An Accurate Indoor Positioning Algorithm using Particle Filter based on the Proximity of Bluetooth Beacons

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***Abstract*—Indoor positioning without GPS is one of the most important problems in indoor pedestrian navigation. In this paper, we propose an accurate indoor positioning algorithm using a particle filter based on a floormap, where we use the proximity of the Bluetooth beacons as well as acceleration and geomagnetic sensors. In designing the likelihood function in the particle filter, we effectively use the *proximity* of the Bluetooth beacons, which just gives rough distance to the target beacon but more stable than conventional RSSI-based distance estimation. In addition to that, by effectively utilizing a floormap, the accumulated positioning errors due to the acceleration and geomagnetic sensors are much reduced. Moreover, when the radio waves from the Bluetooth beacons are blocked by obstacles, we can also take it into account in designing the likelihood function in the particle filter. Experimental results demonstrate that our algorithm can reduce the indoor positioning errors by up to 79% compared to several conventional algorithms.**

I. Introduction

Over the last few years, indoor positioning and navigation for pedestrians using mobile phones are receiving attention as complex buildings and underground malls have been much more increasing. Generally, GPS (Global Positioning System) is mainly used in outdoor positioning where we can receive the radio waves from GPS satellites and know our accurate positions. However, in indoor environment, we cannot well receive the radio waves from GPS satellites and positioning errors of up to several tens of meters can occur even in ideal circumstances. How to obtain an accurate position even in indoor enviroment is one of the large concerns.

Several indoor positioning algorithms have been proposed without using GPS, which utilize wireless LAN systems [2, 7, 9], Bluetooth beacons [8], the indoor message systems (IMES) [6], and acceleration and geomagnetic sensors [1].

In particular, we focus on indoor positioning using Bluetooth beacons combined with acceleration and geomagnetic sensors. In indoor pedestrian navigation, users often walk to their destination while always checking their current positions. It is quite necessary to realize stable positioning. We use the *proximity* of the Bluetooth beacons as one of the most stable radio-field intensity measuring method. However, since the proximity just shows the very *rough* distance to the target beacons, how to utilize it becomes a major challenge.

In this paper, we propose an accurate indoor positioning algorithm using a particle filter based on a floor map, where we use the proximity of the Bluetooth beacons as well as acceleration and geomagnetic sensors.

The contributions of our paper can be summarized as follows:

1) In designing the likelihood function in our particle filter, we effectively use the *proximity* of the Bluetooth beacons, which is rough but more stable than conventional RSSI (Received Signal Strength Indicator) based estimation, and then stable positioning is realized even in an indoor environment where radio wave transmission is unstable.
2) In addition to 1), by effectively introducing obstacle information given by the floor map, the accumulated positioning errors due to the acceleration and geomagnetic sensors are much reduced. When the radio waves from the Bluetooth beacons are blocked by obstacles, we can also take it into account in designing the likelihood function in our particle filter.
3) Experimental results demonstrate that our algorithm can reduce the indoor positioning errors by up to 79% compared to several conventional algorithms.

II. Indoor Positioning using Bluetooth beacons

In this section, we firstly introduce Bluetooth beacons, floor maps, acceleration and geomagnetic sensors. After that, we define our indoor positioning problem.

A. Bluetooth Beacon

In this paper, the proximity of Bluethooth beacons is used to obtain the relative position between the Bluetooth beacon and the positioning device. The proximity gives the approximate position of a target positioning device using the received radio-wave intensity from the Bluetooth beacon. Let b_j be a Bluetooth beacon and $B = \{b_1, b_2, \cdots, b_m\}$ be a set of beacons. Let d_j be the distance between b_j and the positioning device which a user holds. The positioning device monitors the radio waves from each becon b_j every t_s seconds and obtains the proximity value from b_j, where it is (i) Immediate (approximity $d_j \leq$ 1m) , (ii) Near (approximity 1m $\leq d_j \leq$ 3m), (iii) Far (approximity 3m $\leq d_j$), or (iv) Unknown (not receive).

Note that the positioning device cannot receive "Immediate" from every Bluetooth beacon installed on the building floor or ceiling in our preliminary experiment as illustrated in Subsubsection III-B1. This is because the distance between the installation position of each Bluetooth beacon and the positioning device is 1m or larger in most of the cases, since the user holds the positioning device at his/her breast position.

