Accurate Indoor Localization and Tracking Using Mobile Phone Inertial Sensors, WiFi and iBeacon

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***Abstract*—In this paper, we propose a robust and accurate indoor localization and tracking system using smartphone built-in inertial measurement unit (IMU) sensors, WiFi received signal strength measurements and opportunistic iBeacon corrections based on particle filter. We utilize Pedestrian Dead Reckoning (PDR) approach which leverages smartphone equipped accelerometers, gyroscope and magnetometer to estimate the walking distance and direction of user. The position estimated by WiFi fingerprinting based approach is fused with PDR to reduce its drifting error. Since the number of WiFi routers is usually limited for localization in large-scale indoor environment, we employ the emerging iBeacon technology to occasionally correct the drifting error of PDR in poor WiFi coverage area. Extensive experiments have been conducted and verified the superiority of the proposed system in terms of localization accuracy and robustness.**

***Index Terms*—Smartphone inertial sensor, pedestrian dead reckoning, WiFi fingerprinting, iBeacon, indoor localization and tracking**

I. Introduction

Nowadays, precise indoor localization and tracking is becoming extremely indispensable for myriad emerging applications, e.g. smart building, Internet of things, augmented reality, context-aware advertising and indoor navigation. Various sensing techniques have been proposed for indoor positioning in the past two decades [1]. For instance, Radio frequency identification (RFID) based indoor positioning system (IPS) is developed [2]. However, it requires user to carry dedicated device and extra infrastructure are required to be deployed in advance. On the other hand, with the booming development of mobile devices, commercial off-the-shelf (COTS) smartphones are equipped with various types of sensors that make them not only a simple communication tool but also a comprehensive sensing platform [3]. This facilitates Pedestrian Dead Reckoning (PDR) approach makes feasible on smartphone using built-in inertial measurement unit (IMU) sensors (accelerometers, gyroscope and compass) without introducing any extra infrastructure [4]. PDR approach estimates the current position of user based on the previous position, the current walking length and direction of user. Although it is accurate in short range, the bottleneck of PDR is the drifting problem with walking distance [4]. WiFi based IPS has been recognized as the primary alternative to GPS for indoor localization because WiFi network infrastructures are widely available in indoor and nearly every COTS smartphone is WiFi enabled [5]. Nevertheless, existing WiFi based IPSs require installing a dedicated App on the users' smartphones to continuously scan nearby WiFi routers for data acquisition, which consumes substantial amount of battery on smartphone. Thus, there is no sole sensing technique that could provide accurate, robust and consistent localization and tracking services.

To cope with this issue, in this paper, we propose a novel IPS using multiple sensing techniques, including IMU sensors, WiFi fingerprinting and opportunistic iBeacon corrections by sensor fusion based on particle filter. We utilize both gyroscope and magnetometer to estimate the walking direction of user. Since the vertical acceleration signal contains periodic patterns when feet hit the ground during walking, we leverage it to infer the walking length and step detection. Furthermore, we develop a novel wireless sensing system that enables COTS WiFi routers to overhear the existing WiFi traffic between smartphones and routers, and retrieve received signal strength (RSS) readings from the data packets for WiFi fingerprinting based localization algorithm without extra infrastructure or dedicated Apps to be installed on smartphone for data acquisition. The position estimated by WiFi fingerprinting is fused with PDR to reduce its drifting error using particle filter. However, the drift problem of PDR still occurs in some areas of large-scale indoor environment where WiFi coverage is poor. To overcome this problem, we employ the emerging iBeacon technology to occasionally correct the drifting error of PDR in poor WiFi coverage area. iBeacon is built upon Bluetooth Low Energy (BLE) that is much more energy efficient than classic Bluetooth and WiFi [6], [7]. We analyze the transmission property of iBeacon RSS and define an effective correction range for eliminating the drifting error of PDR using particle filter. Extensive experiments have been conducted in a real world office and demonstrated that the proposed approach outperforms existing solutions comprehensively.

