Evaluation of Two WiFi Positioning Systems Based on Autonomous Crowd Sourcing on Handheld Devices for Indoor…

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Evaluation of Two WiFi Positioning Systems Based on Autonomous Crowdsourcing of Handheld Devices for Indoor Navigation

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Abstract—Current WiFi positioning systems (WPSs) require databases – such as locations of WiFi access points and propagation parameters, or a radio map – to assist with positioning. Typically, procedures for building such databases are time-consuming and labour-intensive. In this paper, two autonomous crowdsourcing systems are proposed to build the databases on handheld devices by using our designed algorithms and an inertial navigation solution from a Trusted Portable Navigator (T-PN). The proposed systems, running on smartphones, build and update the database autonomously and adaptively to account for the dynamic environment. To evaluate the performance of automatically generated databases, two improved WiFi positioning schemes (fingerprinting and trilateration) corresponding to these two database building systems, are also discussed. The main contribution of the paper is the proposal of two crowdsourcing-based WPSs that eliminate the various limitations of current crowdsourcing-based systems which (a) require a floor plan or GPS, (b) are suitable only for specific indoor environments, and (c) implement a simple MEMS-based sensors' solution. In addition, these two WPSs are evaluated and compared through field tests. Results in different test scenarios show that average positioning errors of both proposed systems are all less than 5.75 m.

Index Terms—Databases, fingerprinting, indoor localization, pedestrian dead reckoning, trilateration, crowdsourcing

1 Introduction

Accompanied by increasing demand, indoor navigation systems have quickly developed in the last few years. There are several potential technologies available to provide indoor positioning solutions such as Wireless Fidelity (WiFi), global positioning system (GPS), and inertial sensors-based relative navigation, etc. GPS is the most popular navigation system when available [1]. However, GPS cannot provide a reliable indoor navigation solution because its signal is degraded by ceilings, walls, and other objects. Therefore, other technologies have been developed to compensate for this limitations, such as radio frequency identification (RFID) [2], ultra wide band (UWB) [3], micro-electromechanical systems (MEMS) multi-sensors [4], and wireless local area networks (WLAN) [5]. RFID and UWB require dedicated infrastructure and special devices to detect signals for positioning, and can provide accurate positioning solutions. On the other hand, MEMS sensors in most current handheld devices, such as accelerometers, gyroscopes, magnetometers, and barometers, provide navigation solutions without any dedicated infrastructure. However, the accuracy of the MEMS sensors' navigation solution will decrease with time due to the drift characteristic of MEMS sensors [4], [6], [7].

WiFi-based positioning is another potential technology for indoor navigation because it only uses pre-existing WiFi infrastructures. WiFi positioning error does not accumulate with time which makes it a potential source to aid the stand-alone navigation solution based on MEMS sensors [8]. Currently, there are two received signal strength (RSS)-based WiFi localization techniques: trilateration and fingerprinting [9]. Both of them require special databases to estimate the user position. In traditional approaches, professional surveyors are hired to build and maintain the databases. A radio map database is required for fingerprinting, where RSSs of available access points (AP) are mapped to absolute positions. Pre-survey is also needed to build the database of propagation parameters (PPs) and AP locations for trilateration. Pre-survey, a labour-intensive and time-consuming process, makes most current WiFi positioning systems (WPSs) impractical.

The purpose of this paper is to design automatic, practical, and accurate indoor WiFi positioning systems based on the cooperation of WiFi and MEMS sensors through crowdsourcing. It is expected that the cooperation of MEMS sensors and WiFi is an efficient way for indoor navigation applications. In this paper, we focus primarily on the implementation of WPSs on handheld devices because the pedestrian navigation services implemented on handheld devices are low-cost, user friendly, and do not require additional hardware. Furthermore, the WPSs are designed to eliminate the limitations of current crowdsourcing-based systems for indoor positioning, including the need for a floor plan or GPS, the suitability of only specific indoor environments, and the simple implementation of a MEMS-based navigation solution. To achieve this goal, two crowdsourcing-based WPSs are proposed in two schemes: trilateration and

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fingerprinting. In our proposed systems, Trusted Positioning Navigator (T-PN), a commercial software that converts inertial sensors into a navigation solution, is used to provide navigation information such as a timetag as well as position and its accuracy. This information is synchronized with WiFi information (SSID, MAC, and RSS) through timetags, and is used as the only inputs for crowdsourcing. Therefore, a floor plan or GPS is not necessary for the proposed systems. The T-PN solution is an advanced inertial sensor navigation solution based on motion constraints [10], mode detection [11], attitude tuning [12], [13], etc. It is more accurate than most inertial sensor solutions used in current crowdsourcing-based positioning systems. Furthermore, T-PN and the algorithms in our proposed systems do not rely on indoor environments. Therefore, our proposed system is more practical than some systems which only work well in specific indoor environments [14], [15].

In each proposed scheme, a background survey service is running on the operating system of the handheld devices to automatically build databases, and another positioning service is activated to provide a positioning solution for users. In the trilateration scheme, the background survey service estimates AP locations and PPs when there are enough pairs of the T-PN solution and corresponding RSS values to meet the preset requirements. Some algorithms are designed to build accurate databases for trilateration, which is made up of measurements optimization, nonlinear iterative least squares (LSQ), and LSQ results accessment. The aim of the measurements optimization is to denoise the measurements, and output the reliable measurements to build the database. A nonlinear iterative LSQ is designed to estimate AP locations and PPs using the measurements, and the LSQ results accessment removes unreasonable estimated results by judging several values as follows: reasonable PPs, reasonable AP location, and DOP (Dilution of Precision) value. AP locations, their accuracy, and PPs are stored and upated in the database for the future use of WiFi positioning. The database update happens automatically in the background, without any restriction on the user, thus making the crowdsourcing completely autonomous. By using the automatically surveyed database, the positioning service is mainly based on trilateration and positioning result optimization. In the fingerprinting scheme, the background pre-survey automatically builds the radio map database through crowdsourcing as long as the service is running in the background. Because the system does not guarantee that the radio map database contains all the fingerprints in the building, an improved positioning algorithm is designed in the proposed system.

The accuracies of both trilateration-based and fingerprinting-based databases will be improved through autonomous crowdsourcing when more T-PN/WiFi pairs are generated to update these databases. The performances of these two schemes are evaluated and compared using real-world tests. The results show that without the help of pre-surveys, a floor plan, or GPS, the average positioning errors of fingerprinting-based and trilateration-based WPSs in building E are 3.45 and 5.21 m, respectively. The data durations used for building the fingerprinting-based and trilateration-based WPSs through crowdsourcing are 85.41 and 22.95 minutes, respectively.

The main contributions of this paper are:

1. We propose two automatic and practical WPSs based on crowdsourcing. Our proposed methods eliminate the limitations of current crowdsourcing-based systems, such as the need of a floor plan or GPS, the suitability of only specific environments, and the implementation of only a simple MEMS-based navigation solution.
2. We propose the algorithms for background survey services on handheld devices to build databases through autonomous crowdsourcing for both trilateration and fingerprinting-based positioning systems. In both systems, background survey services are labour cost-free for building and maintaining the WiFi databases. Two improved WiFi positioning algorithms for positioning services are also proposed to match the automatically generated database and to improve the positioning accuracy.
3. Both proposed WPSs are implemented on handheld devices and evaluated by real-world experiments. The performance of two WPSs are also compared in this paper.

The remainder of this paper is organized as follows. Section 2 introduces the related work and Section 3 describes the overview of the proposed systems. Section 4 presents the T-PN solution. Section 5 describes and compares two proposed WPSs, and is followed by the evaluation of real-world experiments and discussions. Finally, Section 7 gives conclusions.

