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Indoor Pedestrian Tracking with Sparse RSS Fingerprints

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Abstract: Indoor pedestrian localization is of great importance for diverse mobile applications. Many indoor localization approaches have been proposed; among them, Radio Signal Strength (RSS)-based approaches have the advantage of existing infrastructures and avoid the cost of infrastructure deployment. However, the RSS-based localization approaches suffer from poor localization accuracy when the RSS fingerprints are sparse, as illustrated by actual experiments in this study. Here, we propose a novel indoor pedestrian tracking approach for smartphone users; this approach provides a high localization accuracy when the RSS fingerprints are sparse. Besides using the RSS fingerprints, this approach also utilizes the inertial sensor readings on smartphones. This approach has two components: (i) dead-reckoning subsystem that counts the number of walking steps with off-the-shelf inertial sensor readings on smartphones and (ii) particle filtering that computes the locations with only sparse RSS readings. The proposed approach is implemented on Android-based smartphones. Extensive experiments are carried out in both *small* and *large* testbeds. The evaluation results show that the tracking approach can achieve a high accuracy of 5 m (up to 95%) in indoor environments with only sparse RSS fingerprints.

Key words: localization; pedestrian tracking; sparse; RSS fingerprints

1 Introduction

With the proliferation of pervasive and mobile computing, localization has been a hot research topic and many studies have been conducted[1–6]. Specifically, wireless indoor localization has been extensively studied owing to its applicability and economic benefits, and has been widely adopted in various applications, such as escort service in a hotel or airport[7], inventory management[8], targeted advertisement in a shopping mall[9], rescue and recovery[10], photo-taking of the environment[11], and smartphone-based localization[12, 13].

Although GPS can obtain the location of outdoors with room-level accuracy, it performs poorly indoors because the received signal power decreases dramatically with the lack of line of sight. As a result, most previous localization approaches utilize the Received Signal Strength (RSS) to determine the indoor location as RSS fingerprints are available in most existing wireless infrastructure and offer tremendous cost savings. Compared to RSS, Channel State Information (CSI) is much more fine-grained and exhibits a higher stability. However, indoor localization with CSI[14, 15] requires specific Network Interface Cards (NICs) and driver modification.

With the wide deployment and availability of WiFi infrastructure, many RSS-based localization techniques are implemented on WiFi devices, such as RADAR[16] and Horus[17]. However, the existing literature either relies on the basic assumption that WiFi Access Points (APs) are pervasive in the environment or the location of each AP is known; this is not always true in the real world[18]. As shown in Fig. 1, typical places such as

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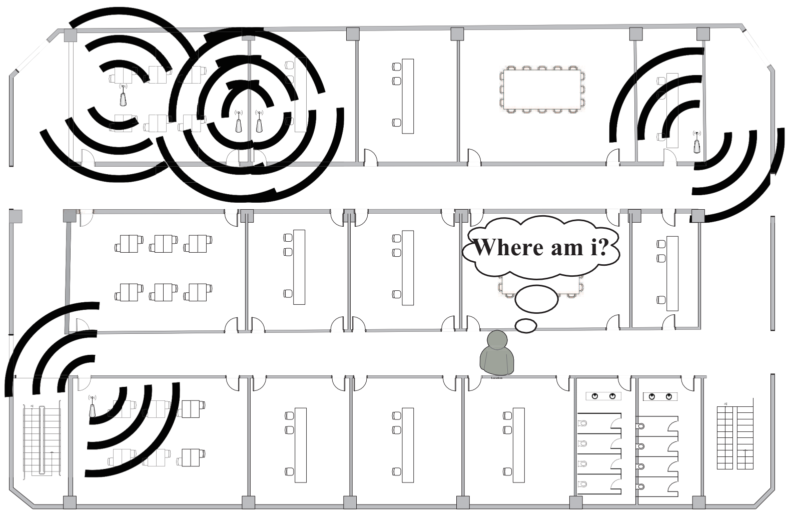

Fig. 1 An example of the scenario.

airports or railway stations are usually partially covered by WiFi signals due to the limited or biased deployment of APs, further resulting in indistinct fingerprints. Therefore, it is difficult to achieve a high accuracy in such a situation by directly adopting previous methodologies to determine the current location.

