An Indoor Localization System by Fusing Smartphone Inertial Sensors and Bluetooth Low Energy Beacons

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Abstract—**Indoor localization becomes a research focus in recent years since. Smartphone-based pedestrian dead reckoning (PDR) is one of the widely-adopted localization techniques with limiting problems such as the drift of inertial sensors. Bluetooth Low Energy (BLE) has better performance result which makes it an auxiliary tool for PDR to correct errors. But BLE fingerprint sampling and calibrating are time-consuming and labor-intensive. In this paper, a Support Vector Machine (SVM) classification algorithm based crowdsourcing method is developed and applied to generate BLE landmarks instead of manual work leveraging smartphone sensors and uploaded BLE signals. A particle filter is also used to fusion PDR and landmarks detection results for better localization performance. The experiments show that the proposed fusion algorithm achieved the accuracy of 3.15 m at 90% of the time with dense landmarks (1 landmark per 5 m), which performs 51.76% better than 6.53 m from PDR algorithm. With sparse landmarks (1 landmark per 15 m), the proposed fusion algorithm achieved the accuracy of 3.26 m at 90% of the time. The proposed tracking system using smartphone inertial sensors and BLE beacons can be a promising methodology in practical usages.**

Keywords-smartphone; indoor localization; pedestrian dead reckoning; Bluetooth Low Energy

I. INTRODUCTION

Indoor localization becomes increasingly important in recent years due to the rapid development of Location Based Services and Internet of Things. Since the accuracy of satellite systems such as GPS, Glonass and BeiDou are degraded in indoor environments, in which case the signal is lost, reflected or distorted, researchers have tried multiple technologies for indoor localization, e.g., WiFi [1], Ultra Wide Band (UWB) [2], Bluetooth [3], Inertial navigation systems (INS) [4]and magnetic field [5].

Pedestrian dead reckoning (PDR) is a widely-adopted localization technique using an Inertial Measurement Unit (IMU) module or handheld devices like smartphones. It determines the current location by adding estimated displacement to the previous location. Displacement is determined based on step detection, step length and walking direction. The PDR technique can provide very high localization accuracy in a short time but it will drift over time. Smartphones with integrated IMUs as well as magnetometer sensors are easy to carry, less expensive for purchase and convenient for combination with other signals e.g., WiFi [6], Bluetooth Low Energy (BLE) [7], that makes them a good platform for indoor localization implementation. Nowadays, more and more smartphones are integrated with coprocessors which are separate from the main CPU and allow the motion sensor to do PDR constantly without draining the device's battery life. So the PDR technology is focused on in this work.

iBeacon is a new technology released by Apple Inc which is established upon BLE. Zhao [8] has found out that BLE can be more accurate than WiFi when used in localization scenarios. Comparing with fingerprint method, the localization accuracy of triangulation method is low which limits its application scenarios [9]. But workers spend most of time in fingerprint sampling, signal calibration, and sampling location measurement when using fingerprint method and crowdsourcing approach is a possible way to reduce extra work of it.

EZ Localization algorithm [10] is the earliest method using crowdsourcing approach to reducing the training efforts of WiFi fingerprint method, it uses the wireless propagation model and occasional signal GPS at the edges of the indoor environment such as entrances and near windows. Zee [11] enables training data to be crowdsourced without any explicit effort on the part of users by leveraging the inertial sensors. LiFS [12] and WILL [13] also use the inertial sensors for the training process, but they require knowledge of the floor plan. This paper proposed a Support Vector Machine (SVM) classification algorithm based crowdsourcing approach to generate BLE landmarks with uploaded data of Received Signal Strength (RSS) and PDR results.

The rest of the paper is organized as follows: Section II describes the architecture of the indoor localization system followed by details of the landmark model training algorithm, the principle of PDR and the fusion approach. This is then followed by experimental setup and the discussion of the experimental results in Section III. Finally, the conclusions are drawn in section IV.

