An Enhanced Map Building Framework Based on the Scan Similarity

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***Abstract*—This paper suggests enhanced map building framework based on the scan similarity. Previous map building techniques which are applied various scan matching algorithms are usually dependent on the geometrical structure of the environment. However, those techniques do not consider the property of the scan matching algorithms. Our proposed method represents the geometrical information of the scan data compactly and computes the similarity between scan data to increase the accuracy of the map and the estimated robot pose. Through the experiments, we compared the result of our proposed map building framework with that of the previous one and also verified our new approach shows higher accuracy than the previous method.**

***Index Terms*—map building, SLAM, robot, scan matching, scan similarity**

I. Introduction

There have been many researches regarding the Simultaneous Localization and Mapping (SLAM) problem. Map building and the pose estimation of the robot in the map, also known as SLAM, are essentially required technique for many robotic applications [1], [2]. Typically, SLAM methods are divided into two categories according to the information types, sparse features and dense point clouds about their surrounding environments. The first method which uses the sparse features is fast and can build the map with only few points. On the other hand, the second method which uses the dense point clouds involves many points. As a result this method is robust to the measurement noise and can build a more accurate map without data association. In this paper, we focus on the second method which adopts the dense point clouds (or scan) data to build a high quality map.

For the point clouds data registration, the scan matching techniques are commonly used. The most popular algorithm is Iterative Closest Point (ICP) algorithm which is suggested by Besl *et al*. [3]. This algorithm iteratively finds the transformation between two scan data until the summation of the distances among all corresponding points becomes the minimum. However, these corresponding method has discrete characteristics thus causing error accumulations as time passes. To improve the ICP, A. Segal *et al*. proposed Generalized-ICP (G-ICP) algorithm [4]. This algorithm combines the neighbor points for each point in the scan data to make cloud sets and calculate the transformation by using the covariance matrix of the cloud sets. There are also other types of algorithms which are not based on ICP method. Normal Distributions Transform (NDT) algorithm which is suggested by P. Bieber divides the scan data into grid and calculates the normal distributions for the points in each grid [5]. The transformation between two scans is computed efficiently with the grid representation. E. Takeuchi et al. expanded the NDT algorithm to the 3D case [6]. A. Diosi *et al*. developed Polar coordinates Scan Matching (PSM) which utilizes the advantage of the polar coordinates system of the Laser Range Finder (LRF) [7]. Also, A. Censi *et al*. proposed Hough Scan Matching (HSM) which uses the Hough transform [8].

As mentioned above, many previous scan matching algorithms focused on improving the performance of the scan matching algorithm itself. However, the results are different according to the experimental environments even in case of the same algorithm. In this paper, we suggest an enhanced map building framework which selects the model scan data dynamically by computing the similarity of the newly acquired scan and the model scan. First of all, we introduce the laser scan descriptor to represent the geometrical information of the scan data and explain how to compute the similarity between two scan data. Secondly, we present the entire map building framework, Real-time Backwards Threshold Matching (RBTM). Through the experiment, we will verify our framework improves the quality of the map and the accuracy of the estimated poses of the robot in the map.

II. Enhanced Map Building Framework

A. Scan Similarity

This subsection introduces a method to represent the similarity between two scan data which are acquired by the Laser Range Finder (LRF). The curvature function is adopted to represent the scan data compactly without loss of the geometrical information [9]. As depicted in Fig. 1 (a), the curvature function is described by (1).

$$\phi_i = \tan^{-1}\left(\frac{y_{i+1} - y_{i-1}}{x_{i+1} - x_{i-1}}\right) \tag{1}$$

here, i represents the index of the LRF sensing order. For a single scan which contains N reflected points, we

