into a database. In the database the elements of the indoor map such as the wall of a room are searchable. Moreover, if the information of indoor map needs to be updated, the changes can be edited in the database directly. Meanwhile, the changes can be reflected to the SVG file from the database.

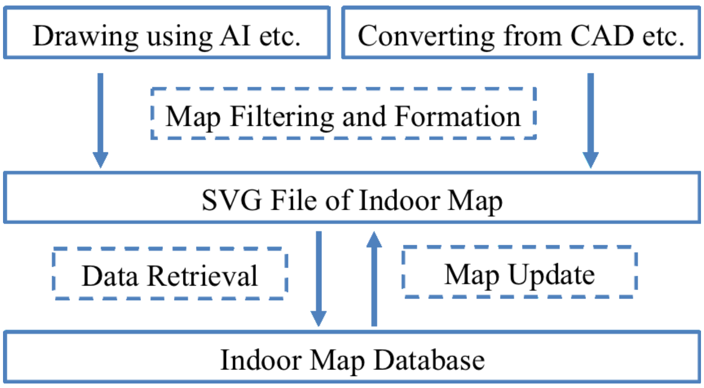



Fig. 3.1 Illustration of the indoor map generation process

The illustration in Fig. 3.2 is a visual representation of one specific floor in a building using vector graphics. The map covers not only the layout of walls and doors but also the semantic properties such as room numbers and types. Each floor plan has its own local coordinates system and belongs to building with floor identity. The object in the map is retrievable by its properties, such as the layout and size of the floor, outline of room and corridor, name and type of room, etc. For example, the coordinates of walls' vertex and doors of a room could be found through searching the room object by room name. Fig. 3.3 is the source code of SVG file representing the three simple rooms in Fig. 3.2.

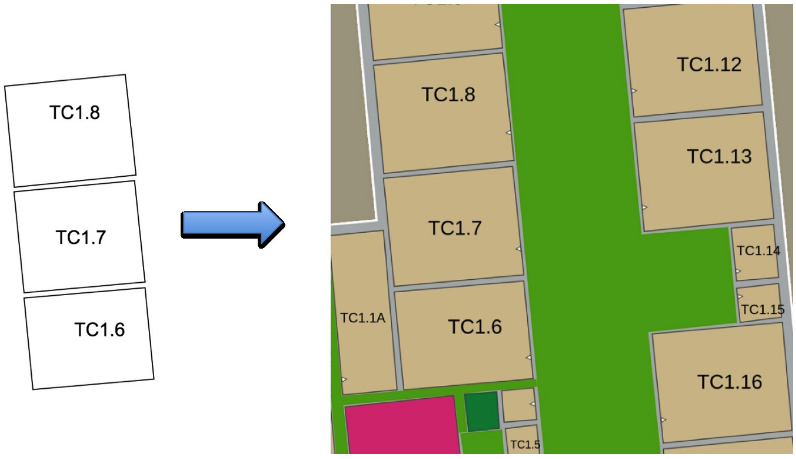



Fig. 3.2 Illustration of the indoor map construction from individual rooms to completed map

```
<polygon fill="#FFFFFF" stroke="#000000" stroke-miterlimit="20"
    points="405.833,346.5 415.167,443.5 532.167,431.833 521.834,335.167 "/>
<polygon fill="#FFFFFF" stroke="#000000" stroke-miterlimit="20"
    points="414.833,447.833 424.5,544.834 540.834,534.5 530.75,437.167 "/>
<polygon fill="#FFFFFF" stroke="#000000" stroke-miterlimit="20"
    points="424.5,549.834 433.029,637.727 549.362,627.727 540.834,539.998 "/>
<text transform="matrix(1 0 0 1 448.5947 378.0977)"
    font-family="'ArialMT'" font-size="18">TC1.8</text>
<text transform="matrix(1 0 0 1 454.5947 498.0918)"
    font-family="'ArialMT'" font-size="18">TC1.7</text>
<text transform="matrix(1 0 0 1 472.5938 586.5879)"
    font-family="'ArialMT'" font-size="18">TC1.6</text>
```

Fig. 3.3 Illustration of the source code of SVG file for a sample map containing 3 individual rooms

Table 3.1 illustrated the structure of the table “locations” in the database that stores the information on an indoor map. Each location means a specified area rather than a single point. The most important field is the polygon, which specifies the vertexes of the polygon representing every location. If the category of a location is room, the walls of it can be found using the vertexes.

Table 3.1 Database structure of table that stores the information on indoor map

| id | name | building | floor | category | polygon | ... |
|---|---|---|---|---|---|---|
| 1 | TC1.8 | 1 | 1 | 2 | 1662.069,1446.386<br>1696,1798.993<br>2121.309,1756.582<br>2083.747,1405.190 | ... |

## 3.2 Data Structure of Fingerprinting Technique

In fingerprint-based positioning, most systems consist of two phases: offline site survey phase and online positioning phase. The fundamental principle of fingerprinting technique has been discussed in the Section 2.2.2. The data structure of fingerprinting technique is presented in this section.

#### 3.2.0.1 Site Survey Phase

In the site survey process, a set of known locations in the interesting venue of positioning are selected as the reference points (RPs), as illustrated in Fig. 2.3, and WiFi received signal strength (RSS) from APs are collected at each RP. The dynamic and unpredictable nature of radio propagation caused by shadowing and multi-path fading leads to a significant variance of RSS observations. To obtain the RSS value that is the closest to the real observations for most of the time, increasing the sample size of RSS observations collected is a typical approach used to reduce the influence of variance of RSS observations. Thus, a set of time-series RSS values at each RP are collected in a successive period, which is called raw

RSS observation set and depicted as

$$\{\psi_{k,i}(\tau), \tau = 1, \ldots, q, q > 1\} \tag{3.1}$$

where $q$ is the number of sequential RSS values of $AP_k$ observed at $RP_i$, for $k = 1, 2, \ldots, M$, $i = 1, 2, \ldots, N$, where $M$ is the number of APs selected as beacons for positioning and $N$ is the number of RPs in the interesting area [28]. $q$ is not a constant and is varied with the change of $AP_k$ and $RP_i$. Then the mean of the raw RSS observation set of each AP at each RP is computed and used as the value indicating the RSS of this AP at this RP. The average RSS value of $AP_k$ at $RP_i$ is

$$\psi_{k,i} = \frac{1}{q}\sum_{\tau=1}^{q} \psi_{k,i}(\tau) \tag{3.2}$$

where $\psi_{k,i}$ is given -100 (or -90 in some work) if $q = 0$ (i.e., $AP_k$ is not observed at $RP_i$), because the weakest signal observed is close to -100 but not less than -100.

The average RSS values of $M$ number of APs at $RP_i$ constitute the fingerprint of $RP_i$, which is

$$\phi_i = [\psi_{1,i}, \ldots, \psi_{M,i}]^T, \tag{3.3}$$

where $\psi_{k,i}$ for $k = 1, 2, \ldots, M$.

The fingerprint $\phi_i$ of $M$ number of APs and collected from $N$ number of RPs compose the WiFi radio map, which is depicted as

$$\Psi = \begin{pmatrix} \psi_{1,1} & \psi_{1,2} & \cdots & \psi_{1,N} \\ \psi_{2,1} & \psi_{2,2} & \cdots & \psi_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ \psi_{M,1} & \psi_{M,2} & \cdots & \psi_{M,N} \end{pmatrix} \tag{3.4}$$

The WiFi radio map is saved as fingerprint database constructed in offline site survey phase and used for online positioning.

#### 3.2.0.2 Positioning Phase

In the online positioning process, when a user requests its current location information using its real-time RSS observation, the positioning algorithm retrieves the radio map from fingerprint database to compare the real-time RSS observation with the records of RSS observation of RPs in the fingerprint database. The real-time RSS observation at an unknown location is denoted as

$$\phi_0 = [\psi_{1,0}, \dots, \psi_{M,0}]^T, \tag{3.5}$$

where $\psi_{k,0}$ for $k = 1, 2, \dots, M$. $M$ is the number of pre-selected APs used as beacons for positioning and $\psi_{k,0} = -100$ if the $AP_k$ is not observed.

The recorded RSS observation of $RP_i$ (i.e., the fingerprint of $RP_i$) in radio map $\Psi$ is

$$\phi_i = [\psi_{1,i}, \dots, \psi_{M,i}]^T, \tag{3.6}$$

where $\psi_{k,i}$ for $k = 1, 2, \dots, M$.

The similarity between real-time RSS observation $\phi_0$ and fingerprint of each RP $\phi_i$ is computed, and the similarity between them is determined based on the Euclidean distance between them, which is expressed as

$$d(\phi_0, \phi_i) = \|\phi_0 - \phi_i\| = \sqrt{\sum_{k=1}^{M} (\psi_{k,0} - \psi_{k,i})^2} \tag{3.7}$$

Finally, the location of RP with most similar RSS observation (i.e., $RP_i$ where $d(\phi_0, \phi_i)$ is minimum among all the RPs) is returned to the user as the estimated location of user [28].

## 3.3 Formulation of AP Placement Problem

In this section, based on the principle of fingerprinting techniques the optimisation model of AP placement is presented firstly. Then the critical parameter and constraint (i.e., the total number of APs to deploy and the area where the APs can be placed) of the optimisation model are discussed. The RSS attenuation caused by walls is a variable in the optimisation model, and the approach how the variable is obtained is discussed in the Section 3.4.

### 3.3.1 AP Placement Optimisation Model

Based on the principle of fingerprinting-based positioning, if there are very similar fingerprints in the radio map, it's difficult to find the best-matched fingerprint of RP correctly. Thus, reducing the similar fingerprints of the radio map can improve the probability to find the correct location. The goal of the optimisation is to work out the locations of APs where the similarity between fingerprints of adjacent RPs can be maximised. To be more specific, for each RP its adjacent RPs within a specific range are obtained. As illustrated in Fig. 3.4, the $RP_j$ is the adjacent RP of $RP_i$, and the similarity between the fingerprints of them can be increased by adjusting the locations of APs.

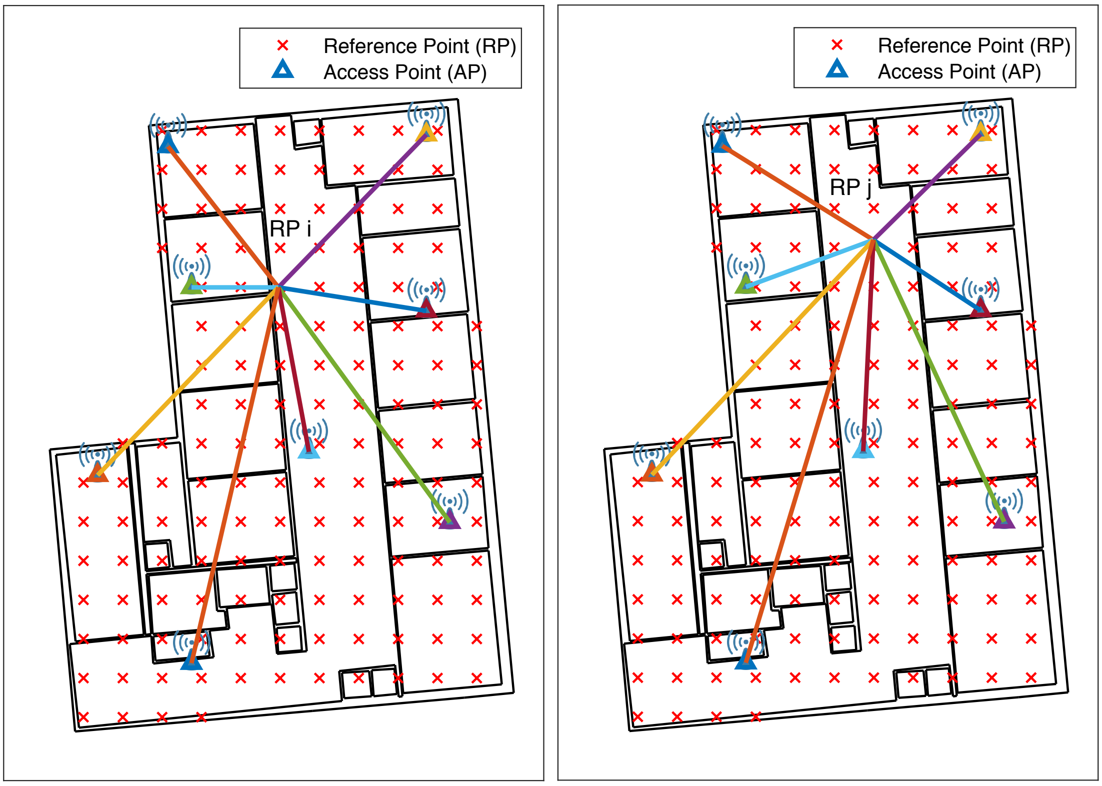



Fig. 3.4 Illustration of fingerprints of $RP_i$ and $RP_j$

As discussed in Section 3.2, the similarity between the two fingerprints is based on Euclidean distance. Therefore the increase of Euclidean distance means enhancement of difference between two fingerprints. As a result, to improve the positioning performance, the Euclidean distance among the fingerprints of RPs should be maximised, which makes it easy to distinguish different RPs.

To increase the difference and diversity of the fingerprints in radio map, this thesis presents the approach to maximise the sum of Euclidean distance among fingerprints of RPs, where the fingerprints are from selected APs among all the RPs. The work of AP placement is conducted when the APs are not deployed so that the work won't be based on real RSS measurement, and the RSS of an AP at a particular location needs to be predicted. Due to the multi-path fading and shadowing caused by obstacles in indoor environments, it is difficult to describe the characteristic of indoor radio propagation accurately. The log-distance path loss model is typically used to predict the RSS at a given distance, which is introduced in Section 2.2.1.1 and illustrated in Fig. 2.2. In this thesis, with the assistance of the indoor map, when predicting the RSS of an AP at an RP, the attenuation caused by walls is considered into the prediction of RSS using log-distance path loss model.

Proposed optimisation model:

$$maximize \quad f = \sum_{i=1}^{N} \sum_{j \in D_i} d(\phi_i, \phi_j) \tag{3.8}$$

$$s.t. \quad D_i = \{j | dist(RP_i, RP_j) \leq r\} \tag{3.9}$$

$$d(\phi_i, \phi_j) = \sqrt{\sum_{k=1}^{M} (\psi_{k,i} - \psi_{k,j})^2} \tag{3.10}$$

$$\psi_{k,i} = L_0 - 10nlog\left(\frac{\sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}}{d_0}\right) - \varphi \tag{3.11}$$

$$(x_k, y_k) \in S \tag{3.12}$$

In the Eq. (3.8), $f$ is the sum of the Euclidean distance of RSS array among all the RPs and $f$ should be maximised, in which $N$ is the number of RPs, and the value of $N$ depends on the granularity of RPs and size of the interested area. $D_i$ are a set of RPs whose geometric distances from $RP_i$ are smaller than $r$, as shown in Eq. (3.9), where $r$ is a constant and in the range of several meters. In the Eq. (3.7), $d(\phi_i, \phi_j)$ is the Euclidean distance of fingerprints between $RP_i$ and $RP_j$, as illustrated in Fig. 3.4, and $M$ is the number of APs. Further discussion about determining the number of APs $M$ is available in Section 3.3.2. In the Eq. (3.11), $\psi_{k,i}$ is the RSS of $AP_k$ at $RP_i$ and predicted by the log-distance path loss model [53, 54, 118]. The geometric distance between $RP_i$ and $AP_k$ is calculated using their coordinates $(x_i, y_i)$ and $(x_k, y_k)$. $L_0$ is the known signal strength at a reference distance $d_0$ and $n$ is the path-loss exponent indicating the rate at which the path loss increases with the increase of distance. $d_0$ is a constant and the value of $n$ is estimated using empirical data in practice. $\varphi$ is the signal strength attenuation caused by walls between $RP_i$ and $AP_k$, which is defined in Section 3.4.2. In the Eq. (3.12), $S$ is the area where the APs are placed and the location coordinates $(x_k, y_k)$ of $AP_k$ is constrained within $S$. The $S$ is a constant in each site of positioning system and further discussion is available in Section 3.3.3.

### 3.3.2 Determining the Number of APs

In the AP placement optimisation model, the number of APs to be placed need to be provided in advance. The number of APs $M$ is calculated by

$$M = \frac{A}{A_{AP} \cdot (1-\rho)}, 0 < \rho < 1 \tag{3.13}$$

where $A$ is denoting the area of the floor, $A_{AP}$ is denoting the coverage area of each AP, and $\rho$ is denoting the coverage overlap ratio. Because the coverage area of each AP is rounded and the APs' locations are optimised for positioning purpose, to achieve higher coverage ratio there must be coverage overlaps from multiple APs. Thus the parameter $\rho$ is introduced in Eq. (3.13) to set the overlap ratio, which is between 0 and 1. The overlap ratio $\rho$ is a heuristic value and depending on the positioning and coverage requirement. Increasing the overlap ratio leads to higher coverage ratio and better positioning accuracy, but cannot guarantee full coverage.

With the assistance of map, the coordinates of floor's vertices (e.g., corners) are already known so that the floor area $A$ can be calculated by

$$A = \left| \frac{(x_1y_2 - y_1x_2) + (x_2y_3 - y_2x_3) \cdots + (x_ny_1 - y_nx_1)}{2} \right| \tag{3.14}$$

where $n$ is denoting the number of vertices in the floor. The Eq. (3.14) works for all polygon types (regular, irregular, convex, concave) to adapt to today's sophisticated buildings.

### 3.3.3 AP Placement Schemes

In this work, two kinds of placement schemes are proposed, random placement and heuristic placement. Both of them use the same optimisation model to work out the placement, but they differ in the area where the APs can be placed, e.g., $S$ in the formulation above. In random placement scheme, $S$ is the full area of the floor, and all of the $M$ number of APs are free to be placed within $S$.

In [119] a practice guide suggests that it is important to ensure that the APs are not solely clustered in the interior of floors. Some APs should be placed on the boundary along the perimeter of the floor to complement the APs located within floor interior area. Such approach to AP placement can ensure good location fidelity within the floor. Inspired by the empirical rules above, in heuristic placement scheme, the floor area is divided into two sections, inner area and the outer boundary. A selected number of APs are placed on the outer boundary, and the rest of APs are placed inside the inner area. The number of APs placing on the outer boundary $M_o$ is determined by

$$M_o = \frac{\mu \cdot C}{A} \cdot M, 0 < \mu \leq \frac{A}{C} \tag{3.15}$$

where $M$ is the total number of APs deployed on the floor. $C$ is the perimeter of the outer boundary. $A$ is the area of the floor. The floor with irregular outer boundary has longer perimeter compared with the floor with regular outer boundary. The irregular boundary causes more complicated signal propagation thus needs more APs placed on the outer boundary to improve the diversity of fingerprints. In this equation, only the proportion is concerned so that the units of both $C$ and $A$ are ignored. $\mu$ is a scaling factor based on real environment, and 5 is chosen in our experiment.

## 3.4 Map-assisted AP Placement Optimisation

In this thesis, with the assistance of the indoor map, the RSS attenuation caused by walls is considered when predicting the RSS of an AP at a location. The attenuation is mainly depending on the thickness of the wall, the number of walls between and the angle of signal's arrival relative to the wall. Thus, in this section, a wall detection algorithm is provided to exploit the information of walls between an AP and an RP using the information of indoor map. Then the approach to calculating the RSS attenuation using the wall information is given.

### 3.4.1 Wall Detection Algorithm

With the assistance of the indoor map using vector format, the parameters required to calculate the RSS attenuation caused by walls can be obtained. As the example shown in Fig. 3.5, the number and angles of walls between RPs and APs are computed by retrieving the line segments representing the walls from the indoor map. A wall detection algorithm to calculate the number of walls and the angle of arrival corresponding to the walls, which the signal travels through from AP to RP, is proposed and the pseudocode is in Algorithm 3.1.

The proposed algorithm computes the intersection of the line segment representing the signal propagation path and line segments that denote the walls in the current floor. Firstly the counter $i$ to count the number of walls that the signal travel through is reset to 0 and all the line segments representing walls $W$ are marked as unchecked in Line 1 and 2. Line 3 starts the main loop that traverses the set of walls $W$ to find the walls intersected with signal propagation path $p$. Line 4 allocates the line segment of next unchecked wall to $q$ and line 5

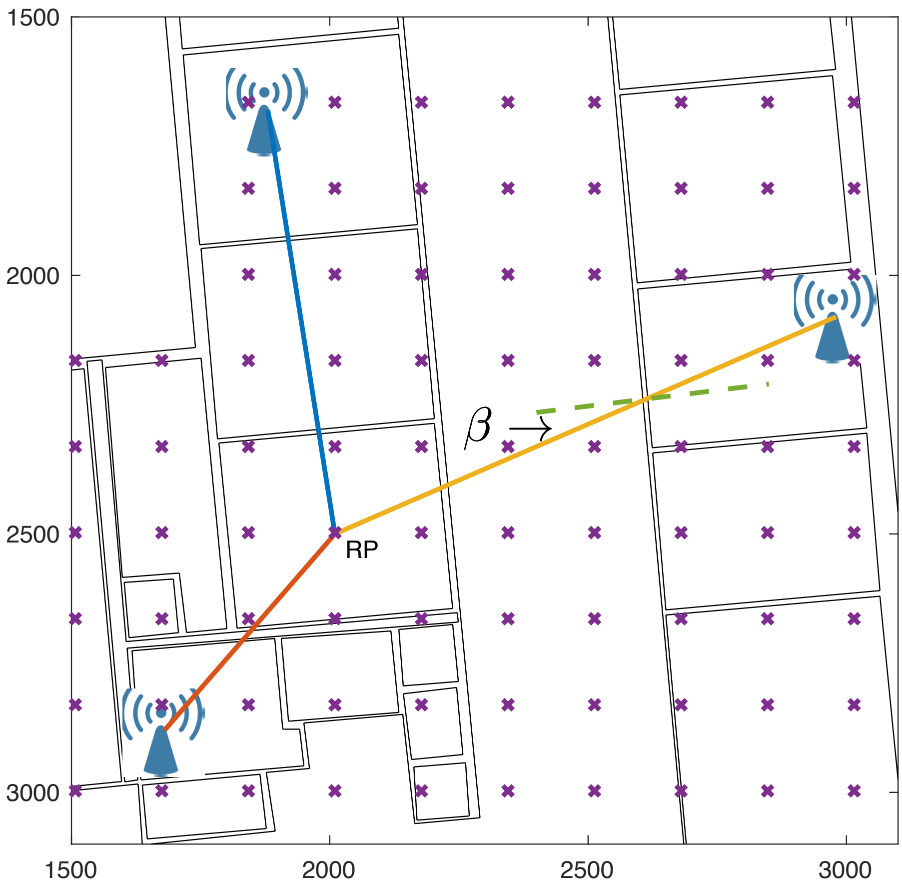



Fig. 3.5 Illustration of walls between RP and AP on indoor map

**Algorithm 3.1** Wall Detection Algorithm

Input:
$p$ - the line segment representing the propagation path between AP and RP;
$W$ - a set of line segments representing the walls in the current floor.
Output:
$i$ - the index of wall between AP and RP;
$A[i]$ - the angle of arrival corresponding to the wall.