II. METHODOLOGY

A. System Architecture

The indoor localization system includes two phases: training phase and server phase. During the training phase,

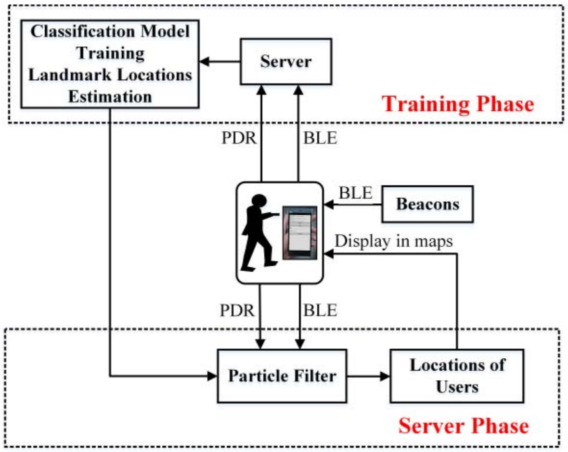

Figure 1. The architecture of the system.

localization relies on PDR based on the smartphone's own sensors. Smartphones upload the localization results of PDR and BLE information to the server. After getting enough data, the server will perform model training of landmarks and estimate the locations of them. During the service phase, since the locations of landmarks are known, they will be used to correct the accumulative errors of PDR to get more accurate locations when someone is passing through the landmarks.

B. Landmark Model Training and Detecting

When a user passes through a beacon, the smartphone reports the maximum RSS of the beacon at the closest place to beacon in ideal conditions. The reality is that due to fluctuations of BLE signal and transmission interval, the maximum RSS may be reported at any place very near to the beacon. The location corresponding to each maximum RSS can be used as landmark and the special BLE signals will help to indicate whether the user encounters a landmark or not. However, real-time detection of the maximum RSS in walking is a challenge during the server phase since the maximum RSS of each beacon is uncertain and may vary between different smartphones. With enough uploaded BLE data, machine learning algorithm is a better way to solve this problem. In each walking instance uploaded to the server, the smartphone detects a series of RSS vectors $<\boldsymbol{r_1},\boldsymbol{r_2},\cdots,\boldsymbol{r_m}>$, where $\boldsymbol{r_k} =< r_{k1},r_{k2},\cdots,r_{kn} >$ $(k=1,2,\cdots,m)$ denotes the RSS of the k_{th} epoch and $r_{ki}(i=1,2,\cdots,n)$ is the RSS from the i_{th} beacon, B_i . Assume that $r_{pj}(p\in k, j\in i)$ denotes the maximum RSS of B_j at p_{th} epoch and r_{pj} is the strongest value among $\boldsymbol{r_p}$. Then, the RSS vector $\boldsymbol{r_p}$ can be labeled as LM_j which denotes the landmark corresponding to B_j, and it can be expressed as $\boldsymbol{r'_p} =< r_{k1},r_{k2},\cdots,r_{kn},LM_j >$. After all the uploaded data has been processed, the processed data can be fed to the SVM classification algorithm to train the model.

Furthermore, there are RSS vectors that do not belong to any landmark. To separate them from all BLE data, an outlier detector is needed. We found that the maximums of labeled RSS vectors satisfy Gaussian distribution. Fig. 2

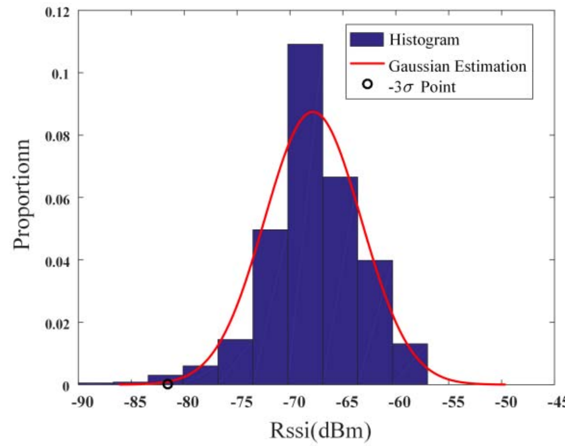

Figure 2. The probability distribution estimation of the maximum of labeled RSS vector.

shows the maximum RSS probability distribution with Gaussian density estimation. We use $R_T = u - 3\sigma$ as a threshold, and if the maximums of a RSS vector is lower than R_T , The RSS vector will be considered belonging to none landmarks. The threshold based outlier detector is used during server phase. when the smartphones of users have received BLE data, the trained model can determine whether it belongs to any landmark or not.

C. Estimating Landmark Locations

Let $s_i^{(j)} =< x_i^{(j)}, y_i^{(j)} >$ denotes the location corresponding to $\boldsymbol{r'_p}$ which is labeled as LM_j and $s_i^{(j)}$ represents the i_{th} estimated location of LM_j . Because the results of PDR is also included in the uploaded data, $s_i^{(j)}$ can be obtained by interpolation with them. The intuition is that the errors of PDR results have been observed random and independent since the noise in sensors and step lengths. The estimated mean combining all this $s_i^{(j)}$ could be the location of LM_j .

