An Adaptive Fingerprint Database Updating Scheme for Indoor Bluetooth Positioning

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Abstract. The accuracy of fingerprint based Bluetooth positioning technology depends on the fingerprint database established in offline phase. However, the change of environment and Access Point (AP) locations has significant impact on wireless signal distribution, resulting a decline in indoor Bluetooth positioning accuracy. In order to solve this problem, this paper presents a fingerprint database updating algorithm. Firstly, RSSI sequence, head, and speed information are extracted from crowdsourcing date. Secondly, the extracted information is used in Pedestrian Dead Reckoning Modification (PDRM) algorithm to get candidate fingerprint. Finally, we propose concepts of standard fingerprint, negative exponential time model, and similarity filtering to update original fingerprint database. The experimental results show that after the proposed fingerprint database updating, fingerprint database positioning accuracy is improved by 0.5 m.

Keywords: Indoor positioning · PDRM · Crowdsourcing · Fingerprint database updating · Bluetooth

1 Introduction

With rapid development of mobile computing, communication network brings a strong impetus for personal Position information service. Therefore, the Location-Based Service (LBS) receives extensive attention. At present, the Global Navigation Satellite System (GNSS) can basically meet the demand of outdoor positioning accuracy. However, satellite signals are easily shielded and have serious multipath effects inside a building, which make GNSS positioning accuracy descend. In response to this phenomenon, many research institutes have proposed a variety of indoor localization systems, including BLE [1], Wireless Local Area Network (WLAN) [2], Radio Frequency Identification (RFID) [3], MEMS sensors [4], Ultra Wideband (UWB) [5].

Some factors such as universality and robustness limit the development of traditional positioning technologies. BLE fingerprint positioning technology has

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the advantages of low power consumption, low cost and long-term high accuracy. In indoor environment, wireless signal propagation environment is constantly changing, so fingerprint database needs regular updating. Traditional fingerprint database update means require professionals to periodically re-collect fingerprint data to update fingerprint database, which is inefficient [6].

The remainder of paper is organized as follows. Section 2 reviews several methods of fingerprint database updating. Section 3 describes the proposed fingerprint database updating framework. Section 4 shows experimental results. Finally, conclusion is provided in Sect. 5.

2 Related Work

In recent years, in order to maintain the stability of fingerprint positioning accuracy, fingerprint database adaptive updating technology has received widespread attention. The authors [7] proposed a completely user-independent fingerprint database updating method, providing an interactive interface for users to actively participate in fingerprint database updating, almost no Professionals are involved in updating fingerprint database, but for larger indoor environments, users are frequently bothered when they first start using the system, which increases the user's burden. The authors [8] proposed a method that does not require prior mapping. Users sensor information can be used to complete the fingerprint database updating process, with the help of inertial sensor in mobile phone and PDR algorithm. However, it is difficult to obtain pedestrian steps and heading information accurately. And current position calculation depends on historical location information of target, which leads to positioning cumulative errors and poor long-time positioning accuracy. Therefore, choosing PDR algorithm as an updating means will inevitably lead an error to updating, and even reduces positioning accuracy. The authors [9] explored indoor plan thoroughly by digging out path information, so as to judge the position of user's moving track in a specific shape on indoor map to realize the fingerprint database updating. However, due to the complexity of indoor environment, there is a certain probability of identifying wrong the location where the user trajectory appears, and this will have a negative impact on fingerprint database updating.

In view of these problems, this paper proposes a fingerprint database adaptive updating method based on crowdsourcing [10]. In positioning phase, users will gradually accumulate a large number of positioning data, and the fingerprint database may be adaptively updated by the data to avoid the high investment caused by the participate of professionals, which improves the universality of fingerprint localization technology, with good engineering application prospects.

3 Algorithm Description

3.1 Algorithm Overview

The overall system framework is shown in Fig. 1, including data preprocessing module and fingerprint database updating module. Firstly, the data of users

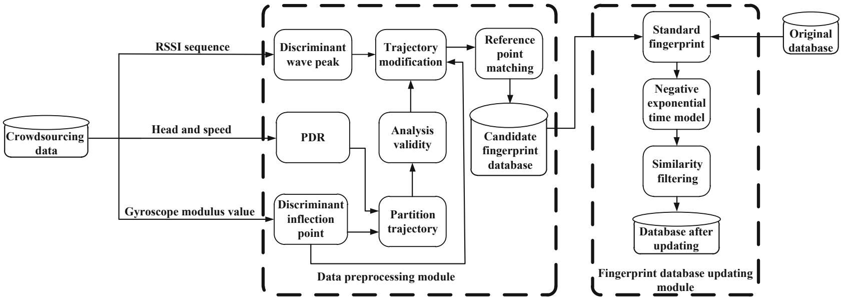

Fig. 1. Framework of fingerprint database updating.