Apart from the sparsity of APs, the performance of RSS-based localization will also decrease significantly when people are moving in dynamic speeds[19]. A previous study[20] proposed an adaptive speed change detection framework that can work with any device-free localization method. However, the proposed mechanism cannot work with sparse RSS fingerprints. To increase the accuracy of pedestrian tracking with sparse RSS fingerprints, one possible way is to use the readings of inertial sensors (e.g., accelerometers and compass) to deduce the walking trail beforehand[21].

In this study, we design and implement Dead-Reckoning-assisted Passive Fingerprinting (DR-PF), a localization system with sparse RSS fingerprints. Despite limited quality of commercial inertial sensors, an efficient methodology is developed to detect the walking steps, finally providing a dead reckoning subsystem to accurately estimate the displacement. By combining the occasionally sensed RSS from ambient APs and applying a particle filter, we are able to alleviate the effect of accumulated error and improve the localization accuracy.

In this study, the following major contributions are made:

- A novel, efficient, and accurate method is introduced to detect the steps in the dead reckoning subsystem. Compared to the state-of-the-art solutions in step detection, this methodology performs better in complexity, commonality, etc.
- Based on the constructed sparse WiFi fingerprint signature and estimated displacement, a particle filter is used to reduce the impact of sparsity and enhance the localization performance.
- This design is fully implemented on the Android platform and extensive experiments are conducted to evaluate the localization performance. The experimental results show that the localization system performs remarkably better even with sparse RSS fingerprints and achieves a better accuracy.

The rest of this paper is organized as follows. Section 2 describes related studies. Section 3 explains the profile of the DR-PF localization system. Sections 4 and 5 provide the details of implementation of the two subsystems, dead reckoning and particle filter. Sections 6 and 7 present the experimental setups and performance evaluation. Section 8 provides the conclusions of this study.

2 Related Studies

In this section, different mechanisms that aim to solve the problem of indoor localization are presented. They can be divided into two categories.

2.1 Fingerprint-based mechanisms

Most state-of-the-art localization schemes on mobile devices are based on fingerprinting a radio map in the areas of interests. Then a matching algorithm helps to locate where we are[16,17]. Some improved schemes leverage the constraints of mobility in addition to RSS to locate the position[7,22]. SurroundSense[23] extends the idea of WiFi RSS fingerprinting to other ambience signatures such as optical, acoustic, and motion attributes. Place Lab[24] also utilizes the signals from GSM base stations and creates a wireless map by war-driving. Previous studies[25–28] use active RFIDs to implement indoor localization, object tracking, and human behavior identification. Considering the high costs of site survey, LiFS[12] exploits the sensor readings in smartphones and user motions to construct the radio map and achieves a high localization accuracy.

2.2 Model-based mechanisms

Some model-based techniques assume that signal attenuation can be mathematically modeled by exploiting the distance to APs. In Refs. [29, 30], the radio propagation model of log-distance path loss is used to estimate the distance to a given AP. In addition to power-distance mapping methods, PinPoint[31] and Cricket[32] utilize time-of-arrival and time difference of arrival to estimate the distance, respectively. Some localization techniques also exploit angle-of-arrival strategies[14, 33] to determine the position.

3 System Overview

Our system consists of two subsystems, dead reckoning and particle filter, as shown in Fig. 2.

In the dead reckoning subsystem, there are three modules that utilize the raw sensor readings of smartphones. The identifiable walking patterns can be extracted from the recorded acceleration, thus making it possible to calculate the number of steps and the time when the pedestrian takes the steps in the module step direction. Using the model of linear relationship between stride length and walking frequency, the step length can be estimated in the second module. Head inferring with smartphone orientating arbitrarily is another challenging topic. In this study, we assume that

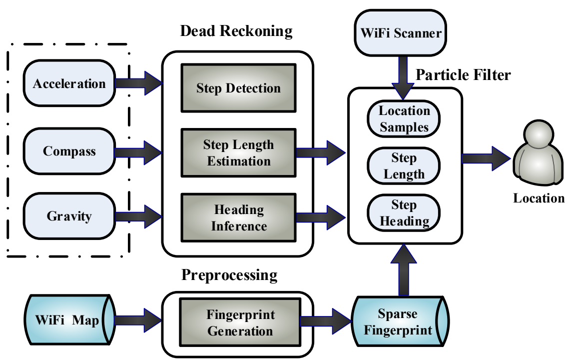

Fig. 2 System architecture.

the phone's relative position is fixed.

