Indoor Positioning Method Integrating Pedestrian Dead Reckoning with Magnetic Field and WiFi Fingerprints

Ryoji Ban*, Katsuhiko Kaji*, Kei Hiroi† and Nobuo Kawaguchi†
*Graduate School of Engineering, Nagoya University
Email: van@ucl.nuee.nagoya-u.ac.jp, kaji@nuee.nagoya-u.ac.jp
†Institute of Innovation for Future Society, Nagoya University
Email: k.hiroi@ucl.nuee.nagoya-u.ac.jp, kawaguti@nagoya-u.jp

***Abstract*—**

In this paper, we propose a high accuracy indoor positioning method that uses residual magnetism in addition to Pedestrian Dead Reckoning (PDR) and WiFi-based localization methods. Our proposed method needs WiFi and magnetic field fingerprints, which are created by measuring in advance the WiFi radio waves and the magnetic field in the target map. The fingerprints are represented by a Gaussian Mixture Models (GMMs) to reduce the amount of computation. Our proposed method estimates positions by comparing the pedestrian sensor and fingerprint values by particle filters. We evaluated this method in real environments and confirmed that it provides accurate indoor positioning with a mean error less than 8 m and more accurate position detection than existing techniques.

I. Introduction

In recent years, services using position information have attracted attention, including navigation services, life-log services, and SNSs. A GPS is generally used to obtain a person's position. However, in indoor environments, the acquisition of positions with sufficient accuracy is difficult because the GPS radio waves from a satellite are blocked by the buildings. Therefore, an indoor positioning method is required. In this paper, we propose a new indoor positioning method that operates by a smartphone. Smartphones are suitable for providing such services because they have become popular in recent years, and their displays have high resolution, a high-speed CPU, and various sensors.

Various researches about indoor positioning methods have been proposed [1]–[5]. Some methods require additional infrastructure; others do not because such additional infrastructure installation is too costly to apply to the former methods. Thus, we examine Pedestrian Dead Reckoning (PDR) and WiFi-based localization, which do not require additional infrastructure and can be achieved at a low cost.

Our proposed method also uses the residual magnetic field of buildings like the above methods. In indoor environments, residual magnetism, which is present in steel frames, has been treated as noise for using geomagnetism to estimate the orientation. In this paper, we propose an indoor positioning method that uses residual magnetic field as the position's feature value. First, our proposed method measures WiFi radio waves and the magnetic intensity of the target map to create fingerprints. Kaji [2] modeled the distribution of WiFi signal intensity using Gaussian Mixture Models (GMMs) to reduce the computational burden. In our method, we expand this approach to model the distribution of the magnetic intensity by GMMs. Then we estimate the position by comparing the observed values of pedestrian sensors with the fingerprint values using a particle filter. Furthermore, our proposed method revises the estimated results based on passage-prohibited information to avoid entering such off-limits areas to realize position estimation that is aligned to the map: map matching. We also evaluated our proposed method in a real environment and confirmed its effectiveness.

II. Relevant Research

In recent years, GPS is generally used for position estimation outdoors. However, in indoors, using GPS is difficult because its radio waves, which are transmitted from a satellite, are blocked. Indoor positioning methods have been researched, most of which are classified into absolute and relative positioning.

Absolute positioning estimates positions using infrastructures that are placed in environments. For example, research has estimated positions using RFID tags in a target environment [3]. Other research has used UWB, Bluetooth, and ultrasound. However, the new infrastructure of these methods is costly to introduce and maintain in the target environments. Thereby, it is difficult to advocate them to provide indoor services. Although other methods reduce costs using existing WiFi base stations [2], their accuracy is about 6 to 10 m. This is insufficient because indoor positioning services require higher accuracy than general outdoor services. For example, accuracy of 5 m or less is required to determine the shop at which a user is just browsing in a shopping mall. Other research used the residual magnetic field caused by a building's steel for estimating a robot's position [6]. The cost of this method is low because it also uses the existing environment. However, the use of residual magnetic field for pedestrians is limited (ex. detection of landmarks such as elevators, escalators and water-fountain [7], [8]). Our proposed method uses not only localized strong magnetic field but also magnetic fluctuations distributed in entire maps.

