Smartphone Inertial Sensor-Based Indoor Localization and Tracking With iBeacon Corrections

Zhenghua Chen, Qingchang Zhu, and Yeng Chai Soh

***Abstract*—The Global Positioning System (GPS) can be readily used for outdoor localization, but GPS signals are degraded in indoor environments. How to develop a robust and accurate indoor localization system is an emergent task. In this paper, we propose a smartphone inertial sensor-based indoor localization and tracking system with occasional iBeacon corrections. Some important issues in a smartphone-based pedestrian dead reckoning (PDR) approach, i.e., step detection, walking direction estimation, and initial point estimation, are studied. One problem of the PDR approach is the drift with walking distance. We apply a recent technology, iBeacon, to occasionally calibrate the drift of the PDR approach. By analyzing iBeacon measurements, we define an efficient calibration range where an extended Kalman filter is utilized. The proposed localization and tracking system can be implemented in resource-limited smartphones. To evaluate the performance of the proposed approach, real experiments under two different environments have been conducted. The experimental results demonstrated the effectiveness of the proposed approach. We also tested the localization accuracy with respect to the number of iBeacons.**

***Index Terms*—Extended Kalman filter, iBeacon, indoor localization and tracking, smartphone inertial sensors.**

I. Introduction

ACCURATE indoor localization and tracking will benefit various applications, such as indoor navigation, location-based services, rescue, etc. Although Global Positioning System (GPS) is commonly used outdoors, its localization accuracy degrades in indoor environments. Due to the problems of accuracy, robustness, and specific requirements in existing indoor localization and tracking methods, no universal solution has been found. Thus, indoor localization and tracking are still an active research topic. One of the most popular indoor localization techniques is the WiFi fingerprinting approach [1], [2]. However, it requires a time-consuming and labor-intensive data collection process, which makes it impractical. Although crowdsourcing-based approaches can overcome this tedious process [3], the quality of the data is difficult to guarantee. Moreover, since WiFi scanning is power hungry, WiFi-based approaches are not very suitable for real-time and long-term localization and tracking services. Recently, a new technology named iBeacon is released by Apple Inc.. It is established upon Bluetooth Low Power (BLE), which is much more energy-efficient than the classic Bluetooth and WiFi. This technology can be used in combination with modern smartphones for indoor localization based on the received signal strength (RSS) of Bluetooth signals [4], [5]. The various sensors embedded in modern smartphones, such as accelerometer, gyroscope, compass, barometers, and so on, can provide efficient ways to achieve localization and tracking. For example, to obtain the displacement of a user, one can double integrate the acceleration values. However, due to the low quality of smartphone sensors, the integration will diverge quickly [6], [7]. Alternatively, a Pedestrian Dead Reckoning (PDR) [8] approach can be leveraged. It states that the current position can be derived from the previous position, the current walking length and direction. Unfortunately, this approach suffers from the drift problem with walking distance [9]. Other feasible solutions for indoor localization include ultrasound [10], ultrawideband [11], radio-frequency identification (RFID) [12], etc., but these solutions require extra receivers instead of portable smartphones.

Among all feasible solutions, the smartphone inertial sensor-based approach is lightweight and requires fewer resources. However, without any corrections, it suffers from the drift problem. In addition, this approach requires manual specification of the initial points which makes it impractical, especially when users go to a new place. Additional techniques have been cooperated to achieve a robust and accurate localization and tracking system. Beauregard and Haas [13] combined PDR with GPS to enhance localization accuracy. They also constructed a neural network model to estimate the step length. A helmet containing the inertial measurement unit and the GPS antenna was used for real experiments. The results showed a significant improvement when combining PDR with GPS. However, since GPS signals are degraded, this solution is not feasible for indoor situations. Girard *et al.* [14] presented an ultrasound ranging assisted PDR system. A particle filter was applied for the fusion of the PDR approach with ultrasound measurements. The portable ultrasound range sensors measured the distance between the pedestrian and adjacent walls, which eliminates the invalid particles to enhance the localization accuracy of the PDR approach. Real experiments showed a significant improvement in localization

Manuscript received August 28, 2015; revised October 19, 2015 and March 29, 2016; accepted May 11, 2016. Date of publication June 09, 2016; date of current version August 04, 2016. This work was supported by the Building Efficiency and Sustainability in the Tropics (SinBerBEST) program which is funded by Singapore's National Research Foundation and led by the University of California, Berkeley in collaboration with Singapore Universities. Paper no. TII-15-1317.

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Digital Object Identifier 10.1109/TII.2016.2579265

accuracy. In their system, extra devices, i.e., ultrasound range sensors, need to be worn by users. Ruiz *et al.* [15] proposed to fuse the PDR approach with active RFID measurements using a Kalman filter. Instead of employing a loose integration that leverages on the estimated position of a separate RFID system, they applied the residuals of PDR-predicted reader-to-tag ranges and the ranges derived from the RFID system. Experimental results demonstrated the effectiveness of their proposed approach in reducing the PDR drifts. However, extra RFID transmitters and receivers are required. Wang *et al.* [16] applied landmarks in environments, e.g., stairs, escalators, elevators, and WiFi signatures, to calibrate the drift of the PDR approach. An unsupervised learning method was employed to identify landmarks in environments. Real experiments were conducted in three different environments with median localization errors of $1.69\,\mathrm{m}$. However, the identification of these landmarks is nontrivial. Another work in [17] presented an inertial sensor-based localization system with chirp spread spectrum (CSS) radio beacons whose locations are unknown. They performed a simultaneous location and mapping (SLAM) technique to localize the pedestrian in indoor environments. Their system was tested using real experiments and achieved good accuracy with a small number of beacons. However, the approach requires extra CSS receivers and cannot be integrated into a portable smartphone platform.

