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An Improved Indoor Localization Method Using Smartphone Inertial Sensors

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***Abstract*—In this paper, an improved indoor localization method based on smartphone inertial sensors is presented. Pedestrian dead reckoning (PDR), which determines the relative location change of a pedestrian without additional infrastructure supports, is combined with a floor plan for a pedestrian positioning in our work. To address the challenges of low sampling frequency and limited processing power in smartphones, reliable and efficient PDR algorithms have been proposed. A robust step detection technique leaves out the preprocessing of raw signal and reduces complex computation. Given the fact that the precision of the stride length estimation is influenced by different pedestrians and motion modes, an adaptive stride length estimation algorithm based on the motion mode classification is developed. Heading estimation is carried out by applying the principal component analysis (PCA) to acceleration measurements projected to the global horizontal plane, which is independent of the orientation of a smartphone. In addition, to eliminate the sensor drift due to the inaccurate distance and direction estimations, a particle filter is introduced to correct the drift and guarantee the localization accuracy. Extensive field tests have been conducted in a laboratory building to verify the performance of proposed algorithm. A pedestrian held a smartphone with arbitrary orientation in the tests. Test results show that the proposed algorithm can achieve significant performance improvements in terms of efficiency, accuracy and reliability.**

Keywords-indoor localization; PDR; PCA; particle filter

I. INTRODUCTION

As one of the most challenging technologies in location-based services (LBS), indoor localization has gained great concerns over the last decade. There are many indoor localization applications that almost are distributed in all our fields of life, such as context detection, health care, emergency events and so on [1]. However, compared to outdoors where global navigation satellite systems (GNSS) are essential and even dominating technologies, indoor localization encounters a series of challenges due to complex indoor environments, e.g. severe multipath effect, Non-Line-of-Sight (NLOS) conditions, high signal attenuations, and noise interferences. Therefore a reliable indoor localization solution with high accuracy is still a challenge.

The localization method is the core constituent of an indoor navigation system. According to various basic measuring principles, localization method can be divided into four main categories: triangulation, direct sensing, pattern recognition, and dead reckoning [2]. Among these methods, triangulation-based and direct-sensing-based localization approaches need infrastructure assistance and depend on the installation of beacons at known positions, e.g. Wi-Fi and RFID. Besides, some of these approaches are susceptible to be interfered in the indoor environment, such as ultrasound, infrared and Bluetooth beacons. Furthermore, the limitation of pattern recognition-based localization methods requires the high storage capacity and significant computing power. Pedestrian dead reckoning (PDR) localization technique, which is based on inertial sensors, estimates a pedestrian's location with lower installation cost and computation over other localization methods. Meanwhile, with the built-in inertial sensors, smartphones have become really ubiquitous portable devices that provide not only communication services for people in their daily life but also personal localization functionalities [3].

PDR localization techniques, however, have a main drawback that they are only able to provide required accuracy for a limited time due to the sensor errors arise from random zero bias and oscillation noise. For the low-cost inertial sensors specially, the accumulating errors grow rapidly with the travel distance of pedestrians. Therefore, to handle this disadvantage, it is necessary to combine PDR techniques with other localization solutions or auxiliary information to correct the accumulating errors and achieve constant high-precision indoor localization.

Recently, several indoor localization technologies that integrate inertial sensors with map information on a smartphone have been researched [4], [5], [6]. While some of these technologies rely on dedicated inertial measurement units (IMUs), they have not leveraged the embedded inertial sensors (e.g. accelerometer and gyroscope) in smartphones to implement indoor localization. Additionally, most of these methods only construct the trajectory of the user by detecting of turning events or path matching, which are prone to fail when the walking routes are intricate such as multi-turn paths. And the feedback mechanism of these methods that is used to improve the localization accuracy makes real-time implement difficult. In this paper, we present a reliable and accurate indoor localization method that relies on smartphone inertial sensors and floor plans. To tackle the drift problem of low-cost inertial sensors, we propose a robust step detection algorithm. Applying the local gravity value crossings detection and autocorrelation operation of measured acceleration signals, we detect steps with a low false rate and low computation. Then the stride length is estimated based on the relationship between stride length and stride interval (reciprocal of stride frequency), and the recognition of pedestrian motion patterns including standstill, walking and running [10], [11]. Heading determination is accompanied through applying the principal component analysis (PCA) to infer the heading offset between the pedestrian and her smartphone, and gained from the yaw angle of the smartphone inertial sensors. A particle filter algorithm, which fuses information from PDR and a floor plan, is introduced to correct the sensor drifts and improve the localization accuracy.