is uploaded to server, which mainly includes Micro Electro Mechanical System (MEMS) and Bluetooth Low Energy (BLE) information. Then, RSSI sequence is extracted to identify AP position beacon by RSSI peak. At the same time, we use corner determination with map information to identify corner position beacon. Then, the AP and corner beacons geographical coordinate information are used to correct PDR trajectory in process of positioning, so as to eliminate accumulated error in positioning information, and generate candidate fingerprint data according to corrected position coordinates of PDR track with corresponding RSSI. Finally, fingerprint database updating is completed based on standard fingerprint, negative exponential time model and similarity filtering.

3.2 Data Preprocessing

Pedestrian Dead Reckoning. PDR algorithm is a kind of algorithm that uses MEMS information to estimate user's speed and head, and deduces user's position. However, most existing smartphones use inexpensive builtin sensors, speed and head obtained from sensor information contains error. Errors will accumulate over time with iteration of PDR algorithm, eventually track will gradually deviate from real track. Figure 2 shows PDR experimental trajectory, red trajectory is result of PDR algorithm and black solid line is real walking trajectory. As we can see from Fig. 2, it is unreliable to use PDR directly to deduce coordinates of each point in moving process as coordinates of fingerprint, so a correction method is proposed to correct PDR trajectory later in this paper.

Trajectories Modification. The signal propagation model is shown in (1), the farther the smart phone is from AP, the weaker the RSSI is. The RSSI is the highest when smartphone is just below AP.

$$RSSI = -(10n \log d + A) \tag{1}$$

where A is RSSI at a distance of 1 m from AP, d is distance from AP, and n is value trained on the measured data.

Therefore, based on time when AP's RSSI peak appears, it is possible to recognize that user has passed AP at that moment. Figure 3 shows RSSI trend

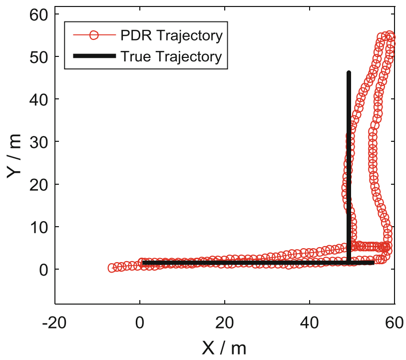

Fig. 2. PDR and true trajectories. (Color figure online)

in a certain test track. When a user passes an AP, peak must be greater than the threshold $RSSI_{\min}$ and since it is impossible for user to continuously pass through same AP in a relatively short period of time, peak occurrence interval must be greater than threshold $T_{\min}$. In summary, the time of pedestrian passing AP can be identified by peak discrimination, AP coordinates at this time can be regarded as current position of user, and it is called RSSI peak beacon in this paper.

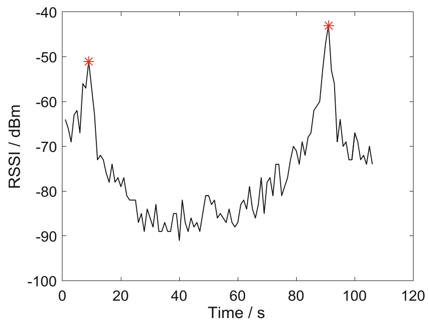

Fig. 3. The RSSI trend of AP.

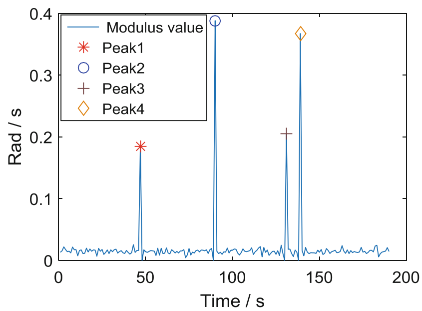

Fig. 4. Gyroscope modulus value.

