Indoor Localization by Map Matching Using One Image of Information Board

Kento Tonosaki, Yoshihiro Sugaya, Tomo Miyazaki, Shinichiro Omachi
Department of Communications Engineering, Graduate School of Engineering
Tohoku University
Sendai, Japan
e-mail: {sea, sugaya, tomo, machi}@iic.ecei.tohoku.ac.jp

***Abstract*—Indoor navigation systems have not become common like an outdoor navigation system, because we cannot correctly receive the signals from Global Positioning System (GPS) satellites in indoor environments, and indoor map databases are unavailable in most locations. Existing indoor localization methods and navigation systems have problems such as management and deployment cost, and limitation of available places. In this paper, we present 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. This method comprises image analysis and map matching. The former is to analyze the picture of information board taken by a smartphone and estimate the passageway region from the image. The latter gives us real-time localization in the map by using inertial sensors in the smartphone after the input of current places by the user at two different positions.**

Keywords- indoor positioning; particle filter; map matching.

I. INTRODUCTION

There are two keys of indoor navigation; positional information and a map. GPS is now contributing outdoor localization, and in combination with an outdoor map database, such as Google Maps, it provides us a good outdoor navigation system. Many modern mobile devices such as smartphones have a built-in GPS receiver. Therefore, we can easily use applications for outdoor navigation.

On the other hand, localization using GPS is inaccurate in indoor environment. GPS positioning is performed by using the signals from some satellites, but the signals cannot arrive at the receiver in indoor environment. Indoor localization is a hot topic now, and various systems are developed; Wi-Fi, radio-frequency identification (RFID), ultrasound, camera image, inertial measurement unit (IMU), and so on. However, 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 approach is pedestrian dead reckoning (PDR) making use of several inertial sensors embedded in smartphones as well as GPS receiver. Owing to no expenses except for smartphone, we can estimate relative position at a low price. The drift of gyroscope is the main cause of error in PDR estimation, then by the combination with other methods, accuracy of localization can be improved [1][2].

Moreover, the absence of indoor map database makes construction of indoor navigation system more difficult. Although "Google Maps" provides several indoor maps, there are not many available places. In some place, e.g., Tokyo Station and Narita Airport in Japan, a special application for navigation of each place is offered. However, it requires for users to install the special application on their smartphone to use the navigation.

In this paper, we propose a novel framework of indoor navigation system using an information board with a floor map (Figure 1) and several functions in smartphone. Since information boards exist in many buildings, we can easily obtain a map by taking a picture of the information board with smartphone's camera. In addition, we can estimate the current position without infrastructure by using PDR with inertial sensors.

The usage scenarios of our approach are as follows. First, a user takes a photo of the map on the information board with his/her smartphone; note that the information boards are usually installed at the entrance of malls or the side of elevators. After the picture is analyzed, the user taps the point on the map displayed on the screen corresponding to his current place. Then, the user walks a little, and taps the screen where the point corresponds to the current position again. By using the information obtained by the two taps, the reduced scale and orientation of the map could be estimated, and inertial sensors enable to estimate current position of the user.

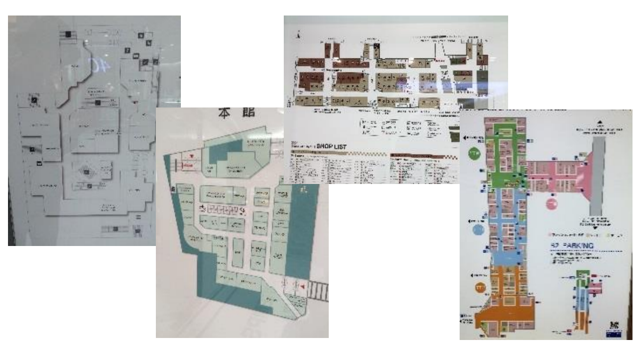


Figure 1. Examples of information board

 ISBN: 978-1-61208-465-7

II. PASSAGEWAY REGION ESTIMATION

We considered that passageway regions are necessary at least to implement a demonstration of the indoor navigation. We develop a method to estimate passageway region from an image of information board, and we show the method in this section.

The estimation is conducted using two conditions that many of information boards meet. These are based on our survey of 104 information boards throughout Japan, and about 92% of them fulfill two conditions: (1) the color of passageways is different from any shops' colors, (2) only one color is used for passageways in a map. The proposed method consists of labeling and passageway label estimation.