II. System Design

A. Pedestrian Dead Reckoning (PDR)

The PDR approach employs the previous position, current walking length and direction to estimate the current position of the user. It can be expressed as

$$\mathbf{P}_k = \mathbf{P}_{k-1} + L_k \begin{bmatrix} \sin(\theta_k) \\ \cos(\theta_k) \end{bmatrix} \tag{1}$$

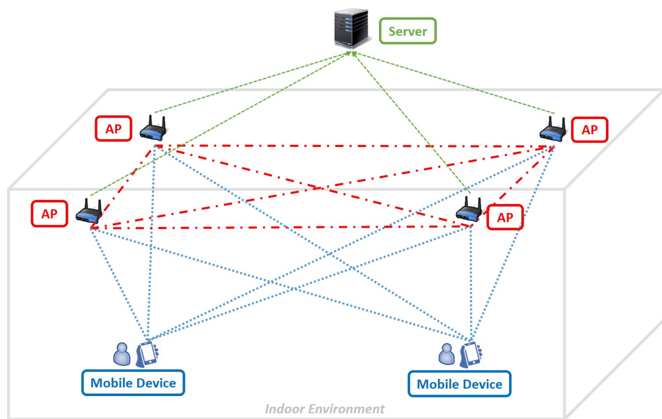

Fig. 1. System Architecture of WinIPS.

where $\mathbf{P}_k$ is the 2D coordinate of the user's position, L_k and θ_k are the walking length and the walking direction of the user at time step k.

We observed that the vertical acceleration signal contains periodic patterns when feet hit the ground during walking. Thus, we leverage a threshold method to identify each step using vertical acceleration measurements. To infer the walking length L, we adopt a sophisticated model proposed in [8] which establishes a relationship between vertical acceleration and walking length as $L = \beta(a_{max} - a_{min})^{1/4}$ where a_{max} and a_{min} are the maximal and minimal vertical accelerations respectively during one step and β is a calibrated coefficient. Magnetometer measurement can be used to determine the walking direction θ. Nonetheless, it fluctuates severely due to the presence of various metal and electronic devices in complex indoor environment. Another method for walking direction estimation is leveraging the integration of gyroscope readings. However, the result of integration will drift continuously due to the sensor noise if no corrections is conducted. Thus, we combine these two methods with a Kalman filter to obtain a better estimation of walking direction of user.

B. WiFi based Non-intrusive IPS

Existing WiFi based IPSs require user to install a dedicated App to conduct active WiFi scanning for RSS data acquisition which is extremely power hungry. To overcome this issue, we propose a WiFi-based non-intrusive IPS (WinIPS) which is capable of estimating the user's location precisely and effectively using existing WiFi infrastructure in a non-intrusive manner.

Figure 1 demonstrates the system architecture of WinIPS, which includes COTS WiFi routers (APs), a back-end server, as well as users and their smartphones. We upgrade the firmware of these routers with OpenWrt and add a designed software based on Libpcap to sniff and capture the data packets transmitted in the existing WiFi traffic. Then, these routers precisely retrieve the RSS values and corresponding MAC addresses as identifications of users from the packets. Since the entire data acquisition procedure is conducted on router side, WinIPS does not introduce any additional battery consumption on smartphone and achieves higher sampling rate which facilitates real-time localization for WiFi fingerprinting based localization. Online sequential extreme learning machine (OS-ELM) is utilized as the localization algorithm for WinIPS [9]. As an adaptive localization algorithm, it is able to provide good generalization performance at an extremely fast learning speed and has an online sequential learning ability that does not require retraining when new RSS data are collected. OS-ELM estimates the locations of users by feeding the RSS readings into the latest revised OS-ELM localization model. The detailed methodology of OS-ELM is presented in [9]. The location estimation by WiFi fingerprinting is employed as the initial position for PDR and also fused with PDR to reduce its drifting error using particle filter.