1: $i \leftarrow 0$
2: Mark all the walls $W$ as unchecked
3: **while** hasUncheckedWall **do**
4:     $q \leftarrow NextUncheckedWall$
5:     $v \leftarrow GetAngleOfArrival(p,q)$
6:     **if** $v \neq -1$ **then**
7:         $A[i] \leftarrow v$
8:         $i \leftarrow i+1$
9:     **end if**
10:     Mark $q$ as checked wall;
11: **end while**

calls the function GetAngleOfArrival to check whether line segment $q$ intersects with $p$ and if it does the angle of arrival $v$ is returned; otherwise, the returned value is -1. If $q$ intersects with $p$, $q$ is counted and the angle of arrival $v$ is stored into array $A$ (Line 6-9). At the end of each iteration, $q$ is marked as checked. The above procedure is repeated until all the walls $W$ in the current floor are checked. Finally, the number of walls that the signal travels through is returned by $i$, and the angle of the signal arriving at each wall is returned by $A[i]$.

The GetAngleOfArrival function is used to calculate the angle of a signal arriving at the wall, which is implemented in Algorithm 3.2. The GetTheAngleOfArrival function checks whether the signal propagation path intersects with a specific wall and return the arrival angle of signal if intersected, otherwise just return -1. Between line 1 and 10, a comparison of the line segments' endpoints is used to quickly exclude the line segments that do not intersect, which is also called bounding box check. If bounding box check cannot determine whether two line segments intersect then further test work is required, as shown in case 5 of Fig. 3.7. In the function GetTheAngleOfArrival, it only checks whether two line segments intersect. If two segments do intersect, the angle of intersection is computed. Thus the value of $\alpha$ and $\beta$ are not needed explicitly, and they only need to be tested against the range $[0,1]$. The

**Algorithm 3.2** GetAngleOfArrival Function

Input:
$p$ - a line segment defined by two points $P_1$ and $P_2$, which represents signal propagation path;
$q$ - a line segment defined by two points $Q_1$ and $Q_2$, which represents wall.
Output:
angle of arrival $\beta$ or $-1$ (no intersection)

**function** GETANGLEOFARRIVAL$(p,q)$
  $\Delta x_P = x_{P_2} - x_{P_1}; \Delta x_Q = x_{Q_2} - x_{Q_1}$
  **if** $\Delta x_P < 0$ **then**
    $x_P^{low} = x_{P_2}; x_P^{high} = x_{P_1};$
  **else**
    $x_P^{low} = x_{P_1}; x_P^{high} = x_{P_2};$
  **end if**
  **if** $\Delta x_Q < 0 \;\&\; (x_{Q_1} < x_P^{low} \, or \, x_{Q_2} > x_P^{High})$ **then return** -1 ▷ case 1
  **end if**
  **if** $\Delta x_Q > 0 \;\&\; (x_{Q_2} < x_P^{low} \, or \, x_{Q_1} > x_P^{High})$ **then return** -1 ▷ case 2
  **end if**
  $\Delta y_P = y_{P_2} - y_{P_1}; \Delta y_Q = y_{Q_2} - y_{Q_1}$
  **if** $\Delta y_P < 0$ **then**
    $y_P^{low} = y_{P_2}; y_P^{high} = y_{P_1};$
  **else**
    $y_P^{low} = y_{P_1}; y_P^{high} = y_{P_2};$
  **end if**
  **if** $\Delta y_Q < 0 \;\&\; (y_{Q_1} < y_P^{low} \, or \, y_{Q_2} > y_P^{High})$ **then return** -1 ▷ case 3
  **end if**
  **if** $\Delta y_Q > 0 \;\&\; (y_{Q_2} < y_P^{low} \, or \, y_{Q_1} > y_P^{High})$ **then return** -1 ▷ case 4
  **end if**
  $\Delta x_R = x_{P_1} - x_{Q_1}; \Delta y_R = y_{P_1} - y_{Q_1}$
  $d = \Delta y_Q \times \Delta x_R - \Delta x_Q \times \Delta y_R$
  $f = \Delta y_P \times \Delta x_Q - \Delta x_P \times \Delta y_Q$
  **if** $f > 0 \;\&\; (d < 0 \;\; or \;\; d > f)$ **then return** -1 ▷ case 5
  **end if**
  **if** $f < 0 \;\&\; (d > 0 \;\; or \;\; d < f)$ **then return** -1
  **end if**
  $e = \Delta x_P \times \Delta y_R - \Delta y_P \times \Delta x_R$
  **if** $f > 0 \;\&\; (e < 0 \;\; or \;\; e > f)$ **then return** -1
  **end if**
  **if** $f < 0 \;\&\; (e > 0 \;\; or \;\; e < f)$ **then return** -1
  **end if**
  $\cos\theta = \frac{\Delta x_P \times \Delta x_Q + \Delta y_P \times \Delta y_Q}{\sqrt{\Delta x_P^2 + \Delta y_P^2} \times \sqrt{\Delta x_Q^2 + \Delta y_Q^2}}$
  $\cos\beta = \sqrt{1 - \cos^2\theta}$
  **return** $\beta$
**end function**

test work is undertaken between line 11 and 18. After all the tests that confirm two line segments are intersected, the angle of intersection and angle of the signal arriving at the wall are computed in line 19 and 20 as shown in case 6 of Fig. 3.7.

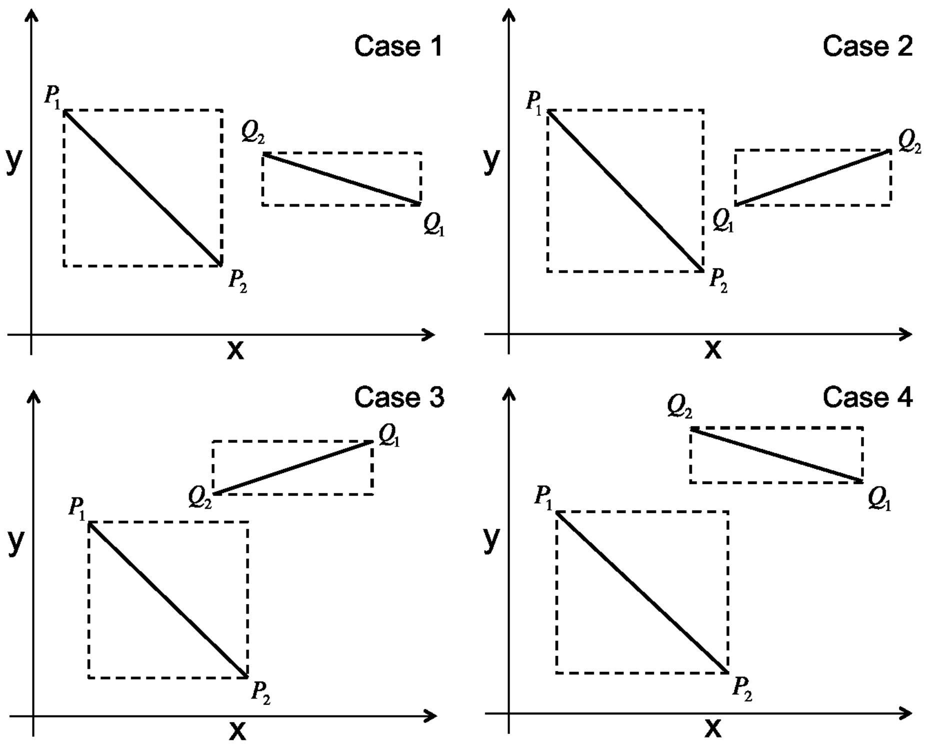



Fig. 3.6 Illustration of the cases where two line segments that do not intersect can be determined by bounding box.

### 3.4.2 Signal Attenuation Caused by Walls

The signal strength attenuation caused by walls between $RP_i$ and $AP_k$ is

$$\varphi = \omega \sum_{i=1}^{w} \frac{t_i}{\cos \beta_i}, \omega > 0, t_i > 0 \tag{3.16}$$

where $w$ is the number of walls between the AP and the receiver, $t_i$ is the thickness of the $i^{th}$ wall, $\beta_i$ is the angle of arrival corresponding to the $i^{th}$ wall, and $\omega$ is the attenuation factor per wall thickness unit [55, 118].

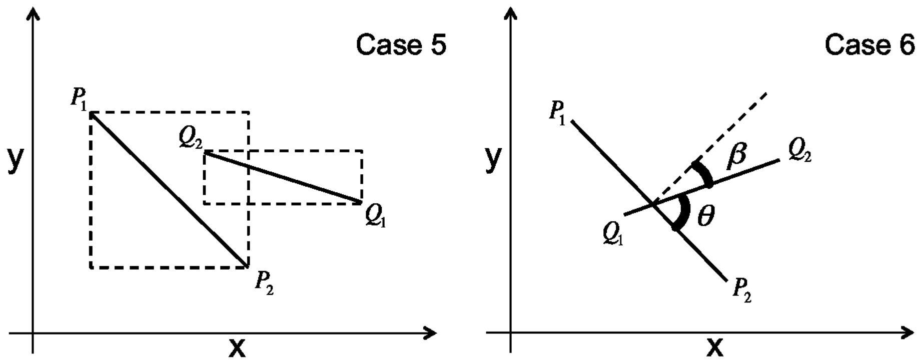



Fig. 3.7 Illustration of the cases where bounding box check fails (case 5) and two line segments intersect (case 6).

### 3.4.3 AP Placement Optimisation Using PSO

In this section, the approach to solve the optimisation model for AP placement is introduced. Particle swarm optimisation (PSO) is an evolutionary algorithm which optimises a problem by iteratively attempting to improve the result of a given fitness function [120][121]. The PSO is inspired and derived from the movement of organisms in a bird flock or fish school, where the easiest and most efficient way to find food is searching for the nearest bird or fish [122]. In PSO each particle in a swarm is a candidate solution in a population of solutions for the optimisation problem. The velocity of a particle determines the movement direction and speed of the particle to guide the movement of particles. To achieve optimisation in the multi-dimension searching space, the velocity is iteratively adjusted by observing the behaviour and experience of itself and its population [123].

At the beginning of PSO algorithm, a swarm of particles are initialised in the search space, and each has three properties of location, velocity and fitness to represent the status of the particle. The fitness of each particle is computed by the corresponding optimisation function in most cases to indicate the quality of the particle. The particle moves around with the current velocity, and the current fitness is compared with the previous fitness to find the best fitness and corresponding location. The particle's own best-known location and population's best-known location are both be recorded and used to update the velocities of the particles. The location and velocity update strategy based on the previous location with the best fitness is manipulated according to the following equations:

$$V_i^{k+1} = \lambda V_i^k + c_1 r_1 (P_i - X_i^k) + c_2 r_2 (P_0 - X_i^k) \tag{3.17}$$

$$X_i^{k+1} = X_i^k + V_i^K + 1 \tag{3.18}$$

In the search space, $X^k = (X_1^k, X_2^k, \ldots, X_n^k)$ is the position of particle swarm with population of $n$ and $X_i^k = (M_1, M_2, \ldots, M_D)^T$ is a vector of $D$ dimension to represent the $i^{th}$ particle at the $k^{th}$ iteration.

In this section, $X$ represents the locations of APs in a placement, and $D$ is the number of APs need to be placed. $M$ donates the coordinate of AP using an array of two variables to indicate $(x_k, y_k)$. The velocity corresponding to the $i^{th}$ particle at the $k^{th}$ iteration is represented as $V_i^k$. $P_i$ is the best position of the $i^{th}$ particle and $P_0$ is the best position among the swarm. In Eq. (3.17), $\lambda$ is the inertia weight allocated to the existing velocity. $c_1$ and $c_2$ are positive constants as the acceleration factors of individual particle and swarm. $c_1$ affects the size of the step the particle takes toward its individual best candidate solution $P_i$. $c_2$ represents the size of the step the particle takes toward the global candidate solution $P_0$. The values of $c_1$ and $c_2$ need to be tuned in the experiments for different scenarios and the values selected in this thesis are listed in Table 3.2. $r_1$ and $r_2$ are random numbers in $[0,1]$ to cause the velocity update has a stochastic influence [124]. Eq. (3.17) is used to update the velocity of next movement and Eq. (3.18) applies the velocity to the existing position.

## 3.5 Experiments and Results

### 3.5.1 Experimental Setup

This section provides details on the experimental evaluation of the proposed AP placement algorithm. The experimental site is the first floor of Tony Rich Teaching Centre at the University of Essex Colchester Campus. The area of the floor is about 1200 square meters and contains 12 teaching rooms and a large lobby, as depicted in Fig. 3.2. The optimisation algorithm is implemented using Matlab on a Dell desktop (Windows 7, 2.8 GHz Intel i5 Processor and 4GB RAM) to search for the optimised AP placement. The positioning system including both site survey and positioning process is implemented in Java as an application that runs on Android mobile devices. The application is installed on a smartphone of HUAWEI Ascend P6 model running Android 4.4.2 with IEEE 802.11b/g/n WiFi adaptor. The WiFi scanning rate of the positioning application is set to once every 500ms. All access points are of TP-Link WR1043ND model that is compliant with IEEE 802.11 b/g/n standards. The deployment of APs in vertical space is not considered in this paper. The experiments are carried out in the daily-used public venue where installation of APs on the ceiling is not allowed, so the APs are placed on the floor for ease of deployment.

The efficiency of the placement algorithm is to be measured by the positioning accuracy. The benchmark used is an AP placement algorithm without map [12]. The impact of walls is explicitly investigated. The proposed algorithm is going to be evaluated under two different placement schemes: random and heuristic. In addition, the reasonable value for the number of iterations in the PSO is also investigated and demonstrated to guarantee the convergence and efficiency. As the indoor positioning algorithm is not the focus of this work, we just employ the classic KNN algorithm for this purpose, which is the most simple and typical deterministic matching algorithm.

The constant parameters of the experiment are defined in Table 3.2.

### 3.5.2 Map-assisted Prediction of RSS

In this thesis, the log-distance path loss model is used to predict the RSS of WiFi signals at reference points, and the AP placement is optimised based on the predicted RSS. In our work, a wall detection algorithm is presented, and the attenuation caused by the walls is considered into the log-distance path loss model ((3.11)). To ensure the AP placement optimisation model can work properly, this log-distance path loss model and its parameters are evaluated in this section.

Table 3.2 Constant parameters of the experiment

| Parameter | Value |
|---|---|
| reference distance $d_0$ | 1 $m$ |
| signal strength at reference distance $L_0$ | -28 $dBm$ |
| comparable RP distance $r$ | 10 $m$ |
| path-loss exponent $n$ | 2.2 |
| attenuation factor per wall thickness unit $\omega$ | 5 |
| particle swarm population | 10 |
| inertia weight of existing velocity $\lambda$ | 1 |
| acceleration factors $c_1$ and $c_2$ | 1.49445 |
| proportion of overlap $\rho$ | 0.5 |
| AP coverage area $A_{AP}$ | 314 $m^2$ |

The Fig. 3.8 shows the heat map of the observed RSS from an AP in the experimental site. The heat map shows the RSS declines with the increase of distance to the AP. The strongest RSS observed is around -45 dBm, which is about 2 meters away to the AP without obstacle. The RSS fluctuates between -60 and -80 dBm in most time. Because without the access to the rooms the RSS is only observed in the corridor. These RSS observed are used as the benchmark to evaluate the precision of the map-assisted log-distance path loss model considering the attenuation of walls.

The RSS from this AP is firstly predicted by the log-distance path loss model (i.e., Eq. (3.11) without the attenuation factor $\varphi$), which also doesn't consider the Gaussian random variable that reflects attenuation. Since it's an empirical model, the coefficient parameters used in this model is selected based on measurements in the real world. $L_0$ is the known signal strength at a reference distance $d_0$ and $n$ is the path-loss exponent indicating the rate at which the path loss increases with the increase of distance. The parameters used in the experiment are provided in Table 3.2. The Fig. 3.9 illustrates the distribution of RSS on the indoor map, which shows a very linear decrease from the AP. Compared with the observation from real-world measurements, overall the predicted RSS is stronger than observation, and the attenuation shows a very slow drop, which reveals significant deviation between them.

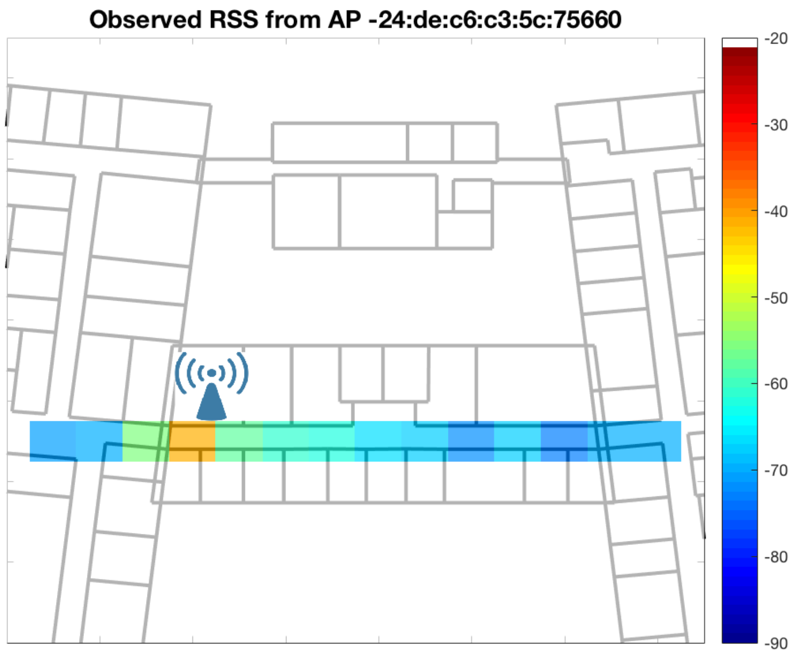



Fig. 3.8 Heat map of the RSS observed in the experimental site.

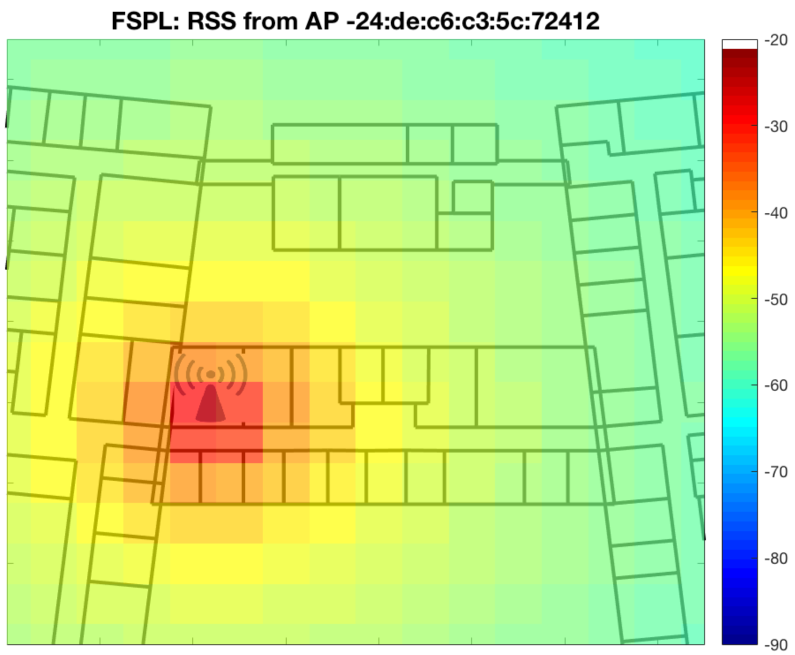



Fig. 3.9 Heat map of the RSS predicted by the FSPL model.

In this work, the RSS attenuation caused by walls are considered and formulated, which is depicted as Eq. (3.16). The effectiveness of it and the coefficient parameter $\omega$ indicating the attenuation factor per wall thickness unit are investigated. The number of walls and the signal's angle of arrival relative to the walls between AP and RP are obtained from the proposed indoor map system using the wall detection algorithm discussed in Section 3.4.1. The RSS attenuation calculation formula takes over the information of walls. In our work the thickness of walls of our experimental building is considered to be the same, i.e., wall thickness unit $t_i$ of the $i^{th}$ wall is constant 1. The attenuation factor per wall thickness is determined based comparison with real-world measurements. The Fig. 3.10 shows the RSS predicted by the log-distance path loss model that considers the attenuation of walls (Eq. (3.11)), where different attenuation factor per wall thickness is applied. In Fig. 3.10 only the area where the RSS is above -90 dBm is shown on the indoor map. The increase of attenuation factor causes the decrease of RSS dramatically and reduces the coverage area of the AP. The difference between observed and predicted RSS using different attenuation factor is compared in all the locations where the RSS are observed, which is evaluated by the cumulative distribution function (CDF), as illustrated in the Fig. 3.11. Setting the attenuation factor to extreme small (i.e., $\omega = 2$) or extreme large (i.e., $\omega = 7$) can lead to excessive error. Through the comparison in Fig. 3.11, when $\omega = 5$, the RSS prediction is the same to the observation in about 30% of the prediction and most cases the RSS deviation is less than 10 dBm, which is the range of typical signal fluctuation in an indoor environment. Thus, the attenuation factor as 5 is selected to be used for the optimisation model of AP placement.

### 3.5.3 PSO Configuration and Evaluation

The reasonable number of iteration is determined from a number of experiments. Fig. 3.12 illustrates the climb of fitness with the increase of iterations up to 5000 and 1000 respectively in random and heuristic placement. In random placement scheme, the fitness function becomes stable after 2500 iterations. The slight rise between 4500 and 5000 is about 2% improvement but costs nearly double number of iterations, so it is ignored. While in heuristic placement, due to the limitation of the area where AP could be placed, the searching space is

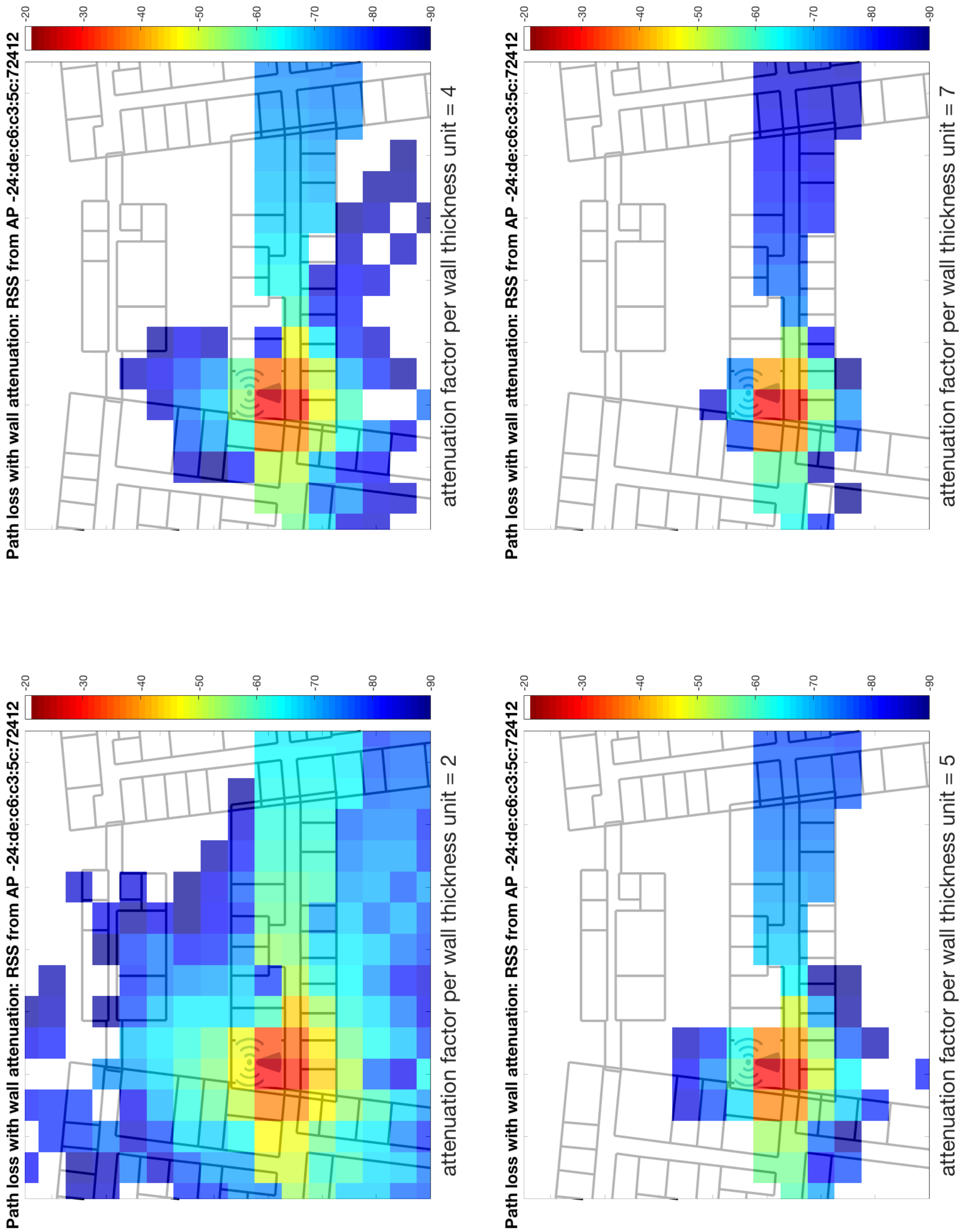



Fig. 3.10 Heat map of the RSS predicted by the log-distance path loss model with wall attenuation using different attenuation factor per wall thickness.