Relative positioning estimates positions using sensors attached to pedestrians to accumulate movement distances that are calculated from sensor values. The methods that are

978-4-907626-12-9/15/$31.00 ©2015 IEEE

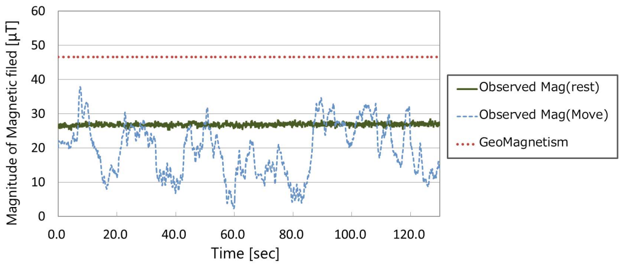

Fig. 1. Variance of magnetic field when sensors move in a building

Fig. 2. Tool for map information collection

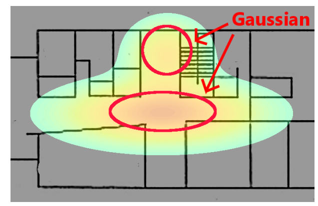

Fig. 3. Gaussian Mixture Model representing WiFi fingerprint model

intended for pedestrians are called PDR. A typical PDR estimates the stride length, the number of steps, and the pedestrian's direction and updates the position by combining them [4] [5]. However, problems remain in long-term use. In relative positioning, error accumulates because the position is estimated by the accumulation of displacement. For example, Li's method [9] has a 4% walking distance error. Since the sensors on smartphones are cheap with poor accuracy due to cost limitations, the error increases when PDR systems work on smartphones. In addition, although users carry smartphones in many different positions or styles, including in pockets or hand-held, a general PDR assumes that sensors are fixed.

To provide such services as navigation, indoor positioning methods must be available for many hours with high accuracy and the ability to operate on smartphones. Thus in this paper, we propose an indoor positioning method that combines relative and absolute positionings to make up for their weaknesses. Since our proposed method estimates the current postures of smartphones, it is available even though the smartphone might be held or stored in various ways.

III. Preparation of Position Estimation

A. Residual Magnetic Field

Our proposed method uses a building's residual magnetic field to estimate positions accurately in addition to WiFi radio waves and PDR, both of which have been previously researched. Residual magnetic field, which is the magnetic field retained by steel, is treated as noise to estimate the directions from geomagnetic field. Fig. 1 shows the change of the magnetic field norm observed when a magnetic sensor is attached to a pedestrian's waist who moves in a building in Nagoya. For comparison, the geomagnetic norms in Nagoya [10] and the magnetic norm at rest are also shown. The observed magnetic norm tends to be smaller than the geomagnetic norm because the outer wall of the building blocks the geomagnetic field. Fig. 1 suggests the magnetic differences by location. They arise from the residual magnetism of the building. Our proposed method estimates position using those differences in the magnetic field.

B. Collecting Map Information

In our proposed method, a target building's map information is required to estimation positions. The map information consists of WiFi radio waves and the magnetic intensity at each point in addition to the passage-prohibited information. We created a tool for collecting information (Fig. 2) that works on Android devices.

First, a user registers the image of the target floor map and selects a floor map to be observed on the tool. Then a corresponding image is displayed. A user taps the target position on the tool and starts observation. The terminal is fixed to make a corresponding north-south X-axis, an east-west Z-axis, and a vertical Y-axis. The tool also uses a mean observation value every 20 sec because fluctuation is present in the field intensity and the sensor values. The WiFi information consists of multiple sets of radio wave strength and BSSID, which is the base station's identifier. These data are stored as text data.

C. Model Creation

We created fingerprint models of WiFi and magnetic field from the map information collected in Section III-B. Conventional WiFi indoor positioning methods require large amounts of computation. Kaji et al. modeled the distribution of WiFi signal intensity by GMM [2] to reduce them. Our proposed method also models the distribution of magnetic intensity by GMM, which is a parametric function represented as a weighted sum of Gaussian distributions (Fig. 3). Magnetic field, which is separately modeled for all three axes, is composed of geomagnetic field and residual magnetic field. Residual magnetic field has two components: positive and negative. In our proposed method, the magnetic models are represented by three parameters: a constant representing geomagnetic field, a GMM representing positive residual magnetic field, and a GMM representing negative residual magnetic field.