In this paper, we present a smartphone inertial sensor-based PDR approach for indoor localization and tracking with occasional iBeacon calibrations. Novel approaches are employed in estimating several important parameters of the PDR approach. To avoid the influence of smartphone tilting in step detection, a quaternion is applied to obtain consistent vertical acceleration, and an efficient step detection scheme is presented. Another important issue in the PDR approach is walking direction estimation. The approaches that leveraged on magnetometers are easily distorted by metal and electronic facilities, and gyroscope integration approaches will accumulate errors. To overcome these problems, we apply a fusion framework using a Kalman filter. Some real tests indicate that this fusion approach is more robust and accurate.

Since the PDR approach will drift with walking distance, we propose an iBeacon-based calibration algorithm using an extended Kalman filter. By analyzing iBeacon measurements, an efficient calibration range is defined. In order to obtain the initial position, we propose a combination framework of existing WiFi routers and installed iBeacon tags using a weighted pass loss (WPL) model [18]. The performance of the proposed approach is evaluated under two different environmental settings.

The rest of the paper is organized as follows. Section II describes the proposed approach, including the parameter estimations of the PDR approach, the analysis of iBeacon measurements, fusion algorithm, and initial point estimation. Section III evaluates the proposed approach under two different environments. We conclude this paper in Section IV.

II. METHODOLOGY

In this section, we will analyze some crucial parameters in the PDR approach. Then, an iBeacon-based calibration approach and a novel initialization strategy will be presented.

A. Pedestrian Dead Reckoning

In the PDR approach, the current position is determined by the previous position, current walking length, and walking direction and can be expressed as

$$\mathbf{S}_{k+1} = \mathbf{S}_k + L_k \begin{bmatrix} \sin\theta_k \\ \cos\theta_k \end{bmatrix} \tag{1}$$

where $\mathbf{S}_k$ is the two-dimensional (2-D) coordinate of the pedestrian, L_k is the walking length, and θ_k is the walking direction at time step k. Some critical issues need to be resolved, such as step detection, walking length estimation, and walking direction estimation.

1) Step Detection: Since the feet hit the ground during walking, the vertical acceleration signal will contain periodic patterns which can be applied for step detection. To overcome the tilting effect and obtain consistent vertical acceleration values, we need to transfer the original acceleration from smartphone coordinate system (SCS) into a fixed reference, i.e., the earth coordinate system (ECS). We leverage on a quaternion, i.e., a four-element vector, to represent any rotation in a 3-D coordinate system [19]. According to Android developers [20], a software sensor, i.e., a rotation vector sensor, will provide real-time quaternions referring to ECS. Based on [19], a rotation matrix $\mathbf{R}$ can be calculated using a real-time quaternion. Assume that $\mathbf{A}_s$ and $\mathbf{A}_e$ are the 3-D acceleration in SCS and ECS, respectively, and then we have

$$\mathbf{A}_e = \mathbf{R}\mathbf{A}_s. \tag{2}$$

In this way, we can obtain a consistent 3-D acceleration in ECS regardless of device orientation.

Since the obtained vertical acceleration contains gravity, we need to eliminate it. Due to the stability of gravity, we leverage on a low-pass filter to obtain the gravity first, and then employ the vertical acceleration to subtract the gravity [20], which can be expressed as

$$\mathbf{G} = \alpha\mathbf{G} + (1-\alpha)\mathbf{A}_e \tag{3}$$

$$\mathbf{L} = \mathbf{A}_e - \mathbf{G} \tag{4}$$

where $\mathbf{G}$ is the gravity, α is the parameter of the low-pass filter, and $\mathbf{L}$ is the required linear acceleration. Due to the limited quality of smartphone sensors, the sensor outputs are very noisy. We perform a smoothing operation to reduce the noise effect. Assume that $\{a_k, k = 1, 2, \ldots, N\}$ is the time series of vertical acceleration, and N is the total length of the data, the mth-order smoothed acceleration $\hat{a}_k$ can be expressed as

$$\hat{a}_k = \frac{\sum_{i=k}^{k+m-1} a_i}{m}. \tag{5}$$

Fig. 1 shows a simple example of vertical acceleration smoothing where the sampling frequency is $20\,\mathrm{Hz}$. After smoothing, most of high-frequency noise is wiped off, which will make the step detection process more accurate and robust. One of the most popular step detection methods is based on peak detection, but it will be easily affected by noise. In this paper, we present a simple and efficient threshold-based step detection algorithm. The set of valid step events for the proposed approach

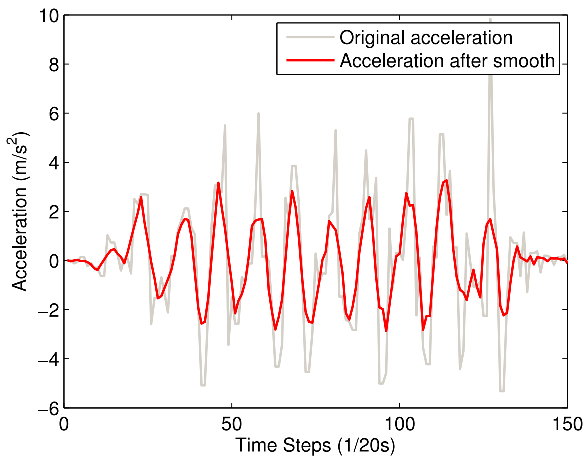


Fig. 1. Example of acceleration smoothing.

is as follows:

$$\{\hat{a}_k > a^+, \hat{a}_{k+p} < a^-, 0 < p < p_{\max}\} \quad (6)$$

where a^+ and a^- are the positive and negative thresholds, respectively, and $p_{\max}$ is the upper-bound of one step duration. In this paper, we set a^+, a^- and $p_{\max}$ as $1.0\,\mathrm{m/s^2}$, $-0.8\,\mathrm{m/s^2}$, and 12 (corresponding to $12 \times 1/20$ s $= 0.6$ s), respectively. Fig. 2 compares the peak detection with the proposed threshold-based algorithms using an example of ten steps. The proposed approach is obviously more robust.