The other type of beacon proposed in this paper is called corner beacon. Firstly, calculate total modulus of 3-axis gyroscope. Secondly, turning behavior of users can be discriminated according to change of modulus of gyroscope. Figure 4 shows change of gyroscope modulus value of a certain trajectory. When user moves forward gently, modulus value of gyroscope fluctuates slightly from a small value to a small value, and once the pedestrian makes a turning behavior, gyroscope modulus value will change suddenly, the bigger the angle of gyration is, the bigger the variation of modulus of gyroscope is. Finally, RSSI information, which at specific time of user's turning, are matched with RSSI information collected from different corner to determine the corner that pedestrian is passing through. The coordinates of that corner can be used as current position of pedestrian, which is called corner beacon.

After completing beacon recognition, we can segment PDR trajectory according to time of turning beacons, segmenting large segments into small straight lines, which is convenient for subsequent effectiveness identification and trajectory correction. Trajectory shows in Fig. 5 are segmented into five segments, different colors and symbols represent different trajectory after segmentation.

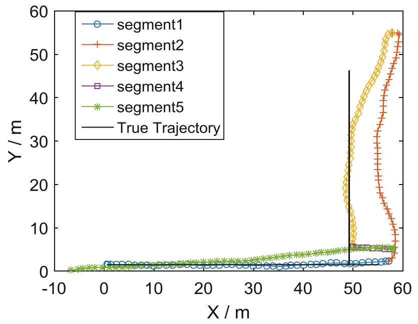

Fig. 5. Trajectories after segmentation. (Color figure online)

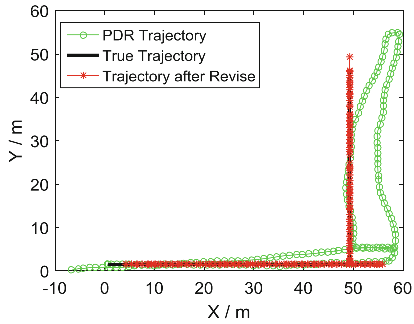

Fig. 6. Trajectory modification.

In this paper, RSSI peak beacon and corner beacon are used to correct PDR trajectory and reduce the cumulative error, so as to improve the accuracy of coordinate estimation of each candidate fingerprint data. The i-th point coordinates correction manner is shown in (2).

$$\begin{cases} x_i = x_0 + \sum\limits_{n=1}^{i} v_n * \sin(\theta_n) + \sum\limits_{n=1}^{i} \varepsilon_{xn} \\ y_i = y_0 + \sum\limits_{n=1}^{i} v_n * \cos(\theta_n) + \sum\limits_{n=1}^{i} \varepsilon_{yn} \\ \varepsilon_{xi} = \frac{v_i \sin(\theta_i)}{\sum v_i \sin(\theta_i)} (L \sin(\psi_1) - L_{PDR} \sin(\psi_2)) \\ \varepsilon_{yi} = \frac{v_i \cos(\theta_i)}{\sum v_i \cos(\theta_i)} (L \cos(\psi_1) - L_{PDR} \cos(\psi_2)) \end{cases} \tag{2}$$

where v_n and θ_n denote velocity and angle information at time n respectively; ε_{xi} and ε_{yi} are error compensation in X and Y directions respectively. L is real trajectory length and $L_{PDR} = \sum\limits_{i=1}^{N} v_i$ is trajectory length deduced by PDR algorithm. ψ_1 is the angle between latter beacon coordinate (x_{end}, y_{end}) and previous beacon coordinate (x_0, y_0); ψ_2 is the angle between PDR estimated end coordinate (x_{PDR}, y_{PDR}) and starting coordinate (x_0, y_0). Figure 6 shows comparison between original PDR trajectory, modified trajectory and real trajectory. Modified trajectory in Fig. 6 is more suitable for real trajectory.

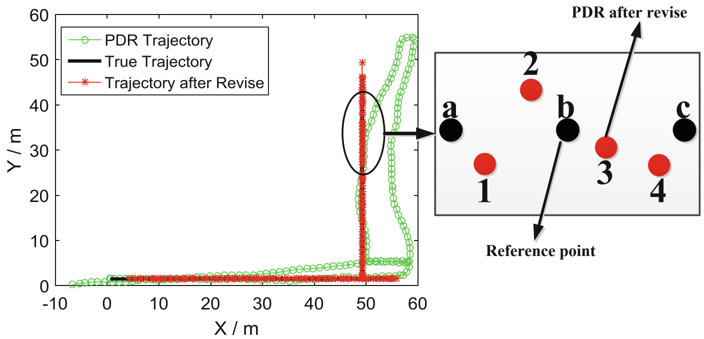

Fig. 7. Reference point matching.

