Multi-Robot SLAM System using Feature Matching for Accurate Mapping

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Abstract—Mapping is essential for the navigation of Autonomous Mobile Robots (AMRs). However, conventional single-robot SLAM requires long mapping time in large-scale environments and suffers from accuracy degradation as drift accumulates with travel distance. To address these issues, we propose a multi-robot SLAM system that automatically merges occupancy grid maps generated by multiple robots via feature-based matching. The process operates fully automatically without any initial pose priors or manual intervention. Experiments with four robots demonstrate accurate and efficient mapping in large-scale environments.

Keywords—SLAM (Simultaneous Localization and Mapping), Multi-Robot, Map merging, Feature matching, AKAZE

I. INTRODUCTION

For autonomous navigation in GPS-denied indoor environments, Simultaneous Localization and Mapping (SLAM) is a critical technology, enabling a robot to localize itself and simultaneously create a map of its surroundings. However, using single-robot SLAM to map a large-scale environment is not only time-consuming, but it also suffers from continuously accumulating pose estimation errors as the robot moves. This accumulation of error, or drift, can lead to significant discrepancies between the generated map and the actual environment, causing the robot to fail in determining its correct position. For example, Fig. 1 shows the result of mapping an environment of approximately 157 m² in a Gazebo simulation using the Gmapping [1]. It is evident that over time, the map becomes distorted from the actual environment due to accumulated error. This inaccurate mapping occurs because the Gmapping method selects incorrect particles as a result of this cumulative error.

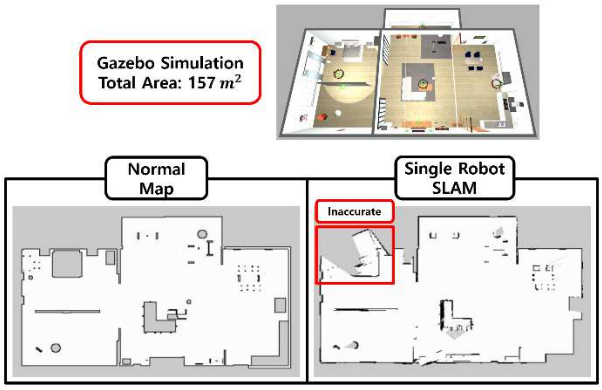

Fig. 1. Inaccuracy of single-robot SLAM.

To mitigate the accumulated error in single-robot SLAM, loop closure and pose-graph optimization are widely employed. Notably, Google Cartographer constructs submaps, performs global loop detection through scan-to-submap matching, and then corrects drift via pose-graph optimization to achieve real-time loop closure in 2D environments [2]. Nevertheless, this approach has limitations in large-scale indoor settings. First, robots often traverse large areas only once, reducing opportunities to revisit past locations. This results in an insufficient number of global constraints (loop constraints), making it difficult to effectively suppress drift. Second, as the scale of the map and the pose graph increases, the computational and memory requirements for optimization surge, which can degrade real-time performance. Therefore, in large-scale indoor environments, multi-robot collaboration-based map merging can be an effective alternative [3, 4].

In this paper, we propose a multi-robot SLAM system that addresses the problem of inaccurate mapping in large environments. The system automatically merges maps created individually by multiple robots, based on feature point matching, to generate a single, integrated map. Through the reliability management of the transformation matrix derived from map feature matching, this system enables automatic map creation without any prior information on the robots' initial poses. This approach allows for the creation of maps of larger environments more accurately and efficiently compared to single-robot SLAM.

II. Related Works

Multi-robot SLAM systems have been actively researched to overcome the limitations of single-robot SLAM, such as time inefficiency and the accumulation of pose estimation errors in large-scale environments. A key element of the system proposed in this paper is the map merging method that integrates local maps generated by individual robots into a single consistent global map.