2 Related Work

2.1 Reduce the Labour for Building WiFi Databases

To make WiFi positioning more practical, much work has been done to reduce the labour-intensive and time-consuming task of building the databases for both trilateration [16], [17], [18] and fingerprinting [16], [19], [20], [21]. First, research based on fingerprinting is summarized. A system is proposed in [16] to reduce the cost of offline training by automatically collecting WiFi fingerprints with the help of vehicles equipped with GNSS receivers. This system is used for outdoors, and is not suitable for indoor applications. Another concept is discussed in [20] where by normal users, not professional surveyors, update fingerprints to the radio map. This is not an automatic system because it requires the active participation of users to update fingerprints. Based on an inertial sensors' solution, an automatic system is proposed in [19] for the offline training phase. The inertial sensor's navigation solution is based on the basic dead reckoning by using accelerometers and magnetometers and is therefore not as accurate and robust as the T-PN. Second, we summarize the algorithms for building the database containing AP locations for trilateration. In PlaceLab [16], AP locations are computed through the use of averaging and weighted averaging of positions derived from the measurement points collected through "war-driving". However, large estimation errors can result from measurement points with poor geometrical distribution. Research given in [22] and Skyhook [17] also use "war-driving" to collect AP locations. Another research provided in [18] estimates the path loss exponent and a constant parameter of the propagation model through rigorous testing. LSQ is then used to estimate AP locations. The challenge of this method is that the pre-surveyed parameters are not suitable for the estimation of AP locations when the environment has changed. A method proposed in [23] improves the accuracy of the AP location survey by using gradient information derived from RSS variations. Besides the large computation load, another drawback of this algorithm is that the gradient information derived from RSS variations is not reliable in indoor environments.

2.2 Crowdsourcing-Based Systems

Until now, several crowdsourcing-based systems have been proposed for indoor navigation [24], [25], [26], [14], [15]. The work in [24] proposes the EZ localization algorithm, which does not require any pre-deployment effort, infrastructure support, priori knowledge about WiFi APs, or active user participation. However, EZ's reliance on "occasional GPS fixes" in indoor environments could be problematic. Another research given in [25] proposes the "Zee" system which has zero-effort crowdsourcing for indoor locations. Zee requires a map showing the pathways and barriers to filter out infeasible locations over time and converge on the true location by using the idea that a user cannot walk through a wall or other barrier marked on the map. However, this map is not available in many real-world cases. Also, Zee uses magnetometers, rather than gyroscopes, for calculating the direction, which is usually affected by the indoor environment. Unlike the Zee, UnLoc, an unsupervised indoor localization scheme that bypasses the need for war-driving, is proposed in the work of [26]. The key idea of this paper is to improve the dead-reckoning-based sensor solution by using the seed landmarks and organic landmarks. A floor plan or GPS is required in this system to find the location of seed landmarks, such as stairs, elevators, entrances, and escalators. The location of seed landmarks could be questionable if a floor plan and GPS are not available. Another work in [14] presents the LiFS, an indoor localization system, which constructs the radio map with the help of a floor plan and sensors in modern mobile phones. The building of the radio map is easy and rapid since little human intervention is needed. LiFS works well in buildings where the corridor connects all other office rooms that are on both sides of the corridor. However, LiFS may fail in large open environments, where users' movements are difficult to analyze. Furthermore, similar to Zee, LiFS needs the floor plan to build the database, which may be not available sometimes. Unlike LiFS, [15] presents Walkie-Markie – a crowdsourcing-capable pathway mapping system that leverages ordinary pedestrians with their sensor-equipped mobile phones and builds indoor pathway maps without any a priori knowledge of the building. Central to Walkie-Markie is a novel exploitation of the WiFi infrastructure to define landmarks (WiFi-Marks) to fuse crowdsourced user trajectories obtained from inertial sensors on users' mobile phones. Walkie-Markie can provide accurate indoor localization results in narrow pathways. However, Walkie-Markie does not work well in wide pathways where WiFi-Mark detection and clustering will deteriorate if users walk arbitrarily.

While these crowdsourcing-based systems have made indoor positioning more practical than before, they still suffer from various limitations; mainly, the need for floor plans [25], [26], [14] or GPS [24], [26], are suitable only for specific indoor environments [14], [15], and only implement a simple MEMS-based sensor solution [25], [26], [14], [15]. On the other hand, our proposed systems eliminate these limitations. In the proposed systems, a floor plan or GPS is not necessary, and the systems work well in all indoor environments. An advanced sensor solution, T-PN, is also used in the proposed systems, which is based on motion constraints [10], mode detection [11], attitude tuning [12], [13] and more.

2.3 RSS-Based WiFi Positioning

Typically, there are two schemes for RSS-based user position estimation: trilateration and fingerprinting [9]. In the trilateration scheme, ranges between the user and WiFi APs are first determined by using a propagation model [27]. Interference, multipath fading and shadowing in the environment make it hard to build a reasonable propagation model [27]. In real-world environments, it is difficult to determine PPs in real-time and make them adaptive to the changes in the environment [16]. Another limitation of this scheme is that the AP locations need to be known beforehand for user position estimation. Fingerprinting is introduced in [28] for WiFi positioning by the use of radio map database, which includes off-line pre-survey and on-line location estimation. A main challenge of these positioning techniques is the variation of the RSS values caused by reflection and scattering in indoor environments [29]. Fingerprinting [28] has another limitation that the pre-survey is labour intensive. Besides these two methods, there are other methods such as Kalman Filter (KF) and extended Kalman Filter (EKF) to improve the accuracy of WiFi positioning [30], [31]. However, KF and EKF can slightly improve WiFi positioning at the cost of more computation.

2.4 WiFi SLAM

WiFi SLAM (simultaneous localization and mapping) is another group of algorithms [32], [33], [34], [35] for localization and WiFi information mapping (radio map and AP location). Researchers in [32] implemented a WiFi SLAM system by using the Gaussian Processes Latent Variables Model (GP-LVM). More specifically, a WiFi radio map was generated by using GP-LVM to extrapolate from the existing fingerprints. The result showed the mean error of user localization was about 4 m. However, this system is limited by its large computation load when processing large sets of data. Another WiFi SLAM algorithm is provided in [35], which builds the WiFi radio map based on GraphSLAM. The localization error of this system is about 2 m. The WiSLAM algorithm for improving FootSLAM with WiFi is provided in [33]. A drawback of this algorithm is that the path loss exponent is set to two when using the propagation model. Research in [34] proposes a smartSLAM scheme which contains Pedestrian Dead Reckoning (PDR), Fingerprint Extended Kalman Filter (FEKF), Fingerprint Extended Kalman Filter SLAM (FEKFSLAM) and Distributed Particle SLAM (DPSLAM). It also provides the process of building a WiFi radio map if it is not readily available. The large computation load of WiFi SLAM algorithms [32], [33], [34], [35]

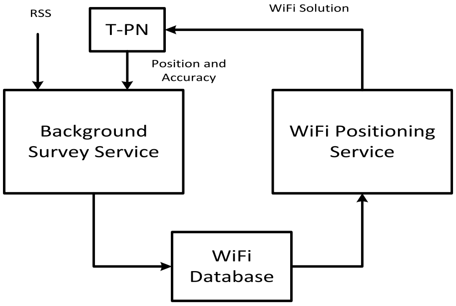


Fig. 1. System overview of automatic WPSs.

reduces the efficiency of microprocessors and increases battery consumption, which makes these algorithms unsuitable for implementation in handheld devices.

