Indoor SLAM based on line observation probability using a hand-drawn map

Ryuki Suzuki, Yonghoon Ji, Sarthak Pathak, and Kazunori Umeda

***Abstract*— In this paper, we propose a novel method of building indoor map information under the condition that a hand-drawn map as prior information is given. So far, previous studies using the hand-drawn map have been limited to robot pose estimation and navigation. Therefore, we propose a novel method to build a map by finding the correspondence between the shape of the real environment and the shape of the hand-drawn map. In addition, even if the estimation of the robot pose on the hand-drawn map fails, our method can continue to construct the map by re-estimating the robot pose on the hand-drawn map based on the previous corresponding information. In the simulations, we verified the accuracy of the built map in a simulation environment using three hand-drawn maps.**

I. INTRODUCTION

The use of autonomous mobile robots to replace human workers is currently attracting attention. Simultaneous localization and mapping (SLAM) technology is indispensable for the operation of autonomous mobile robots. In order to improve the accuracy of map building, several methods that utilize prior information have been proposed. Machinaka et al. estimated the robot pose based on Google Maps as the prior information [1]. However, this method requires time to prepare the prior information and adjust the parameters which are tedious tasks.

On the other hand, it is easy to prepare a hand-drawn map based on human prior knowledge. Bahram et al. suggested Monte Carlo localization (MCL) [2] that is possible on the hand-drawn map in order to estimate not only the robot pose but also the scale of the map at the same time [3]. Additionally, many methods for operating autonomous mobile robots using the hand-drawn map have been proposed [4,5,6]. However, these methods are limited to the navigation and localization of mobile robots on the hand-drawn map, and no mapping has been implemented.

In this respect, we propose a map building system for indoor use that extends the method of Bahram et al. by calculating the probability of line observation on the hand-drawn map and use it for SLAM. Specifically, we estimate the robot's position using the error of straight lines in which lines in the real environment correspond with lines on the hand-drawn map, as shown in Fig. 1. In addition, we use the probability of line observation to re-estimate the robot pose.

The remainder of this paper is organized as follows. Section II discusses the overall structure of the proposed framework for mapping with the hand-drawn map, and the probability of line observation is explained in Section III. Section IV presents the robot re-estimation on the hand-drawn map with probability of line observation. Section V describes the method for the correcting the robot pose in SLAM. Our proposed method and the simulation results are discussed in Section VI. Finally, Section VII presents the conclusions of this article and future work.

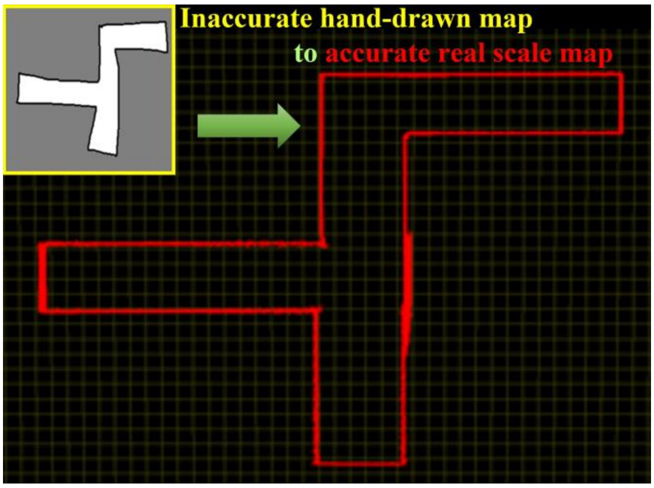

Figure 1. Our proposed method.

II. OVERVIEW

The proposed method assumes a wheeled mobile robot equipped with a laser range finder (LRF). The overall process of the proposed method is shown in Fig. 2. The proposed method can be divided into two main parts: the process on a hand-drawn map and the process on the real environment.

The process on the hand-drawn map is as follows. First, the straight line is extracted from the hand-drawn map by using the probabilistic Hough transform. Next, we perform the method by Bahram et al. [3] to estimate the robot pose on the hand-drawn map. It uses particles including map scale information as state variables to estimate the robot pose and the scale of the hand-drawn map at the same time. Then, we apply ray tracing to acquire the pseudo-range. At this time,

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correspondences between straight lines on the hand-drawn map and the range data are simultaneously calculated. Meanwhile, if the MCL on the hand-drawn map [3] is not performed correctly, the recovery process to re-estimate the robot pose on the hand-drawn map is executed. The detailed process is presented in Section IV.

The process on the real environment is as follows. First, we extract straight lines using random sample consensus (RANSAC) from the actual range data observed by the LRF mounted on the robot. Then, we calculate the correspondence between the straight lines on the hand-drawn map and the straight lines observed by the robot. After that, we calculate the observation probabilities for each straight line by finding the correspondence between the pseudo-range data and the actual range data. A detailed description of the line observation probabilities is given in Section III. Next, the actual robot orientation and position are respectively estimated based on straight lines and a scan matching process. The detailed estimation methods are described in Section IV. Finally, map building is performed based on the estimated actual robot position and orientation.

