# Indoor Positioning Systems for Different Mobile Terminal Devices

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## Abstract

With the growing affordability of smartphones, increasing emphasis has been placed on smartphone location-based services (LBSs) aimed at providing users with information about their immediate environments. In addition to identifying user locations, LBSs can be extended to navigation systems and the provision of traffic information. However, the Global Positioning System, which is used extensively, requires an unobstructed line of sight between system satellites and mobile devices. Any obstruction between these components would result in positioning errors. Studies have adopted Wi-Fi access points (APs) in in a Wi-Fi environment for developing indoor systems. Although pattern matching (PM) is a relatively accurate positioning method in such systems, the PM method entails establishing multiple received signal strength indicators (RSSI) databases for different types of mobile devices during the offline phase. The proposed methods do not necessitate creating multiple radio maps for different smartphones, and can thereby reduce the labor and time costs of establishing multiple RSSI databases during the offline phase. Therefore, this study adopted signal differences among wireless APs to establish radio propagation models and mitigate the aforementioned positioning errors, with a maximal increase of 59.6% in positioning accuracy.

**Keywords:** Indoor positioning system, Location-based services, Pattern matching, Radio propagation model, Received signal strength indicator

## 1 Introduction

Smart mobile devices have become a fundamental feature of modern life. They provide various functions to increase the convenience of everyday life activities. Regarding these functions, this study focused on the application of location-based services (LBSs). LBSs can provide users with information about their current surroundings and can be integrated with other applications to enhance users' convenience. The Global Positioning System (GPS) is a considerably mature positioning service. Nevertheless, a line-of-sight must be maintained between GPS satellites and mobile devices because any obstruction between these components would result in positioning errors or even failure [1-3]. Consequently, although GPS is fully developed for outdoor environments and provides numerous additional services, it cannot be satisfactorily applied to indoor spaces involving various obstructions [4]. In 2000, Microsoft [5] proposed the world's first indoor positioning system [1], called radio detection and ranging (RADAR). RADAR mainly involves offline and online phases. Wireless network signals collected in the offline phase are developed into a fingerprinting database. In the online phase, users match the wireless network signals received by their mobile devices with signal patterns in the database to determine their locations. However, this method of establishing multiple RSSI databases during the offline phase is considerably labor- and time-intensive.

Smart mobile devices have undergone rapid development in recent years. Mobile operating systems such as Android and iOS are highly prevalent, with Android enjoying the highest market share. Even with the same operating system, different types of cell phones could receive different Wi-Fi RSSIs, which may result in positioning errors.

To establish a radio propagation model, wireless network signals received by smartphones in a Wi-Fi environment and the RSSI differences between four APs in the environment were adopted. This method facilitates effectively rectifying the positioning errors induced by the differences in the Wi-Fi RSSIs received by cell phones of different types.

This paper comprises five sections. Section 1 introduces the research background, motivation, objective, and the overall structure and direction of this study. Section 2 reviews system-related technologies and the literature. Section 3 presents the research methods proposed in this study, the experimental environment, and the system architecture. The research results are presented and analyzed in Section 4. Section 5 concludes the study and proposes future research

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directions.

## 2 Literature Review

### 2.1 RADAR Positioning Technology

Bahl et al. proposed the RADAR positioning technology [5-6] in IEEE INFOCOM 2000. The system architecture of RADAR mainly consists of two status levels: offline and online phases (Figure 1). In the offline phase, a user collects the RSSIs and characteristics of wireless APs from various directions at each sampling point. Subsequently, when the user receives RSSIs at an anchor point in the online phase, the Euclidean distance equation (1) is adopted to calculate the user's location. This process embodies the pattern matching method.

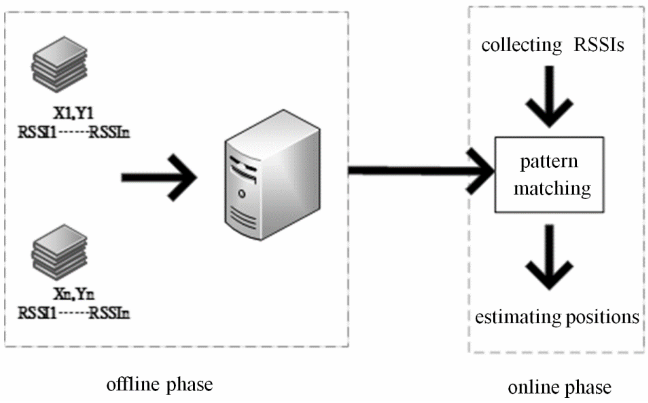



**Figure 1.** Operating procedures of pattern matching

$$d(X,Y)=\sqrt{(X_1-Y_1)^2+\cdots+(X_n-Y_n)^2}$$
$$d(X,Y)=\sqrt{\sum_{i=1}^{n}X_i(X_1-Y_1)^2} \qquad \textbf{(1)}$$

After RSSIs are substituted into $X_1$, $X_2$ … $X_n$ and calculated with $Y_1$, $Y_2$ … $Y_n$ in the database, the resultant $d(X,Y)$ is matched with the database, and the nearest point represents the user's location.