2) Walking Length Estimation: One of the most influential parameters in the PDR approach is the walking length. It has large variance among different subjects. Even for the same subject, it varies significantly at different times during walking. Alzantot and Youssef [21] presented constant walking lengths for different activity modes, i.e., walking, jogging, and running. Another work in [22] estimated walking length based on the height of a pedestrian. These approaches did not take into consideration the variations of walking length during walking. One sophisticated approach can be found in [23] where the author constructed a relationship between walking length and vertical acceleration, which is given by

$$L = \beta(\hat{a}_{\max} - \hat{a}_{\min})^{1/4} \quad (7)$$

where $\hat{a}_{\max}$ and $\hat{a}_{\min}$ are the maximal and minimal smoothed vertical accelerations during one step, respectively, and β is a parameter that needs to be specified for different subjects. We adopt this approach in our proposed system for walking length estimation. Note that since we have transferred the acceleration into ECS, the tilting of smartphones during walking will have no effect on this walking length estimation algorithm.

3) Walking Direction Estimation: The most direct way to estimate walking direction is based on magnetometer readings. However, they can be easily distorted by metal and electronic devices in indoor environments. An alternative way to estimate walking direction is based on the integration of gyroscope readings, i.e., angular velocities. Due to the sensor noise in smartphone gyroscope, the integration will slowly drift. In this paper, we fuse these two approaches together using a Kalman filter

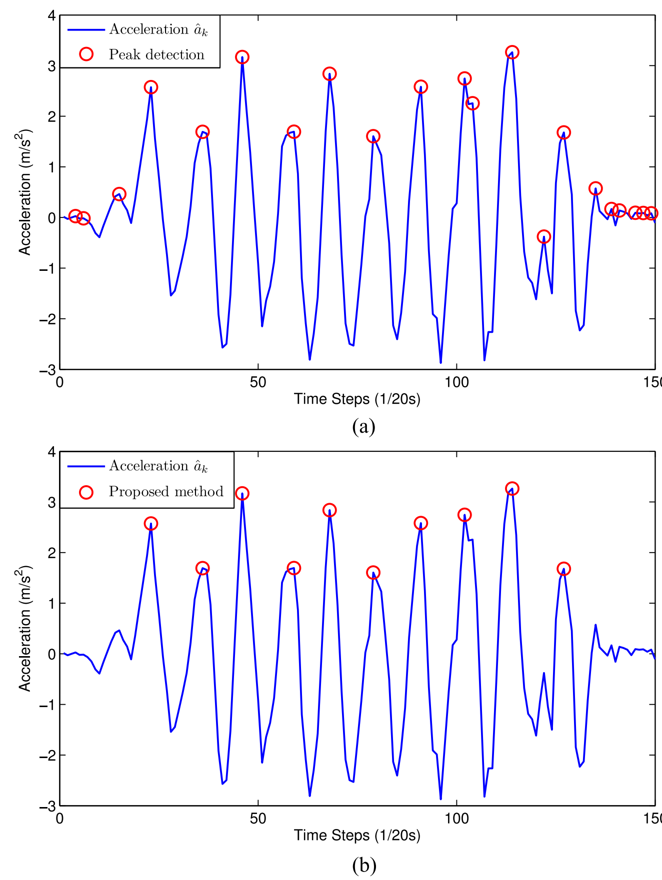


Fig. 2. Step detection based on (a) the peak detection algorithm and (b) the proposed threshold-based detection algorithm using an example of 10 steps.

which is computationally efficient. We assume that users will point their smartphones toward their walking direction in hand-held situation, but the tilting of smartphones will have no effect because of the coordinate transformation. The corresponding state transition and observation functions are expressed as

$$\theta_t = \theta_{t-1} + \Delta t V_t + \mu \quad (8)$$

$$M_t = \theta_t + \varphi \quad (9)$$

where θ_t is the walking direction, V_t is the vertical gyroscope in ECS after coordinate transformation, M_t is the pointing direction derived from magnetometer outputs, Δt is the time interval, μ is assumed to follow the Gaussian error with zero mean and variance P, and φ is assumed to follow the Gaussian error with zero mean and variance Q.

Several simple tests have been conducted to evaluate the performance of this fusion approach. We fixed the route with three 90° turns. The experiments were repeated nine times using a Google Nexus 5 smartphone. Fig. 3 shows the experimental results. Since no prior knowledge of initial heading is available, we choose the initial magnetometer reading as the initial value for the gyroscope integration and the fusion approaches. Therefore, at the beginning with low drift of the gyroscope integration, the performances of the three approaches are very similar.

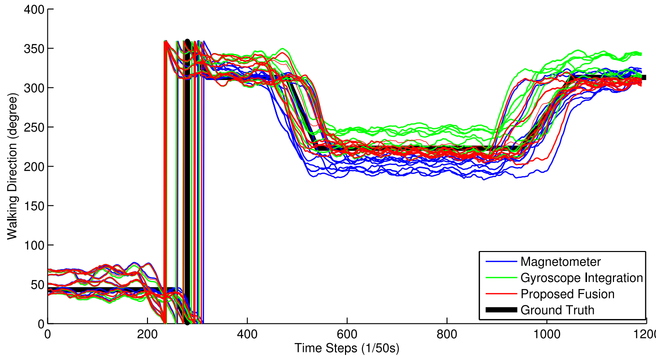


Fig. 3. Test results of walking direction estimation.

