Fast WiFi Access Point Localization and Autonomous Crowdsourcing

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Abstract—The locations of WiFi access points (APs) are important for WiFi positioning, especially when a propagation model is used. However, AP localization is usually challenging in a new environment because it is hard to obtain parameters for the propagation model, such as the path-loss exponent without the presence of surveyed database. This paper introduces a novel crowdsourcing method for automatic AP localization and propagation parameters (PPs) estimation based on the navigation solution from the Trusted Portable Navigator (T-PN). The estimation for PPs and AP locations based on non-linear weighted least squares (LSQ) is carried out automatically when enough measurements are collected, and the results are recorded in the database for future use. The fast estimation method calculates the propagation parameters autonomously and adaptively to account for the dynamic indoor environment. The autonomous system will also reduce the labour and time costs for the pre-survey and maintenance of databases, as the crowdsourcing is always done in background processes on devices. The accuracy of AP localization is also estimated and recorded in the database, providing an important indicator when using the AP localization results. The performance of the proposed system is evaluated by both simulations and field tests, and the result shows that the average AP localization errors are less than 6 meters.

Keywords—Access points localization; propagation parameters; crowdsourcing; least squares; WiFi; smartphone

I. INTRODUCTION

The increasing deployment of IEEE 802.11 WLAN (WiFi: Wireless Fidelity) in indoor premises such as offices, schools, hospitals, homes, malls and airports, makes it possible to use WiFi signals for positioning in places where GNSS is usually unavailable or unreliable. However, WiFi positioning is challenging due to complex indoor wireless signal propagation characteristics, unknown access points’ (AP) locations and a lack of propagation models. Propagation-model-based WiFi positioning systems usually assume that AP locations and propagation parameters (PPs) are available from offline site surveys. Even if this a priori information is available, it may not be useful for real-time WiFi positioning due to the changing indoor environment which can be introduced by several factors such as: 1) removal or addition of WiFi APs, or 2) temporary loss of signals from one or more APs. Therefore, fast and automatic estimation of the AP locations and PPs is an effective way to ensure accurate WiFi positioning. An autonomous crowdsourcing system will also eliminate the requirements of offline site surveys and the maintenance of the database.

Researches have been done for AP localization and PPs estimation based on the propagation model. Averages and weighted averages of the positions of the measurement points are used to compute the AP locations in [1]. Obviously, a large positioning error will be produced if the measurement points are located with a bad geometrical distribution. The ‘multilateration’ approach for AP localization is introduced in [2] [3] [4]. The distances among the unknown AP and known APs are required to calculate the unknown AP’s location [2]. However, it is hard to know the distances a priori. The approach provided in [3] linearly approximates the exponential relationship between the received signal strength (RSS) and the distance. Then, the multilateration is applied to estimate the AP locations. This approach estimates the AP locations without the requirement of knowing the path-loss exponent. Nevertheless, the linearization error probably causes the result of this approach to be inaccurate. Reference [4] proposes a method for AP localization which estimates and saves the path-loss exponent and the constant parameter in the propagation model with extensive tests and uses the least squares (LSQ) to estimate the AP locations. Note that previously saved PPs may not be suitable for the estimation of AP locations due to the changing indoor environment.

AP locations are obtained by using the gradient information derived from RSS variations in [5]. The main drawback is that the gradient information derived from RSS variations is not reliable indoors. Additionally, this method has a large computation load. Another system for estimating the AP locations and PPs is proposed in [6] based on iterative reweighted LSQ (equivalent to the Gauss-Newton method). However, note that a tablet computer is used to collect the RSSs, and the measurement points are set manually on the floor plan figure. It is important to note that none of the above methods are capable of automatically estimating AP locations and PPs.
In this paper, a novel and autonomous crowdsourcing method is introduced for AP localization, based on the navigation solution from T-PN. The T-PN is a highly customizable software that converts any quality and grade of inertial sensors into navigation capable sensors. T-PN determines the 3D position, velocity and attitude of the system, and can be used on many available smartphone/tablet operating systems such as Android [7] [8] [9] [10].

This engine improves the navigation results by taking any available absolute measurements, such as the Assisted Global Positioning System (AGPS) as filter updates [11]. Similar to other sensor-based navigation solutions, navigation error of T-PN solution increases with time and therefore, other aiding sources, such as GPS and WiFi, are required to reduce the navigation error due to drift. 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. In addition to AGPS and inertial sensors, many handheld devices now have magnetometers and/or barometer. If these additional sensors are present and properly calibrated, their readings can be used as optional updates by the T-PN to improve the solution.