As mentioned above, the displacement may drift a lot without calibration. Thus, the subsystem particle filter is implemented to further improve the accuracy of tracking with sensed WiFi RSS, and the displacement will be estimated more accurately. Particle filter is a widely used filtering method, where the particles with high similarity to the measurement are allowed to survive with a high probability.

In the following two sections, the designs of the subsystems are discussed.

4 Dead Reckoning Subsystem

In this section, we mainly investigate how to compute the displacement of a pedestrian by accurate step counting and heading estimation. As mentioned above, the subsystem can be divided into three modules. The module "Step Detection" should reliably detect whether the pedestrian is taking steps (walking) or standing still. Then the well-studied linear relationship between step length and walking frequency is used to infer the step length. Considering that the walking direction might change over time, the step heading is inferred. It is assumed that the yaw angle of smartphones is known beforehand and remains constant during the movements.

4.1 Step detection

When a pedestrian is walking, the acceleration exhibits recurrence as shown in Fig. 3. Specifically, the vertical direction exhibits obvious regularity compared to the horizontal direction in the East-North-Up coordinate because the body of the pedestrian will move up and down periodically. To count the walking steps, most previous studies applied either self-correlation or dynamic time wrapping on the periodical data sequence. However, these methods have high complexity and may misdetect or overdetect the actual steps. Thus, it is necessary to propose an efficient and accurate method to count steps.

As shown in Fig. 4, the periodicity will be further amplified by integrating acceleration to obtain velocity. The initial velocity is assumed to be 0 m/s. If there are several local extremes around a certain instant (e.g., the second step in Fig. 5), a threshold can be simply set for the difference between adjacent local extremes to remove the points merely reflecting the slight shaking of the human body. Only when the difference exceeds

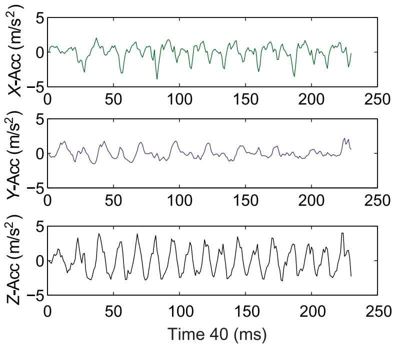

Fig. 3 3-axes acc readings walking on hand.

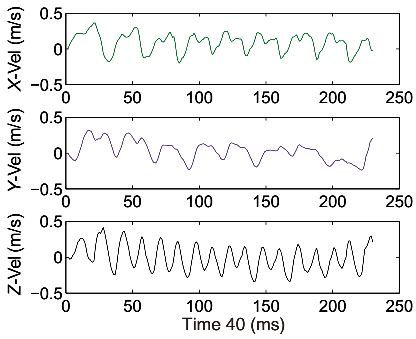

Fig. 4 3-axes estimated walking velocity on hand.

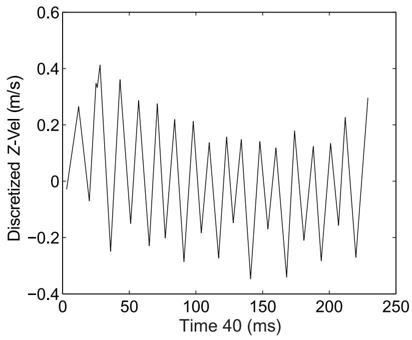

Fig. 5 Discretized velocity along z-axis on hand.

the threshold, the corresponding duration is claimed as a valid step. In the following sections, the empirical value of the threshold is set as 0.2. Compared to the state-of-the-art methodologies, our algorithm outperforms as follows:

Lower Complexity. Finding the local extremes and valid step has linear complexity. Compared to previous study, our algorithm is more likely to be efficiently implemented on smartphones.

