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Improvement of Map Matching for Indoor Navigation Exploiting Photo of Information Board

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***Abstract*—Although pedestrian navigation systems in outdoor environment have become popular, there are several difficulties in indoor environment. The Global Positioning System (GPS) is not available in indoor environment, and indoor map databases are unavailable in most location. We proposed a novel method of indoor navigation using an information board and several functions of a smartphone. Our framework does not require large-scale preparations and expenses for owners of buildings unlike existing methods, and is available wherever an information board exists. We implemented the system and found some problems. One of them is disappearance of all particles in map matching with particle filter (PF) because of distortion or deformation of map. In this paper, we add the process of particle diffusion in PF to avoid all the disappearance. Moreover, we improv the map image analyzer to enrich the understanding of the map. Through experiments, we confirm large improvement of the repeatability of localization.**

Keywords—indoor positioning; particle filter; map matching;

I. INTRODUCTION

With the spread of smartphones, pedestrian navigation systems have become popular. There are two key components for navigation; one is positional information and another is a map. Positional information is usually obtained by using GPS in outdoor environment, and outdoor maps are provided universally, e.g., Google Maps. Since many mobile devices including smartphones have a built-in GPS receiver and outdoor maps can be obtained from the Internet, we can easily use outdoor navigation.

On the other hand, there are several difficulties in indoor navigation. The GPS positioning is not available because signals from GPS satellite cannot arrive at the receiver in indoor environment sufficiently. Although various localization systems, which includes Wi-Fi, radio-frequency identification (RFID), ultrasound, camera image, inertial measurement unit (IMU), and so on, have been developed, these methods do not have decisive superiority that can be considered as a de facto standard because they require some infrastructure and it limits available places. Another method is pedestrian dead reckoning (PDR), which is a method to obtain a change in the relative location, not an absolute coordinate. It can be achieved only by inertial sensors embedded in smartphones. Although the drift of gyroscope is the main cause of error in PDR estimation, accuracy of localization can be improved by the combination with other methods [1][2].

Moreover, the absence of indoor map database is another problem. Although "Google Maps" provides several indoor maps, they are available in very limited number of facilities.

We proposed a novel framework of indoor navigation system using an information board with a floor map (Figure 1) [3]. In our method, the user firstly takes a photo of floor maps on the information board with his/her smartphone's camera. After the photo is analyzed, the user should tap the current place on the map displayed on the screen. Then the user walks a few steps, and taps the current position again. By using the information obtained by the two taps, the initial location, scale and orientation on the photo of the floor map can be estimated. Then, the current position can be estimated by PDR, and our system displays it on the map.

However, using a photo of map for the navigation is very challenging because the scale and the orientation are unknown, and furthermore, the pictures of maps are not always correct. Although the existing method employs the particle filter for map matching in order to handle inaccurate maps, there are cases where all the particles are vanished. In this paper, we tackle the problem by improving the map matching algorithm.

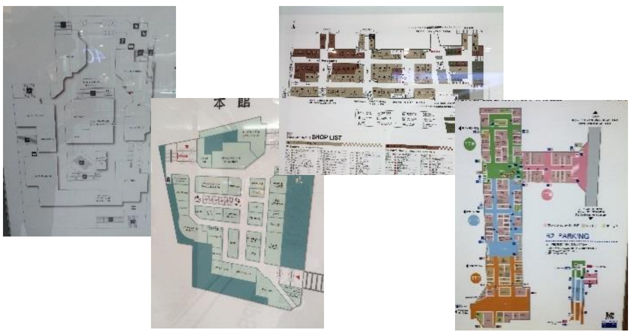

Figure 1. Examples of information board

II. UNDERSTANGING PASSAGEWAY REGION

In our method, at first we estimate the passageway region from the photo of the map. In this section, we explain the

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method to obtain passageway region and to understand the region attributes.

The passageway region is obtained by labeling of the picture. We conduct segmentation and edge detection to the photo of the map, and perform labeling based on the two information. Then, we select the passageway labels using each label's area, color, and bounding box. Finally, we regard the set of the passageway labels as the passageway region. The above procedure of the passageway extraction is same as [3].

In this paper, we create a passageway attribute map to enrich understanding of the passageway region. The map contains the information of passageway width and direction, and is used for localization.

To estimate the passageway direction, the graph of the passageway region (Fig. 2(b)) is extracted by thinning process of the passageway region. The thinned image is a binary image, where the values of skeleton pixels are one (true) and others are zero (false). The vertices and edges are obtained by scanning 8-neighborhood pixels. That is to say, a pixel is regarded as edge if and only if its two neighbors are true. Otherwise, it is regarded as a node. We can obtain the graph with the connection between node and edge pixels. (Fig. 2(c)).