In the rest of this paper, we introduce first the overall architecture of our indoor localization system in Section II. Then Section III presents the PDR algorithm employed in our work and it is followed by detailed description of the algorithms for step detection, stride length estimation and heading determination. As one main module, particle filter algorithm then is presented in Section IV. Afterward, the performance of the proposed algorithms is evaluated through an indoor experiment conducted in our laboratory building in Section V. Finally, the conclusion and future works are drawn in the last section.

II. The Design Of System Architecture

As shown in Fig. 1, our indoor localization system architecture consists of three main modules: smartphone sensors, PDR, and particle filter. The smartphone sensors module is utilized to collect embedded sensor data including accelerometer, gyroscope and magnetometer, and then send the data that have been calibrated and interpolated at preprocessing phase to the PDR module. For indoor localization application, the latter two modules are core algorithms in the system. After receiving the data from smartphone sensors module, the PDR module starts to estimate and update the position of the pedestrian at each step if the initial position has been obtained through GNSS or user input. In addition, the particle filter module is responsible for outputting the final localization results for external applications by iterative calculation and providing feedback information to correct the stride length and heading error from PDR with the constraint condition of a floor plan. With regard to the details of sub-modules of PDR module and the specific algorithms of particle filter module, they will be elaborated in following sections.

III. PDR Localization Technologies

Pedestrian dead reckoning (PDR) is a relative navigation technique, which determines the relative location of a pedestrian by using step detection, stride length estimation, and heading determination. The PDR algorithm can provide means of reducing the accumulative error to the navigation solution by

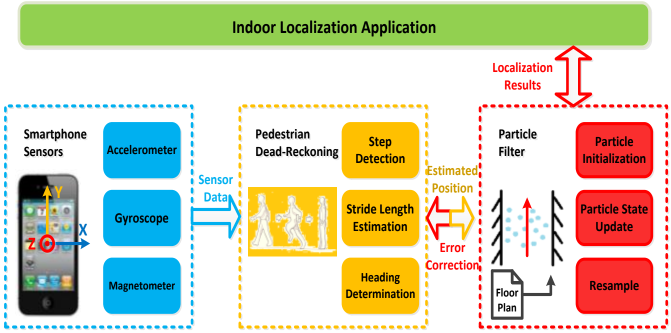

Figure 1. The overall system architecture

taking advantage of the sequential characteristics of the pedestrian motion [7]. Typically, the accelerometer measurements are utilized to implement step detection and stride length estimation, and heading determination is simultaneously completed by fusing the information from gyroscopes and magnetometers.

In the PDR system, the position of the pedestrian can be propagated as the following equations:

$$\begin{cases} X_{k+1} = X_k + SL * \sin(\theta_{k^*}) \\ Y_{k+1} = Y_k + SL * \cos(\theta_{k^*}) \end{cases} \tag{1}$$

where X and Y are the coordinates in north and east directions, SL is the stride length and θ is the heading at epoch k^*, which is not necessary same as subscript k that denotes the index of steps and defined in the subsection of Heading Determination. From Eq. (1), it is shown that we can estimate the position of the pedestrian at any moment when the initial position, the stride length and the heading of the pedestrian are known.

A. Step Detection

Step detection algorithm, as a basic technique of a PDR system, is crucial to influence the performance of the pedestrian navigation system. As previously mentioned, the accelerometer signal is usually used to detect the steps of the pedestrian. In general, the output of accelerometer may present harmonic oscillation waveforms that result from walking behaviors [8]. Fig. 2 shows the triaxial acceleration signal collected from a smartphone in hand during normal walking and the magnitude of total acceleration.