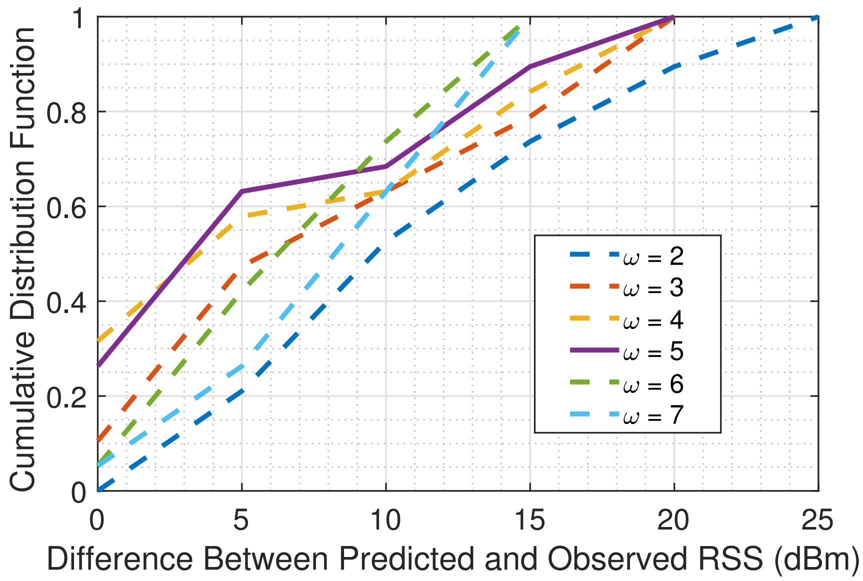



Fig. 3.11 CDF of the difference between predicted and observed RSS (dBm) using different attenuation factor per wall thickness.

reduced. Therefore the fitness function converges much faster than that of random placement. The heuristic placement achieves convergence at around 500 iterations, 5 times faster than random placement, which indicates that the heuristic placement is a more efficient scheme. As a result, the number of iteration for random and heuristic placement is set as 2500 and 500 respectively in the following experiments.

Moreover, through the comparison of y-axis in Fig. 3.12, we can see that the peak fitness value of optimised placement by random scheme exceeds that by the heuristic scheme eventually, which means the heuristic way compromises the diversity of fingerprints. Further evaluation of positioning accuracy reveals whether the compromise is worthy or not. Also, the top graph in Fig. 3.12 shows that the trend of the stepwise curve is not smooth. The fitness jumps sharply and suddenly at particular iteration, and it remains unchanged at a specific level for hundreds of iterations. That accurately demonstrates the drawback of PSO that it is easily be trapped into a local minimum or maximum, which is named as premature convergence.

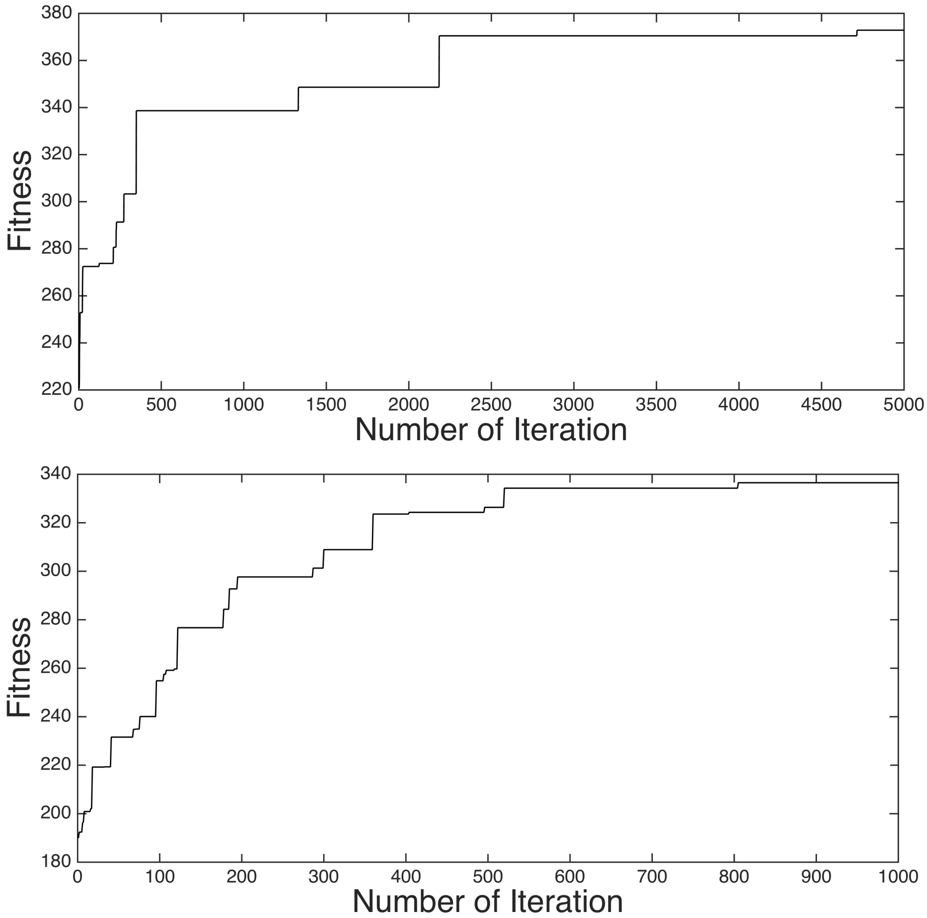



Fig. 3.12 Plots of the number of iteration in PSO to achieve convergence between random (top) and heuristic (bottom) placement strategy.

### 3.5.4 Results of Optimised AP Placement

The placement results computed by different placement schemes are illustrated in Fig. 3.13. For the given indoor floor plan, 8 APs are required through the calculation using Eq. (3.13). The AP locations chosen by the random scheme are evenly distributed in the floor layout. Most of them are away from the outline of the floor. A few of APs are adjacent to each other, which is not preferred because abundant APs at the nearly same location does not help the positioning system and the APs located closely cause interference to each other. Heuristic scheme adopts the empirical rules from previous research and industrial products. A selected number of APs are placed evenly on the outline of the floor. In this case of 8 APs totally, 5 of them are placed on the outline, and the rest are placed in the centre area.

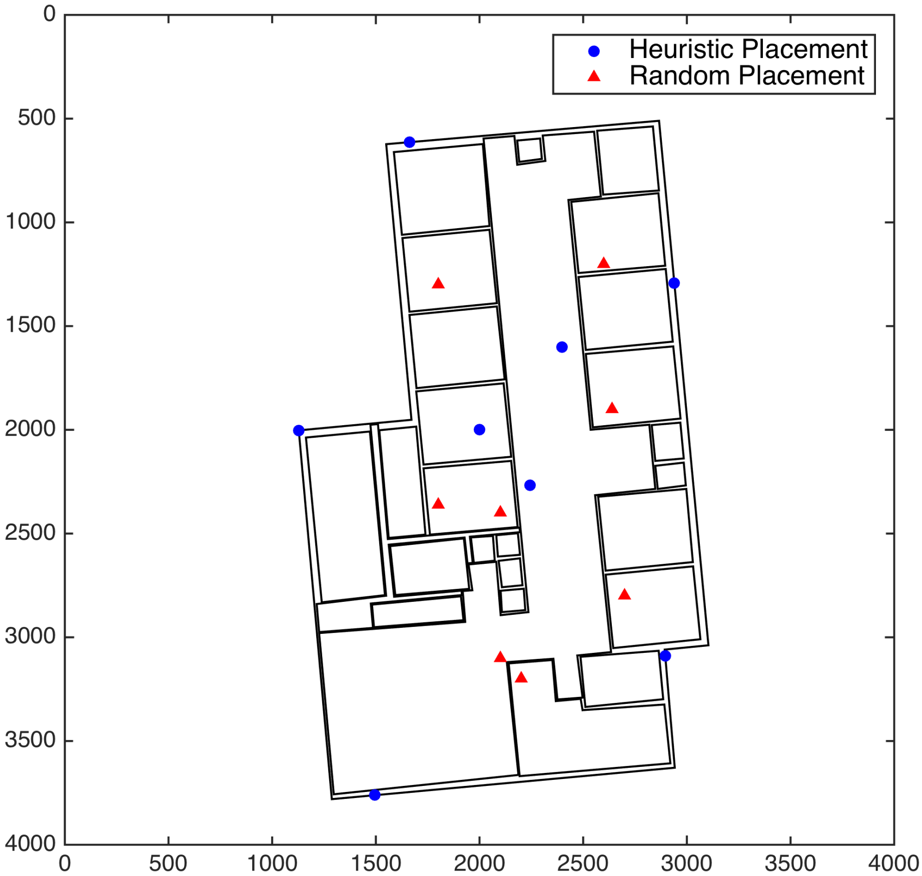



Fig. 3.13 Plots of the placement results computed by different placement schemes: random and heuristic placement, shown in red triangles and blue dots respectively.

### 3.5.5 Effectiveness of AP Placement for Positioning

Since the AP placement is optimised for indoor positioning, the effectiveness of AP placement is evaluated from the aspect of positioning accuracy. The location error distance of the positioning system using the AP placement generated by both heuristic and random schemes are evaluated by the CDF of location error distance, which is illustrated in Fig. 3.14. The map-assisted optimisation model is adopted for both schemes. Overall the heuristic placement shows better effectiveness because it overtakes random placement all the way from beginning to the end. The heuristic scheme does not show a substantial advantage for the relatively-accurate positioning results, e.g., the cases where the location error distance is within 2 meters. Both schemes have probabilities of about 50% to maintain the location error distance within 2 meters. However, for the CDF over 50%, the positioning accuracy of random scheme falls behind heuristic scheme dramatically, and the difference grows up significantly at the later stage. Under 90% situations, the location error distance of heuristic scheme is about or less than 4 meters, and there is a nearly 2-meter lead compared with the random scheme. The gap between them increases gradually and eventual the location error distance of random scheme rises nearly up to 11 meters. In conclusion, the AP placement using heuristic scheme shows advantages over the random scheme and especially can reduce the maximum location error distance, i.e., the worst cases can be avoided.

An optimisation model that removes the wall detection and walls' attenuation calculation is proposed to evaluate the effectiveness of considering the attenuation of walls into the prediction of RSS, which is called none map-assisted placement. The Fig. 3.15 compares the positioning accuracy of AP placement using optimisation model with and without map assistance, where the heuristic scheme is used for both cases. In general, the Fig. 3.15 reveals that map-assisted placement has better performance than none map-assisted placement in all the circumstances. The percentage of location error distance within 3 meters achieves approximately 70% in the map-assisted placement, while that achieves less than 56% in the none map-assisted placement. In 90% of the positioning results, the placements with and without map assistance provide positioning accuracy of $4m$ and $5.5m$ respectively. Through the comparison of the location error distances when the CDF reaches 1, it is apparent that the

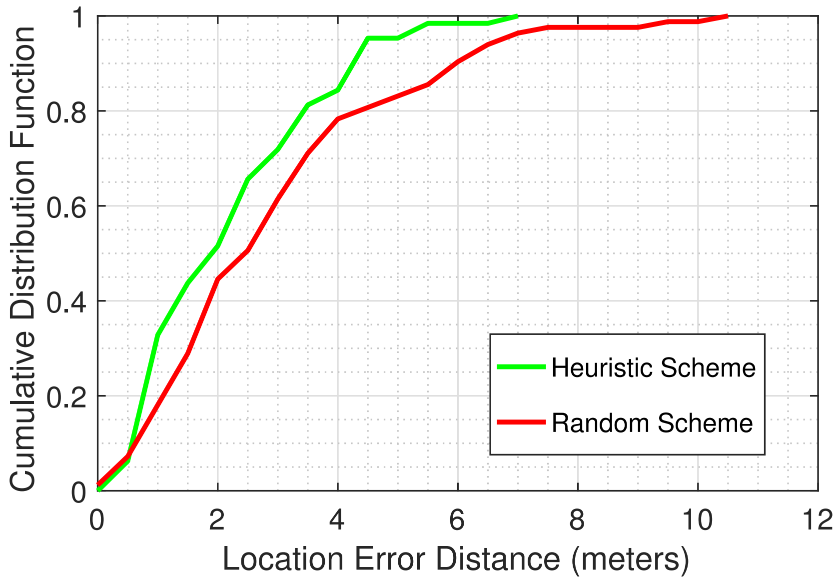



Fig. 3.14 Plots of CDF of location error distance by heuristic and random scheme using map-aided placement.

maximum location error distance of none map-assisted placement is almost 10 meters, while the placement with the assistance of map can decrease it to 7 meters. In summary, it is the witness that the map-assisted AP placement helps the positioning system obtain optimised performance.

## 3.6 Chapter Summary

In this chapter, an indoor map system adopting vector graphic technology is first introduced. Then an optimisation model for AP placement in fingerprint-based indoor positioning system is proposed to improve the accuracy of the positioning system. The wall information of the indoor map is utilised thoroughly in the optimisation model. The effectiveness of it has been verified by applying its generated placement to a KNN-based positioning system, and the accuracy has been analysed. The performance of our map-aided placement with heuristic scheme has been compared with none map-aided placement and placement without the heuristic scheme, i.e., random placement. The results have shown significant improvement

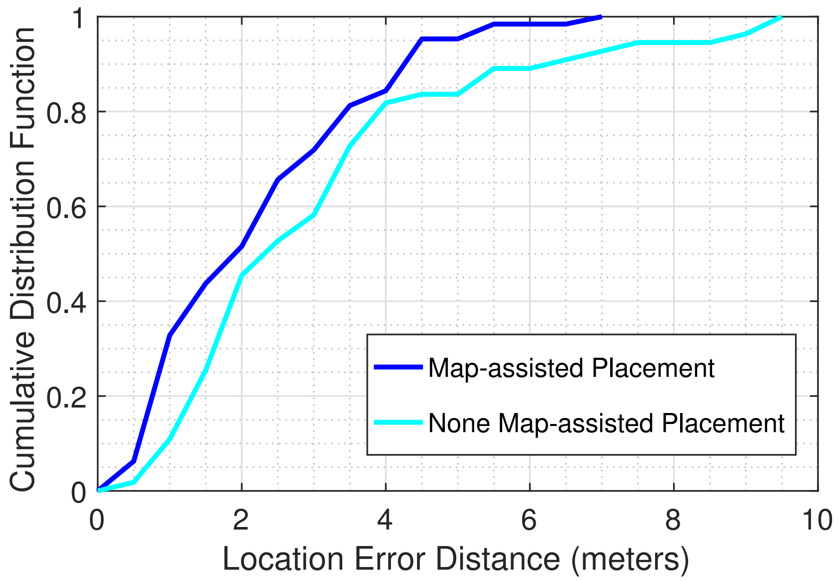



Fig. 3.15 Plots of CDF of location error distance in heuristic placement using map-aided and no map-aided optimisation model.

of the map-aided placement, and especially it reduces the maximum location error distance dramatically. The work of this chapter has been partially published in [125].

# Chapter 4

# Positioning using Signal Patterns and Pathway Map

In this chapter, the work is proposed based on two key observations in conventional fingerprint-based positioning systems. Firstly, the RSS observations used in both site survey and positioning stages are readings of absolute values. However, the MHs involved in either stage are usually different in hardware, and the MHs are held in a different orientation and places, such as on the hand or in the pocket. Both device diversity and usage diversity cause severe RSS variance, which is well-known practical concerns in real-world deployment [86]. The use of absolute RSS value could result in a certain error of positioning accuracy. Secondly, the RSS observation is collected by an MH at each discrete reference points in site survey process. To obtain best observations reflecting real RSS values, in practice the person holding the MH is usually in stationary and collecting many samples at each reference point. While in positioning process the MH is in movement and RSS is observed by the MH in moving state. Movement causes fluctuation of RSS and much fewer samples at each location depending on the speed of movement, which could lead to massive error when comparing with RSS observed in site survey stage.

## 4.1 Analysis of WiFi Signal Observations

To decide how to use the WiFi signals efficiently and adequately, the WiFi signals in our experimental site, i.e., central campus building at University of Essex Colchester Campus, are deeply analysed. Each single AP is uniquely identified by the Basic Service Set Identifier (BSSID). Around 200 APs are observed during the 25 seconds' movement.

The pie chart of Fig. 4.1 (left) shows the percentage of observed APs with different appearance frequency (denoted by N) when a mobile handheld is moving along a corridor for 25 seconds. With the increase of appearance frequency, the number of APs decreases significantly. Around one-third of APs are observed only once and about a quarter of APs are observed for more than three times. The AP is appearing fewer times normally means its signal strength are weak and it can be observed only within a short period. The bar chart of Fig. 4.1 (right) shows the distribution of observed APs in 2.4 GHz and 5 GHz frequency band respectively. The APs of 5 GHz dominates the observations with smallest and largest appearance frequency, which reveals that 5 GHz channels may be less crowded and weak signals in 5 GHz are more likely to be observed than that in 2.4 GHz [126].

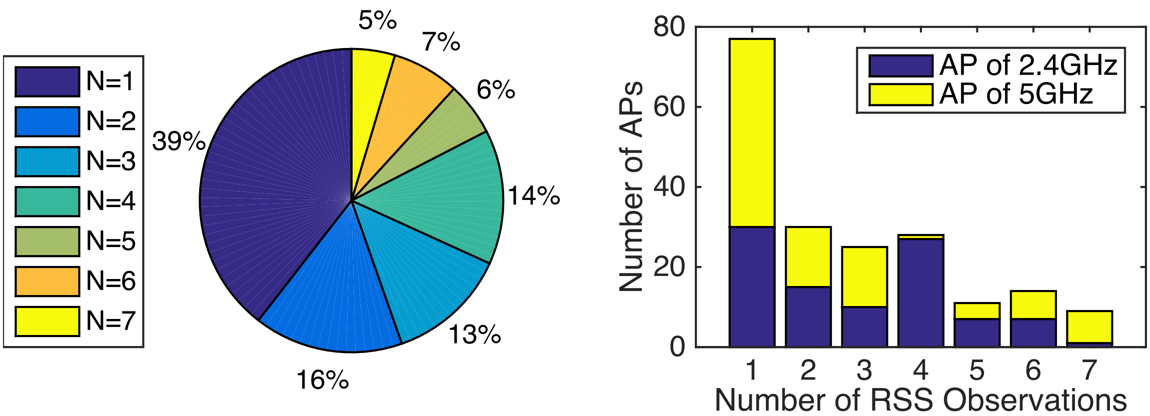



Fig. 4.1 Analysis of WiFi signal observations: occupancy of 195 observed APs with different number of observations (left) and frequency band (right).

Through empirical investigation of the WiFi networks in our experimental site, one primary reason caused the excessive number of APs is the virtual access point (VAP) functionality of enterprise WLAN infrastructure, which allows one physical AP to have multiple separate WLAN with its BSSID and SSID (service set identifier). Along with VAP, another reason is the AP's Simultaneous Dual-Band functionality that enables each WLAN to operate in both 2.4 GHz and 5 GHz frequency band, which uses two different BSSID but the same SSID. In this paper, we name the APs from the same physical AP as **sibling APs**.

The idea of fingerprint-based positioning was initially proposed based on the principle that several APs located at different places can provide different RSS observations in different observation point. However, nowadays the APs observed by users are heterogeneous, and some of them are coming from the same physical AP, i.e., the RSS observed from multiple APs are transmitted from the same location. Thus, the concept of **sibling signal patterns** (SSP) is proposed to describe the correlation between the sibling APs.

The sibling signal patterns are investigated in our work. Since the VAPs from the same physical AP share the same radio frequency, which has been verified in our experiment, we believe the signals of these VAPs suffer similar interference in the environment, and the RSS of them observed at the same location are supposed to be the same. This thought is proved by the real data collected in our experiment, which is depicted in Fig. 4.2. The top and bottom bar chart in Fig. 4.2 shows the time-series RSS observations of VAPs operating in both 2.4 GHz and 5 GHz frequency band respectively, which are observed by a mobile device moving along a corridor for 25 seconds. In total, there are 9 BSSID coming from the same physical AP. The bar charts illustrate that the RSS of VAPs coming from the same physical AP and operating in the same frequency band are almost identical at the same time and location. Apart from fluctuation caused by complex environment, the minor difference of RSS between VAPs may also come from the measurement tolerance of the mobile device. At certain locations, the APs with weak signals are not observed. In general, the RSS observations in 5 GHz has better integrity than that in 2.4 GHz.