Beyond the use of all available sensors, physical movements of the user, such as pedestrian dead reckoning, zero velocity updates and non-holonomic constraints are used as constraints to further improve the navigation solution. These constraints are also tailored to user transit mode to ensure the most robust navigation solution for the user. The user transit mode is automatically detected on a continuous basis.

In our proposed algorithm, T-PN solution is used to estimate the AP locations and PPs only when the T-PN position error is less than a threshold. Overall, T-PN and WiFi can work as a cooperative system to provide a navigation solution for indoor users. In the cooperative system, when T-PN solution is accurate, it is used to estimate the AP locations and PPs. On the other hand, when WiFi localization is available, it is used to aid T-PN to reduce the navigation error.

In this paper, we focus on the performance evaluation of AP localization and PPs estimation based on crowdsourcing using the stand-alone T-PN software. The proposed method starts without any priori information on PPs and AP locations. Navigation solutions from T-PN and corresponding RSS values are automatically collected together in the background of handheld devices such as smartphones. If some pairs of the navigation solutions and corresponding RSS value satisfy the requirements for estimating AP locations and PPs, non-linear weighted LSQ comes into effect automatically, and the estimated results are recorded in the database.

The proposed system also estimates the accuracy of AP locations for future positioning usage. AP locations are updated to keep the accuracy of the database as new measurements become available using sequential least squares. This AP location update is also processed automatically in the background without any restriction on the user. Therefore, the whole system, which includes the calculation and update of AP locations and PPs, is an autonomous crowdsourcing system. If the user stays indoors for some time period, the automatically computed AP locations and PPs on the user’s device can be used to compute user position which is used as an independent update for the sensor solution of T-PN.

II. METHODOLOGY

A. System Overview

As shown in Fig. 1, a novel system is proposed for smartphones for AP localization and crowdsourcing. The system runs in the background. The position and RSS pairs are collected automatically if they meet the requirements. The position information is then translated from geodetic coordinates (LLH: latitude, longitude and height) to local ENU coordinates (east, north and up). LLH coordinates are converted to ENU coordinates to avoid potential numerical problems when computing the LSQ since the latitudes and longitudes of different pairs used for estimation are numerically close to each other. Note that the position of the first uploaded measurement in the server is chosen as the origin of ENU frame for all the APs. Correspondingly, the RSS/position pairs change to RSS/ENU pairs.

Next, the RSS/ENU pairs are checked for duplication. The duplication problem exists when the RSS values of the two pairs are totally different while ENU values are close together. The duplication problem is mainly caused by the fluctuation of RSS values and T-PN navigation errors. If this duplicated problem is detected, an average value is used to keep the pairs reasonable. When given more than four pairs of measurements for one AP, non-linear LSQ is used to estimate the AP location, PPs and their accuracies. The dilution of precision (DOP) is also calculated after the LSQ. Then, several criteria are used to check whether the LSQ result is reasonable. If the LSQ result is reasonable, it will be recorded in the database. If this AP is previously stored in the database, LSQ results are used to update the AP information in the database.

Fig. 1. Flow chart of the proposed system
B. Autonomous Crowdsourcing

The key technology used in this paper is autonomous crowdsourcing, which automatically and efficiently builds and maintains the WiFi database. Professionals are usually employed to survey the fingerprints for creating and maintaining a robust WiFi database. Both the creation and maintenance of the database are labour-intensive and time-consuming, especially for large areas. In this paper, an approach based on autonomous crowdsourcing is developed to reduce the cost of building and maintaining the database of AP locations. In this approach, regular users collect RSS values at specified points, which makes the process easier and more labor-saving. When the number of measurements is sufficient, the result is updated to the WiFi database by autonomous crowdsourcing. When the number of observed RSS/ENU pairs for a specific AP is larger than 10, AP locations and PPs are estimated again and updated to the database. In different conditions, the update uses batch or sequential processing [12] [13] for LSQ. When the number of RSS/ENU pairs for the estimation is less than 10, batch processing is executed to estimate AP locations and PPs. The batch processing also provides a reliable initial estimate for the sequential processing. When the number is larger than 10, the sequential processing is used to further update the estimate. This hybrid structure is used to balance the computation speed and estimation accuracy. Overall, the key goal of autonomous crowdsourcing is to keep the AP locations and PPs accurate in the database without the cost of labour and time.