C. Opportunistic iBeacon Corrections

With the sensor fusion of WiFi, the drifting issue of PDR is mitigated to some extent. However, in certain large-scale indoor environments, such as shopping mall, stadium and airport, the number of WiFi routers is usually limited since their primary objective is to provide Internet service instead of indoor localization. The drifting problem of PDR still occurs in the area where WiFi coverage is poor. Therefore, we leverage the emerging iBeacon technology to occasionally correct the drifting error in this circumstance. iBeacon is an advanced Bluetooth protocol proposed by Apple [10]. It broadcasts its unique identifier to nearby smartphones using BLE proximity sensing and trigger a location-based action on these devices. An iBeacon is able to run on a coin cell battery for months or even for years because it adopts short duration messages and does not need a paired connection with mobile devices. In this manner, it is much more power efficient than classical Bluetooth protocols and less power hungry than WiFi and GPS.

Owing to these merits, we only deploy a few iBeacons as landmarks to cover the poor WiFi area for PDR drifting correction. The RSS broadcast from an iBeacon B_j can be formulated based on a path loss model as:

$$B_j = B_0 - 10\alpha \log(d_j) + X_\sigma, \tag{2}$$

where B_0 is the RSS value at the reference distance ($1m$), α is the path loss exponent, and X_σ represents a zero Gaussian random noise with standard deviation σ. The distance d_j between the smartphone and the iBeacon can be calculated by:

$$d_j = 10^{\frac{B_0 - B_j + X_\sigma}{10\alpha}} \tag{3}$$

We conducted real experiments to analyze the effects of Non-line-of-sight (NLOS) and the orientation of smartphone on the RSS from iBeacons. According to our analysis, the RSS reading becomes stable and reliable when the distance between smartphone and iBeacon is within $3m$. Therefore, we define that when the RSS of an iBeacon is larger than $-64dBm$, it indicates that the smatphone as well as its user is entering the effective correction range of that iBeacon and it then triggers the PDR drifting correction process.

D. Sensor Fusion with Particle Filter

Although the PDR method is able to achieve precise localization in a short range, it drifts along with the walking distance continuously. WiFi fingerprinting approach can estimate the exact location of user consistently. However, it is vulnerable to environmental dynamics which introduce high variation of RSS. Thus, we combine these two approaches to compensate their individual flaws using particle filter. In addition, opportunistic iBeacon correction is also integrated to improve the overall accuracy of our system in poor WiFi coverage area.

Sequential Importance Resampling (SIR), which approximates the posterior distribution by a weighted set of particles, is adopted as the sensor fusion algorithm for our system. Its methodology is summarized as follows:

Initialization: Suppose we have an initial position $\mathbf{P}_0$ which is estimated by WiFi fingerprinting approach, m particles will randomly generate around the initial position as

$$\mathbf{P}_0^i \sim \mathbf{N}(\mathbf{P}_0, \sigma^2), i = 1, 2, \ldots, m \tag{4}$$

where $\mathbf{P}_0^i$ is the position of ith particle at the initialization phase.

Prediction: With the IMU sensor measurements, both walking length L_k and direction θ_k during each step are estimated. Thus, the position of each particle is predicted as

$$\mathbf{P}_k^i = \mathbf{P}_{k-1}^i + L_k \begin{bmatrix} \sin(\theta_k) \\ \cos(\theta_k) \end{bmatrix} \tag{5}$$

Updating: Suppose the position estimation by WiFi at time step k is $\mathbf{P}_k^W$. The distance between each particle and the WiFi estimation is calculated as $\|\mathbf{P}_k^w - \mathbf{P}_k^i\|$. If the user is in a iBeacon correction zone, the distance between each particle and the iBeacon is determined by $\|\mathbf{P}^B - \mathbf{P}_k^i\|$, where $\mathbf{P}^B$ is the position of the iBeacon. Then, we define a combined distance d_k^i for weight calculation of each particle, which can be expressed as

$$d_k^i = \beta_W \|\mathbf{P}_k^w - \mathbf{P}_k^i\| + \beta_B \|\mathbf{P}^B - \mathbf{P}_k^i\| \tag{6}$$