Reference Point Matching. According to modified PDR results, geographic coordinates are extracted and combined with RSSI at corresponding time to generate candidate fingerprint data. The approach of matching reference points is shown in Fig. 7, point a, point b and point c are reference points. Point 1, point 2, point 3 and point 4 are points after PDR result revised by beacon. Formula (3) is specific matching manner.

$$(x_{RF}, y_{RF}) = \arg\min(\sqrt{(x - x_{RF})^2 + (y - y_{RF})^2}) \tag{3}$$

where x_{RF} and y_{RF} are reference point coordinates, x and y are coordinates of revised PDR result. By matching RSSI sequence to corresponding reference point, we can get candidate fingerprint data.

3.3 Fingerprint Database Updating

Standard Fingerprint. After obtaining candidate fingerprint data, the original fingerprint database can be updated by negative exponential time model, standard fingerprint, and similarity filtering updating rules.

First of all, according to candidate fingerprint data and original fingerprint database, we calculate the standard fingerprint. Suppose a reference point which from original fingerprint database already have contained M fingerprint sequences, and the mth fingerprint sequence is

$$S^{\mathrm{m}}_{\mathrm{original}} = \{RSS_{\mathrm{m1}}, RSS_{\mathrm{m2}}, ..., RSS_{\mathrm{mn}}\} \tag{4}$$

At the sametime the same reference point has K candidate fingerprint sequences and the kth fingerprint sequence is

$$S^{k}_{\mathrm{candidate}} = \{RSS_{k1}, RSS_{k2}, ..., RSS_{kn}\} \tag{5}$$

Then standard fingerprint of the reference point can be defined as (6). Standard fingerprint can be used for similarity calculation with the original fingerprint database and candidate fingerprint to regulate fingerprint data of reference point. Accuracy and stability of fingerprint database can be dynamically maintained by filtering low similarity fingerprint and retaining high similarity fingerprint.

$$S_{\text{standard}} = \frac{\Sigma_{i=1}^{M} S_{\text{original}}^{i} + \Sigma_{i=1}^{K} S_{\text{candidate}}^{i}}{M + K} \tag{6}$$

Negative Exponential Time Model. Then, when the amount of updated data $S_{candidate}$ is small, candidate data has a smaller impact on standard fingerprints in (6). As a result, standard fingerprint is still similar to original fingerprint database and it is difficult to accurately reflect changes in fingerprint database. Therefore, negative exponential time model is introduced to standard fingerprint. Original fingerprint information will gradually reduce its weight and reduce its impact on standard fingerprint. The standard fingerprint is then redefined as (7), where $R(\mathrm{t})$ is negative exponential time model and defined as (8).

$$S_{\text{standard}} = \frac{\Sigma_{i=1}^{M} S_{\text{original}}^{i} \times R(\mathrm{t}_i) + \Sigma_{i=1}^{K} S_{\text{candidate}}^{i} \times R(\mathrm{t}_i)}{\Sigma_{i=1}^{M} R(\mathrm{t}_i) + \Sigma_{i=1}^{K} R(\mathrm{t}_i)} \tag{7}$$

$$R(t) = \begin{cases} \exp(-3.725 \times 10^{-6}(t - t_0)) & t - t_0 < days \\ 0 \qquad t - t_0 \geq days \end{cases} \tag{8}$$

Where t is the time when fingerprint data to be updated are collected, t_0 is the time when original fingerprint data are collected.

Similarity Filtering. Finally, fingerprint of same reference point are filtered according to similarity with standard fingerprint, and some fingerprints with low similarities will be filtered. Similarity is related to Euclidean distance of signal strength between fingerprints, defined as (9).

$$Sim_i = (|\mathrm{S}_i - \mathrm{S}_{\text{standard}}|)^{-1} \tag{9}$$

where $|\mathrm{S}_i - \mathrm{S}_{\text{standard}}|$ is Euclidean distance of signal strength between candidate fingerprint and standard fingerprint. The larger $|\mathrm{S}_i - \mathrm{S}_{\text{standard}}|$ is, the smaller similarity is.

4 Performance Evaluation

One floor of a building is selected as experimental environment, plane structure is shown in Fig. 8. This environment is a typical office environment consists of hall, corridor and several office rooms. Experimental environment has a total area of about $65 \times 17\,\mathrm{m}^2$, of which hall area is about $140\,\mathrm{m}^2$, corridor area is about $116\,\mathrm{m}^2$. Small red tower in Fig. 8 is positions of AP. Red linear trajectory distributed area is test area.