C. Propagation Model

There are many different propagation models. Some of them consider the effects of walls and floors [14] [15]; however, they are not suitable for real-time AP localizations because a priori information of walls and floors are usually unavailable. In this paper, a typical path-loss propagation model is used and given by

\[ RSS = C -10n \log_{10}(d) + X_\alpha \]  

(1)

where RSS represents the received signal strength in dBm at a distance \( d \) from the transmitter. \( C \) represents a constant which depends on several factors: averaged fast and slow fading, transmitter gain, receiver gain and transmitted power. Therefore, in practice, its value is usually known beforehand. \( n \) represents the path-loss exponent with typical values between 2 - 6 for indoors. \( X_\alpha \) represents the shadow noise modeled as a Gaussian random variable with zero mean and standard deviation \( \sigma_{\text{RSS}} \). The distance between the AP located at \((x_i, y_i)\) and the \( i \)th measurement point \(( x_i, y_i) \) is defined as

\[ d_i = \sqrt{(x_i-x)^2 + (y_i-y)^2} \]  

(2)

D. Nonlinear Weighted LSQ

Several techniques can be used to estimate \( n \), \( A \), \( x_0 \) and \( y_0 \). Two popular candidates are LSQ and the Extended Kalman Filter (EKF). With the help of the system model, EKF is better than LSQ when estimating the dynamic trajectory. However, LSQ and EKF have similar performance when estimating the static point’s position. APs are static, therefore, LSQ is chosen because it has a simpler implementation than EKF. The non-linear observation model, using LSQ, is provided in (3) by combining (1) and (2), then adding an error vector \( \nu \).

\[ \text{RSS} = -10n \log_{10}(\sqrt{(x_i-x)^2 + (y_i-y)^2}) - A + \nu \]  

(3)

where \( \text{RSS} = [\text{RSS}_1, \text{RSS}_2, \ldots, \text{RSS}_k]^T \), \( x_0 = [x_i, x_2, \ldots, x_i]^T \) and \( y_0 = [y_i, y_2, \ldots, y_i]^T \) represent an RSS vector and two dimensional position vectors for \( k \) measurement points. \( A \) equals \(-C\) in (1). Typical observation model for the LSQ is adapted from [12] and is given by

\[ z = h(x) + \nu \]  

(4)

where \( z \) represents the measurement vector, and \( h(x) \) is a function of the state vector \( x \). The linear observation model is obtained by using the Taylor series to expand the terms around the current state \( x \) and keep the first order term in the linearization as shown in (5). Note that the linearization here has much smaller high-order errors than that in [3] because the expanding point \( x \) is very close to final estimate of the state vector after several iterations of LSQ.

\[ z = h(x) + v \]  

\[ h(x) + \frac{dh(x)}{dx} |_{x=x_0} (x-x_0) + \cdots + v \]  

(5)

\[ z = h(x) + H \delta x + \nu \]  

where \( \delta x = x - x_0 \) represents the change of the state vector; and \( H = \frac{dh(x)}{dx} \) is the design matrix. Rearranging (5) gives a measurement misclosure vector (\( \delta z \)) as shown in (6).

\[ z - h(x) = H \delta x + \nu \]  

\[ \delta z = H \delta x + \nu \]  

(6)

Equation (6) is a linear observation model. The solution \( \delta x \) and its covariance matrix \( C_{\delta x} \) is given in [3] and provided as follows:

\[ \delta x = (H^T R^{-1} H)^{-1} H^T R^{-1} \delta z \]  

\[ C_{\delta x} = (H^T R^{-1} H)^{-1} \]  

(7)

where \( R \) represents the covariance matrix of RSS. The new state vector is calculated as follows:

\[ x_{\text{updated}} = x + \delta x \]  

(8)
And the observation model is expanded at the new state vector $x_{updated}$. It is an iterative process until $|\delta x| < \text{threshold}$.

