Performance Improvement of SLAM Based on Global Registration Using LiDAR Intensity and Measurement Data of Puddle*

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***Abstract*— The accuracy of scan matching-based SLAM strongly depends on the result of the initial alignments. In this paper, we improve the accuracy of scan matching-based SLAM by applying accurate initial alignments calculated by global registration using measurements from LiDAR intensity and water puddles as features, which are often found in damaged nuclear power plants. From the experimental results in the real environment, the proposed method can improve the accuracy of the map and the trajectory of the robot by taking these features observed from the environment into account.**

I. Introduction

Robotic exploration is underway inside the building of Fukushima Daiichi Nuclear Power Plant, which was damaged by 2011 Tohoku earthquake and tsunami. However, a number of accidents have occurred during these explorations because of not enough information about the damage of the building. Therefore, it is necessary to understand the scale of the damage accurately by generating a map of inside the buildings.

Environmental mapping is one of the most important methods to understand the structural information of the environment, and approaches based on simultaneous localization and mapping (SLAM) have been widely used for generating feature-based environmental maps. Among them, SLAM using laser scan matching has been widely used due to its scalability and usefulness. A typical example of the scan matching method is the iterative closest point (ICP)[1], which precisely aligns point clouds whose approximate positional relationships are known.

Since the result by ICP is strongly affected by the accuracy of the initial alignment, it is very important to pre-calculate the accurate initial alignment for ICP. This initial alignment is often calculated by odometry, which is obtained from the encoder mounted on the mobile robot. However, most of the mobile robots used in the exploration of the damaged nuclear reactor building are equipped with crawlers so that the odometry is not reliable since the encoder data of the crawler has large noises. Thus, it is not suitable for giving the initial alignment for ICP. In this respect, the performance of SLAM is improved by providing a highly accurate initial alignment through global registration for point clouds in this paper.

Global registration is a typical scheme that provides a rough alignment between points [2][3]. Godin et al. realized highly accurate global registration by utilizing information other than shape such as color [3]. However, it is hard to use color as a feature for registration because inside the damaged nuclear plants is dark.

In this paper, we propose a global registration method that utilizes LiDAR reflection intensity and information of water puddles, which are often found in damaged nuclear power plants, as environmental features. Near-infrared information and shape information of the environment are acquired by sensor fusion using a near-infrared camera and LiDAR in order to build accurate map information. Furthermore, by adding environmental features to the map generated by the proposed method, it is possible to visualize water puddles as dangerous areas, which can be used for the exploration of nuclear reactor buildings.

II. System Overview

A. Framework

The proposed system, shown in Fig. 1, performs scan matching-based SLAM and outputs the robot trajectory and point cloud map as the result. The robot moves in an environment and observes point clouds with physical features for n frames. The point clouds with physical features are described in detail in subsection II. The first step is to perform scan matching of the point clouds. The point clouds to be aligned are all combinations of point clouds from frame 0 to frame n-1. The point clouds are initially aligned by the proposed method of global registration with physical features. In this paper, we focus on this part. After that, the point cloud after the initial alignment is precisely aligned by ICP. Then, the robot trajectory is calculated from the result of scan matching. Next, pose adjustment [4] is performed on the robot trajectory. In the pose adjustment, the trajectory is optimized based on the uncertainty of the alignment result. Finally, a point cloud map is built by transforming the point clouds according to the optimized trajectory.

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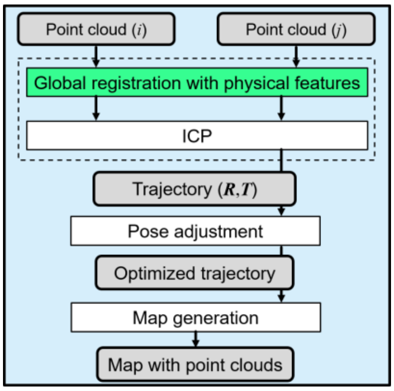


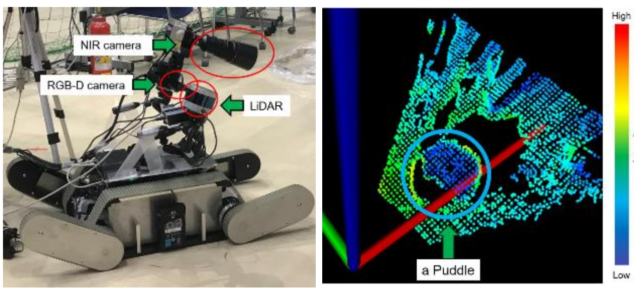
Fig. 1. System overview.