After two turns, the gyroscope-based approach starts to drift, and the fusion algorithm outperforms the two individual methods in robustness and accuracy. Note that the exact turning times are different for different runs, so the curves shift forward or backward randomly. And the turning time of the ground truth path is chosen as the mean of all the runs.

B. iBeacon Measurements

According to (1), only relative information is leveraged in the PDR approach. Therefore, errors will accumulate leading to the drift with walking distance. In this paper, we apply a new technology, i.e., iBeacon, which is built upon BLE. Comparing to WiFi, it is much more energy efficient. Since the localization is performed in a portable smartphone platform, power consumption is a big concern. Scanning BLE devices requires much less power than scanning WiFi routers [5], which makes iBeacon more suitable for our application. Owing to the low power consumption of BLE, a button cell can support an iBeacon for more than one year [24]. Thus, the iBeacon can be very small and easy to be deployed. An iBeacon package contains a unique ID, a reference RSS at 1 m distance and the RSS between the iBeacon and a device. Various approaches, such as fingerprinting, triangulation, and WPL, can be applied for iBeacon-based localization, but the dense deployment of iBeacons is required [4], [5]. Therefore, the deployment cost will be high, which is not suitable for industrial applications. In this paper, we attempt to develop a low-cost and high-efficient localization and navigation system. Thus, the sparse deployment of iBeacons is recommended. Instead of utilizing iBeacons for precise localization, we employ them to calibrate the PDR approach occasionally with distance measurements. Based on Bluetooth signal propagation, the distance between the device and the iBeacon can be derived using a path loss model in [18], which can be expressed as

$$R_k^i = R^0 - 10\gamma \log\left(d_k^i / d^0\right) \tag{10}$$

where R_k^i is the RSS of ith iBeacon, R^0 is the reference RSS value at 1 m distance, γ is the path loss exponent, d_k^i is the distance between the device, and ith iBeacon, and d^0 equals

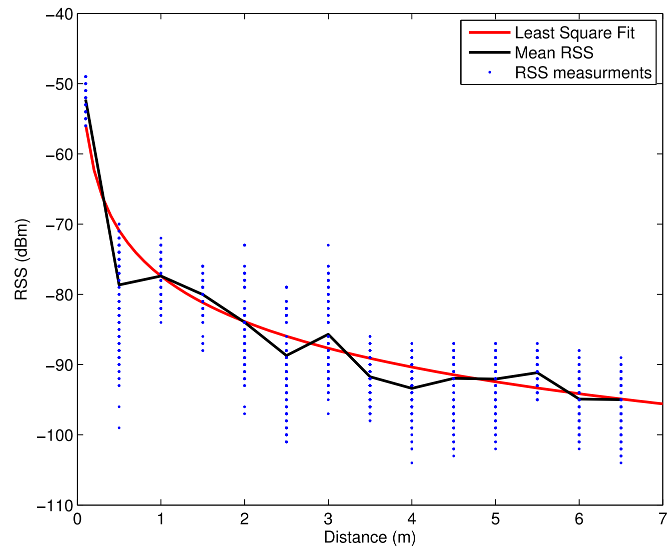


Fig. 4. RSS measurements at 14 reference points, the mean RSS values at each point and the curve of least-squares fit.

1 m. Then, the distance d_k^i can be derived as

$$d_k^i = 10^{\frac{R^0 - R_k^i}{10\gamma}} \tag{11}$$

To determine the parameters R^0 and γ, we chose 14 reference points ($0.1, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6$, and 6.5 m) and collected 500 RSS values at each point. The parameter R^0 equals the mean RSS value at 1 m distance. And the parameter γ can be determined using a least-squares fit. In our experiment, the final estimated values of R^0 and γ are -77.39 and 2.1529, respectively. Fig. 4 shows the RSS measurements at the reference points, the corresponding mean RSS values at each reference point and the curve of the least-squares model. We can find that the least-squares model fits the data very well. Another observation is that the differences of RSS values after 3 m are minor. Since the RSS measurements of iBeacons are used for calibrating the drift of the PDR approach, accurate measurements are necessary. Therefore, we define that the calibration using iBeacon measurements will only be performed when the estimated distance between a device and an iBeacon is equal to or less than 3 m.

C. Fusion

The PDR approach is simple and effective, but it will drift with walking distance. With sparse deployment of iBeacons, we attempt to calibrate the PDR approach occasionally with iBeacon measurements. Based on the PDR approach, we formulate the system dynamics as

$$\mathbf{S}_{k+1} = \mathbf{S}_k + \mathbf{u}_k + \mathbf{w} \tag{12}$$

where

$$\mathbf{u}_k = L_k \begin{bmatrix} \sin\theta_k \\ \cos\theta_k \end{bmatrix},$$

and $\mathbf{w}$ follows normal distribution with zero mean and variance $\mathbf{R}$. Based on the RSS between a device and an iBeacon, the distance between them can be derived using (11). Then, the observation model can be formulated as

$$z_{k+1} = \|\mathbf{S}_{k+1} - \mathbf{S}^i\| + v \tag{13}$$

where z_{k+1} is the estimated distance between the device and the iBeacon, $\mathbf{S}^i$ is the location of ith iBeacon, $\|\cdot\|$ is the Euclidean norm, and v follows a normal distribution with zero mean and variance G. Since the observation function is nonlinear, the traditional Kalman filter cannot be applied. A particle filter is a good candidate, but due to its high computational load, it is not suitable for a resource-limited smartphone platform. In this paper, we leverage on an extended Kalman filter which is much more computational efficient than a particle filter. Since the observation function [see (13)] is nonlinear, we need to calculate its Jacobian matrix. Assume that $\|\mathbf{S}_{k+1} - \mathbf{S}^i\| = f(\mathbf{S}_{k+1} - \mathbf{S}^i)$, $\mathbf{S}_{k+1} = [x_{k+1} \quad y_{k+1} \quad]$ and $\mathbf{S}^i = [x^i \quad y^i \quad]$, the Jacobian matrix $\mathbf{F}$ can computed as

