SLAM System for Sparse Feature Environments Using Marker Matching Evaluation

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***Abstract*— GMapping, a Particle Filter-based SLAM algorithm, is widely used due to its robustness against odometric drift. However, in sparse feature environments such as long corridors, its localization accuracy deteriorates because of scan-matching ambiguity. To overcome this limitation, we propose an enhancement to the weight update stage of the Particle Filter pipeline. Specifically, we introduce a marker matching evaluation step that measures the consistency between observed marker data and the map from the previous frame. This enhancement enables reliable localization even in low-feature environments. Preliminary experiments demonstrate that the proposed method improves pose estimation accuracy in corridor-like indoor settings without requiring additional sensors or prior maps.**

Keywords—SLAM, Particle Filter Localization, Marker Matching

I. INTRODUCTION

As the demand for indoor autonomous robots continues to grow, the importance of accurate Simultaneous Localization and Mapping (SLAM) has become increasingly evident. GMapping [1], a Particle Filter-based 2D SLAM algorithm [2], is robust against odometric drift but often struggles in feature-sparse environments such as long corridors. In Fig. 1, Robot can recognize the changed position on Fig. 1 (a). However, on Fig. 1 (b), it cannot recognize the changed position from LiDAR Data. In such settings, the scan-matching ambiguity between similar LiDAR scans can significantly degrade localization accuracy. To overcome this limitation, we propose a fusion-based SLAM system that integrates 2D LiDAR and a monocular camera to detect ArUco markers as artificial landmarks. By incorporating a marker matching process into the weight update stage, the proposed method achieves more stable and accurate localization in simple indoor environments.

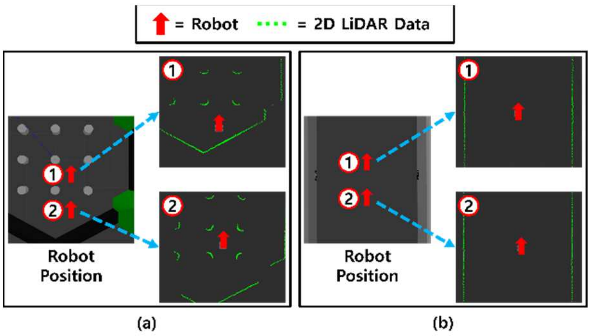

Fig. 1. (a) Environment with features, (b) Environment without features

II. RELATED WORKS

Recent research on SLAM in sparse feature environments has increasingly focused on improving robustness in situations where conventional geometric or visual cues are insufficient for reliable localization. Such conditions commonly arise in large-scale indoor spaces, industrial facilities, outdoor environments, or planetary-analog terrains, where limited structural features and reduced observability often lead to odometry degeneracy and long-term drift [3], [4].

A prominent line of work addresses these challenges through optimization-based SLAM frameworks with refined sensor modeling. In particular, recent studies emphasize improving the observability and stability of state estimation by enhancing LiDAR, visual, and inertial measurement models within factor graph or smoothing-based formulations [5]. By explicitly analyzing degeneracy conditions and uncertainty propagation, these approaches aim to achieve robust localization in unstructured or feature-poor environments through improved backend optimization and global consistency. Such methods highlight the importance of accurate sensor modeling and principled optimization in maintaining SLAM performance over long trajectories.

In parallel, visual–LiDAR fusion approaches have been widely explored in environments characterized by texture scarcity and severe illumination variations. By leveraging LiDAR measurements to complement unreliable visual depth estimation, and by introducing additional structural constraints such as ground-plane priors or motion regularization, these systems demonstrate improved robustness in challenging conditions [6]. Long-range drift is typically mitigated through frame-to-map or feature-to-map optimization strategies that reinforce global consistency [7].

Alongside these developments, recent studies suggest that improving SLAM robustness does not necessarily require increasingly complex system architectures. Motivated by this observation, our work explores an alternative perspective by focusing on the inference process of Particle Filter-based SLAM. Rather than introducing additional sensors or relying on global optimization frameworks, we investigate how marker-based similarity information can be incorporated directly into the particle weighting mechanism. This approach follows recent trends in addressing feature sparsity, while examining a lightweight and structurally simple modification to the SLAM inference pipeline.

III. SYSTEM OVERVIEW

A. Experimental Environment

As Fig. 4, Experiments were conducted in a Gazebo 11 simulation environment using the TurtleBot3 Waffle Pi robot. Fig. 4 (a) shows the virtual environment consisted of a 50-meter-long corridor with flat walls devoid of natural features. ArUco markers were placed at 4-meter intervals along both walls to serve as artificial landmarks. In Fig. 4 (b), The robot was equipped with a 2D LiDAR and a monocular camera positioned at different heights to prevent interference. In Fig. 4 (c), the ArUco markers had a side length of 0.4 m and were placed near the floor for optimal visibility.