A. Point clouds with physical features

In this paper, characteristic physical quantities in environment are used as features for alignment. In addition to shape information (x, y, z), variables representing features are added to the point clouds. We use the near-infrared information and the LiDAR reflection intensity information as features for alignments. Therefore, a point $\boldsymbol{p}_i$ is represented as follows.

$$\boldsymbol{p}_i = [x_i \quad y_i \quad z_i \quad I_{\mathrm{IR},i} \quad I_{\mathrm{Laser},i}]^T \tag{1}$$

where $I_{\mathrm{IR},i}$ and $I_{\mathrm{Laser},i}$ denote intensity of near-infrared and intensity of LiDAR, respectively. By combining LiDAR which can obtain point clouds including intensity with other types of sensors, it is possible to obtain various information in addition to shape information of the surrounding environment. Fujii et al. visualized the three-dimensional (3D) shape of puddles by generating point clouds with near-infrared information using a sensor system that combines a near-infrared camera and a depth camera, as shown in Fig. 2 [5]. In this paper, we incorporate LiDAR into sensor system in [4] and acquire point clouds with LiDAR intensity and near-infrared intensity to improve the accuracy of SLAM by taking these two features into account.



(a) Sensor system (b) Point cloud of puddle

Fig. 2. Visualization of a puddle.

II. Global Registration with Physical Features

A. Overview

Our method uses fast point feature histograms (FPFH) from the point cloud, near-infrared information, and laser reflection intensity information as features for registration. FPFH is a vector quantity that is a histogram of shape information [2]. On the other hand, the near-infrared information and the laser reflection intensity information are scalar quantities. In this method, we first perform a nearest neighbor search for each feature to obtain point correspondences. Then, based on subsection III.B, we select reliable point correspondences for each feature. Finally, based on subsection III.C, we further refine the best set of selected correspondences and output rigid body transformations using the selected point correspondences.

B. Correspondences Considering Spatial Variance

The point correspondences that contribute to the alignment are preferentially selected from the set of point correspondences obtained by the neighbor point search based on each feature value. In the case of point correspondence-based registration, if points with close feature values (i.e., $I_{\mathrm{IR},i}$ and $I_{\mathrm{Laser},i}$) are clustered in a large area in the environment, they are unlikely to contribute to the registration. Therefore, the correspondences with points that have a small spatial variance for a particular value of a feature contribute more to the alignment.

First, in a point cloud, we find the set of points that are close in feature value to the points belonging to a certain correspondence, and then calculate the spatial variance of the set. Then, the set of correspondences that contribute to the alignment is obtained by selecting the correspondences with a small variance. The spatial variance of the point correspondences is obtained by calculating the covariance matrix of the set of points with similar feature values of the two points belonging to the point correspondence and then summing the diagonal components of the covariance matrix. Because the diagonal component of the covariance matrix represents the variance of the point cloud in the x, y, and z directions, the sum of these components can be used to determine the variance of the point distribution.

C. Correspondences Considering Geometric Constraints

Geometric relationships are taken into account and point correspondences satisfying the constraints are preferentially selected. As shown in Fig. 3, when a set of point correspondences is obtained from two point clouds measuring the same shape, the distances between the points obtained from the two section of the measured location (i.e. $l_{i,12}$, $l_{i,23}$, and $l_{i,34}$) should be approximately equal to the distances between the two points in the another point cloud (i.e. $l_{j,12}$, $l_{j,23}$, and $l_{j,34}$), assuming that the correspondences are correct. In this case, the distances $l_{i,23}$ and $l_{j,23}$, $l_{i,34}$ and $l_{j,34}$ have similar size respectively, and the choice of correspondences is correct. In other words, if the distances between two corresponding points are similar, the set of point correspondence is geometrically selected without contradiction.

Therefore, we select the subsets that satisfy the abovementioned geometric constraints from the point correspondences, and generate each of rigid body transformations from the correspondences that are considered to be more correct as follows. First, we combine all the point correspondences of each feature obtained in subsection III.B, and then generate subsets of them for all combinations. Next, we select only those that satisfy the geometric constraints. Each of rigid body transformations ($\boldsymbol{R}$, $\boldsymbol{T}$) are then computed by applying the following equation to the selected correspondences and solving the minimization problem of E.

$$E = \sum_{i=1}^{N} \left| \boldsymbol{p}_{k_i} - (\boldsymbol{q}_i \boldsymbol{R} + \boldsymbol{T}) \right|^2 \qquad (2)$$

- E: sum of the squared distance (i.e., evaluation value)
- $\boldsymbol{p}$: a point in the source point cloud
- $\boldsymbol{q}$: a point in the target point cloud
- N: the number of a points in the source point cloud
- k_i: the reference scan data point corresponding to the point i in the source point cloud
- $\boldsymbol{R}$: the rotation matrix
- $\boldsymbol{T}$: the translation vector

Then, Euclidean distances between the two point clouds are calculated, after applying each of rigid body transformations to the two point clouds. Finally, optimal registration is performed by finally selected rigid body transformation ($\boldsymbol{R}$, $\boldsymbol{T}$) that minimize the Euclidean distance between the two point clouds.

