Graph Structure-based Simultaneous Localization and Mapping with Iterative Closest Point Constraints in Uneven Outdoor Terrain

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Abstract. The purpose of this study is to propose a novel mobile robot localization method applicable to outdoor environments, such as an uneven terrain. In order to solve the robot localization problem, we exploit state of the art graph-based SLAM (Simultaneous Localization and Mapping) algorithm and ICP (Iterative Closest Point) algorithm considering the gyroscopic data as a constraint for a graph structure. We confirm our method by testing actual sensor data acquired from a vehicle in outdoor environments and show that our proposed method is improved and suitable for uneven terrain.

Keywords: SLAM, Graph Structure, ICP, Point Cloud, UGV

1 Introduction

In recent years, the field robot for performing various tasks in a variety of environments has emerged with advancement of robot technologies whereas the industrial robot repeatedly executes the same work at a fixed location from the past. There are a lot of difficulties for robot automation, since the field robot works in various environments. One of the key issues in the automation of field robot is to solve the robot localization problem [1].

There are a wide range of sensors and algorithms for the robot localization problem. A GPS (Global Positioning System) and IMU (Inertial Measurement Unit) are generally used as positioning sensors and the VO (Visual Odometry) [2] algorithm using camera images and ICP (Iterative Closest Point) [3] algorithm using laser scanner data are employed for obtaining a robot's pose. However, in some situation like a non-line-of-sight, a significant position error occurs because GPS signal cannot be received directly from the satellite [4]. In case of IMU and VO algorithm, error is accumulated when used for a long period of time. Also ICP algorithm causes errors, if the algorithm is processed using data from an uneven surface. In this case, an alternative method is necessary and SLAM (Simultaneous Localization and Mapping) might be a solution to this problem [5-12].

In this paper, we propose a novel method for the robot localization exploiting the graph structure-based SLAM algorithm considering the constraint of graph structure

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from ICP algorithm for point cloud data matching with roll and pitch angles from the IMU and kinematics for a wheeled robot to reduce the robot pose error in exhaustive out door such as rough terrain.

The remainder of this paper is organized as follows. Section 2 explains our approach on how to minimize the robot pose error using graph-based SLAM and constraint from ICP algorithm. In Section 3, we then provide overall experimental environments and system and describe the experimental results with our approach to confirm our method. Detailed conclusion and future work are discussed in Section 4.

2 Graph SLAM with ICP Constraint

In this section we introduce a novel graph SLAM with ICP Constraint. First, we present the ICP algorithm considering the gyroscopic data for the graph structure constraints. Then we describe how to generate constraints of the graph structure. The overall localization algorithm is shown in Fig. 1.