Pattern matching entails collecting all signal characteristics of an environment before positioning, which is considerably labor- and time-intensive that increases with the scale of the positioning environment. To reduce the labor costs of establishing databases in the offline phase, RADAR provides a predictive model [6], which is expressed as follows:

$$p(d)=p(d_0)-10n\log(\frac{d}{d_0})\begin{cases}nW\times WAF & nW<C\\ C\times WAF & nW\geq C\end{cases} \qquad \textbf{(2)}$$

where $P(d)$ represents the RSSI of the sampling point; $P(d_0)$ represents the RSSI of the reference point; $d$ represents the distance from the sampling point; $d_0$ represents the distance between the reference point and the signal transmission source; $n$ represents the parameter of distance-induced attenuation in signals; $nW$ represents the number of walls; $C$ represents the maximal number of walls; and $WAF$ represents the attenuation factor of walls, which varies according to wall materials

### 2.2 Location-based Services

The combination of LBSs and mobile advertising has been highly effective. When users are close to a store, LBSs provide the store's advertisements (ads) to the users, thus substantially increasing the rate of viewing mobile ads and effectively attracting the users to the store. Numerous data regarding ad exchange platforms have indicated that location-based ad viewing rates have increased by approximately 100%. Moreover, LBSs have been recently effectively integrated with social networking websites and other applications (e.g., Facebook, Google, and Twitter) to facilitate users in marking their locations and sharing location-related information with their family members and friends. Liu et al. [7-8] proposed positioning methods integrated with "sensors built-in smartphones" to achieve location-based services.

### 2.3 Positioning Method Using Wireless Signals As Propagation Models

Although pattern matching is currently the most accurate indoor positioning method, it is marred by the fact that it requires complex calculation because the data in the database must constantly be matched during the online phase. Moreover, the amount of data in the database is directly proportional to the scale of the environment. Accordingly, larger positioning environments require a higher number of patterns in the database and higher matching frequency. Consequently, several studies have involved attempting to reduce computational complexity by proposing the replacement of complex matching with models if resultant positioning errors are acceptable.

Several studies have investigated the RSSI-distance relations between wireless APs and mobile devices [9-14]. These studies have indicated that, despite RSSIs being inversely proportional to distance, they are characterized more by a wave-like relationship than they are by a linear relationship [15-17]. Pei et al. [9] used the Weibull function to improve the accuracy of fingerprinting databases. In [10], to reduce computational complexity, a problem solving approach was adopted in place of signal matching and the original signal curve was substituted with a second-order linear model.

## 3 System Architecture and Research Methods

### 3.1 System Architecture

The system proposed in this study was established in a Wi-Fi environment and involved setting four wireless APs individually at the four corners of this environment and using RSSIs to realize a pattern database and then calculate positions. Figure 2 illustrates the system architecture. The system operates in offline and online phases during positioning processes.

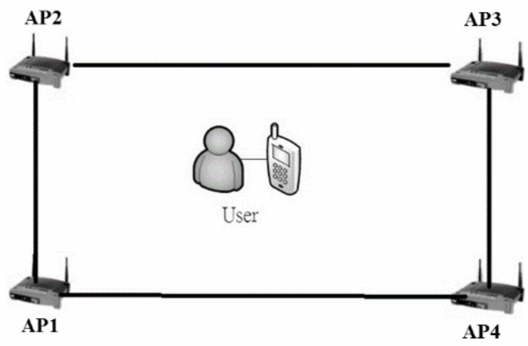



**Figure 2.** System architecture in the offline phase

**Operating procedure of the system in the offline phase.** In the offline phase, the system adopted the scanning function of smartphones to collect RSSIs sent by the wireless APs in the experimental environment. Initially, four APs were set in the experimental environment and separately labeled as AP1, AP2, AP3, and AP4. Data were collected by holding a smartphone and walking clockwise and counterclockwise from AP1 to AP4. The environment contained 90 sampling points, and data were collected individually from the directions of east, south, west, and north at each point. For example, collecting 30 data samples from one direction at one point required 2 min, and the required time increased with the number of APs in the environment. Data collected in the offline phase were categorized according to the four directions. Subsequently, a radio propagation model was established according to the RSSI differences among the four APs to rectify positioning errors generated from the use of mobile devices of different brands for data collection.

After the RSSIs from four directions at each AP were collected, erroneous data were deleted, and the remaining RSSIs from all APs were averaged and used as the RSSI of the sampling point. Furthermore, after all the data were processed, the RSSI differences among the four APs were used to establish a radio propagation model and a fingerprinting database for use in the online phase. Figure 3 shows the flowchart of the offline phase.

**Operating procedure of the system in the online phase.** In the positioning environment, the positioning program of the online phase must be activated to scan the RSSIs of the APs in this environment to identify the three APs with the strongest RSSIs and obtain their signal differences; this is also necessary to calculate the user's position by matching the scanned data with the radio propagation model or the fingerprinting database, as expressed in Figure 4.

