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iBILL: Using iBeacon and Inertial Sensors for Accurate Indoor Localization in Large Open Areas

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ABSTRACT As a key technology that is widely adopted in location-based services (LBS), indoor localization has received considerable attention in both research and industrial areas. Despite the huge efforts made for localization using smartphone inertial sensors, its performance is still unsatisfactory in large open areas, such as halls, supermarkets, and museums, due to accumulated errors arising from the uncertainty of users' mobility and fluctuations of magnetic field. Regarding that, this paper presents iBILL, an indoor localization approach that jointly uses iBeacon and inertial sensors in large open areas. With users' real-time locations estimated by inertial sensors through an improved particle filter, we revise the algorithm of augmented particle filter to cope with fluctuations of magnetic field. When users enter vicinity of iBeacon devices clusters, their locations are accurately determined based on received signal strength of iBeacon devices, and accumulated errors can, therefore, be corrected. Proposed by Apple Inc. for developing LBS market, iBeacon is a type of Bluetooth low energy, and we characterize both the advantages and limitations of localization when it is utilized. Moreover, with the help of iBeacon devices, we also provide solutions of two localization problems that have long remained tough due to the increasingly large computational overhead and arbitrarily placed smartphones. Through extensive experiments in the library on our campus, we demonstrate that iBILL exhibits 90% errors within 3.5 m in large open areas.

INDEX TERMS Indoor navigation, inertial navigation, mobile computing.

I. INTRODUCTION

Indoor localization with high accuracy is the key technology for Location Based Services (LBS), whose market value is estimated to reach more than 4 billion dollars by 2019 [1], [2]. Real world applications of LBS include navigation in airports, railway stations and advertising push in shopping malls and museums, where users need to know their own exact locations in unfamiliar scenes and services providers need to know the location context of every user to provide personalized services. Recently, Apple Inc. proposed a new kind of Bluetooth Low Energy for developing LBS market named iBeacon. iBeacon devices can realize the connection between physical world and digital world in their vicinities [3]–[5]. This gives a new line of thinking for LBS systems and indoor localization technologies.

Among huge efforts devoted to the study of indoor localization technologies from both academia and industry, the majority of existing work focus on two different technologies, including fingerprint of radio frequency signals [6]–[8], with the most representative one being WiFi [9], [10], [12], and mobility estimation using inertial sensors [13]–[15]. Although WiFi fingerprint based indoor localization has been studied for years, its accuracy still needs improvement, especially in large open indoor scenes [10], [11]. This is attributed to random signal strength fluctuations arising from inevitable multi-path effects, dynamical states of signal transmission channels, and transmission power control techniques of WiFi routers. The expensive energy consumption is another preventing factor since battery capacity in smartphones is limited. The mobility estimation technology using inertial sensors in smartphones (accelerometer, gyroscope and magnetometer) also fails to work well in large open environments [13]. Since users' walkable paths are diverse in these scenes, floor plans are unable to restrain errors arising from noise of inertial sensors by constraining users' possible mobility in location estimating process. Smartphones being placed arbitrarily (shaken in hand or put into pocket) will bring much noise to inertial sensors, this is a long-standing tough problem for this technology. Moreover, the accumulated errors in localization process using inertial sensors further undermine its fidelity.

Recently, a novel series of indoor localization approaches has been presented, represented by Magicol in [16], Maloc in [17] and FollowMe in [18], which fuse inertial sensors and geomagnetism, and their performances are superior to the two technologies aforementioned. Recognizing that indoor magnetic field anomalies are omnipresent, location specific and temporally stable, the authors leverage the locally disturbed magnetic signals as location-specific signatures. Besides, the magnetic sensing consumes much less energy than WiFi scanning. The localization process is realized through an augmented particle filter, in which the similarity between the magnetic strength collected online and that in a pre-constructed database is used to weigh particles. And the inertial sensors and map information are used to drive particles. Magicol can achieve a localization accuracy of 0.9m for tracking in office environments, while only 8m in supermarkets. The reason is that in large open areas like supermarkets, users' movements have higher uncertainty, magnetic measuring has larger noise, and error accumulation of particle filter is unavoidable. Increasingly large computational overhead of particle filter is another challenging factor for its usage of many users.

As highly accurate indoor localization is essential to LBS, following question arise naturally: can we further improve the performance of inertial sensors and geomagnetism based indoor localization in large open areas?

Motivated by this, in this paper we show that using *iBeacon* can improve the performance of inertial sensors and geomagnetism based localization. iBeacon, which is an important module in modern LBS systems, is proposed by Apple Inc. for developing LBS market [3]. Users can be localized accurately in proximity of pre-deployed iBeacon devices using trilateration [19]. Since iBeacon devices are designed as core modules for LBS systems such as mobile advertisements, ticket validation [20], using them for localization will not bring additional cost for LBS providers. However, valid distance measuring range of iBeacon devices is only several meters [19] and they cannot be always used for localization for their role in LBS systems. As a result, accurate and real time localization using iBeacon only is impractical (the analysis is in Section III), and deploying iBeacon devices sparsely to opportunistically calibrate inertial sensors and geomagnetism based real time localization is a practical scheme. With the best of our knowledge, utilizing this scheme to realize accurate localization in large open areas is the first time introduced in this paper.

This paper presents iBILL, an indoor localization system using *iBeacon, inertial sensors and geomagnetism* in large open environments. We first give fundamental insights on iBeacon based localization system and provide analyses on both its advantages and limitations. With users' real time locations determined according to the estimated mobility and magnetism through an improved particle filter, we revise the algorithm of augmented particle filter to cope with magnetic fluctuations and complexity of users' mobility. And we further take advantages of iBeacon to guarantee the improved particle filter always achieves better performance in localization process. When users enter vicinity of at least three iBeacon devices, their locations can be accurately determined based on Received Signal Strength (RSS) of iBeacon devices and the accumulated errors therefore are corrected. In addition, we give solutions to two long-stand tough problems of localization using inertial sensors, increasingly large computational overhead of particle filter [17] and smartphones be placed arbitrarily [13], to improve robustness of iBILL. We have implemented experiments in the library on our campus which has diverse complex scenes (e.g. reading rooms and a services hall). Comparing with commonly used dead reckoning and magnetic fingerprint based localization systems, we demonstrate that iBILL achieves higher accuracy in large open areas.