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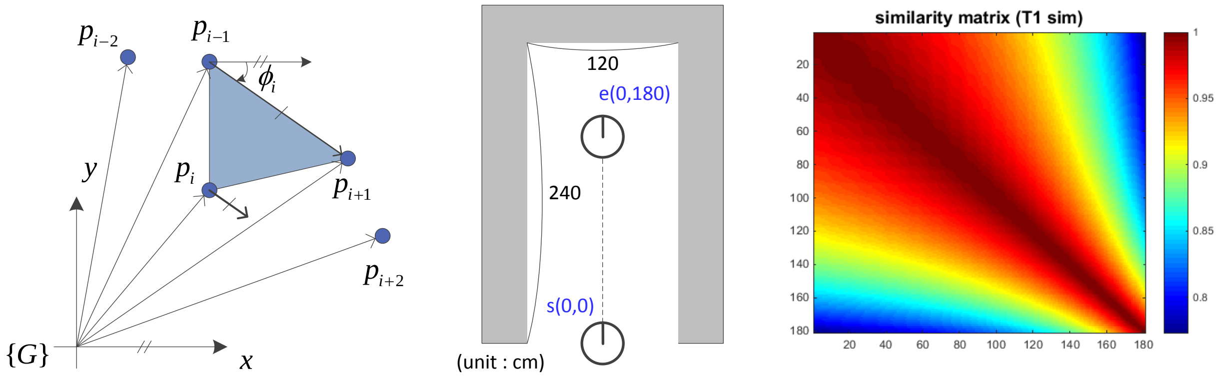
can calculate N curvature values $\phi_1 \cdots \phi_N$. These values are defined as a laser descriptor vector and described by (2).

$$D_j = [\phi_1 \ \cdots \ \phi_{i-1} \ \phi_i \ \phi_{i+1} \ \cdots \ \phi_N]^T \tag{2}$$

Now, the vector described in (2) includes the geometrical information of j-th single scan. To compute the similarity of the scan data, we calculated the cross correlation coefficient with the two laser descriptor vectors and this is described by (3).

$$S_{j,k} = \frac{Cov(D_j, D_k)}{\sqrt{Var(D_j)Var(D_k)}} \tag{3}$$



(a) (b) (c)

Figure 1. Representation of the curvature value and the can similarity. (a) Geometrical representation of the curvature value. Each curvature value consists the laser scan descriptor and this descriptor is used to represent the similarity between two scan data by using the cross correlation. (b) Example of the simple environment. (c) Similarity matrix of the example environment. Each (j,k) element of this matrix represents the similarity between the j-th and the k-th scan data.

To validate our proposed scan similarity comparing method, we conducted an experiment for a simple environment as depicted in Fig. 1 (b). The similarity matrix of the simple environment is described in Fig. 1 (c). Each (j,k) element of this matrix is $S_{j,k}$ which is acquired by (3). This value decreases as the gap between j and k increases because the overlapping area between two scan data decreases. From this experiment, we could verify that our proposed method is reasonable.

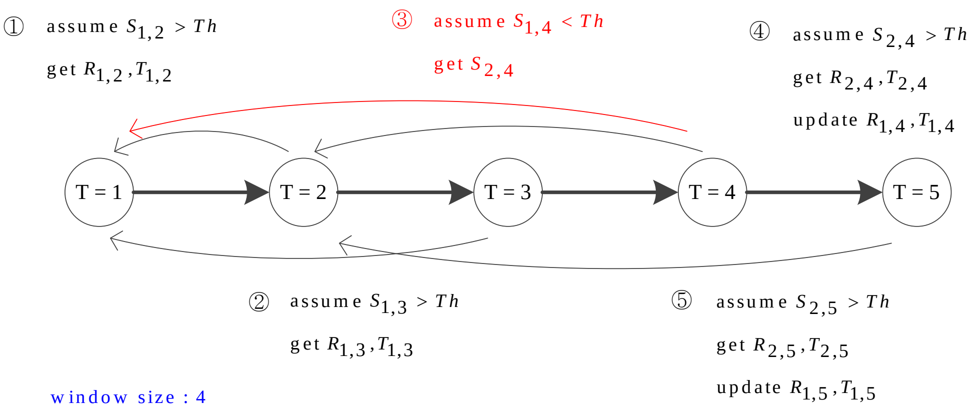


Figure 2. Real-time backwards threshold matching. At the third step, if the similarity cannot exceed user-defined threshold, the matching is not performed and move on to the next model data as depicted in the fourth step.