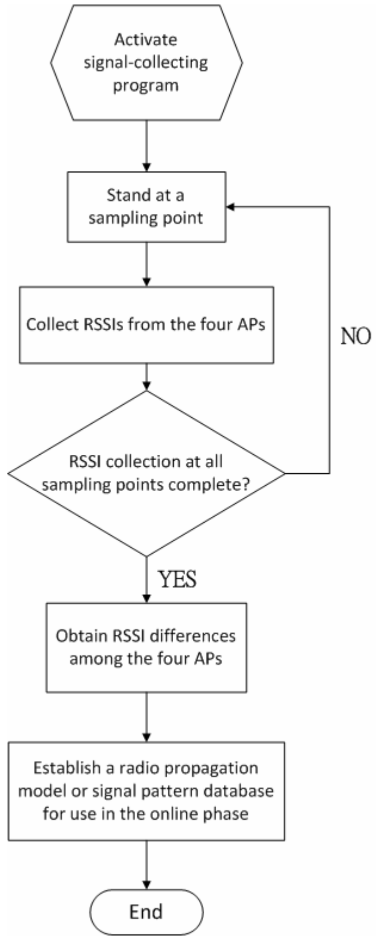



**Figure 3.** Flowchart of the offline phase

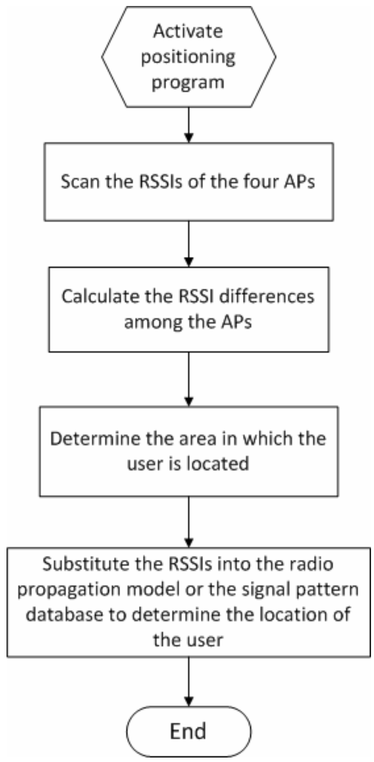



**Figure 4.** Flowchart of the online phase

## 3.2 Research Methods and Procedure

This section describes the procedures involved in combining the inter-AP RSSI differences with the radio propagation model and mitigating the positioning errors induced by the use of smartphones of different specifications or brands. The RSSI difference was calculated using equation (3), where $R_1$, $R_2$ … $R_m$ denote the RSSIs of different smartphones; $R_0$ denotes the RSSI at one unit of distance; $d$ denotes the distance between sampling points; $n$ denotes signal attenuation; $d_0$ denotes the distance between the reference point and the source of signal transmission; $F_0$ denotes the environmental attenuation; and $F_{ag}$ denotes antenna gain. The variation of $F_{ag}$ ($\triangle F_{ag}$), which is equivalent to the RSSI difference, can be obtained by taking the absolute value of an RSSI difference between two smartphones.

$$R_i = R_0 - 10 \times n \times \log_{10}(\frac{d}{d_0}) - F_0 + F_{agi}, \quad i = 1...n \tag{3}$$

**Offline phase.** Of all APs, the three APs with the strongest RSSIs among all RSSIs were used to establish a radio propagation model. However, we used only one half of sampling points to decrease the workload in the experimental environment. The polynomial fitting function in Matlab [18] was adopted to establish a polynomial approximation function in equation (4), where $y$ is the RSSI difference, $a$ is the environmental relationship derived from the polynomial approximation function, and $t$ is the distance between the user and the AP currently behind the user.

$$y = a_2 t^2 + a_1 t + a_0 \tag{4}$$

In the proposed method, it is necessary to determine the locations of APs to reduce the labor and time costs and thereby gather the RSSIs from all of the sampling points. The propagation models can thereby be established during the offline phase. Additionally, the experimental environment was divided into eight areas to reduce the computing complexity and improve the positioning accuracy (Figure 5). In each area, the RSSI differences among the three APs associated with the strongest RSSIs were used to calculate $a_2$, $a_1$, and $a_0$ by using the polynomial approximation function; these were then stored for use in the online phase.

The signal difference among the three APs with the strongest RSSIs at each sampling point was substituted into the polynomial approximation function, with 1 m serving as the basic unit, to obtain the environmental relationship and the polynomial approximation function curve (Figure 6(a) and Figure(b)). The x-axis represents the sampling points according to their designated numbers, and the y-axis represents the RSSI difference, (unit: dBm). The $a_2$, $a_1$, and $a_0$ coefficients of each area were stored in the program for use in the online phase.

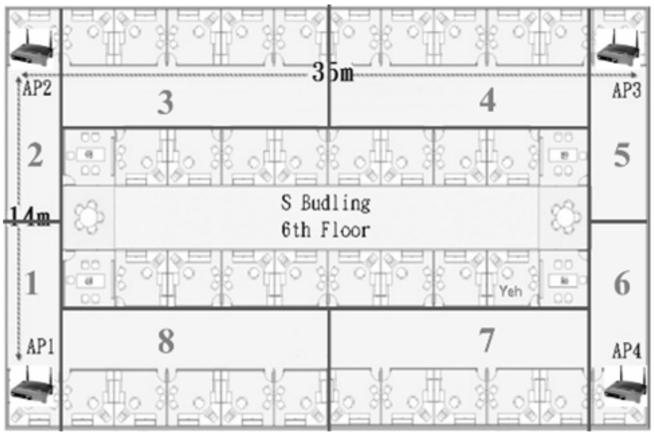
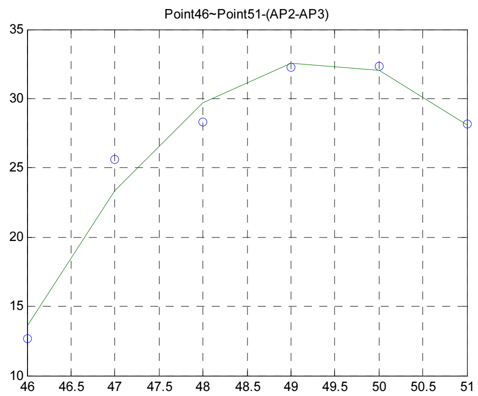
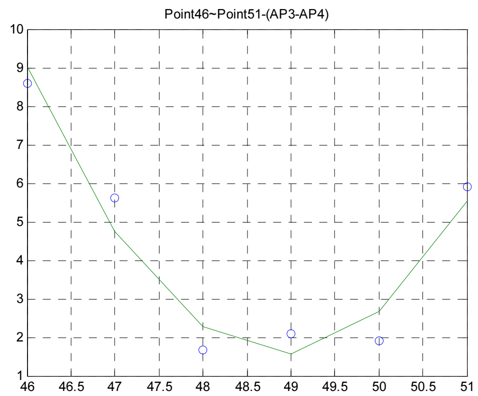



**Figure 5.** Divisions conducted according to polynomial function approximation




(a) AP2-AP3




(b) AP3-AP4

**Figure 6.** Polynomial approximation function curve for Points 46-51

**Online phase.** The methods adopted in this study are described as follows:

Method 1: Combination of inter-AP RSSI differences and pattern matching

Method 2: Combination of inter-AP RSSI differences and a radio propagation model

Method 1 was executed in the offline phase. The absolute values of the RSSI differences among the four APs were used to establish a fingerprinting database for use in the online phase. In the online phase, the user scanned the RSSIs of the APs in the environment and substituted the absolute values of the RSSI differences into the fingerprinting database to determine the present location.