## 4.2 Pathway Map

Like the outdoor map in which the road is the skeleton, and the points of interests (PoI) are referenced by road name and number, we believe in the indoor space the pathway is the vital

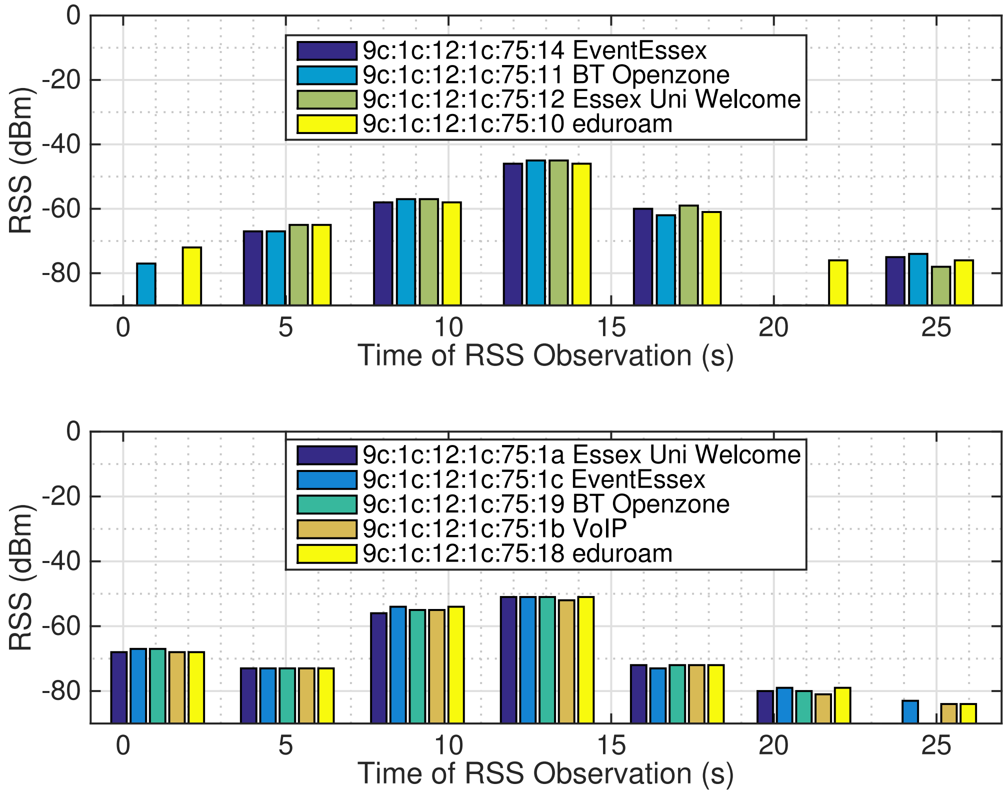



Fig. 4.2 The RSS observations of VAPs operating in 2.4 GHz (top) and 5 GHz (bottom) frequency band from the same physical AP when moving along a corridor for 25 seconds.

part of the indoor map, and most indoor activities are related to people's movement along the pathway.

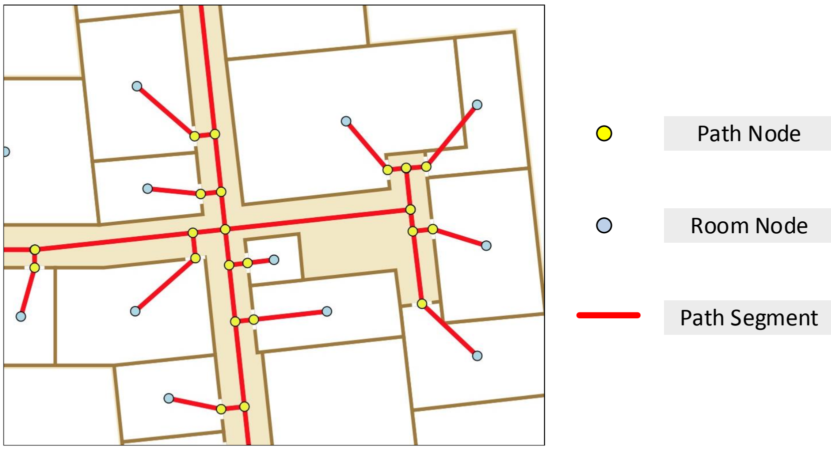


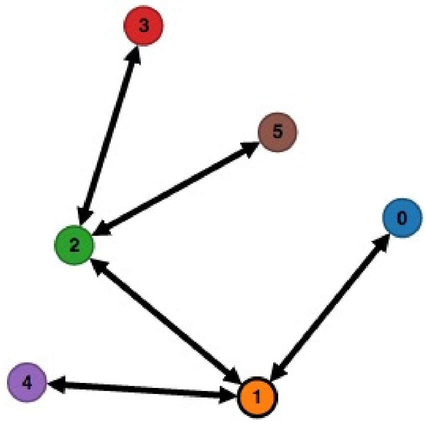

Fig. 4.3 Illustration of pathway map.

The data of indoor map is structured by the Scalable Vector Graphic (SVG) format and contains the polygons representing rooms' outline, coordinates of rooms' door and polylines indicating the corridors. Based on these data the pathway map is generated to represent the available indoor walking routes between rooms, i.e., the possible path people may move along. Fig. 4.3 shows the structure of pathway map. Pathway map is depicted in diagrammatic form as a set of dots for the nodes, joined by lines for the path segments. The nodes are constituted by path nodes and room nodes. Path nodes and room nodes are represented by its ID and its coordinates are stored in a table of nodes entries. Each path segment is directed and expressed by its start node ID, end node ID, length and type. Path segments are divided into two types: access and trunk. Access path segment is a dedicated link connects corridor to the centre of a room. Trunk path segment is the path shared by all the people walking around to reach different rooms.

### 4.2.1 Data Structure of Pathway Map

The pathway map is $G = (V, E)$, where $V$ is a non-empty set of nodes and $E$ is a set of ordered pairs of these nodes to represent path segments. A path segment $e \in E \subset V \times V$, where $e = (u, v)$ and $u, v \in V$. A path segment $(u, v)$ is considered to be directed from $u$ to $v$, where $u$ is start node and $v$ is end node.

The data of nodes are stored as an array, and the path segments are stored as an adjacency matrix to represent the connectivity between nodes. As the illustration in Fig. 4.4, a pathway map with $n$ nodes $\{v_1, v_2, \ldots v_n\}$ can be represented by an $n \times n$ adjacency matrix $A$, in which $a_i j$ is the number of path segments joining $v_i$ and $v_j$. As the path segment is directed, in the adjacency matrix the entry in the row is the start node, and the entry in the column is the end node.




| | $v_0$ | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ |
|---|---|---|---|---|---|---|
| $v_0$ | 0 | 1 | 0 | 0 | 0 | 0 |
| $v_1$ | 1 | 0 | 1 | 0 | 1 | 0 |
| $v_2$ | 0 | 1 | 0 | 1 | 0 | 1 |
| $v_3$ | 0 | 0 | 1 | 0 | 0 | 0 |
| $v_4$ | 0 | 1 | 0 | 0 | 0 | 0 |
| $v_5$ | 0 | 0 | 1 | 0 | 0 | 0 |

Fig. 4.4 Illustration of pathway's nodes and its adjacency matrix representing the connectivity between nodes.

### 4.2.2 WiFi Signals Collected on Pathway Map

A path segment is a directed line segment consisting of a sequence of points in the corridor and defined by a start node and an end node, as illustrated in Fig. 4.5. When the mobile handheld of a surveyor is moving along a path segment, a set of continuously observed raw RSS from surrounding APs are collected.

The RSS observation collected at path segment $e_i$ from $K$ number of APs is denoted as

$$\mathbf{S}_i \equiv (\mathbf{x}_1, \ldots, \mathbf{x}_K), \tag{4.1}$$

Table 4.1 Part Of The Notations.

| Notation | Description |
|---|---|
| $G$ | A pathway map |
| $v$ | A node in the pathway map |
| $e$ | A path segment |
| $\mathbf{S}_i$ | RSS values observed from $e_i$ |
| $\mathbf{T}_i$ | Observation timestamps from $e_i$ |
| $K$ | Number of APs |
| $N$ | Number of observations |
| $\mathbf{x}_k$ | RSS values from $k^{th}$ AP |
| $x_n$ | RSS value of the $n^{th}$ observation |
| $b_k$ | BSSID of $k^{th}$ AP |
| $f_k$ | Frequency of $k^{th}$ AP |

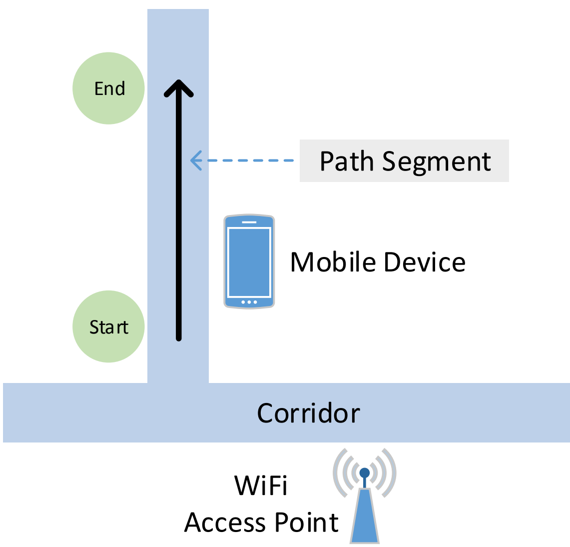



Fig. 4.5 Illustration of a path segment where the WiFi signals are collected.

where $\mathbf{x}$ denotes a vector of time-series RSS observation value $x$ with size of $N$, which is denoted as

$$\mathbf{x} \equiv (x_1, ..., x_N)^{\mathbf{T}}. \tag{4.2}$$

The number of observations $N$ can be different in $\mathbf{x}_k$ from different APs.

With the RSS observation $\mathbf{S}_i$, the corresponding observation timestamp of the RSS values are collected as well, which is denoted as

$$\mathbf{T}_i \equiv (\mathbf{t}_1, ..., \mathbf{t}_K), \mathbf{t} \equiv (t_1, ..., t_N)^{\mathbf{T}} \tag{4.3}$$

Meanwhile the BSSID and frequency of APs are also recorded and denoted as

$$\mathbf{b} \equiv (b_1, ..., b_K)^{\mathbf{T}} \tag{4.4}$$

and

$$\mathbf{f} \equiv (f_1, ..., f_K)^{\mathbf{T}}. \tag{4.5}$$

### 4.2.3 Instructed Site Survey

In the site survey phase, a dedicated surveyor holding a mobile device is walking through the pathways to build up the database of fingerprints. Because the signal pattern is binding to path segment and path segment is directed, the surveyor is required to not only cover every path segment but also walk through the path segment in both directions. To not miss any path segment and give the surveyor a step-by-step instruction to collect signal patterns, a guided console is provided and running on the surveyor's device, meanwhile more importantly an algorithm to select next path segment for surveyor is proposed.

The surveyor in the site survey phase need walk through the whole pathway map to collect the signals and its patterns relative to pathway map. To make sure the surveyor cover all of the path segments easily, a path segments traversal algorithm is proposed to provide an instructive walking route. Its pseudocode is in Algorithm 4.1.

**Algorithm 4.1** Path Segments Traversal (PST) Algorithm

Input:
$G$ - a directed graph of pathway map;
$v$ - a starting node to traverse.

1: call function PST($G$, $v$)
2: **function** PST(graph $G$, node $v$)
3:     $V \leftarrow G.adjacentNodes(v)$
4:     **for** $i \leftarrow 1$ **to** $V.size$ **do**
5:         $u \leftarrow V_i$
6:         **if** $(v,u)$ is uncollected **then**
7:             collect signal pattern along path segment $(u,v)$
8:             mark path segment $(u,v)$ as collected
9:             PST$(G,u)$
10:         **end if**
11:     **end for**
12: **end function**

The Algorithm 4.1 is searching the whole pathway map and selecting the next path segment iteratively from a staring node, i.e., the place where the surveyor starts the site survey work. The algorithm takes a graph representing the pathway map and a starting node as the inputs, which are parsed into function PST in line 1. The parameters of function PST are a graph of pathway map and a node where the surveyor is located at that time. Line 3 searches for all the adjacent nodes of the node in the graph and saves it into an array. Each adjacent node in the array $V$ is checked by copying it to $u$. The adjacent node $u$ and current node $v$ forms a path segment $(v,u)$, i.e., one of the available path segments to walk next from current node $v$. If the signal pattern of path segment $(v,u)$ has not been collected, this path segment is selected as the next path segment, and the surveyor is walking and collecting signal pattern along it (line 6-7). Then the path segment $(v,u)$ is marked as collected, and node $u$ becomes the current node the surveyor staying at (line 8). The PST function is called again using $G$ and $u$ as inputs. If the signal pattern of path segment $(v,u)$ has been collected then next adjacent node is to be checked until the signal patterns of all the path segments in the pathway map $G$ are collected.

## 4.3 Beacon APs Generation

The analysis of WiFi signals concludes that the overall quantity of available APs is massive and the appearance frequency of APs differs significantly. Using all the observed APs for positioning leads to high computation complexity and may cause additional errors. Thus, the overall quantity of APs need to be reduced, and quality of APs needs to be evaluated and filtered. Eventually, only a small portion of high-quality WiFi signals are used for positioning.

The analysis reveals that the VAPs from the same physical AP present similar observed RSS. Thus, the concept of **Beacon AP** is proposed and a Beacon AP is defined as a delegation to the VAPs from the same physical AP and in the same frequency. The fingerprints of Beacon APs are finally saved into fingerprint database and used for positioning.

### 4.3.1 Beacon AP Generation Algorithm

The steps to generate Beacon APs using sibling signal patterns are as the pseudocode in Algorithm 4.2. The Beacon AP generation algorithm takes the raw observations of WiFi signals from each path segment as input and generates Beacon APs of the path segment as output. Firstly, considering strong signal (i.e., signals with large RSS value) shows higher confidence than weak ones and APs appearing fewer times are relatively weak. Therefore APs with low appearance frequency are filtered out. A threshold indicating appearance frequency is used to control the APs which need to be removed. Secondly, the remaining APs are divided into groups by their frequency. Each group may contain APs of the same frequency but from more than one physical APs because more than one APs may operate at the same frequency. Thus, thirdly, the APs in each group are grouped again to form the cluster of APs which are at the same frequency and from the same physical AP, i.e., the VAPs from a physical AP. The approach to cluster the VAPs is based on empirical practice and theoretical verification. Finally, each VAP cluster is processed to generate a Beacon AP. The processed observation of signals in different stages are illustrated in Fig. 4.6 using one path segment of our experimental site as an example.

**Algorithm 4.2** Beacon AP Generation Algorithm

Input: $\mathbf{S}, \mathbf{T}, \mathbf{b}, \mathbf{f}$

Output: $\mathbf{W}$ - RSS values of Beacon APs.

*// Step 1: remove APs appearing few times.*
$Max \leftarrow$ maximum size of $\mathbf{x}_k$ in $\mathbf{S}$.
**for each** $\mathbf{x}_k \in \mathbf{S}$ **do**
    **if** $sizeof(\mathbf{x}_k) < Max \times 0.7$ **then**
        remove $\mathbf{x}_k$ from $\mathbf{S}$
    **end if**
**end for**
*// Step 2: group remaining APs by frequency.*
$q \leftarrow$ number of different frequency appeared in $\mathbf{f}$.
$\mathbf{v} \leftarrow$ a vector of size $q$ to store the unique frequencies.
$\mathbf{M} \leftarrow$ initialize $q$ number of groups.
**for each** $\mathbf{x}_k \in \mathbf{S}$ **do**
    add $\mathbf{x}_k$ to group $\mathbf{m}_q$ where $f_k == v_q$
**end for**
*// Step 3: cluster the VAPs in each frequency group.*
**for each** $\mathbf{m}_q \in \mathbf{M}$ **do**
    $\mathbf{r} \leftarrow$ initialize a vector of size $k$.
    $r_k \leftarrow b_k$ without last 4 bits.
    $\mathbf{D} \leftarrow$ cluster $\mathbf{x}_k$ of the same $r_k$
    **for each** $\mathbf{d} \in \mathbf{D}$ **do**
        $u_{k,l} \leftarrow$ Euclidean distance between $\mathbf{x}_k$ and $\mathbf{x}_l$
        **if** $u_{k,l} > Et \ \& \ sizeof(d) > 2$ **then**
            $\mathbf{C} \leftarrow$ add cluster $\mathbf{d}$ into $\mathbf{C}$
        **end if**
    **end for**
**end for**
*// Step 4: generate Beacon AP of each cluster.*
$p \leftarrow sizeof(\mathbf{C})$
$\mathbf{W} \leftarrow$ initialize to store RSS values of Beacon APs.
**for each** $\mathbf{c}_p \in \mathbf{C}$ **do**
    $\mathbf{s}_n \leftarrow$ add $x_n$ which has less than 1s difference in $t_n$
    $w_{pn} \leftarrow mean(\mathbf{s}_n)$
**end for**
**return W**

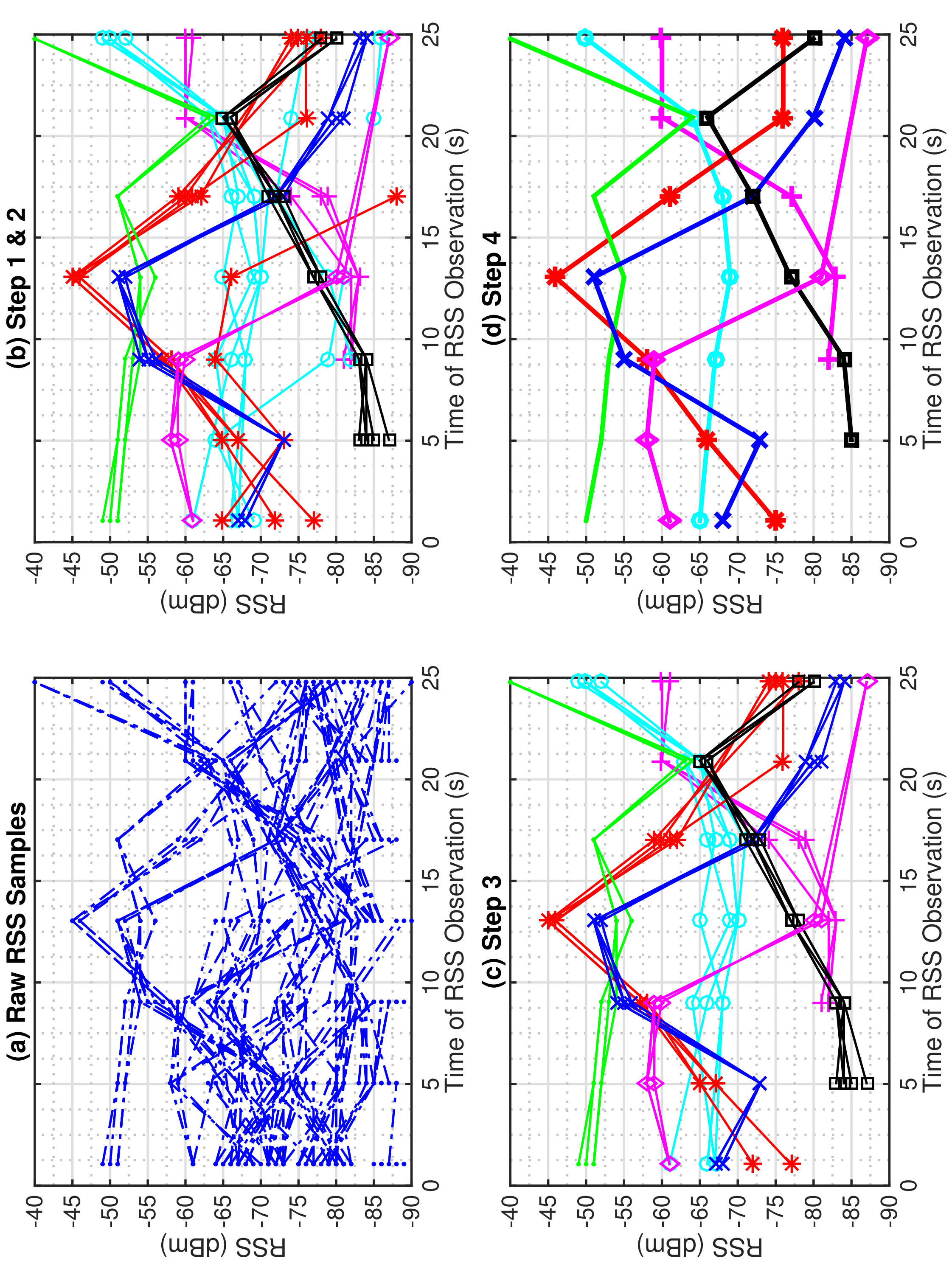



Fig. 4.6 Illustration of signal patterns processing from raw RSS samples observed from APs in one path segment of our experimental site

#### 4.3.1.1 Clustering VAPs

The empirical practice is that the BSSID of VAPs from the same physical AP normally has a certain correlation. The MAC address of AP is usually used as the BSSID and contains 48 bits. The MAC addresses of VAPs in the same physical AP are usually the same except last 4 bits. Thus, VAP key is defined as $\{BSSID[1:44], Frequency\}$, for example, {24:de:c6:c3:5b:b, 2412}. The VAPs are identified and clustered based on their keys. To make sure the empirical practice always work correctly, the clustered VAPs are verified by checking the similarity between signal patterns. The similarity between temporal signal patterns from two APs is determined based on the Euclidean distance between them, which is denoted as

$$u_{kl} = \sqrt{\sum_{m=1}^{M} \{\mathbf{x}_{k,m} - \mathbf{x}_{l,m}\}^2} \tag{4.6}$$

where $M$ is the number of RSS observations in which both APs appear at the same timestamp and in the same channel. If the Euclidean distance between any two APs in the cluster is larger than the threshold, the VAPs in this cluster may not be from the same physical AP, and this cluster is abandoned and not used for the further process.

#### 4.3.1.2 Beacon AP Finalisation

Before the clustered VAPs are used to generate Beacon AP, the number of VAPs in each cluster is checked against a threshold, and if it is too few, we can believe the VAPs in this cluster have fewer opportunities to be spotted. Our experiment also shows the VAPs in the cluster of small size have relatively weak signal strength. Thus, only the clusters with more than two VAPs are kept to generate Beacon APs. Finally, in each cluster, if the observations of different VAPs are captured in the same time, the mean of their RSS values is computed and used as the RSS value of Beacon AP at that timestamp, which is then used to construct the RSS map (i.e., fingerprint database) for positioning.

### 4.3.2 Construction of Beacon AP RSS Map

To map the signal observations to the spatial locations, the reference points are employed like most fingerprint-based approaches [28]. However, the RPs proposed in our work are closely associated with pathway map, and the nearby RPs can easily be identified, which can ease the prediction and reduce the searching space if needed in the positioning phase. Each RP's identity is coded as $[P.S.I]$, where $P$ is the ID of path segment where the RP exists, $S$ is the number of RPs existing in this path segment, and $I$ is the sequential number of this RP in $S$. For example, RP [238.5.2] and [238.5.3] are adjacent to each other. Furthermore, RPs from adjacent path segments can also be retrieved by querying the pathway map.