Variation Tolerant. The method of counting steps does not involve time durations and copes with the velocity directly. Thus it can work well in different settings, such as walking, jogging, running, or any combination thereof.

Alignment Independent. Any instant can be chosen as the beginning of walking to count steps because the algorithm merely relies on the difference between the local maximum and local minimum to determine a valid step. However, the performance of similarity-based methods suffers if the start time is not well estimated.

4.2 Estimation of step length

Step length is one of the critical points to compute the displacement, because it varies from person to person, and even differs from time to time for one person due to a variation in mood, ground type, and health status.

Each step length can be estimated using the widely applied linear relationship of the step model proposed in the literature[34,35], represented as $L_s = a \times f + b$, where L_s and f refer to the length of each step and walking frequency, respectively; a and b are two coefficients that determine the linear relationship.

To infer the coefficients, GPS modules are assumed to be embedded in smartphones to obtain GPS readings if they are available. As both the location information and time stamps are recorded by the GPS module, the step length L_s and walking frequency f can be calculated to train the two coefficients. Specifically, our method is based on a previous study[36]. The GPS data are collected while the person is walking outdoors. As the GPS data can be slightly noisy, filtering methods are used to eliminate the noise and reduce error. For example, in the case of unrealistic movements and much higher estimated walking speed than the normal value (e.g., the sum of average and two times of standard deviation), the corresponding trace should be divided into segments. Then, the segments are smoothened to remove the random noises and flatten the jagged or curved GPS traces. However, smoothing might distort the actual path if the pedestrian makes turns. Thus, the GPS readings corresponding to a straight line are chosen to avoid such a situation. The details of the straight-line identification method are shown in Ref. [36].

4.3 Heading inference

Heading determination is another key process to compute the displacement. The sensor readings are recorded with relative coordinates but the pedestrian's orientation can be arbitrary. Thus, the recorded data should be transferred into the East-North-Up coordinate to obtain the actual heading.

Extensive studies have been conducted to determine the moving direction with arbitrary device orientation; this topic is beyond the scope of our study. Here we assume that the yaw angle of the smartphone is fixed when the pedestrian is walking and the magnetic offsets at different locations are uniformly random in the Gaussian model with a mean of θ. The gravity removed from the measured acceleration and the readings from the magnetometer are denoted as G and M, respectively. Note that the direction of G reported from Android API is in the opposite direction to the real gravity direction, and the direction of M is not parallel to the horizontal plane.

Therefore, the horizontal magnetic direction can be represented as $\dfrac{G \times M \times G}{|G \times (M \times G)|}$. The geographical north can be represented as $N = \sin\theta \dfrac{M \times G}{|M \times G|} + \cos\theta \dfrac{G \times (M \times G)}{|G \times (M \times G)|}$, and the geographical east can be represented as $E = \cos\theta \dfrac{M \times G}{|M \times G|} - \sin\theta \dfrac{G \times (M \times G)}{|G \times (M \times G)|}$. The moving direction is determined by the intersection angle between $(0,1,0)^{\mathrm{T}}$ and geographical north N represented in the smartphone's coordinate system. In this paper, α denotes the heading angle clockwise from the geographical north.

5 Particle Filter Subsystem

5.1 Characterization of RSS signature

The variation in sensed RSS from AP ap_i at location l_j is modeled using a Gaussian random variable with mean $\mu_{r_i^j}$ and standard deviation $\delta_{r_i^j}$. The RSSs from different APs are independent of each other. If a smartphone collects a measurement $R = \langle r_1, r_2, \ldots, r_{N_r} \rangle$ where N_r denotes the total number of APs, the probability of the smartphone at location l_j can be computed as follows:

$$Pr(R|l_j) = \prod_{i=1}^{N_r} Pr(r_i|l_j) \tag{1}$$

Traditionally, the probability of measurement r_i sensed from ap_i and taken at location l_j can be computed as follows:

$$Pr(r_i|l_j) = \frac{1}{\sqrt{2\pi}\delta_{r_i^j}} \exp\left[-\frac{(r_i - \mu_{r_i^j})^2}{2\delta^2_{r_i^j}}\right] \tag{2}$$

