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EVALUATION OF LIDAR ODOMETRY AND MAPPING BASED ON REFERENCE LASER SCANNING

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ABSTRACT:

Simultaneous localization and mapping (SLAM) is essential for the robot to operate in an unknown, vast environment. LiDAR-based SLAM can be utilizable in environments where other sensors cannot deliver reliable measurements. Providing accurate map results requires particular attention due to deviations originating from the device. This study is aimed to assess LiDAR-based mapping quality in a vast environment. The measurements are conducted on a mobile platform. Accuracy of the map collected with the LeGO-LOAM method was performed by making a comparison to a map gathered with geodetic scanning using ICP. The results provided 60% of fitted points in a distance lower than 5 cm and 80% in a distance lower than 10 cm. The findings prove the mileage of the map created with this method for other tasks, including autonomous driving and semantic segmentation.

1. INTRODUCTION

Mobile robots can navigate in hazardous environments where some types of tasks require high precision of movement (Buratowski et al. 2022). Simultaneous localization and mapping (SLAM) is one of the crucial tasks for robots deployment in these surroundings (Zuo et al. 2019). The approach provides not only information on the position and orientation of the robot during motion but also allows for map collection that can be useful for higher-level tasks involving semantic segmentation (Chen et al. 2019).

The performance of SLAM methods depends on the sensors equipped on the robot. The quality of measurement devices and the number of sensors can impact the localization error estimation and the accuracy of acquired map. Although numerous sensors can be fused to improve SLAM performance and reduce the influence of uncertainties and incorrect readings, not all sensors can be deployed in any environment. While instruments such as GPS can only be used outdoors (Deng et al. 2018), RGB cameras are limited by lighting conditions. In some applications SLAM can be performed using only one type of sensor (Wang et al. 2018). Such applications have to be based on a sensor providing visual output to obtain a map. A common approach to this problem is LiDAR-based SLAM. Depending on a single-sensor system might require evaluation of mapping accuracy for deploying methods in an industrial environment.

Collecting a map in the form of a point cloud can provide crucial information about the localization, which in LiDAR-based SLAM system is estimated on the basis of comparing subsequent maps. Accurate maps not only help maintain the correct position during the movement but also can assist in the detection of manual robot relocation or enable map merging from robots working in swarms (Chen et al. 2021). Another asset emerging from accurate mapping is that additional information on the objects in the surroundings can be obtained. In recent years, semantic segmentation on point clouds has been developed, enabling extraction and identification of the class of object (Wang et al. 2019). It allowed the concept of SLAM to be extended to include semantic maps on which it is possible to recognize objects (Qi et al. 2018). The quality of the given map has significant impact on the object recognition in the scene. Providing a proper map with high accuracy and density can enhance the performance of these methods.

Moreover, with determined mapping accuracy that directly affects localization, it can influence positioning repeatability. Establishing accuracy is crucial for obtaining precise poses and resolving higher-level problems.

2. RELATED WORKS

With constant development of SLAM methods and emerging possibilities of point cloud application, the assessment of various strategies has become indispensable. Below, selected papers in which a comparison of different SLAM techniques has been analyzed are discussed.

In (Nanayakkara et al. 2020), the authors made a comparison of 2D SLAM techniques. The authors considered four methods: HectorSLAM, Frontier exploration, KartoSLAM and Gmapping. Their performances were analysed by calculating the error between the obtained maps and a model of the environment. The study was carried out in a real-world scenario and gathered maps were compared to a prepared model. To quantify the discrepancies, RMSE and standard deviation (SD) were calculated. The research was performed with deployment of Kinect sensor on a robot. The outcome of the study provided the most accurate results for the Gmapping method.

In literature (Olalekan et al. 2021), the researchers made a comparative study of two SLAM methods available in ROS environment, i.e. GMapping and HectorSLAM. The research was conducted in a primarily unknown and dynamic environment. The comparison included the average time of travel and accuracy of the map. The space in which the robot navigated was created in Gazebo simulator. The acquired 2D maps were stored in PGM format. The authors indicated that the

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robot provided with a map gathered with grid-based particle filter approach requires slightly more time to find path to the goal with use of AMCL algorithm than HectorSLAM. Additionally, Gmapping requires using a pose estimator in contrary to the other analysed algorithm. The first technique outperformed HectorSLAM in terms of map quality.

The authors of (Tuna et al. 2012) provided a comparison of three SLAM methods - Extended Kalman Filter (EKF), Compressed Extended Kalman Filter (CEKF) and Unscented Kalman Filter (UKF) in terms of computing resources usage. The study shows that CEKF method provided the best computing time among the investigated algorithms.