The RSS of Beacon APs processed from raw signal observations are mapped to the indoor map to form RSS map of Beacon APs. The RSS map consists of RSS from Beacon APs at RPs of each path segments. The RSS from $P$ number of Beacon APs at $N$ number of RPs of path segment $e_i$ is denoted as

$$W_i = \begin{pmatrix} w_{1,1} & \cdots & w_{1,N} \\ \vdots & \ddots & \vdots \\ w_{P,1} & \cdots & w_{P,N} \end{pmatrix} \tag{4.7}$$

where $w_{pn} = -100$ if Beacon AP $p$ is not observed at RP $n$, because the weakest signal observed is close to -100 but not less than -100. Because in the Beacon AP generation algorithm the APs appearing few times in the path segment have been removed, we believe the Beacon AP can be seen in the path segment for most of the time. The number of RPs of each path segment is determined based on its length. Since Beacon APs are elected based on path segment and just represent signal patterns over that path segment, size and identity of Beacon APs in different path segments are not consistent, as illustrated in Fig. 4.7. The RSS of each Beacon AP is shown on map as illustrated in Fig. 4.8

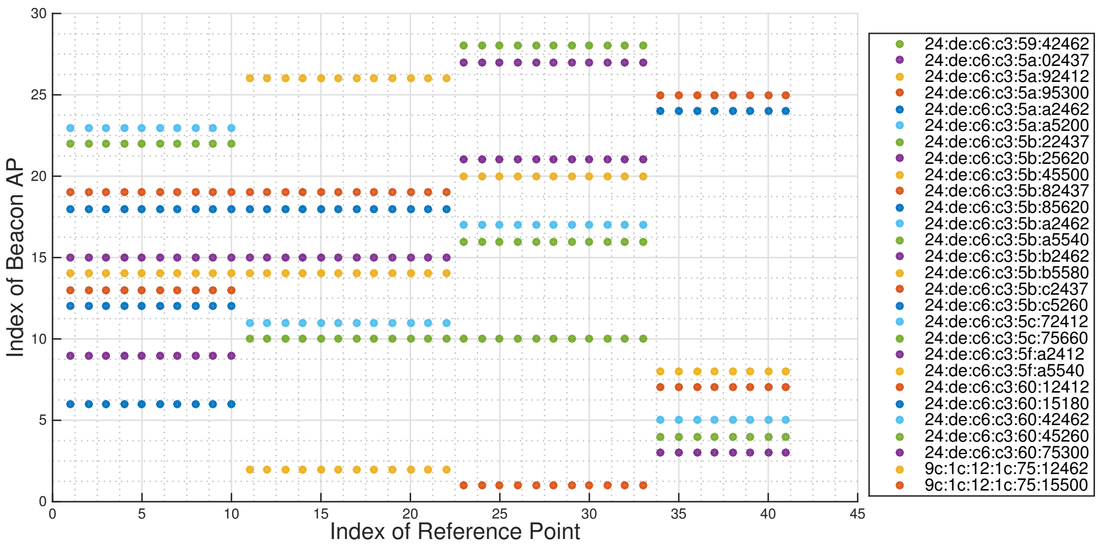



Fig. 4.7 Illustration of Beacon APs Map at RPs on Path Segments.

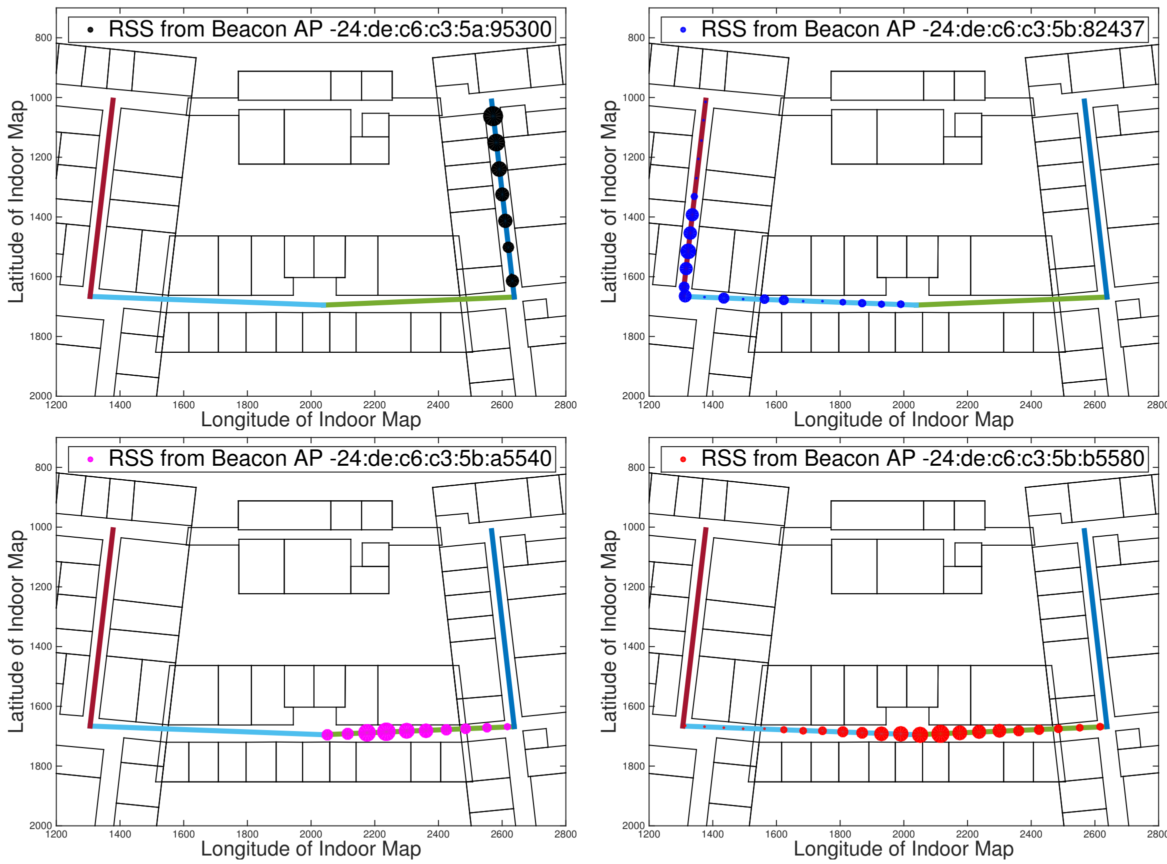



Fig. 4.8 RSS of different Beacon AP at RPs along path segments.

## 4.4 Signal Coverage Constraint

Based on the fact that the signal from an AP only covers the surrounding area of AP, geographically distributed APs lead to geographically dispersed signals patterns. Observation of spatial signal patterns can hence be used to constrain the searching space into a limited area.

By processing the raw signal observations using sibling signal pattern, the Beacon APs are generated as quality-improved metrics to represent the surrounding signal measurements along path segments. The same Beacon AP may appear in different path segments, most probably in adjacent path segments. The number of RPs of each path segment is determined based on the length of path segment and walking speed of the surveyor in the process of the site survey. The number of Beacon APs depends on the number of available raw APs and length of the path segment. At our experimental site about 7-10 Beacon APs are elected in a path segment of 10 meters' length. The Fig. 4.9 illustrates the distribution of beacon APs' appearance in the RPs using some of our experimental samples in a two-dimension scatter diagram, where the AP with RSS of -100 (i.e., AP unobserved) is not shown to reveal the real-world observations. As the illustration in the Fig. 4.9, there are 41 RPs in the 4 continuous path segments and 28 Beacon APs in total are elected over these path segments. Each Beacon AP is typically shown in a group of continuous RPs, which can take up one or two adjacent path segments. The geographical distribution of RPs from the same Beacon AP shows strong aggregation. Thus, the spatial patterns of multiple Beacon APs can be used to constrain the searching space of user's location.

To obtain a better-visualised insight of the spatial signal pattern, the Fig. 4.10 illustrates the geographic mapping between beacon APs' appearance and pathway map using the signal observations collected over several continuous path segments in our experimental site. Based on the spatial signal pattern, the concept of **signal coverage constraint** (SCC) is proposed. The signal coverage constraint is intended to check if the current observed Beacon APs match the Beacon APs elected for each path segment in the fingerprint database. Through signal coverage constraint, the user's potential location can be limited to one specific path segment, or more than one in some cases when the Beacon APs of more than one path segment are

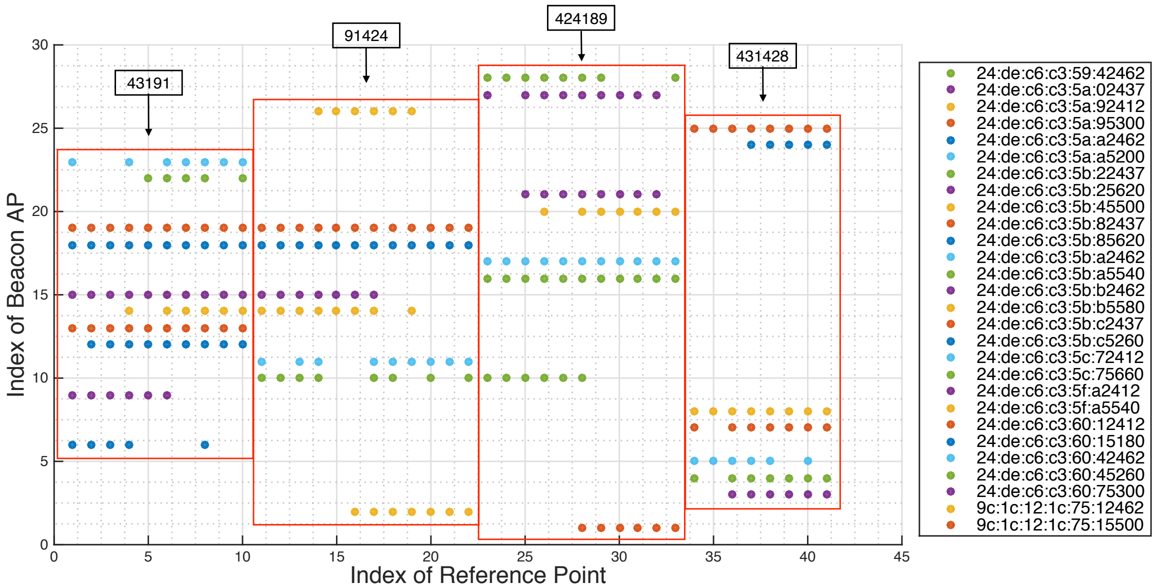



Fig. 4.9 Illustration of mapping Beacon APs to reference points based on the signals collected at our experimental site.

similar and all match the current observation. The approach we define the match is that the Beacon APs of current observation can take up that of the path segment for more than a threshold, which is signal coverage constraint ratio (SCC ratio). For example, when SCC ratio is 80%, if 8 out of 10 Beacon APs of a path segment are shown as Beacon APs of the current observation, then this path segment is considered as the area of users' potential location. In such approach, the search space can be reduced to a small area consisting of the RPs of this path segment.

## 4.5 Positioning Schemes using Signal Patterns

### 4.5.1 System Architecture

The system consists of the mobile client on users' smartphones and backend service running on the cloud server. As the system architecture depicted in Fig. 4.11, the system is divided into two phases: offline site survey and online positioning. In the offline phase, a dedicated surveyor holding an MH running Signal Pattern Collection (SPC) module is instructed to collect raw RSS observations. Then the server-side Signal Pattern Processing modules

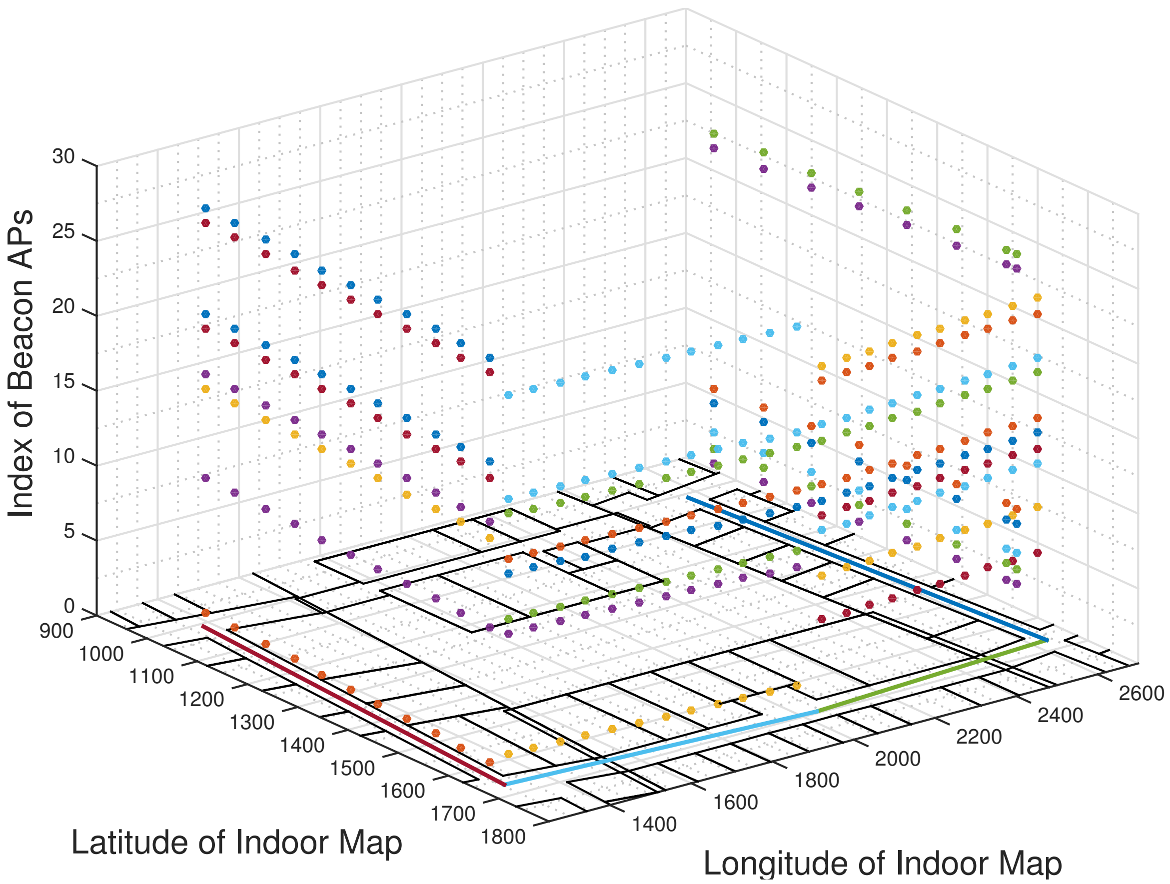



Fig. 4.10 Illustration of mapping Beacon APs to pathway map based on the signals collected at our experimental site.

process the collected signal patterns for use in online phase. In the online phase, positioning module is running on the targeted MH to observe the real-time signal pattern and compare it with the signal patterns in the database to compute the location of a device. The system consists of three databases to store indoor map, signal patterns and raw RSS observations respectively. Database of signal patterns contains the signal pattern from multiple APs at the pathway, where locations are referenced by indoor map database.

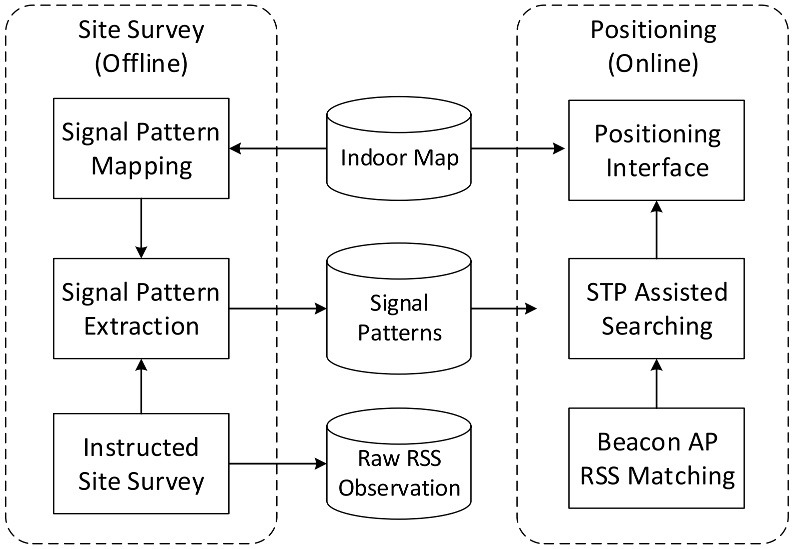



Fig. 4.11 System architecture of positioning using temporal signal patterns

## 4.5.2 Positioning Schemes

### 4.5.2.1 Robust Searching Scheme

In the robust searching scheme, the search space is the RSS map of the whole site, consisting of all the reference points over the path segments. All the RPs are candidate RPs, and the similarity between the fingerprint of RP and the real-time measurement is the Euclidean distance between the RSS vectors of all the APs shown at the RP. If any AP is not shown in the real-time measurement, the RSS value of -90 is given to the AP. The KNN algorithm is used to find the best-matched fingerprint of RPs where K=1, and the location of the best-matched RP is the estimated location.

#### 4.5.2.2 Selective Searching Scheme

An extensive search space can lead to not only dispersed positioning results but also very high computation cost. Thus, inspired by spatial signal pattern, a selective searching scheme is introduced by adding the signal coverage constraint function to the robust searching algorithm. In the selective searching scheme, the candidate RPs are selected by checking the APs' signal coverage, as discussed in Section 4.4. The selective searching scheme can narrow down the search space. For each path segment in the RSS map, the mutual APs appeared in both the path segment and current observation are obtained. The number of mutual APs is checked against the total number of APs of this path segment because the path segment is possible to be the estimated location only when most of the APs in the path segment are present. The selective searching scheme works as the pseudocode in Algorithm 4.3.

**Algorithm 4.3** Selective Searching Algorithm

Input:
$h_0$ - RSS observation values;
$W$ - RSS map;
$r$ - SCC ratio.
Output:
$L$ - coordinate of user's location.

$\mathbf{a} \leftarrow$ get all the APs of $h_0$
$\mathbf{e} \leftarrow$ initialize an array to save similarity to each $\mathbf{x}_k$
**for each** $\mathbf{x}_k \in W$ **do**
  $\mathbf{b} \leftarrow$ get all the APs of $\mathbf{x}_k$
  $n \leftarrow$ get number of APs in $\mathbf{a}$
  $\mathbf{c} = \mathbf{a} \cap \mathbf{b}$
  **if** $sizeof(\mathbf{c})/sizeof(\mathbf{b}) > r$ **then**
    $e_o \leftarrow$ calculate Euclidean distance between $\mathbf{x}_k(\mathbf{c})$ and $\mathbf{h}_0(\mathbf{c})$
    $e_k \leftarrow e_o/sizeof(\mathbf{c})$
  **end if**
**end for**
$L \leftarrow$ get location of $x_{min(\mathbf{e})}$
**return** $L$

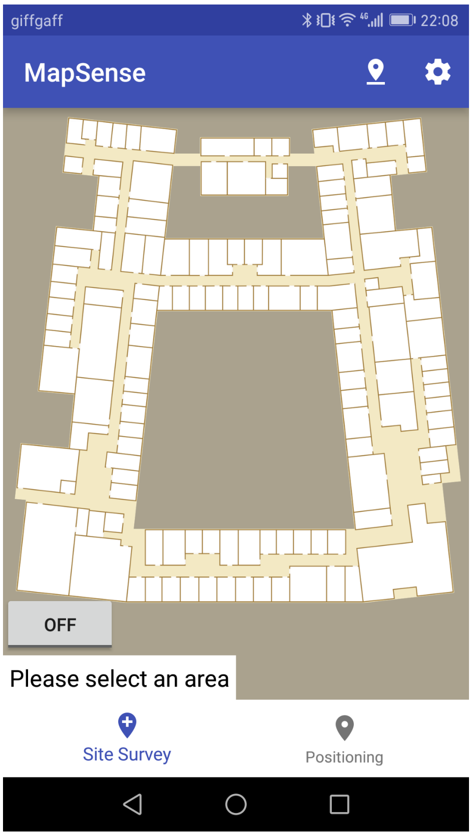
The selective searching algorithm (Algorithm 4.3) takes current RSS observation and RSS map as inputs and outputs the estimated location. The SCC ratio is used to control the proportion of mutual APs. If the path segment passes the SCC ratio check, the RPs of the path segment becomes candidate RP, and the Euclidean distance between the RSS vectors from mutual APs is calculated. The Euclidean distance divided by the number of mutual APs is used as the similarity between the RP and current observation. Finally, the candidate RP of smallest similarity value is elected as the estimated location.

## 4.6 Evaluation

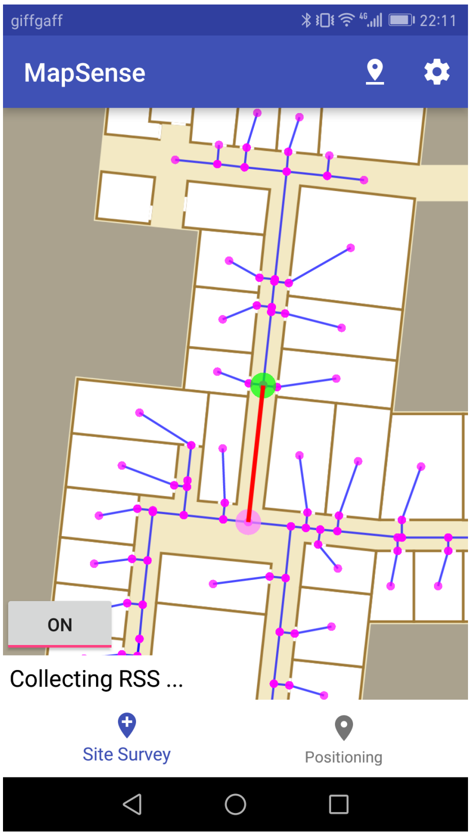
### 4.6.1 Experimental Setup

We develop the prototype in which the site survey and positioning modules are implemented on Android platform and the Beacon AP generation module on Matlab. All the data collected on Android smartphone are saved into SQLite database, which is retrieved by Matlab to process and then send back to the smartphone to fulfil positioning eventually. The experiments are conducted on the 5th floor of the central campus building at the University of Essex Colchester Campus, which is about 50 meters' length, as depicted in Fig. 4.12a. Since the positioning performance of movement in corridors is our main concern and corridors are just all accessible area, the office or seminar rooms are not covered in our experiment. The site is covered by about 50 wireless APs (250 VAPs) of Aruba which belongs to the campus WiFi infrastructure mounted on the ceiling.

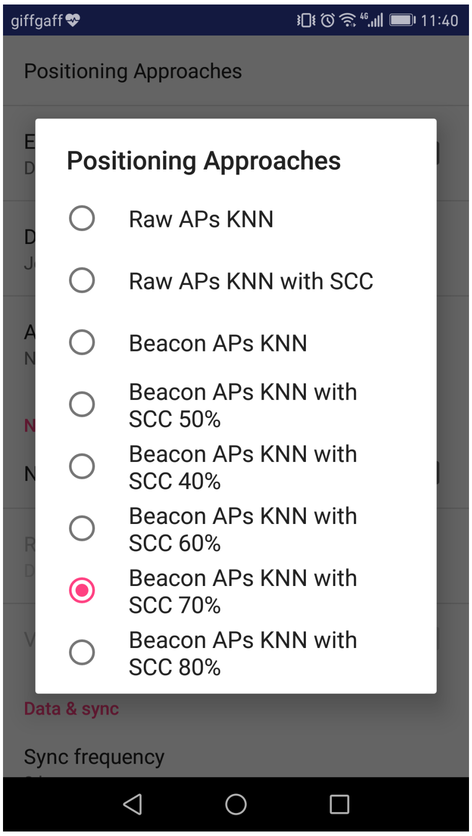
The system is evaluated from several aspects, and the major benchmark is the raw AP RSS scheme, i.e., the traditional approach used by many systems. Multiple positioning schemes, raw AP RSS, Beacon AP RSS and selective searching schemes with different SCC ratio, are implemented in the Android app and allow users to switchover in the setting menu, as illustrated in Fig. 4.12c. In raw RSS scheme, reference points are sampled approximately every 3-5 meters, and each RP is trained for around 10 seconds. In the Beacon AP RSS scheme involving sibling signal patterns, the space is profiled by site survey at a steady speed (about 1 meter per second), as shown in Fig. 4.12b. In positioning stage, no matter what scheme is applied, the positioning result is shown as a red dot on the map, as shown in Fig. 4.12d. In the evaluation of the accuracy, ground truth is marked by tapping the real location on the map and saved into positioning logs. Location error is defined as the



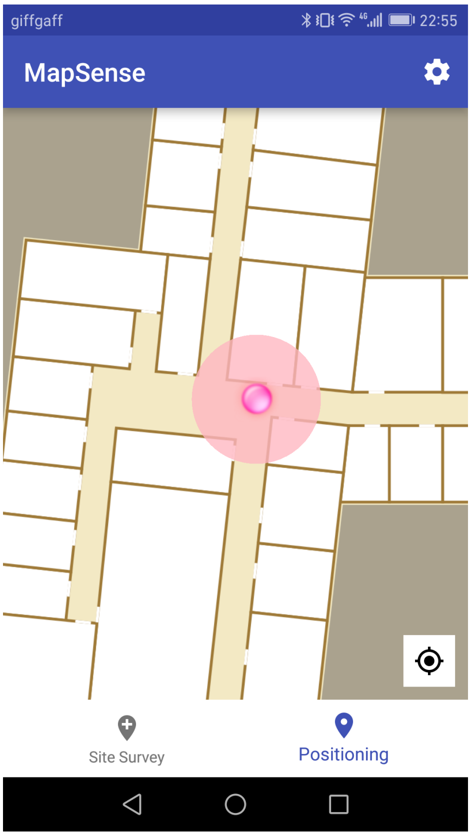

(a) indoor map of the experimental site




(b) user interface of site survey




(c) positioning schemes selection




(d) positioning result

Fig. 4.12 Illustration of implementation on Android app.