Bluetooth AP in experiment is made by TI's CC2540 chip. Millet 4 phone are selected as terminal device, which integrate BLE module, magnetometer, gyroscope, accelerometer, and other sensor modules. Through Bluetooth RSSI and MEMS data acquisition APP under Android 6.0 operating system and Java positioning server, experimental platform can simultaneously detect RSSI and MEMS sensor data from each Bluetooth AP and locate users. APP can upload data to positioning server to complete the fingerprint database updating process.

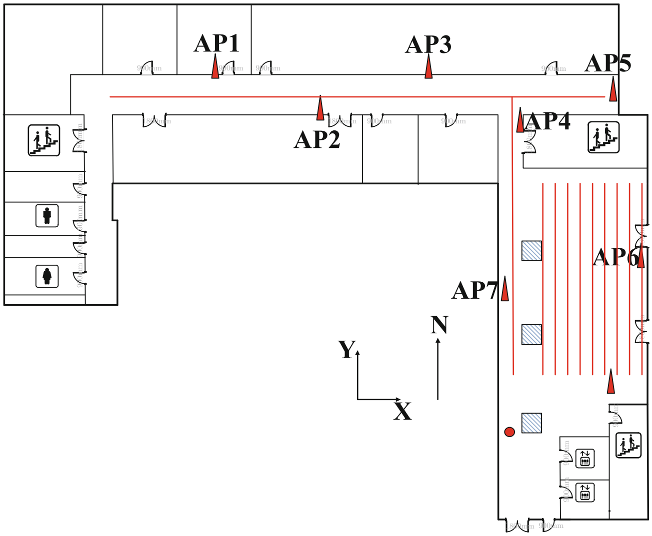

Fig. 8. Physical layout of target environment. (Color figure online)

Project personnel holds smart phones walking in test area at a uniform speed. Updating data is collected for three days and time of collection is 30 min a day. Test data is collected in third day at same place. Figure 9 shows Bluetooth positioning result, black solid line is real test trajectory, green trajectory is result of fingerprint positioning before updating, and red line is result of fingerprint positioning after three times updating. As shown in Fig. 9, after updating fingerprint database, result of positioning is more close to the real trajectory than result of positioning by original fingerprint database.

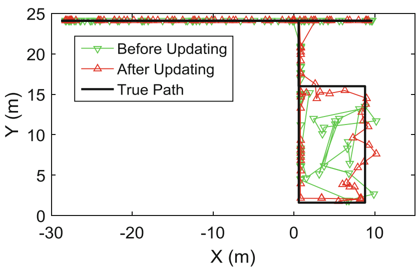

Fig. 9. Bluetooth positioning result. (Color figure online)

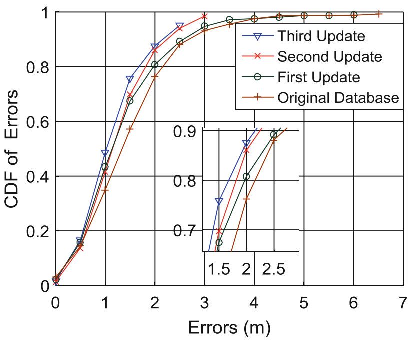

Fig. 10. CDFs of positioning errors.

Table 1 shows different percentile localization errors which use original and updated fingerprint database. In addition, Fig. 10 shows localization Cumulative Distribution Function (CDF) of original fingerprint database and after three updating. After three times updating, average positioning accuracy is increased from 1.4 m to 1.1 m, while tailing error is reduced from 6.8 m to 2.5 m.

Table 1. Positioning error under different percentile values

Percentile value	Original database	First update	Second update	Third update
50%	<1.4 m	<1.2 m	<1.2 m	<1.1 m
70%	<1.8 m	<1.6 m	<1.5 m	<1.4 m
90%	<2.7 m	<2.6 m	<2.3 m	<2.2 m

5 Conclusion

Aiming at the problem that fingerprint database needs to be updated due to change of environment in BLE indoor positioning technology, this paper presents an algorithm that uses crowdsourced data to realize adaptive fingerprint database updating. Experimental results show that the proposed algorithm can updating fingerprint database and improve positioning accuracy. At the same time, the proposed algorithm only uses users positioning data to update fingerprint database. Comparing with traditional fingerprint database updating methods which need participation of professionals this methods can reduce labor cost.

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