$$\mathbf{F}_{k+1} = \left.\frac{\partial f}{\partial \mathbf{S}}\right|_{\mathbf{S}_{k+1|k}} = \left[\begin{array}{cc} \frac{x_{k+1|k} - x^i}{f(\mathbf{S}_{k+1|k} - \mathbf{S}^i)} & \frac{y_{k+1|k} - y^i}{f(\mathbf{S}_{k+1|k} - \mathbf{S}^i)} \end{array}\right]. \tag{14}$$

The extended Kalman filter contains two phases shown below:
Predicting:

$$\mathbf{S}_{k+1|k} = \mathbf{S}_k + \mathbf{u}_k \tag{15}$$

$$\mathbf{P}_{k+1|k} = \mathbf{P}_k + \mathbf{R} \tag{16}$$

Updating:

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1|k}\mathbf{F}_{k+1}^T(\mathbf{F}_{k+1}\mathbf{P}_{k+1|k}\mathbf{F}_{k+1}^T + G)^{-1} \tag{17}$$

$$\mathbf{S}_{k+1} = \mathbf{S}_{k+1|k} + \mathbf{K}_{k+1}(z_{k+1} - f(\mathbf{S}_{k+1|k} - \mathbf{S}^i)) \tag{18}$$

$$\mathbf{P}_{k+1} = (\mathbf{I} - \mathbf{K}_{k+1}\mathbf{F}_{k+1})\mathbf{P}_{k+1|k} \tag{19}$$

where $\mathbf{P}$ is the estimate covariance, $\mathbf{K}$ is the Kalman gain, and $\mathbf{I}$ is the identity matrix.

In most of the cases, iBeacons are attached to walls. In this situation, the iBeacon signals at the other side of the wall will be expected to be very weak. Once the estimated distance between the iBeacon and the device is in the calibration range (equal to or less than 3 m), we can ensure that the pedestrian is on the side where the iBeacon is attached. We can add this simple constraint into the fusion algorithm. If the output position of the fusion algorithm is at an invalid side of an iBeacon, we can mirror the position to the valid side. This is similar to the operation that kills the particles crossing a wall in a particle filter [25].

D. Initial Position Estimation

It is not practical to assume that the initial position is known [8], [16]. Various initial position estimation methods have been proposed. Errington *et al.* [26] presented a least-squares solution for initial position estimation using RFID. Their system requires extra devices, i.e., RFID receivers and readers. Woodman *et al.* [27] presented a WiFi-based initial position estimation for inertial pedestrian tracking. The WiFi RSS provided a

Fig. 5. User interface.

prior knowledge of particle weights in a particle filter algorithm. This will increase the convergence rate of their map matching approach. Due to the sparse deployment of existing WiFi infrastructures in indoor environments, the accuracy of WiFi-based approach is limited. In this paper, we present an initial position estimation scheme using existing WiFi routers and iBeacons. One possible approach is fingerprinting which constructs a fingerprint database, and then performs localization according to the database. This approach requires a labor-intensive data collection process. When a new WiFi router or an iBeacon is added, or some facilities are changed, fingerprinting approach needs to re-collect the whole data. A more efficient and practical solution is the model-based WPL algorithm. Since the mechanisms of WiFi and iBeacon are different, the RSSs of WiFi and iBeacon are not comparable. To solve this heterogeneous problem, we transfer the RSSs into distances using (11) with different parameters for WiFi and iBeacon. Then, a WPL algorithm can be employed using the distances. The details are elaborated as follows: based on (11), the distance between a device and ith iBeacon at time step k, d_k^i, can be calculated. The distance between the device and jth WiFi routers at time step k, D_k^j, can be computed using the same equation of iBeacons with different parameters, i.e., R^0 and γ. Assume that we have N sensible iBeacons and M sensible WiFi routers, and the locations of ith iBeacon, (a^i, b^i), and jth WiFi routers, (A^j, B^j) are known. The weights of ith iBeacon w^i and jth WiFi router W^j can be expressed as

$$w_k^i = \frac{\frac{1}{d_k^i}}{\sum_{i=1}^N \frac{1}{d_k^i} + \sum_{j=1}^M \frac{1}{D_k^j}} \tag{20}$$

$$W_k^j = \frac{\frac{1}{D_k^j}}{\sum_{i=1}^N \frac{1}{d_k^i} + \sum_{j=1}^M \frac{1}{D_k^j}}. \tag{21}$$

Then, the location of the device (a_k, b_k) can be calculated as

$$(a_k, b_k) = \sum_{i=1}^N w_k^i (a^i, b^i) + \sum_{j=1}^M W_k^j (A^j, B^j). \tag{22}$$

Considering that our system is running on a resource-limited smartphone platform, the WPL algorithm is simpler and more efficient compared with the fingerprinting approach. Since existing WiFi infrastructures and installed iBeacons are sparsely distributed, an approach that is only based on WiFi or iBeacons may not resolve the localization problem or will have low accuracy. Our proposed scheme leverages on all resources in

Fig. 6. Layouts of the experimental environments. (a) A research lab. (b) An empty hall.