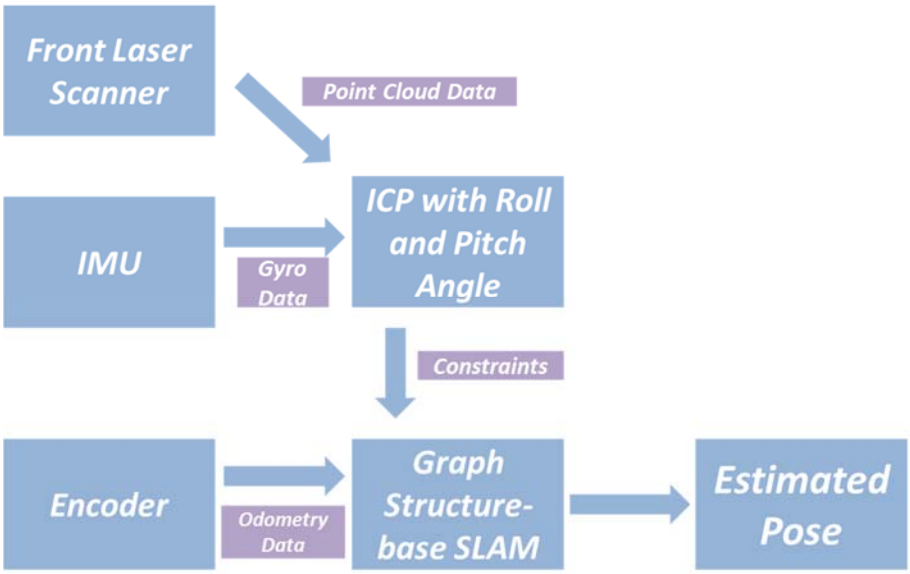


Fig. 1. The overview of the localization algorithm

2.1 ICP with Roll and Pitch angle

The widely used two dimensional ICP is a method to match two dimensional point cloud data generated from a laser scanner. The two dimensional ICP is able to estimate pose relationship successfully in indoor environments. However the method induces the pose error in outdoor environments when the surface is not even with the laser scanner looking forward. The laser scanner fluctuates in outdoor, because the floor is uneven. Therefore, it is necessary to consider the roll and pitch angles of the laser scanner as shown in Fig. 2. We conducted the ICP algorithm using point cloud data generated from a 2D laser scanner and IMU instead of conducting a naïve ICP algorithm. If the laser scanner fluctuates on uneven road, the error of ICP is inevitable.

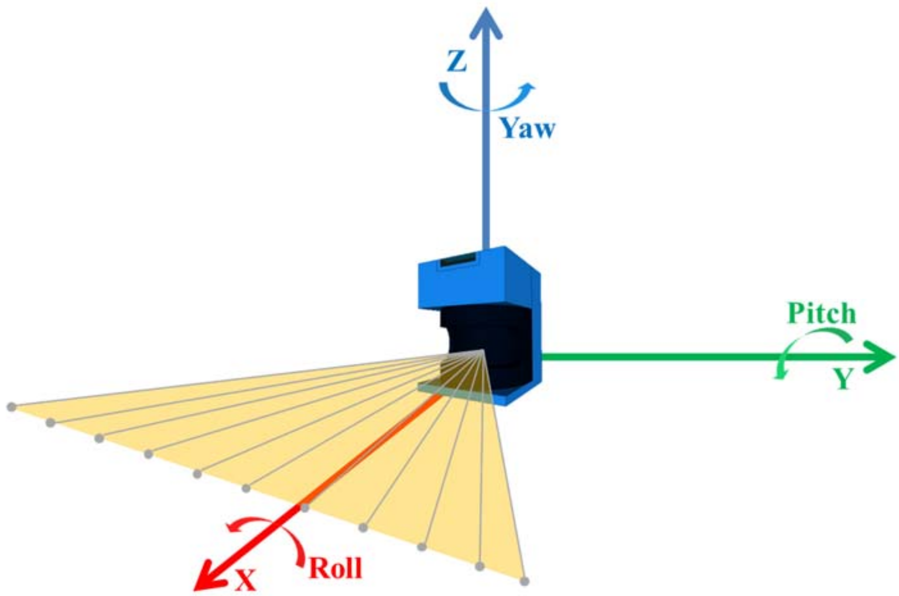


Fig. 2. The axis of the laser scanner

2.2 Constraints of Graph Structure

The constraints of a graph-structure are important in a graph-based SLAM, because it is possible to induce the pose error due to improper constraint. When the robot moves one meter by using the odometry obtained from encoder, we generate a node and form constraints of the graph structure and valid constraints can be generated from the ICP using the method of Section 2.1. Also we incorporate the wheeled robot kinematics. That is, if the rotation angle of the ICP result exceeds the range of wheeled robot kinematics or the translation of the ICP result moves rapidly to sideways along to the robot axis, it was considered an invalid constraint. In comparison with odometry, if the translation of the ICP result is too small or too large, it was also considered an invalid constraint.

3 Experiments

This section presents an experimental setup and the results of our method. For the experiments, we used our sensor system and tested experiments in outdoor. We compared ICP without any preprocessing and ICP considering roll and pitch angles. Also we examined the graph SLAM with only ICP and with the proposed method.

3.1 Experimental Setup

Fig. 3 presents experimental environment and our sensor system for experiment. The system is composed of a road vehicle, three laser scanners, four cameras, a GPS, an IMU, two wheel encoders and a PC. For the experiment, we only used a front laser scanner, an IMU and two wheel encoders. Our framework was implemented in the Matlab platform based on an open source including GTSAM [13].

The experimental site is National Science Museum in Daejeon, South Korea and is shown in Fig. 3 (a). The size of the experimental environment is about 300m x 440m.