The remainder of the paper is organized as follows. Section II presents related work. Section III gives insights on localization using iBeacon and then illustrates design rationale for iBILL. Based on this, we present iBILL in Section IV. Section V provides experimental setup and results. Conclusions and future work are given in Section VI.

II. RELATED WORK

This paper combines iBeacon devices, magnetic field signals and inertial sensors for indoor localization. There have been much work on using sensor fusion (inertial sensors and radio frequency signals) and magnetic field for localization. We only discuss closely related work in this section.

A. SENSOR FUSION APPROACHES FOR INDOOR LOCALIZATION

The design rationale for sensor fusion is that mobility estimated by inertial sensors is by nature related to location in the physical world [13], and a position is characterized by its detected fingerprint of radio frequency signal patterns [10]. Integrating mobility and fingerprint can lower the separate localization errors, and the most popular integrating approach is particle filter [17], [21], [22].

GIFT [23] is a system using the spatial correlation of WiFi signals as locations' features. A gradient-based fingerprint map (Gmap) is constructed by comparing absolute RSS values at nearby positions. Users' motion and RSS observations are combined through an extended particle filter. Particles are driven by detected mobility and their weights are determined by comparing results between RSS observations and Gmap. Using gradient of RSS values can handle the changing transmission power of WiFi routers. SLAC [12] is a system that fuses step counter and WiFi fingerprints to optimize locations estimating problem, in which wireless signals and users' mobility are jointly used through a specialized particle filter. It learns parameters in step mode of each user (the relationship between step length and stride frequency), calibrates RSS measurements of heterogeneous devices and, simultaneously estimates locations of walking targets by solving a convex optimization problem. However, existing works fail to achieve satisfactory accuracy in large open areas as wireless signals are vulnerable to changing environments. The high probability for RSS deviation may change the RSS gradients and parameters learning may be error-prone under this condition. Furthermore, due to the large computational overhead for solving a convex optimization problem, SLAC is incapable to serve many users.

B. MAGNETIC FIELD BASED INDOOR LOCALIZATION

The magnetic filed is omnipresent and nonuniform in indoor environments due to the anomalies arising from steel, concrete structures and electric systems. Since the location-specific magnetic field readings are stable over time and magnetic sensing consumes little energy, it is feasible to take magnetic filed as locations' signatures for indoor localization [16], [24], [25]. Chung *et al.* [26] designed a geomagnetism based localization system, which estimates users' locations by comparing magnetic field measurements with a pre-established magnetic fingerprint database. The system uses magnetic fingerprint only, as a result the sensing noise therefore dominates the localization errors. Moreover, another drawback of the system lies in commanding magnetic sensors remain at the same orientation, which makes it impractical for pedestrian tracking.

FollowMe [18] is a novel indoor navigation system based on magnetism. In trace-collection module, it records both a leader's walking trace (inertial sensors' readings) from a origin to a destination and magnetic fingerprints along the trace. In navigation module, it estimates followers' locations by matching magnetic measurements and then generates navigation notifications according to their positions on restored walking trace. However, in large open areas, it is difficult to obtain a complete collection of the trips to a same destination due to the large diversity exhibited, and users are easily get lost for large magnetic sensing noise. Above reasons hinder FollowMe's usage in airports, museums and large shopping malls etc.

In iBILL, we use the strength of magnetic signals as locations' features, which is independent from phone orientation. We consider the sensing noise and fluctuations of magnetic field and then revise the algorithm of traditional particle filter to relieve the problem. We further use iBeacon devices to approach errors accumulation problem and reduce computational overhead in localization process.

III. INSIGHTS ON LOCALIZATION USING iBeacon

In iBILL, we use iBeacon devices to improve the performance of inertial sensors and magnetic filed based localization in large open scenes. In this section, we give the fundamental insight on localization using iBeacon to further illustrate the design rationale for iBILL. We first introduce LBS systems based on iBeacon devices, and then analyze the advantages and limitations of iBeacon based localization technologies.

A. INTRODUCTION TO iBeacon BASED LBS SYSTEMS

iBeacon is announced by Apple Inc. in 2013 as a new technology for accurate indoor localization. A great advantage of iBeacon lies in low power consumption for utilizing BLE (the forth major revision of the Bluetooth specification), and it is consequently applicable to mobile usages. Smartphones which run on Apple iOS 7+ and Android 4.3+ operation systems all support iBeacon protocol [27]. iBeacon devices are designed to work as an important module in location-context-aware systems. Taking museum as an example, as shown in Fig. 1, a visitor comes into a museum, his smartphone receives broadcast packets transmitted by iBeacon devices deployed at entrance. The packets contains the URL for ticket purchase, then visitors can buy ticket through the URL instead of queueing for manual ticket. When visitors want to learn more knowledge about an exhibit, they can obtain the transmitted packets from the iBeacon devices nearby through a manner similar to "WeChat Shake". They can also finish selection and payment in souvenir retail stores conveniently with the help of iBeacon devices. These applications are also in demand in large shopping malls, airports and cinemas etc. Therefore, iBeacon based LBS systems can improve the effectiveness of business management and lower commercial cost especially the labor cost.

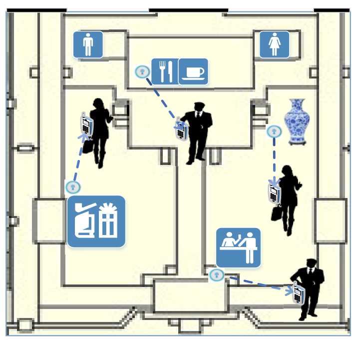

FIGURE 1. An example of LBS system using iBeacon in museum.

