An Effective BLE Fingerprint Database Construction Method Based on MEMS

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Abstract. In indoor positioning system based on fingerprint, the traditional fingerprint database construction method consumes much manpower and time cost. To solve this problem, we propose an effective method for constructing fingerprint database by using Microelectro Mechanical System (MEMS) to assist Bluetooth Low Energy (BLE), which overcomes the low efficiency of traditional methods. Meanwhile, the method achieves the comparable positioning accuracy and reduces workload more than 70%. In the optimization procedure, we use affine propagation clustering, outlier detection and filtering of Received Signal Strength Indication (RSSI) to optimize fingerprint database. Finally, the BLE positioning error conducted by the effective database is about 2 m.

Keywords: Indoor positioning
Fingerprint database construction method · BLE

1 Introduction

With the development of wireless positioning technology, the demand for Location Based Service (LBS) is becoming popular. At present, the Global Positioning System (GPS) technology can not meet the needs of indoor positioning accuracy [1]. Aiming at the complex signal propagation environment, many indoor positioning technologies have been proposed, such as Bluetooth [2], MEMS sensor [3] and Wire Local Area Networks (WLAN) [4]. The cost of equipment, scalability and accuracy limit the development of WLAN positioning technology. Meanwhile, the traditional fingerprint database constructing method receives RSSI at Reference Points (RPs), which is not suitable for large indoor scenes. The BLE technology is of low power consumption, low cost and short delay, which greatly reduces the cost of the BLE anchor. And compared with WLAN signal, the BLE signal is more stable.

To solve the inefficiency of traditional database constructing method, we propose an effective BLE fingerprint database constructing system based on MEMS. Firstly, the test staff holds the mobile phone and goes along the designated path, RSSI and MEMS data are uploaded to the server. The server tracks the change

X. Gu et al. (Eds.): MLICOM 2017, Part I, LNICST 226, pp. 133–141, 2018.
https://doi.org/10.1007/978-3-319-73564-1_14

of heading angle and signal peak of RSSI propagation model to determine the coordinate of the beacons, which are used for correcting Pedestrian Dead Reckoning (PDR). Then, we use affinity propagation clustering, outlier detection and RSSI filter to eliminate noise and generate fingerprint sub-database. Thus in positioning phase, we firstly determine the sub-database and then do fingerprint positioning, which also reduces the server load.

The remainder of the paper is organized as follows. Section 2 reviews some related work about effective construction methods of fingerprint database. In Sect. 3, we introduce the proposed algorithm in detail. Section 4 shows the experimental results. Finally, the conclusion is provided in Sect. 5.

2 Related Work

In recent years, the effective construction methods of fingerprint database have been widely concerned. An automatic database construction system based on crowdsourcing is introduced in [5]. In the system, fixed landmark nodes, invisible landmarks and particle filtering technology are used to correct crowdsourcing path. However, the system does not filter low quality data, which can not guarantee that all fingerprints are valid. In order to reduce the labor cost of the off-line phase, a method is proposed to solve fingerprint identification in [6]. The off-line analytical fingerprint database is generated automatically by the server, which avoids the link of the actual survey and construction. However, this method requires a low SNR in environment, and the data from MATLAB simulation experiments are not verified by the actual project. In [7], the system uses a relative RSSI value vector group to replace the absolute RSSI value as the fingerprint data, but failed to solve the problem of low efficiency of traditional method. The main contribution of this paper is that we construct a more effective and accurate fingerprint database by using beacons to constantly correct the PDR trajectory, which reduces the error of the fingerprint coordinate. At the same time, we also use clustering, sub-database generating and filtering algorithm to further optimize the fingerprint database, which improves the efficiency of online fingerprint matching.

3 Algorithm Description

3.1 Algorithm Overview

The overall framework of the system is shown in Fig. 1, which includes the speed and heading reckoning module, the fingerprint database generation module and the fingerprint database optimization module. Firstly, based on the accelerometer, gyroscope and magnetometer data from MEMS sensor, gait detection and pedestrian attitude heading reckoning are used to get the speed and heading of the target. Secondly, the beacons are determined by observing the change of heading angle and the peak of signal propagation model. The beacons are used to correct PDR trajectory, and then the fingerprint coordinates and RSSI

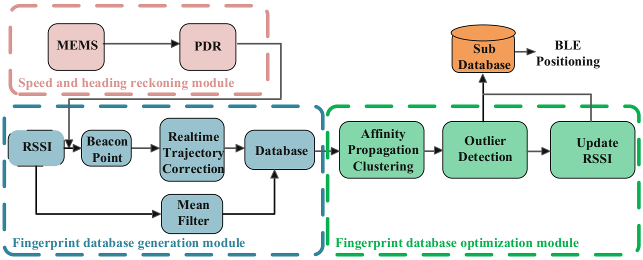

Fig. 1. The BLE fingerprint database construction method block.

are successively stored into the fingerprint database. Thirdly, the optimization steps include affinity propagation clustering, outlier detection and RSSI filter. In the BLE positioning phase, we firstly compare the real-time RSSI with all sub-database, and then position the target.