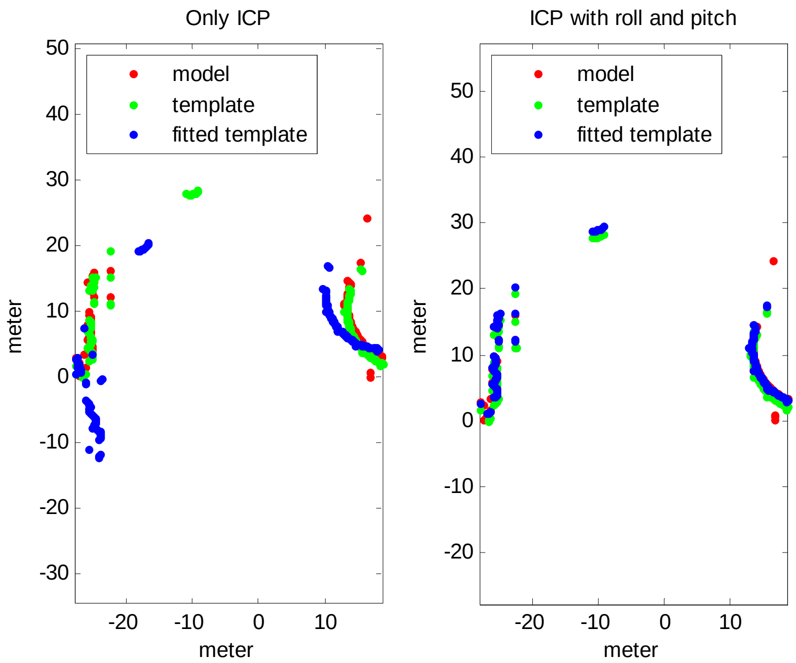
(a) (b)

Fig. 3. Experimental setup (a) experimental environment, (b) sensor system

3.2 Results

Fig. 4 presents the results of ICP without any preprocessing and ICP with the preprocessing considering roll and pitch angles. The result of the ICP without a gyroscopic data is shown in Fig. 4 (a) and the result of the ICP performed in consideration of the roll and pitch angles is shown in Fig. 4 (b). The red dots indicate a model data and the green dots template data. The blue dots represent fitting results obtained from the ICP algorithm. Fig. 4 (a) shows the wrong fitted result caused by uneven surface, while Fig. 4 (b) shows good matching result even with rough terrain because of compensation of roll and pitch angles.

The overall SLAM results are shown in Fig. 5. The red solid line is raw pose data from the odometry and the green square shows graph SLAM results with ICP without considering roll and pitch angles. The blue dashed line indicates the results of our approach. The error exists in the green square results because of the invalid constraint generated by ICP without consideration of gyroscopic data. In order to confirm performance of our method, Fig. 5 is enlarged. Fig. 6 shows the enlarged Section A of Fig. 5 and Fig. 7 shows the enlarged Section B of Fig. 5. As can be seen in Fig. 6 and Fig. 7, the proposed method seems to be more accurate. In Sections A and B, a loop closing occurred where the front laser scanner views the previously-seen feature data. The raw data accumulates the error in a long run time. However, proposed method generates a constraint by loop closing and the accumulated pose error is minimized by the optimization of the graph structure.



(b) (b)

Fig. 4. The results of ICP (a) without any preprocessing and (b) ICP with the preprocessing considering roll and pitch angles from a gyroscope