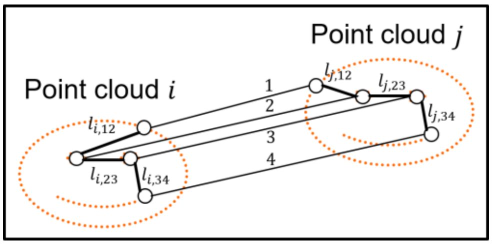


Fig. 3. Geometric constraint.

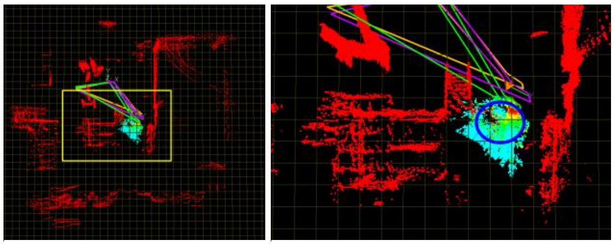
III. Experiment

A. Overview

An environmental map is constructed by SLAM from point clouds with physical features measured by the sensor system consisting of a near-infrared camera, an RGB-D sensor, and a LiDAR. The experiment was conducted in the test building of the Naraha Center for Remote Control Technology Development, shown in Fig. 4. This test area has many characteristic shapes, such as mock-up staircases, which are suitable for conducting SLAM experiments.

Fig. 5 shows the true map generated by the true trajectory of the robot. In order to realize a water-rich environment, artificial puddles were placed in the environment. In Fig. 4 and Fig. 5, the puddle is located at the blue ellipse. In Fig. 5, the purple, orange, and green lines show the robot trajectories (i.e., straight lines connected between measuring positions) of true value, conventional method, and proposed method each other. Note that the true trajectory is obtained by the rigid body transformations given by the result of the manual alignment of point clouds. The color of the points in Fig. 5 represents the magnitude of I_{IR}; the smaller the I_{IR}, the bluer the color, and the larger the I_{IR}, the redder the color. Since the near-infrared sensor has a narrower measurement range than LiDAR, many points in the point clouds do not have near-infrared information and the I_{IR} value is constant, resulting in overall red color.

Fig. 4. Bird's-eye view of experimental environment.



(a) Entire map (b) Expanded view of yellow area

Fig. 5. Map built by true trajectory.

B. Experimental Equipment

Fig. 2(a) shows the experimental equipment used in our experiment. TABLE I shows the specifications of the robot. As the LiDAR sensor, we used a Velodyne LiDAR VLP-16, which can acquire 3D point clouds and laser reflection intensity of the environment. A near-infrared lens (Kowa LM8HC-SW) and a teleconversion lens (Raynox DCR-2025PRO) were attached to the near-infrared camera (BITRAN BK51-IGA). An Intel RealSense D415 was used for RGB-D sensor. More details of the sensor system are described in [5]. Here, the sensors are fixed to each other and the relative position of the measured data is known.

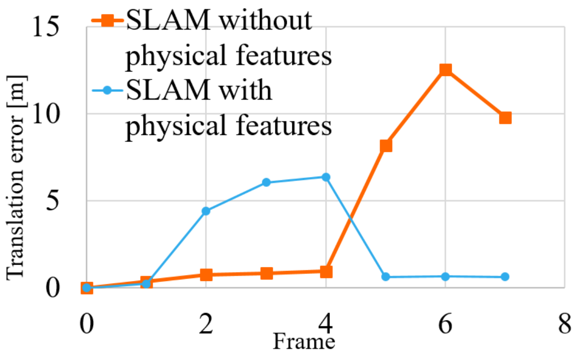
TABLE I SPECIFICATION OF EXPLORATION ROBOT

Uphill slope angle [deg]	45
Payload [kg]	5
Traveling speed [mm/s]	100
Length [mm]	1000
Width [mm]	400
Height [mm]	200

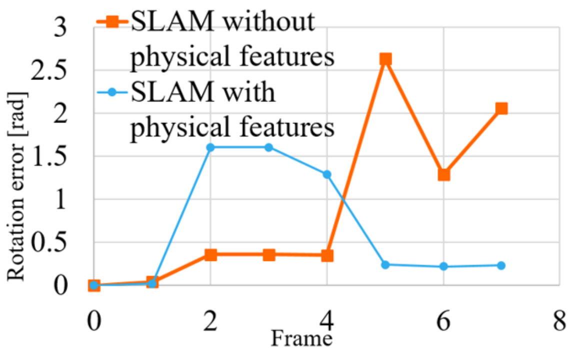
C. Experimental Result

The proposed method and the conventional method were evaluated by performing SLAM and comparing the generated trajectories and the map. We conducted experiments under the same conditions using two different methods: SLAM shown in Fig. 1 for the proposed method, and that of SAC-IA [2] used as global registration for the conventional method.