In (Ren et al. 2022), the authors tested five 3D SLAM algorithms: Lidar Odometry and Mapping (LOAM), Lightweight and Ground-Optimized Lidar Odometry and Mapping (LeGO-LOAM), Fast LiDAR Odometry and Mapping (F-LOAM), Bundle adjustment for lidar mapping (BALM), and Versatile LiDAR SLAM via Multi-metric Linear Least Square (MULLS). The measure of comparison was absolute pose error (APE). The authors concluded that MULLS method provided the most accurate results of the robot pose among the tested methods. While the BALM algorithm provides the worst outcome, positions resulting from the remaining methods are comparable. Nevertheless, MULLS is computationally heavy and requires much time to acquire a map. LeGO-LOAM is the most computationally efficient SLAM technique of all methods considered in the article.

A research study (Trybała et al. 2023) assessed three LiDAR-based systems suitable for building a map for underground tunnels. The accuracy and completeness of the maps were evaluated in the paper. The authors divided the obtained point cloud into voxel grids for the assessment. The acquired point clouds were registered with the Iterative Closest Point (ICP) method to a reference map. The authors measured global accuracy with the M3C2 method, and local accuracy by calculating standard deviation and completeness with them.

The literature review proves that there is a necessity for assessing various SLAM approaches due to the diversification in computational complexity, accuracy, point cloud density and map consistency. Therefore in this paper we discuss the performance of the LiDAR-based SLAM method called Lightweight and Ground-Optimized Lidar Odometry and Mapping (LeGO-LOAM) (Shan and Englot, 2018). The position estimation in the implemented technique is performed subsequently by segmenting the acquired point cloud and extracting features. The later step takes into account both edge and planar features. Planar features influence the estimation of z, roll and pitch, while the edge features affect x, y and yaw. In the next step the consecutive point clouds are compared with point-to-edge and point-to-plane methods. Iterative closest point (ICP) approach is utilized to provide loop closure detection that eliminates the drift.

3. METHODS

3.1 Theory

LeGO-LOAM algorithm permits mapping the environment in addition to obtaining pose with regard to the coordinate origin. In the original paper in which the method was proposed, the pose estimation error was discussed, but the mapping quality was not addressed. The accuracy of the obtained map, however, may be the significant factor when it comes to the point cloud use. The mapping quality can be heavily influenced by the accuracy of the measurement device, its resolution and number of beams and the processing algorithm. Here, the map collected by the robot was matched with a reference map gathered by an accurate geodetic scanning devices to evaluate the LeGO-LOAM performance.

Evaluation of accuracy is performed with the Iterative Closest Point (ICP) algorithm. ICP enables aligning two consequent point clouds. It delivers transformation between given measurements. In the process, each point is assigned the closest point from the preceding point cloud and the Euclidean distance between them is calculated. The distances between closest points are minimized by applying transformation of the point cloud. The ICP method can be computationally exhausting for point clouds with a large number of points (Tiar et al. 2015).

3.2 Setup

The SLAM maps were generated using the mobile platform shown in Figure 1. The robot was equipped with Velodyne VLP-16 LiDAR sensor providing up to 3 cm accuracy. LiDAR sensor had a 30° vertical field of view and full angular horizontal range. The rover has two wheels on each side with separate motors and one passive wheel at the back to support construction and avoid necessity of balancing the mechanism. The robot's rotation is achieved by driving the wheels at different speeds or setting opposite directions to yaw. Such construction provides high manoeuvrability. The robot was travelling with a linear speed up to 0.4 m/s, with a reduced velocity when making turns.

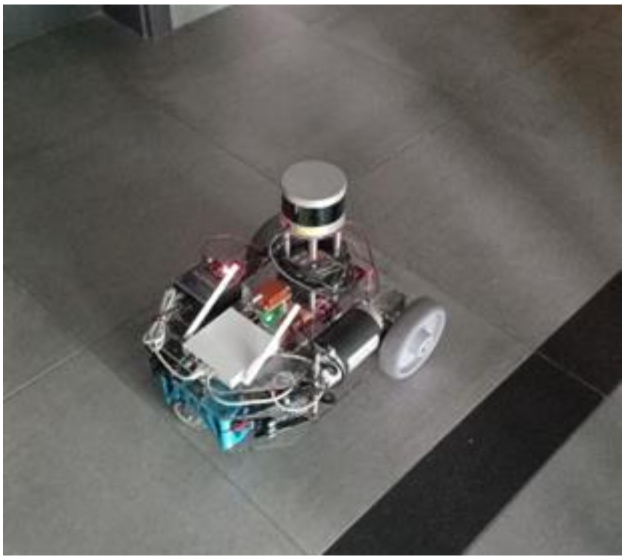

Figure 1. Mobile robot with mounted Velodyne VLP-16.

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Figure 2. Experimental environment in C5 AGH building. Measurements were conducted with diverse space occupation by cars.