Method 2 was executed in the offline phase. The RSSIs of the four APs (AP1, AP2, AP3, AP4) in the environment were scanned, and the three APs with the strongest signals were used to establish a radio propagation model for use in the online phase. In the online phase, the RSSIs of the four APs in the environment were scanned, and the RSSI differences were substituted (for example, AP1-AP2, AP1-AP3, AP2-AP3) into the radio propagation model to determine the user's location.

The azimuth is a measurement of the angle between the locations of the user and sensor on the reference plane and can be determined by the smartphone identifying each individual corner during the online phase. The environment and area in which the user is located must be identified in Method 2 in the online phase. Therefore, this study incorporated azimuth determination and smartphone sensors to enhance the positioning accuracy.

## 4 Research Results and Analysis

### 4.1 System Environment

The experiment was set on the sixth floor of the Information Building; on this floor, offices are arranged in a two-layer rectangular configuration comprising a smaller (inner) rectangle surrounded by a larger (outer) rectangle. This indoor environment is 35 m long and 14 m wide. The sampling points were distributed along the corridor. The four APs were placed in the four corners of the environment (Figure 5). In this experimental environment, the sampling points were set at an interval of 1 m starting from an AP, and a total of 90 sampling points were set around the environment. Subsequently, smartphones were used to collect the Wi-Fi RSSIs of the four APs from four directions at each sampling point.

This study adopted Linksys WRT54GS routers, which support 802.11 b/g Wi-Fi protocols, as the APs. The smartphones used in this study were the HTC M8, HTC Sensation XL, Samsung Galaxy Nexus, and Sony C3 (hereafter denoted as HTC-M8, HTC-XL, Samsung-Nexus, and Sony-C3, respectively) [19-22].

### 4.2 RSSI Analysis on Different Smartphones

Wi-Fi functions have become a prerequisite for smart mobile devices because of the rapid development of such devices. Indoor positioning can be achieved by connecting to wireless APs in an environment through Wi-Fi networks. Nevertheless, smart mobile devices vary in the signals they receive at the same point. Therefore, in this study, distance and RSSI were compared by using four smartphones of different brands and types (i.e., HTC-M8, HTC-XL, Samsung-Nexus, and Sony-C3). During the experiment, RSSIs were collected using the smartphones at sampling points separated by a 1-m interval from AP1 to AP4 (clockwise) in the experimental environment. Finally, RSSIs at a total of 90 sampling points were collected for comparison. Figure 7, Figure 8, Figure 9, and Figure 10 illustrate the RSSIs of AP1, AP2, AP3, and AP4, respectively, as received by the four smartphones.

According to the experimental data, the average differences in the Wi-Fi signals of AP1, AP2, AP3, and AP4 received by the Samsung-Nexus and HTC-XL were 8.891, 8.903, 10.042, and 9.782 dBm, respectively. These differences can result in positioning errors in the online phase. Therefore, a radio propagation model was established in this study through a polynomial approximation function. The following subsection presents the data analysis and results of conventional methods and the methods used in the current study.