Euclidean distance from the estimated location to ground truth. Meanwhile, some other data such as real-time observed APs and candidate RPs in positioning algorithm are also recorded into positioning log sat in SQLite database.

### 4.6.2 Effectiveness of Beacon APs

As the RSS variance is a significant problem of WiFi-based positioning, the effectiveness of sibling signal pattern is evaluated against different device setups. As described in Table 4.2, two devices with different physical setup and software setting are employed to evaluate positioning performance while the site survey is conducted by Huawei P9. As shown in Fig. 4.13, in this test Beacon AP RSS leads raw RSS in the overall performance. Beacon AP RSS scheme provides positioning result within 2 meters from the ground truth in over 90%. The maximum location error distance is reduced by 2 meters to just over 3 meters against raw RSS scheme. The critical point is how two different schemes are affected in M4 setup. Based on raw RSS the location error is amplified when the MH running positioning module is not the MH performed the site survey. Under such situation using Beacon AP RSS, the positioning accuracy is also affected, but just a small drop, which reveals Beacon APs generated by sibling signal patterns are more robust to device variance.

Table 4.2 Device Setups

| Setup | Device Model | Platform Version | WiFi Scan Frequency |
|---|---|---|---|
| P9 | Huawei P9 | Android 6.0 | every 4s |
| M4 | Xiaomi 4 | Android 5.0 | every 6s |

Since the Beacon APs are generated based on RSS observations collected in the movement while the raw RSSs are collected in the stationary, the positioning accuracy is evaluated in both stationary and moving state. As illustrated in Fig. 4.14, Beacon AP RSS scheme offers the best performance when the MH is in movement. When the Beacon AP RSS scheme is used in the stationary, the performance decreases a bit, and its maximum error distance overtakes raw RSS scheme in the stationary. We believe the Beacon AP RSS scheme performs better in the movement because the Beacon APs and their RSSs are generated from RSS observations in the movement. While the raw RSS scheme in the movement performs

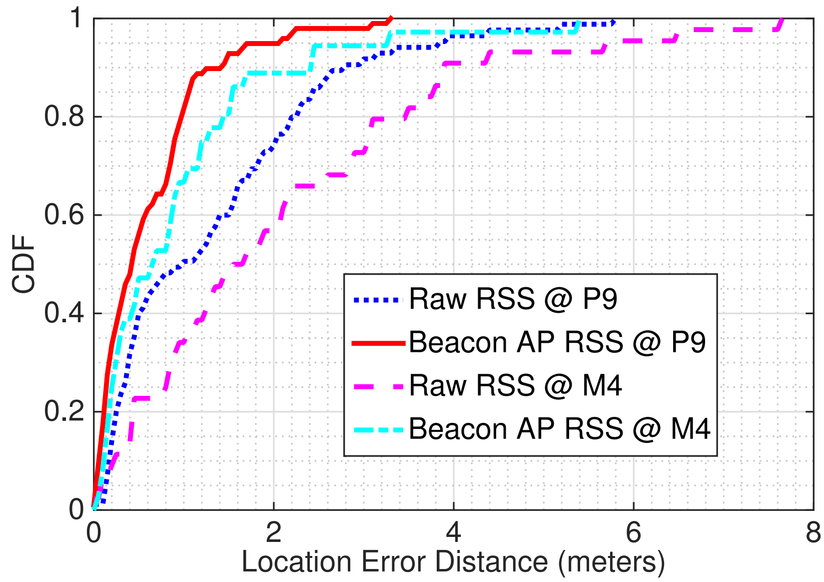



Fig. 4.13 CDF of location error distance using different device setups.

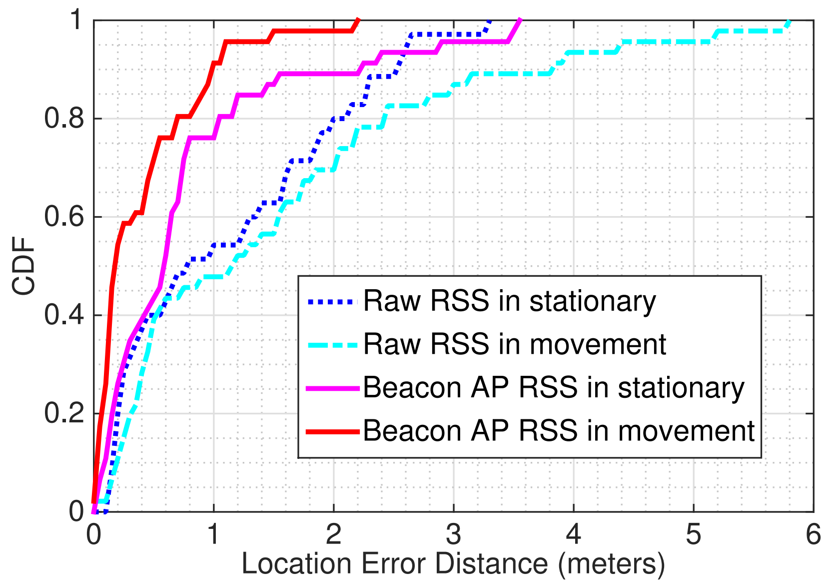



Fig. 4.14 CDF of location error distance in different usage scenarios.

worst. From which we can see Beacon AP RSS scheme are more suitable for application scenarios of moving MH.

During the positioning process the number of APs observed, Beacon APs generated and the respective location error distance are all saved in the positioning log. Based on the data from positioning log, the relationship between location error distance and number of Beacon APs used for positioning are shown in Fig. 4.15. The positioning accuracy is increasing with the increase of the number of APs. Compared with Fig. 4.16, which illustrates the relationship between accuracy and number of APs observed, the number of APs used for positioning is reduced dramatically by using Beacon APs. The number of APs observed in most cases is around 40 to 70.

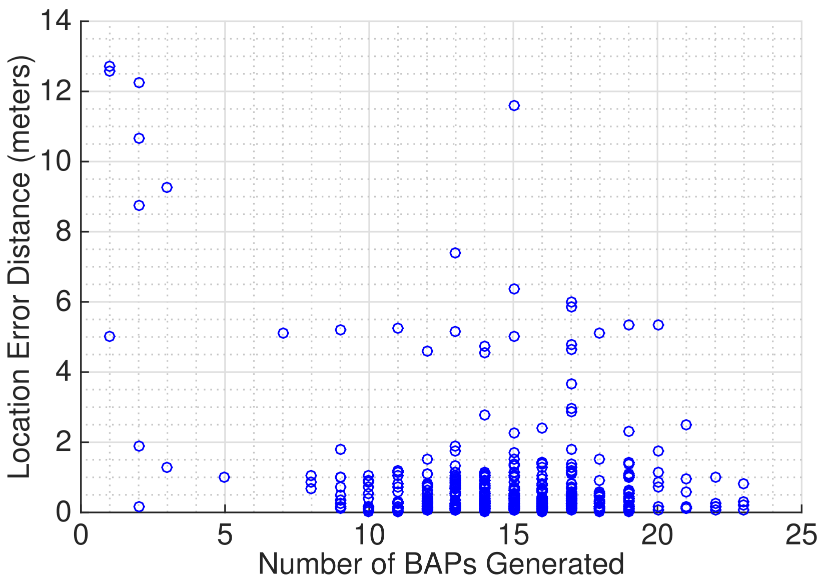



Fig. 4.15 Relationship between location error distance and number of Beacon APs generated in robust searching scheme.

### 4.6.3 Effectiveness of Signal Coverage Constraint

The selective searching scheme utilises the signal coverage of APs to narrow down the search space by filtering the candidate RPs through the SCC ratio. To evaluate the effectiveness of signal coverage constraint and the influence of different SCC ratio, experiments of the

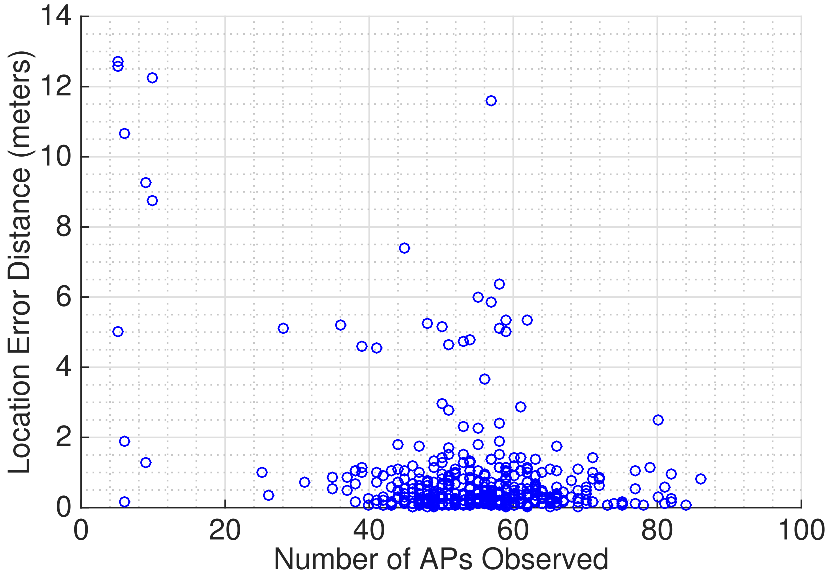



Fig. 4.16 Relationship between location error distance and number of APs observed in robust searching scheme.

robust searching scheme and the selective searching scheme using different SCC ratio are conducted. As the CDF shown in the Fig. 4.17, the robust searching scheme (i.e., none SCC) performs worst overall and with the maximum error distance of more than 12 meters. With signal coverage constraint, the accuracy is improved dramatically. Even though with SCC ratio of 40%, the maximum error distance is reduced to around 6 meters. With the increase of SCC ratio, the accuracy keeps increasing. When the SCC ratio is 80%, the accuracy is within 1 meter in all cases, which means the estimated location is always the nearest RP. The change of positioning accuracy affected by SCC reveals that constraining the estimated location through the signal coverage of APs can give the positioning accuracy huge boost, especially it can reduce the maximum error distance significantly.

The signal coverage constraint can improve the positioning accuracy massively, but it can lead to the problem that no candidate RP matches the online measurements, and hence no estimated location can be provided. In the positioning phase, for every location estimation job when the latest WiFi scan results are available, the number of measured APs, number of APs used in estimation and the candidate RPs are saved into logs. The Fig. 4.18 illustrates the CDF of the number of candidate RPs occurred when it is filtered using different SCC

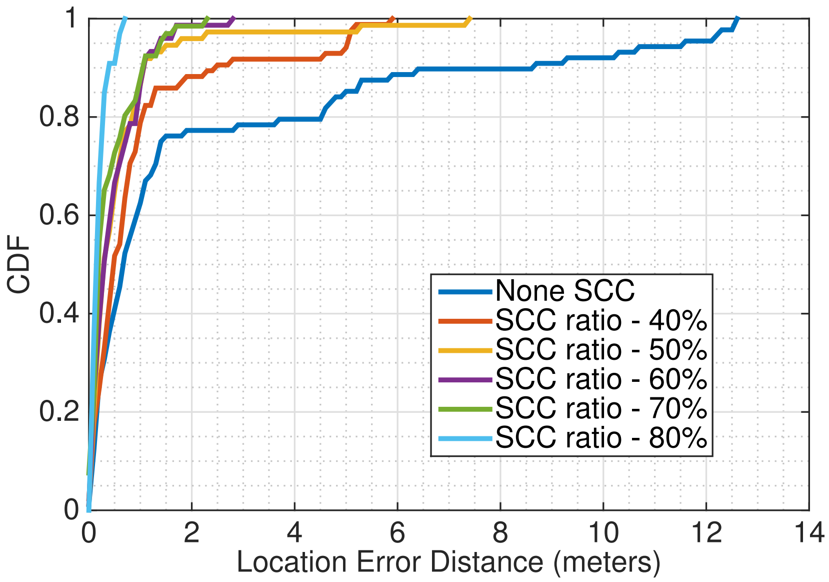



Fig. 4.17 CDF of location error distance using different SCC ratio in selective searching scheme.

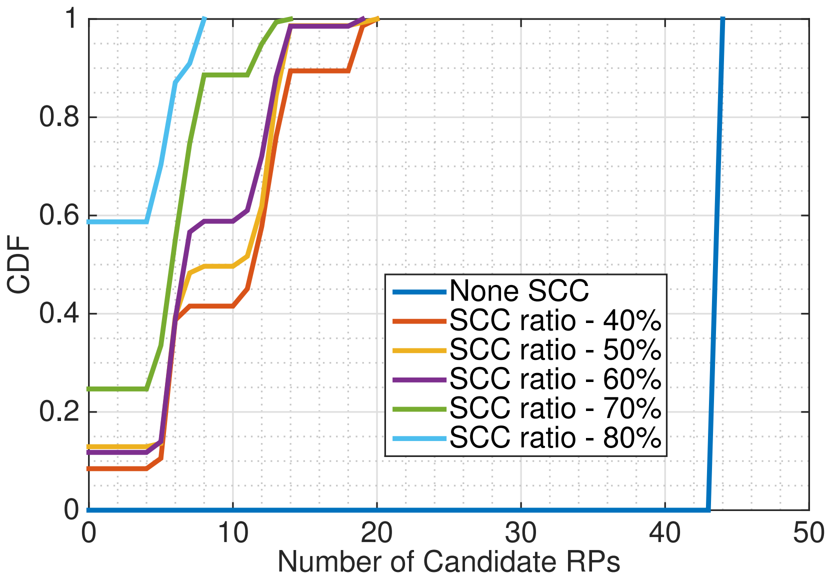



Fig. 4.18 CDF of number of candidate RPs using different SCC ratio in selective searching scheme.

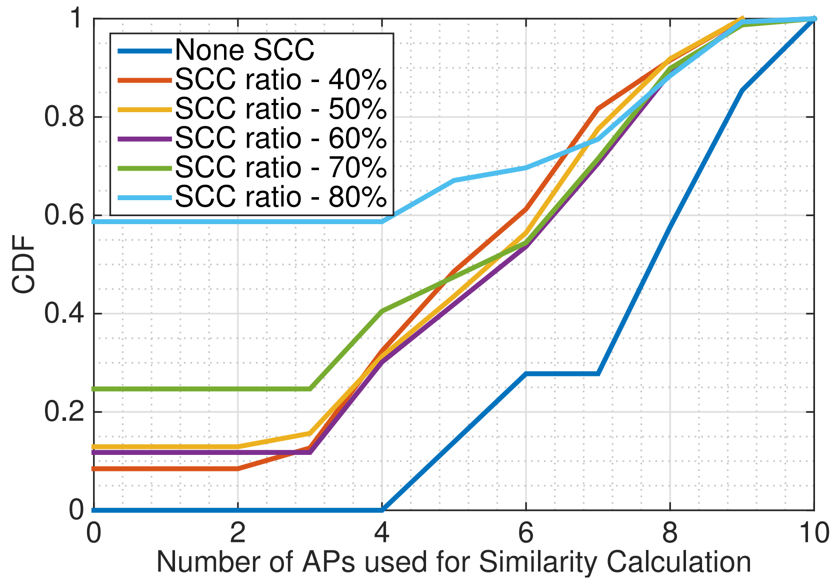



Fig. 4.19 CDF of number of APs used for similarity calculation of positioning using different SCC ratio in selective searching scheme.

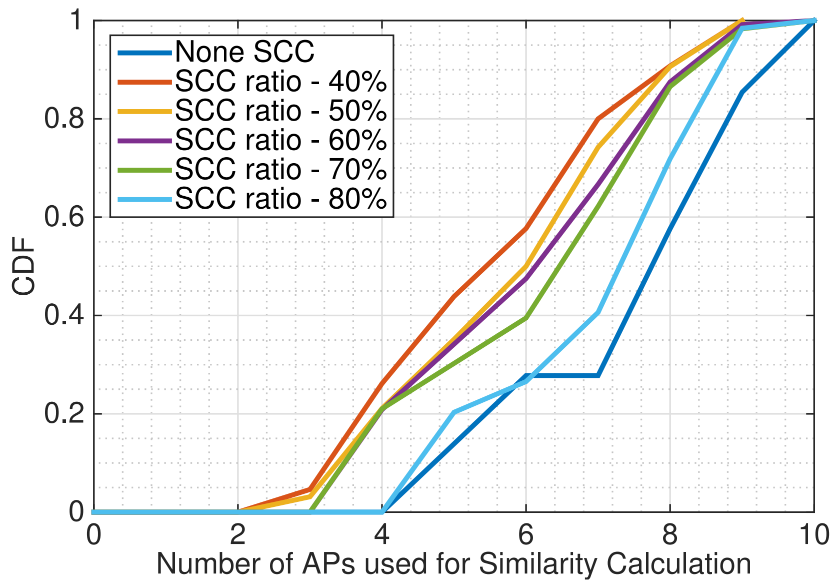



Fig. 4.20 CDF of number of APs used for similarity calculation of positioning using different SCC ratio in selective searching scheme excluding the cases when no location can be found.

ratio. From which we can see that, with the increase of SCC ratio the probability that no candidate RPs are available is increasing at a growing pace. When the SCC ratio is 80% there is about 60% probability that no positioning result can be given, which is also shown in Fig. 4.19. The number of APs used for positioning excluding the cases where no location can be found is illustrated in Fig. 4.20. We can see the number of APs does increase with the increase of SCC ratio, and better accuracy can be provided as shown in Fig. 4.17. However, the availability of service (i.e., no positioning can be given) is decreased. Thus, a trade-off between accuracy and availability is existing, and we think SCC ratio of 60% is the best choice. The number of APs used for positioning and its accuracy when SCC ratio is 60% are shown in Fig. 4.21, which shows the accuracy is increased when more APs are used for positioning. However, there is an exception when the number of APs is 8, which should also reflect that these worst cases occur at the same location

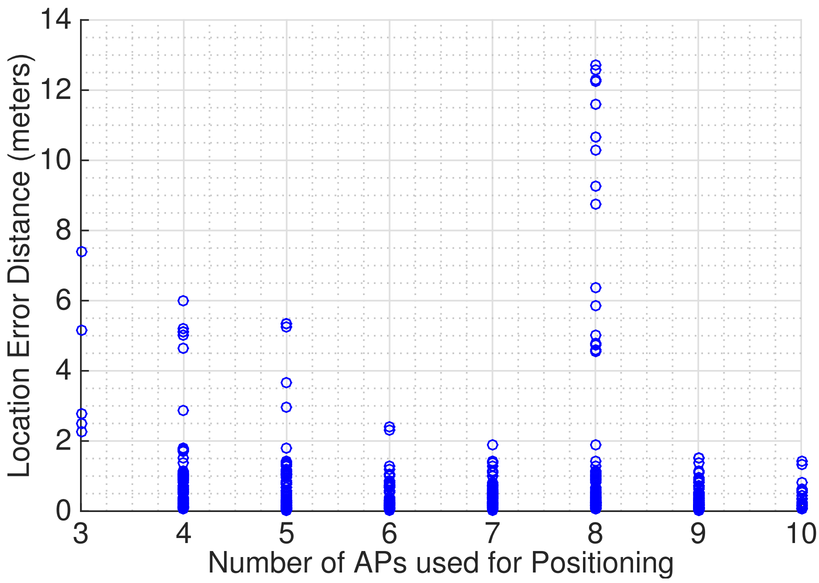



Fig. 4.21 Relationship between location error distance and number of APs used for positioning in selective searching scheme when SCC ratio is 60%.

### 4.6.4 Efficiency Comparison

Apart from positioning accuracy, the system efficiency is becoming another significant concern in the real-world deployment. In the site survey stage, the Beacon AP RSS approach can cover corridor of 20-meter length for less than 30 seconds. However, the traditional predefined RP iteration method can take more than 5 minutes depending on the grid size of RPs and sample size at each RP.

As the plot in Fig. 4.22, compared with the size of all raw APs detected, by using Beacon APs as the fingerprints of RPs the number of APs is reduced dramatically. At each path segment, the number of APs is only about one fifth of all raw APs detected, which can reduce the dimension of fingerprint database significantly.

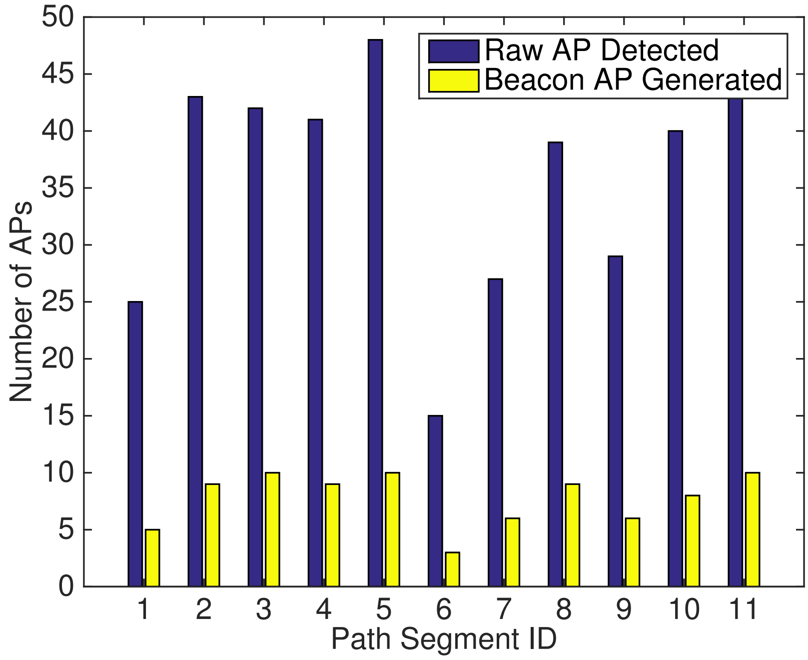



Fig. 4.22 Plot of bar chart showing the number of APs of raw APs detected and Beacon APs generated at some of path segments in the experimental site in offline site survey.

In the positioning stage, the RSS matching algorithm that calculates the similarity between RP and real-time RSS observation spends most computational resource and energy. The computation cost of RSS matching algorithm mainly depends on the size of RSS vector (i.e., the number of APs) and the number of candidate RPs to search for the best-matched location. As shown in Fig. 4.23, the number of APs used for location estimation in the Beacon AP approach is about 30% of that using raw AP. Using Beacon AP reduces the size of RSS vector to less than 20 in most cases. With the assistance of signal coverage constraint, the size of candidate RPs is also decreased significantly, as illustrated in Fig. 4.18. Beacon AP and SCC together reduce the computation cost dramatically.