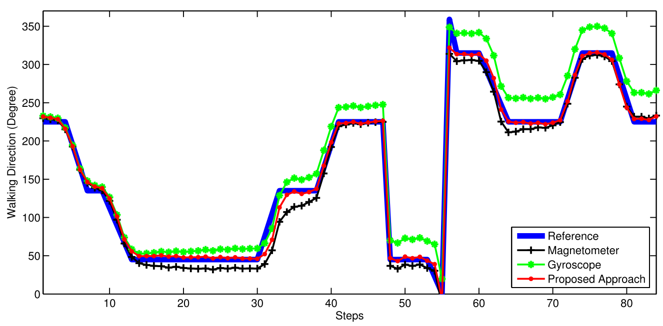


Fig. 7. Walking direction estimation based on magnetometer, gyroscope, and our proposed fusion approach.

the environment including WiFi routers and iBeacons. To solve the heterogeneous problem of the different facilities, i.e., WiFi routers and iBeacons, we transfer the RSSs into distances, and then perform a WPL algorithm to determine the location of the device.

III. Evaluation

In this section, we will first introduce the experiment setup. Then, the experimental results and discussions under two different environments will be presented. Finally, we will compare our proposed approach with some related works.

A. Experiment Setup

Real experiments have been conducted to evaluate the performance of the proposed approach. The device used in the experiments is a Google Nexus 5 smartphone. And four Estimote iBeacons [24] are employed in the experiments. Moreover, an Android app has been developed for real-time localization and tracking. The user interface is shown in Fig. 5 where the circle represents the location of the user, and the arrow inside the circle indicates the pointing direction of the smartphone. The coordinate of the user is shown in the top right corner. Note that we define the coordinate origin as the top left corner, the x-axis pointing to the right, and the y-axis pointing downward.

The experiments have been carried out under two environments, i.e., a research lab and an empty hall in the campus of Nanyang Technological University. The layouts are shown in Fig. 6 where the yellow stars represent the locations of iBeacons. In order to obtain the ground truth trajectory of a pedestrian, we use a camera to record the entire walking process and manually measure each step. In the experiments, we only consider handheld situation. This position is reasonable because a user should frequently check the current location on the screen of a smartphone in real-time navigation. Note that, in this situation, the walking direction of the user will almost be aligned with the pointing direction of the smartphone.

B. Experiment Results

The first scenario is a $19.0\,\mathrm{m} \times 16.2\,\mathrm{m}$ research lab [see Fig. 6(a)]. Due to the limited size of the environment, only one iBeacon is employed. Multiple experiments have been conducted in this scenario, and the average results are shown. Fig. 7 shows the walking direction estimation using a magnetometer, a gyroscope, and the fusion algorithm. Note that we leverage on the mean of direction values during each step as the final walking direction. In this way, the random noise effect is reduced. Due to the effects of electronic facilities, e.g., computers, printers, and the metal frameworks of cubicles, the magnetometer values are distorted. Moreover, vibrations during walking will also affect the measurements. The gyroscope based approach matches very well at the beginning, but it drifts after several turns. The fusion algorithm matches the ground truth reference direction very well. It is much more stable comparing to the magnetometer-based approach and avoids the drift problem in the gyroscope-based approach. We can conclude that the fusion algorithm has the highest estimation accuracy and resolves the problems of individual sensors.

Fig. 8 illustrates the trajectories of the true path, the PDR approach, and the proposed approach. Each step is shown in the figure where the start and end points are indicated. Based on WiFi measurements of existing routers and the measurement of the iBeacon, the initial location is estimated using the WPL

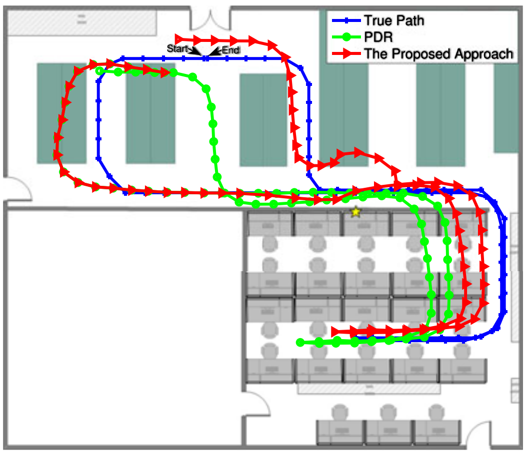


Fig. 8. Trajectories of the true path, the PDR approach, and the proposed approach.

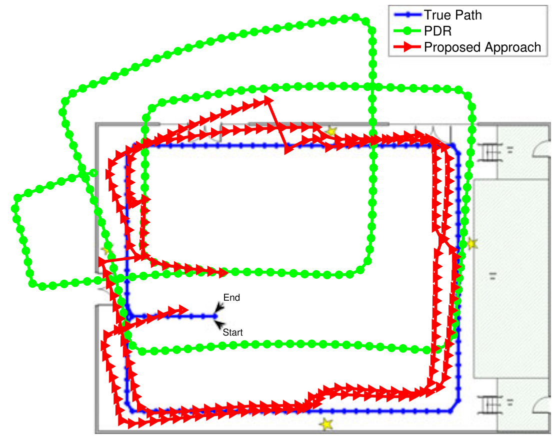


Fig. 11. Trajectories of the true path, the PDR approach, and the proposed approach with four iBeacons.

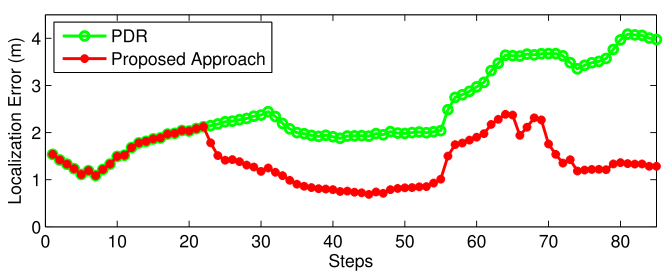


Fig. 9. Localization error with respect to each step.