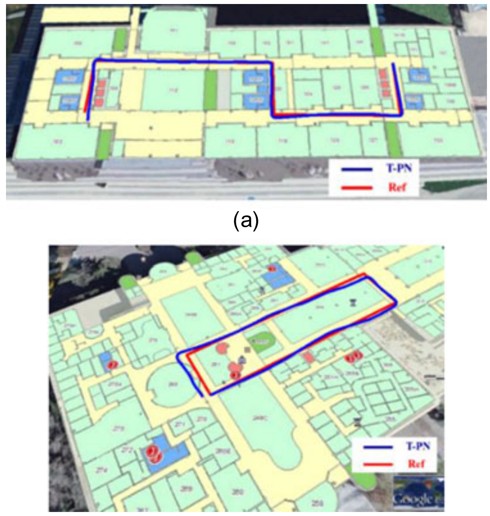
3 System Overview

Two WPSs based on autonomous crowdsourcing are proposed in this paper for handheld devices with the help of T-PN. Fig. 1 shows the same structure for both proposed systems, respectively based on fingerprinting and trilateration. In both systems, background survey service and WiFi positioning service are two significant services running on the handheld devices. RSS values and position information from T-PN are inputs for the background survey service. This service outputs the fingerprints or AP information (AP locations and PPs) to the WiFi database. Background survey service is mainly based on crowdsourcing, and reduces the labour consumption for the survey process. WiFi positioning service provides a WiFi position solution through improved algorithms based on trilateration or fingerprinting with the help of database. WiFi solution also can be used as an aiding source for T-PN to improve its performance. Fig. 1 shows the architecture of the proposed systems which are both automatic and practical. Details about these systems are described in Section 5.

4 T-PN Solution

The T-PN is a highly customizable software that converts any quality and grade of inertial sensors into navigation capable sensors and can be used on many of the available smartphone/tablet operating systems such as Android [10], [11], [12], [13], [36]. This engine improves the navigation results by taking any available absolute measurements as filter updates. Assisted-GPS (AGPS) is the most common type of external update that provides absolute position and velocity information to the inertial engine and limits the drift errors.

Physical movements of the user, such as pedestrian dead reckoning, zero velocity updates, and non holonomic constraints are used as constraints to improve the navigation solution [10]. The constraints are also tailored to user transit mode to ensure the most robust navigation solution for the user. Mode of transit is automatically detected on a continuous basis [11]. If additional sensors such as a magnetometer and barometer are present and properly calibrated, their readings can be used as optional updates for T-PN. Most of handheld devices today usually have both magnetometer and barometer. The T-PN provides 3D position, 3D velocity, and attitude of the system.



(a)

(b)

Fig. 2. Examples of the navigation solution from the T-PN with respect to reference. Building E is about 120 m $\times$ 40 m, and the west part of Building M is about 90 m $\times$ 70 m. (a) Building E. (b) Building M.

T-PN navigation solutions from two scenarios are shown in Fig. 2. The results show that the average error of T-PN in these two trajectories is about 2 m. Therefore, T-PN is a reliable position provider for WiFi database generation through autonomous crowdsourcing. T-PN also provides accuracy indicator for its navigation solution. This accuracy indicator is a significant factor in the proposed automatic database generation algorithms. T-PN is thought as useless if the accuracy indictor shows T-PN is inaccurate.

Some may ask why we need the WiFi positioning when the accurate inertial navigation solution, T-PN, is available. Our reasoning is as follows; when a good inertial navigation system is available, it may not drift very quickly. However, it still drifts. Therefore, it does not provide a long-time accurate indoor navigation solution. Thus, some wireless positioning systems (GPS or WiFi) are required to aid the inertial navigation system to achieve a long-time accurate indoor navigation solution. Since GPS is unavailable or inaccurate in indoor environments, a WiFi solution is needed to aid the inertial navigation in achieving an accurate indoor solution. The key idea behind this paper is that T-PN is used to automatically build the databases for WiFi through crowdsourcing when it is accurate, and when databases are successfully built, the WiFi solution is used to aid T-PN. Our proposed systems are cooperative systems based on T-PN and WiFi. The proposed systems can be used for long-time navigation in deep indoor environments where GPS is usually not available.

5 WPSs Based on Fingerprinting and Trilateration

Before designing algorithms for WPSs, we associate the T-PN solution with RSSs to build the database. T-PN is a real-time navigation solution which provides the position, velocity, and attitude, as well as their accuracies, at the same time by using the multi-sensors in the smartphone. We also obtain a WiFi time tag, the AP number, and information pertaining to each AP (MAC, SSID, and RSS) from the smartphone. Locations from the T-PN and RSS information are synchronized by using the T-PN time tag and the WiFi time tag. After the T-PN-based locations and RSS information are synchronized, we design algorithms to build databases for trilateration and fingerprinting through crowdsourcing. We also design algorithms for trilateration-based and fingerprinting-based positioning, and discuss the details in this section.

5.1 Measurements Optimization

For any WiFi based positioning, the first step usually records the signals before they are used for any positioning or navigation related applications. When analyzing preliminary results, we found that some APs with weak signals are not always recorded even when the user is standing still. Therefore, the response rate is introduced to evaluate the stability of AP signals. Our preliminary results show that APs with RSS values of greater than − 75 dBm provided a response rate of over 90 percent; APs with RSS values between − 75 and − 85 dBm provided a response rate of about 70 percent ; and APs with RSS of less than – 85 dBm provided a response rate of about 30 percent. If the user can stand at a specific location for a long time, this response rate can be used to determine the quantity and quality of the recorded fingerprint information. However, in this paper, measurements are collected by background services on handheld devices as mobile users go about their daily lives. A high response rate was used by setting the threshold to – 85 dBm to increase the number of RSS values in the fingerprint database to potentially increase the database reliability.

The fluctuation of RSS values also requires to be considered beyond the AP response rate. A three-point average is used to improve the reliability of RSS values. Current RSS value is redetermined by averaging previous RSS, current RSS and next RSS values. Of course, the averaging can improve the accuracy of measured RSS value if the user is static. If the user is walking, previous RSS and next RSS may be measured at different points from current RSS. However, previous RSS and next RSS are close to current RSS because they only have one epoch's difference. Previous and next measurement points are usually located at two opposite sides of current measurement point, and thus these RSS values are usually complementary. This is helpful as the WiFi measurements are highly noisy. Therefore, no matter whether the user is static or moving, averaging of three epochs' RSSs will remove some noise.

Position and RSS are collected as pairs to build the database in both background survey services for fingerprinting and trilateration. Position information from T-PN solution includes latitude, longitude and height (LLH) coordinates, and their accuracies. RSS values are read from the operating system running on the handheld devices. To optimize the measurements, algorithms are designed to detect and solve the RSS ambiguity problem (i.e. RSS values of two pairs are totally different, while LLH coordinates are almost the same). This ambiguity problem is mainly caused by the fluctuation of RSS values and the navigation errors of T-PN.

The RSS ambiguity problem is detected by using (1):

$$\begin{cases} (horizontal\_dis(\mathrm{LLH}_1, \mathrm{LLH}_2) \ < \ hor\_th) \\ \textbf{and}\,(height\_dis(\mathrm{LLH}_1, \mathrm{LLH}_2) \ < \ floor\_th) \\ \sigma_{h,1} \ < \ acc\_th\,\textbf{and}\,\sigma_{h,2} \ < \ acc\_th \\ \sigma_{a,1} \ < \ floor\_th\,\textbf{and}\,\sigma_{a,2} \ < \ floor\_th \\ \mathrm{E}[\mathrm{abs}(\mathrm{S}_1 - \mathrm{S}_2)] \ > \ \mathrm{RSS\_th}, \end{cases} \tag{1}$$

where, LLH_1 and LLH_2 represent the LLH coordinates of two pairs. $horizontal\_dis$ and $height\_dis$ represent the calculations of horizontal distance and height distance, respectively. hor_th and $floor\_th$ represent the horizontal and floor thresholds for determining whether coordinates of two pairs are almost the same. $\sigma_{h,1}$ and $\sigma_{h,2}$ represent horizontal accuracies of two pairs, while $\sigma_{a,1}$ and $\sigma_{a,2}$ represent the altitude accuracies of two pairs. acc_th and RSS_th are thresholds of horizontal accuracy and RSS. S_1 and S_2 are RSS vectors of available APs. $\mathrm{E}[\bullet]$ represents expectation. These thresholds will affect the performance of WPSs. Before discussing the setting of these thresholds, we first state how to appropriately set the grid spacing for the WPSs. If it is set too large, it decreases the accuracy of WiFi positioning. If it is set too small, it needs more data to build the database and uses more memory. In this paper, the grid spacing is set to a balanced value of 3 m, which is determined by experimentation. hor_th is set to the same as the grid spacing, and $floor\_th$ is set to a typical floor height (3 m). We set acc_th to 5 m, which is larger than the hor_th. We do not set it to a smaller value since more useful data can be used for building the databases through crowdsourcing. Also, it is not set to a larger value, in which case T-PN is not accurate enough to provide navigation solutions. RSS_th is set to 5 dBm, which is the standard deviation of RSS values in the static field tests. If the RSS ambiguity is detected, these two pairs will be replaced by a new pair given in (2):