Recently, Zick et al. [5] proposed a map fusion technique utilizing ORB (Oriented FAST and Rotated BRIEF) [6] feature matching to robustly handle variations in map scale and orientation, and to enhance pairwise connections through precise position transformation. However, while this method offers the advantage of fast computational speed, it presents certain limitations regarding feature matching accuracy. Consequently, this study adopts AKAZE (Accelerated-KAZE) [7], which excels in preserving detailed information within nonlinear scale spaces and offers superior matching robustness, replacing the ORB method used by Zick et al. to improve basic matching performance.

In a similar vein, Zhang et al. [8] presented an efficient map merging algorithm utilizing AKAZE features for scenarios with unknown initial poses. Through experiments, they demonstrated that the AKAZE-based method outperforms the ORB-based method in terms of matching robustness and transformation estimation confidence. While the system proposed in this paper utilizes AKAZE based on Zhang et al.'s findings, it distinguishes itself from existing methods that rely on simple feature matching by introducing a novel Reliability-Based Transformation Matrix Accuracy Management technique. This approach ensures more precise and stable automatic map merging compared to simple AKAZE-based approaches.

III. Multi-Robot SLAM System Architecture

As illustrated in Fig. 2, the proposed system proceeds in the following order: (1) Feature Extraction and Matching, (2) Reliability-Based Transformation Matrix Accuracy Management, and (3) Map Merging and Robot TF Merging.

First, in the Feature Extraction and Matching step, when the maps generated by each robot via SLAM are input, feature extraction and matching are performed. Second, in the Reliability-Based Transformation Matrix Accuracy Management step, a transformation matrix is calculated and its reliability is evaluated based on the results from the previous step. In this step, the transformation matrix with the highest reliability is stored by iteratively comparing it against previous reliability values. Finally, using the stored transformation matrix, the map merging and the merging of the robot's TF (Transform) are executed.

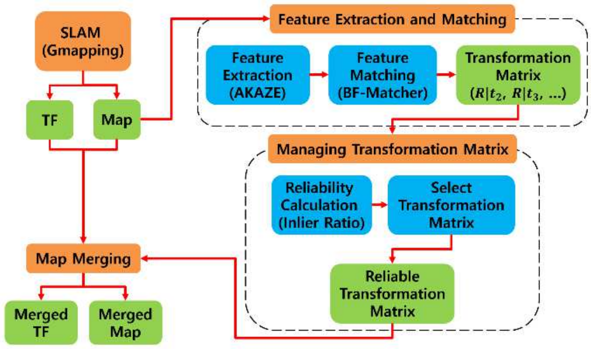

Fig. 2. System Flowchart.

A. Image Feature Extraction and Matching

For image matching, the LiDAR Map, which is in Occupancy Grid format, is first converted into an image. Then, image feature extraction and matching are conducted.

Since image feature extraction and matching are processed using only two images at a time, it is not possible to match multiple maps simultaneously. Therefore, it is necessary to establish a reference map to merge multiple maps. As shown in Fig. 3, a method was adopted where Map 1 is set as the reference, and the feature points of the remaining maps are matched against it.

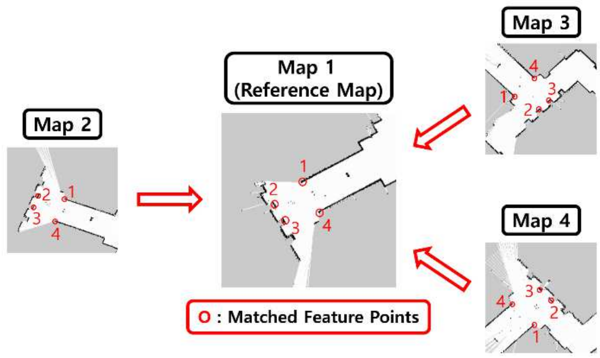

Fig. 3. Feature point matching against a reference map.

For feature extraction, the AKAZE (Accelerated-KAZE) [7] was used, as it offers faster computation speeds than SIFT [9] or SURF [10], making it advantageous for real-time matching. For matching, the Brute Force Matcher (BFMatcher) was employed.

After image matching, the transformation matrix for the images is calculated. As illustrated in Fig. 4, since matching is performed against Map 1 (the reference), merging four maps results in the calculation of three transformation matrices.