When using LSQ, the first step is to determine the parameters $x, z, R, H$, and $x$. The measurement vector is $z = \text{RSS}$ and the state vector is $x = [x_o, y_o, n, A]^T$ for RSS-based estimation. Initial $x = [\text{mean}(x_o), \text{mean}(y_o), 3, 35]^T$ with 3 and 35 as the typical values for “n” and “A” in indoor environments. Coordinates of the measurement points $(x_i, y_i)$ are provided by the T-PN solution. By comparing (3) and (4), we find that

$$h(x) = -10 \log_{10}(\sqrt{(x_o - x_n)^2 + (y_o - y_n)^2}) - A$$

(9)

Therefore, the design matrix is given by

$$H = \frac{dh(x)}{dx} = \begin{bmatrix}
-10n(x_0 - x_n) & -10n(x_0 - x_n) \\
-10n(y_0 - y_n) & -10n(y_0 - y_n) \\
-10\log_{10}(d_1) & -10\log_{10}(d_1) \\
-1 & \vdots & -1 & \vdots & -1
\end{bmatrix}$$

(10)

The measurement covariance matrix can be written as

$$R = \sigma_0^2 Q_R$$

(11)

where $\sigma_0^2$ represents the a priori variance factor, and $Q_R$ represents the cofactor matrix of $R$. The solution of the nonlinear LSQ is given by [6]

$$\delta \hat{x} = (H^T Q_R^{-1} H)^{-1} H^T Q_R^{-1} \delta z$$

$$C_{\delta \hat{x}} = \sigma_0^2 (H^T Q_R^{-1} H)^{-1}$$

(12)

Note that the estimation of $\delta \hat{x}$ is independent of $\sigma_0^2$. However, $\sigma_0^2$ scales $C_{\delta \hat{x}}$ directly, as shown in (7). On the other hand, $Q_R$ affects $\delta z$ and $C_{\delta \hat{x}}$. $Q_R$ is a diagonal matrix because the RSS values are independent for all the measurements, and is given by

$$Q_R = \text{diag}(Q_{R,11}, Q_{R,22}, \ldots, Q_{R,nn})$$

(13)

where $Q_{R,11}, Q_{R,22}, \ldots, Q_{R,nn}$ represent the diagonal elements of $Q_R$. Note that $\sigma_0^2$ is often not provided, or if provided, unreliable. Therefore, one empirical value is set for $\sigma_0^2$ at first. Equation (7) provides a normal or typical LSQ estimate equation when the weights of $Q_R$ are equal. If the weights are not equal, the LSQ is called weighted LSQ. In this case, the RSS values can be used as weights for the measurement variances. The terms of $R$ are given by

$$R_i = \frac{\text{RSS}_i}{\text{sum(RSS)}}$$

(14)

Through the field tests, it is determined that the standard deviation of RSS values is about 6 dB, and the RSS measurements are uncorrelated with each other. Therefore, the measurement covariance matrix $R$ is a diagonal matrix, and its diagonal terms are set to 36 in this paper.

E. Measurement Optimization

Two problems need to be considered for measurement optimization: AP response rate and duplication of RSS/ENU pairs. When analyzing preliminary experimental results, we found that some APs with weak signals are not always recorded even when the user is static. Therefore, the response rate is introduced to evaluate the stability of AP signals. Our preliminary results show that APs with weak signals have low AP response rate. Therefore, RSS values which are greater than -85 dBm are chosen for the efficient collection. The second problem is the duplication of RSS/ENU pairs. As we discussed before, a duplication problem may exist in the system when RSS values are different but ENU values are similar. In this paper, an average is used to eliminate the duplication problem.

F. LSQ Results Evaluation

After computing the LSQ results, several terms need to be checked before recording the estimation result to the database. These terms are listed as follows:

(a) Pass loss exponent;
(b) Constant value $A$;
(c) Reasonable AP location; and
(d) DOP value.

The typical range of pass loss exponent is 2 - 6; and the typical range of ‘$A$’ is 0 ~ 100. If the estimation results are not in these ranges, the estimation results are ignored. The AP location always stays within about 200 meters from the measurement points according to the propagation model. Therefore, if the AP location is far away from the measurement points, the estimation result is unreasonable. DOP values also need to be assessed to ensure the reasonability of the results. The $i^{th}$ state of DOP [12] is given in

$$iDOP = \sqrt{(Q_i)}$$

(15)

where $(Q_i)_i$ is the element in the $i^{th}$ row, $i^{th}$ column of a matrix and $Q_i$ is calculated by

$$Q_i = (H^T Q_i H)^{-1}$$

(16)

where $H$ and $Q_i$ are design matrix and cofactor matrix of $R$. For the details of DOP calculation and application, please refer to [12] [16] [17]. Similar applications of DOPs for WiFi indoor navigation are discussed in [4] [18]. The estimation results are thought as acceptable only when the DOP value is less than 4.0 in this paper.
III. SIMULATION

To evaluate the performance of the proposed method, a simulation is conducted in this section. The simulated area is a 60 m × 60 m square. Fig. 2(a) shows the first simulated area with a good geometric distribution, whereas Fig. 2(b) is provided to show the results of bad geometric distribution for the same area. RSS values are generated by the proposed indoor propagation model in (1). \( C \) is set to -30dBm and \( n \) is set to 3. The Gaussian random variable \( X_n \) in (1) is pre-set such that it has zero mean value, and a standard deviation of 2.