A. Labeling

According to the conditions, it is considered that segmentation of a map picture based on its color information is useful for the estimation of passageway regions.

At first, we create a segmentation image with mean shift [3] and an edge image with the Canny method [4] from the original image. Then, we scan the segmentation image from upper left. When we find unlabeled pixel (i, j), we also search the pixel (k, l) satisfying (1) in 4-neighborhood pixels around (i, j) except for edge pixel, and assign the same label. Although we can do labeling only using the segmentation image, which is obtained by mean shift, the labeling results are not sufficient. Therefore, we use the edge image together with segmentation image to improve the accuracy of labeling. If the area size of label is smaller than the threshold τ_l, we give them no label.

$$\begin{cases} |R(i,j) - R(k,l)| \le \tau_d \\ |G(i,j) - G(k,l)| \le \tau_d . \\ |B(i,j) - B(k,l)| \le \tau_d \end{cases} \qquad (1)$$

$R(i, j)$, $G(i, j)$ and $B(i, j)$ are red, green and blue values of the pixel (i, j), respectively. The symbol τ_d is a threshold.

B. Passageway Region Estimation

After labeling, we estimate the labels of passageway region. A set of passageway labels often contains larger areas than shop ones, and according to the above-mentioned conditions, only one color different from every shop labels' colors is used for passageway labels. We estimate the passageway region by using these conditions.

At first, we decide the first passageway labels (FPL), which is the most likely passageway label, and we estimate it along the flow chart (Figure 2). We assumed that L_1 or L_2 or both are the passageway labels, where L_1 is the first largest label and L_2 is the second. We compare the label sizes because we suppose that the passageway region would be much bigger than any shop's regions. If $L_1 > \alpha L_2$, FPL is L_1. Otherwise, we compare the label colors in consideration that the passageway region in the map are divided by some lines such as arrows. If the Euclidian distance between the color averages of L_1 and L_2 in RGB color space is lower than threshold τ_c, FPL is the combination of L_1 and L_2. Otherwise, we compare the sizes of bounding boxes of them, and we consider that the larger one is passageway region.

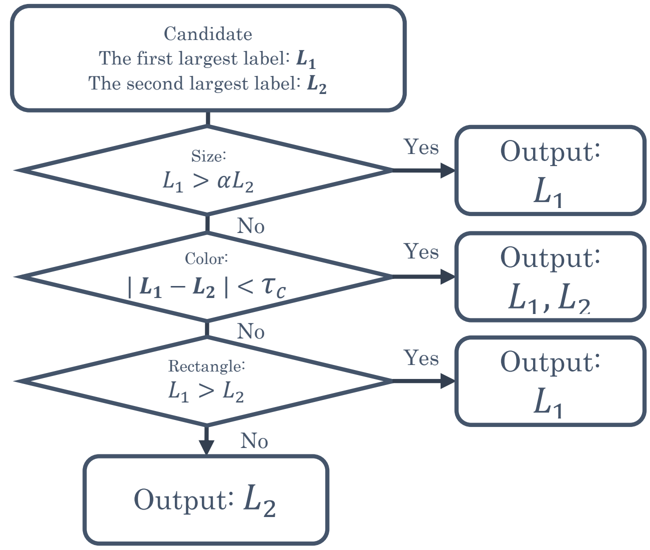


Figure 2. Flow chart of the method to decide the first passageway labels

After FPL is decided, we search other passageway labels using color information of FPL. We compare the average color of FPL and other labels, and when Euclidian distance between them in RGB color space is lower than threshold τ_c, they are determined as the passageway label.

III. PARTICLE FILTER AND MAP MATCHING

In this method, the scale and the orientation of a map are unknown because the map is a picture of information board. To estimate them to a certain extent, the user taps the screen to show where they are in the map at two different positions. In addition, a map of information board is inaccurate, owing to noises and distortions resulting from light reflection and the direction of taking the picture. We employ map matching with particle filter (PF), which can cope with these problems flexibly.

PF is a method to estimate a state in non-linear and non-Gaussian state place model, and is sometimes implemented to apply map filtering technique [2][5][6]. PF is the algorithm by Monte-Carlo method 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 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

$$\mathrm{s}_k = [x_k, y_k, mpp_k, \theta_k]. \quad (2)$$

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 heading direction h_k when the device turns toward x-axis of ICS.