B. LOCALIZATION BASED ON iBeacon

In localization applications, iBeacon devices transmit advertisement data packets which contain three binary numbers: universally unique identifier (UUID) is an ID with 128 bits for iBeacon devices in a same application, Major value and Minor value are both 16 bits which can be used to uniquely define iBeacon devices in same applications. Smartphones scan signals at 2.4G Hz, then identify source iBeacon devices according to above three parameters. The distance between smartphones and iBeacon devices are calculated from the RSS values denoted by P_R and reference signal strengths at a

d_0 meters distance denoted by P_0 according to Equation (1)

$$P_R = P_0 - 10\eta \log_{10}(\frac{d}{d_0}), \tag{1}$$

where η denotes the decay rate of signal strength in propagation and d is the calculated distance value. This distance determining approach is accurate in the vicinity of each iBeacon device [19]. Smartphones obtain iBeacon devices' positions and reference signal strengths from a central server. After estimating distance values between three or more different iBeacon devices, the user's position can be calculated. In iBILL, we use gradient descent algorithm which is a classical optimal algorithm in machine learning theory to resolve the position. The algorithm's detail and parameters settings are explained in Section V. Therefore, if a user is in the common vicinity of three or more iBeacon devices, his or her location can be accurately determined based on the RSS values of iBeacon devices.

For the great advantage of iBeacon devices, a natural question to ask is: can iBeacon devices be used to replace the all existing indoor localization technologies? We answer this question in following content of this section.

C. ANALYSIS FOR COLLOCATION OF iBeacon DEVICES

Due to the limited accurate distance estimating range for each iBeacon device, we use a circle centering on a blue point to denote the range as shown in Fig. 2. Each point in localization area needs to be covered by at least three different circles, that is to say the density of circle configuration is demand to more than 3. Under this condition, the number of used iBeacon devices should be minimized to cut deployment cost, so does the densest circle packing manner should be used to maximize utilization rate of each circle. According to Thue's Theorem [28], regular hexagonal packing is the densest circle packing as shown in Fig. 2. In large open area, the number of triangles is double of number of circles if circles are packed as shown in Fig. 2. This is because the sum of a triangle's three interior angles is π, and a circle's angle is 2π. Denoting N as the circles' number, we can express the triangles' number as

$$\frac{N \times 2\pi}{\pi} = 2N, \tag{2}$$

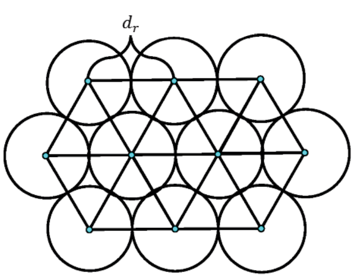

FIGURE 2. Densest circle packing manner.

and the density of circle configuration is

$$\frac{N \times \pi \times \left(\frac{d_r}{2}\right)^2}{2N \times \frac{\sqrt{3}}{4} \times d_r^2} = \frac{\pi}{2\sqrt{3}}. \tag{3}$$

To improve the density, the length of triangles' sides is demand to be shorten. When the length is equal to circles' radius as shown in Fig. 3, the blue area is covered by three different circles and users can be localized there, then the density becomes

$$\frac{N \times \pi \times \left(\frac{d_r}{2}\right)^2}{2N \times \frac{\sqrt{3}}{4} \times \left(\frac{d_r}{2}\right)^2} = \frac{2\pi}{\sqrt{3}} \approx 3.6. \tag{4}$$

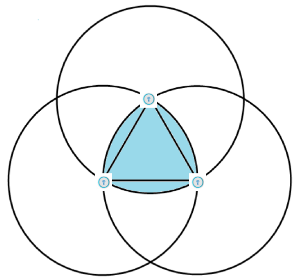

FIGURE 3. Accurate localization area of iBeacon devices clusters.

Since the circles are packed in a regular manner, it can be guaranteed that each point in the area is covered by at least three different circles.

D. ANALYSIS FOR LIMITATION OF LOCALIZATION USING iBeacon

The accuracy of localization using iBeacon devices mainly depends on the accuracy of distance measurements. The relationship between distance values and RSS is represented as $d = d_0 \cdot 10^{\frac{P_0 - P_R}{10\eta}}$, where the parameters are same to those in Equation (1). Due to the non-linearity of the relationship, small signal strength fluctuations can result in large distance measurement errors when computing large distance values. This is why the accurate distance measurement range for a single iBeacon device is only several meters [19], [20]. According to analysis above, the number of needed iBeacon devices can be scaled as $\mathbf{\Theta(S/r^2)}$, where S is acreage of whole localization area and r is radius of accurate distance measuring range, that is too great for large open areas. Furthermore, the design motivation of iBeacon is not only for localization, but serving as core modules for LBS systems as well. Note that iBeacon devices need to transmit packets that contain specific content in real applications instead of simply transmitting advertisement packets only, and sometimes even need to establish connections with smartphones. As a result, it is unsuitable to directly use iBeacon devices for providing real time localization and deploying iBeacon devices sparsely to opportunistically calibrate inertial sensors and geomagnetism based real time localization is a practical scheme. In next section, we will explain how to use iBeacon devices to improve inertial sensors based localization in large open areas.

IV. iBILL DESIGN

According to the analyses in last section, deploying clusters of iBeacon devices (a cluster contains three or more nodes) sparsely in some important positions is a reasonable scheme in iBILL, which consequently consists of two modes in its workflow as depicted in Fig. 4. In this section, we illustrate how to achieve accurate localization in large open area. We fuse the collected strength of magnetic signals and estimated users' mobility through an improved particle filter. We revise the algorithm of traditional particle filter in order that it can adapt to variable magnetic signals in crowded areas. Then we use iBeacon devices to approach the errors accumulation problem of particle filter and make our improved particle filter always has better performance. We further show how to reduce the computational overhead and improve robustness with the help of iBeacon devices clusters.

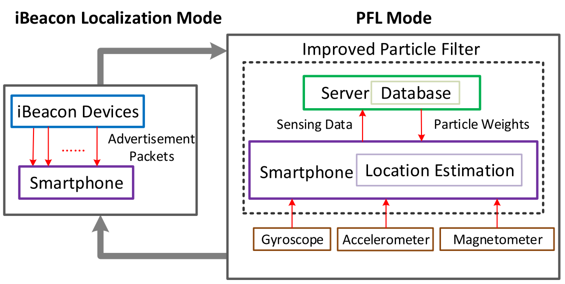

FIGURE 4. iBILL architecture.