D. Pedestrian Dead Reckoning

PDR determines the current location by adding estimated displacement to the previous location. Displacement is determined based on step detection, step length and walking direction. Let (x_k, y_k) be the location of the smartphone at k_{th} step, then:

$$\begin{bmatrix} x_k \\ y_k \end{bmatrix} = \begin{bmatrix} x_{k-1} \\ y_{k-1} \end{bmatrix} + l_k \cdot \begin{bmatrix} \sin(\theta_k) \\ \cos(\theta_k) \end{bmatrix} \tag{1}$$

where l_k is the step length of k_{th} step and θ_k is the corresponding heading direction. An estimation of the initial position (x_0, y_0) is assumed to be (a priori) available. Which can be got from landmarks.

The common method which can be used to detect steps with acceleration data is peak detection which detects the maximum peak and minimum peak in sequence in a certain interval. A new step occurs when the difference between maxima and minima is lower than high threshold and greater than low threshold. The difference that exceeds high threshold is considered as other actions rather than walking. Since the maxima and minima of acceleration can also be used to estimate the step length, this paper employs peak detection method as well as time interval threshold using to reject false step detection.

Magnitude of acceleration is often used in step detection since it makes no difference whether the smartphone is tilted or not. The magnitude of acceleration is filtered through a low-pass filter to smooth the signal and reduce random noise.

A dynamic method, Weinberg method [14], is used in this paper, and the step length will be estimated in every valid detected step as (2).

$$l_k = K \cdot \sqrt[4]{a_{k\max} - a_{k\min}} \tag{2}$$

where $a_{k\max}$ and $a_{k\min}$ are the maximum and minimum values of acceleration during the k_{th} step. K is a constant parameter depending on each person and it can be calibrated with steps and distance between two BLE landmarks in this work. According to prior test, K equal to 0.5 before calibrating in this paper.

Since battery saving and processing time are crucial for a smartphone APP, a gradient descent based orientation filter designed by Madgwick [15] is used in this paper to provide attitudes of the experimental smartphones. The heading direction is considered as yaw angle of the smartphone.

E. Fusion Algorithm

Particle filter techniques are statistical methods widely used in complex (possibly nonlinear) estimation problems, therefore, it is used as fusion algorithm in this work. The fusion algorithm receives BLE data from beacons, step length and heading from PDR and landmark detection results from machine learning model. This data is provided as input to the filtering estimator. When the model and locations of landmarks are available, the fusion algorithm will begin to work.

The position of the i_{th} particle at time t is updated similarly as (1):

$$X_{i,t} = \begin{bmatrix} x_{i,t} \\ y_{i,t} \end{bmatrix} = \begin{bmatrix} x_{i,t-1} \\ y_{i,t-1} \end{bmatrix} + l_{i,t} \cdot \begin{bmatrix} \sin(\theta_{i,t}) \\ \cos(\theta_{i,t}) \end{bmatrix} \tag{3}$$

where $\theta_{i,t}$ and $l_{i,t}$ are randomly sampled from the proper Gaussian distributions: $\theta_{i,t} \sim N(\theta_t, \sigma_\theta^2)$, $l_{i,t} \sim N(l_t, \sigma_l^2)$. θ_t and l_t are calculated by inertial sensor data at time t, σ_θ and σ_l are set to proper constant values(σ_θ =5°, σ_l =0.1m).

Typically, the localization error of each landmark is assumed to be normally distributed. The likelihood function describes the probability of taking a certain measurement $Z_k = (u_k, v_k)$ from a certain landmark and is given by (4):

$$P(Z_k \mid X_k^{(i)}) = \frac{1}{2\pi\sigma_z^2} e^{-\frac{1}{2}\left(\frac{\left(x_k^{(i)}-u_k\right)^2}{\sigma_z^2} + \frac{\left(y_k^{(i)}-v_k\right)^2}{\sigma_z^2}\right)} \tag{4}$$

The particle weights are updated as follows:

$$\omega_k^{(i)} = \omega_{k-1}^{(i)} \cdot P(Z_k \mid X_k^{(i)}) \tag{5}$$

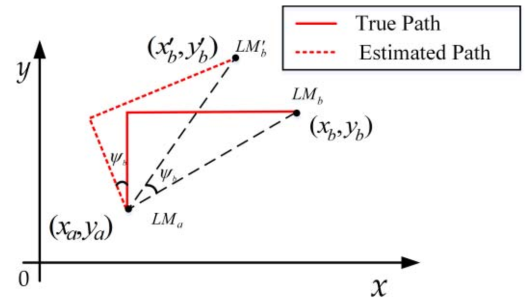

Figure 3. Correcting walking direction using BLE landmarks.