A. Particle Initialization

We show the method to create an initial distribution $p(s_0|\emptyset)$ of the state s_0 at the step event $k = 0$. Let the two coordinates pointed by the user be $(x_{tap,n}^{ICS}{}', y_{tap,n}^{ICS}{}')(n = 1{,}2)$, which is in ICS. Because the designation of the points is performed with the user's visual, there may be an error between the designated position and the user's real position $(x_{tap,n}^{ICS}, y_{tap,n}^{ICS})(n = 1{,}2)$. Assuming that the probability distribution of the error is a Gaussian distribution with standard deviation σ_{tap}, this probability distribution $P(x_{tap,n}^{ICS}, y_{tap,n}^{ICS})$ is

$$P(x_{tap,n}^{ICS}, y_{tap,n}^{ICS}) = N(x_{tap,n}^{ICS}{}', \sigma_{tap}{}^2)N(y_{tap,n}^{ICS}{}', \sigma_{tap}{}^2) \quad (3)$$

where $N(\mu, \sigma^2)$ is an error model generated using a Gaussian distribution with a mean μ and a variance σ^2.

When step events between two taps are detected k' times, the motion on x-axis and y-axis in GCS is represented as

$$\begin{bmatrix} x_{move}^{GCS} \\ y_{move}^{GCS} \end{bmatrix} = \sum_{s=1}^{k'} l_s \begin{bmatrix} \cos h_s \\ \sin h_s \end{bmatrix}. \quad (4)$$

The moving length l_{move} and the direction θ_{move} between two taps are

$$l_{move} = \sqrt{(x_{move}^{GCS})^2 + (y_{move}^{GCS})^2} \quad (5)$$

$$\theta_{move} = \mathrm{atan2}(y_{move}^{GCS}, x_{move}^{GCS}). \quad (6)$$

Where the function $\mathrm{atan2}(y, x)$ is defined as

$$\mathrm{atan2}(\mathrm{y}, \mathrm{x}) = 2\tan^{-1}\left(\frac{y}{\sqrt{x^2+y^2}+x}\right). \quad (7)$$

We can also calculate the length l_{tap} and the direction θ_{tap} in ICS between two taps with a similar equation.

Therefore, the initial state $\mathrm{s}_0^{(i)} = [x_0^{(i)}, y_0^{(i)}, mpp_0^{(i)}, \theta_0^{(i)}]$ of i-th particle is decided with the following equations.

$$\begin{aligned} x_0^{(i)} &= x_{tap,2}^{GCS}{}^{(i)} \\ y_0^{(i)} &= y_{tap,2}^{GCS}{}^{(i)} \\ mpp_0^{(i)} &= l_{move}/l_{tap}^{(i)} \\ \theta_0^{(i)} &= \theta_{move} - \theta_{tap}^{(i)} \end{aligned} \quad (8)$$

B. Particle Propagation

The particle's state s_k after the k-th step event $step_k$ is created by a posterior distribution $p(s_k|s_{k-1}, step_k)$ with the previous state s_{k-1} and $step_k$. With paying attention that $\mathrm{x}_k^{(i)}$ and $\mathrm{y}_k^{(i)}$ are coordinates in ICS, the state $\mathrm{s}_k^{(i)} = s_{k|k-1}^{(i)}$ of ith particle is decided as follows.

$$\begin{aligned} mpp_k^{(i)} &= mpp_{k-1}^{(i)} + N(0, \sigma_{mpp}{}^2) \\ \theta_k^{(i)} &= \theta_{k-1}^{(i)} + N(0, \sigma_\theta{}^2) \\ x_k^{(i)} &= x_{k-1}^{(i)} + l_k \cos(h_k - \theta_k^{(i)})/mpp_k^{(i)} \\ y_k^{(i)} &= y_{k-1}^{(i)} + l_k \sin(h_k - \theta_k^{(i)})/mpp_k^{(i)} \end{aligned} \quad (9)$$

Here, $N(0, \sigma_{mpp}{}^2)$ and $N(0, \sigma_\theta{}^2)$ are error models of $mpp_k^{(i)}$ and $\theta_k^{(i)}$ based on Gaussian distributions with deviations $\sigma_{mpp}{}^2$ and $\sigma_\theta{}^2$, respectively. These models also affect the moving length and direction.