A. iBILL ARCHITECTURE

When the RSS values of iBeacon devices indicate that a user is in the accurate localization area of one iBeacon devices cluster, localization process enters iBeacon localization mode. In this mode, the user's location is resolved based on the RSS of iBeacon devices through trilateration method as described in Section III. When the user leaves the accurate localization area of an iBeacon devices' cluster, his or her locations are determined in the particle filter localization (PFL) mode. In PFL mode, the collected magnetic signals and the data of inertial sensors are used to estimate the user's position through an improved particle filter.

1) PARTICLE MOTION MODEL IN PFL MODE

Unlike previous work where users' initial locations and directions cannot be determined, iBILL can determine them by iBeacon devices. The initial location in PFL mode is the last location in iBeacon localization mode which is denoted by $\overrightarrow{P}_L = (x_l, y_l)$, and the initial heading θ direction can be determined by $\overrightarrow{P}_L$ and the last location before $\overrightarrow{P}_L$ denoted by $\overrightarrow{P}_{L-1} = (x_{l-1}, y_{l-1})$, through Equation (5)

$$\theta = \arctan \frac{y_l - y_{l-1}}{x_l - x_{l-1}}. \tag{5}$$

Then particles are driven by data from inertial sensors which indicate user's walking distance and direction. These particles represent possible locations and directions of a user:

$$\mathbb{P}_i = (x_i, y_i, \theta_i), \quad i = 1, 2, 3, \ldots. \tag{6}$$

When the data from accelerometer indicate that a user makes a step forward, locations of particles are updated. Since the step length of different users and a particular user at different moments is a random variable ℓ, a particle $\mathbb{P}_i$ is needed to be resampled as several new particles $\mathbb{P}_{ij} (j = 1, 2, \ldots)$ to cover new possible positions of the user. The location of each particle is updated as Equation (7)

$$\begin{bmatrix} x_{ij} \\ y_{ij} \end{bmatrix} = \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} \cos\theta_i \\ \sin\theta_i \end{bmatrix} \times l_{ij}, \tag{7}$$

where l_{ij} is a random value of ℓ. ℓ is a random variable with Gaussian distribution, we use l to denote its mean value and its variance is $0.2l$ according to [16]. Hence, the probability density function of ℓ is

$$f(\ell) = \frac{1}{\sqrt{2\pi} \cdot \sqrt{0.2l}} \exp\left(-\frac{(\ell - l)^2}{2 \cdot 0.2l}\right). \tag{8}$$

To cope with errors of step length estimation and false positive or negative of step counting, new particles are sampled in the 80% confidence interval of step length distribution

$$\left[l - \varphi^{-1}(0.9) \cdot \sqrt{0.2l}, \quad l + \varphi^{-1}(0.9) \cdot \sqrt{0.2l}\right], \tag{9}$$

the length of sampling range is $2 \cdot \varphi^{-1}(0.9) \cdot \sqrt{0.2l}$, where $\varphi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx$. When data from gyroscope indicate that user makes turns, directions of particles are updated accordingly in resampling process, making the sampling area yield to a 2-D range.Ssince users can turn to all directions in large open areas, the turning angle θ is also a random variable for the sensing errors and false positive measurement of gyroscope. θ follows a Gaussian distribution, of which the mean value being the measurement of gyroscope denoted by $\overline{\theta}$ and the variance is set to $\frac{\pi}{18}$ rads according to [16]. Based on those conditions, the probability density function of θ can be expressed as

$$f(\theta) = \frac{1}{\sqrt{2\pi} \cdot \sqrt{\frac{\pi}{18}}} \exp\left(-\frac{(\theta - \overline{\theta})^2}{2 \cdot \frac{\pi}{18}}\right). \tag{10}$$

Since the gyroscope seldom gives false negative conclusions of turning, new particles are sampled in the 70% confidence interval of turning angle distribution

$$\left[\overline{\theta} - \varphi^{-1}(0.85) \cdot \sqrt{\frac{\pi}{18}}, \quad \overline{\theta} + \varphi^{-1}(0.85) \cdot \sqrt{\frac{\pi}{18}}\right]. \tag{11}$$

The 2-D sampling area is shown in Fig. 5, its acreage is

$$\int_{\overline{\theta}-\varphi^{-1}(0.85)\sqrt{\frac{\pi}{18}}}^{\overline{\theta}+\varphi^{-1}(0.85)\sqrt{\frac{\pi}{18}}} \int_{l-\varphi^{-1}(0.9)\sqrt{0.2l}}^{l+\varphi^{-1}(0.9)\sqrt{0.2l}} \rho \, \mathrm{d}\rho \, \mathrm{d}\theta \tag{12}$$

$$= 4 \cdot \varphi^{-1}(0.85)\varphi^{-1}(0.9) \cdot l\sqrt{0.2l}\sqrt{\frac{\pi}{18}}. \tag{13}$$

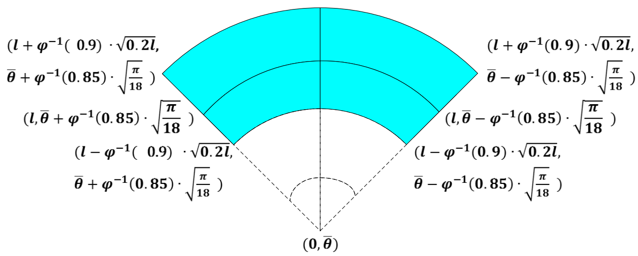

FIGURE 5. 2-D resampling range.

2) LOCATION ESTIMATING METHOD IN PFL MODE

iBILL uses magnetic signals as particle filter's observing value. In the localization process, the mean value of collected magnetic signals strength during each step is recorded as an observing value. And we design a sliding window to store the last k observing values, which constitute the observing vector. For each particle, its location is updated after each step, then iBILL extracts k values according to its last k locations from the pre-constructed magnetic fingerprint database, which constitute a particle vector. We construct a magnetic fingerprint database of experimental area, and each value in database maps a 0.5m $\times$ 0.5m grid. Using multiple values as observing vector can improve discernibility of magnetic signals compared to a single value, because magnetic signals of neighboring locations have high similarity in large open areas. The similarity between observing vector and each particle vector is an important factor for determining the weight of each particle denoted by w and particles with low weights will be killed. The weights determining method of the improved particle filter will be introduced in next subsection. We use $\mathbb{V}$ to denote the set of the remaining particles after weights updating, then user's location is determined with the normalized weighted average of remaining particles' locations as shown in Equation (14)

$$(\bar{x},\bar{y}) = \left(\sum_{p_i\in\mathbb{V}} \overline{w_i}\cdot x_i, \sum_{p_i\in\mathbb{V}} \overline{w_i}\cdot y_i\right). \tag{14}$$

B. COPING WITH MAGNETIC FLUCTUATIONS

In PFL mode, localization accuracy largely depends on the reliability of particles' weights, whereas algorithms for weights determining in existing works [16], [24] cannot work well in large open areas for the fluctuations of magnetic signals. In this subsection, we will illustrate the design for weights determining algorithm in iBILL.