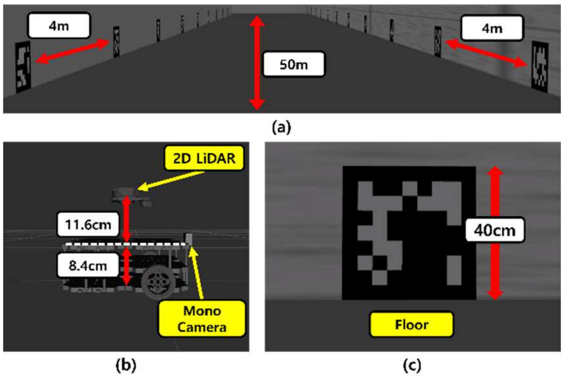

Fig. 4. (a) Virtual environment with ArUco Markers, (b) The Robot's appearance and sensor's position, (c) Attached ArUco Marker's appearance

B. Overall Framework

Fig. 5 shows overview of the proposed system. The proposed system enhances the weight computation process in the Particle Filter by introducing marker matching. This process evaluates the similarity between predicted LiDAR scans and the previously built map using ArUco marker information. The system pipeline consists of four stages: data preprocessing, particle propagation, weight update, and map update.

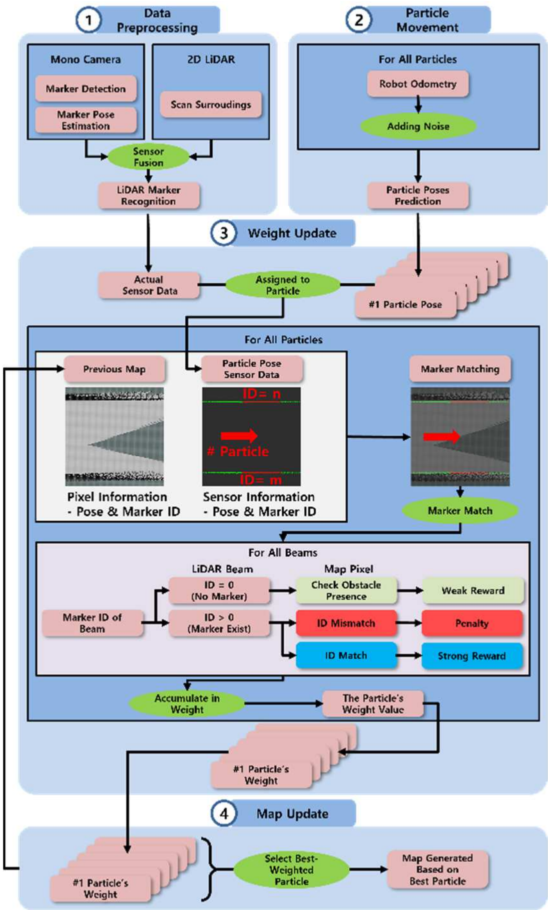

Fig. 5. Proposed SLAM System overview

IV. Implementation

A. Data-Preprocessing

As Fig. 6, In the preprocessing step, the monocular camera detects ArUco markers and estimates their poses using the solvePnP algorithm [8], [9]. The detected marker positions are projected onto the LiDAR scan to assign marker IDs to corresponding beams. If a beam intersects with a marker, its ID is recorded; otherwise, a zero value is assigned, indicating no marker detection.

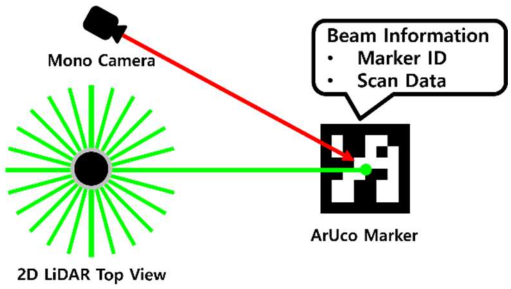

Fig. 6. Data preprocessing description

B. Particle Movement

Each particle represents a potential robot pose. The propagation process follows the standard prediction step of the Particle Filter, using wheel encoder data and adding rotational noise to ensure diversity among particle hypotheses. In Fig. 7, the Particle Movement process is described. By adding random error noise, we can ensure the diversity of possible particle states.