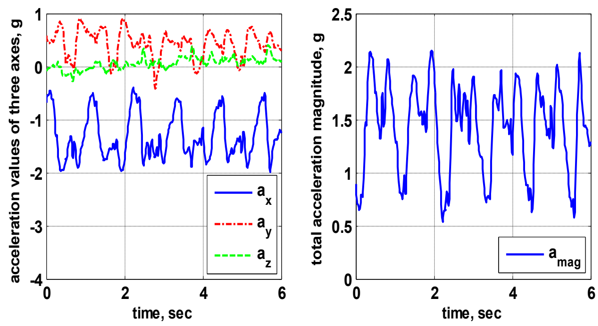

Figure 2. Acceleration signal and its total magnitude during walking

As shown in Fig. 2, the total acceleration magnitude, as well as all the output acceleration signals of three axes, has approximately bimodal oscillation mode with interferences that arise from perturbations of the hand. And the magnitude a_{mag} can be expressed as [9]:

$$a_{mag,k} = \sqrt{a_{x,k}^2 + a_{y,k}^2 + a_{z,k}^2} \quad (2)$$

where $a_{x,k}$, $a_{y,k}$ and $a_{z,k}$ are the measurements from the triaxial accelerometer. Unlike other approaches that use vertical direction of the acceleration to detect steps [12], [13], the total acceleration magnitude is used in our algorithm, which is insensitive to the orientation of a smartphone. Therefore, this variable can adapted to different walking patterns.

According to the value of a_{mag} , a candidate step at time t_k , where k denotes the index of steps, is identified by following criteria (as shown in Fig. 3):

C1.The total acceleration magnitude a_{mag} has to cross the threshold δ_{th} from negative to positive.

C2.The time interval Δt between two consecutive steps defined by C1 must be within the interval threshold from $\Delta t_{\min}$ to $\Delta t_{\max}$.

C3.The difference a_m between extreme values of a_{mag} during a step phase and the threshold δ_{th} has to be among $a_{\min}$ to $a_{\max}$, otherwise a perturbation point is recorded.

In view of the irregular fluctuations of a_{mag} due to various individual way of walking, the threshold δ_{th} in C1 is updated dynamically according to the mean value of a_{mag} over a step period, i.e.

$$\delta_{th} = \frac{1}{\Delta t_k} \int_{t_k}^{t_{k+1}} a_{mag}(t)dt \quad (3)$$

In order to distinguish walking motions from other pedestrian activities, a finite state machine (FSM) is defined and it contains two states, S1 *Stance* and S2 *Walking*. The state transitions of the FSM are determined by the autocorrelation of a_{mag} and candidate step counts within a sliding window of the length T_s . The criteria of state transitions are given as follows (see as Fig. 4):

C4.Transition from S2 to S1: there is no candidate step or there exist perturbation points in the sliding window.

C5.Transition from S1 to S2: the candidate step number is more than one and there is not any perturbation point within the sliding window, meanwhile the autocorrelation value r_{mag} is larger than threshold r_{th} .

Note that the autocorrelation mentioned in C5 does not need to be computed if the state maintains S2 *walking* when the candidate steps become valid steps. The purpose of this scheme is to effectively reduce unnecessary calculations and thus save power consumption.

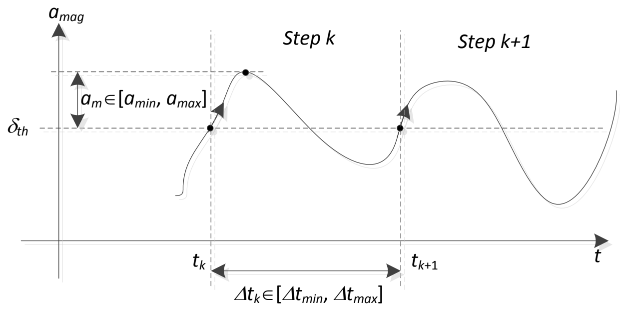

Figure 3. Identification of candidate steps

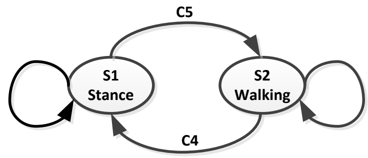

Figure 4. Step detection for activities during actual walking

B. Stride Length Estimation

In the PDR system, stride length estimation, combined with heading determination, is utilized to compute the traveled distance and update the position of the pedestrian on condition that the previous position is known. As described in related IMUs based PDR system, the step length of a pedestrian is not constant and varies with walking speed, step frequency, acceleration variance and so on [14], [15], [16]. In order to estimate the travel distance of the PDR system accurately, adaptive stride length estimation must be adopted according to these variations. Generally, the stride length is estimated using a linear combination of step frequency and acceleration variance through following equations:

$$\text{Stride Length } L = \alpha \cdot f + \beta \cdot v + \gamma \quad (4)$$

where f is step frequency, v is acceleration variance during one step; α and β are weighting factors of step frequency and acceleration variance; γ is constant. For different pedestrians, the model parameters α , β , γ are different and required by offline training. And the step frequency and acceleration variance in Eq. (3) are obtained as:

$$\begin{cases} f_k = 1/(t_k - t_{k-1}) \\ v_k = \sum_{t=t_{k-1}}^{t_k} \frac{(a_k - \bar{a}_k)^2}{n} \end{cases} \quad (5)$$

where f_k and v_k are step frequency and acceleration variance at t_k ; t_k means timestamp of the step k ; a_k is acceleration signal and $\bar{a}_k$ is average acceleration during on step; n is the number of sensor sampling points.

However, according to the result of our experiment, the stride length is also influenced by different motion modes such as walking and running. Fig. 5 shows that the relations between stride length and step frequency in both walking and running situations.

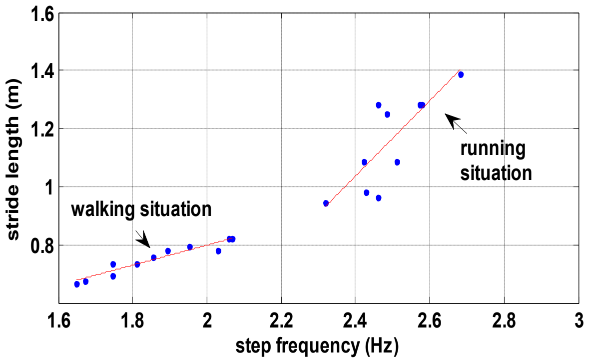

Figure 5. Polynomial fitting of stride length and step frequency

It is obvious that the stride length cannot be estimated accurately with single model. Therefore, an adaptive stride length estimation algorithm based on motion modes classification needs to be developed.

Furthermore, in view of the differences in acceleration changes vary greatly among different motion modes, we use the slope of acceleration to distinguish three motion modes: standstill, walking and running. The benefit of choosing slope as decision variable is that it can separate walking and running modes with high accuracy. With respect to step frequency and velocity, fast walking and slow running are very close and hard to distinguish each other, but slope differentiates them by detecting the impact between foot and ground, which is large enough even when the pedestrian is fast walking or slow running. From the triaxial acceleration, the slope is obtained as:

$$slope = \sqrt{(x_{\max} - x_{\min})^2 + (y_{\max} - y_{\min})^2 + (z_{\max} - z_{\min})^2} \qquad (6)$$

where $x_{\max}$ and $x_{\min}$, the same as $y_{\max}, y_{\min}, z_{\max}, z_{\min}$, are the maximum and minimum values of acceleration in x-axis respectively.

Fig. 6 shows that the results of motion modes classification in actual situation using the slope of acceleration. It is noted obviously that different motions can be classified with high accuracy by setting several thresholds. Accordingly, the PDR system can adaptively estimate the stride length with different model parameters.

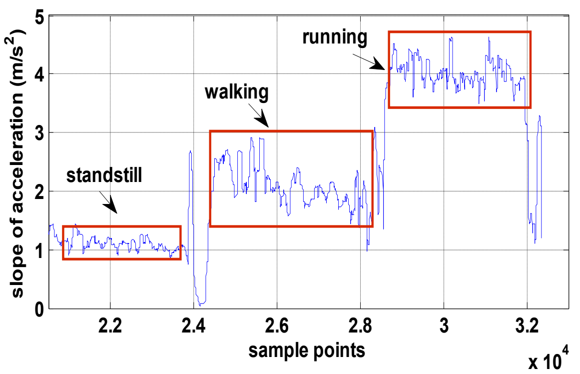

Figure 6. The slope of acceleration in different motion modes

C. Heading Determination

Heading determination is one of the most challenging parts of a PDR system, because the error of heading leads to a fast growth of localization error and reliable heading determination is difficult to achieve specifically in indoor environments where magnetometer may become invalid due to various interferences. For indoor localization on a smartphone, there exists another problem that the smartphone heading may be different from the pedestrian's heading. Therefore, two main work need to be finished before we implement an indoor localization. One is to obtain the heading of a smartphone, the other is to infer the heading offset between the smartphone and the pedestrian.