B. Real-Time Backwards Threshold Matching

This subsection introduces the main contribution of this paper which selects the most proper scan which shows the least errors when the scan matching algorithm is applied. Previous algorithms registered the scan data by using the data of the time sequence order. However, this is not efficient because of the scan matching property that two scan data obtained at different locations cannot be aligned perfectly. In other words, there always exist small errors when the data are aligned perfectly. In our previous work, we showed that these small errors abruptly increases when the similarity of the scan data decreases under some threshold [10]. By using this property, Real-time Backwards Threshold Matching (RBTM) is developed which varies the scan interval while maintaining proper ratio of the overlapping areas between two scan data. Basically, uncertainty of the estimated robot pose and the map information increases as time step increases. To reduce the uncertainty growth, current newly obtained scan should be registered with the scan which is the nearest to the starting position of the robot.

To sum up there are three conditions to make our algorithm efficient, 1) the similarity of the two scans should exceed some threshold which could guarantee successful alignment. 2) there should exist the smallest overlapping areas which could also guarantee successful alignment. 3) newly obtained scan at the current position should be matched with the model scan which is the nearest to the starting position of the robot. Fig. 2 shows our proposed framework RBTM method. Here, we assumed the window size is 4 and this is necessary to maintain the smallest overlapping areas. Also, Th means user-defined similarity threshold.

First of all, when the two data at time step 1 and 2 are acquired, the similarity between these two data is calculated. If the similarity exceeds the user-defined similarity threshold, rotational and translational matrices are computed. Secondly, when the scan data at time step 3 are acquired, the similarity betwen the scan data at time step 1 and 3 is calculated and if this similarity exceeds user-defined threshold, the first and the third scan data are registered. Next, when the scan data at time step 4 is acquired, the similarity computation representives are the scans at time step 1, 2 and 3 because we set the windows size as 4(The winsdow size is set to maintain the smallest overlapping areas between two scan data.). As we mentioned above, the scan data which are nearest to the starting position have the smaller uncertatinty thus the comparison start from the scan at the time step 1.

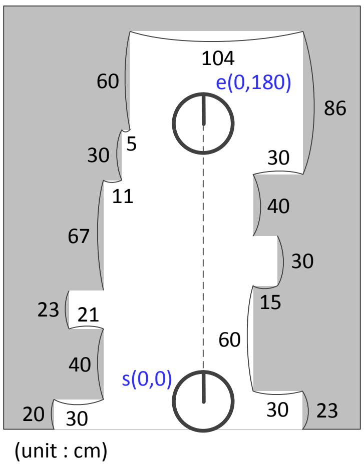
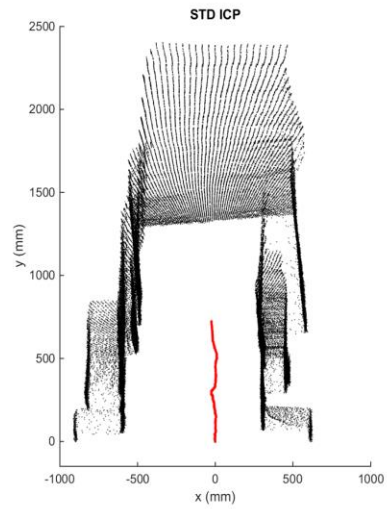


Figure 3. Experimental environment. Detailed specification is described in centimeter unit.

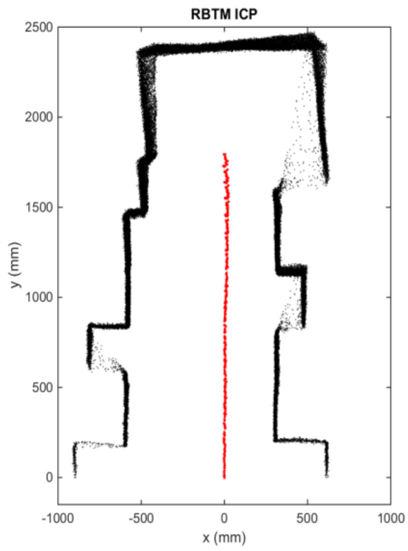
If the similarity between scan 1 and 4 is smaller than the user-defined threshold, the registration is not performed (see Fig. 2 red line). The following similarity computation representative is the scan at time step 2. If the similarity between the scans at time 2 and 4 is greater than the thrshold, the rotational and translational matrices between these two scans are computed and $R_{1,4}$, $T_{1,4}$ are updated. These process is iterated whenever new scan data is acquired. Till now, the most accurate map building scan path is 1,2 and 4. This path can be changed when new data is acquired in the future. This is why we named our algorithm as Real-time Backwards Threshold Matching.