The result of the proposed method is shown in Table I. For the case in Fig. 2(a), AP location has an estimation error of about 1.1 meters, and PP has a relative estimation error less than 10%. Due to the DOP value, Fig. 2(b) has a worse estimation performance than (a). This example shows that DOP is a significant indicator for the accuracy of AP localization result. Note that the case in Fig. 2(a) is used for the rest of the simulations.

![Fig. 2. Simulation area. True AP position (circle) is (0, 0); and (a): RSSs measurement points (stars) are (0, 30), (-22.5, 0), (0, -15), and (7.5, 0); (b): measurement points are (-30, -30), (0, -20), (-10, -30) and (20, -30).](image_url)

AP localization results of different approaches (M1: average in [1], M2: weighted average in [1], M3: the approach in [3], M4: the approach in [4], and M5: the proposed method) are shown in Table II. The proposed method M5 is the one with the best performance. AP localization results in different indoor environments are given in Table III. Different PP are simulated for the various indoor environments. As shown in Table III, the proposed method successfully copes with changes in the dynamic indoor environment.

![Fig. 3. Experimental areas (red circles = APs). (a) ARTC building; and (b) EEEL building](image_url)

![TABLE II. AP LOCALIZATION RESULTS OF DIFFERENT APPROACHES](image_url)

<table>
<thead>
<tr>
<th>Method</th>
<th>East (m)</th>
<th>North (m)</th>
<th>Error (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>-3.75</td>
<td>3.75</td>
<td>5.30</td>
</tr>
<tr>
<td>M2</td>
<td>-4.45</td>
<td>4.63</td>
<td>6.43</td>
</tr>
<tr>
<td>M3</td>
<td>0.32</td>
<td>9.83</td>
<td>9.84</td>
</tr>
<tr>
<td>M4</td>
<td>-0.59</td>
<td>1.84</td>
<td>1.93</td>
</tr>
<tr>
<td>M5</td>
<td>0.43</td>
<td>1.04</td>
<td>1.12</td>
</tr>
</tbody>
</table>

![TABLE III. RESULTS OF AP LOCALIZATION IN DIFFERENT INDOOR ENVIRONMENTS](image_url)

<table>
<thead>
<tr>
<th>Set n: A</th>
<th>East(m)</th>
<th>North(m)</th>
<th>Est n</th>
<th>Est A</th>
</tr>
</thead>
<tbody>
<tr>
<td>2: 30</td>
<td>-3.86</td>
<td>-1.03</td>
<td>2.02</td>
<td>30.18</td>
</tr>
<tr>
<td>3: 30</td>
<td>0.43</td>
<td>1.04</td>
<td>3.08</td>
<td>27.41</td>
</tr>
<tr>
<td>4: 30</td>
<td>1.15</td>
<td>-1.91</td>
<td>4.00</td>
<td>29.32</td>
</tr>
<tr>
<td>2: 40</td>
<td>-0.23</td>
<td>-0.81</td>
<td>1.86</td>
<td>41.22</td>
</tr>
<tr>
<td>3: 40</td>
<td>-2.65</td>
<td>1.21</td>
<td>2.85</td>
<td>40.43</td>
</tr>
<tr>
<td>4: 40</td>
<td>-0.94</td>
<td>-1.05</td>
<td>3.75</td>
<td>41.86</td>
</tr>
</tbody>
</table>

IV. FIELD EXPERIMENTS

To evaluate the performance of the proposed system in the real-world environments, we implemented the proposed system on Android smartphones, which are equipped with accelerometers, gyroscopes, magnetometers, and a WiFi receiver. As shown in Fig. 3, two sites in Calgary are selected for the performance evaluation. The first experimental site was in the Alastair Ross Technology Center (ARTC, about 100m × 70m), with seven known APs. The other site was in the Energy Environment Experimental Learning building (EEEL, about 120m × 40m) with eight APs.
The sample T-PN navigation solution is shown in Fig. 4. The result illustrates that the T-PN solution is accurate and close to the reference trajectory. Note that the initial values for the T-PN navigation solution in these two figures are given manually. In this example, the maximum position error is less than 5 meters, which demonstrates T-PN is an accurate position provider for the AP location estimation and autonomous crowdsourcing.