1) LIMITATIONS OF USING MAGNETIC SIGNALS ONLY

The weights determining algorithms in [16] and [24] are only based on the magnetic signals. While according to our magnetic sensing experimental results shown in Fig. 6, the strength of magnetic signals have a higher possibility for large fluctuations in scenes like services hall. That's why Magicol [16] achieves only a accuracy of 8m in a supermarket. Fig. 6(a) and Fig. 6(b) both demonstrate strength of magnetic signals collected in the large service hall of the library on our campus, the data in Fig. 6(a) are collected at 2:00 pm when there are few people, and data in Fig. 6(b) are collected at 10:00 pm when there are a lot of people waking around due to the fact that library is going to be closed. As shown in Fig. 6, the magnetic signals in most locations are stable which is a favorable property for localization based on magnetic field. However, the locations where magnetic signals have large fluctuations should not be ignored, which are the source of localization errors. The main reason for magnetic signal fluctuating is that people holding metal or electronic equipments will affect the magnetic sensing results in their neighborhood, and the sensing noise of magnetometer is larger in scenes like services hall than those with less people. Furthermore, particles walking along wrong trace cannot be killed with the help of floor plans in open areas. As a result, using magnetic signals alone for determining weights of particles is unsuitable in these scenes, the fluctuations of magnetism will dominant localization errors.

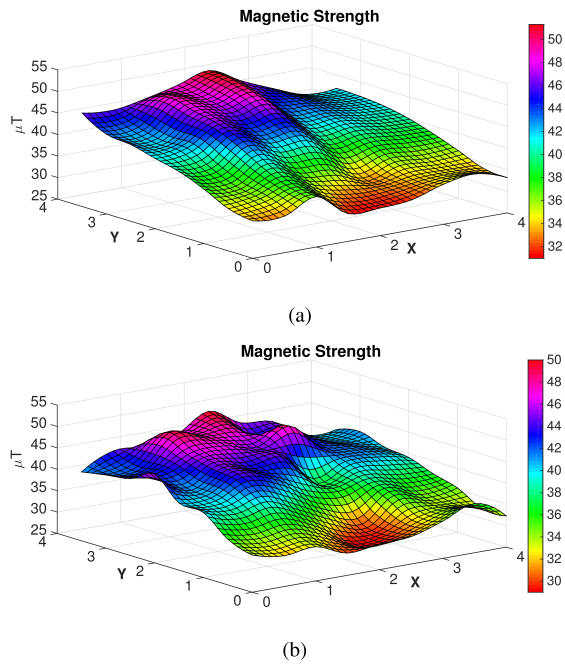

FIGURE 6. Magnetic strength of experimental area. (a) Magnetic strength at 2:00 pm. (b) Magnetic strength at 10:00 pm.

2) WEIGHTS DETERMINING METHOD OF IMPROVED PARTICLE FILTER

To restrain the effect of magnetic sensing fluctuations for localization errors, another factor is needed to co-determine the particles' weights. In iBILL, we adopt the probability distribution of particles' two attributes (step length and turning angles) (PPA) estimated according to the measurements of inertial sensors to co-determine the weights. When users enter the PFL mode, their initial locations and heading directions are known as said in last subsection, which is superior to existing works in which the initial states of users are unknown.

Furthermore, on the basis of the statistical data in [13], the error rate of step counter is below 10% and the errors of gyroscope is within 30° in modern smartphones. As a result, PPA is reliable for reflecting the probability distribution of users' locations if the moving distance is not very long, this is why we take advantages of PPA in weights determining. Therefore, in every particle resampling and weights updating process, the weight of $\forall \mathbb{P}_i \in \mathbb{V}$ is determined by the following three parameters

$$\begin{cases} w_i^{\prime(1)} = \dfrac{\frac{1}{\sqrt{2\pi}\cdot\sqrt{0.2l}}\cdot\exp\left(-\frac{(l_i-l)^2}{2\cdot 0.2l}\right)}{\sum_{p_k\in\mathbb{V}}\frac{1}{\sqrt{2\pi}\cdot\sqrt{0.2l}}\cdot\exp\left(-\frac{(l_k-l)^2}{2\cdot 0.2l}\right)}, & (15) \\ w_i^{\prime(2)} = \dfrac{\frac{1}{\sqrt{2\pi}\cdot\sqrt{\frac{\pi}{18}}}\cdot\exp\left(-\frac{(\theta_i-\bar{\theta})^2}{2\cdot\frac{\pi}{18}}\right)}{\sum_{p_k\in\mathbb{V}}\frac{1}{\sqrt{2\pi}\cdot\sqrt{\frac{\pi}{18}}}\cdot\exp\left(-\frac{(\theta_k-\bar{\theta})^2}{2\cdot\frac{\pi}{18}}\right)}, & (16) \\ w_i^{\prime(3)} = \dfrac{\exp\left(-\frac{s_i^2}{2\delta^2}\right)}{\sum_{p_k\in\mathbb{V}}\exp\left(-\frac{s_k^2}{2\delta^2}\right)}, & (17) \end{cases}$$

where l_i and θ_i are the step length and turning angle of particle $\mathbb{P}_i$, respectively, s_i is the similarity between particle vector and observing vector and δ is a constant that reflects the fluctuations of magnetic signals. w'_{i1} is determined by the probability distribution of particles' step length, w'_{i2} is determined by that of turning angles (w'_{i2} is set to 1 when the user walks straightly during a step), and w'_{i3} is determined by the similarity between observing vector and particle vectors. All the three parameters are normalized so that they can determine the weights with same importance. To kill particles that walk along wrong traces, the weights of particles are genetic. In other words, if $\mathbb{P}_{m+1}$ is resampled from $\mathbb{P}_m$, the weight w_{m+1} is calculated by

$$w_{m+1} = \overline{w_m}\cdot w'^{(1)}_{m+1}\cdot w'^{(2)}_{m+1}\cdot w'^{(3)}_{m+1}. \quad (18)$$

As a result, the weights of particles walk along wrong traces will continuously be reduced and these particles will eventually be killed in resampling process. When a particle walks entered unreachable areas such as the outside of walls, it will be killed certainly because there are no matching magnetic fingerprints in the database. Then the weights of remaining particles are normalized to calculate user's estimated location, i.e., $\overline{w_i} = \frac{w_i}{\sum_{p_i\in\mathbb{V}} w_i}$.