where β_W is set to be 1 or 0 when the user is in the good or poor WiFi coverage area respectively, and β_B is set to be 1 in iBeacon correction zone and otherwise to be 0. The weight of each particle is calculated as $w_k^i = \frac{w_{k-1}^i P(d_k|d_k^i)}{\sum_{i=1}^m w_{k-1}^i P(d_k|d_k^i)}$ where $P(d_k|d_k^i) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(d_k - d_k^i)^2}{2\sigma^2}}$. Then, the user's position estimated by our sensor fusion approach is calculated as

$$\mathbf{P}_k = \sum_{i=1}^m w_k^i \mathbf{P}_k^i \tag{7}$$

III. Evaluation

To validate the performance of the proposed approach, extensive experiments were conducted in a $600m^2$ multi-functional office using a Google Nexus 6 smartphone. As demonstrated in Figure 2(d), 8 TP-LINK N750 routers and 8 Estimote iBeacons were leveraged for WiFi fingerprinting and iBeacon corrections respectively. We tracked the walking path of an occupant for 168 steps using the proposed approach and compared it with PDR, WiFi and integrated PDR and WiFi using particle filter. Figure 2 presents the tracking trajectories comparison of the four approaches with the ground truth. Figure 3 depicts the detailed localization error with respect to each step and Figure 4 illustrates the cumulative error distributions of the four approaches. As demonstrated in Table I, the mean localization accuracy of the proposed approach is 0.594 m, which obtains a tremendous improvement of 78.25%, 69.81% and 59.84% over PDR, WiFi and integrated PDR + WiFi, respectively. As shown in Figure 3 and Figure 4, the proposed approach outperforms existing solutions consistently and comprehensively.

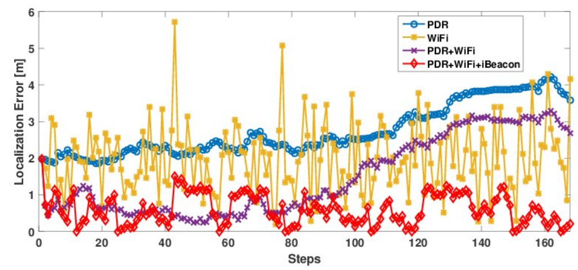

Fig. 3. Detailed localization error of the four approaches with respect to each step.

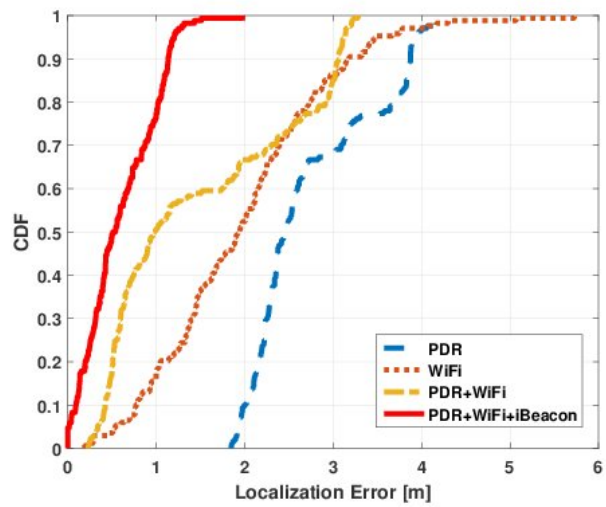

Fig. 4. Cumulative error distributions of PDR, WiFi fingerprinting, particle filter (PDR+WiFi) and the proposed approach (sensor fusion of PDR, WiFi and iBeacon using particle filter).

IV. Conclusion

In this paper, we proposed a novel indoor localization and tracking system that fuses PDR approach using smartphone built-in IMU sensors, WiFi fingerprinting and opportunistic iBeacon corrections based on particle filter. Extensive experiments have been conducted which verified the superiority and effectiveness of the proposed method. The developed system makes substantial progress towards providing accurate, practical and large-scale indoor location based services.