The attitude and heading of a smartphone are essential for determining the pedestrian's heading. Common attitude and heading reference system (AHRS) algorithm fuses data from magnetic angular rate and gravity (MARG) sensor arrays (including accelerometers, gyroscopes and magnetometers) to acquire the smartphone sensor's attitude represented in Euler angle or quaternion. However, when facing indoor environment, one has to deal with the magnetic distortion arising from modern buildings composed of reinforced concrete. Several researches point out that heading error may be the main cause that degrades localization accuracy. Unbounded heading error can be more than 40 degrees in some situation [17].

Fig. 7 shows that the flowchart of true attitude acquisition algorithm. To acquire the true attitude of the smartphone free from the distortion of magnetic anomalies, we have to distinguish the good magnetic components from the abnormal ones. Thus, a two-phase filter, as shown in Fig. 7, is implemented in our work. At the first phase, features of magnetic field including magnitude, horizontal component and inclination are compared with their reference values [18]. If the differences are within the thresholds, then the algorithm enters the second phase where the differences in trend between yaw angles from 9-DOF (degree of freedom) and 6-DOF fused AHRS are compared to determine which attitude fusing method is utilized.

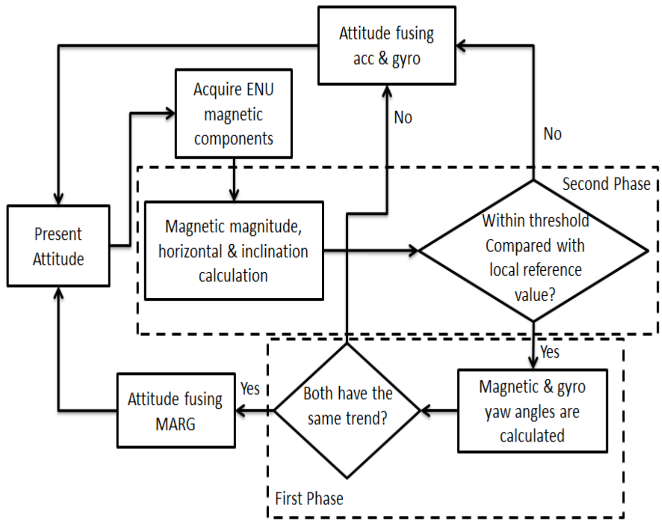

Figure 7. Flowchart of true attitude acquisition algorithm

Some PDR systems use body mounted MARG to provide accurate heading information. However, a smartphone has diverse ways of placements and much higher degree of freedom. We usually use a smartphone to text, to make a call; it may be swinging with hands or be placed in pocket. In this paper, we deal with these situations and provide reliable heading determination in following four scenarios:

- Compass: User is holding the smartphone stably with the screen up. She may be checking the map or texting.
- Calling: User is making a call, so the smartphone is close to her ear.
- Pocket: Smartphone is placed in the user's trousers' pocket.
- Hand-swinging: User is holding the smartphone in hand, and the smartphone is swinging with the hand.

For the first two situations, Compass and Calling, the smartphone sensor's yaw angles are relatively stable, thus the heading can be determined at any time. On the contrary, in the latter two situations, Pocket and Hand-swinging, the yaw angles change dynamically even the pedestrian is walking straight ahead. Therefore, to determine the heading in dynamic state, we take advantage of the characteristics of walking behaviors.

As demonstrated before, when a pedestrian is walking, the MARG attached to her will give a periodic signal which represents the walking motion. The magnitude of acceleration is not only useful in detecting steps but also effective to determine the pedestrian's heading when the smartphone is in pocket or swinging with the hand. During every step, a moment that the acceleration magnitude crosses the gravity can be observed. At that time, the orientation offset between sensor's yaw and user heading is approximately the same as the moment when user is at standstill. As illustrated in Fig. 8, despite of the dynamic changing of sensor's yaw angle, the moment to access the true heading can be determined by the time when the magnitude of acceleration cross the threshold of gravity.