$$T_{new} = \mathrm{E}[T_1, T_2], \tag{2}$$

where, $T_i = \{\,\mathrm{LLH_i} \quad \mathrm{S_i}\,\}$ represents the measurement pair which contains LLH coordinates, $\mathrm{LLH_i}$, and RSSs, $\mathrm{S_i}$. $\mathrm{E}[\,\bullet\,]$ represents the calculation of averaging. The detection and solution of RSS ambiguity problem improve the reliability of measurements. Note that the average of two tuples may not be the perfect way to solve the ambiguity problems, however, at the moment this seems sufficient for our needs. How to better solve the ambiguity problems will be one of our future work.

5.2 Fingerprinting-Based WPS

5.2.1 Background Survey Service

The flow chart of the background survey service is shown in Fig. 3. After the measurements optimization, fingerprints are used to record to or update the database. As previously discussed, the grid space is an important factor that affects the performance of WiFi positioning. By considering the normal walking speed of a user, an empirical grid space of 3 m is selected.

The tuple stored at each grid has the following form [37]:

$$T = \{\mathrm{LLH}, \sigma_h, \sigma_a, S\}, \tag{3}$$

where, LLH represents the latitude, longitude and height coordinates of the grid; σ_h and σ_a represent the horizontal and altitude positioning accuracy; and S is the RSS set received from the observable APs. LLH, σ_h, and σ_a are all provided by T-PN. S is stored as:

$$S = \{(SSID_1, MAC_1, RSS_1), \ldots, (SSID_k, MAC_k, RSS_k)\}, \tag{4}$$

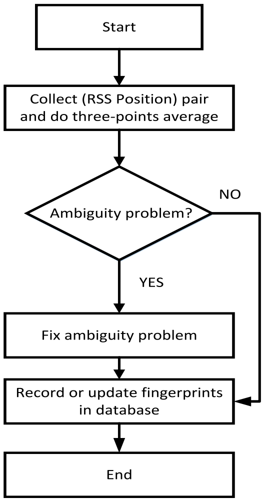


Fig. 3. Flow chart of background survey service of fingerprinting-based WPS.

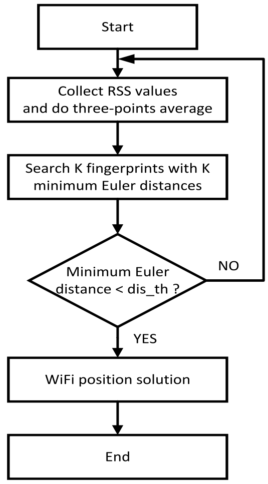


Fig. 5. Flow chart of WiFi positioning service of fingerprinting-based WPS.

where, $SSID$ and MAC represent the SSID name and MAC address of each AP. RSS represents the three-point averaged RSS vector. k represents the number of APs.

In the proposed system, fingerprint tuples are automatically saved, and if needed can be uploaded to the database through the background survey service. This crowdsourcing-based system requires no active participation of the user, which is a substantial improvement over the existing expert survey systems. Autonomous crowdsourcing ensures the creation and maintenance of radio map database efficiently. RSS values and corresponding positioning solutions from T-PN are collected as measurements automatically by the background service during users' daily routines in the proposed approach. An example for radio map database generation from user daily trajectories is shown Fig. 4. When more and more measurements are collected and updated to the radio map database, the database becomes increasingly accurate through autonomous crowdsourcing without additional operations.

5.2.2 WiFi Positioning Service

In the proposed system, user position can be calculated by using the RSS radio map database. The position of the mobile user is adjusted to the average position of the closest K matching fingerprints with K minimum Euler distances on the radio map database, as shown in Fig. 5. However, the system does not guarantee that the radio map database contains all the fingerprints in the building. Therefore, the smallest Euler distance should be less than a threshold "dis_th" to ensure the positioning result is reliable. When the WiFi position is calculated, it can be used to aid T-PN to improve the accuracy of the user's position estimation.

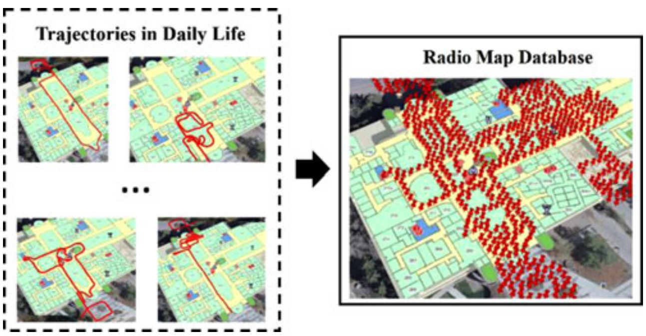


Fig. 4. An example of radio map database generation from several trajectories through the background survey service.

5.3 Trilateration-Based WPS

5.3.1 Background Survey Service

In trilateration-based WPS, there are AP locations and PPs in the database. Therefore, the goal of background survey service is to estimate AP locations and PPs, and store the information to the database as shown in Fig. 6. The RSS values and position solution from the T-PN are collected as pairs. Next, position information converts from LLH coordinates to east, north, and up (ENU) coordinates, and paired with the corresponding RSS values. Finally, the RSS ambiguity problem is checked and fixed as discussed in Section 5.1. Nonlinear iterative LSQ is used for estimation of the AP location, PPs, and their accuracies if multiple measurements from the same APs are collected. There are several criteria to check the computed results and will be discussed in this section. If the computed results are reasonable, and no information about this AP is found in the database, this AP information from LSQ results are recorded in the database. In case the AP information is already present in the database, the computed results are used to update AP information in the database.

First, the estimation for AP locations and PPs is based on iterative nonlinear LSQ using RSS values as observations with the position information from T-PN. In the design of LSQ, the state vector to estimate AP locations (x_0 and y_0) and PPs (n and A) is $\mathbf{x} = [x_0, y_0, n, A]^T$, while the measurement vector is $\mathbf{z} = \mathbf{RSS}$.

The typical path loss model follows the distance power law:

$$P_r = P_0 - 10nlog_{10}(d/l_0) + X_\sigma, \tag{5}$$

where, P_r is the RSS value received at the receiver in dBm at a distance d from the transmitter, P_0 is the RSS value with distance l_0 from the transmitter, n is the path loss exponent

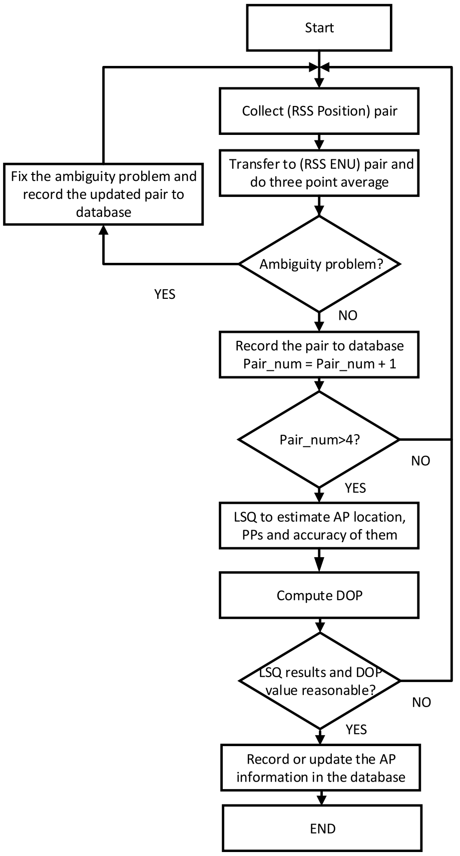


Fig. 6. Flow chart of background survey service of trilateration-based WPS.

with typical values in the range of $2\sim 6$ indoors and X_σ represents the shadow noise which is modeled as a Gaussian random variable with zero mean. Note that there are other propagation models that consider the effect of walls and floors [28], [38]. However, they are not suitable for real-time AP localizations because a priori information of walls and floors are usually unavailable.