C. Correction and Re-Sampling

In this paper, we assume that users go to their destination along a passageway, namely users do not go out of the passageway region from navigating start to end. Hence, we estimate user's position with map matching using passageway region created by the proposed method. In our method, map matching is applied to compute particles' weight, and the weight $\mathrm{w}_k^{(i)}$ of the i-th particle $s_{k|k-1}^{(i)}$ is

$$\mathrm{w}_k^{(i)} = \begin{cases} 0 & if\ (x_k^{(i)}, y_k^{(i)})\ is\ not\ passageway\ region \\ 1/M & otherwise \end{cases}, \quad (10)$$

where, M is the number of particles after the correction. The output of the current position is the average of M particles.

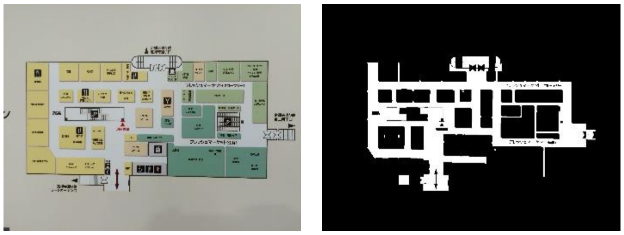
Re-sampling is the process that reallocates all the particles. In our method, re-sampling is based on random sampling, but each particle has the same weight before re-sampling. Therefore, a particle after re-sampling is decided from M particles randomly.

IV. EXPERIMENT

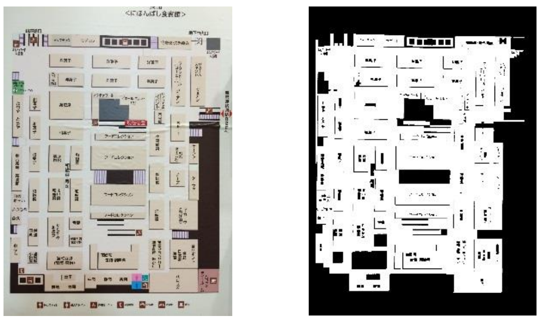
The proposed method has several thresholds and parameters, and we set them shown as Table I, which were decided by the preliminary experiments.

TABLE I. SYMBOLS AND VALUES

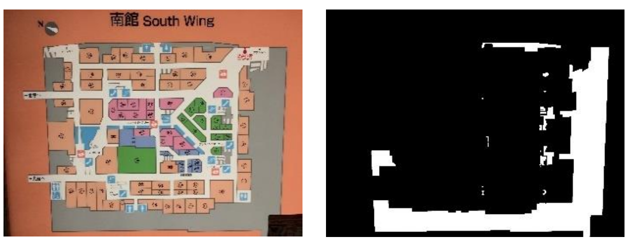
Symbol	Value	Symbol	Value
τ_d	3	σ_{tap}	25
τ_c	15	σ_θ	$5\pi/180$
α	2		
Symbol		**Value**	
τ_l		1/500 of the image size	
σ_{mpp}		1/60 of $mpp_{k-1}^{(i)}$	



(a)



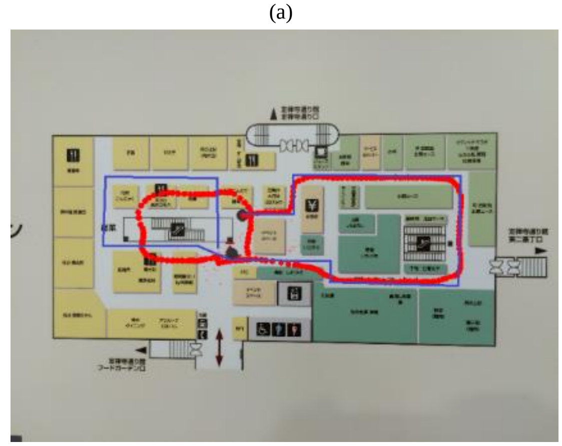
(b)



(c)

Figure 3. Results of passageway region estimation:
original images (left) and estimated passageway region (right)

(a)



(b)

Figure 4. Result of the paths estimated using PDR and map matching: gray points are 2 tapped positions, red are user's estimated position and blue lines are real path.

A. *Passageway Region Estimation*

We conducted passageway region estimation using the proposed method. We applied the method to 92 pictures of information boards satisfying two conditions described in Section II except for some pictures with extremely low quality. In the method, an estimated passageway region consists of a set of labels and it has gaps at boundaries between each region of labels. To remove them, we applied erosion and dilation to each region, so that we can create passageway region more suitable for the position estimation.