Fig. 6, TABLE II and TABLE III show that the error of the robot position is reduced when the proposed method is used. In addition, TABLE IV and Fig. 7 show that the accuracy of the map generated by the proposed method is improved. One possible reason for this is the improvement of the scan matching results between the frames where the puddle was measured. However, as shown in Fig. 6, the error of the robot position in the proposed method temporarily increased in the middle of the frame. The reason for this is that the places where measured point clouds in some frames far apart, and so the shape information required for registration may have been insufficient. Although our method improves the scan matching by considering features other than shape information, it has been found that the method does not work well when the shape information is extremely insufficient. One solution to this problem is to adapt scan matching to environments where shape information is not rich.



(a) Translation error



(b) Rotation error

Fig. 6. Comparison of errors of robot position

TABLE II MEAN OF TRANSLATION ERRORS [m]

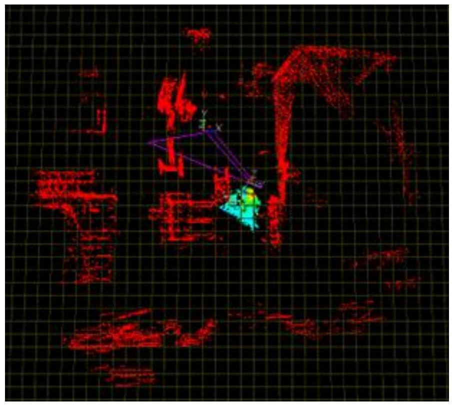
SLAM without physical features	4.775
SLAM with physical features	2.719

TABLE III MEAN OF ANGLE ERRORS [m]

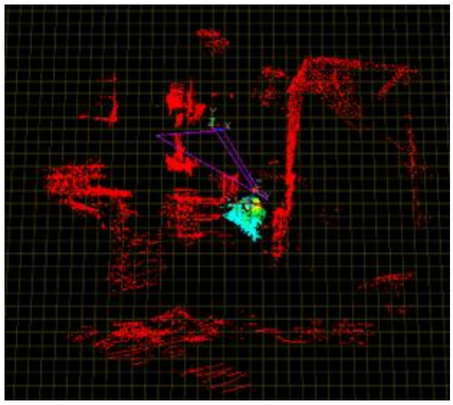
SLAM without physical features	1.012
SLAM with physical features	0.744

TABLE IV MEAN OF MAP ERRORS [m]

SLAM without physical features	7.134
SLAM with physical features	4.660



(a) SLAM without physical features



(b) SLAM with physical features

Fig. 7. Built map by SLAM.

IV. CONCLUSIONS

In this paper, we propose a method to generate an environmental map by using LiDAR reflection intensity and the water puddles as features. In our method, the matching accuracy is improved by considering features other than shape in the selection of point correspondences in global registration. In the future, we will address the problem that the method does not work well in an environment with poor shape information.

REFERENCES

[1] P. J. Besl and N. D. McKay, “A Method for Registration of 3D Shapes,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.8, No. 6, pp. 679–698, 1986.

[2] R. B. Rusu, N. Blodow, and M. Beetz, “Fast Point Feature Histograms (FPFH) for 3D registration,” Proceedings of the 2009 IEEE International Conference on Robotics and Automation, pp. 3212–3217, 2009.

[3] G. Godin, D. Laurendeau, and R. Bergevin, “A Method for the Registration of Attributed Range Image,” Proceedings of the 2001 International Conference on 3D Imaging and Modeling, pp. 179–86, 2001.

[4] J. Folkesson and H. I. Christensen, “Closing the Loop with gGraphical SLAM,” IEEE Transactions on Robotics, Vol. 23, No. 4, pp. 731–41, 2007.

[5] H. Fujii, M. Sugawara, H. Kono, and Y. Ji, “3D Visualization of Near-Infrared Information for Detecting Water Source,” Proceedings of Fukushima Research Conference on Remote Technologies for Nuclear Facilities 2019, p. 5, 2019.