B. Floormap

A floormap is given as follows: [3] Let $s_k = (V_k, E_k)$ be a structure of a given floormap, which is composed of a set V_k of nodes and a set E_k of edges. s_k also has its entering flag in_k and its logical layer number l_k. If $in_k = 0$, then the structure is an un-enterable area and the user cannot enter s_k. If $in_k = 1$, then the structure is an enterable area and the user can enter s_k. If $l_k = 0$, it shows that s_k is located at the lowest layer on the target floor and every structure is overlapped in the order of l_k. Let $S = \{s_1, s_2, \cdots, s_l\}$ be a set of such structures, which gives a floormap.

Fig. 1 shows an example of the floormap $S = \{s_1, s_2\}$. The structure $s_1 \in S$ shows an un-enterable area composed of the four nodes $\{v_1, v_2, v_3, v_4\}$ and we have $in_1 = 0$ and $l_1 = 0$. The structure $s_2 \in S$ shows an enterable area inside the target floormap composed of the 12 nodes $\{v_5, v_6, \cdots, v_{16}\}$ and we have $in_1 = 1$ and $l_1 = 1$. The structure s_1 is the lowest layer

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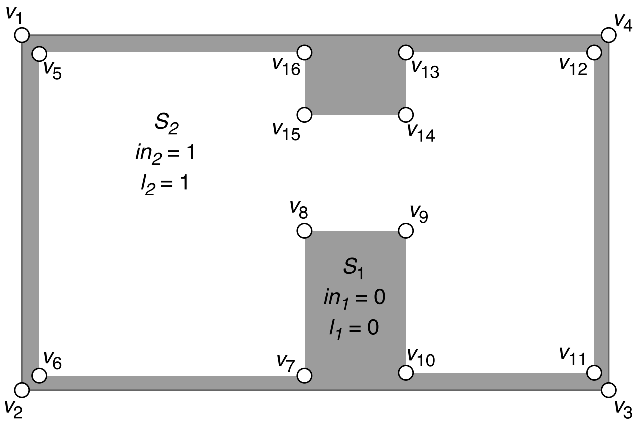


Fig. 1: An example of a floormap.

and the structure s_2 is overlapped on s_1. Since $in_1 = 0$ and $in_2 = 1$, we can enter s_2 but we cannot enter s_1.

Fig. 6 in Section IV shows another floormap depicting a floormap of the building No. 55 in Nishi-Waseda Campus, Waseda University. We can enter the white area and the grey areas show the obstacles, un-enterable areas.

C. Acceleration and geomagnetic sensors

When a user walks along the floormap, his/her walking motion and direction can be detected by an acceleration sensor and geomagnetic sensor and his/her relative position starting from the initial position can be measured [3].

Detect walking motion: The acceleration sensor can detect user's walking motion. When a user walks forward holding an acceleration sensor, he/she moves up and down and his/her acceleration value also goes up and down. By detecting these minimum and maximum acceleration values, we can know a single step of the user.

Detet walking direction: By using a geomagnetic sensor, we can also know which direction the geomagnetic sensor goes to and thus the user goes to.

D. Indoor Positioning Problem

Assume that a user walks around an indoor area holding a positioning device equipped with a Bluetooth receiver and acceleration and geomagnetic sensors. A floormap S of the indoor area is given beforehand. The measuring time interval t_s is also given beforehand. Then, our indoor positioning problem is defined as follows:

Definition 1 *Our indoor positioning problem is, for given the sensing values of the acceleration and geomagnetic sensors every t_s seconds, the proximity values of Bluetooth beacons every t_s seconds, and the floormap S, to obtain the coordinates of the current position of the positioning device every t_s seconds.* ■

III. An Indoor Positioning Algorithm using Particle Filter

As discussed in Section I, we utilize a particle filter [4] for indoor positioning based on the proximity values of Bluetooth beacons. First, let $P = \{p_1, p_2, \cdots, p_n\}$ be a set of virtual particles or just particles in short. At time t, each particle $p_i \in P$ has its position coordinates $(x_p^i(t), y_p^i(t))$ and the likelihood $w_i(t)$.