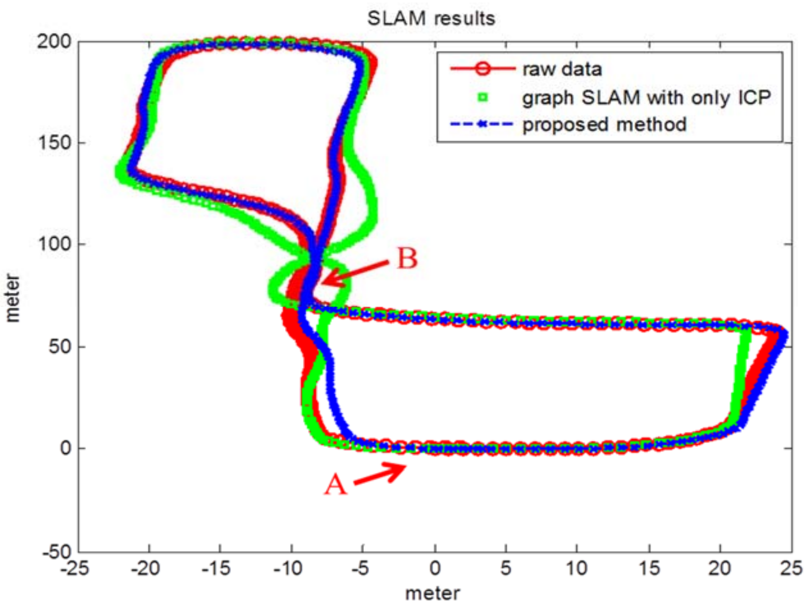


Fig. 3. Experiment results

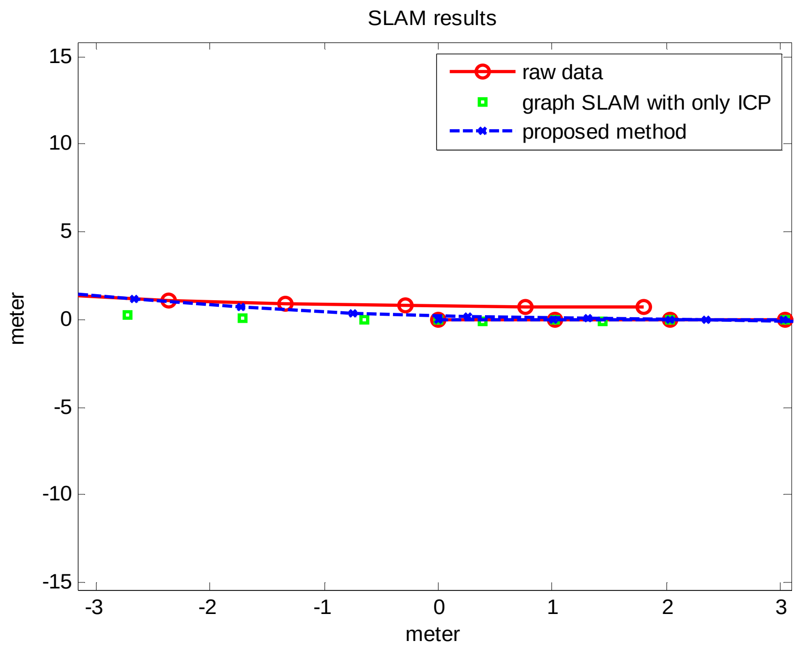


Fig. 4. Section A of Fig. 5

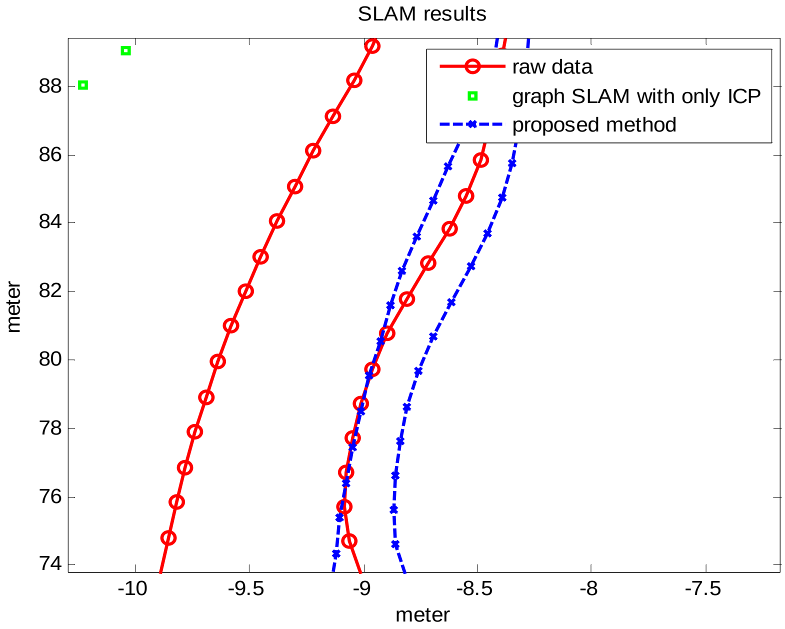


Fig. 5. Section B of Fig. 5

4 Conclusion and Future Work

We proposed a novel method for robot localization by incorporating gyroscopic data in the ICP scan-matching. We confirmed that the localization error is reduced even in a rough terrain. This method is efficient for the areas where GPS signal is denied. However, since this method is based on a 2D graph SLAM, the method can cause problems when the robot exhibits dynamic 3D motion. Furthermore, we did not consider a probabilistic model for building constraints.

For future works, we will expand our method to a 3D graph SLAM taking the probabilistic model into account when generating the constraints.

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