Figure 3 shows examples of the results. We subjectively evaluated whether passageway region could be estimated to a certain extent, and we found that the estimation went well on 77% of information boards. We conducted the experiment using 92% of images that meet two conditions mentioned in Section II; therefore it means that the proposed method could estimate passageway region for about 70% of information boards.

The failures to obtain passageway region were mainly caused by labeling mistakes (Figure 3(b)) and failure to get FPL (Figure 3(c)). The former means that passageway and shop regions were mistakenly connected when labeling. The failure often happened when a shop label had similar color to passageway label and their edges are unclear. The latter means that a label unrelated to passageway region became FPL. The failure happened when FPL was not decided using sizes and colors.

B. *Localization*

We evaluated whether the proposed method can estimate positions by map matching with a picture of information board. The experiments were conducted on B1 floor in Jozenji-Dori building of Sendai Mitsukoshi (Fig. 3(a)). The proposed system was implemented on Sony Xperia S Tablet, and the sampling rate of each inertial sensors is 15 Hz. The users held the device on their right palm. The application for the experiment indicates the estimated path where the user walked in real time after tapping at two different position. We set the number of particles as 2000. We conducted the experiments four times.

Figure 4 shows examples of the results. A successful case is Figure 4(a), where the step events are totally 245 (11 steps between 2 taps). A failure case is Figure 4(b), where the step events are totally 218 (9 steps between 2 taps). Estimation error increased at the left area of the map in both cases. Of the four experiments, we succeed two times and failed two times.

We consider that the error was caused by the way to decide a current position. Now, the position is computed as the average of particle's positions before re-sampling, however, in case that particles are divided into two or more clusters, the output has a large error even if one of the clusters lies at the correct position.

V. CONCLUSION

In this paper, we proposed an indoor localization method using information board and several functions in smartphone. To estimate passageway region, we apply labeling to the picture of information board based on its color and edge, and make use of label information. Furthermore, we developed a method to estimate position on passageway region using PDR and map matching with PF. Through our experiments, we confirmed that the proposed method can accurately estimate passage region from 70% of information board, and the analysis results are useful for map matching with particle filter.

At the same time, we found out some problems. The method of labeling and passageway label estimation cannot obtain satisfactory results from some information boards. In reference to this, labeling results depend on the ambience when taking the picture. It is necessary to develop the method to analyze the picture resistant to light reflection. We were pointed out that using Lab color space might bring better results when labeling because the color space is designed to approximate human vision. Moreover, the labeling method is time consuming and requires high machine performance. Therefore, we are considering use of servers for the map picture analysis.

Furthermore, the proposed method has great limitation, and the method to decide a position from a distribution of particles has a room to be improved; we can track only on the passageway. To estimate the position on both passageway and shops, we would have to improve not only the method of map matching but also the method to analyze the picture of information board. Additionally, we have only confirmed whether the proposed method can trace the pass the user walks. It is necessary to evaluate our localization method quantitatively. They are remained as future works.

ACKNOWLEDGMENT

A part of this research was supported by JSPS KAKENHI Grant Number 15K12014. This research was also supported in part by JST, CREST.

REFERENCES

[1] V. Renaudin, O. Yalak, P. Tomé, and B. Merminod, "Indoor navigation of emergency agents,", Europian Journal of Navigation, vol. 5, no. 3, pp. 36-45, 2007.

[2] F. Zampella, A. R. J. Ruiz, and F. S. Granja, "Indoor Positioning Using Efficient Map Matching, RSS Measurements, and an Improved Motion Model, " IEEE Trans. on Vehicular Technology, vol. 64, pp. 1304-1317, no. 4, April 2015.

[3] D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis," IEEE Trans. on PAMI, vol. 24, no. 5, pp. 603-619, 2002.

[4] J. Canny, "A Computational Approach To Edge Detection," IEEE Trans. on PAMI, vol. 8, no. 6, pp. 679-714, 1986.

[5] C. Ascher, A. Kesseler, M. Wankerl, and G. F. Trommer, "Dual IMU Indoor Navigation with Particle Filter based Map-Matching on a Smartphone," Int. Conf. on IPIN, September 2010, pp. 1-5.

[6] O. Woodman and R. Harle, "Pedestrian Localisation for Indoor Environments," in Proc. 10th Int. Conf. UbiComp, 2008, pp. 114–123.

[7] W. Hang and Y. Han, "SmartPDR: Smartphone-Based Pedestrian Dead Reckoning for Indoor Localization," IEEE Sensor Journal, vol. 15, pp 2906-2916, no. 5, May 2015.