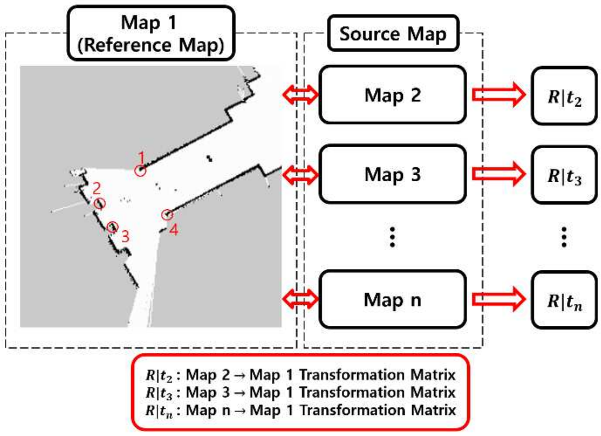

Fig. 4. Calculation of transformation matrices for n maps.

The transformation matrix is calculated using the RANSAC (Random Sample Consensus) method [11] based on the matching points obtained from feature matching. This allows for the estimation of a consistent transformation even if some incorrect matches are included.

B. Reliability-Based Transformation Matrix Accuracy Management

Directly using the transformation matrix calculated in the previous step for map merging can cause instability, as the matrix may fluctuate frequently depending on the feature matching results. For this reason, our system manages the transformation matrix by utilizing inlier and outlier matches from the RANSAC method. As illustrated in Figure 5, matches that align well when the maps are merged are classified as inliers, while those that do not align well are classified as outliers

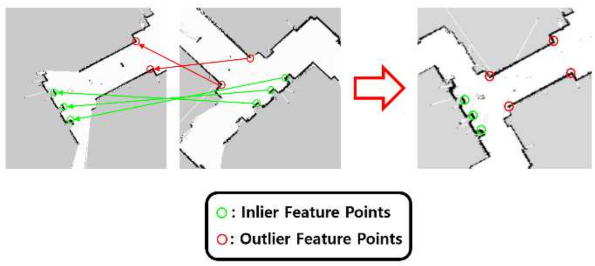

Fig. 5. Inlier and Outlier Matching.

The reliability is calculated using the ratio of inlier matches to the total number of matches (Inlier Ratio), as shown in (1). We define this ratio as the reliability score.

$$Inlier\ Ratio = \frac{N_{inlier}}{N_{inlier} + N_{outlier}} \tag{1}$$

N_{inlier}: The number of inlier matching pairs

$N_{outlier}$: The number of outlier matching pairs

Based on this score, the system manages the accuracy of the transformation matrix by only adopting matrices that yield a higher reliability score. This process ensures the consistency and continuity of the map merging process.

C. Map Merging and Robot TF Merging

Using the high-reliability transformation matrix, the images of the remaining maps are transformed relative to Map 1 (the reference map). For overlapping regions, pixel values are determined based on priority: Occupied (black), Free (white), and Unknown (gray).

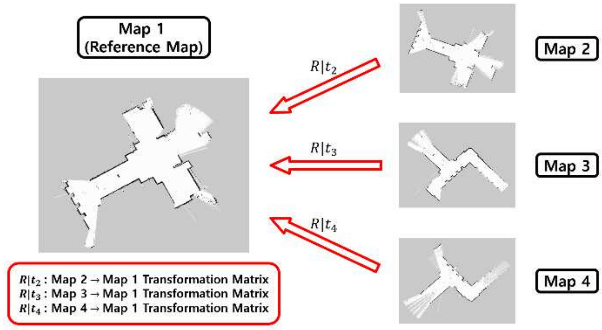

Fig. 6. Merging the remaining maps onto Map 1.

The odometry of each robot, calculated via SLAM, is only valid within the local map created by that specific robot. Consequently, the odometry information within the merged global map is unknown. Therefore, to ascertain the robot's odometry in the merged map, the robot's TF (Transform) is merged using the image transformation matrix.