First, we consider the magnetic field's mean intensity in the target map as the constant. Second, our proposed method creates a GMM by applying the method of Kaji et al. to the observation points with higher magnetic intensity than the mean. Our proposed method also creates a GMM from the observation points with lower magnetic intensity. It adapts the above procedure to all the X-, Y-, and Z-axes and creates fingerprint models representing the distribution of each magnetic component. The fingerprint model outputs WiFi or magnetic intensity that corresponds to the input coordinates.

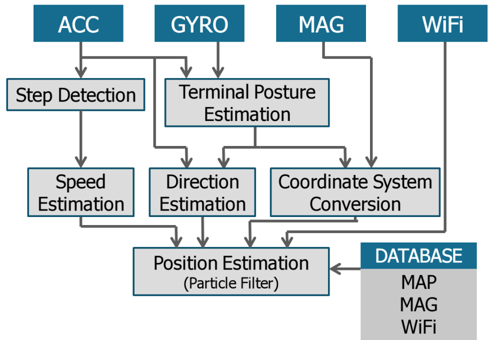

Fig. 4. Indoor positioning flowchart

IV. Position Estimation Process

Our proposed method estimates positions by combining map information and PDR. PDR has high, short-term precision but low, long-term precision because it has relative positioning, which estimates positions by the accumulation of displacement. We reduce the long-term error by combining absolute positioning, map information, and PDR.

Figure 4 shows a flowchart of our proposed method. As described in Section III-B, the system holds the fingerprint of the map information, which was collected in advance, and has input of the acceleration, gyro, magnetic, and WiFi sensor values. These sensors are increasingly included in smartphones in recent years. For using magnetic sensors, the terminal posture is crucial. Magnetic sensors detect different values based on the posture of the terminal because they obtain values in terminal coordinate systems. Since the terminal posture of the pedestrian is dynamically changed, directly comparing sensor and fingerprint values is not possible. The norm of the magnetic vector is similar; however, in this way, the information about each axis of the magnetic vector is not available. Therefore, in our proposed method, first the terminal posture is estimated. Using the terminal posture information, we can convert the terminal coordinate system into a world coordinate system to use the information about each axis of the magnetic vector. Second, as part of PDR, the direction and the speed of pedestrians are estimated. Finally, the position is estimated by a particle filter, which receives the WiFi sensor values and the values estimated above.

A. Estimation of Pedestrian Walking Speed

Pedestrian walking speed is estimated in the step detection and speed estimation blocks. The step detection block identifies the foot-ground contact at the time of walking. Fig. 5 shows the typical time variation of the acceleration while walking. Because there are maximum and minimum values in every walking period, step detection is made possible by identifying these maximum and minimum values. Our proposed method uses the automaton created by Alzantot [4] as the step detection algorithm. Fig. 6 shows the state transition diagram of a finite automaton. Each state refers to the following values: S0: stay, S1: start of operation, S2: observe maximum, S3: observe minimum, S4: complete motion, and S5: detect steps. There are four thresholds. The state is transitioned if the norm of input acceleration X satisfies the conditions shown in Fig. 6. Each threshold has the following meanings: $Move$: whether it is moving, Pos_Peek: maximum, Neg_Peek: minimum, and $Step\_End$: end of motion. In the proposed method, on the basis of preliminary experiments, we determined that $Move = 0.05\ G$, $Pos\_Peek = 1.15\ G$, $Neg\_Peek = 0.85\ G$, $Step\_End = 0.95\ G$.

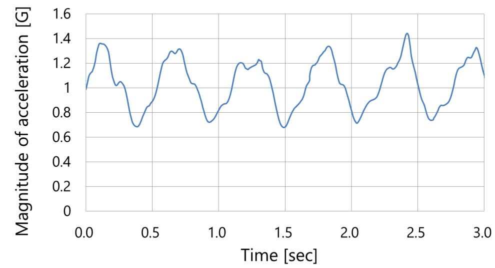

Fig. 5. Acceleration while walking

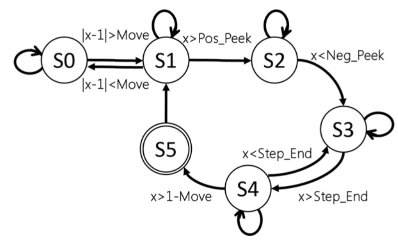

Fig. 6. FSM for step detection

The speed estimation block estimates the pedestrian walking speed by combining the detected steps and the stride length. The stride length is estimated by $stature \times 0.46\ m$ [5], and the movement distance is calculated by $step\ number \times stridelength$. Finally, the pedestrian walking speed is estimated by the time derivative of the movement distance.