Equation (5) can be simplified by averaging as follows:

$$RSS = -10n\ log_{10}(d) - A, \tag{6}$$

where, $A = -mean(P_0(l_0 = 1m))$ represents a constant which depends on several factors: averaged fast and slow fading, transmitter gain, receiver gain, and transmitted power [39]. d represents the distance between AP and the measurement point. Through rewriting (6), the nonlinear observation model using LSQ is provided in (7),

$$\mathbf{RSS} = -10nlog_{10}(\sqrt{(x_0 - \mathbf{x_u})^2 + (y_0 - \mathbf{y_u})^2}) - A + \mathbf{v}, \tag{7}$$

where, $\mathbf{RSS} = [RSS_1, RSS_2, \dots, RSS_k]^T$ is an RSS vector for k measurement points. $\mathbf{x_u} = [x_1, x_2, \dots, x_k]^T$ and $\mathbf{y_u} = [y_1, y_2, \dots, y_k]^T$. $\mathbf{v}$ is the measurement error vector. The initial $\hat{\mathbf{x}} = [mean(\mathbf{x_u}), mean(\mathbf{y_u}), 3, 35]^T$ with 3 and 35 as the typical values for "n" and "A" in indoor environments. Measurement point coordinates (x_i, y_i) can be obtained from T-PN. The equation of mathematical model can be obtained as follows:

$$h(\mathbf{x}) = -10nlog_{10}(\sqrt{(x_0 - \mathbf{x_u})^2 + (y_0 - \mathbf{y_u})^2}) - A. \tag{8}$$

The derivative of (8) is the design matrix and it is provided below:

$$\mathbf{H} = \frac{dh(\mathbf{x})}{d\mathbf{x}} = \begin{pmatrix} \frac{-10n(x_0 - x_{u_1})}{d_1^2 ln10}, \dots, \frac{-10n(x_0 - x_{u_k})}{d_k^2 ln10} \\ \frac{-10n(y_0 - y_{u_1})}{d_1^2 ln10}, \dots, \frac{-10n(y_0 - y_{u_k})}{d_k^2 ln10} \\ -10\log_{10}(d_1), \dots, -10\log_{10}(d_k) \\ -1, \dots, -1 \end{pmatrix}. \tag{9}$$

$\mathbf{Q_R}$ is a diagonal matrix because the RSS values are independent for all the measurements, and is given by:

$$\mathbf{Q_R} = diag(Q_{R,11}, Q_{R,22}, \dots, Q_{R,_kk})^T. \tag{10}$$

$\mathbf{Q_R}$ is an identity matrix if the weights are equal and the algorithm is called simple LSQ. On the other hand, if the weights are not equal, the algorithm is called weighed LSQ. In this case, RSS values can be used as weights for the measurement variances as given in (11):

$$R_{ii} = RSS_i/sum(RSS_i), i = 1, 2, \dots k. \tag{11}$$

The solution of the nonlinear LSQ is given by [6]:

$$\begin{aligned} \delta\hat{\mathbf{x}} &= (\mathbf{H}^T\mathbf{Q_R}^{-1}\mathbf{H})^{-1}\mathbf{H}^T\mathbf{Q_R}^{-1}\delta\mathbf{z}, \\ C_{\delta\hat{\mathbf{x}}} &= \sigma_0^2(\mathbf{H}^T\mathbf{Q_R}^{-1}\mathbf{H})^{-1}. \end{aligned} \tag{12}$$

The new state vector is calculated as

$$\hat{\mathbf{x}}_{\mathbf{updated}} = \hat{\mathbf{x}} + \delta\hat{\mathbf{x}}, \tag{13}$$

where, $\delta\mathbf{z}$ represents a measurement misclosure vector. σ_0^2 is a priori variance factor, and is usually set as an empirical value. It is an iterative process until $|\delta\hat{\mathbf{x}}| < threshold$.

To improve the estimation performance for AP locations and PPs, it is important to ensure that the algorithm is converged and several terms, listed below, are checked for their convergence: 1) Path loss exponent "n"; 2) Constant value "A"; 3) Reasonable AP location; and 4) DOP value. Typical ranges of path loss exponent "n" and constant "A" in the propagation model are $2\sim 6$ and $0 \sim 100$. The estimation result is ignored if it is not located in these typical ranges. According to typical propagation models and real-world tests, AP always stays within 200 m of the WiFi measurement point. Therefore, estimation results are ignored and deemed unreliable if the estimated AP location is far away from the measurement points. The last value needs to be evaluated is the DOP value of the measurements, which are used for LSQ computation. The ith state of DOP [40] is given in

$$i\text{DOP} = \sqrt{(\mathbf{Q_P})_{ii}}, \tag{14}$$

where, $(\mathbf{Q_P})_{ii}$ represents the element in the ith row, ith column of a matrix and $\mathbf{Q_P}$ is calculated by

$$\mathbf{Q_P} = (\mathbf{H}^T\mathbf{Q_R}^{-1}\mathbf{H})^{-1}, \tag{15}$$

where, $\mathbf{H}$ and $\mathbf{Q_R}$ are design matrix and cofactor matrix of R. For the details of DOP calculation and application, please refer to [40], [41], [42]. Similar applications of DOPs for WiFi positioning are given in [18], [43]. In this paper, estimated results for AP locations and PPs are used only when DOP values are less than the pre-set threshold of 4.0.

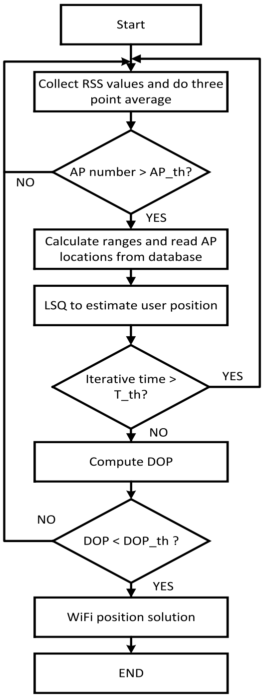


Fig. 7. Flow chart of WiFi positioning service of trilateration-based WPS.

In this paper, the autonomous crowdsourcing-based approach is developed to reduce the cost of building and maintaining the database. Background survey service collects RSS values and corresponding T-PN solutions as measurements by the use of handheld devices during users' daily routines in the proposed approach. When measurements are enough, they are used to automatically estimate the AP locations and PPs. And, estimation results are updated to the database in the background service. Crowdsourcing keeps the AP information in the database (locations and PPs) accurate for the future positioning usage.