The likelihood of p_i shows how likely the positioning device is located at the same position of p_i. The particle filter estimates that the positioning device exists around the particles with the large likelihood values. Let $prox_j(t)$ be the proximity of every beacon $b_j \in B$ that the positioning device measures at time t.

Then our proposed indoor positioning algorithm is summarized below:

Step 1 (Initialize): Prepare a set $P = \{p_1, p_2, \cdots, p_n\}$ of n particles and $w_i(0) = 0$ for every particle p_i $(1 \leq i \leq n)$. Set randomly $(x_p^i(0), y_p^i(0))$ for each particle p_i in the enterable areas in S that a user can enter. Here, these particles are distributed logically inside the target indoor area, not physically. Let the current time t be zero $(t = 0)$.

Step 2 (Move): Let $t = t + t_s$, where t_s shows the given time interval. If walking motion is detected by the acceleration sensor during the last t_s seconds, detect the walking direction by the geomagnetic sensor. Let $dist$ [degrees] be the walking direction obtained. Move every particle p_i towards $dist \pm 15$ [degree] by 65cm $\pm$10cm.

Step 3 (Update the likelihoods): Update the likelihood $w_i(t)$ of each particle $p_i \in P$ as below:

$$w_i(t) = \max\{w_i(t - t_s) + \Delta w_i(t), 0\} \tag{1}$$

where $\Delta w_i(t)$ shows the difference between the current likelihood and updated likelihood and we apply the $\max$ operation in Eqn. (1) in order not to have the negative value for every $w_i(t)$.

Step 4 (Estimate): Obtain the estimated position $(x_e(t), y_e(t))$ of the positioning device using the weighted average of the positions of all the particles in P at time t.

$$x_e(t) = \frac{\sum_{i \in P} x_i(t) \cdot w_i(t)}{\sum_{i \in P} w_i(t)} \tag{2}$$

$$y_e(t) = \frac{\sum_{i \in P} y_i(t) \cdot w_i(t)}{\sum_{i \in P} w_i(t)} \tag{3}$$

Step 5 (Re-sample): For every particle p_i, re-distribute it by stratified resampling and its likelihood is re-set to same as resampling target particle. Return to **Step 2**.

Example 1 *The positioning example in walking in the H type floor holding a positioning device by using our proposed algorithm is illustrated in Fig. 2. For simplicity, we assume $t_s = 1$.*

*In **Step 1 (Initialize)** $(t = 0)$, a set P of particles are distributed randomly and logically inside the target indoor area as illustrated in Fig. 2(a).*

*In **Step 2 (Move)** $(t = 1)$, we assume that we detect that the positioning device moves toward the lower right during the last $t_s = 1$ seconds. Then we move all the particles in P toward the lower right as illustrated in Fig. 2(b).*

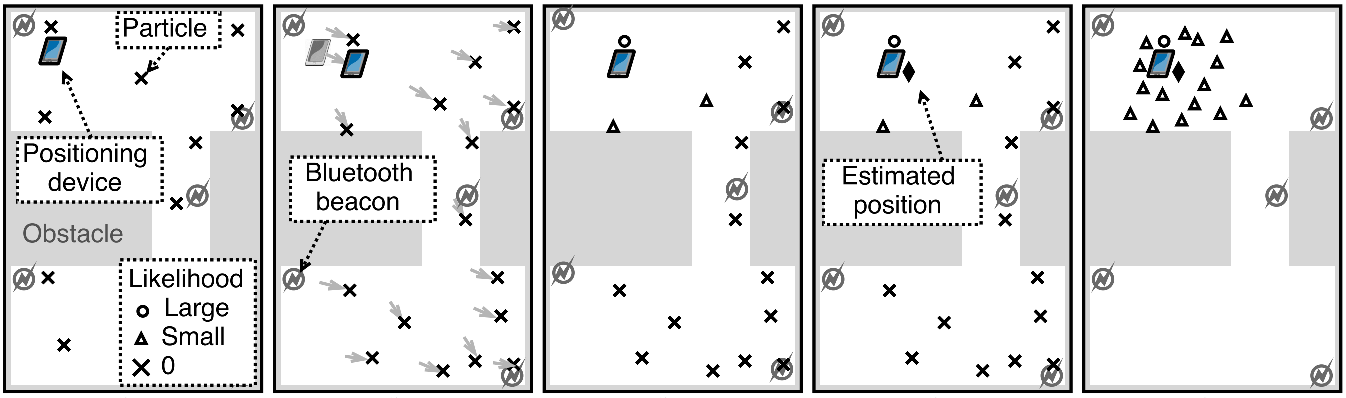
*In **Step 3 (Update the likelihoods)** $(t = 1)$, we estimate the likelihood of each particle $p_i \in P$ using the proximity of each Bluetooth beacon $b_j \in B$ and the floormap S as illustrated in Fig. 2(c).*