Then, the weights are scaled in order to be normalized to one and resample n particles and set

$$\omega_k^{(i)} = 1/n \tag{6}$$

The server has stored the location of every BLE landmark. When the user encounters a BLE landmark LM_a, the location of LM_a will correct the PDR estimation at this time. Later, the user encounters another BLE landmark LM_b and the estimation location before landmark correcting is (x'_b, y'_b), shown in Fig. 3. The bias angle ψ can be computed by (7).

$$\psi_b = \arctan\left(\frac{y'_b - y_a}{x'_b - x_a}\right) - \arctan\left(\frac{y_b - y_a}{x_b - x_a}\right) \tag{7}$$

Then, the heading is corrected by (8).

$$\psi' = \psi - \psi_b \tag{8}$$

As shown in Fig. 3, the true distance l_T between LM_a and LM_b is stored in the server. In addition, the estimation distance l_O is obtained by the number of steps and step length of every step. The parameter in (2) can be corrected by (9).

$$K' = K \frac{l_T}{l_O} \tag{9}$$

Then, the step length can be calculated as:

$$l'_k = K' \cdot \sqrt[4]{a_{k\max} - a_{k\min}} \tag{10}$$

III. Evaluation Results

The experiments were performed in the Department of Precision Instrument building at Tsinghua University where is a 28 m × 46 m area with two different deployments of BLE beacons as shown in Fig. 4: (a) Dense Deployment (DD, total: 12 beacons; average: 1 beacon per 5 m) and (b) Sparse Deployment (SD, total: 5 beacons; average: 1 beacon per 15 m). All these beacons made by Bright Beacon were evenly placed in the corridors at a height of approximately 2.5 m. Beacon broadcasting parameters were set to the advertising interval of 500 ms and the TX power of -8 dBm. The locations of BLE beacons were measured using a laser rangefinder. In the experiments, smartphones were taken by experimenters to sample the sensors (accelerometer and gyroscope) at 50Hz and BLE signals at 1Hz. This paper only considers the hand-held situation, and the other situations are future works.

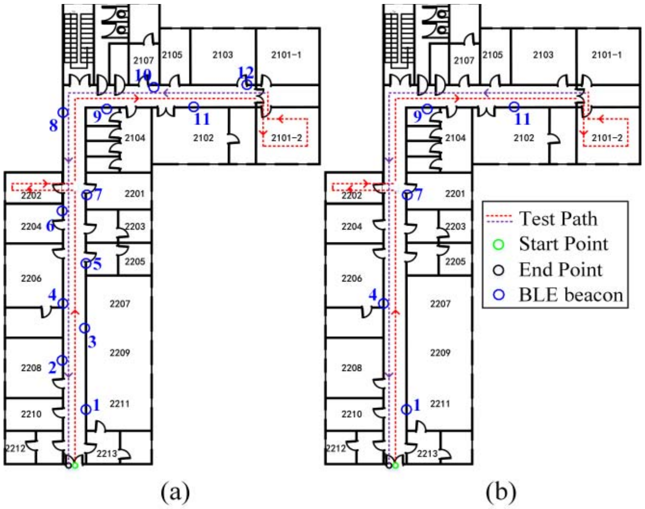

Figure 4. Experimental area:(a) dense deployment; (b)sparse deployment.

A. Landmark Detection Performance

The training dataset was acquired by 6 volunteers with three phones (XiaoMi Mi 3, HuaWei P7 and MeiZu MX3) during one week. In total, 180 measurements were performed consisting 8397 BLE RSSI samples. The processed data of walking were fed to SVM classification algorithm for training.

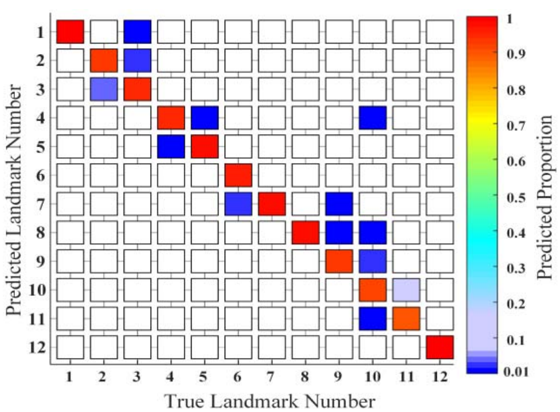

Figure 5. The results of the cross-validation with dense deployment.