5.3.2 WiFi Positioning Service

The flow chart of trilateration-based WiFi positioning service is shown in Fig. 7. In trilateration-based system, iterative nonlinear LSQ is used for WiFi positioning if the AP number is larger than the threshold "AP_th". AP locations and ranges between the user and APs are necessary information for user position estimation. AP locations are obtained from background survey service, as we discussed in in Section 5.3.1. The ranges are calculated by substituting the real-time collected RSS values to (6), whose parameters are from the automatically generated database. To estimate user position (x_u and y_u), the state vector is set to $\mathbf{x} = [x_u, y_u]^T$. The height is not estimated in the state vector because it is inaccurate indoors in the absence of a barometer. The measurement vector $\mathbf{z}$ is the range between user and APs ($\mathbf{z} = \mathbf{range}$), which is calculated using propagation model. The nonlinear observation model is provided as:

$$\mathbf{range} = \sqrt{(x_{user} - \mathbf{x}_{AP})^2 + (y_{user} - \mathbf{y}_{AP})^2} + \mathbf{v}, \tag{16}$$

where, $\mathbf{range} = [range_1, range_2, \ldots, range_k]^T$ is a range vector for k measurement points. $\mathbf{x}_{AP} = [x_{AP1}, x_{AP2}, \ldots, x_{APk}]^T$ and $\mathbf{y}_{AP} = [y_{AP1}, y_{AP2}, \ldots, y_{APk}]^T$ are the vectors of AP locations. $\hat{\mathbf{x}} = [mean(\mathbf{x}_{AP}), mean(\mathbf{y}_{AP})]^T$ is set as the initial value for iterative LSQ. Then, mathematical model and the design matrix are given in (17) and (18):

$$h(\mathbf{x}) = \sqrt{(x_{user} - \mathbf{x}_{AP})^2 + (y_{user} - \mathbf{y}_{AP})^2}, \tag{17}$$

$$H = \frac{dh(\mathbf{x})}{d\mathbf{x}} = \begin{pmatrix} \frac{-(x_{user}-x_{AP1})}{RANGE_1} & \cdots & \frac{-(x_{user}-x_{APk})}{RANGE_k} \\ \frac{-(y_{user}-y_{AP1})}{RANGE_1} & \cdots & \frac{-(y_{user}-y_{APk})}{RANGE_k} \end{pmatrix}, \tag{18}$$

where, $RANGE_1$, $RANGE_2$, ...,$RANGE_k$ are the elements in the vector $\mathbf{RANGE} = [RANGE_1, RANGE_2, \ldots, RANGE_k]^T$, which is given as:

$$\mathbf{RANGE} = \sqrt{(x_{user} - \mathbf{x}_{AP})^2 + (y_{user} - \mathbf{y}_{AP})^2}. \tag{19}$$

Cofactor matrix $\mathbf{Q_R}$ for WiFi positioning is given by:

$$\mathbf{Q_R} = diag(Q_{R,11}, Q_{R,22}, \ldots, Q_{R,kk})^T. \tag{20}$$

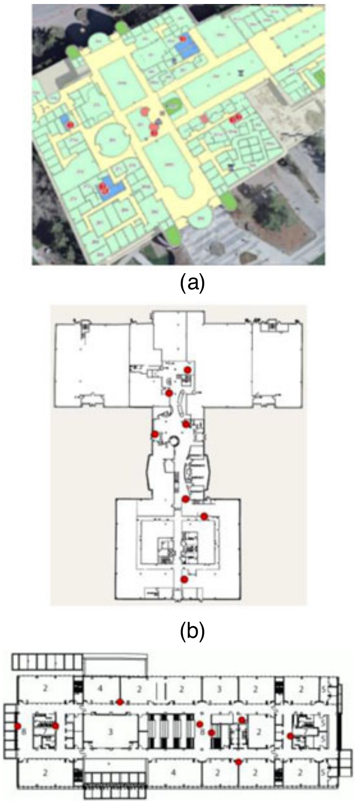
The setting of $\mathbf{Q_R}$ is from the estimated accuracies of AP locations in the database. After the design, WiFi positioning result is calculated by LSQ. Next, there are some criteria that should be met to ensure improved performance of WiFi positioning. First of all, the number of observed APs must be over a minimum number to ensure the accuracy of WiFi positioning system. Next criterion is the DOP value requirement, which should be less than a threshold to make sure the distribution of the measurements are appropriate. Finally, if the iterative time goes beyond a pre-set threshold, the algorithm will stop LSQ, and process the data for the next epoch. All the thresholds stated here are set by experimental tests.

5.3 Comparison of Two WPSs

Two proposed automatic systems are compared in this Section. There are several differences between these two systems. First, accuracy of trilateration-based WPS relies on the propagation model, which is affected by several factors such as multipath and fading characteristics. Fingerprinting-based WPS calculates user position based on fingerprint matching, which is less affected by multipath and fading characteristics. Second, a radio map database, typically, has more data than database for trilateration in the same area, which means that a radio map database costs more memory. Third, building and maintenance of a radio map database consumes more time and labour than a trilateration-based database.

6 Results and Discussions

To evaluate the performance of the proposed systems in real-world environments, we implemented the algorithms as background survey services and WiFi positioning services on Android-based handheld devices (Samsung Galaxy SIII smartphone and Google Nexus 7 tablet). For evaluations, we selected three sites which had different environments. As shown in Fig. 8a, the first experimental site was



(a)

(b)

(c)

Fig. 8. Experimental area. (a) Building M. (b) Building A (red circles = APs). (c) Building E (red circles = APs).

(a) (b) (c)

Fig. 9. Radio map database in building M by using different number of trajectories. (a) Use six trajectories. (b) Use 12 trajectories. (c) Use 16 trajectories.

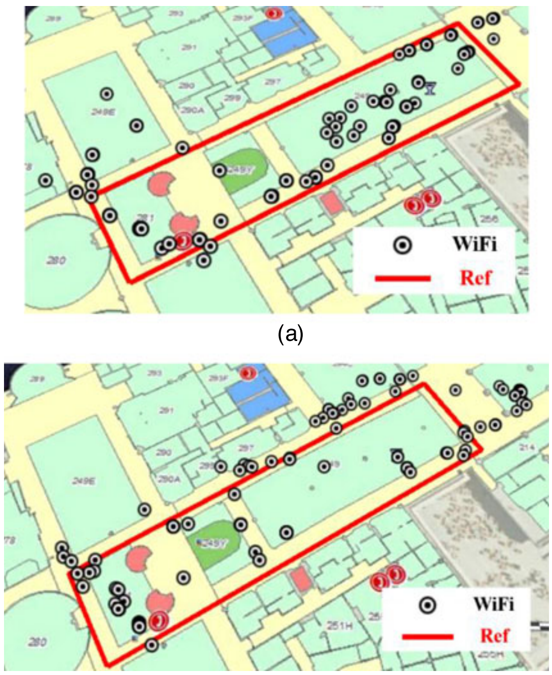
the west area (about 90 m × 70 m) of Building M. The second experimental site was building A (about 100 m × 70 m), with seven location-known APs as shown in Fig. 8b. Building E (about 120 m × 40 m) with eight location-known APs was chosen as the third testing site, as shown in Fig. 8c. Note that there are more APs in building A and building E, but they were not used for assessing the performance of AP localization. However, their locations and PPs are also estimated and recorded to the database for the usage of WiFi positioning.

Three groups of experiments were carried out for the evaluation and comparison of the performance of proposed systems. First group of experiments was carried out to evaluate the performance of fingerprinting-based automatic WPS in building M. Second, the performance of trilateration-based automatic WPS is validated in building A. Last, we compare the performance of both WPSs in building E.

6.1 Validation of Fingerprinting-Based WPS

In this section, the performance of two services based on fingerprinting (background survey service and positioning service) is validated. To simulate the crowdsourcing in daily life, the tester went to building M to collect sixteen trajectories by using the background survey service. The durations of these trajectories are between 106 and 346 seconds, and most of them are around 300 seconds. These trajectories are distributed in most accessible areas of the west section of the building M. The radio map database is also automatically built and updated at the same time. Fig. 9 shows the generated radio map database by using different numbers of trajectories from the user's daily life by the use of the handheld device. Figs. 9a, 9b, and 9c show the radio map database in building M generated from six, 12, and 16 trajectories. It shows that more fingerprints are collected in the database when more trajectories are collected by the background service to generate the database. Through the WiFi positioning results, which will be discussed next, the performance of WiFi positioning also becomes better when using the radio map database generated from more trajectories.

