NORTHEASTERN UNIVERSITY

EECE 5554

Robot Sensing and Navigation

Project Report

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"Comparative Analysis of LiDAR based Mapping"

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1 Introduction

Autonomous localization and mapping are the most fundamental prerequisites in an intelligent robot. LiDAR, short for Light Detection and Ranging, is a remote sensing technology that utilizes laser pulses to measure distances to objects and surfaces with exceptional precision and accuracy. Operating on similar principles to radar, the LiDAR sensor emits laser beams towards a target area and measures the time it takes for the emitted light to return, allowing for highly detailed 3D maps of the environment to be created. This has proven to be a better method when it comes to mapping compared to vision-based methods. Their sensitivity to light and single viewpoint may not produce efficient results. Therefore, the integration of LiDAR sensors with sophisticated SLAM algorithms propels robots toward understanding and navigating complex surroundings with remarkable efficiency.

Considering the unique properties of LiDAR technology, the objective is to conduct a comprehensive comparative analysis of two prominent LiDAR-based 3D mapping techniques: LeGO-LOAM (Light and effectively Grounded Lidar Odometry and Mapping) and LIO-SAM (Lidar Inertial Odometry via Smoothing and Mapping). By systematically evaluating these methodologies, the study aims to assess their performance, accuracy, and computational efficiency in mapping environments using LiDAR data. Through this study, valuable insights that can inform decision-making processes can be provided and the selection of appropriate mapping techniques for various applications in robotics and autonomous navigation is researched.

2 Background

SLAM Algorithms play a significant role in the advancement of robots, enabling autonomous systems to navigate, explore, and interact with dynamic environments. The ability to create real-time six-degree-of-freedom localization and mapping is crucial in various applications.

While both LeGO-LOAM and LIO-SAM excel in LiDAR-based SLAM tasks, their comparative advantages lie in various aspects. LeGO-LOAM's lightweight design and efficient computation make it ideal for resource-constrained platforms, ensuring real-time mapping and localization. On the other hand, LIO-SAM's robust optimization framework and integration of IMU data enhance mapping accuracy and stability, particularly in dynamic and fast-paced environments.

In this comparative analysis, the algorithms of LeGO-LOAM and LIO-SAM, performance metrics evaluation, computational efficiency, mapping accuracy, and the error calculated in both the algorithms between the actual path and the mapped path have been investigated. By explaining these issues, this report provides valuable insights for researchers, developers, and practitioners in the field of LiDAR-based SLAM.

2.1 LeGO-LOAM Algorithm

LeGO-LOAM is lightweight since it can achieve real-time pose estimation on a low-power embedded system. Its core functionalities are designed to accurately estimate the robot's pose in real time while concurrently constructing a detailed map of the surrounding environment. As shown in Figure 1, this system consists of five main parts: point cloud segmentation from 3D LiDAR, feature extraction, LiDAR odometry, LiDAR mapping, and pose estimation. The first step uses the ground point cloud to extract roll, pitch, and height from planar features, and X, Y coordinates, and yaw from edge features. It then matches the edge points and surface points in the segmented point cloud to obtain the pose transformation matrix. Then, it performs loopback detection to correct the motion estimation drift. Finally, the transform module combines the results given out from LiDAR odometry and LiDAR mapping which acts as a two-step optimization to give the pose estimation. This improves the efficiency of the operation.