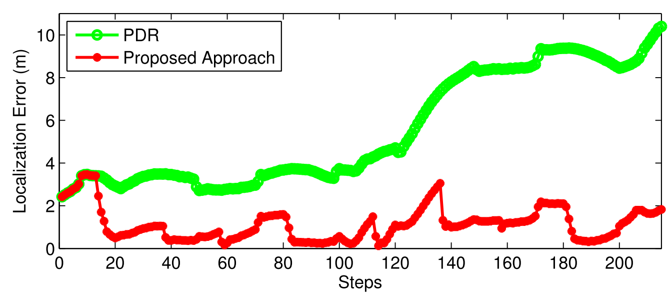


Fig. 12. Localization error with respect to each step.

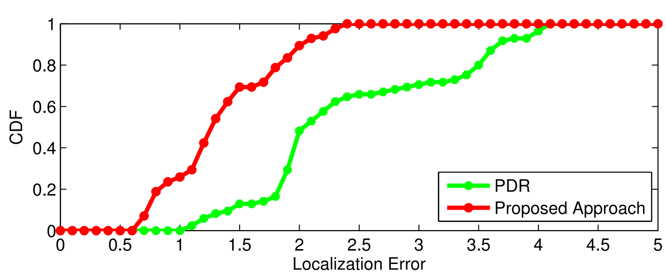


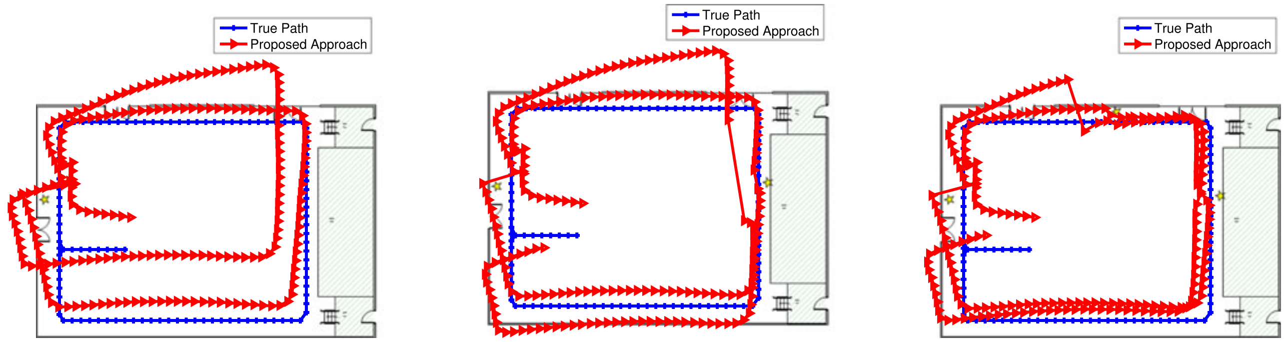
Fig. 10. Cumulative error distributions of the PDR approach and our proposed approach.

approach mentioned in Section II-D. According to the true trajectory, we can infer that the system will be calibrated twice when the estimated distance between the pedestrian and the iBeacon is equal or less than 3 m.

Fig. 9 depicts the localization error with respect to each step. Generally, the localization errors of the PDR-based approaches will increase with walking distance because of the estimation errors of step detection, walking length estimation, and walking direction estimation. However, our proposed approach corrects the drift using occasional iBeacon measurements, which is shown as two significant reductions of localization errors in the figure. The cumulative error distribution of the results is shown in Fig. 10. The mean localization accuracies of the PDR approach and the proposed approach are 2.46 and 1.39 m, respectively. This indicates the effectiveness of the proposed algorithm.

Another scenario is a 25.0 m $\times$ 17.0 m empty hall environment whose layout is shown in Fig. 6(b). The iBeacon on the right-hand side is attached to a tripod; therefore, this iBeacon cannot use the constraint mentioned in Section II-C. And the others are attached to walls, which satisfies the required condition of applying the constraint. In the experiments, a pedestrian walks around the layout twice, producing a shape of two rectangles. Fig. 11 depicts the trajectories of the true path, the PDR approach, and the proposed approach. Starting and ending points are shown in the figure. Since no WiFi routers are contained in the environment, we only apply iBeacon measurements to determine the initial location using the WPL approach mentioned in Section II-D. It can be found that the proposed approach significantly reduces the drift when walking through iBeacons. The calibration will be performed when the estimated distance between the user and an iBeacon is equal or less than 3 m. Fig. 12 illustrates the localization error with respect to each step. The PDR approach slowly drifts to more than 10 m after 200 steps. Owing to the correction of iBeacons, the proposed algorithm achieves a high localization accuracy. The mean localization accuracies of the PDR approach and our proposed approach are 5.55 and 1.28 m, respectively.

Next, we evaluate the number of iBeacons with respect to the localization accuracy. Fig. 13 shows the trajectories of the proposed approach with different numbers of iBeacons, i.e., one to three iBeacons. The trajectories of the PDR approach and our proposed approach with four iBeacons are depicted in Fig. 11.



(a) (b) (c)

Fig. 13. Trajectories of the proposed approach with different numbers of iBeacons. (a) The proposed approach with one iBeacon. (b) The proposed approach with two iBeacons. (c) The proposed approach with three iBeacons.