WiFi positioning results based on the automatically generated radio maps are shown in Fig. 10. Table 1 also depicts the statistical numbers of the WiFi positioning results in building M. Through the figure and the table, we found that the WiFi positioning accuracy improves as more trajectories are collected for generating the radio map database. The table shows that the mean, root mean square (RMS), 80 percent (i.e., error within which the probability is 80 percent), and maximum value of positioning errors are 5.11, 5.74, 7.47, and 23.49 m, respectively when using the maximum number of available trajectories (16) for building the radio map database. Fig. 11 shows the error probabilities for WiFi positioning in building A, achieved by using different radio map



(a)

(b)

Fig. 10 WiFi positioning results of rectangle trajectory in building M by using different radio map database. (a) By the use the radio map database built from six trajectories. (b) By the use the radio map database built from 16 trajectories.

TABLE 1
WiFi Positioning Result Based on Different Radio Map Databases in Building M

Number of Trajectories for Radio Map	WiFi Positioning Error (m)			
	Mean	RMS	80%	Max
6	9.46	10.69	12.46	44.38
12	6.42	7.45	8.70	21.64
16	5.11	5.74	7.47	23.49

databases. It also supports that using more trajectories for building the database improved WiFi positioning accuracy.

6.2 Validation of Trilateration-Based WPS

The performance of two services based on trilateration (background survey service and positioning service) are validated in this section. To simulate crowdsourcing in daily life, the tester went to building A four times to collect trajectories by using the background survey service as shown in Fig. 12. AP locations and PPs is estimated, and used for building and updating the database.

Experimental results of AP localization and PPs estimation in Building A are shown in Fig. 13. The estimated and true locations of APs are shown in Fig. 13a. The estimation result is calculated by nonlinear LSQ, and its accuracy mainly depends on the fluctuation of RSS signals, accuracy of T-PN solutions and the geometrical distribution of measurements. It shows that estimated AP locations are close to the true values; this supports the efficiency of the proposed system in Fig. 13a. In Fig. 13b, the estimated path loss exponent “n” and constant “A” are located in the range of typical values. In Fig. 13c, estimated AP localization error is close to the true value. Therefore, the estimated AP localization error is an efficient parameter to evaluate the performance of AP localization. It is also recorded to the database, and used as an indicator for the accuracy of AP locations.

Table 2 depicts the trend that the accuracy of AP localization is improved along with increased RSS and T-PN pairs, which demonstrates the efficiency of crowdsourcing for AP localization. In Table 2, “AP Localization Error” represents the difference between estimated AP location and true value. “Accuracy Estimation Error” equals to the difference between estimated AP location error and true AP location error, which is used to determine whether estimated AP location error is an efficient indicator for the accuracy of AP

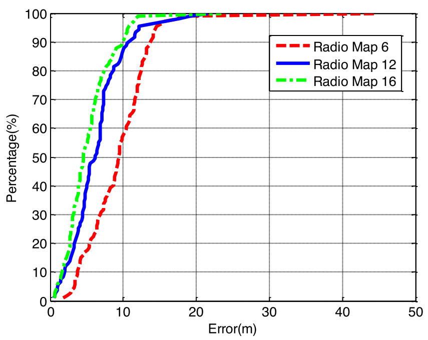


Fig. 11. Cumulative distribution function (CDF) of WiFi positioning by using different radio map databases in building M.

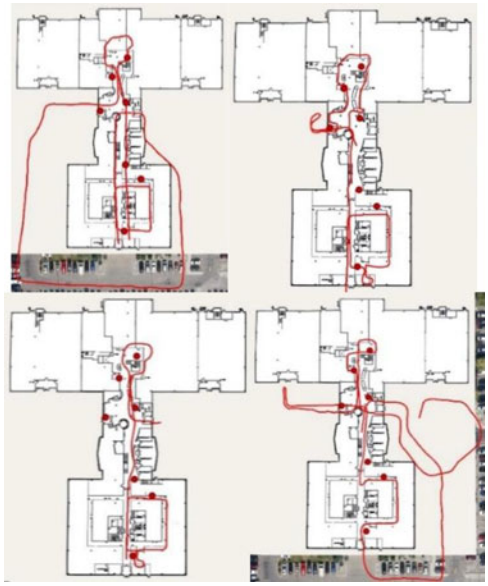


Fig. 12. Four T-PN trajectories used for AP localization and PPs estimation in Building A.

localization. Table 2 shows that the “AP Localization Error” and “Accuracy Estimation Error” decrease as the number of trajectories increase. However, this does not apply if the measurement error of a trajectory is larger which was the case of “Trajectory 4” where “AP Localization Error” showed an increase.

As shown in Fig. 14, two trajectories estimated by the use of trilateration-based WiFi positioning are close to the reference trajectories, which further support the efficiency of the proposed system. Table 3 shows that mean, RMS, 80 percent, and maximum value of WiFi positioning errors and accuracy estimation error in building A. In Table 3, average WiFi positioning errors in different trajectories are all less than 5.8 m. The results also show that accurate positioning solution is possible without heavy costs for pre-surveys. “Accuracy Estimation Error” in Table 3 equals to the difference between estimated WiFi positioning error and true WiFi positioning error, which is used to determine whether estimated WiFi positioning error is an efficient indicator for the accuracy of WiFi positioning. “Accuracy Estimation Error” in different trajectories are all less than 3.1 m in Table 3. Therefore, it can be concluded that estimated positioning accuracy is representative of the positioning performance of the proposed system. Fig. 15 shows that the error probabilities for WiFi positioning and accuracy estimation of the two trajectories in building A, which also clearly shows the performance of the proposed system.

6.3 Performance Comparison of Both WPSs

Experiments were made in building E to compare the performance of both WPSs. In the fingerprinting-based background survey service, 20 trajectories (Total data time: 85.41 minutes) were collected to build the radio map database to cover most of the area of building E. In the trilateration-based background survey service, six trajectories (Total data time: 22.95 minutes) were collected to get about 5 m average error of AP locations in the database of building E. Five different trajectories were selected to compare

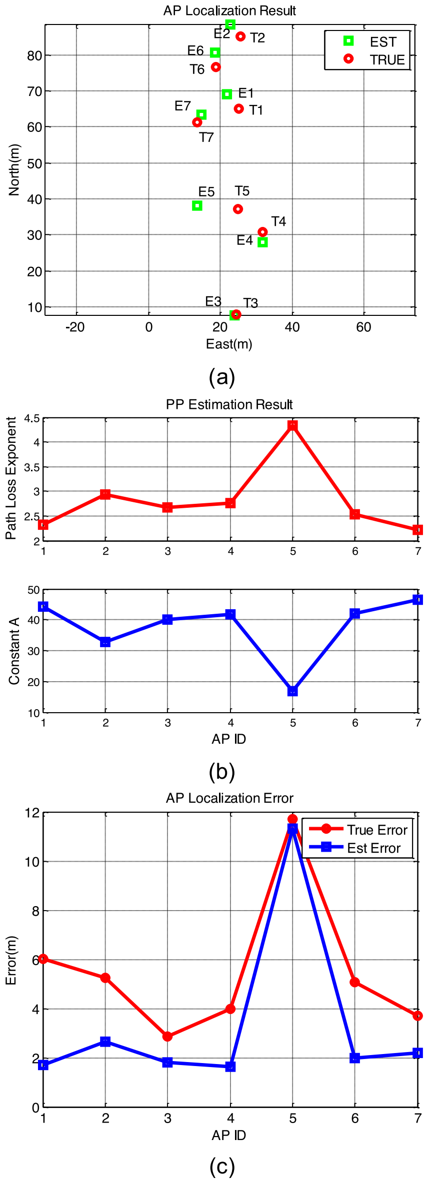


Fig. 13. Results of AP localization and PPs estimation in building A. (a) Result of AP localization. (b) Result of PPs estimation. (c) Estimated and true accuracy of AP localization.

positioning performance of two systems. As an example, Fig. 16 shows the performance of two systems in the first trajectory. The summary of positioning results of all five trajectories is shown in Table 4. Fig. 17 shows that the error probabilities of all five trajectories in building E, achieved