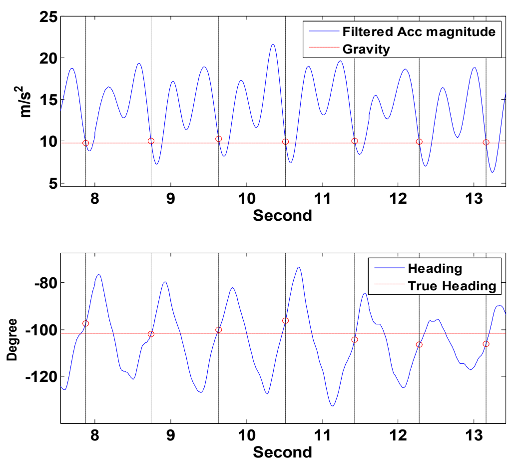

Figure 8. Heading determination corresponding to acceleration magnitude

Consequently, if the offset between sensor's yaw angle and pedestrian heading is known, the heading determination can then be accomplished. This is reasonable because there always be a chance for the user to check her smartphone when she points the smartphone at her direction. On the other hand, there are some situations when the offset is unknown, for example the phone is placed in user's pockets. It has been observed that the most variations in the horizontal plane of the acceleration signal are parallel to the direction of motion while walking. Thus the heading of user can be determined by principal component analysis (PCA) of acceleration components [19].

To apply PCA to acquire heading, sensor frame acceleration is first rotated to global East-North-Up frame using the present attitude of the sensor. A low-pass filter then takes place to eliminate jitters in acceleration. After that, PCA is employed to the horizontal acceleration components to determine the heading axis. However the heading acquired from PCA has the problem of 180° ambiguity. A pedestrian's motion feature can help to solve the problem of ambiguity as shown in Fig. 9. When the phone has been placed in the pocket of the user, every a short period before foot impacts with the ground, the leg is swinging forward, and the sensor is rotating. Among the rotation axis which is in the horizontal plane and perpendicular to the heading axis, there should be an ascending angular movement a short period before foot impact with ground. Therefore, we can align the user heading by applying the trend of angular movement among rotation axis before the foot touches the ground.

IV. Particle Filter Algorithm

Particle filter is a sophisticated model estimation technique based on simulation to deal with system with non-Gaussian noise. The algorithm fused information from PDR and constraint from the floor plan to acquire the posterior distribution of pedestrian's location. We implemented a particle filter using binary weight and having the ability of correcting heading by utilizing the information from last generation of surviving particles to ensure both robust performance and mild calculations.

At the beginning of particle filtering, particles are initialized by user defined start position. Then state updates and resample takes place one after another.

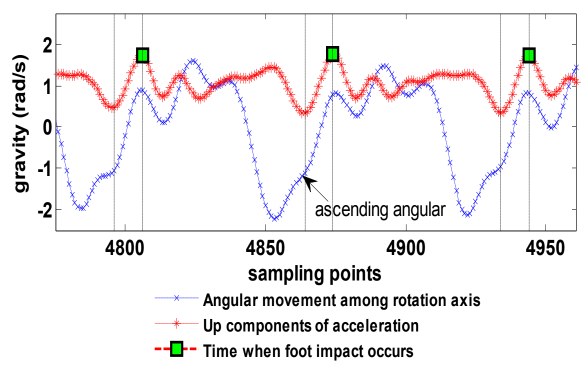

Figure 9. Heading acquired from PCA

At the phase of state update, first particles' location is updated using information from PDR, and then particles' weight is updated based on the indoor floor plan. The time interval and acceleration variance between steps as well as the estimated heading of the user is applied to update particles' location. The stride length and heading for an individual particle are defined in Eq. (7) and (8) respectively, where $SLError_i$ and $headingError_i$ are artificially added noises which satisfy zero mean normal distributions, and i is iteration index, similarly hereinafter.

$$SL_i = a * freq + b * var + c + SLError_i \tag{7}$$

$$heading_i = heading^{estimation} + heading^{bias} + headingError_i \tag{8}$$

However, severe magnetic distortion in indoor environment results in deviation in estimated headings, even though consideration has been taken to eliminate the effect of magnetic anomalies when the attitude is calculated. Extra heading correction can be achieved by investigating the heading of surviving particles as following:

$$heading^{bias} = \alpha * \sum_{i=1}^{k} headingError_i / k \tag{9}$$

Suppose that there are k survivors in the last generation before resampling, and α is a scaling factor which indicates the degree of heading correction. Normally, the $heading^{bias}$ will be close to zeros since it is drawn from zero-mean Gaussian distribution. But when the estimated heading is deviated from the true heading, surviving particles bias $heading^{bias}$ will be no longer zero, and it is used to correct particles' heading in next generation as illustrated in Eq. (8). Then the locations of particles are propagated base on Eq. (1).