3.2 Speed and Heading Angle Estimation

The system uses 3-axis accelerometer, 3-axis magnetometer and 3-axis gyroscope in smartphone to estimate the speed and heading angle of the target.

Speed estimation. In order to avoid additional error caused by the difference of equipments, we firstly calculate the total acceleration of the 3-axis acceleration as once smoothing filter, $a_i^{total} = \sqrt{(a_i^x)^2 + (a_i^y)^2 + (a_i^z)^2}$, (a_i^x, a_i^y, a_i^z) are accelerometer value at point i. From [8], the acceleration is of sinusoidal variation, so we judge the pedestrian step by comparing the peak of a_i^{total} with the given threshold. The sampling frequency of the MEMS sensor is f_s, the number of sampling points between adjacent peaks is ΔN, the time required for pedestrian step k is $t_k = \Delta N / f_s$, P_k is the step size of pedestrian step k, the corresponding average velocity is

$$v_k = \frac{P_k}{t_k} = \frac{P_k f_s}{\Delta N} \tag{1}$$

Heading angle estimation. To estimate the heading angle, we update the attitude angle matrix through quaternion [9]. The mutual relation between the quaternion and attitude angle is in [10], so we estimate the parameters of quaternion and then solve the corresponding attitude angle matrix. Thus, we can get the real-time attitude angle of the carrier. The attitude information of gyro is corrected by the observation data of the gravity vector and the geomagnetic vector of the geomagnetic sensor. Finally, the quaternion is updated by EKF model [11], the target heading angle is

$$\varphi = \arctan(-\frac{2(q_1 q_2 + q_0 q_3)}{q_0^2 + q_1^2 - q_2^2 - q_3^2}) \tag{2}$$

3.3 BLE Fingerprint Database Generation

Standard fingerprint database generation. At the beginning of database constructing phase, standard fingerprint coordinates are generated

$$\begin{cases} X_i = x_0 + i * L_{step\_x} \\ Y_i = y_0 + i * L_{step\_y} \end{cases} (\mathrm{i} \in 1, 2, ..., \frac{|x_{end} - x_0|}{L_{step\_x}}) \tag{3}$$

In the formula, (x_0, y_0) and (x_{end}, y_{end}) are starting coordinate and ending coordinate of each trajectory. L_{step_x} and L_{step_y} are interval constant between two RPs. In our system, the interval constant is 0.6 m.

Location estimation and correction. In the process of dynamic acquisition of fingerprint data, PDR algorithm is used to calculate corresponding coordinates of each RSSI. With the increase of time, PDR trajectory will be offset, which leads to the error of the estimated coordinate, so its necessary to correct the error

$$\begin{cases} x_i = x_0 + \sum_{n=1}^{i} vx_n + \sum_{n=1}^{i} \varepsilon x_n \\ y_i = y_0 + \sum_{n=1}^{i} vy_n + \sum_{n=1}^{i} \varepsilon y_n \end{cases} \tag{4}$$

In the formula, (x_i, y_i) is the corrected coordinates at point i, vx_n and vy_n are the estimated velocity at point n, ε_{xn} and ε_{yn} are respectively the coordinate correction of x and y at point n.

$$\begin{cases} \varepsilon_{xi} = \frac{vx_i}{\sum_{n=1}^{end} vx_n}(L_x - L_{xpdr}) \\ \varepsilon_{yi} = \frac{vy_i}{\sum_{n=1}^{end} vy_n}(L_y - L_{ypdr}) \end{cases} \tag{5}$$

In the formula, (L_x, L_y) is the coordinate of beacon, $L_{xpdr} = \sum_{n=1}^{end} vx_n$ and $L_{ypdr} = \sum_{n=1}^{end} vy_n$ are respectively the projection of the PDR trajectory on the X axis and Y axis, vx_i and vy_i are respectively the projection of velocity at point i on the X axis and Y axis

$$\begin{cases} vx_i = v_i \sin(head_i) \\ vy_i = v_i \cos(head_i) \end{cases} \tag{6}$$

Standard fingerprint database generation. By formula (4), we get the estimated coordinate and perform Nearest Neighbor (NN) algorithm between the estimated coordinate and the standard coordinate. RSSI is stored in standard database at each second and then we seek the mean value of RSSI.

$$RSSI_n = \frac{\sum_{i=1}^{M} rssi_i}{M} \tag{7}$$

In the formula, $RSSI_n$ represents the RSSI at point n, $rssi_i$ is the RSSI received at point n, at the i time, we store the fingerprint data M times at point n.