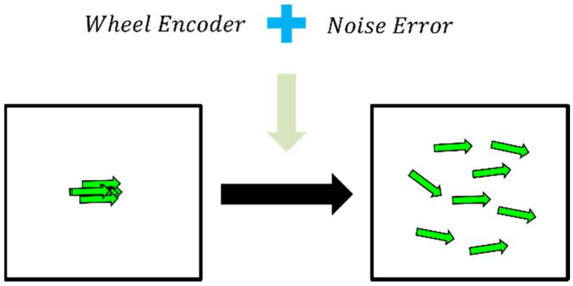

Fig. 7. Adding rotational error to wheel encoder data

C. Weight Update

The weight update is the core process of the system. Each particle receives the preprocessed sensor data, and the system evaluates the consistency between the particle's predicted LiDAR scan and the previously built occupancy grid map. For each LiDAR beam, the corresponding grid cell is identified, and their marker IDs are compared. As Fig. 8 shows, there are three cases to classify the result of comparison. If the marker IDs match, a high score is assigned(Strong Reward), or if they differ, the score decreases(Penalty). When both are outside marker regions, a smaller score is assigned(Weak Reward). The total weight for each particle is obtained by summing the scores of all beams.

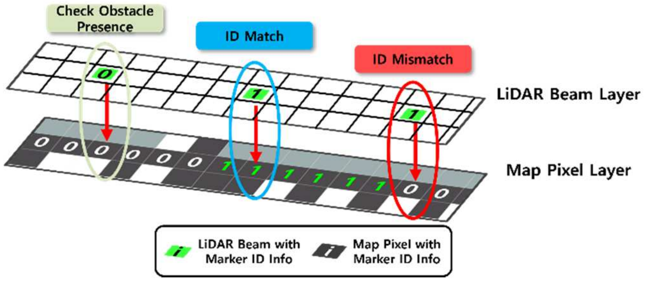

Fig. 8. Comparison between LiDAR scan data and map pixels

D. Map Update

After the weight update step, the particle with the highest weight is selected as the robot's estimated pose, shown in Fig. 9. The occupancy grid map is then updated based on this particle's sensor data, including marker ID and spatial information. The updated map is used in the next iteration of the weight update process.

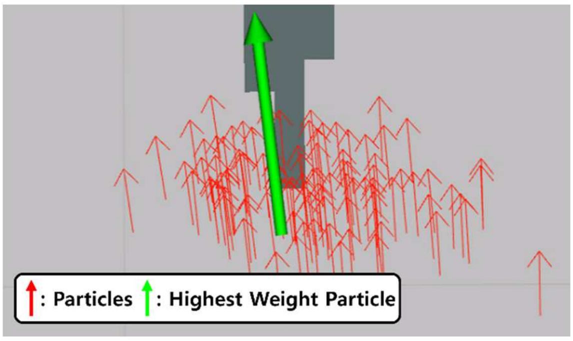

Fig. 9. Selecting the highest weight particle

V. Results and Comparison

To evaluate the proposed system, we compared its mapping accuracy with that of conventional GMapping under identical conditions. The robot moved along a 50-meter corridor at a speed of 0.1 m/s. Fig. 10 (a) shows the simulated environment, (b) the map generated by GMapping, and (c) the map generated by the proposed system. According to Table I, the results indicate that while GMapping reconstructed only 20.7 meters of the corridor (41.4% accuracy), the proposed method achieved 49.6 meters (99.2% accuracy).

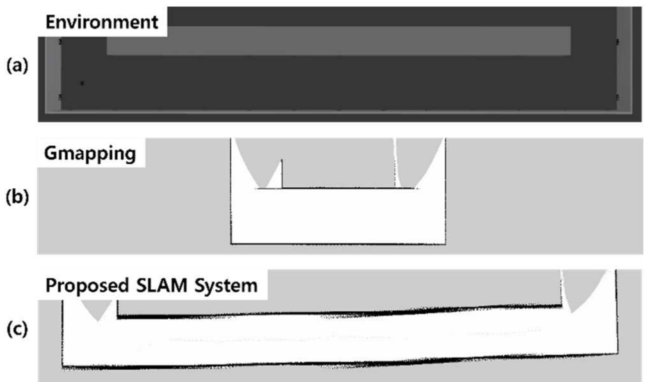

Fig. 10. (a) Experimental corridor environment in Gazebo 11 simulation world, (b) Result of GMapping's case, (c) Result of the Proposed System's case

TABLE I. The result comparison between GMapping and Proposed SLAM System.

Case	Pixel Length	Corridor Length	Pixel Count	Map Length	Accuracy
GMapping	0.05m/ pixel	50m	414pixel	20.7m	41.4%
Proposed SLAM System			992pixel	49.6m	99.2%

VI. Conclusion and Future Work

This paper presented a SLAM system that enables a 2D LiDAR to perceive visual markers through sensor fusion with a monocular camera. By integrating marker matching evaluation into the Particle Filter's weight update process, the proposed method achieves accurate mapping even in feature-sparse corridors. Experimental results demonstrated a 58% improvement in mapping accuracy over conventional GMapping. This system can be applied to industrial environments with repetitive structures or long featureless passages. Future work will focus on extending the framework to use object detection instead of markers, eliminating the need for pre-installed landmarks.

Acknowledgment

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