Particles' weight is then updated using the floor plan constraint. The objects in floor plan including walls, furniture etc. are implemented to limit the user's path. Whenever a particle's path intersects with any object in the floor plan, that path is inaccessible, thus the particle's weight is reset to 0. Our system adopts the binary particle weight, which means the particle only has two possible weights: one or zero indicates live or dead.

As particle filtering has been regarded as a computationally intensive algorithm, our goal is to achieve a real-time which is feasible on a platform of a commercial smartphone. To reduce the computational load of particle filter two methods are implemented, one is binary weight; the other is reduction in particle number. When particle's weight is binary, the computation of state update and resampling is lighter. Especially in resampling, living particles are randomly selected and copied to fill up the dead ones. Our system can achieve the same accuracy but using half the amount of particle than previous research does since:

- Our smartphone based PDR algorithm is quite robust and accuracy, and
- Heading correcting strategy simultaneously improves the performance when running particle filter.

V. INDOOR LOCALIZATION TESTS

In this section, to verify the performance of proposed indoor localization method in practical situations, an experiment with arbitrary orientation of smartphone usage was performed.

A. *Experiment Setup*

The experiment site was situated at our laboratory building which is a 18 meters × 12 meters area and the total length of one lap is about 60 meters. The map information was gained from the floor plan of our laboratory building in the form of a DXF file, which contained various entities including segments, polylines and arcs. To simplify computing, we transformed polylines and arcs into segments artificially and established a database to store all the entities. In the experiment, an iPhone 4 was utilized and the output rate of the smartphone was set to 32 Hz. The output sensor data were calibrated and the output rate of the data was increased to 64 Hz by interpolation when proposed system was in operation. Three subjects, one woman and two man, who participated in the experiment, walked along the ground truth naturally ten circles for each scenario as descriptions in heading determination section.

B. *Experiment Results*

Fig. 10 shows that the estimated trajectory in Compass situation using proposed indoor localization method in this paper. The red lines represent pedestrian's trajectory and black squares represent ground truth that is demarcated by using laser rangefinder. Yellow star and green diamond denote start point and end point respectively. They are almost overlapping due to the high precision localization result. The result indicates that the positioning accuracy of our algorithm is reliable and accurate. Table 1 lists the detailed localization accuracy of the experiments in four scenarios. Obviously, the worst result is Pocket situation, the mean error is 0.74 meters and 95th percentile error is only 1.71 meters.

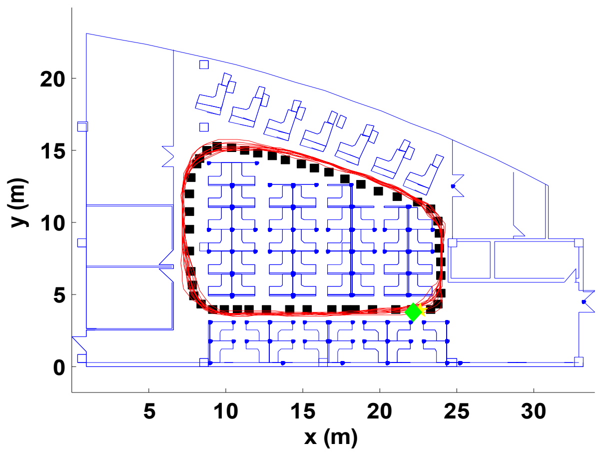

Figure 10. Estimated trajectory in Compass situation using proposed indoor localization method

TABLE I. ESTIMATED ERRORS IN FOUR SCENARIOS

Scenarios	Mean Error (m)	95th Percentile Error (m)
Compass	0.51	0.80
Calling	0.45	0.88
Hand-swinging	0.50	1.00
Pocket	0.74	1.71

VI. CONCLUSIONS

In this paper, we have presented an improved indoor localization method based on inertial sensors of a commercial off-the-shelf smartphone. This method allows us to implement high-precision indoor positioning by integrating PDR algorithm and floor plan information. Field test results demonstrate that the proposed method, which is applicable to diverse usage scenarios of smartphones, could be a promising scheme to be deployed into various smart mobile devices.

For future wok, we plan to improve the algorithm in all aspects of PDR technologies especially heading determination, which is still an unsolved problem in indoor environment. In addition, other indoor localization technologies, such as Wi-Fi or RFID, can be integrated into the current system to further improve the localization accuracy.

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REFERENCES

[1] M. Rainer, "Indoor positioning technologies," Ph.D. thesis, Swiss Federal Institute of Technology Zurich, Switzerland, 2012.