However, the localization errors are unavoidable, and the locations of particles updated after last step is used as initial locations of next step. As a result, the errors are accumulated as the increase of walking distance. Due to the error accumulation problem, reliability of PPA decays as increase of walking distance. Therefore, the conclusion that weights determining method of iBILL outperforms existing methods is conditional. In next paragraph, we will explain how to combine iBeacon devices to maintain the conditional conclusion.

3) USING iBeacon TO GUARANTEE BETTER PERFORMANCE

As depicted in last paragraph, the weights determining method of iBILL having better performance is conditional. We use X to denote the localization errors of taking use PPA as weights and Y to denote that of using magnetic filed signals only, according to the weights determining approach shown in Equation (18) the condition is

$$\mathbf{E}(XY) \le \mathbf{E}(Y). \quad (19)$$

According to Cauchy-Schwarz Inequality, we have

$$\sqrt{\mathbf{E}(X^2)}\cdot\sqrt{\mathbf{E}(Y^2)} \le \mathbf{E}(Y). \quad (20)$$

The probability of magnetic signals having large deviation is p, and the localization error arising from the deviation is denoted by α, if magnetic signals are stable, this error approximates zero, then the condition becomes

$$\sqrt{\mathbf{E}(X^2)}\cdot\sqrt{p\alpha^2} \le p\alpha, \quad (21)$$

$$\sqrt{\mathbf{E}(X^2)} \le \sqrt{p}, \quad (22)$$

$$\mathbf{E}(X^2) \le p, \quad (23)$$

the $\mathbf{E}(X^2)$ has positive correlation with the walking distance and the number of making turns, and p is correlated with peoples' activities in different scenes. When users enter iBeacon localization mode, accumulated errors in PFL mode can be corrected. Thus combining iBeacon devices can impose restrictions on the value of $\mathbf{E}(X^2)$ and then recover the reliability of PPA in next PFL mode. Furthermore, the condition indicates that more frequent the fluctuations of magnetic signals is (higher p is), the better relative performance of our improved particle filter to existing methods is. And for higher accuracy, the density of iBeacon devices clusters is needed to be higher to correct the errors in PFL mode more frequently, at the same time, the deployment cost must be higher.

C. SOLUTIONS TO TWO LONG-STANDING TOUGH PROBLEMS

1) REDUCING COMPUTATIONAL OVERHEAD

In PFL mode, the computational overhead is proportional to numbers of particles. In each resampling process, with the average number of newborn particles being m, the computational overhead for one user after n steps is scaled as $\mathbf{\Theta(mn)}$, implying that the computational overhead increases with walking distance. Reducing newborn particles in each resampling process can reduce the overhead, while the robustness of particle filter may degrade. That's because the remaining particles could not cover the real positions or directions of the user due to the sensing noise of inertial sensors. However, in iBILL the computational overhead of particle filter can be reduced periodically as the increase of walking distance. When a user enters iBeacon localization mode, his or her location can be accurately determined according to RSS values of iBeacon devices, then computational overhead of localizing the user can be decreased to $\mathbf{\Theta(N_d)}$, N_d is the number of possible directions. If the following several steps are also in iBeacon localization mode, the heading direction can be determined as described in subsection IV-A. Thus the initial computational overhead is therefore reduced to $\mathbf{\Theta(1)}$ when the user enters next PFL mode with accurate initial location and direction. The result verifies the idea that combining iBeacon devices can largely reduce the computational overhead of particle filter in localization process.

2) IMPROVING ROBUSTNESS OF iBILL

In PFL mode, the following two cases may lead localization systems unworkable: (1) the initial location and direction are unknown; (2) shaking smartphone heavily or putting it into pocket. For the first case that localization begins at an unknown position, then the initial location can be roughly determined based on the RSS values of the nearest iBeacon devices cluster as shown in Fig.7. Because the initial location is out of any cluster's accurate localization range, the RSS is given by

$$P_R = P_0 - 10\eta \log_{10}(\frac{d}{d_0}) + X, \tag{24}$$

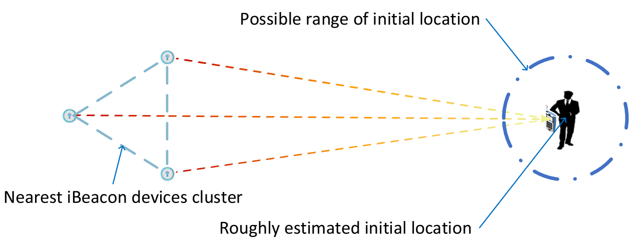

FIGURE 7. Illustration of the approach to estimate initial location.