Next, we add attribute to each pixel of the passageway attribute map. Let the set of the edges in the graph be $\{e_1, e_2, \dots, e_n\}$ (n is the number of edges). Each passageway pixel has a passageway direction $\theta_{nearest}$ $(nearest = 1\sim n)$ which is the direction of the nearest edge $e_{nearest}$. Pixels of wide area are labeled as WS (wide space). We detect wide space with Stroke Width Transform (SWT) [4]. SWT is the method often used to detect text and can compute stroke width. We assume that the passageway widths are almost equal in the map, and we regard mode value in the result of SWT as the passageway width. Finally we set the pixel that has 1.5 times wider than the passageway width as wide space.

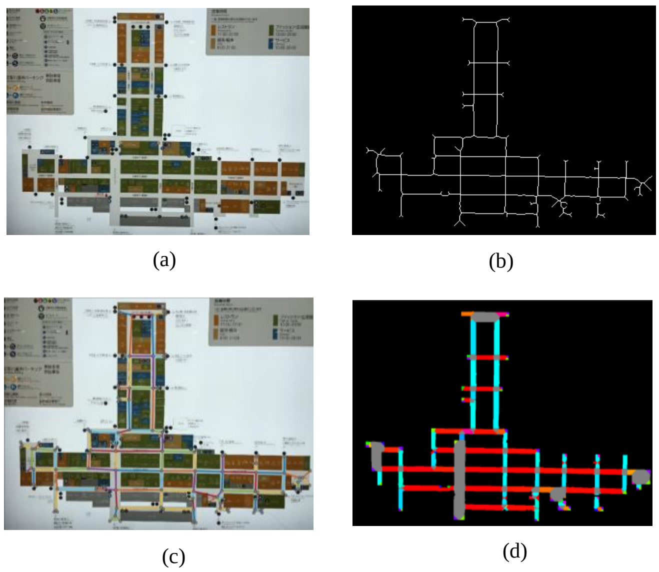
Summarizing the above, the pixel (i, j) in the passageway attribute map has the following information $PAM(i, j)$. An example of passageway attribute map is displayed in Fig. 2(d).

$$PAM(i,j) = \begin{cases} 0 & if\ (i,j)\ is\ not\ passageway\ region \\ WS & if\ (i,j)\ is\ wide\ space \\ \theta_{nearest} & otherwise \end{cases} \quad (1)$$

III. LOCALIZATION

As described above, the scale and the orientation of a map are unknown. To estimate them to a certain extent, the user taps current positions on the screen at two different positions. In addition, a map of information board is not always correct. Therefore, a map matching with particle filter (PF) is employed, which can cope with these problems flexibly.

PF is a method to estimate a state with non-linear and non-Gaussian state place model, and is sometimes employed for map matching [2][5][6]. PF is composed of propagation, correction and re-sampling. To obtain an observation z_t at time t, the state $s_{t|t-1}$ at time t estimated by the state s_{t-1} at time $t-1$ (particle) and its likelihood (weight) are generated



(a) (b) (c) (d)

Figure 2. The creation process of a passageway attribute map: (a) original image, (b) thinned image, (c) created graph and (d) passageway attribute map. In (d), hue is passageway direction and gray area is wide space.

using pseudorandom number, and z_t is decided with particles' distribution and weights.

In our model, particles are updated only after each step event. The k-th step event $step_k$ is represented by step time t_k, step length l_k and heading direction h_k in global coordinate system (GCS). These parameters are computed by the method of SmartPDR [7] by using accelerometer, magnetometer and gyroscope in a smartphone. In our method, each particle has a state s_k after the k-th step event, and s_k is defined as

$$s_k = [x_k, y_k, mpp_k, \theta_k]. \quad (2)$$

Here, (x_k, y_k) is a particle's position in image coordinate system (ICS), but we possess them with not integer but float. The parameter mpp_k (meter-per-pixel) is the length in GCS per one pixel, and θ_k is the azimuth in GCS corresponding to x-axis in ICS.

A. Particle Propagation

The particle's state s_k after the k-th step event $Step_k$ is created by a posterior distribution $p(s_k|s_{k-1}, step_k)$. The state $s_k^{(i)} = s_{k|k-1}^{(i)} = [x_k^{(i)}, y_k^{(i)}, mpp_k^{(i)}, \theta_k^{(i)}]$ is obtained by adding some noise to $mpp_{k-1}^{(i)}$ and $\theta_{k-1}^{(i)}$, and replacing the particle based on $mpp_k^{(i)}$ and $\theta_k^{(i)}$. The existing method [3] adds a noise to $\theta_k^{(i)}$. However, particles spread too wide if the adding noise is large (Fig. 3(a)), whereas the particles cannot adjust to distortion or deformation of the map when the adding noise is small (Fig. 3(b)). Therefore, we add some noise not only to $\theta_k^{(i)}$ but to the coordinates $x_k^{(i)}$ and $y_k^{(i)}$, in order to avoid these weaknesses as shown in Fig. 3(c).