3.4 Optimization of the Fingerprint Database

The fingerprint positioning method includes offline and online phases. The offline phase includes database construction and optimization, which includes affinity propagation clustering, outlier detection and RSSI filter, the online phase mainly determines the coordinate of the target. To save the time cost of fingerprint matching, we use the affine propagation clustering algorithm [12] to separate the fingerprint database into sub-database. In the online phase, we match the real-time RSSI with each sub-database center and select the optimal sub-database for position calculation. The RSSI collected by the effective construction method is easily affected by factors such as signal jitter and environmental noise, so we filter the fingerprint. The specific process is: traverse each fingerprint sub-database for outlier detection [13], when the outlier factor of a certain point is greater than a given threshold, we judge that the point is a outlier. And update the RSSI of the point according to the k adjacent RSSI. The flowchart for separating fingerprint sub-database is shown in Fig. 2.

Assuming that $density(x,k)$ and $rel\_density(x,k)$ indicate the density and relative density of point x about their adjacent points

$$density(x,k) = \left(\frac{\sum_{y \in N(x,k)} distance(x,y)}{|N(x,k)|} \right)^{-1} \tag{8}$$

$$rel\_density(x,k) = \frac{density(x,k)}{\sum_{y \in N(x,k)} \frac{density(y,k)}{|N(x,k)|}} \tag{9}$$

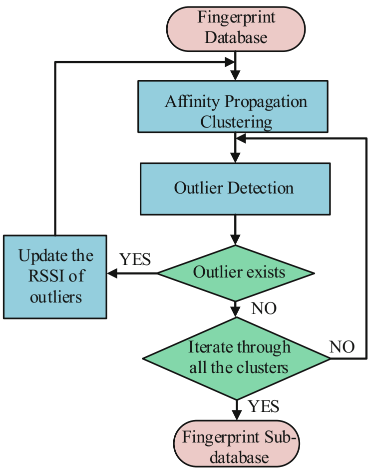

Fig. 2. The fingerprint sub-database separating flowchart.

In the formula, distance(x, y) is the Euclidean distance between x and y, $N(x, k)$ is a collection of k nearest neighbor points of point x, $|N(x, k)|$ indicates the number of elements of $N(x, k)$.

4 Performance Evaluation

4.1 Experimental Setup

To investigate the performance of the proposed approach, we conducted experiments in a real indoor environment with the size of 62 m by 62 m on the third floor of an office building, as shown in Fig. 3. The shadow section is the test area, and 10 Anchors are arranged in the whole location area. We design the BLE Anchor independently, which contains a Bluetooth signal transmitting antenna and is powered by a lithium battery. We select TI company's CC2540 as its built-in chip and HUAWEI mate9 mobile phone as terminal equipment, in which integrates BLE, accelerometer, gyroscope and magnetometer module. At the same time, we design an application for the acquisition of RSSI and MEMS data, and the application uploads data to the server periodically. The hardware platform of the system is shown in Fig. 4.

Figure 5 shows the change curve of RSSI within 30 min from an Anchor 1.5 m, it is clear that in such a long time, the BLE signal floats in a fixed range, so the stability of BLE signal is good. However, from previous analysis, the WLAN signal is likely to hop because of the pedestrian interference and other factors, so the stability is not as good as BLE signal. Figure 6 is a test of the signal strength and distance change of a BLE Anchor, the abscissa represents the distance between the test terminal and Anchor, the ordinate indicates the signal strength of Anchor received by terminal. We can find that the signal

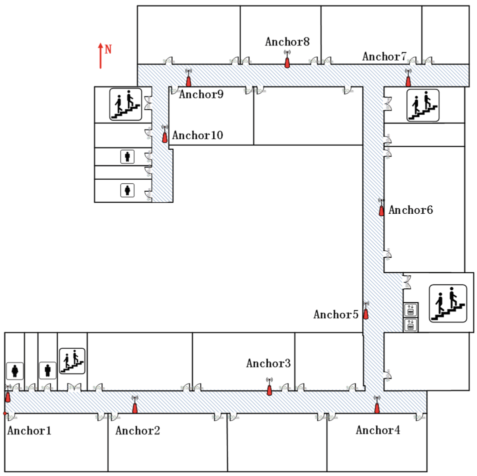

Fig. 3. Physical layout of target environment.