where X denotes fluctuation and noise of signal strength which obeys a Gaussian distribution with zero mean [29] and its variance denoted by σ^2 depends on environments and transmission distance. Then the estimated distance is

$$\hat{d} = d_0 \cdot 10^{\frac{P_0 - P_R + X}{10\eta}}. \tag{25}$$

Since $d = d_0 \cdot 10^{\frac{P_0 - P_R}{10\eta}}$, the estimated distance can be expressed as

$$\hat{d} = d \cdot 10^{\frac{X}{10\eta}} = d \cdot e^{\frac{\ln 10 \cdot X}{10\eta}} = d \cdot e^{\frac{X}{\eta'}}, \tag{26}$$

where $\eta' = \frac{10\eta}{\ln 10}$. The mathematical expectation of $\hat{d}$ is

$$\mathbf{E}(\hat{d}) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{+\infty} d \cdot e^{\frac{x}{\eta'}} \cdot e^{-\frac{x^2}{2\sigma^2}} \mathrm{d}x \tag{27}$$

$$= \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{+\infty} d \cdot e^{-\frac{1}{2\sigma^2}[(x - \frac{\sigma^2}{\eta'})^2 - \frac{\sigma^4}{\eta'^2}]} \mathrm{d}x \tag{28}$$

$$= d \cdot e^{\frac{\sigma^2}{2\eta'^2}} \cdot \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{+\infty} e^{-\frac{1}{2\sigma^2} \cdot (x - \frac{\sigma^2}{\eta'})^2} \mathrm{d}x \tag{29}$$

$$= d \cdot e^{\frac{\sigma^2}{2\eta'^2}}. \tag{30}$$

Since $\mathbf{E}(\hat{d} \cdot e^{-\frac{\sigma^2}{2\eta'^2}}) = d$, $\hat{d} \cdot e^{-\frac{\sigma^2}{2\eta'^2}}$ is used as the estimated distance to roughly determine initial location. The user's real location is in the proximity around the roughly estimated location represented by the blue circle in Fig. 7. Then PFL mode starts with $N_d \cdot N_l$ initial particles in the blue circle. Here, N_d is the number of possible directions and N_l is the number of possible locations sampled in the circle randomly. In this scene, since PPA is unreliable due to the uncertain initial location and direction, the weights of particles can only be determined by magnetic signals until the user enters iBeacon localization mode. Then in the next PFL mode, particle filter can work as usual. For the second case, putting smartphone into pocket or shaking in hand will result in unreliability of mobility estimation and bring much noise to magnetic sensing, which are fatal to PFL mode. The two smartphone patterns can be recognized through classification in [30], and localization process can be disrupted when smartphone recognizes such two patterns. The reason behind is that when users need real time navigation, smartphones must be put in front of them for location and map reading. And a conclusion can be drawn that users do not necessarily need to know their real time locations under such two patterns. When the smartphone withdraws to the usual holding pattern, localization process can be restarted with the initialization approach being same to the solution to the first case.

V. EXPERIMENTAL EVALUATION

In this section, we will show experimental results of iBILL. As shown in Figs. 8 and 9, the experimental areas are a reading room and a services hall in the library on our campus. The reading room is consist of many corridors. And the services hall is an large open area which covers an area of

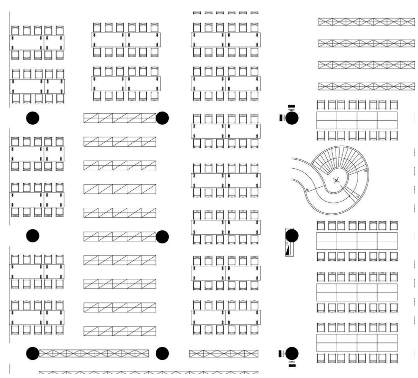

FIGURE 8. Map of reading room.

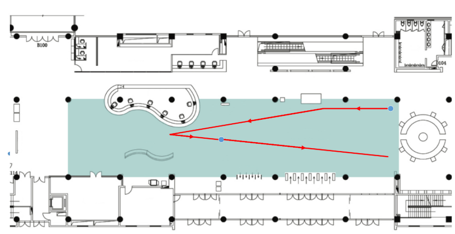

FIGURE 9. Map of services hall.

about $1800m^2$. We first present the accuracy of localization using iBeacon devices to show its advantages and limitations. Then, we compare the accuracy of iBILL with Magicol and Dead Reckoning (DR) scheme, and conclusion is that iBILL has a better performance in large open areas. In experiments, magnetic strength, number of steps and turning angles are all collected by an iPhone6 smartphone.

Algorithm 1 Gradient Descent Localization

1: Randomly Initialize θ.
2: Set training times $N = 50$, $n = 0$.
3: Set learning rate $\alpha = 0.1$.
4: **while** $n \leq N$ **do**
5: Compute Loss Function's partial differential $\frac{\partial}{\partial \theta_j} J(\theta) = \sum_{i=1}^{m} 2 \times \frac{h_\theta(x^{(i)}) - y^{(i)}}{h_\theta^{(i)}} \times (\theta_j - x_j^{(i)})$.
6: Update θ value $\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta} J(\theta)$.
7: $n = n + 1$.
8: **end while**
9: Return θ value.

A. ACCURACY OF iBeacon LOCALIZATION MODE

In our experiments, we use CC2541 chips running iBeacon protocol as iBeacon devices. The distance estimation approach is described in section III. We utilize the gradient descent algorithm to get the location estimation after we get the distance values d between smartphone and iBeacon devices. The solving process is shown in Algorithm 1. In this algorithm, our hypothesis function is

$$h_\theta(x^{(i)}) = \sqrt{(\theta_1 - x_1^{(i)})^2 + (\theta_2 - x_2^{(i)})^2}, \tag{31}$$

which indicates the distance between estimation point's location and each device's location. Since we focus on the two dimensional indoor localization, the θ includes two elements, indicating x location and y location, respectively. Afterwards we could get the loss function of gradient descent algorithm and our goal is to minimize the loss function $\min_\theta J(\theta)$ and get corresponding θ value

$$J(\theta) = \frac{1}{2} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - d^{(i)})^2, \tag{32}$$

where m represents the number of iBeacon devices. The performance of iBeacon localization mode is shown in Fig.10, the value of X-axis is the distance between smartphone and one device of a cluster. We set distance between each device in a same cluster as 4 meters, and localization accuracy in the blue area in Fig. 3 is within 0.5 meters.