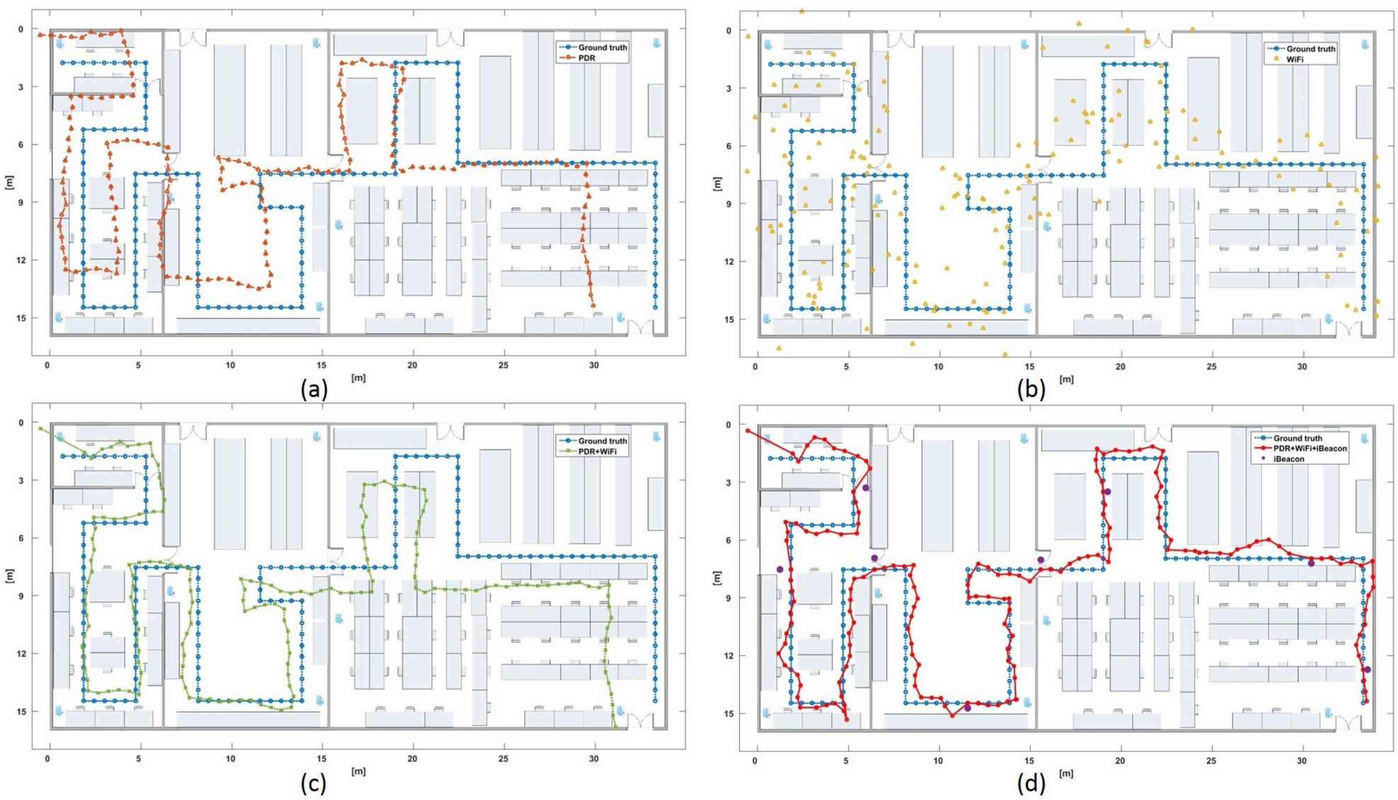

Fig. 2. Comparison of tracking trajectories (a) PDR approach vs ground truth (b) WiFi fingerprinting approach vs ground truth (c) particle filter (PDR+WiFi) approach vs ground truth d) the proposed approach (sensor fusion of PDR, WiFi and iBeacon using particle filter) vs ground truth.

TABLE I
COMPARISON OF LOCALIZATION ACCURACY (M)

Approach	Mean Error	Standard Deviation	Worst-case Error
Pedestrian Dead Reckoning (PDR)	2.732	0.700	4.225
WiFi fingerprinting	1.968	0.965	5.725
Particle filter (PDR+WiFi)	1.480	1.050	3.283
Particle filter (PDR+WiFi+iBeacon)	**0.594**	**0.406**	**1.974**

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