*In **Step 4 (Estimate)** $(t = 1)$, we calculate the weighted average according to Eqn. (2) by using the coordinates $(x_p^i(1), y_p^i(1))$ and the likelihood $w_i(1)$ for all the particles and decide the estimate current position as illustrated in Fig. 2(d).*

*In **Step 5 (Re-sample)** $(t = 1)$, we re-set the coordinates of the particles using stratified resampling.*

We repeat the above steps while the user finishes the indoor positioning. ■

In our proposed algorithm, how to design a movement model (**Step 2**) and a likelihood function (**Step 3**) is the most important.



(a) **Step 1**. (b) **Step 2**. (c) **Step 3**. (d) **Step 4**. (e) **Step 5**.

Fig. 2: Summary of our proposed indoor positioning algorithm.

The movement model in **Step 2** is designed by using acceleration and geomagnetic sensors. The likelihood function in **Step 3** is designed based on the two ideas: (a) using the proximity of each Bluetooth beacon at the positioning point and the distance between the beacon and each particle and (b) using a floormap to prevent the user from entering un-enterable areas such as walls and obstacles. Then the likelihood difference $\Delta w_i(t)$ of each particle p_i is composed of the two terms $\Delta w_b^i(t)$ and $\Delta w_f^i(t)$, which is given by:

$$\Delta w_i(t) = \Delta w_b^i(t) + \Delta w_f^i(t) \tag{4}$$

where $\Delta w_b^i(t)$ mainly shows the idea (a) and $\Delta w_f^i(t)$ mainly shows the idea (b) above.

Other than Steps 2 and 3, the algorithm can be easily implemented and then we propose **Step 2** (Section III-A) and **Step 3** (Sections III-B and III-C) in the rest of this section.

*A. Movement model using acceleration and geomagnetic sensors (**Step 2**)*

In **Step 2**, if the positioning device detects walking motion and walking direction using its acceleration and geomagnetic sensors based on [3] during the last t_s seconds, we move all the particles $p_i \in P$ as below:

Let $dist$ [degrees] be the walking direction obtained by the geomagnetic sensor. Then we move each particle $p_i \in P$ towards $dist \pm 15$ [degree] by 65cm $\pm$10cm, where 65cm shows a user's standard single step length [5] and $\pm$15 and $\pm$10 show random noises given to p_i,[1] since the particle filter determines the user's position stochastically and thus several amount of randomness is necessary for them.

*B. Update the likelihoods using Bluetooth beacons and floormap (**Step 3**)*

In **Step 3**, we update the likelihoods of particles using Bluetooth beacons and the given floormap.

Firstly, for each particle $p_i \in P$, we design the first term $\Delta w_b^i(t)$ of the likelihood difference in Eqn. (4). We utilize (i) the proximity $prox_j(t)$ of every Bluetooth beacon b_j to the target positioning device and (ii) the distance $d_{ij}(t)$ from p_i to b_j at time t.

1) Preliminary experiment: In order to evaluate the relationship between the proximity value and the distance to the Bluetooth beacon, we have firstly measured the proximity $prox_j(t)$ of the target beacon b_j varying the distance between b_j and the positioning device as the preliminary experiment. In this preliminary experiment, we have used Nexus 9 [11] as a positioning device and MyBeacon TM Pro (MB004) [10] as a Bluetooth beacon.

We divide a 7.5m square room into 30cm square cells and place the Bluetooth beacon on the floor of the center cell facing the west (see Fig. 3). A tester holding the positioning device at his/her breast position (1.0m high from the floor) stands at each cell and measures the proximity of the beacon.