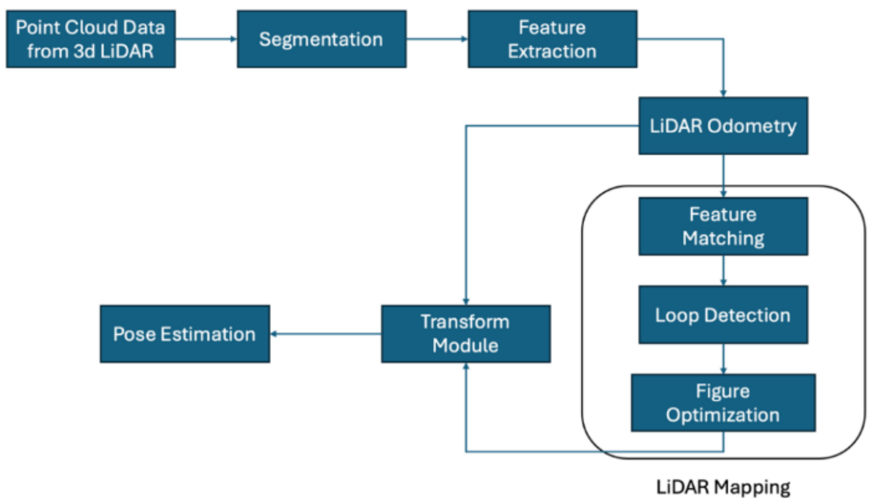


Figure 1: LeGO-LOAM Algorithm Flowchart

2.2 LIO-SAM Algorithm

LIO-SAM refers to Laser Inertial Odometry via Smoothing and Mapping. This means it combines data using factor graph optimization from LiDAR sensors and inertial sensors (like accelerometers and gyroscopes) for simultaneous localization and mapping. The algorithm takes the point cloud data as a nonlinear model. In addition to de-skewing point clouds, the estimated motion of the sensor from the IMU measurements acts as an initial guess in LiDAR odometry optimization. The obtained LiDAR odometry solution is then used to estimate the bias of the IMU in the factor graph which allows accurate sensor fusion. A global factor graph is introduced as seen in Figure 2 which estimates the robot's trajectory by combining data from LiDAR, IMU, and GPS data which is optional. The optimization process aims to minimize errors and smooth out the uncertainties in the robot's estimated trajectory and in turn produce a map of the environment.

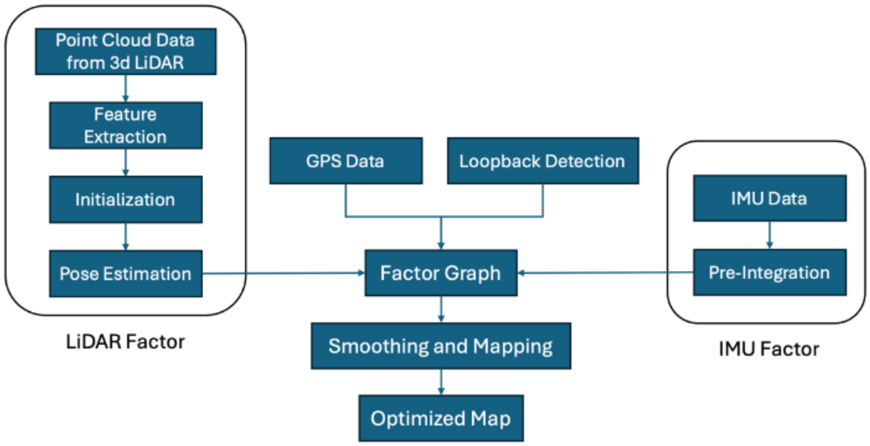


Figure 2: LIO-SAM Algorithm Flowchart

3 Methodology

LeGO-LOAM and LIO-SAM algorithms were implemented to perform 3D mapping using LiDAR and IMU sensor data in both real-world datasets and simulated environments. These algorithms will be configured to process LiDAR scans and estimate the robot's trajectory and the surrounding environment's 3D structure in real-time data to construct accurate maps while simultaneously tracking the robot's movement, facilitating navigation, and mapping tasks within the simulated environment.

3.1 Dataset Collection

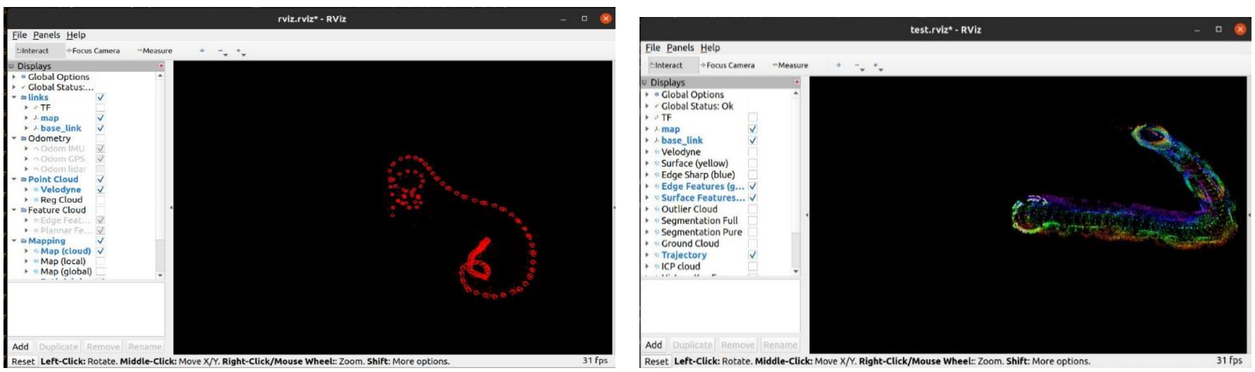
Two distinct datasets were gathered to facilitate the comparative analysis of LeGO-LOAM and LIO-SAM algorithms, encompassing both real-world and simulated environments:

- **KITTI Dataset:** The KITTI dataset stands as a prevalent resource within the mobile robotics and autonomous vehicle testing community. It encompasses ground truth data alongside LiDAR sensor readings, providing a comprehensive basis for algorithm evaluation. Specifically, the dataset furnishes crucial information regarding the actual position of the vehicle as well as the corresponding LiDAR data, offering a robust foundation for assessing the performance of SLAM algorithms in real-world scenarios.

- **Simulated Dataset:** Complementary to the KITTI dataset, a simulated dataset was curated within the Gazebo virtual environment. This dataset was meticulously designed to emulate real-world conditions, offering simulated LiDAR data alongside position information obtained through Gazebo. By simulating various environmental conditions and scenarios, this dataset provides an invaluable resource for validating the efficacy of SLAM algorithms under controlled yet diverse circumstances.

3.2 Algorithm Implementation on Outdoor Environment

To commence the project, both the LIO-SAM and LeGO-LOAM SLAM techniques were implemented meticulously. Leveraging the open-source KITTI dataset, widely utilized in autonomous vehicle testing, the 3D mapping process was initiated. However, during the mapping utilizing LIO-SAM, a significant IMU drift was observed, leading to unexpected results that contradicted initial expectations. Despite the meticulous implementation, the cloud mapping outcomes of both LIO-SAM and LeGO-LOAM techniques unveiled surprising disparities. These findings underscore the importance of robust sensor fusion techniques and highlight potential challenges in real-world applications, emphasizing the need for further investigation and refinement in SLAM algorithm development.



(a) LIO-SAM

(b) LeGO-LOAM

Figure 3: Trajectory Mapping of KITTI data set using LIO SLAM and LeGO LOAM

3.3 Algorithm Implementation on Indoor Environment

For Indoor mapping, we meticulously constructed a physical environment and equipped a robot model with a LiDAR sensor and an IMU, integrating these sensors using plugin modules. The robot was programmed to execute various trajectories, including straight lines, circles, and squares, allowing for a comprehensive assessment of the SLAM system's performance. As the robot traversed the environment, the LiDAR sensor scanned its surroundings, capturing data points used for real-time mapping. Additionally, teleoperation via teleop keys facilitated manual control, enabling targeted data collection. Subsequently, indoor cloud 3D mapping techniques were applied, utilizing the LIO-SAM technique to generate detailed three-dimensional maps of the environment. This dataset provides valuable insights into the SLAM system's accuracy and efficiency in mapping and localization tasks within complex indoor environments.