Because all the APs are not available at a specific location, the model should be calibrated. If an AP cannot be sensed by the smartphone, the Bernoulli distribution $B(1, p_i^j)$ is used to model the probability.

$$Pr(r_i|l_j) = \begin{cases} \dfrac{p_i^j}{\sqrt{2\pi}\delta_{r_i^j}} \exp[-\dfrac{(r_i - \mu_{r_i^j})^2}{2\delta^2_{r_i^j}}], & \text{if } r_i^j \neq \Phi; \\ 1 - p_i^j & \text{, if } r_i^j = \Phi \end{cases} \tag{3}$$

5.2 Particle filter

Particle filter, a member of the family of sequential Monte Carlo, is a probabilistic approximation algorithm to estimate the distribution of a variable at a specific time, given all observations up to that time. The main idea is to represent the required posterior probability by a set of random samples (also called particles) with associated weights and to compute estimates based on these samples and weights. The details are provided below.

5.2.1 Initialization

In the special case when the initial position is known, the particles are initialized with N_s identical samples $\{S_0^i = (x_0, y_0)^{\mathrm{T}}\}, i = 1, 2, \ldots, N_s$.

If the starting location is unknown, the scanned RSSs can be used for initialization, i.e., the locations of particles are randomly selected based on the probability of its measured WiFi signal to the location's probability computed using Eq. (3). The above step is repeated until the size of the particle swarm reaches a predefined size of N_{s}.

5.2.2 Propagation

Assume that the dead reckoning subsystem detects N_k steps between the $(k-1)^{\mathrm{th}}$ and k^{th} RSS measurements. Because the length and walking direction of the pedestrian just taken have been estimated, based on the previous estimated position, the next position of the pedestrian can be estimated. The j^{th} particle's position (x_k^j, y_k^j) after the pedestrian takes N_k steps can be updated as follows:

$$\begin{aligned} x_k^j &= x_{k-1}^j + \sum_{i=1}^{N_k} (s_{k,i}^j + \delta_{s_{k,i}^j}) \cos(\alpha_{k,i}^j + \delta_{\alpha_{k,i}^j}); \\ y_k^j &= y_{k-1}^j + \sum_{i=1}^{N_k} (s_{k,i}^j + \delta_{s_{k,i}^j}) \sin(\alpha_{k,i}^j + \delta_{\alpha_{k,i}^j}) \end{aligned} \tag{4}$$

where $s_{k,i}^j$ is the estimated stride length based on the walking frequency; $\delta_{s_{k,i}^j}$ is the random noise added to the length to prevent the side effect of overfitting. $\delta_{\alpha_{k,i}^j}$ is perturbed to account the compass measurement error due to the local magnetic offset.

5.2.3 Resampling

In the resampling process, the trustworthiness of our predicted location is assessed upon preconstructed RSS fingerprints, and the particles with high trustworthiness are allowed to survive with a high rate. The trustworthiness is determined from the similarity between sensed and computed RSSs using Eq. (3). A location is randomly selected based on the computed probability, and the step is repeated for N_s times to pertain the sample size.

5.2.4 Location estimator

After the particles of the k^{th} RSS measurements are determined, the location of measurement can be efficiently computed as follows:

$$(x_k, y_k) = \left(\frac{1}{N_s}\sum_{i=1}^{N_s} x_k^i, \frac{1}{N_s}\sum_{i=1}^{N_s} y_k^i\right) \tag{5}$$

6 Experiments and Discussion

6.1 Parameter selection for subsystems

6.1.1 Dead reckoning subsystem

The dead reckoning subsystem requires the determination of two parameters, namely, the standard deviation error of the estimated stride length δ_s and the standard deviation error of the estimated orientation δ_α.

To obtain the standard deviation error of the estimated stride length, 30 ten-step straight-line walking trials are conducted. The actual walking length in each trial is measured. If each stride is treated as independent and identically distributed (iid) random variables, δ_s for each step can be estimated using the maximum likelihood.

The standard deviation error of the estimated orientation is determined at the same time. Because the pedestrian walks in a straight-line, each step can be estimated using the maximum likelihood, and the variation of the sensed orientation can be computed as δ_α.