The results are shown in Fig. 3. The center black cell shows the one where the Bluetooth beacon is installed. The yellow cells show the ones where the positioning device measures "Near" to the beacon. The white cells show the ones where the positioning device measures "Far" to the beacon. Note that, as mentioned before, "Immediate" are not measured in any cells.

As depicted in Fig. 3, even if the distance between the positioning device and the Bluetooth beacon is the same, some of the cells show "Near" and the other cells show "Far" although the proximity of the beacon is stable compared to the other approaches. This is due to the direction of the target beacon as well as the random noises. Since we do not always know which direction every Bluetooth beacon is installed at and also the random noises can affect the proximity, we can only know the *probability* indicating how likely the positioning device shows "Near" when the distance d is given.

2) Designing likelihood function based on proximity: Now, we focus on a Bluetooth beacon b_j and a particle p_i. At time t, we assume that the positioning device measures "Near" from the beacon b_j, i.e., $prox_j(t) =$ "Near", which demonstrates that the positioning device and the beacon b_j are located close to each other. In our algorithm, we design the first term $\Delta w_{b_j}^i(t)$ of the likelihood difference in Eqn. (4) to indicate how much close to the positioning device the particle p_i is using the distance $d_{ij}(t)$ between p_i and b_j.

As discussed before, even if the distance d between the positioning device and the target beacon is given, we can only know the probability $P(d)$ indicating how likely the positioning device shows "Near" and $P(d)$ can be estimated by the preliminary experiment as follows. Now we count up $N_y(d)$ showing how many yellow cells are located in Fig. 3 when the distance d between the positioning device and the center beacon is given. We also count up all the cells $N(d)$ located at the distance d from the the center beacon. Then we can estimate $P(d) = N_y(d)/N(d)$. For example, the circle with a 2.4-meter radius centered on the Bluetooth beacon is shown in Fig. 3. In this case, since $N_y(2.4) = 19$ and $N(2.4) = 56$, we have $P(2.4) = 19/56 = 0.339$. Fig. 4 plots the $P(d)$ values from $d = 0$ to $d = 2.4$. By interpolating these

[1] In order to determine the appropriate randomness given to $dist$ and a single step length, we have performed the preliminary experiments and determined that ±15 and ±10 are the best ones.

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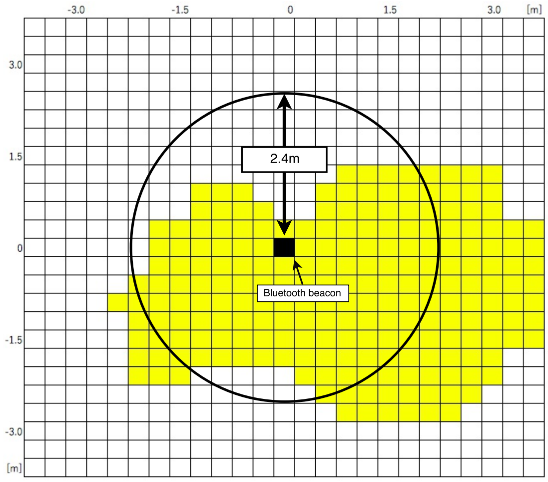

Fig. 3: Preliminary experimental results (the yellow cells show "Near" and the white cells show "Far"). A circle with a 2.4-meter radius is also shown.

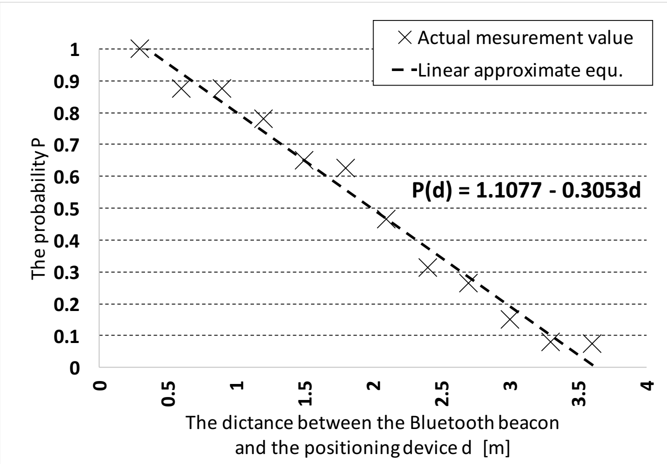

Fig. 4: Relationship between the distance d and the probability $P(d)$.