B. Estimation of Terminal Posture

In our proposed method, the terminal posture is estimated using gyro sensor and acceleration sensor values. We previously proposed a method to estimate the terminal posture using acceleration, gyro, and geomagnetic values [11]. Our proposed method uses only acceleration and gyro sensors, because we assume that it will be used in indoor environments, where residual magnetic field complicates using geomagnetic values. Thus, direction estimation using geomagnetic field is impossible, and the degree of freedom about the Y-axis remains at an estimated posture. Fig. 7 shows a flowchart of the posture estimation. The terminal posture is expressed by a square matrix of 3×3, which indicates the difference from the reference state in which the terminal display faces south in the portrait mode. This square matrix is mutually convertible to the three parameters related to the rotation of each XYZ-axis.

Gyro sensors detect the device's rotation, and posture estimation is assumed to be possible by integrating gyro sensor readings. However, there are several problems to integrate gyro sensor readings to calculate posture. First, the integral's initial value is unknown. Second, errors accumulate. Therefore, our method estimates the gravity direction and also uses the posture determined by the gravity direction. Defective postures are combined by a Kalman filter to estimate high-precision

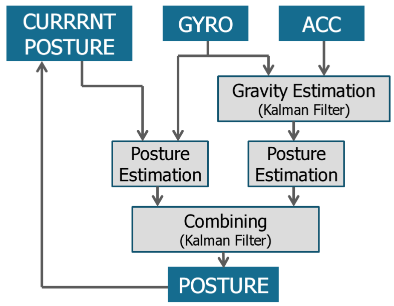

Fig. 7. Flowchart for posture estimation

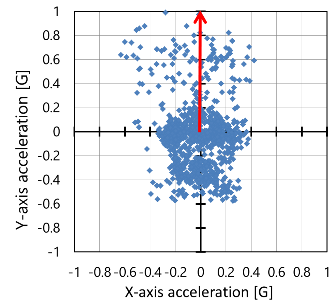

Fig. 8. Distribution of plane acceleration

postures. A Kalman filter estimates the state of a discrete-time linear system that contains noise, and two defective postures are input into the filter as observations. Since the posture estimated by the gravity direction has no cumulative error, it can compensate for the weak points of the gyro sensors for more accurate estimation of postures. As a method for estimating gravity direction, we employed the Kalman filter of Korogi et al. [12] that uses gyro and acceleration sensors as observations. That is, it uses acceleration as a value that is composed of gravity and noise, while tracking the gravity direction by integrating gyros. In estimating the posture by gravity direction vectors, the degree of freedom of the Y-axis remains at the estimated posture. Thereby, the posture can't be determined uniquely. The parameters of the X- and Z-axes are only used as observations of the Kalman filter to estimate posture.

C. Estimation of Pedestrian Direction

The direction estimation block estimates the pedestrian direction based on the acceleration and terminal postures. We assume that pedestrians walk in a constant direction compared with terminal posture when users move with a fixed terminal. We also speculate that accelerations are distributed around the walking or reverse directions because the walking motion is repeats of acceleration and deceleration in the walking direction. Fig. 8 shows our preliminary experiment results. In the preliminary experiment, the terminal was secured to the front of the waist, and subjects walked in a straight path. In Fig. 8, the flat components of accelerations are sampled. The pedestrian direction is the positive direction of the vertical axis, and we infer that the accelerations are distributed around the walking direction. Our proposed method only uses acceleration that exceeds the threshold; it excludes accelerations that are read while at rest. Based on the above, as a pedestrian direction, our proposed method uses the mean of the angle defined by two vectors: a vector representing a straight line of the intersection between the horizontal plane and the terminal display surface, and another of the plane component of the acceleration that exceeds threshold 0.5 G.

D. Coordinate Transformation of Magnetic Sensor Reading

The coordinate system conversion block changes the coordinate system of the magnetic sensor values. These values cannot be compared directly with the values of the fingerprint models and their world coordinate system because the magnetic sensor values are in a terminal coordinate system. Therefore, magnetic sensor values are converted into a world coordinate system by applying a rotation matrix that represents the terminal posture to be compared. Because the estimated posture has one degree of freedom about the Y-axis, as mentioned in Section IV-B, the plane components of the magnetic value (X- and Z-axis component) also have degrees of freedom. Therefore, our method uses two components: a plane component, which is the norm of the X- and Z-axis values, and a vertical component, which is the Y-axis component. The coordinate system conversion block outputs these parameters.