6.1.2 Particle filter subsystem

Recall that in the particle filter subsystem, we need to determine the probability of obtaining RSS measurement from a given AP at each location and its distribution parameter; in this case, they are the mean and standard deviation. RSS is measured for 500 times at each location and the frequency of RSS is used as the probability. The mean and standard deviation are determined using the parameter obtained from curve fitting into a Gaussian function.

Unfortunately, heavy site survey is required to build the fingerprint map. Recently several participating systems have been designed to overcome such laborious work. In this system, a WiFi signature collection platform is also designed and implemented on an Android-based smartphone. Once a user conveys his/her location by clicking the corresponding point on the electronic map, the smartphone starts scanning the ambient WiFi signature and saves the data for later upload.

6.2 Experimental setup

6.2.1 Testbed

The experiments are conducted both in a *SMALL* L-shaped laboratory and a *LARGE* floor of a building. The layouts of the floor and laboratory are shown in Figs. 6 and 7, respectively. The radio map is constructed from 133 walkable locations each with an average size of 1.44 m^2 from a total of 55 APs to reach a fine-grained level and 78 coarse-grained locations with an average size of 5.52 m^2 from a total of 216 APs.

6.2.2 Ground truth collection

For the experiments, several walking paths on the floor are predefined, as shown in Figs. 6 and 7. Along the walking path, distinct locations are marked as the waypoints on the floor. Each time we pass the waypoint, the corresponding position in our developed experimental platform on Android smartphone is clicked to record the timestamp.

7 Evaluation

In this section, we evaluate the performance of the system and the effects of different factors.

7.1 Accuracy of step detection

Step detection is crucial for accurate localization and tracking. In the experiments, the smartphone is placed in several different positions. The accuracy of step

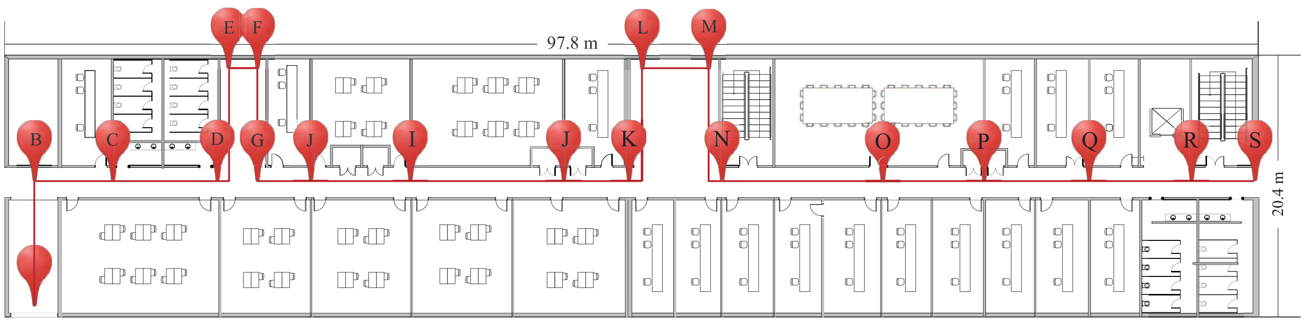

Fig. 6 An entire floor of the building.

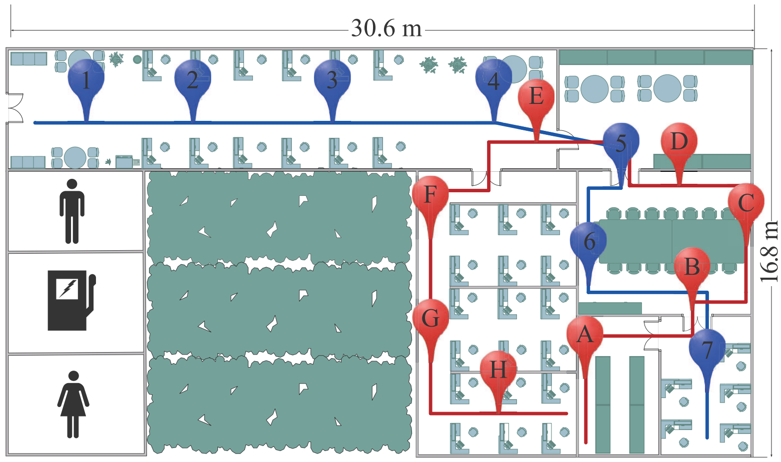

Fig. 7 Floor plan of L-shaped laboratory.

detection is shown in Table 1. Our approach achieves a high accuracy no matter where the smartphone is placed and false alarms are rare. The step counter program on Android platform is available at `https://github.com/dingdd/BL/`.