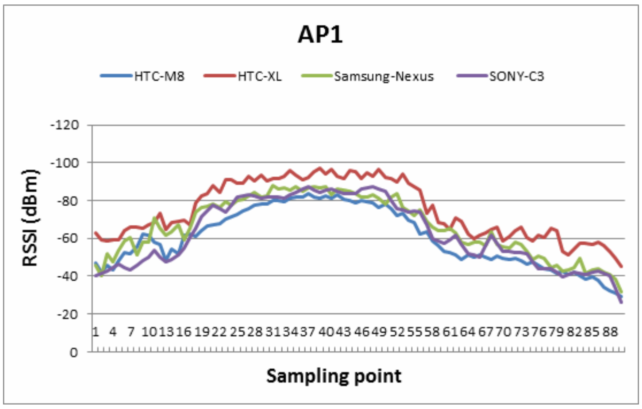



**Figure 7.** RSSI distribution of AP1

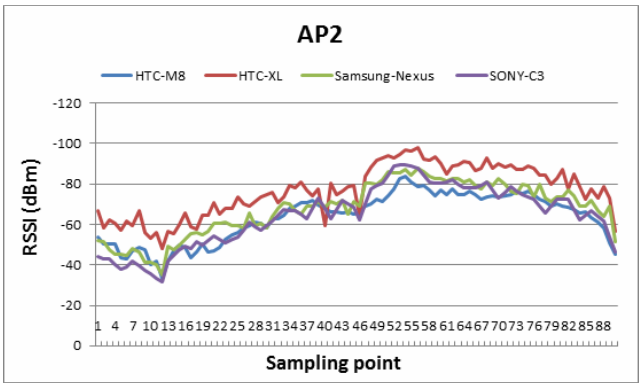



**Figure 8.** RSSI distribution of AP2

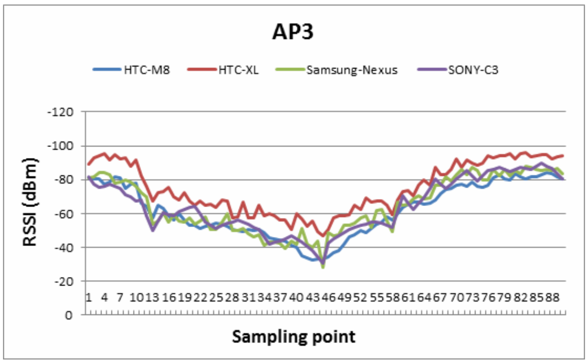



**Figure 9.** RSSI distribution of AP3

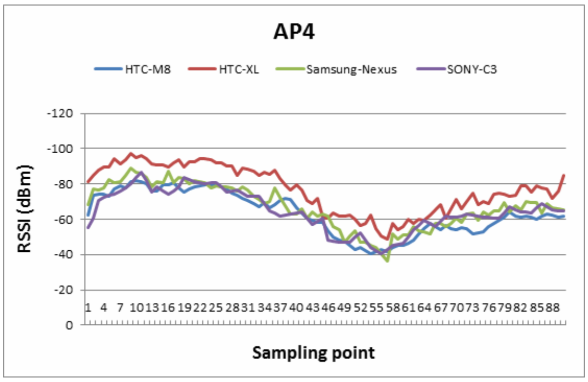



**Figure 10.** RSSI distribution of AP4

## 4.3 Comparison of Research Methods

**Conventional pattern matching.** In this study, a fingerprinting database was established for Samsung-Nexus and the conventional pattern matching approach was used to compare the mean errors of the four smartphones (Figure 11). The mean errors of the Samsung-Nexus, HTC-M8, HTC-XL, and SONY-C3 were 1.26, 2.89, 4.57, and 2.24 m, respectively. According to the conventional pattern matching approach, a difference of approximately 10 dBm was observed in the Wi-Fi RSSIs of the Samsung-Nexus and HTC-XL, and such a difference was the main cause of positioning errors.

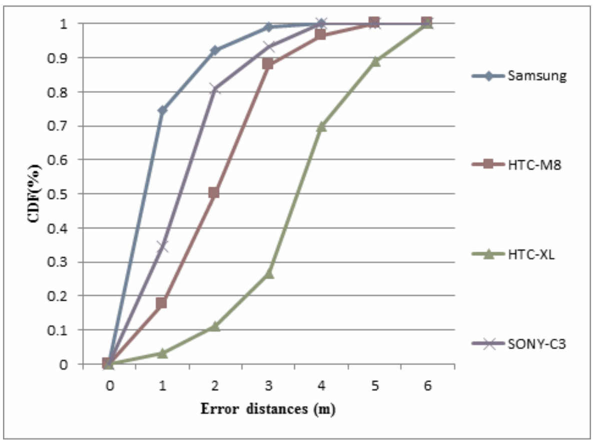



**Figure 11.** Cumulative distribution functions (CDFs) of the mean errors associated with the use of the conventional pattern matching approach

**Conventional pattern matching and azimuth determination.** Because conventional pattern matching can result in positioning errors, pattern matching and azimuth determination were combined in this study to enhance the positioning accuracy (Figure 12). When the two methods were combined, the mean errors of the Samsung-Nexus, HTC-M8, HTC-XL, and SONY-C3 were 0.986, 2.32, 4.05, and 1.93 m, respectively

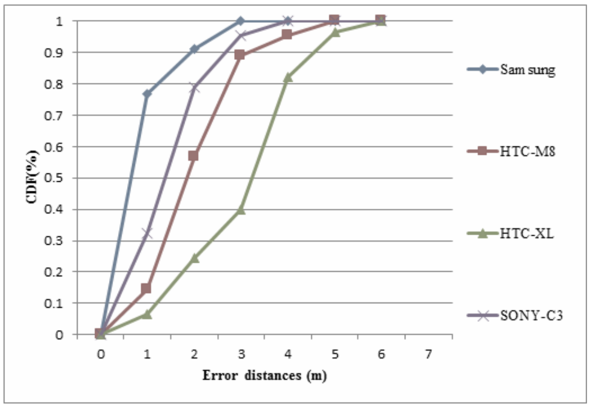



**Figure 12.** CDFs of the mean errors associated with the combined use of the conventional pattern matching and azimuth determination approaches

**Method 1.** In the experimental environment, the various smartphones received dissimilar RSSIs at the same sampling point mainly because the devices exhibited inherently dissimilar performance. Therefore, signal differences were used to establish a fingerprinting database, and the absolute values of the differences among the original RSSIs of AP1, AP2, AP3, and AP4 were derived to establish an RSSI database for use during the online phase; Figure 13 illustrates the results. The mean errors of the Samsung-Nexus, HTC-M8, HTC-XL, and SONY-C3 were 1.13, 2.74, 3.77, and 1.92 m, respectively.

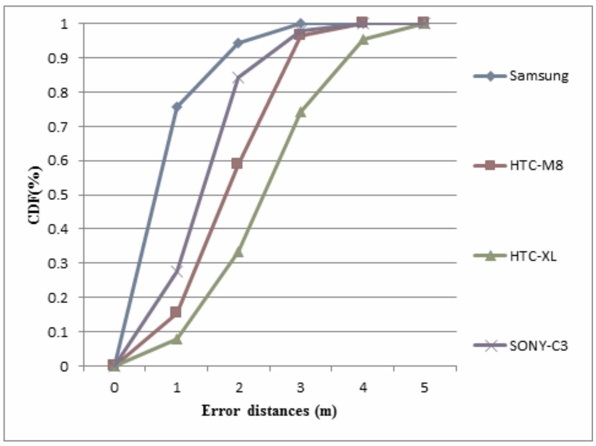



**Figure 13.** CDFs of the mean errors associated with the use of the conventional signal difference matching approach

**Method 1 and azimuth determination.** To derive precise positioning, this study incorporated the conventional signal difference matching approach with the azimuth determination method, and Figure 14 shows the results. The mean errors of the Samsung-Nexus, HTC-M8, HTC-XL, and SONY-C3 were 0.992, 2.56, 3.49, and 1.72 m, respectively.