E. Position Estimation

The position estimation block estimates the pedestrian position using a particle filter, which is a kind of time-series filtering method that estimates the subject's state from the observed values, including noise. It approximates any probability density function by a large number of samples (particles) and outputs the weighted mean based on the likelihood of each particle in the state. In our proposed method, a particle at time t holds four states that consist of position (Px_t, Py_t), speed Pv_t, and direction $P\theta_t$. The initial state is given on the assumption that the GPS location just before going indoors can be used as the initial state. The position estimation is composed of four steps: prediction, likelihood calculation, state estimation, and resampling.

1) Prediction: In prediction, each particle's state is transited based on the following equation using two inputs: speed vel_t and walking direction dir_t:

$$Pv_t = Pv_{t-1} + \Delta vel_t + randV \tag{1}$$

$$P\theta_t = P\theta_{t-1} + \Delta dir_t + rand\theta \tag{2}$$

$$Px_t = Px_{t-1} + Pv_t \times sin(P\theta_t) \times \Delta t \tag{3}$$

$$Py_t = Py_{t-1} + Pv_t \times cos(P\theta_t) \times \Delta t. \tag{4}$$

The values of $randV$ and $rand\theta$ are random numbers determined within the set value.

The presence of a random number makes it possible to approximate the state by considering the noise. On the basis of the empirical rule, we determine the following parameters:

$$-4.0\ m/s < randV < 4.0\ m/s \tag{5}$$

$$-30^\circ < rand\theta < 30^\circ \tag{6}$$

Under these circumstances, if particles enter prohibited areas, their likelihoods become 0 in the likelihood calculation of Section IV-E2.

2) Likelihood Calculation: Next we update the likelihood of each particle. To calculate the likelihoods, we used the inputs: speed, magnetic field, and WiFi. A particle's likelihood is calculated from the product of the likelihoods of speed $l_{v,t}$, magnetic field $l_{m,t}$, and WiFi level $l_{w,t}$. All likelihoods are calculated from a normal distribution whose variable is the value of the particles obtained from the fingerprint and whose mean is the input value. The standard deviations of these normal distributions are important parameters. If they are too small, the system cannot permit noise; if they are too large, the influence of the observations becomes too small. As the result of preliminary experiments, we set the standard deviation of velocity to 2 m/s, the standard deviation of the magnetic field to 30 dBm, and the standard deviation of the WiFi level to 30 μT. In general, there is a plurality of the WiFi level and BSSID sets. Thus, $l_{w,t}$ is calculated from the product of the likelihoods that is evaluated by the WiFi level of each BSSID. After calculating the likelihoods of all the particles, they are normalized to 1.

3) State Estimation: Next we calculated the result of the position estimation at time t. We evaluated the sums of the likelihood of the particles on each floor of the target building and determined the maximum floor as the current floor. Then the mean weighted by the likelihood of particles, which are on the current floor, is calculated and regarded as the estimation result.

4) Resampling: Here, the particles at time $t+1$ are created based on their likelihoods at time t. First, a particle was selected at a random weight by the likelihood from the particles at time t. Next, a new particle is generated by slightly shifting the selected particle to avoid a situation where there are multiple particles in the same coordinates. The particles at time $t+1$ are created by repeating this process. Thus, new particles tend to be located around particles with a high likelihood at time t.

V. Evaluation Experiment

A. Experiment Condition

We evaluated our proposed method by collecting pedestrian walking data indoors in an experiment that was conducted in Nagoya Daigaku station, where there are many WiFi base stations and 5 or more BSSIDs that are always observable. This experiment targeted two routes: Route 1 of full length 71 m to move around the same floor (Fig. 9), and Route 2 of full length 118 m to move from the ticket barrier to the station platform by stairs (Fig. 10). As preparation for performing the position estimation described in Section III-B, we collected environment information using Nexus 4. The subjects were four males and wore sensors on two places: the front center of their waists, which is the center of the human body's mass, and on their hands when viewing the display to provide navigation services. We measured each person three times on every terminal holding method and on every route. 48 pieces of data were collected, each of which was evaluated on a PC after it was collected. In the evaluation, we estimated the positions every 0.25 sec and calculated the error between