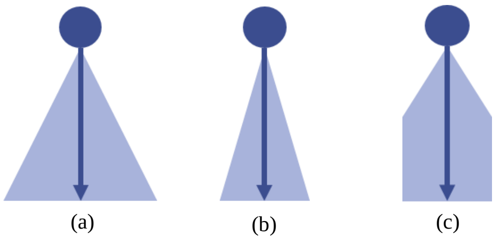


Figure 3. Overviews of heading direction when going straight. When the noise added to theta is large (a) or small (b), and when the coordination is also added some noise (c).

B. Particle Correction

All particles on the passageway have the same weight in the existing method [3], whereas the weights of particles vary and change in this method. We calculate the weight based on the passageway attribute map created in Section II. The weight $w_k^{(i)}$ of the i-th particle $s_{k|k-1}^{(i)}$ is

$$w_k^{(i)} = \begin{cases} 0 & if\ PAM\left(x_k^{(i)}, y_k^{(i)}\right) = 0 \\ c & if\ PAM\left(x_k^{(i)}, y_k^{(i)}\right) = WS, \\ c(0.5 + \exp(-\lambda\vartheta)) & otherwise \end{cases} \quad (1)$$

where, c is a parameter, and ϑ is the angle between $PAM\left(x_k^{(i)}, y_k^{(i)}\right)$ and the movement direction of the particle after $step_k$. Particles outside the passageway vanish, and the ones on a wide space have a constant parameter c as the weight. The weight of particles existing on a narrow area is decided based on the angle ϑ.

In likelihood calculation, there are some cases that all the particles disappear. It happens when all particles turn around a corner, for example. In this case, all particles seldom vanish in one step and some predictor can often be observed. That is to say, many particles vanish in the likelihood calculations before disappearance of all particles. Therefore, when the sign of vanishing of all particles is shown, we make the particles be diffused. We explain the way of diffusion in the next subsection.

C. Re-sampling

All particles are sampled according to their particles' weights $\{w_k^{(i)}\}_i$. The centroid of all particles after re-sampling is the result of localization after the k-th step event $Step_k$.

When the predictor of disappearance of all particles is observed, in other word, when many particles vanish in likelihood calcuration, we make all particles be diffused after re-sampling. That is performed by updating coordinates of all particles with the following formula.

$$\begin{bmatrix} x_k^{(i)} \\ y_k^{(i)} \end{bmatrix} = \begin{bmatrix} x_k^{(i)} \\ y_k^{(i)} \end{bmatrix} + \begin{bmatrix} \mathrm{N}\left(0, {\sigma_{dif}}^2\right) \\ \mathrm{N}\left(0, {\sigma_{dif}}^2\right) \end{bmatrix} \quad (3)$$

where $\mathrm{N}\left(0, {\sigma_{dif}}^2\right)$ is a replacement model based on the Gaussian distribution with deviation ${\sigma_{dif}}^2$.

IV. Experiment

We evaluate the repeatability of the proposed method, and confirm the improvement compared with the existing method [3]. We acquired several series of samples of the inertial sensors in Sendai Mitsukoshi, Fujisaki, and Yaesu shopping mall. We simulate localization 100 times for each route, and count how many times estimates of paths roughly succeed. We obtained the values of the inertial sensors with Google Nexus 9 and implemented the simulation by MATLAB. We set the number of particles as 2000.

Figure 4 shows the simulation results and Fig. 5 displays examples of the estimated paths. We confirmed improvement on many routes. Avoiding disappearance of all particles and usage of passage direction contributes accurate localization. Since the map of Mitsukoshi (Fig. 5(a)) and Fujisaki (Fig. 5(b)) have some deformation, and disappearance of all particles (right of Fig. 5(a)) or inaccurate localization (right of Fig. 5(b)) occurred with the existing method. On the other hand, the proposed method is improved at this point (left of Fig. 5(a)(b)).

However, temporary failures stand out in the proposed method. This often caused by the tendency that particles move more than their actual movement when going straight (Fig. 5(c)(d)). It causes a degradation in "YAESU 2" and temporary failures in some route. We have not identified the cause of this tendency, so we will investigate it in the future.