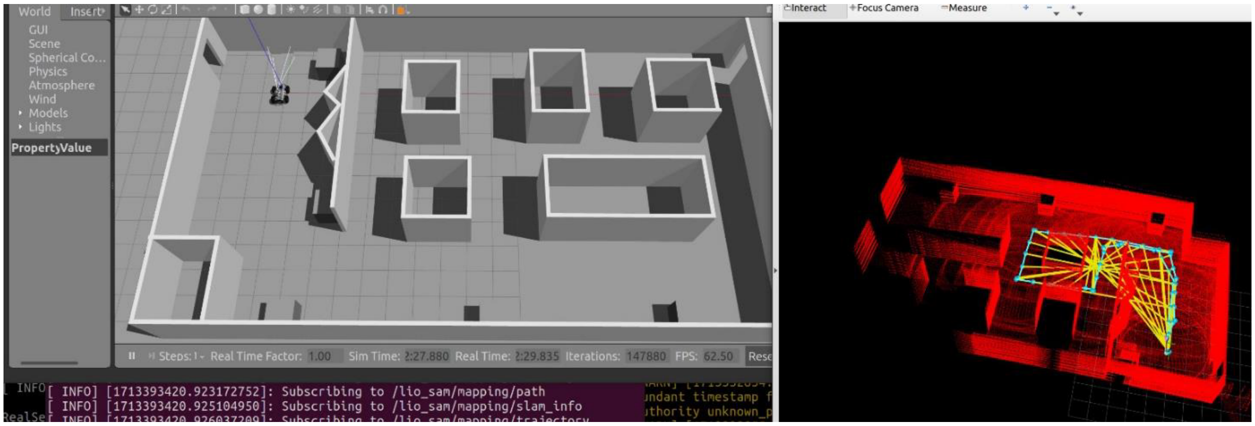


Figure 4: Indoor Mapping using the LIO-SLAM Technique in Gazebo Environment

The estimated trajectories obtained from LeGO-LOAM and LIO-SAM will be compared with the ground truth trajectories generated within the simulation environment. Root Path error (RPE) and absolute trajectory error (ATE) metrics will be utilized to quantify the disparities between the estimated and received trajectories for each path type, providing a comprehensive assessment of the performance of the mapping algorithms.

Absolute Trajectory Error (ATE) and Root Path Error (RPE) are defined as follows:

$$\text{ATE} = \sum \|\mathbf{p}_i - \mathbf{p}_{gt}\| \quad (1) \tag{1}$$

where $\mathbf{p}_i$ represents the position from the algorithm at time index i, and $\mathbf{p}_{gt}$ represents the ground truth position at the same index.

$$\text{RPE} = \sqrt{\sum (\mathbf{p}_i^2 - \mathbf{p}_{gt}^2)} \quad (2) \tag{2}$$

RPE calculates the square root of the sum of the squared differences between the algorithm's position and the ground truth at each time index.

4 Results

In this section, the results obtained from both the algorithms have been discussed with the help of figures. Figure 5 illustrates a comparison of results obtained from LIO-SAM and LeGO-LOAM on the KITTI dataset, plotted against ground truth data. A significant deviation of results from LIO-SAM is evident. This difference can potentially be attributed to cumulative effects of drift accumulation on IMU data. LeGO-LOAM's results may still be deemed viable through a transformation using a scale factor and a rotation matrix. 1 mentions the errors of the same.

Table 1: Errors of respective algorithms obtained on the KITTI dataset.

Slam Techniques (Kitti Data)	Absolute Path Error (m)	Root Path Error (m)
LeGO-LOAM	65.24	0.64
LIO-SAM	248.17	4.24

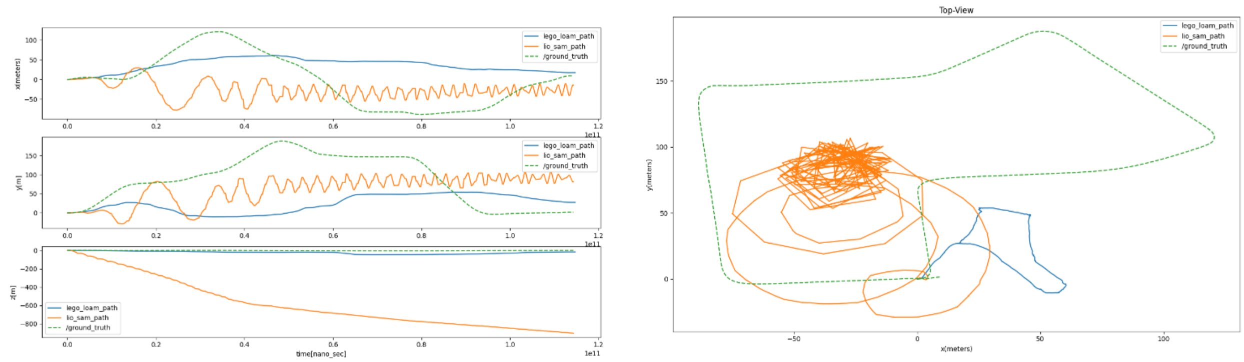


Figure 5: KITTI dataset: (Left)Results obtained in X,Y,Z axis after remapping trajectory compared to Ground truth. (Right) Path obtained after remapping trajectory compared to Ground truth.

Figure 6 has results obtained through remapping of circular and square trajectories in a simulated Gazebo environment. Figure 7 depicts remapped trajectories of a path taken across the Gazebo environment.