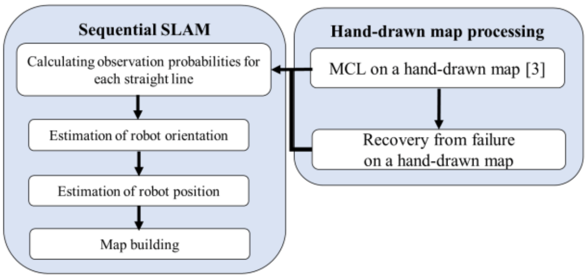


Figure 2. Outline of the method.

III. LINE OBSERVATION PROBABILITY

In this method, the following equation for calculating the probability $f(r)$ of the existence of each line is used to determine whether each line on the hand-drawn map has been observed.

$$f(r) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(r_i - sl_i)^2}{2\sigma^2}\right\} \quad (1)$$

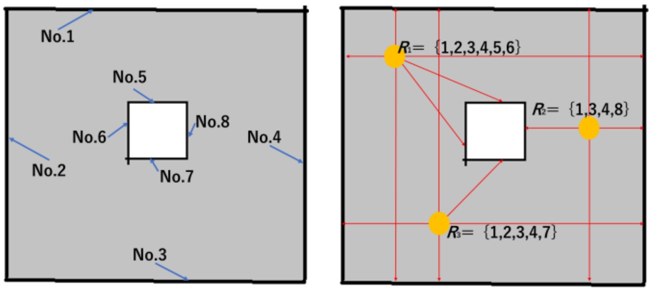
where r_i and l_i are the i-th points of the actual range data and the pseudo-range data from the robot pose on the hand-drawn map, respectively. Index i denotes the order of the corresponding range data. σ is the uncertainty of the LRF. s is the scale of the hand-drawn map estimated in each frame. The correspondence between the actual range data and the pseudo-range data is obtained as the index of the range data. Then, when the observation probability in Eq. (1) exceeds the threshold, the straight line is considered to have been observed.

IV. RECOVERY FROM FAILURE ON HAND DRAWN MAP

When the MCL on the hand-drawn map [3] is not performed well, it is possible to recover the robot pose based on the straight lines considered to have been observed in the previous frame (i.e., probability $f(r)$ exceeds the threshold). The recovery process is divided into three parts: the pre-processing of the hand-drawn map, and the determination of the observation points to redistribute particles for MCL [3] based on observation points.

In the pre-processing, candidate observation points R_i are spread out at random. Then, we register the indices of the lines on the hand-drawn map that can be observed at each candidate observation point as shown in Fig. 3. Here, black and gray areas represent the walls (i.e., occupied areas) and unoccupied areas, respectively. Yellow circles represent candidate observation points, and red arrows represent pseudo-range data.

Next, in the process of determining observation points, we calculate which line on the hand-drawn map is being observed at each frame. This means that even if the MCL [3] is not successful, the robot pose is likely to be in the vicinity of the point where it can observe the line on the hand-drawn map that is observed just before. Therefore, we can recover the robot pose by finding multiple observation points that can observe the straight line on the hand-drawn map observed by the robot in the previous frame, spreading particles around these points, and executing MCL [3] again.



(a) Indices of lines (b) Observation points

Figure 3. Determination of observation points.

V. SEQUENTIAL SLAM BY POSE CORRECTION

With the observed lines on the hand-drawn map and the lines observed in the real environment, the following equation is used to correct the robot orientation.

$$\theta = \frac{1}{N}\sum_{i=1}^{M}(\theta_{k_i} - \theta_i) \quad (2)$$

where θ is the amount of correction for the robot in the rotation, and k_i is the index of the line on the hand-drawn map corresponding to the i-th observation line. M is the number of lines for which correspondence has been calculated. Next, the robot position is also corrected by the iterative closest point (ICP) [7] which is a well-known scan matching process. The amount of movement in the translational is calculated as the sum of the squares of the distances between the range data E, as follows.

$$E = \min \sum_{i=1}^{N} \left\| \boldsymbol{n}^T \left(\boldsymbol{y}_{u_i} - (\boldsymbol{x}_i + \boldsymbol{T})\right) \right\|^2 \quad (3)$$

where $\boldsymbol{x}$ and $\boldsymbol{y}$ are the range data measured in the previous frame (i.e., the target range data) and the current frame (i.e., the source range data), respectively. $\boldsymbol{n}$ is the normal vector. N and u_i are the number of points in the source range data and the index of the source range data corresponding to the i-

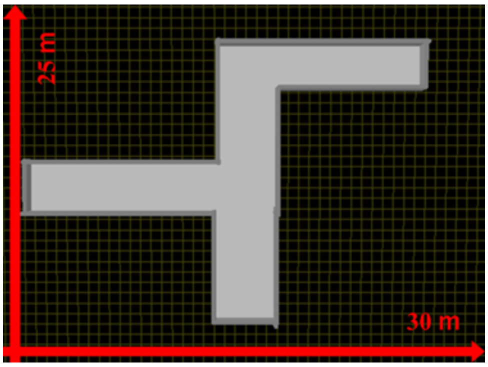
th point in the target range data, respectively. ***T*** is the vector of translational components of the transformation matrix.