7.2 Size of particle samples

To study the effect of the size of particle samples on the localization accuracy, the number of particle samples is varied to determine the order for setting the sample size to reach a fine accuracy. As expected, Fig. 8 shows that the more the samples predicted, the more accurate the localization result. When the sample size increases from 200 to 500, the performance does not improve much. This indicates that a sample size of 200 is sufficient to simulate the random distribute.

7.3 Performance under different AP densities

Figure 9 shows the effect of AP density on the localization accuracy of DR-PF, Horus[17], and FreeLoc[37]. To emulate the scenario of different sparse levels, several APs are randomly selected in the *LARGE* testbed assuming that only these can be sensed. As shown, the proposed method DR-PF is robust to the number of available APs and still works well in an AP-sparse environment. The average error is less than 5 m, whereas the performance of both the previous methods significantly decreases when a few APs are provided. This is because Horus and FreeLoc require multiple APs to formulate a signature and perform localization.

7.4 Overall performance in SMALL L-shaped laboratory

To investigate the overall performance of the proposed method DR-PF, experiments are conducted in the fine-grained environment. Figure 10 shows the cumulative distribution of localization errors obtained from three

Table 1 Step detection accuracy with smartphone in different positions.

	Pant Front Pocket (%)	Pant Back Pocket (%)	Shirt in Pocket (%)	Holding in Hand (%)	Overall (%)
False positive	1	0	0	0	0.25
True positive	100	100	100	100	100

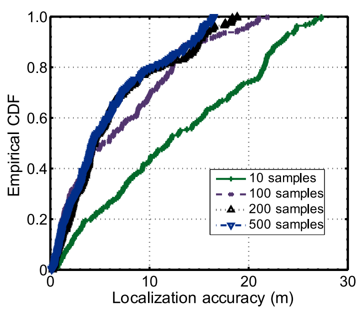

Fig. 8 Performance of varying sample size.

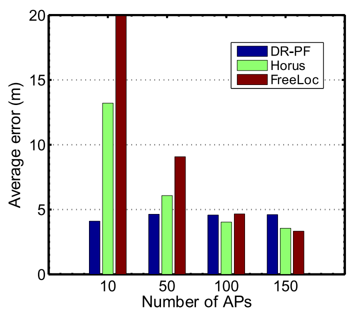

Fig. 9 Performance under different AP densities.

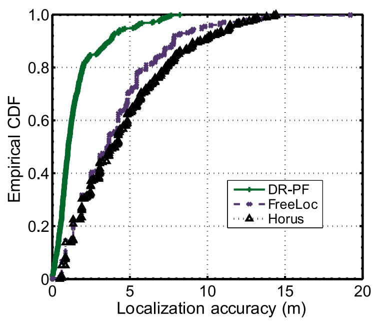

Fig. 10 Performance of different methods.

localization schemes. DR-PF performs best with about 50th and 80th percentile error under 1.1 m and 2 m, respectively. FreeLoc and Horus are almost the same with over 60th percentile error under 5 m. DR-PF achieves its competitive advantages mainly owing to the minor accumulated error of dead reckoning sub-system.

8 Conclusion

In this paper, we propose an indoor pedestrian tracking approach that can work well in indoor environments where only sparse RSS readings are available. This approach consists of two components. The dead reckoning component counts the number of walking steps with off-the-shelf inertial sensor readings on smartphones. The other component uses particle filters to compute the locations with only sparse RSS readings. The proposed approach is implemented on Android-based smartphones. The experimental results show that the localization approach can achieve a high accuracy even in both small and large indoor environments with only sparse RSS fingerprints.

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