(a) The BLE Anchor (b) The Android APP interface

Fig. 4. The system hardware platform.

is attenuated obviously in the range of 10 m, and accords with the propagation model of the theoretical signal. Therefore, the BLE signal is reliable and suitable in RSSI estimation at each point. Above all, we use the BLE signal for fingerprint database construction and positioning.

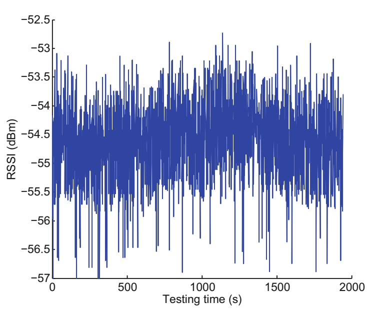

Fig. 5. The change curve of RSSI in a long time.

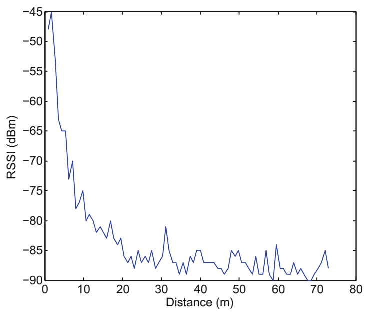

Fig. 6. The test result about the signal strength and distance change of the same Anchor.

Figures 7 and 8 show the clustering results before and after the original database denoising, respectively. Obviously, after removing singular points, the fingerprints of each region are comparatively pure. Therefore, denoising is beneficial to get the physical neighborhood RPs into a same cluster, which improves the efficiency of fingerprint matching in the online phase.

In view of the fingerprint database based on traditional fingerprint database construction method and the effective construction method proposed in this

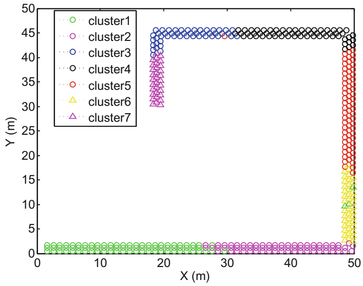

Fig. 7. Fingerprint database clustering result before de-noising.

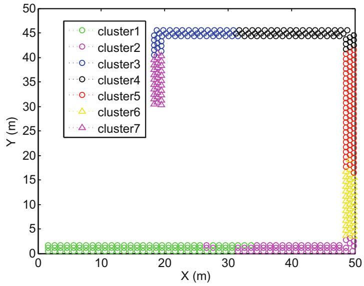

Fig. 8. Fingerprint database clustering result after de-noising.

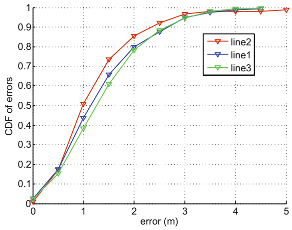

Fig. 9. The CDF of BLE positioning error with the traditional fingerprint database.

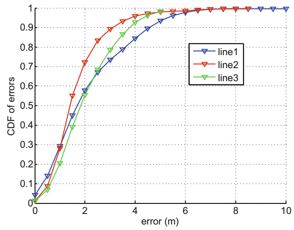

Fig. 10. The CDF of BLE positioning error with the effective fingerprint database.

paper, we research the accuracy and time cost in BLE positioning. We select three tracks for BLE positioning test, Figs. 9 and 10 are cumulative distribution function (CDF) based on two kinds of database. We can find that the BLE positioning accuracy based on effective fingerprint database has declined, but the 2.5 m accuracy under the condition of confidence rate of 70% is still able to meet the needs of indoor pedestrian positioning. Figure 11 shows the time cost on two methods of constructing fingerprint database in two test areas. Obviously, the effective BLE fingerprint database construction method saves a lot of time, and greatly improves the efficiency of database construction phase.

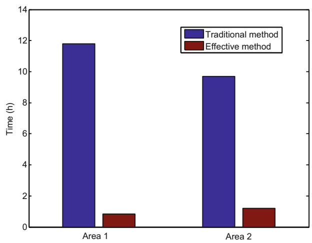

Fig. 11. The time cost of two kinds of database construction methods in different areas.

5 Conclusion

In order to solve the inefficiency of the traditional database construction method, an effective BLE fingerprint database construction method based on MEMS is proposed. In the process of constructing fingerprint database, we use the beacon point to correct PDR trajectory, which avoids the error caused by the large offset of PDR in a long time and improves the accuracy of fingerprint database. Then we use affine propagation clustering, outlier detection and RSSI filter to optimize the fingerprint database, and the sub-database saves much time on fingerprint matching. According to the experimental results, the effective fingerprint database construction method saves about 70% of the time cost and keeps the BLE positioning accuracy without significant decline, so the effective method is of great application prospect.

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