plots linearly, we have:

$$P(d) = 1.1077 - 0.3053d. \tag{5}$$

The distance between p_i and b_j at time t is given by:

$$d_{ij}(t) = \sqrt{(x_p^i(t) - x_b^j)^2 + (y_p^i(t) - y_b^j)^2} \tag{6}$$

Then we can directly derive $\Delta w_{b_j}^i(t)$ from each Bluetooth beacon b_j to the particle p_i by using the probability $P(d)$:

$$\Delta w_{b_j}^i(t) = \begin{cases} P(d_{ij}(t)) & (\text{if } prox_j(t) = \text{"Near"}) \\ 0 & (\text{if } prox_j(t) \neq \text{"Near"}) \end{cases} \tag{7}$$

By summing up all the values above for every particle, we have the first term $\Delta w_{b_j}^i(t)$ of the likelihood difference in Eqn. (4) as below:

$$\Delta w_b^i(t) = \sum_{b_j \in B} w_{b_j}^i(t) \tag{8}$$

*C. Update the likelihoods based on map matching (**Step 3**)*

Now we utilize the floormap S and check whether every particle goes into an un-enterable area or not. We also check whether a wall or obstacle exists or not between every particle p_i and Bluetooth beacon b_j. Based on them, we effectively design the likelihood function as below:

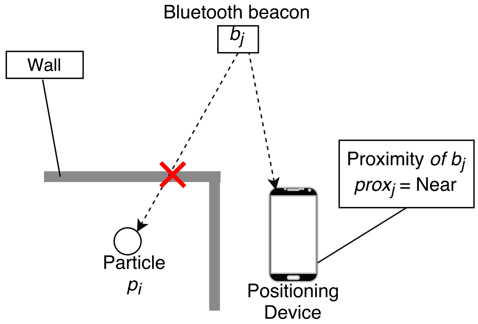

Fig. 5: A wall exists between the particle p_i and the Bluetooth beacon b_j.

1) If p_i goes into an un-enterable area: For the particle $p_i \in P$, we design the second term $\Delta w_f^i(t)$ of the likelihood difference in Eqn. (4) as follows:

At time t, a particle p_i may move into the structure s_k whose in_k is zero in **Step 2**, which is definitely impossible since the user holding the positioning device cannot enter an un-enterable area. In this case, we just move the particle p_i just before the structure s_k and give the penalty $\Delta w_f^i(t)$ below:[2]

$$\Delta w_f^i(t) = \begin{cases} -0.5 & (\text{if } p_i \text{ moves into an un-enterable area}) \\ 0 & (\text{otherwise}) \end{cases} \tag{9}$$

2) If there exists a wall or obstacle between p_i and b_j: At time t, we assume that the positioning device measures the proximity $prox_j(t) =$ "Near" from the Bluetooth beacon b_j. As discussed in Section III-B, the first term $\Delta w_b^i(t)$ of the likelihood difference in Eqn. (4) is given by Eqns. (7) and (8) for every particle p_i in this case.

However, we further assume that there is a wall or obstacle between p_i and the target beacon b_j as in Fig. 5. The radio wave from the beacon b_j is blocked by the wall or obstacle and will not reach p_i even if the distance between them is close. In this case, we set $w_{b_j}^i(t) = 0$ for the particle p_i even if $prox_j(t) =$ "Near".

IV. Experiments

We have implemented our proposed algorithm in Java on Nexus 9 [11] and applied it to a real indoor environment.

A. Setup

We use the building No. 55 in Nishi-Waseda Campus, Waseda University, as an indoor environment in this experiment. The positioning device is Nexus 9 [11] and the Bluetooth beacon is My Beacon Pro (MB004) [10]. The floormap and the installation location of the Bluetooth beacons used in the experiment is shown in Fig. 6. In this experiment, the number n of particles is set to be $n = 500$. The number m of Bluetooth beacons used is $m = 9$. The positioning interval t_s is set to be $t_s = 0.5$ seconds.

Fig. 6 also shows the walking course, which is 70m long with six turns. When a tester walks along the walking course, we record the the estimated position coordinates of the positioning device at Point 1 and Point 2. We have performed five trials and measured the positioning errors in these two points.