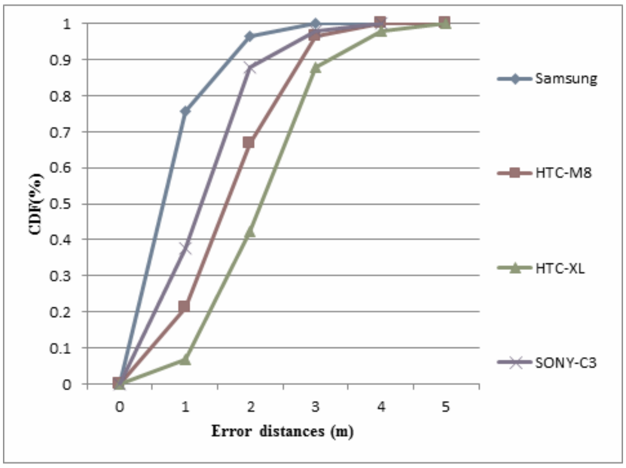



**Figure 14.** CDFs of the mean errors associated with the combination of the conventional signal difference matching and azimuth determination methods

**Method 2.** Figure 15 illustrates the positioning errors observed when the inter-AP RSSI differences were used to build the radio propagation models. The mean errors of the Samsung-Nexus, HTC-M8, HTC-XL, and SONY-C3 were 1.67, 1.872, 2.067, and 1.675 m, respectively.

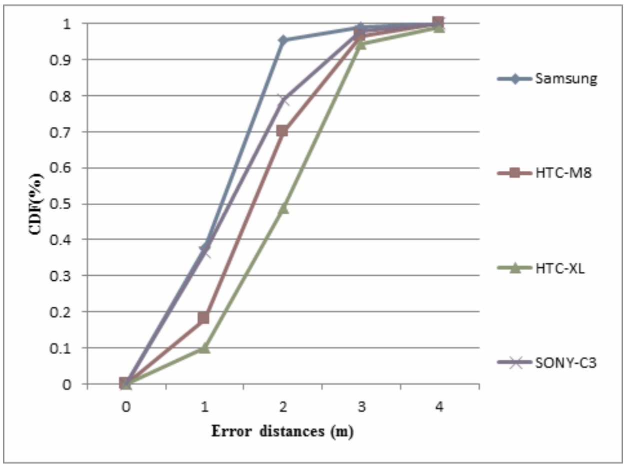



**Figure 15.** CDFs of the mean errors associated with the use of Method 2

**Method 2 and azimuth determination.** Because Method 2 was affected by environmental factors Azimuth determination entailing identifying the area in which the user was located was incorporated to enhance positioning accuracy. Figure 16 shows the positioning errors observed when Method 2 was combined with the azimuth determination approach. The mean errors of the Samsung-Nexus, HTC-M8, HTC-XL, and SONY-C3 are 1.456, 1.575, 1.843, and 1.512 m, respectively.

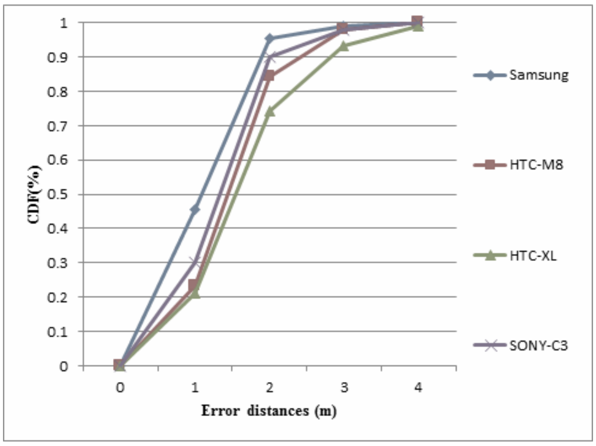



**Figure 16.** CDFs of the mean errors associated with the combination of Method 2 and the azimuth determination approach

**Radio propagation model.** To determine the accuracy of Method 2, the matching of polynomial approximation functions was slightly adjusted by replacing the y value in the original polynomial approximation function with the RSSI value. After the four APs were scanned in the environment, the absolute values of the differences among the three strongest RSSIs were obtained. Subsequently, RSSIs were directly substituted with y of the radio propagation model. Figure 17 illustrates the results. The mean errors of the Samsung-Nexus, HTC-M8, HTC-XL, and SONY-C3 are 1.862, 2.366, 2.879, 2.297 m, respectively.

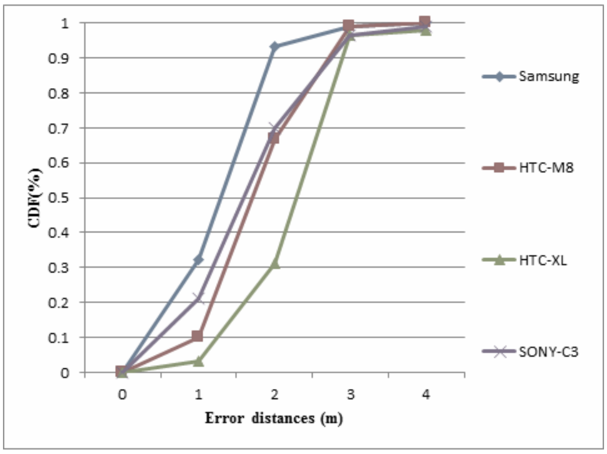



**Figure 17.** CDFs of the mean errors associated with the use of the radio propagation model

**Radio propagation models and azimuth determination.** The azimuth determination approach was combined with the radio propagation model to adjust the positioning errors incurred by this model in the online phase (Figure 18). The mean errors of Samsung-Nexus, HTC-M8, HTC-XL, and SONY-C3 were 1.7, 2.13, 2.777, 2.561 m, respectively.