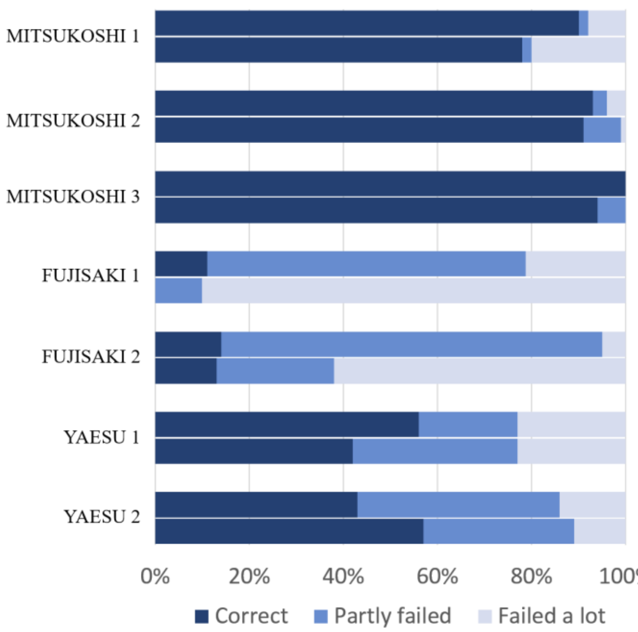
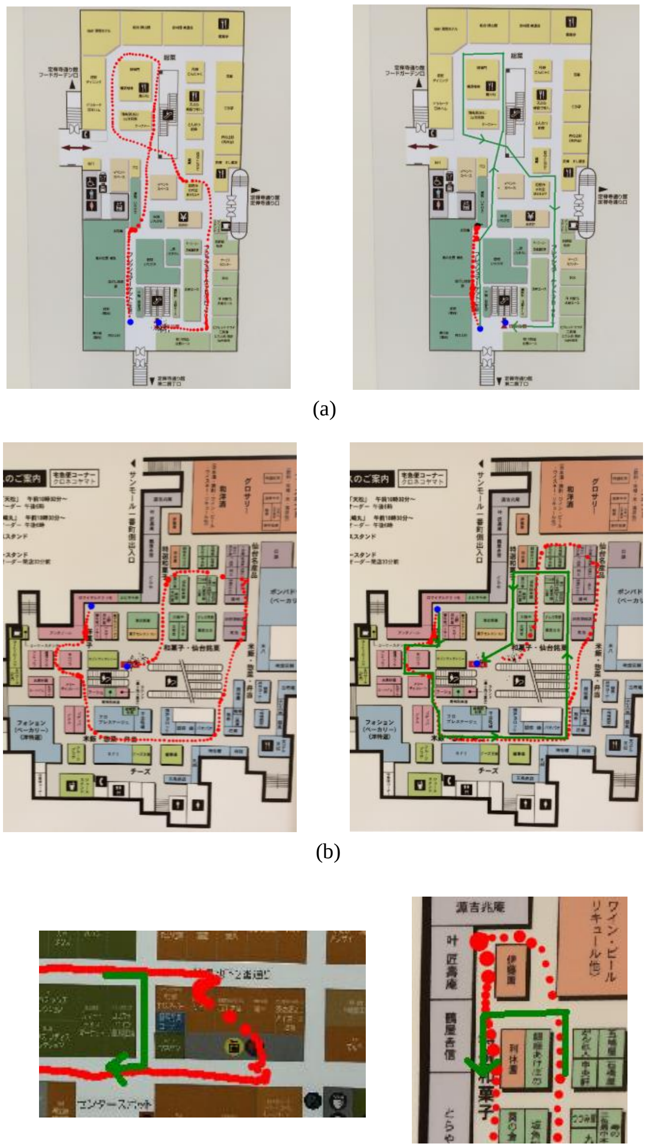


Figure 4. Results of the experiment
(Top: proposed method, Bottom: existing method)



(a)

(b)

(c) (d)

Figure 5. Result of the estimation paths: red points indicate estimated position and green lines are real paths.

V. Conclusion

We proposed a method of indoor localization using an information board and several functions of a smartphone. The proposed method comprises image analysis and map matching. The former is to estimate the passageway region from the map image. The latter is localization with particle filter using the region and the inertial sensors.

In this paper, we improved the existing method by modifying the method of particle filter and enriching understanding of the passageway region. To add weight to particles, we implemented a method to create the passageway attribute map containing the passageway direction and wide space. The map is created by the passageway graph and SWT. Moreover, to avoid disappearance of all particles, we added a process to make particles be diffused after re-sampling. Experimental results show the effectiveness of the above improvements. However, it also revealed following two problems. One is that the proposed method cannot deal with inaccuracy of the map completely. The other is that the reduced rate of particles affect the localization result largely.

In the future, to improve the repeatability of localization, we have to make the estimation of the particle movement more correct when going straight. Particle's mpp sometimes changes largely now. Furthermore, it is necessary to reconsider the method to compute output of positioning. We consider that we could make output better if we would do clustering after re-sampling and let the centroid of the biggest cluster be output position. In our method, the accuracy of localization depends on image recognition quality. Therefore, it is necessary to make image recognition method better.

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