The first experiment was conducted in the ARTC building. Four trajectories with the T-PN solutions are used for estimating AP locations and PPs as shown in Fig. 5. These four red trajectories represent automatically generated T-PN solutions when the T-PN software is running in the background of the smartphone. In the proposed system, the accuracy of AP locations is improved when more RSS/ENU pairs are observed. This trend is shown in Table IV. In Table IV, ‘AP Localization Error’ represents the error of the estimated AP location, illustrating the performance of the AP localization. The ‘Accuracy Estimation Error’ equals the difference between the estimated AP location error (from the state covariance matrix of LSQ estimation) and the true AP location error. This value is used to determine whether the estimated AP location error is an efficient indicator for the accuracy of AP locations. Note from Table IV that often times the ‘AP Localization Error’ and ‘Accuracy Estimation Error’ decrease as the number of trajectories increase. ‘AP Localization Error’ slightly breaks this rule only when the trajectory number increases from 3 to 4. This phenomenon is probably caused by the relatively larger observation error in the last trajectory.

Results of AP localization and PPs estimation in the ARTC are shown in Fig. 6 and Fig. 7, separately. The accuracy of AP localization and PPs estimation mainly depends on the fluctuation of RSS values, the accuracy of T-PN solutions and the geometry of observed pairs. Fig. 6 shows that estimated AP locations are close to the true locations. As shown in Fig. 7, the estimated path-loss exponent and the constant ‘A’ are located in their typical ranges. The true errors of PPs estimation are unknown in this environment. However, the efficiency of PPs estimation has been illustrated in Section III. Table IV. AP LOCALIZATION RESULTS USING DIFFERENT NUMBER OF TRAJECTORIES IN THE ARTC

<table>
<thead>
<tr>
<th>Number of Trajectories</th>
<th>Number of Estimated APs</th>
<th>AP Localization Error</th>
<th>Accuracy Estimation Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7</td>
<td>6.34m 6.65m</td>
<td>3.33m 4.17m</td>
</tr>
<tr>
<td>2</td>
<td>7</td>
<td>5.72m 5.89m</td>
<td>2.85m 3.15m</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
<td>5.27m 5.47m</td>
<td>2.68m 2.94m</td>
</tr>
<tr>
<td>4</td>
<td>7</td>
<td>5.51m 6.14m</td>
<td>2.18m 2.50m</td>
</tr>
</tbody>
</table>

Fig. 5. Four T-PN trajectories in the ARTC used for the estimation of AP locations and PPs.

Table IV. AP Localization Results Using Different Number of Trajectories in the ARTC

![Fig. 6. Result of AP localization in the ARTC.](image-url)
In the second experiment, six trajectories with the T-PN solutions in EEEL are used for estimating AP locations and PPs, as shown in Fig. 9. Table V shows that the estimation results of AP locations when using a different number of trajectories is similar to the results in Table IV, in that ‘AP Localization Error’ and ‘Accuracy Estimation Error’ often decrease as the number of trajectories increase.

Results of AP localization and PPs estimation in EEEL are shown in Fig. 10 and Fig. 11, separately. Fig. 10 shows that estimated AP locations are closer to the true locations. As shown in Fig. 11, the estimated path-loss exponent and the constant ‘A’ are located in their typical ranges. Fig. 12 depicts the estimated and true errors of the AP locations in EEEL. The estimated AP localization errors are occasionally not close to the true values. However, these estimation errors still can be taken as a rough estimate for the AP locations’ accuracy.
A novel crowdsourcing method for automatic AP localization and propagation parameter estimation is proposed in this paper based on the navigation solution from the T-PN. If the requirements and AP locations are satisfied, the process of estimation, mainly based on nonlinear weighted LSQ, is carried out automatically, and the estimation results are recorded in the database. The method can adaptively determine or change the parameters of the propagation model as the environment changes, which is convenient for the maintenance of the database. The proposed system in this paper is a natural and robust crowdsourcing method. Results of simulation and filed tests illustrate the efficiency of the proposed method. The average AP localization errors are less than 6 meters in the field tests, and the estimation results improve when more measurements are available.

REFERENCES