LeGO-LOAM package was compiled in an open-source Robotic Operating System (ROS) programming environment. ROS kinetic version was installed on the Ubuntu 16.04 Xenial Xerus operating system. Data from LiDAR was collected with the velodyne ROS package.

The reference map was collected using the Z+F IMAGER 5010C laser scanner, which features super high resolution (20,000 pixels/360°) and high quality (each subsequent higher quality setting reduces range noise by a factor of 1.4). With these settings, the scanning time at one station was approximately 13 minutes. A tachymetric control network was established within the local coordinate system, and the scanning targets were measured. The scans from 3 stations were then aligned to a common coordinate system based on the coordinates determined through precise adjustment.

All the point clouds were collected in an underground parking lot shown in Figure 2. The space is utilized daily, so the environment changed between the acquisition of the reference map and the LeGO-LOAM point cloud. Some cars were moved, left, or arrived to the space.

3.3 Data Acquisition

The robot was driving in the same space where precise geodetic measurements were taken. The results of the LeGO-LOAM algorithm executed during robot operation in the test environment was shown in Figure 3. RviZ tool available in ROS was used to observe map creation during robot movement. The robot's trajectory and the map gathered with LeGO-LOAM was shown in Figure 4.

The trajectory is calculated on the basis of mapping so the quality and accuracy of mapping are prominently significant to obtain precise pose estimation.

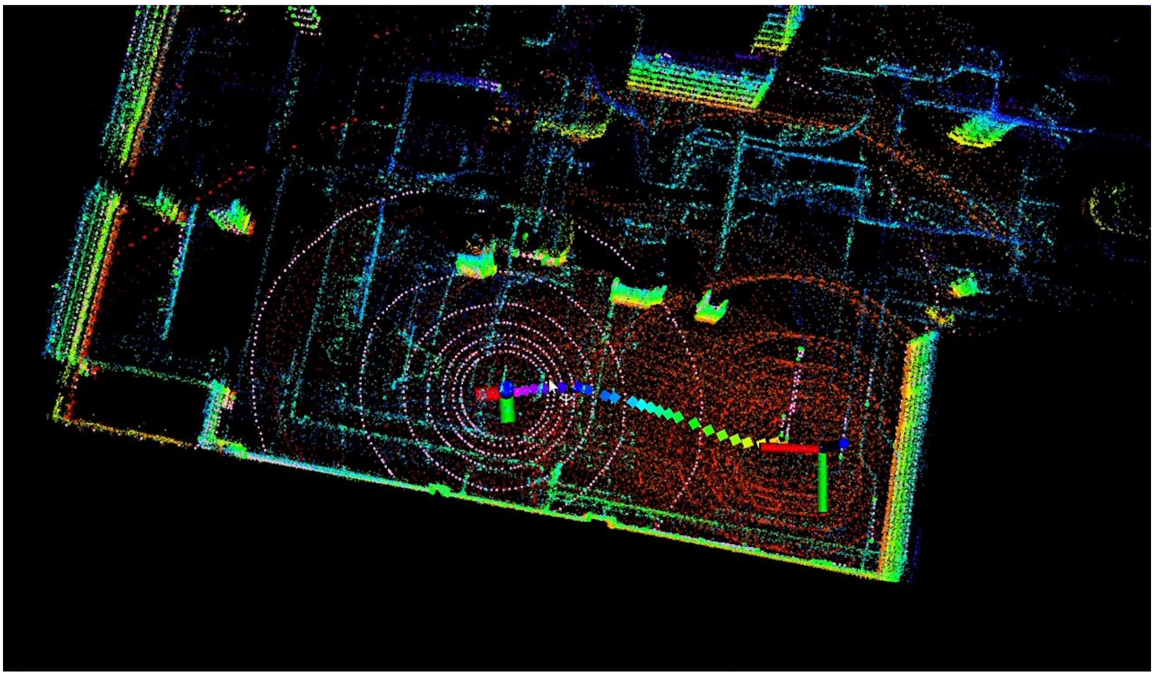
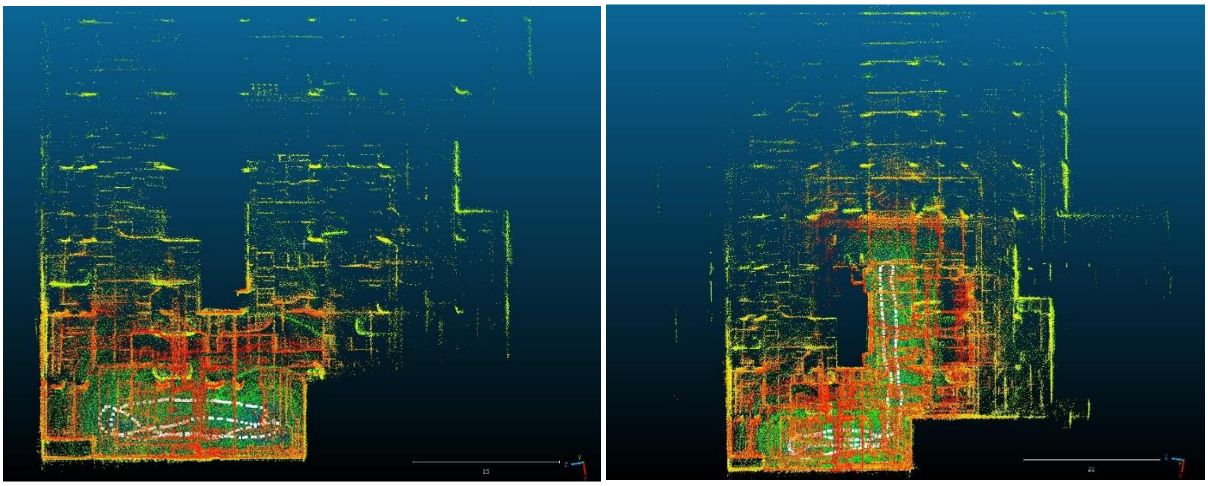