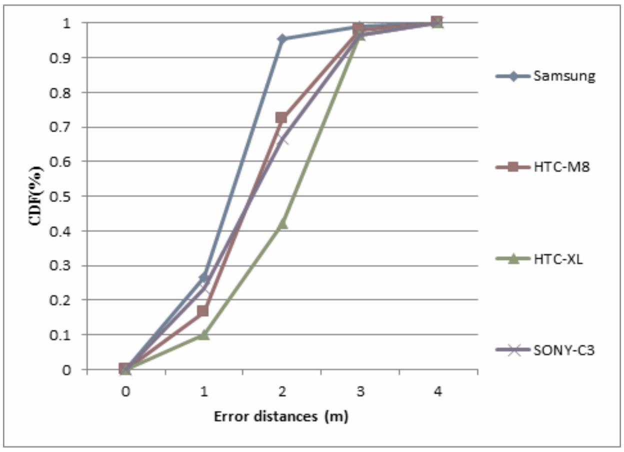



**Figure 18.** CDFs of the mean errors associated with the combination of the radio propagation model and azimuth determination approach

Table 1 shows a comparison of the mean errors of the three positioning methods and the conventional pattern matching approach. In this study, establishing a fingerprinting database for a Samsung-Nexus by using the conventional pattern matching method resulted in a mean error of 4.57 m when an HTC-XL was used. This error was mainly attributable to the compromised positioning effectiveness induced by the various RSSIs received by the various smartphones in the same environment. Therefore, to address the problem of positioning errors arising from the use of traditional pattern matching among different smartphones, this study integrated the azimuth determination approach with Method 2, reducing the positioning errors to 1.843 m.

**Table 1.** Comprehensive comparison (m)

| Methods | Samsung-Nexus | HTC-M8 | HTC-XL | Sony-C3 |
|---|---|---|---|---|
| Conventional pattern matching | 1.26 | 2.89 | 4.57 | 2.24 |
| Conventional pattern matching + azimuth determination | 0.986 | 2.32 | 4.05 | 1.93 |
| Method 1 | 1.13 | 2.74 | 3.77 | 1.92 |
| Method 1 + azimuth determination | 0.992 | 2.56 | 3.49 | 1.72 |
| Method 2 | 1.67 | 1.872 | 2.067 | 1.675 |
| Method 2 + azimuth determination | 1.456 | 1.575 | 1.843 | 1.512 |
| Radio propagation model | 1.862 | 2.366 | 2.879 | 2.297 |
| Radio propagation model + azimuth determination | 1.7 | 2.13 | 2.777 | 2.561 |

According to the results of this study, the fingerprinting database established for a Samsung-Next by using the conventional pattern matching approach resulted in a positioning error of 4.57 m when an HTC-XL was use. Figure 19 illustrates a comparison of the CDFs of the positioning errors associated with the use of the conventional pattern matching approach and Method 2 in an HTC-XL.

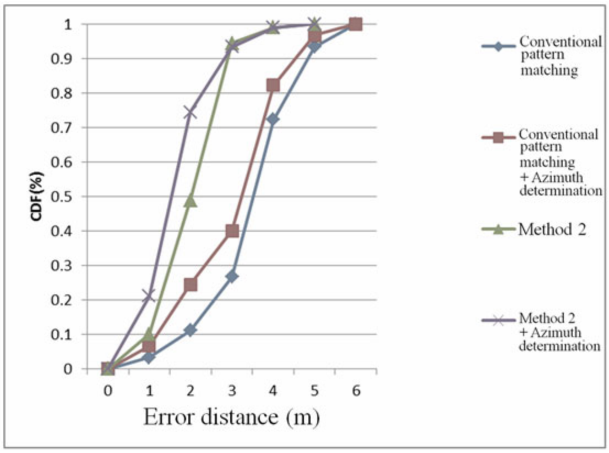



**Figure 19.** CDFs of the positioning errors in an HTC-XL

In this study, the division of the experimental environment was modified for Method 2 and the resulting positioning errors were analyzed. In the original environment, Method 2 involved dividing each side of corridor into two areas, yielding eight areas in the environment. In the modified environment, every side of corridor was considered an area, obtaining a total of only four areas (Figure 20). Figure 21 shows the circular areas formed using each AP as the center of the circles.

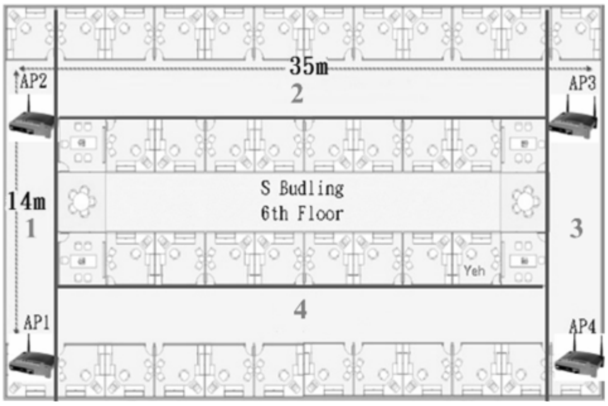



**Figure 20.** Divisions of the corridor

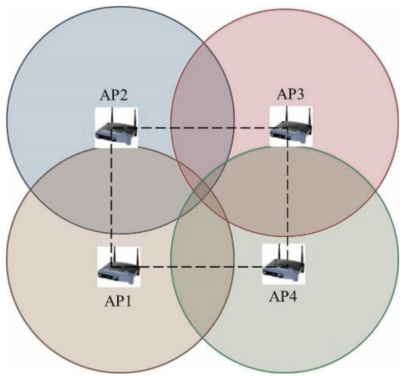



**Figure 21.** Circular areas formed using the APs as centers

Table 2 shows the positioning errors associated with the use of Method 2 in the three division types for the four smartphones. The performance levels of all the four smartphones were highest in the eight-area division (mean error = 1.597 m), followed by the four-area division (mean error = 2.665 m), and then the circular division (mean error = 3.116 m). The circular division involving the use of the APs as centers registered the lowest performance in all the smartphones because it was prone to erroneous positioning. Figure 22, Figure 23, Figure 24, and Figure 25 illustrate the CDFs of the positioning errors of the Samsung-Nexus, HTC-M8, HTC-XL, and SONY-C3 smartphones, respectively, in the three types of divisions.