B. LOCALIZATION PERFORMANCE OF iBILL

We first compare the localization performances of iBILL, Magicol and DR in our library. The database consistof magnetic filed strength collected at 2:00 pm, and observing values are that collected at 10:00 pm. Observing vectors and

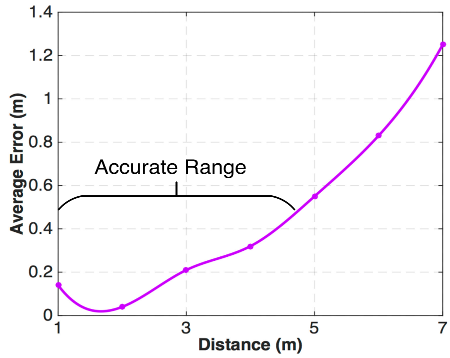

FIGURE 10. Distance-accuracy of iBeacon devices.

particle vectors all consist of the last 5 magnetic strength values. Fig. 11 shows localization errors against walking steps of three approaches. In experiments, the accuracy of step counting is about 90%. We can see that iBILL can efficiently restrain errors from increasing with walking distance, which is because the locations and directions can be corrected in iBeacon localization mode. Errors of DR and Magicol both increase with steps due to the noise of inertial sensors and magnetic strength fluctuations, and they are unable to kill wrong particles using floor plans in large open areas. Fig. 12 shows the Cumulative Distribution Function (CDF) of localization errors of the three systems, from which we can see that iBILL significantly outperforms DR and Magicol schemes.

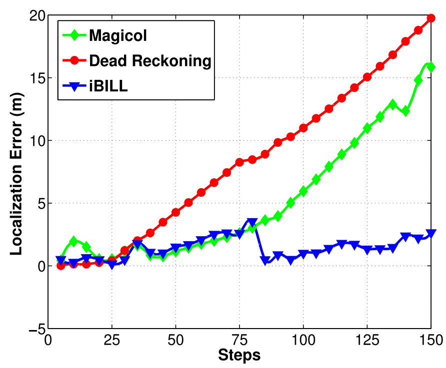

FIGURE 11. Error vs step numbers of three approaches.

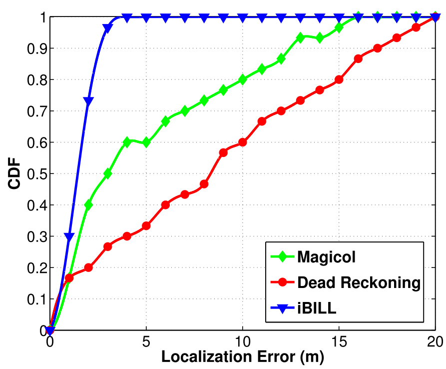

FIGURE 12. CDF comparison of three approaches.

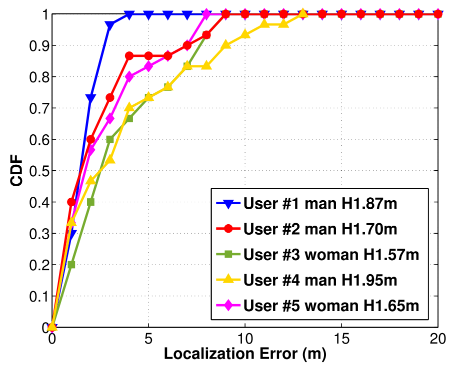

FIGURE 13. Performance of iBILL for different users.

The 90 percentile errors of iBILL, Magicol and DR is within 3.5m, 12m and 17m, respectively. The experimental results corroborate that iBILL can restrict the vast majority of errors into an acceptable range.

Now, we specifically show the comparisons of the performance of the improved particle filter in PFL mode and the augmented particle filter in Magicol. To compare them in the large open areas, we select one general trace as shown in Fig.9 which is represented by the red line. And iBeacon clusters are deployed at the two blue dots, the distance between them is about 50m. Fig. 14 shows localization errors of the two algorithms against the number of walking steps along the same trace. We can see that the accuracy of two algorithms during beginning straight trace are both very high due to the known initial location and direction. PFL mode can achieve a better performance when walking distance is not very long. Then, with the increase of walking distance, performances of two algorithms tend to be the same due to the fluctuations of magnetic strength and the accumulated errors in localization process.

We further evaluate the robustness of iBILL when it is used by people with different step length. We employed five users (three men and two women) with different heights (from 1.57m to 1.95m) in our experiments. The CDF of localization error for the five users is shown in Fig. 13. From which we can see that iBILL achieves high accuracy for users with common step length. The worst performance is that of user #4 whose height is 1.95m, because his step length is longer than common people and then degrades the reliability of PPA. Even so, the 90 percentile localization errors for user #4 is within 9m, which is still better than Magicol and DR. Hence, the experimental results demonstrate the robustness of iBILL.

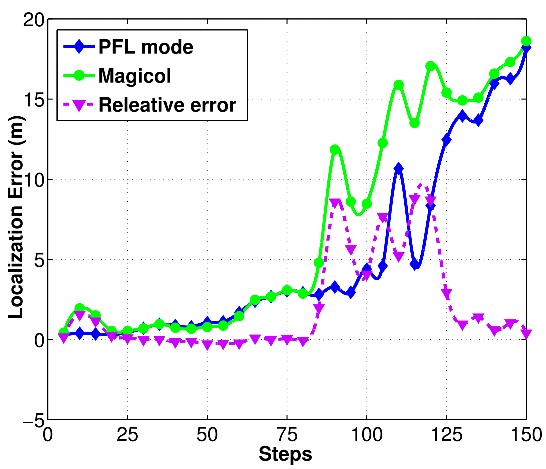

FIGURE 14. Comparison between PFL and Magicol.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we proposed iBILL, an accurate indoor localization system that jointly uses iBeacon and inertial sensors in large open areas. iBILL consists of two modes, iBeacon localization mode and Particle Filter Localization (PFL) mode. iBeacon devices clusters can accurately localize users in their vicinity, and we show advantages and limitations of localization utilizing them. PFL mode provides real time localization for users walking in large open areas through an improved particle filter. We improve the algorithm of existing particle filters to cope with the fluctuations of magnetic filed. As a result, iBeacon devices can prevent errors in PFL mode from accumulating with walking distance increase and guarantee the errors in an acceptable range. iBeacon devices can also be used to reduce computational overhead of particle filter and improve robustness of iBILL. Our experimental results corroborate that using iBeacon can improve the performance of inertial sensors based localization technologies in large open areas. Our future work is to further study how to use iBeacon and inertial sensors to improve the performance of location based services in user-centric commercial modes.

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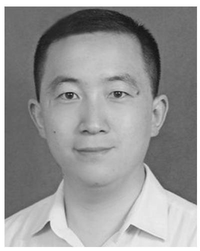

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