III. Experimental Results

Fig. 3 shows the experimental environment. The regions described by white color represent empty spaces and the regions sketched by gray color represent walls where the robot cannot enter. Two circles describe the robot at the starting position and the ending position and the line in the circle means the heading direction of the robot. Dashed line shows the path of the robot. The robot moved 1.8 meters along this straight line path. To verify the performance of our new proposed framework, we compared with the standard ICP method. First of all, the maps which are constructed by the two methods are plotted in Fig. 4. The black dots represent the map data and the red dots represent the estimated robot pose at each time step. From Fig. 4, we can verify that the map with our new method shows better quality than the map with the standard ICP method. The path of the robot in Fig. 4 (b) shows straight line but the path in Fig. 4(a) shows curved line.



(a)



(b)

Figure 4. Experimental results. (a) Result of the map (black) and the estimated pose (red) with standard ICP. (b) Result of the map (black) and the estimated pose (red) with RBTM ICP.

TABLE I. ERROR COMPARISON BETWEEN STANDARD ICP ALGORITHM AND OUR PROPOSED NEW FRAMEWORK METHOD

Method	STD-ICP	RBTM
Final Pose Error (mm)	1076.3	7.423

Secondly, we measured the error between the final estimated pose and the final ground truth pose and compared with the two methods. The final pose errors are calculated and depicted in Table I. From the error data we could verify that our proposed method showed smaller error. To sum up, as we expected previously, our algorithm enhanced the quality of the map and the accuracy of the estimated robot pose.

IV. CONCLUSIONS

In this paper, we suggested enhanced map building framework based on the scan similarity. Previous point cloud based registration algorithms did not consider the distribution of the scan data which influence the result of the registration. To represent a scan data as an informative vector, a laser scan descriptor is introduced by using the curvature function. With this descriptor, the similarity between two scan data is computed by using the cross correlation of them. Finally, considering the similarity between scans, a new map building framework (RBTM) is proposed. The performance is verified through the experiment. We compared the proposed framework with the standard ICP algorithm and showed our newly proposed method enhanced the map quality and the accuracy of the estimated robot pose.

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REFERENCES

[1] H. Durrant-Whyte and T. Bailey, "Simultaneous localization and mapping: Part I," *IEEE Robotics & Automation Magazine*, vol. 13, no. 2, pp. 99-110, June 2006.

[2] T. Bailey and H. Durrant-Whyte, "Simultaneous Localization and Mapping (SLAM): Part II," *IEEE Robotics & Automation Magazine*, vol. 13, no. 3, pp. 108-117, September 2006.

[3] P. J. Besl and N. D. McKay, "A method for registration of 3-D shapes," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 14, no. 2, pp. 239-256, February 1992.

[4] A. Segal, D. Haehne, and S. Thrun, "Generalized-ICP," *Robotics: Science and Systems*, 2009.

[5] P. Biber, "The normal distributions transform: A new approach to laser scan matching," in *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 2003, pp. 2743-2748.

[6] E. Takeuchi and T. Tsubouchi, "A 3-D scan matching using improved 3-D normal distributions transform for mobile robotic mapping," in *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 2006, pp. 3068-3073.

[7] A. Diosi and L. Kleeman, "Laser scan matching in polar coordinates with application to SLAM," in *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 2005, pp. 3317-3322.

[8] A. Censi, L. Iocchi, and G. Grisetti, "Scan matching in the hough domain," in *Proc. IEEE Int. Conf. on Robotics and Automation*, 2005, pp. 2739-2744.

[9] H. C. Lee, S. H. Lee, J. Kim, and B. H. Lee, "Robust scan matching with curvature-based matching region selection," in *Proc. IEEE/SICE Int. Symposium on System Integration*, 2011, pp. 1257-1262.

[10] W. Yoo and B. H. Lee, "Scan matching error analysis with regard to the similarity of the scans," presented at the Korea Robotics Society Annual Conference (KRoC), Daejeon, Korea, May 6-8, 2015.

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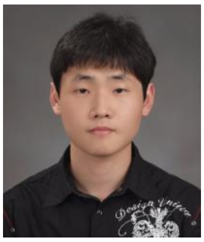

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