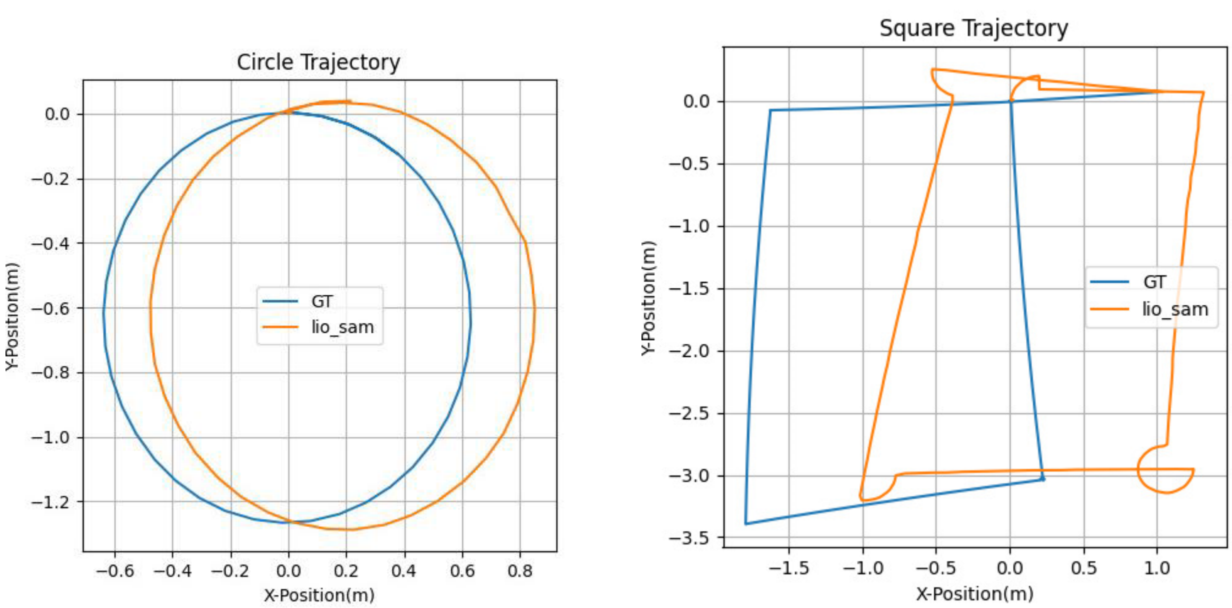


Figure 6: Gazebo dataset: (Left)Results after remapping circular trajectory compared to Ground truth. (Right) Path obtained after remapping square trajectory compared to Ground truth.

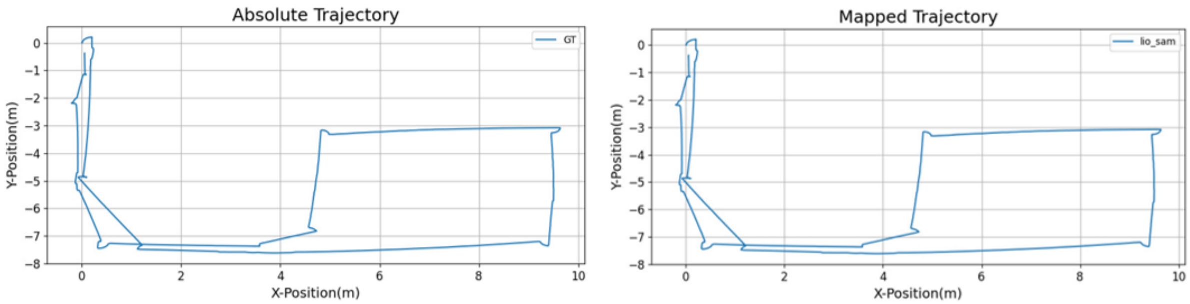


Figure 7: Gazebo dataset: (Left)Ground truth Trajectory. (Right) Path obtained after remapping.

Table 2: Errors on the Gazebo dataset

LIO-SAM (Gazebo)	Absolute Path Error (units)	Root Path Error (units)
Circle	5.04	0.825
Square	90.87	8.177

5 Conclusion and Future Scope

The integration of the mentioned algorithms into ROS (Robot Operating System) has been conducted, allowing seamless interaction and control within the robotic ecosystem. A quantitative analysis of their performance has been conducted, comparing LiDAR odometry against IMU integration methods to assess their respective accuracies and robustness. Future scope will involve enhancing performance through more sensor fusion techniques, leveraging the complementary strengths of LiDAR and IMU data to improve localization and mapping capabilities. This integrated approach holds promise for achieving higher accuracy and reliability in navigation tasks, paving the way for more sophisticated applications in robotics and autonomous systems.

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