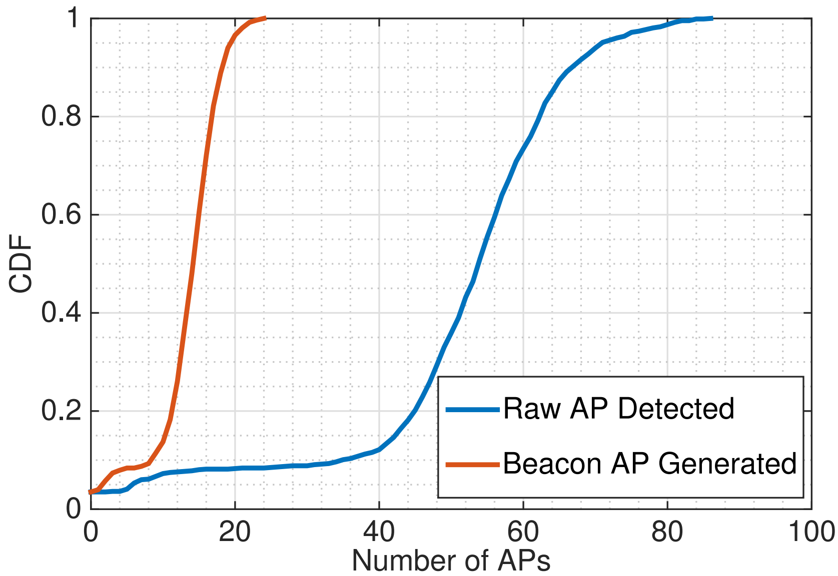



Fig. 4.23 CDF of the number of candidate RPs from positioning log.

## 4.7 Chapter Summary

In this chapter, the sibling and spatial signal patterns are investigated. A positioning approach using Beacon APs and signal coverage constraint is proposed and shows better performance in both positioning accuracy and efficiency. In conclusion, the spatial and temporal signal patterns can help reduce the problems caused by signal fluctuation and improve the positioning accuracy. To the best of our knowledge, the sibling signal pattern (i.e., signals from multiple virtual APs which are transmitted from the same physical AP) is firstly defined and investigated to be used for positioning. The only work in the literature utilised the virtual AP feature for positioning is [127], where they mentioned that averaging the RSS values of signals from the same physical AP over time can obtain more stable RSS values. But, they failed to provide details about how the signal observations are processed to identify the virtual APs and afterwards used for positioning.

However, the signal patterns only work well under the certain area of an indoor floor plan. In the experiments, for the path segment which is relatively short-distance, it has just a few number of RSS observations, in which case the Beacon AP cannot be generated, so other strategies like limiting the minimum length of path segment are necessary to be considered in the future work. Meanwhile, the site survey needs to accommodate the required approach of collecting signals, and these signals need to be processed to generate the features of signal patterns. In this thesis, the information of indoor map is used to assist the discovery and usage of signal patterns in both site survey and positioning to achieve better accuracy and efficiency. The work of this chapter has been partially published in [128, 129].

# Chapter 5

# Access Point-centred Positioning with Fingerprint Technique

In terms of the architecture of WiFi-based indoor positioning systems, the mainstream approach is MH-based. In the MH-based architecture, most functional modules are running on the MH. The APs only act as the beacons to provide WiFi signal and don't participate in any positioning work. The MH includes WiFi collection module to scan the surrounding APs actively and frequently, location computing module to run the positioning algorithm and storage module to store the indoor map and fingerprint database if fingerprint technique is used.

Based on the fact of existing MH-based system, there are several problems. Firstly, the software installation on MH is inevitable so that the user of MH must be involved in advance. The MH involvement can be a real problem in the commercial scenarios where the user of MH does not use the location information directly, such as shopping malls analysing the customers' movement. Secondly, to support simultaneous positioning of multiple MHs, not only the positioning modules need to be installed and running on each MHs, but also the consolidation of each MH's positioning results is required, which causes further deployment overhead and communication cost. Thirdly, all the modules of positioning system are deployed on the MH, where the computing resources and battery capacity are limited [25, 36, 89–91].

In this chapter, an AP-centred indoor positioning system is designed, developed and evaluated to address the problems of the MH-based system. The major contribution is as follows.

- An AP-centred system architecture is proposed to fulfil the positioning of single and multiple target devices. Also, the protocols among AP, MH and positioning server are proposed.
- The widely-used fingerprint technique in traditional MH-based positioning is combined into the AP-centred architecture to achieve better accuracy.
- The AP-centred approach shows improved accuracy in comparison with the MH-based approach. The energy-consuming WiFi scanning and location computing modules are both be moved from MH to AP, which relaxes the battery limitation issue on MH.

## 5.1 System Architecture and Protocols

### 5.1.1 Preliminary Architecture

The architecture of the proposed system is depicted in Fig. 5.1. The system consists of a Joint Positioning Server (JPS), a set of APs, a Web User Interface (UI) and a WiFi-enabled Mobile Handheld as a survey MH. On the JPS there is a Receiving interface and a Sending interface, which connect the JPS to external devices (e.g., APs and Web UI). Each AP measures the MH's WiFi signal strength and then sends it to the Receiving interface of JPS. The positioning results computed by JPS are exposed by the Sending interface. In our proposed system the Sending interface sends the positioning results to a Web UI, which can be any other kind of device to display or utilise the positioning results.

On the JPS, the Fingerprint Collection Module (FCM) is used in offline site survey phase, and the Location Computing Module (LCM) is used in online positioning phase. The FCM includes a Fingerprint Collector running on survey MH to assist the FCM. In offline phase, the FCM saves fingerprints to the Fingerprint Database (FD), which serves the LCM in online

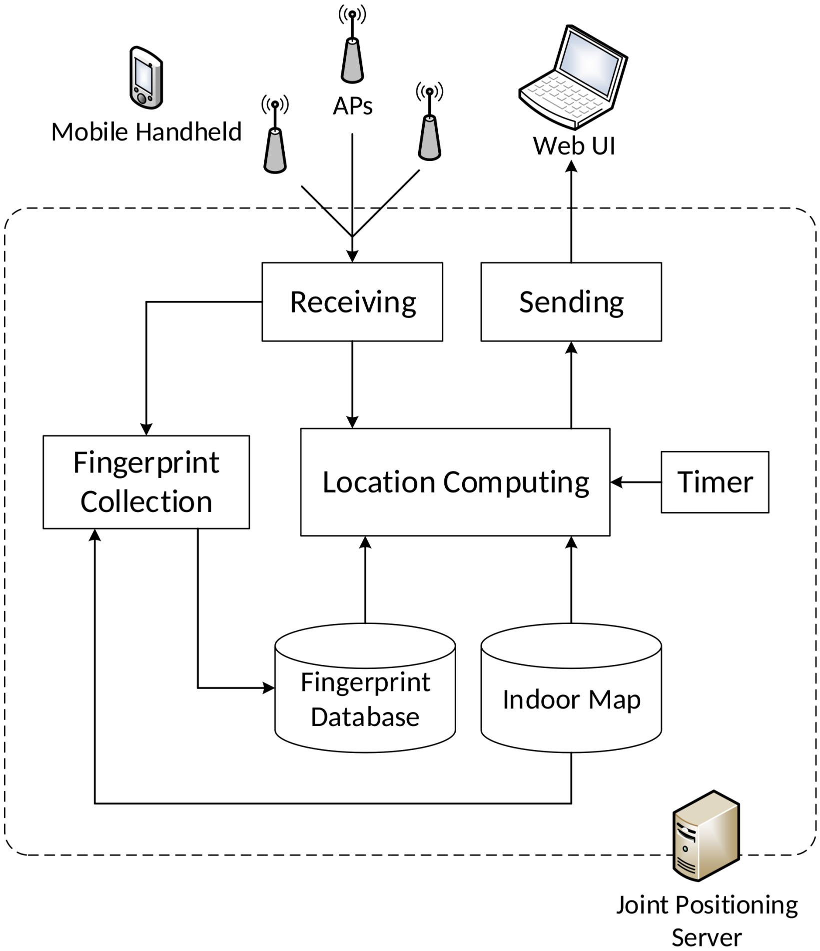



Fig. 5.1 Architecture of proposed system

phase. The FD contains MH's WiFi signal strength received by the APs at reference points, whose locations are referenced by Indoor Map Database (IMD). The IMD is composed of geographic data (e.g., coordinates system) and visualised presentation on top of that to support the system. Also, a timer is used to control the frequency of AP detection and location computing.

The sequence diagram of the proposed system is depicted in Fig. 5.2, which illustrates the collaboration and message passing among JPS, survey MH, APs and Web UI. The survey MH is involved in offline site survey phase only, and Web UI is just active in online positioning phase.

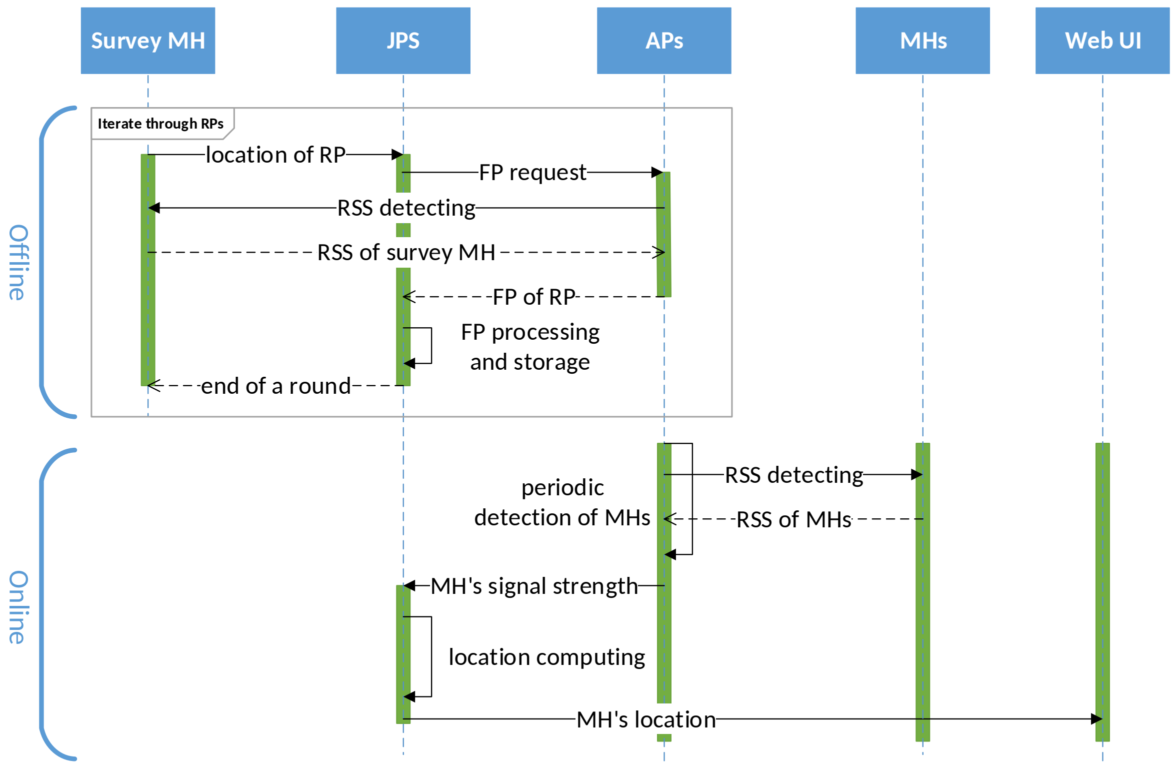



Fig. 5.2 Sequence diagram of proposed system

In the offline phase, a set of RPs are selected in the interesting area. The survey MH conducts the site survey work by iterating through all the RPs. Firstly, the Fingerprint Collector running on survey MH enables Wi-Fi background scanning module to ensure the MH is always visible to each of the APs. At each RP, Fingerprint Collector starts the survey process by allowing the surveyor to select the location of RP on the indoor map. The survey

MH sends the location to JPS, and the surveyor need stay at the RP. Then the JPS sends a fingerprint (FP) request to all the APs, which gather the received signal strength (RSS) of the survey MH. The RSS collected by all the APs are returned to the JPS. The FCM on JPS processes the RSS collection with RP's location as an FP record, then save it to the FD. A round of survey ends, and the surveyor moves to the next RP. The overall time stayed at each single RP depends on the system setting and ranges from 20 to 30 seconds.

In the online phase, the APs are periodically detecting the surrounding anonymous MHs and sending the RSS of MHs to the JPS. The format of the data sent from AP to JPS is illustrated in Fig. 5.3. The timer on JPS controls the interval of location computing. For each MH, the PCM receives the RSS of it from all different APs and retrieves the FD to compute the location of MH. This process for different MHs can be running simultaneously to fulfil multiple MH positioning. The location of MH is sent to the Web UI for monitoring or analysing purpose.

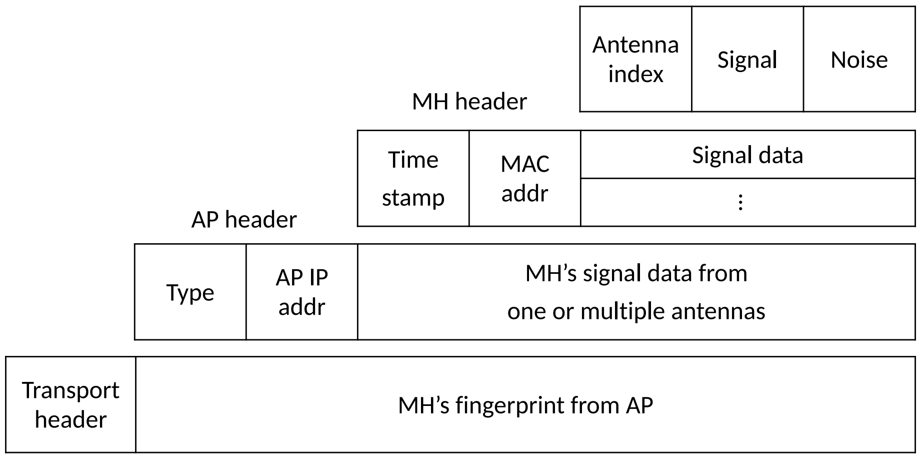



Fig. 5.3 Format of the data from AP to JPS

### 5.1.2 Enhanced Architecture

An enhanced architecture of the proposed system is provided and depicted in Fig. 5.4. The system is built and running based on modules located in two places: *i)* the WiFi infrastructure deployed in the site and covered the area of interest and *ii)* the in-cloud centralised server sitting at a location where computation and storage resources can be provided, which can be either the traditional cloud in the datacentres or the mobile cloud in the edge of the Internet and closed to the WiFi infrastructure (i.e., end users). The modules located in the WiFi infrastructure can naturally use the Internet connection provided by WiFi infrastructure to communicate with the in-cloud centralised server. The indoor positioning service is exposed to the Internet from the in-cloud centralised server, hence if the end users of MDs want to consume their own location information they can reach via a 3G/4G link or through the WiFi link (if the MD is connected to the WiFi infrastructure). Placing the in-cloud centralised server to the edge of the Internet can reduce the transmission latency and improve the real-time performance of positioning service, especially when the end users want to consume their indoor location information directly [130].

The Sniffer Module (SM), installed over each AP of the WiFi infrastructure involved in the positioning service, can obtain the RSS of the MD at each AP. The WiFi-based positioning makes use of the management frames, which is designed for the maintenance of communication in the IEEE 802.11 specification [131, 132]. In the traditional MD-based system, the RSS of AP received by the MD is obtained through calling the API (Application Programming Interface) of the MD's operating system (e.g., Android), and the RSS information is extracted from the WiFi beacon frame or probe response frame sent from AP, which depends on the operating system of MD. In contrast, in the proposed AP-centred positioning system, the SM on AP obtains the RSS of MD received by the AP from the WiFi probe request frame sent from the MD. In Fig. 5.4 RSS values are represented with small coloured rectangles where the colour level indicates the amount of power from MD sensed by a specific AP (a red rectangle for $AP_1$, a green rectangle for $AP_2$ and a blue one for $AP_M$). The RSS data obtained from each SM are then sent over the Internet to the in-cloud centralised server.

The in-cloud centralised server will process the data from WiFi infrastructure depending on the Phase Selector (PS) configuration: *i)* training (offline site survey) phase or *ii)* positioning (online) phase. During the training phase, the RSS values are stored in a database called Real-Time RSS Database (RTRD), located within the In-Cloud Centralized Server. Successively, such RSS data are used by the Fingerprint Collector (FC) to map the RSS data to a reference point and build the Radio Map that will be stored on the RadioMap Database (RMD) (see the indoor environment RadioMap icon in Fig. 5.4). On the other hand, when the positioning phase is occurring, RSS data are used by the Positioning Module (PM) which runs to compute the location of the MD from the previously stored RadioMap. Such information, extracted from the RMD (see the mobile device estimated position icon in Fig. 5.4), is then back-propagated towards the MD if the end user wants to obtain their position. Otherwise, the position of MD can be shown on a monitoring console for the third-party usage.

## 5.2 Online Joint Positioning

The fingerprinting technique is the same as the description in Section 3.2. In offline phase, a collection of known locations in the positioning venue are selected as the reference points (RPs). The WiFi received signal strength (RSS) of MH by APs are collected at each RPs. In the online positioning phase, providing the fingerprint database and the live RSS readings from the same set of APs in the fingerprint database, the positioning algorithms compute the most similar fingerprint and find the corresponding location stored in the database.

The KNN (K-Nearest Neighbours)-based positioning algorithm is proposed to compute the location of an MH, whose pseudocode is in Algorithm 5.1. The KNN algorithm is a non-parametric method used for classification in pattern recognition. The proposed positioning algorithm needs online RSS reading of an MH $\psi_0$ and fingerprint database $\Psi$ as inputs. The output is the computed coordinate indicating the MH's location on the indoor map.

The main steps of the algorithm are as follows. At first, the number of fingerprints in the database is counted and saved to $j$. Then the *minED* that stores the minimum Euclidean distance is initialised to MAXVALUE and the *minEDid* that indicates the fingerprint with minimum Euclidean distance is initialised to 0. Line 5 starts the main loop of the algorithm that traverses the matrix $\Psi$ to find the fingerprint record with minimum Euclidean distance to the online RSS reading. In line 7 the Euclidean distance between each fingerprint and online reading is calculated using the Eq. 3.7 and saved into temporary variable *ED*. Following the

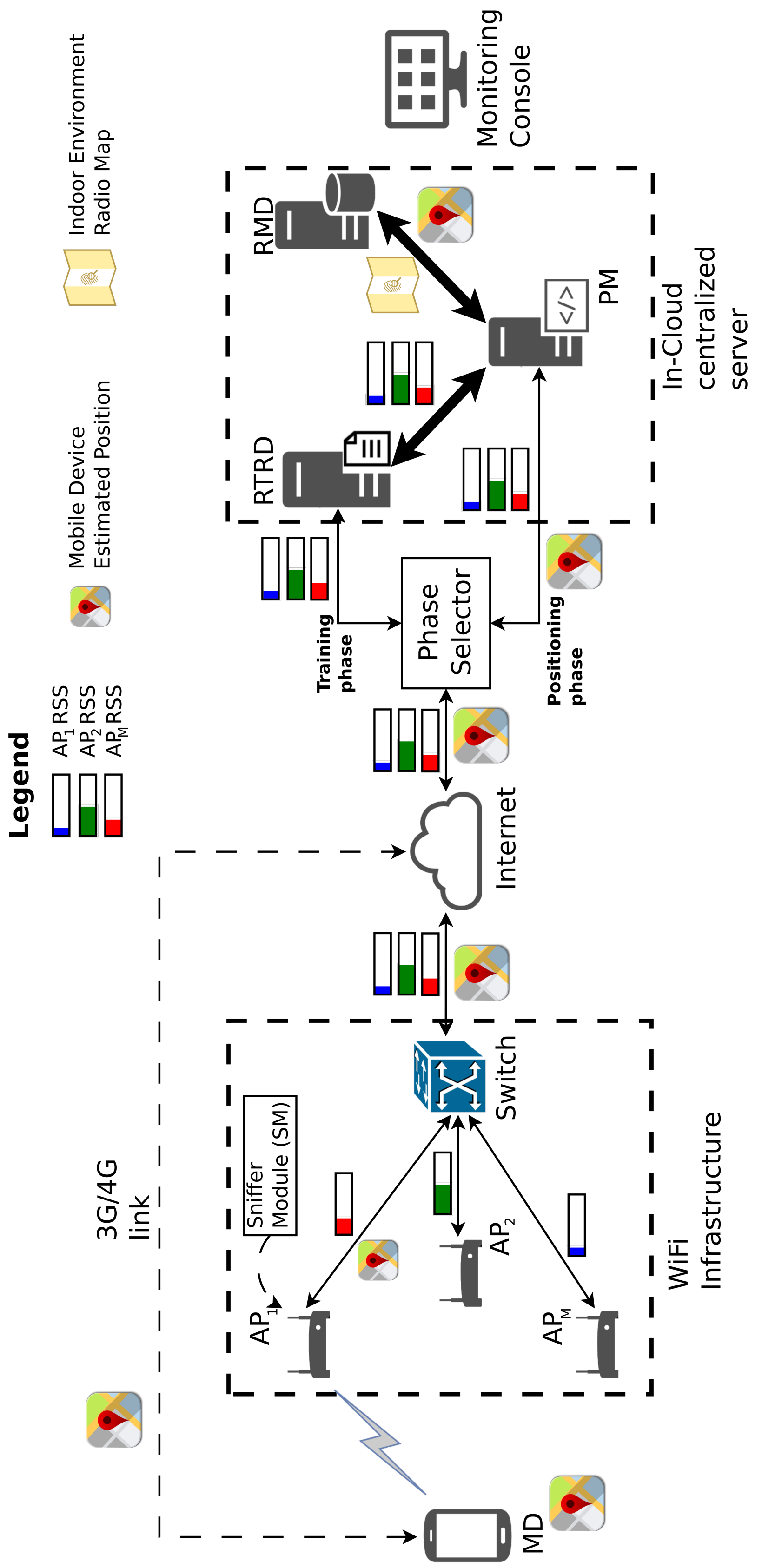



Fig. 5.4 Enhanced architecture of proposed system

**Algorithm 5.1** Online Joint Positioning Algorithm

Input:
$\psi_0$ - an online RSS reading of a MH;
$\Psi$ - a fingerprint database of the interesting area
Output:
$L$ - a coordinate indicating the MH's location

$j \leftarrow$ number of fingerprint records in database
$minED \leftarrow$ MAXVALUE
$minEDid \leftarrow 0$
$i \leftarrow 0$
**while** $i < j$ **do**
  $\psi_i \leftarrow$ RSS reading of fingerprint $i$
  $ED \leftarrow$ calculate similarity between $\psi_i$ and $\psi_0$ using Eq. 3.7
  **if** $ED < minED$ **then**
    $minED \leftarrow ED$
    $minEDid \leftarrow i$
  **end if**
  $i \leftarrow i + 1$
**end while**
$L \leftarrow$ retrieve coordinate of fingerprint $\psi_{minEDid}$
**return** $L$

above process, the *minED* is checked with every *ED* to update the *minED* and the ID of the fingerprint with *minED* is saved into *minEDid*. The above procedure is repeated until all the fingerprints in the database are examined. Finally, the corresponding coordinate of the fingerprint with $\psi_{minEDid}$ is stored into $L$ and returned by the algorithm.