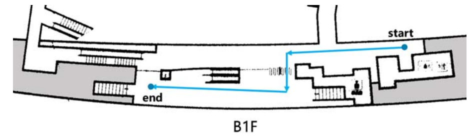

Fig. 9. Route 1: Movement on same floor

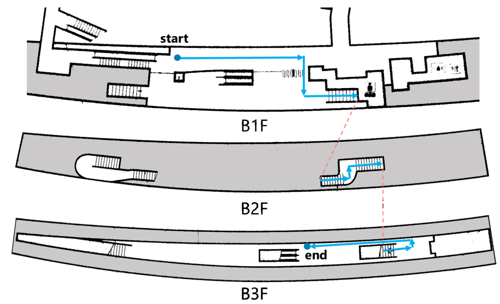

Fig. 10. Route 2: Movement from the ticket barrier to the station platform by stairs

the estimated and correct positions. We derived the correct position by assuming the percentage of the elapsed time in the total time equals the percentage of the walking distance in the total distance of the path.

B. Mean Error of Position Estimation

For each route, we calculated the mean of the proposed method's error to examine the effect on the accuracy of PDR, magnetic field, and WiFi. We also calculated and compared the mean error when each function was disabled. In all the above cases, map matching was employed. In the evaluation of route 2, the error cannot be represented by distance when the estimated floor is different from the correct floor. First, we evaluated whether the estimated floor equaled the correct floor. Second, we only calculated the error when the estimated floor was correct. The particle filter outputs different results every trial even if the particle filter used the same data. Thereby, the mean of 10 repeated trials for the data is regarded as the data error.

Table I shows the evaluation result of route 1, and Table II shows the evaluation result of route 2. In route 1, the proposed method estimates the pedestrian position with error of 5.1 m when the terminal is fixed to the waist and error of 5.6 m when the terminal is hand-held. In route 2, the error is 7.6 m, and floor accuracy rate is 74% when the terminal is fixed to the waist, and the error is 6.0 m and the floor accuracy rate is 77% when the terminal is hand-held. We concluded that our method estimates the pedestrian position with an error of no more than 8 m overall. In addition, the error of route 1 became smallest when only the magnetic and PDR values were enabled. Thus, we confirmed the effectiveness of using residual magnetic field.

In both routes 1 and 2, the error increased when only the WiFi or magnetic values were used. We assumed that sensor noise is one main cause of the error. In particular, WiFi sensors have problems; both those that are installed on the smartphones used in our evaluation and also those on other smartphones. Sensor values lag for real situations. This problem can be mitigated by combining PDR with WiFi-based localization. In

TABLE I. MEAN ERROR IN ROUTE 1

Method	Waist [m]	Hand [m]
PDR	12.9	10.7
WiFi	19.0	18.6
MAG	19.0	18.6
PDR+WiFi	5.5	7.6
PDR+MAG	4.9	5.0
Proposed method	5.1	5.6

TABLE II. MEAN ERROR AND ACCURACY IN ROUTE 2

	Waist		Hand	
Method	Floor acc. [%]	Error [m]	Floor acc. [%]	Error [m]
PDR	71	8.8	75	8.4
WiFi	47	6.2	51	7.1
MAG	50	16.4	50	17.2
PDR+WiFi	77	8.3	81	6.4
PDR+MAG	70	8.8	60	7.9
Proposed method	74	7.6	77	6.0

the evaluation of route 1, using magnetic field and PDR has the least error, and our proposed method, which use magnetic field, PDR and WiFi, has greater error than it. On the other hand, in the evaluation of route 2, using WiFi and PDR has the best floor accuracy rate. We assume that our proposed method estimates a long-term rough position using WiFi, and it estimates a short-term high accurate position by combining PDR and magnetic field. The following are potential causes of the error: sensor error, stride estimation error, and fluctuations in the magnetic and WiFi environments. To improve the utility, we must investigate stride estimation with higher accuracy as well as a method of dynamically updating the fingerprint models that use the observed value of users.