TABLE I. TRAINING MODEL PERFORMANCE

Beacon Distribution	10-fold Cross-validation Accuracy
Dense Deployment	95.31%
Sparse Deployment	99.17%

Fig. 5 and Table 1 show the results of the 10-folds cross-validation. It is obvious that most of the incorrectly predictions appear on nearby landmarks. The prediction accuracy is higher than 95%.

B. Localization Performance

The localization performance of the proposed algorithm was evaluated in indoor environments with densely and sparsely distributed BLE beacons. The proposed algorithm was also compared with PDR algorithm.

As shown in Fig. 6, the proposed algorithm with two different beacon deployments have less localization errors than PDR at most of the time. Table 2 summarizes the localization errors using the proposed algorithm and PDR Fig. 7 shows the CDF of localization errors using these three approaches. As shown in Fig. 7 and Table 2, the 90% localization error of the proposed algorithm with dense deployment is 3.15 m, which is reduced by 51.76% over PDR (6.53 m) and the 90% localization error of the proposed algorithm with sparse deployment is 3.26 m, which is reduced by 50.07% over PDR (6.53 m). These results demonstrate that the proposed algorithm achieves around 3 m 90% localization error in the trajectory, which performs better than PDR when there is dense or sparse deployment of BLE beacons.

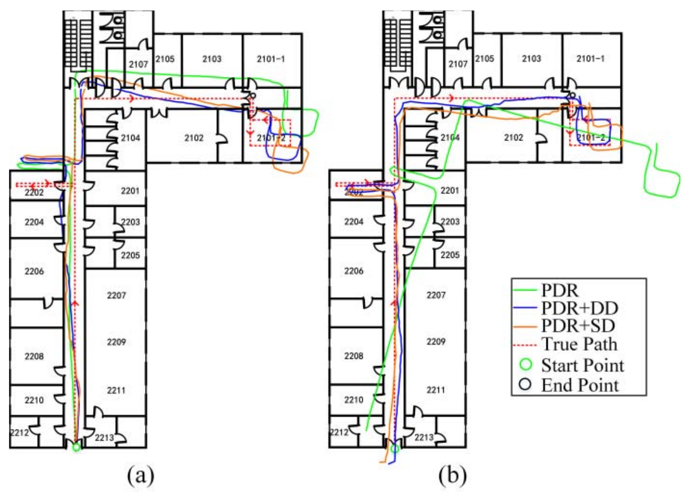

Figure 6. Part of estimated trajectories with PDR and the proposed algorithm:(a) first lap;(b) second lap.

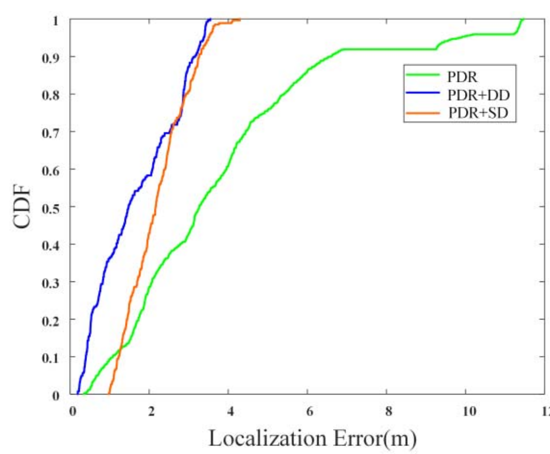

Figure 7. CDFs of localization errors of the trajectories with PDR and the proposed algorithm.

TABLE II. THE LOCALIZAION ERRORS OF THIS TRAJECTORIES USING PDR ALGORITHM AND THE PROPOSED ALGORITHM

Algorithm	**Localization Error(m)**		
	CDF-70%	***CDF-90%***	***Mean***
PDR	4.44	6.53	3.78
PDR+Dense Deployment	2.51	3.15	1.68
PDR+Sparse Deployment	2.56	3.26	2.20

IV. CONCLUSIONS

This paper proposed a smartphone based real-time indoor localization algorithm by leveraging the fusion of PDR and BLE landmarks. Note that the fingerprint sampling and calibration of BLE beacons are time-consuming and labor-intensive, a SVM classification algorithm based crowdsourcing method have been presented leveraging upload data. Experimental results demonstrate that the proposed algorithm provided an accuracy of <3.15 m at 90% of the time with dense deployment of BLE beacons (1 beacon per 5 m) and an accuracy of <3.26 m at 90% of the time with sparse deployment (1 beacon per 15 m), which performed better than <6.53 m of the PDR algorithm.

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