## 5.3 Evaluation

### 5.3.1 Experimental Setup

This section provides details in the experiments of the proposed system. The experiments are conducted at the 5th floor of Network Building in the Colchester Campus of University of Essex. The area of the experimental site is about 300 $m^2$, including a large lobby, a common room, offices and hallway, as depicted in Fig. 5.5. The site is covered by 8 wireless access points of the same model (NETGEAR WNDR 4300V1), and these APs are placed on the floor. All the APs have the OpenWRT 15.05 firmware installed, support IEEE 802.11 b/g/n standards and work on the 2.4 GHz frequency band. Since the firmware is not explicitly designed for network traffic monitoring purpose, we developed a specific packet-sniffing program installed in the APs in order to sniff Probe Request of 802.11 management frames that are emitted from surrounding WiFi-enabled wireless devices. During the experiment, the packet-sniffing program is running at each of the APs and responsible for saving the captured data into a MySQL database in the remote server. There is also an Apache Tomcat lightweight web application server deployed on the same PC (Windows 10, 3.20 GHz Intel i7 Processor and 16GB RAM) as the database server. The mobile handheld used in the experiment is Samsung Galaxy S6 Edge running Android 5.1.1. All the devices mentioned above are connected wirelessly to set up a WLAN infrastructure. To reduce the cost of building the fingerprint database of the experimental site, we developed an Android application (Fingerprint Collector) for collecting fingerprints in the site survey stage, which is depicted in Fig. 5.5. The positioning algorithm is fully implemented on the application server using the Java Web Technologies, e.g., JSP, Servlet and the JDBC API. The frequency of location computing is set to once every 2s in the experiment.

On the experimental site, 30 reference points are selected in the accessible area, and the spacing between them is about 2 to 4 meters, as depicted in Fig. 5.5. The site survey process costs about 30 minutes. The direction of holding the mobile handheld is not specified when performing the site survey.

The evaluation is carried out in two steps. Firstly we validate the effectiveness of the system showing that the expected functions are fulfilled by the system, in particular, multiple users tracking. Secondly, we evaluate its performance on positioning accuracy. Totally 43 evaluation points are selected to exam the location error of positioning result. The performance is evaluated against the case where the traditional MH-based approach is applied. The MH-based approach is fully implemented using different architecture but the same positioning algorithm as AP-centred system.

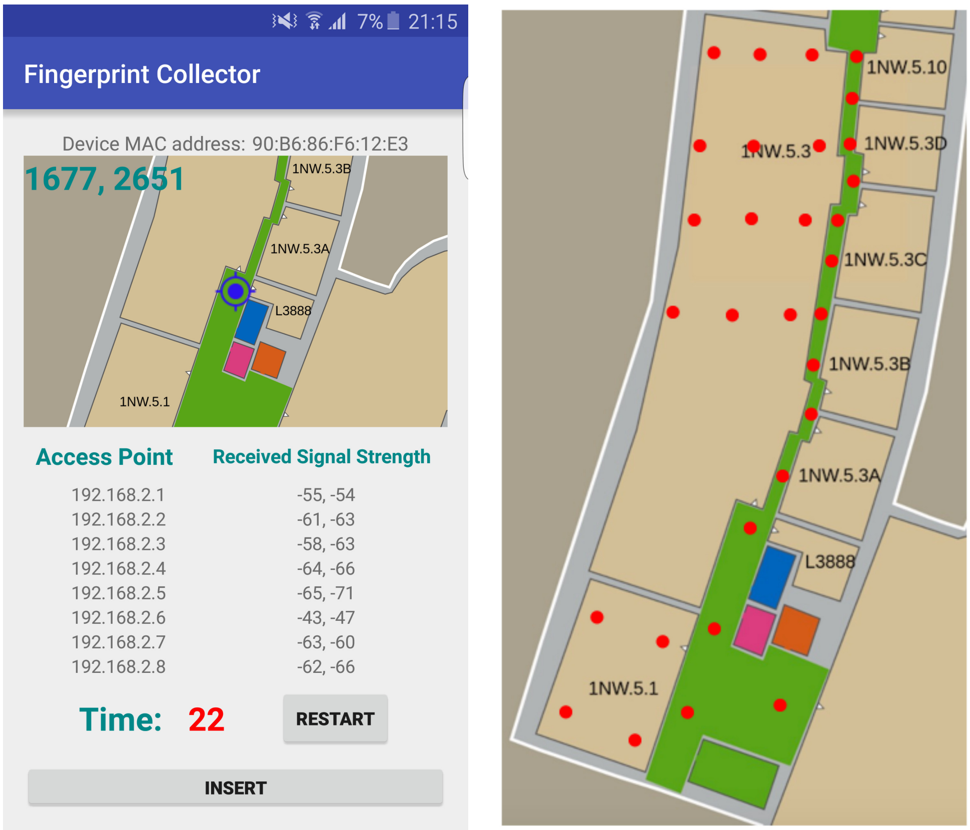



Fig. 5.5 The Fingerprint Collector app running on the survey MH (left) and the location of reference points selected in the experiment (right)

### 5.3.2 Effectiveness of AP-centred Architecture

The proposed system successfully fulfils the expected functionalities. Firstly, the location of an MH can be obtained without running any process on the MH. Any WiFi-enable MH appearing in the system-deployed area can be located. Secondly, the positioning of multiple MHs simultaneously is fulfilled, as depicted in Fig. 5.6. Thirdly, the fingerprint technique for positioning is applied to the AP-centred system, where a survey MH is involved in the site survey phase to assist the building of fingerprint database. Behind the functional achievement, more importantly, the system reveals the feasibility of AP-centred positioning by developing and implementing based on OpenWRT. Positioning services can be developed and running on the OpenWRT-based APs. Compared with the MH-based positioning system, AP-centred architecture is easier to be deployed and cheaper to maintain, because it doesn't need to develop positioning services for different MH platforms, such as iOS and Android.

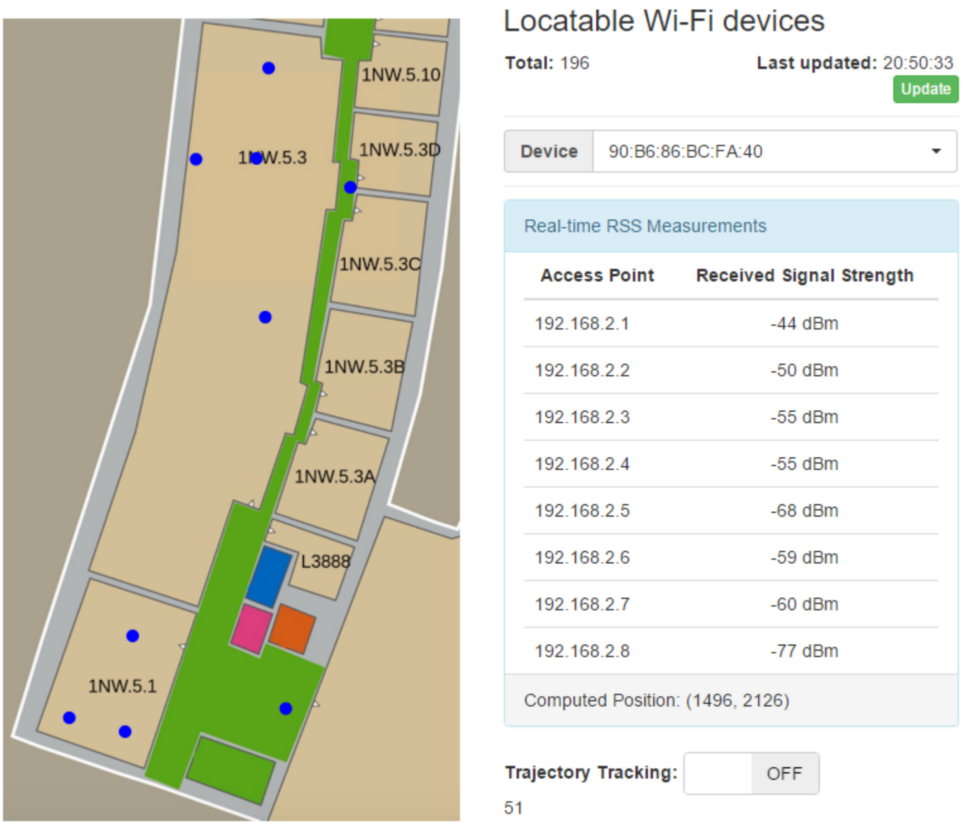



Fig. 5.6 The Web UI displaying the location of multiple MHs (left) and console to check the RSS of each individual MH (right)

### 5.3.3 Efficiency of AP-centred Architecture

The positioning accuracy is used to evaluate the efficiency of the proposed positioning system through the cumulative percentage of location error. The proposed AP-centred positioning system is compared with the conventional MH-based system. The CDF of location error for both systems is illustrated in Fig. 5.7. Overall the AP-centred approach shows better efficiency because it overtakes MH-based system all the way from begins to the end. The percentage of accuracy within 1 meter achieves approximately 70% in the AP-centred system, while that achieves only about 35% in the MH-based system. In 90% of positioning results, the AP-centred and MH-based systems provide accuracy of 3 meters and 5 meters respectively. Through the comparison of the location errors when the CDF is 100%, it is apparent that the maximum error distance of MH-based system is almost 7.5 meters, while the AP-centred system can decrease it to 4.5 meters. In summary, it is the witness that the AP-centred system can provide more accurate locations. We believe the reason AP-centred architecture outperforms MH-based one is that AP-centred system prevents the device diversity issue of MHs and AP's WiFi module has better performance of RSS reading than MHs.

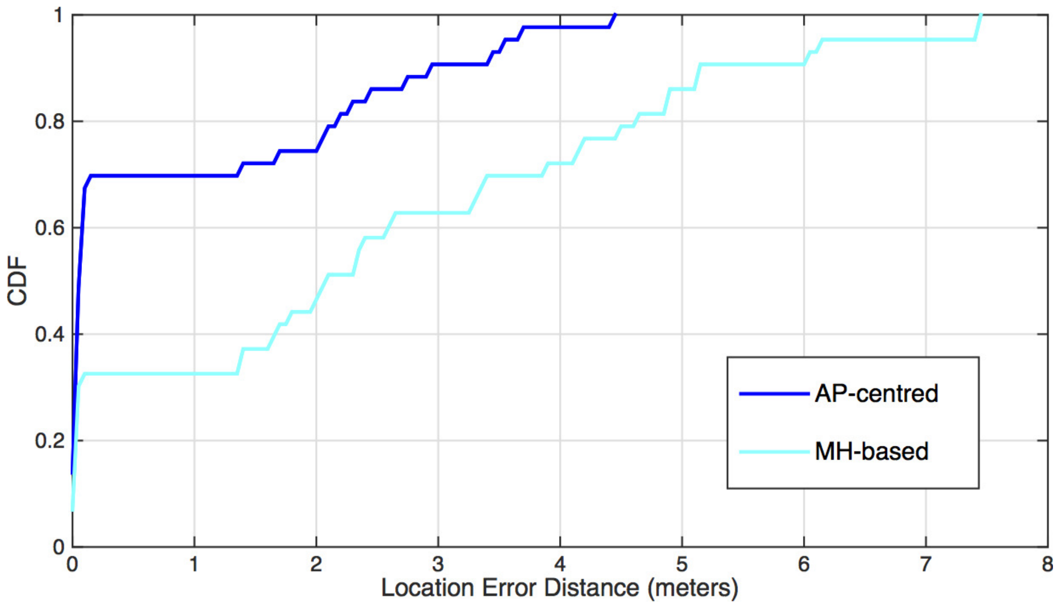



Fig. 5.7 Comparision of CDF between AP-centred and MH-based system

Fig. 5.8 shows a more detailed view of the location errors of both AP-centred and MH-based systems in the evaluation points of two categories. The errors for the evaluation points in the centre area of the building (first 7 points) are significantly smaller compared to the evaluation points in the edge area of building (points 8 through 14). We believe that this fact is caused by the limited coverage of APs in the edge area, where only a few APs surround the mobile handheld.

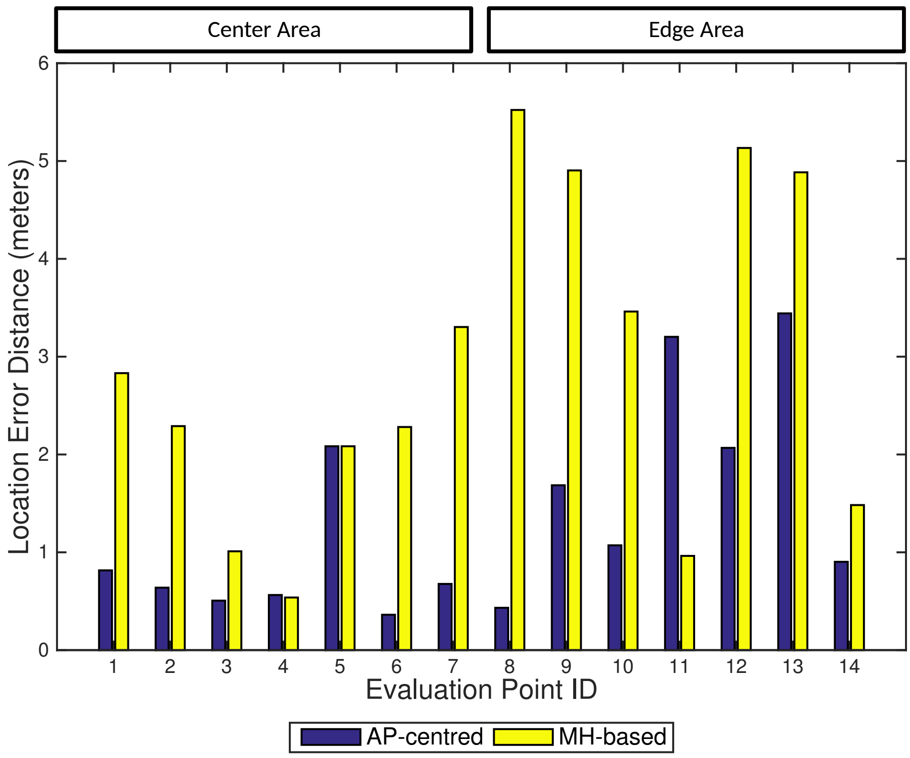



Fig. 5.8 Location error distance at each evaluation point by AP-centred and MH-based system

The AP-centred indoor positioning system relaxes the limited battery capacity on MH intensively, and the basic idea is illustrated in Fig. 5.9. In the traditional MH-based approach the energy consumption consists of location computation and WiFi scanning work. The energy consumed to compute location largely depends on the complexity of positioning algorithm. The WiFi scanning process includes sending the Probe Request, receiving and processing the Probe Response from APs. In the AP-centred system, the only consumption happened in the MH is sending Probe Request and all the other process are offloading to the AP.

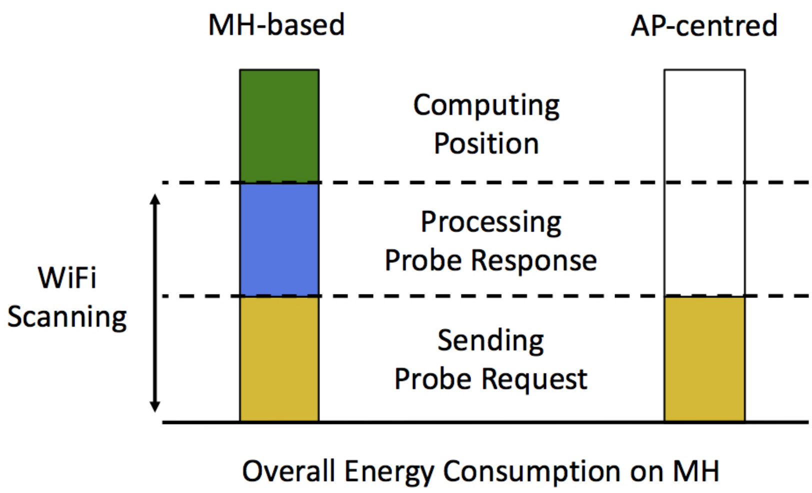



Fig. 5.9 Overall energy consumption on MH in MH-based and AP-centred systems

## 5.4 Chapter Summary

In this chapter, an AP-centred architecture is proposed to fulfil the positioning of MH on the AP side successfully, in which the MH doesn't need to be involved in the positioning phase. Meanwhile, the fingerprint technique is applied in the AP- centred architecture and shows better performance than the conventional MH-based positioning using fingerprinting. In addition, the proposed system fulfils multiple-user positioning easily and addresses the energy consumption issue on the MH. The future work is to investigate the collaborative positioning between the APs to improve the site survey efficiency and positioning accuracy. The work of this chapter has been partially published in [133, 134].

# Chapter 6

# Conclusion and Future Work

In this thesis, motivated by the recent development and future prediction of indoor positioning, several contributions for indoor positioning from the aspects of the indoor map and WiFi access points are presented to improve the positioning accuracy and system efficiency. All of the proposed works have been fully implemented and evaluated in the real-world setup, which not only shows the effectiveness of the proposed work but also reveals the future direction of research in indoor positioning.

## 6.1 Conclusion

The contributions can be summarised as follows, which includes the proposed algorithms, schemes and architecture.

In Chapter 3, an AP placement algorithm using the wall information from an indoor map is introduced to enhance the accuracy of WiFi-based indoor positioning. Firstly, an indoor map system that provides a coordinate system and graphic representation is presented. The approach how the detailed map information such as walls can be explicitly expressed is illustrated. Then the data structure of how fingerprinting technique works is provided in order to support the formulation of AP placement for fingerprint-based positioning. Next, an optimisation model considering the attenuation caused by walls is provided and how the attenuation of walls can be extracted from the indoor map is discussed. Finally, the optimisation problem is solved by PSO and the effectiveness and efficiency of the proposed AP placement algorithm are measured via the accuracy of the positioning system in the real world.

In Chapter 4, the WiFi signals under modern enterprise WiFi infrastructure are analysed firstly, and the signal patterns of coexisting access points are identified, where the SSP is defined for the first time. The SSP is processed to generate Beacon APs which have higher confidence in positioning. From the aspect of spatial signal patterns, the signals' correlation with indoor pathway map is investigated to address the problem of inconsistent WiFi signal observations. The positioning schemes using SCC are used to bring the estimated location into a limited area. The use of Beacon APs and SCC in the positioning shows improvement in both positioning accuracy and efficiency.

In Chapter 5, an AP-centred architecture is proposed to fulfil the positioning of MH on the AP side successfully, in which the MH doesn't need to be involved in the positioning phase. Meanwhile, the fingerprint technique is applied in the AP-centred architecture and shows better performance than the conventional MH-based positioning using fingerprinting. Also, the proposed system fulfils multiple-user positioning easily and addresses the energy consumption issue on the MH.

From the aspect of implementation during experiments, some experience and tips are summarised. In the implementation of positioning application on Android platform, the information about surrounding detected APs are acquired by *android.net.wifi.ScanResult* class from WiFi service of Android. Each *ScanResult* is binding to a specific AP. From Android API level 17, the timestamp when the *ScanResult* was last seen is added to the *ScanResult*, which enables more fine tuning of RSS observations. In our work, the timestamp is always checked to ensure the RSS observed is latest or can be mapped to the previous location based on moving trajectory. In addition, the frequency to obtain the latest *ScanResult* is not controlled by the user while depending on the performance of WiFi card. In our system implementation, a *BroadcastReceiver* is listening on the *ScanResultsAvailableAction* of WifiManager to receive the *ScanResult*.

## 6.2 Future Work

In this thesis, several works are proposed and evaluated through experiments to show its effectiveness, but there are still some aspects which are not considered in this thesis but worth considering in the future work to continue improving the performance of positioning system. Some of the specific future works are discussed as follows.

For the proposed optimisation model of AP placement, the wall detection process costs most of the computing time in the propagation model. Thus it takes a relatively long time for the PSO to converge. The efficiency of the proposed algorithm can be enhanced in the future work. In addition, we assume the thickness of walls is the same, and the attenuation factor for the different material of the wall is the same as well. In real scenarios, the construction material of walls is various in a large building. Hence more properties of objects in the indoor map are necessary to be added in the future work. Now the APs are placed on the floor for ease of deployment, in which the signal coverage is worse than that placing on the ceiling. In the future, the APs' vertical deployment in the experiments needs to be considered. Apart from AP placement, a map-assisted hybrid site survey approach is also feasible to make the site survey work less time-consuming and laborious than conventional site survey. On the other hand, in the AP-centred architecture, it is possible to improve the site survey efficiency and positioning accuracy through investigating the collaborative positioning scheme between the APs.

This thesis is just a brick we have contributed to the field of indoor positioning and the scientific community. Several future research initiatives are suggested as follows.

Firstly, for most positioning systems, their work can be divided into modules including signal collection, signal processing, signal storage and location estimation. Typically researchers are investigating the indoor positioning problem from a specific aspect, i.e., they won't contribute to all of the modules mentioned above. But in order to evaluate their proposed work, they need to design and implement all of the modules, which not only leads to an unnecessarily time-consuming task but also causes inconsistency and uncertainty for evaluation. Thus, to facilitate the effective research of indoor positioning and standard of evaluation, investigating the positioning frameworks (which also includes protocols and architectures) that can work with various signals and different algorithms is a direction of research in indoor positioning.

Secondly, unlike the outdoor positioning in which the working environment is consistent, the indoor environment is very complicated and can be diverse, so the technology and technique for positioning need to aim at specific environment and application scenarios. We believe a generic and universal indoor positioning system won't exist, even though it exists it needs support multiple signals and different scenarios to achieve seamless switching, that's also the reason of previous suggestion to investigate positioning framework. Therefore, the research work of indoor positioning should be more targeted to specific application scenarios. For example, we believe the WiFi-based indoor positioning is more suitable for scenarios which don't require very high accuracy, so it's more sensible to investigate more on the deployment efficiency of WiFi-based positioning.

Finally, research on the intelligent algorithms such as pattern recognition and machine learning in the field of indoor positioning can be interesting and potentially helpful, because the indoor environment is very complex and dynamic, which leads to lots of uncertainties that cannot be addressed by pre-defined schemes.

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# Appendix A

# List of Related Publications


1. X. Du, K. Yang, "A Map-Assisted WiFi AP Placement Algorithm Enabling Mobile Device's Indoor Positioning," in *IEEE Systems Journal*, vol. 11, no. 3, pp. 1467-1475, Sept. 2017.

2. X. Du, J. Wu, K. Yang and L. Wang, "An AP-Centred Indoor Positioning System Combining Fingerprint Technique," *2016 IEEE Global Communications Conference (GLOBECOM)*, Washington, DC, 2016, pp. 1-6.

3. X. Du, K. Yang, X. Lu and X. Wei, "An indoor positioning approach using sibling signal patterns in enterprise WiFi infrastructure," *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*, Valencia, 2017, pp. 1728-1733.

4. X. Du, K. Yang and D. Zhou, "MapSense: Mitigating Inconsistent WiFi Signals using Signal Patterns and Pathway Map for Indoor Positioning," in *IEEE Internet Of Things Journal*, 2017. vol. PP, no. 99, pp. 1-1.

5. X. Du, K. Yang, I. Bisio, F. Lavagetto and A. Sciarrone, "An AP-centred Smart Probabilistic Fingerprint System for Indoor Positioning," in *2018 IEEE International Conference on Communications (ICC)*, 2018. Accepted.