[2] F. Navid, A. Ilias, B. Kostas and F. Eelke, "Indoor human navigation systems: A Survey," Interacting with Computers, vol. 25.1, 2013, pp. 21–33.

[3] R. Guenther and H. Tobias, "Investigation of location capabilities of four different smartphones for LBS navigation applications," Indoor Positioning and Indoor Navigation (IPIN), International Conference on. IEEE, 2012, pp. 1–6.

[4] Ascher C., Kessler C., Wankerl M. and Trommer G.F., "Dual IMU indoor navigation with particle filter based map-matching on a smartphone," Indoor Positioning and Indoor Navigation (IPIN), International Conference on. IEEE, 2010, pp. 1–5.

[5] L. Jo Agila Bitsch, S. Paul, V. Nicolai and W. Klaus, "FootPath: accurate map-based indoor navigation using smartphones," Indoor Positioning and Indoor Navigation (IPIN), International Conference on. IEEE, 2011, pp. 1–8.

[6] S. Wen-Yuah and L. Kun-chan, "Using smartphone with un-scaled map for indoor localization," 9th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON), 2012.

[7] B. Inge, W. Maarten and K. Martin, "Mobile phone-base displacement estimation for opportunistic localization systems," Mobile Ubiquitous Computing, Systems, Services and Technologies, UBICOMM'09. Third International Conference on. IEEE, 2009, pp. 113-118.

[8] Q. Jiuchao, M. Jiabin, Y. Rendong and L. Peilin, "RPNOS: reliable pedestrian navigation on a smartphone," International Conference on Geo-Informatics in Resource Management and Sustainable Ecosystem (GRMSE), 2013, in press.

[9] S. Melania, R. Valerie and L. Gerard, "Motion mode recognition and step detection algorithms for mobile phone users," Sensors, 13.2, 2013, pp. 1539-1562.

[10] P. Ling, L. Jingbin, G. Robert, C. Yuwei, K. Heidi, C. Ruizhi. "Using LS-SVM Based Motion Recognition for Smartphone Indoor Wireless Positioning." Sensors 12(5), pp. 6155-6175.

[11] P. Ling, C. Ruizhic L. Jingbin, C. Wei, K. Heidi, T Tomi., K. Tuomo, C. Yuwei, L. Helena, and T. Jarmo. "Motion recognition assisted indoor wireless navigation on a mobile phone." In Proceedings of the 23rd International Technical Meeting of The Satellite Division of the Institute of Navigation (ION GNSS 2010), pp. 3366-3375.

[12] Z. Shizhe, X. Yongping, M. Jian, S. Zheng and W. Wendong, "Indoor location based on independent sensors and WIFI," Computer Science and Network Technology (ICCSNT), International Conference on. IEEE, vol. 4, 2011, pp. 2640-2643.

[13] C. Yan and A. Kartik B., "Pedestrian navigation with INS measurements and gait models," ION GNSS, 2011, pp. 1409-1418.

[14] C. Seong Yun and P. Chan Gook, "MEMS based pedestrain navigation system," Journal of Navigation, 2006, 59(01), pp. 135–153.

[15] K. Wei-Wen, C. Ching-Kun and L. Jing-Shian, "Step-length estimation using wrist-worn accelerometer and GPS," Proceeding of the 24th International Technical Meeting of The Satellite Division of the Institute of Navigation, 2011, pp. 3274-3280.

[16] C. Ruizhi, P. Ling and C. Yuwei, "A smartphone based PDR solution for indoor navigation," ION GNSS, 2011, pp. 1404-1408.

[17] L. Fan, Z. Chunshui, D. Guanzhong, G. Jian, L. Chenxing and Z. Feng, "A reliable and accurate indoor localization method using phone inertial sensors," in Proceedings of the ACM Conference on Ubiquitous Computing. ACM, 2012, pp. 421-430.

[18] A. Muhammud Haris, R. Valerie and L. Gerard, "Magnetic field based heading estimation for pedestrian navigation environments," Indoor Positioning and Indoor Navigation (IPIN), International Conference on. IEEE, 2011, pp. 1–10.

[19] U. Steinhoff and S. Bernt, "Dead reckoning from the pocket-an experiment study," Pervasive Computing and Communications (PerCom), IEEE International Conference on. IEEE, 2010, pp. 162-170.