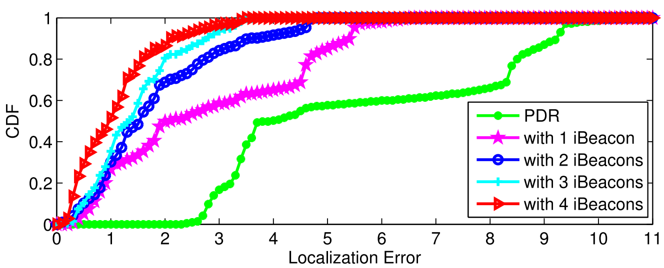


Fig. 14. Cumulative error distributions of the PDR approach and our proposed approach with different numbers of iBeacons.

Fig. 14 illustrates the cumulative error distribution of the PDR approach and the proposed approach with different numbers of iBeacons. As expected, the accuracy of the proposed approach degrades with fewer iBeacons. But, even with one iBeacon, the proposed approach has yielded significant improvement over the PDR approach in the localization accuracy. When the number of iBeacons is larger than 2, only slight improvements of localization accuracy are observed. Thus, if taking device (iBeacon) and deployment cost into consideration, the proposed approach with two iBeacons can achieve a reasonable accuracy in this environment. In conclusion, the localization error of the proposed approach will decrease with an increase in the number of iBeacons. And, we can roughly determine an optimal number of iBeacons when given a required localization accuracy.

C. Compared With WiFi Fingerprinting

WiFi fingerprinting is the most popular technique for indoor localization and tracking. Thus, we compared our proposed approach with WiFi fingerprinting-based approaches on three criteria, i.e., localization accuracy, calibration time, and power consumption. The WiFi fingerprinting approach was performed in our first testing scenario [see Fig. 6(a)]. Five WiFi access points (APs) were used, and 40 reference points were selected for data collection. At each reference point, we collected 3000 samples in four different orientations. The APs that we used are TP-LINE WDR4300.

1) Localization Accuracy: Each algorithm has been run for five times and the average results are shown. With the above experimental setting, the WiFi fingerprinting approach can achieve a mean localization accuracy of 2.2 m. Many research studies have demonstrated the effectiveness of the fusion of WiFi-based approaches with smartphone inertial sensors [28]–[30]. Therefore, we attempted to fuse WiFi fingerprinting approach with PDR using a particle filter which is the most popular algorithm in localization and tracking [28], [31]. One thousand particles were used in the experiment. The final mean localization accuracy of this fusion approach is 1.54 m. For our proposed approach, we only employed one iBeacon device and we achieved a mean localization accuracy of 1.39 m.

2) Calibration Time: In the experiments, we set the sampling frequency of WiFi scanning and iBeacon scanning to be 1 Hz. The WiFi fingerprinting approach requires a collection of 40×3000 data samples (40 reference points and 3000 samples for each reference point), which requires approximately 33.3 h. While our proposed approach only needs to calibrate R^0 and γ in (10) referring to 12×500 data samples (12 reference points and 500 samples for each reference point), which requires some 1.7 h. In this regard, our proposed approach requires much less calibration time.

3) Power Consumption: Since the whole system will be running on a portable smartphone, power consumption will be crucial. We developed a simple Android application to test the power consumption of WiFi scanning and iBeacon scanning. A Google Nexus 5 smartphone with a battery capacity of 2300 mAh was used. The scanning frequency of WiFi and iBeacon is 1 Hz. First, we ran the application without scanning WiFi or iBeacon as the basic battery usage for 1 h, and then, we performed WiFi scanning and iBeacon scanning separately for 1 h. Finally, the basic battery usage was subtracted for the calculations of the power consumption of WiFi scanning and iBeacon scanning, respectively. In the experiment, WiFi scanning for 1 h consumes 115 mAh, while iBeacon scanning for 1 h only consumes 46 mAh, which translates to a battery power saving of around 60%.

IV. Conclusion

In this paper, we have proposed an iBeacon assisted indoor localization system using built-in smartphone inertial sensors. In the PDR approach, we have presented a coordinate transformation and an efficient scheme for step detection. Moreover, a novel initial point estimation scheme has been proposed by combining existing WiFi routers and iBeacons. Based on the distribution of iBeacon measurements, we have defined a calibration range where an extended Kalman filter is applied. Moreover, we have presented a WPL model to determine the initial position using existing WiFi routers and installed iBeacons. To evaluate the performance of the proposed approach, real experiments have been conducted under two different environments, i.e., a research lab and an empty hall. With sparse deployment of iBeacons, we can significantly improve the localization accuracy. We have also evaluated the localization performance of the proposed approach with respect to the number of iBeacons and concluded that the optimum number of iBeacons can be determined depending on the required localization accuracy.

In summary, the main contributions of this paper are as follows.

1) We propose a smartphone inertial sensor-based indoor localization and tracking system with occasional iBeacon corrections. Comparing to WiFi, iBeacon technology is much more power efficient which is curial for a portable smartphone platform and can be easily deployed in any situations.
2) A coordinate transformation is applied to overcome the tilting effect in step detection. And a simple and efficient threshold-based step detection algorithm is presented. Moreover, we also presented a novel initial point estimation scheme by combining existing WiFi routers and iBeacons.
3) The property of iBeacon measurements is studied. We defined an efficient calibration range where an extended Kalman filter is developed for iBeacon corrections. Since the algorithm is running on a resource-limited smartphone platform, the lightweight and computational efficiency of the extended Kalman filter is more suitable than the widely used particle filter.
4) We evaluated the performance of the proposed approach under two different environments with sparse deployment of iBeacons. Moreover, we also tested the impact of the number of iBeacons with regard to localization accuracies.

It is obvious that the iBeacon placement will have a great impact on the localization accuracy. In our future works, we will attempt to determine the optimal locations for each iBeacon using some optimization approaches in sensor placement [32]. In this paper, we assume that the locations of iBeacons are known. We will relax this assumption in our future works. A popular SLAM algorithm [33] in robotics may be applied for pedestrian localization and the estimation of iBeacon locations.

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