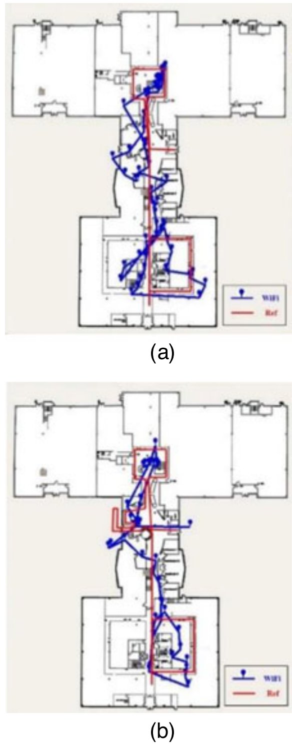


Fig. 14. Trilateration-based WiFi positioning results of two trajectories in building A by using automatically generated database. (a) Trajectory I. (b) Trajectory II.

by using two proposed systems. In Table 4 and Fig. 17, it appears that the fingerprinting-based system has better positioning performance than trilateration in all five trajectories. Table 5 compare the results of two systems, which include average positioning error, memory of database, and total data time. As shown in Table 5, the average positioning error of the fingerprinting-based system is about 1.8 m less than the trilateration method. Memory cost for the radio map database is about seven times of the trilateration database. And, the total data used to build the radio map database is about four times the data for building the trilateration database. Overall, fingerprinting-based WPS provides a more accurate positioning solution at the cost of more labour and memory for the database.

7 Conclusion

The main contribution of the paper is to propose two crowdsourcing-based WPSs, which eliminate various limitations of current crowdsourcing-based systems that need a

TABLE 2
AP Localization Results Using Different Number of Trajectories in Building A

Number of Trajectories	Number of Estimated APs	AP Localization Error (m)		Accuracy Estimation Error (m)	
		MEAN	RMS	MEAN	RMS
1	7	6.34	6.65	3.33	4.17
2	7	5.72	5.89	2.85	3.15
3	7	5.27	5.47	2.68	2.94
4	7	5.51	6.14	2.18	2.50

TABLE 3
Performance of WiFi Positioning in Building A

Trajectory		I	II
WiFi Positioning Error (m)	Mean	5.73	5.34
	RMS	7.39	5.98
	80%	6.60	7.62
	Max	28.29	11.79
Accuracy Estimation Error (m)	Mean	3.02	2.24
	RMS	4.72	2.78
	80%	3.58	3.75
	Max	22.57	6.96

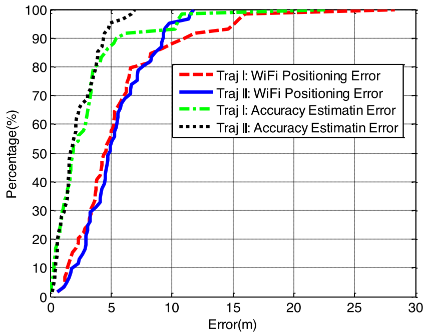
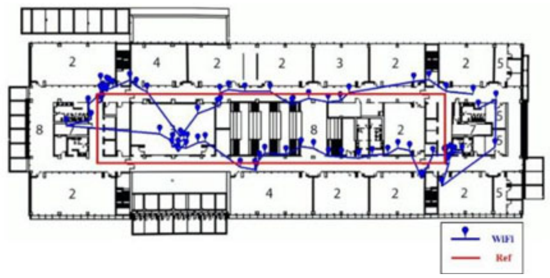


Fig. 15. CDF of WiFi positioning and accuracy estimation in building A.

(a)



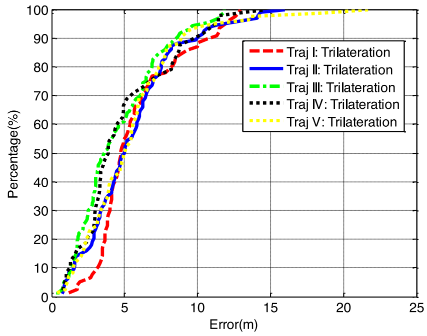
(b)

Fig. 16. The first trajectory (Rectangle) for performance comparison of WiFi positioning. (a) Fingerprinting-based WiFi positioning service. (b) Trilateration-based WiFi positioning service.

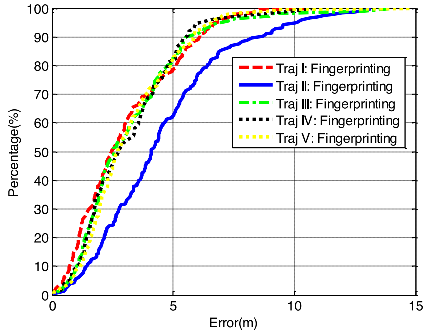
TABLE 4
Positioning Performance Comparison of Two Systems in Building E

Positioning Error \ Trajectory		I	II	III	IV	V
Trilateration(m)	Mean	5.78	5.44	4.49	4.95	5.41
	RMS	6.46	6.34	5.32	5.92	6.48
	80%	8.30	7.50	6.86	8.22	7.37
	Max	12.91	15.99	11.85	14.63	21.69
Fingerprinting (m)	Mean	3.24	4.55	3.03	3.21	3.22
	RMS	3.99	4.92	3.70	3.79	3.80
	80%	5.14	6.41	4.76	4.75	4.89
	Max	10.74	13.14	13.92	10.74	14.80

floor plan or GPS, are suitable only for specific indoor environments, and use a simple implementation for MEMS sensors' solution. These two systems are based on fingerprinting and trilateration schemes. Both systems contain a background survey service and WiFi positioning service. Normal handheld-device-users use the background survey service, based on autonomous crowdsourcing to build and maintain the databases. It is automatic and the survey process is virtually labour-free, which is also a contribution of



(a)



(b)

Fig. 17. CDF of WiFi positioning in building E. (a) Trilateration. (b) Fingerprinting.

TABLE 5
Comparison Results of Two Systems in Building E

	Fingerprinting	Trilateration
Average Position Error (m)	3.45	5.21
Memory of Database (byte)	690,188	10,300
Total Data Time (min)	85.41	22.95

this work. Another contribution of the work is to compare the performance of these two WPSs.

In the fingerprinting-based WPS, a method to automatically generate fingerprints is presented based on the proposed background service and the T-PN, which run on handheld devices. The fingerprints are collected to build the radio map database after specific selection and updating algorithms of the survey service. Next, fingerprinting-based WiFi positioning is discussed, and its performance is evaluated through real-world tests. The results show that average WiFi positioning errors is about 5.1 m in building M, which demonstrate the efficiency of the automatic fingerprinting-based WPS.

In the trilateration-based WPS, a novel crowdsourcing method for automatic AP localization and PPs' estimation based on the inertial navigation solution from the T-PN is introduced. The method is user friendly and robust to the changing indoor environments because the database can update continuously, through the background survey service, without any special survey costs. Results of field tests support the efficiency of building and maintaining database through the estimates of AP locations and PPs, and autonomous crowdsourcing. Experimental results show that the average estimation error of AP localization is about 5.5 m. Trilateration-based positioning algorithms include two parts: LSQ estimation for user position and optimization of the estimated results. Results show that the average positioning errors in two trajectories are all less than 5.8 m in building A.

Two different WPSs are also compared in this paper. Typically, it is easier to survey the database for trilateration than fingerprinting, which is also proved by the experiments. The fingerpinting database usually costs more memory than the trilateration database for the same area. Field test results show that a fingerprinting-based system has better positioning performance than trilateration. Overall, both systems based on crowdsourcing of handheld devices, without special hardware, are automatic and practical, and can provide accurate positioning solutions in indoors.

Acknowledgments

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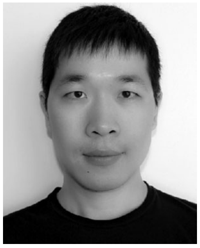

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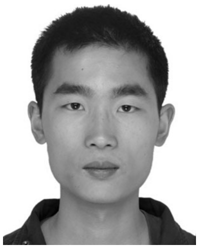

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