VI. SIMULATION

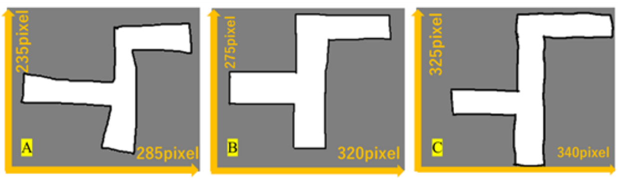
A. Simulation conditions

To verify our method, we conducted simulations in the environment shown in Fig. 4(a). The maximum range distance of the virtual LRF was set to 30 m, and the error of the virtual encoder was defined by using a normally distributed random number.

Hand-drawn maps were easily created using the Windows 10 built-in software "Paint." We defined one pixel in created hand-drawn maps as 10 cm. Figure 4(b) shows hand-drawn maps used in this simulation. In hand-drawn map A, curves are conspicuous because of the messy drawing. On the other hand, the hand-drawn map B has a discrepancy in the horizontal ratio of the shape on the left as compared to the simulation environment. Hand-drawn map C also has discrepancies in the horizontal ratio of the left shape and the vertical ratio of the path leading to the upper region.



(a) Simulation environment



(b) Hand-drawn maps for simulation

Figure 4. Simulation environment and hand-drawn maps.

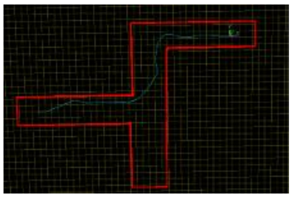
B. Simulation results

In the simulations, we evaluated the accuracy of our sequential SLAM process in comparison with SLAM by odometry and conventional ICP. From the results shown in Fig. 5 and Table 1, the scatter of the map was reduced by using the hand-drawn maps. In the case of using hand-drawn map A and hand-drawn map B, maps were built without the failure of MCL [3]. However, in the case of using the hand-drawn map C, the MCL [3] broke down in the middle region because the aspect ratio of the corridor on the hand-drawn map differs greatly; thus, the recovery process described in Section IV was performed as shown in Fig. 6. Here, the green line represents the line exceeding the threshold of the observation probability. Red points are particles for the MCL process.

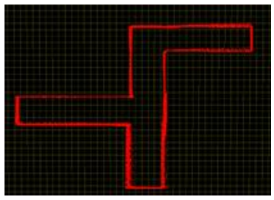
As a result, a reliable map was built by our proposed scheme using the hand-drawn map. Note that a previous study [4] mentioned that robot pose estimation cannot be done correctly when the aspect ratio of the real environment and the hand-drawn map is significantly different. On the other hand, when hand-drawn map B was used, the MCL [3] did not break down, although there was a large discrepancy in the aspect ratio as shown in Fig. 5(c). This is because there is no significant difference in the aspect ratio of the map, although the size of the entire map is different.

Table 1. Recognition rate for each position.

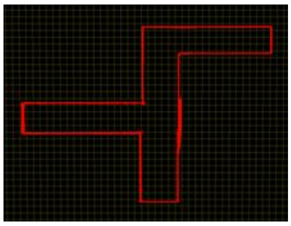
methods	**measurement error [m]**
Odometry	6.157
ICP-SLAM	2.72
hand-drawn map A	0.270
hand-drawn map B	0.297
hand-drawn map C	0.300



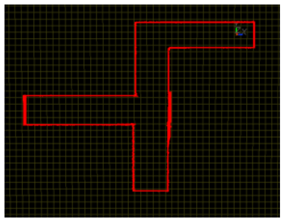
(a) True map



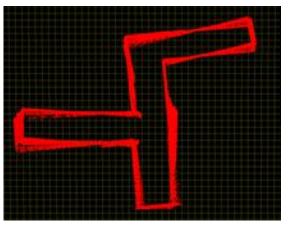
(b) Result of hand-drawn map A



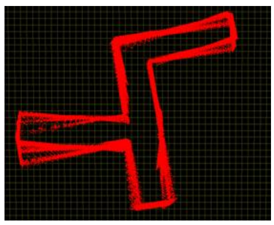
(c) Result of hand-drawn map B



(d) Result of hand-drawn map C



(e) Result of ICP-SLAM



(f) Result of odometry

Figure 5. The determination of observation points

(a) Determination of observed straight line
(b) Particle redistribution
(c) Recovery by MCL [3]

Figure 6. Recovery from failure

VII. Conclusion

In this study, we proposed a novel SLAM scheme for indoor use based on the hand-drawn map by matching line information. The simulations were conducted in a simulation environment. In the simulations, we were able to build maps with higher accuracy by using hand-drawn maps than by conventional methods.

In the future, we will start to develop a system that automatically builds a map of the real environment by obtaining the trajectory from the hand-drawn map using our proposed approach.

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