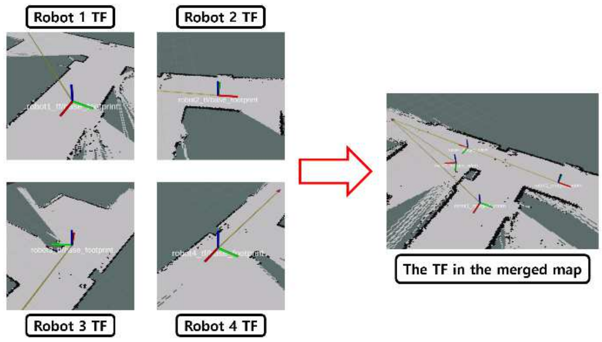

Fig. 7. TF merging from local maps to the merged map.

IV. Experiments

In this paper's experiment, four Turtlebot3 Burger (ROBOTIS) robots running ROS Noetic were used. Each robot was equipped with an LDS-02 LiDAR sensor, and the Gmapping algorithm was utilized for SLAM mapping. The specifications of the LiDAR sensor are shown in Fig. 8.

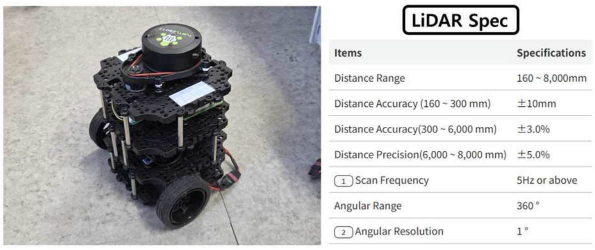

Fig. 8. The Turtlebot3 Burger robot and its LiDAR sensor specifications.

The mapping was conducted in an environment with a total area of approximately 117 m², and the generated maps were merged in real-time. The experimental procedure is shown in Fig. 9. First, the TurtleBots start from the same initial location. Subsequently, they move in different directions to map distinct areas (①, ②, ③, ④). As a result, all robots initially create an identical map of the starting area, and then proceed to map different, separate areas, ultimately completing a single, comprehensive map.

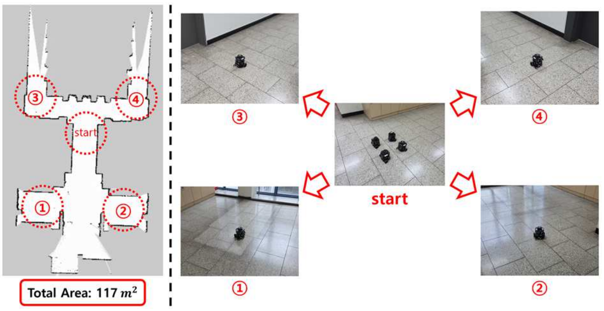

Fig. 9. Experimental Procedure.

V. Experimental Results

To evaluate the accuracy of the proposed system, this paper establishes a "ground truth map" generated using an Ouster OS1-128 LiDAR, which is more precise than the LiDAR used on the TurtleBots. The evaluation is conducted by comparing against this ground truth map.

The evaluation method involves aligning the ground truth map and the experimental map using the ICP (Iterative Closest Point) algorithm and measuring the Fitness and Inlier RMSE (Root Mean Square Error). Fitness indicates the structural correspondence between the two maps, while Inlier RMSE represents the average distance error between matched inlier points after alignment. This paper compares the accuracy of a map generated by a single TurtleBot (conventional method) with the map generated by four TurtleBots (proposed method).

As shown in Table 1, the Fitness value for the multi-robot map was measured at 0.9105. This confirms that the resulting accuracy of the multi-robot SLAM system is over 90%. The RMSE was 0.076m (7.6cm), which is considered a very low level of error, accounting for sensor noise and minor driving errors. In contrast, the single-robot map was distorted due to accumulated error, resulting in a Fitness of 0.7024, confirming an accuracy below 80%.