VI. CONCLUSION

In this paper, we proposed an indoor positioning method that uses a building's residual magnetic field in addition to WiFi and PDR positioning. We evaluated this method by collecting 48 pieces of indoor walking data and confirmed that it estimated indoor position with a mean error less than 8 m when the terminal is attached to the waist or is held-hand. Future work will address the following points:

Stride Length Estimation
: In our proposed method, the estimated stride length threatens to become very different from the original stride when the user is hurrying amid congested surroundings because the stride length is estimated by $stature \times 0.46\ m$. We require a method to dynamically estimate the stride length based on the current situation, for example, using the correlation between stride length and the vertical component of acceleration [13].

Inclusion of Stairs Information into Map
: Our proposed method may incorrectly estimate the position when users move on stairs because it applied the same algorithm in two cases: walking on a flat area and up and down stairs. Thus, we apply another algorithm to particles on stairs by including their information in our map.

Evaluation in More Depth
: We plan to investigate the correlation between the accuracy of position estimation and the density of the observation point. The investigation can minimize the required preparation while maintaining accuracy.

In future, we will apply this method to underground mall of the Nagoya station, which is more large scale environments, and provide indoor services. We believe that this method work in practice and contribute to development of ubiquitous computing.

ACKNOWLEDGEMENT

Part of this research was supported by the Strategic Information and Communication RD Promotion Program (SCOPE) 132306007.

REFERENCES

[1] Paramvir Bahl and Venkata N. Padmanabhan. RADAR: An In-Building RF-Based User Location and Tracking System. *INFOCOM*, pp. 775–784, 2000.

[2] Katsuhiko Kaji and Nobuo Kawaguchi. Design and Implementation of WiFi Indoor Localization based on Gaussian Mixture Model and Particle Filter. *IPIN2012*, pp. 1–9, 2012.

[3] A. Bekkali and M. Sanson, H.and Matsumoto. RFID Indoor Positioning Based on Probabilistic RFID Map and Kalman Filtering. *WiMOB 2007*, p. 21, 2007.

[4] Moustafa Alzantot and Moustafa Youssef. UPTIME: Ubiquitous Pedestrian Tracking using Mobile Phones. *Wireless Communications and Networking Conference (WCNC), 2012 IEEE*, pp. 3204–3209, 2012.

[5] Kamisaka Daisuke *et al.* Design and Implementation of Pedestrian Dead Reckoning System on a Mobile Phone. *IEICE transactions on information and systems*, Vol. 94, No. 6, pp. 1137–1146, 6 2011.

[6] Naoki Akai *et al.* Implementation of a Long-Distance Navigation Method of Low Cost Structure That Combines a Localization Using Magnetic Information and a Lateral Position Compensation. *Transactions of the JSME (in Japanese)*, Vol. 79, No. 799, pp. 681–690, 2013. (in Japanese).

[7] Moustafa Alzantot and Moustafa Youssef. Crowdinside: automatic construction of indoor floorplans. *ACM SIGSPATIAL GIS 2012*, pp. 99–108, 2012.

[8] He Wang *et al.* No need to war-drive: unsupervised indoor localization. *MobiSys 2012*, pp. 197–210, 2012.

[9] Jin-feng Li *et al.* A Pedestrian Dead Reckoning System Integrating Low-Cost MEMS Inertial Sensors and GPS Receiver. *Journal of Engineering Science and Technology Review*, Vol. 7, No. 2, pp. 197–203, 2014.

[10] Geospatial Information Authority of Japan. Magnetic chart. *Technical Data of Geospatial Information Authority of Japan B·1*, No. 2, 2012. https://vldb.gsi.go.jp/sokuchi/geomag/menu_03/magnetic_chart.html. (in Japanese).

[11] Ryoji Ban, Katsuhiko Kaji, and Nobuo Kawaguchi. An Indoor Positioning Method Integrating Pedestrian Dead Reckoning with Magnetic Filed and WiFi Map. *IEICE Technical Report*, Vol. 113, No. 399, pp. 23–28, 2014. (in Japanese).

[12] Masakatsu Kourogi, Takashi Okuma, and Takeshi Kurata. Indoor positioning system using a self-contained sensor module for pedestrian navigation and its evaluation. *Symposium on Mobile Interactions 2008*, pp. 151–156, 2008. (in Japanese).

[13] Lei Fang *et al.* Design of a wireless assisted pedestrian dead reckoning system - the NavMote experience. *IEEE Transactions on Instrumentation and Measurement*, Vol. 54, No. 6, pp. 2342–2358, 2005.