**Table 2.** Positioning errors of the various smartphones (m)

| | Four-area division of the corridor | Eight-area division of the corridor | Division using the APs as centers |
|---|---|---|---|
| Samsung | 2.38 | 1.456 | 2.74 |
| HTC-M8 | 2.671 | 1.575 | 3.106 |
| HTC-XL | 3.02 | 1.843 | 3.448 |
| Sony-C3 | 2.59 | 1.512 | 3.171 |
| Mean Error | 2.665 | 1.597 | 3.116 |

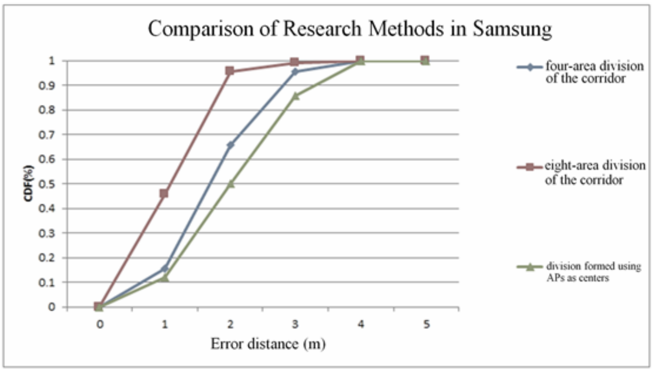



**Figure 22.** CDFs of the division-related positioning errors in Samsung-Nexus

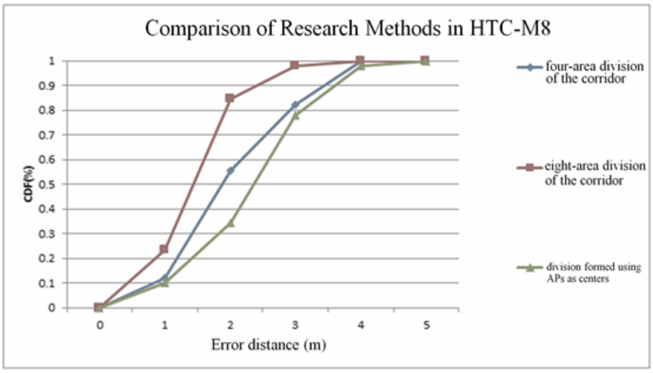



**Figure 23.** CDFs of the division-related positioning errors in HTC-M8

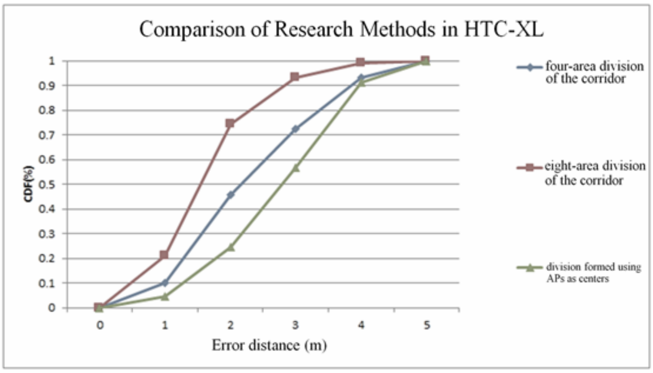



**Figure 24.** CDFs of the division-related positioning errors in HTC-XL

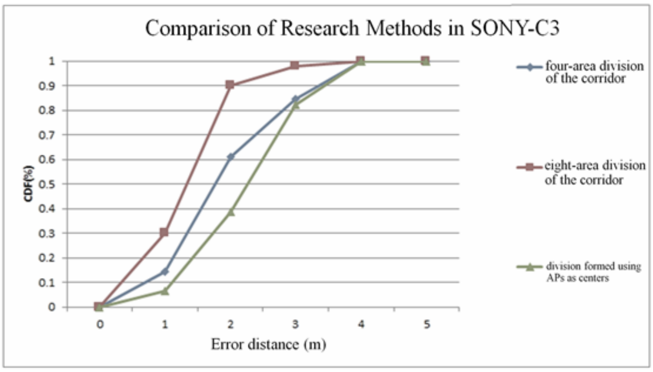



**Figure 25.** CDFs of the division-related positioning errors in SONY-C3

## 5 Conclusion and Future Research Directions

This study involved using inter-AP RSSI differences to build a fingerprinting database and radio propagation models to resolve the problem of positioning errors among smartphones of different brands in indoor environments. The proposed methods do not require creating multiple radio maps for different smartphones, and can thus reduce labor and time costs during the offline phase.

The experimental results indicate that the fingerprinting database established for the Samsung-Nexus by using conventional pattern matching approach resulted in positioning errors of 2.89, 4.57, 2.24 m when HTC-M8, HTC-XL, and SONY-C3 were used, respectively. Using Method 2 rectified and reduced the positioning errors to 1.872, 2.067, and 1.675 m in the HTC-M8, HTC-XL, and SONY-C3, respectively. Furthermore, combining Method 2 and the azimuth determination approach reduced the positioning errors to 1.575, 1.843, and 1.512 m in the HTC-M8, HTC-XL, and SONY-C3, respectively. After the conventional pattern matching approach was modified using Method 2, the positioning errors in the HTC-M8, HTC-XL, and SONY-C3 dropped by 45.5%, 59.67%, and 32.5%, respectively.

Crowd flows or changes in environment layout tend to cause positioning errors when pattern matching is employed because fingerprinting databases are established in the offline phase. A potential future research direction would involve improving the positioning errors caused by people-induced shadowing effects and indoor environmental changes, and developing an indoor positioning program on the iOS platform [23] to enable iPhone users to acquire accurate positioning.

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