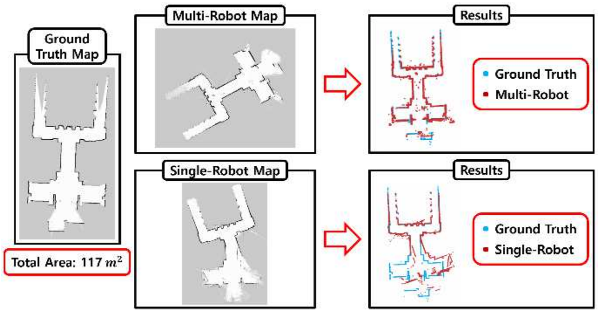

Fig. 10. ICP Matching Results.

TABLE 1. Fitness and RMSE Results

	Multi-Robot	Single-Robot
Fitness	0.9105 (91.05%)	0.7024 (70.24%)
Inlier RMSE	0.076m (7.6cm)	0.085m (8.5cm)

The experimental results show that although there is some minor noise in the multi-robot map, it is at a level that does not significantly affect the accuracy of the overall structure. Therefore, this paper demonstrates that the proposed multi-robot SLAM system is capable of generating highly reliable maps.

VI. Conclusion

Conventional single-robot SLAM methods for map creation are not only time-consuming for large environments but also suffer from difficulties in accurate mapping due to the problem of accumulating errors. To address this, this paper proposed a multi-robot SLAM system. This system performs real-time map merging by utilizing reliability-based accuracy management of the transformation matrix, which is calculated from feature point matching. Furthermore, its performance was validated through experiments involving mapping a real-world environment with four robots. Although four robots were used in the experiment, it is expected that using more robots could enable even faster and more accurate map creation.

For future work, we plan to conduct research on methods to further enhance the accuracy of map merging by adding sensors that can measure inter-robot positioning information, such as UWB (Ultra-Wideband).

Acknowledgment

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REFERENCES

[1] G. Grisetti, C. Stachniss, and W. Burgard, "Improved techniques for grid mapping with rao-blackwellized particle filters," IEEE transactions on Robotics, vol. 23, no. 1, pp. 34–46, 2007.

[2] W. Hess, D. Kohler, H. Rapp, and D. Andor, "Real-time loop closure in 2D LIDAR SLAM," in 2016 IEEE international conference on robotics and automation (ICRA), 2016: IEEE, pp. 1271–1278.

[3] R. Yuan, B. Ji, Y. Gao, and H. Tao, "A review of LiDAR simultaneous localization and mapping techniques for multi-robot," Robotica, pp. 1–41, 2025.

[4] W. Chen et al., "Overview of multi-robot collaborative SLAM from the perspective of data fusion," Machines, vol. 11, no. 6, p. 653, 2023.

[5] L. A. Zick, D. Martinelli, A. S. de Oliveira, and V. C. Kalempa, "ORB-Based Map Fusion with Position Transformation for Enhanced Pairwise Connection."

[6] E. Rublee, V. Rabaud, K. Konolige, and G. Bradski, "ORB: An efficient alternative to SIFT or SURF," in 2011 International conference on computer vision, 2011: Ieee, pp. 2564–2571.

[7] P. F. Alcantarilla and T. Solutions, "Fast explicit diffusion for accelerated features in nonlinear scale spaces," IEEE Trans. Patt. Anal. Mach. Intell, vol. 34, no. 7, pp. 1281–1298, 2011.

[8] L. Zhang, C. Jiao, J. Huang, and X. Su, "Akaze feature-based map merging for multi-robot slam with unknown initial pose," in 2022 34th Chinese Control and Decision Conference (CCDC), 2022: IEEE, pp. 5637–5642.

[9] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," International journal of computer vision, vol. 60, no. 2, pp. 91–110, 2004.

[10] H. Bay, T. Tuytelaars, and L. Van Gool, "Surf: Speeded up robust features," in European conference on computer vision, 2006: Springer, pp. 404–417.

[11] M. A. Fischler and R. C. Bolles, "Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography," Communications of the ACM, vol. 24, no. 6, pp. 381–395, 1981.