[2] The penalty value given by Eqn. (9) is experimentally set up to $\Delta w_f^i(t) = -5$. If the penalty is too large ($\Delta w_f^i(t) = -10$ or less), many particles have a likelihood of zero according to Eqn. (1) and thus we cannot estimate the user's current position. If the penalty is too small ($\Delta w_f^i(t) = -1$ or more), many particles go into un-enterable areas and thus the estimate positions will be wrong.

TABLE I: Result of positioning errors.

	Positioning error [m]							
	Algorithm A [7]		Algorithm B		Algorithm C		Ours	
	Point 1	Point 2	Point 1	Point 2	Point 1	Point 2	Point 1	Point 2
1	4.397	6.094	4.573	3.029	3.300	3.605	0.427	0.806
2	3.845	5.430	3.528	5.361	1.643	1.326	1.377	0.940
3	1.951	5.960	5.059	5.585	2.188	0.085	1.307	0.974
4	5.467	4.355	6.952	2.965	4.058	3.762	0.667	1.000
5	4.047	5.656	5.730	6.427	3.845	3.297	1.840	0.650
Ave.	4.72		4.921		2.711		0.999	
Min.	1.951		2.965		0.085		0.427	
Max.	6.094		6.952		4.058		1.840	

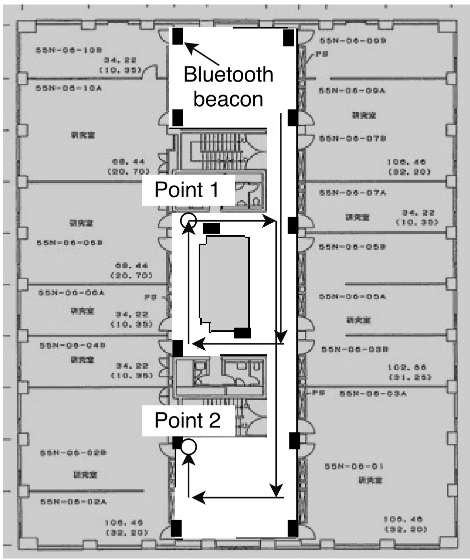

Fig. 6: Location of Bluetooth beacon.

B. Comparison

For comparison purpose, we use the four algorithms below:

Algorithm A [7] (Trilateration + Map matching): Based on [7], we use RSSI of Bluetooth beacons to measure the distance between the positioning device and the target beacon and then we apply a particle filter to estimate a current position. The trilateration approach is used to obtain the location of the positioning device. The acceleration and geomagnetic sensors are used as in Subsection III-A and we also utilize the floormap in this algorithm. For fair comparison, we do not use correction coefficients in [7] in this experiment.

Algorithm B (Trilateration): Algorithm B is also based on [7] but does not utilize the floormap. As in Algorithm A above, we use RSSI of Bluetooth beacons to measure the distance between the positioning device and the target beacon and then we apply a particle filter to estimate a current position. The trilateration approach is used to obtain the location of the positioning device. The acceleration and geomagnetic sensors are used as in Subsection III-A.

Algorithm C (Proximity only): We use our proposed algorithm without using a floormap.

Ours (Proximity + Map matching): In Ours, we use our proposed algorithm.

C. Results

Table I summarizes the experimental results. As in this table, our proposed algorithm outperforms the others in all the cases. The average error of **Ours** is just 0.999m. By utilizing the map matching introduced in Section III-C, we can reduce average positioning errors by 63% compared to **Algorithm C**. Since **Ours** uses the stable proximity of Bluetooth beacons and then we can always have stable positioning, we can reduce average positioning errors by 78% and 79% compared to **Algorithm A** and **Algorithm B**, respectively. In summary, we have successfully reduced the average positioning errors by up to 79% compared to existing algorithms.

V. CONCLUSIONS

In this paper, we propose an accurate indoor positioning algorithm using a particle filter based on a floormap, where we use the proximity of the Bluetooth beacons as well as acceleration and geomagnetic sensors. The experimental results demonstrate that our proposed algorithm successfully reduced the average positioning errors by up to 79% compared to existing algorithms.

In the future, we will realize seamless positioning by connecting outdoor positioning using GPS and indoor position positioning using our proposed algorithm.

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