Figure 3. Results of LeGO-LOAM algorithm during operation. Consequent scans from lidar are assembled into a complete map.



(a) (b)

Figure 4. Maps collected by the mobile robot with plotted trajectory from two scannings: (a) short route, (b) long route.

ROS environment provided packages that enabled control and verification over functioning of the implemented solution. Rqt graph, presented in Figure 5, was used as a visualization tool to illustrate nodes and topic functioning across ROS environment and their connectivity. Rqt graph shows crucial components of the system and which information is sent and received by each node.

3.4 Results

The ICP algorithm was applied to align the map from the robot to the reference map. The result was shown in Figure 6. Well-fitted points were marked with blue color. The discrepancy of the remaining points was color-coded using a color scale reaching from green to red. Most of the differences arise from the change to the car's presence and/or location during the reference and SLAM scanning. Additionally, operator station was visible when mapping with the robot. In general, robots often operate in dynamic environments where similar differences would also occur. There were also residues on the edges of walls resulting from the manner of the SLAM algorithm execution that were not taken into account in further scan matching in LeGO-LOAM.

The results of point cloud matching provided 60 percent of fitted points in distances lower than 5 cm and 80 percent of points for less than 10 cm. The findings are influenced by the aforementioned differences between the matched maps. From the LeGO-LOAM result, a sparse optimized map with lower point density and the trajectory in the form of a point were extracted and presented in Figure 4.

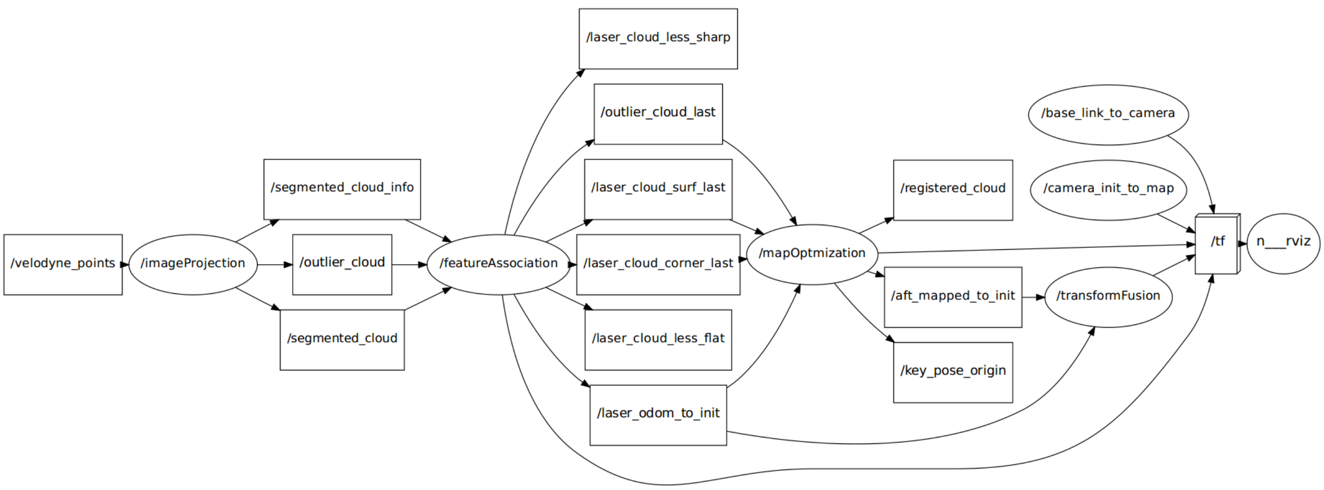


Figure 5. ROS rqt graph showing connectivity between nodes and topics.

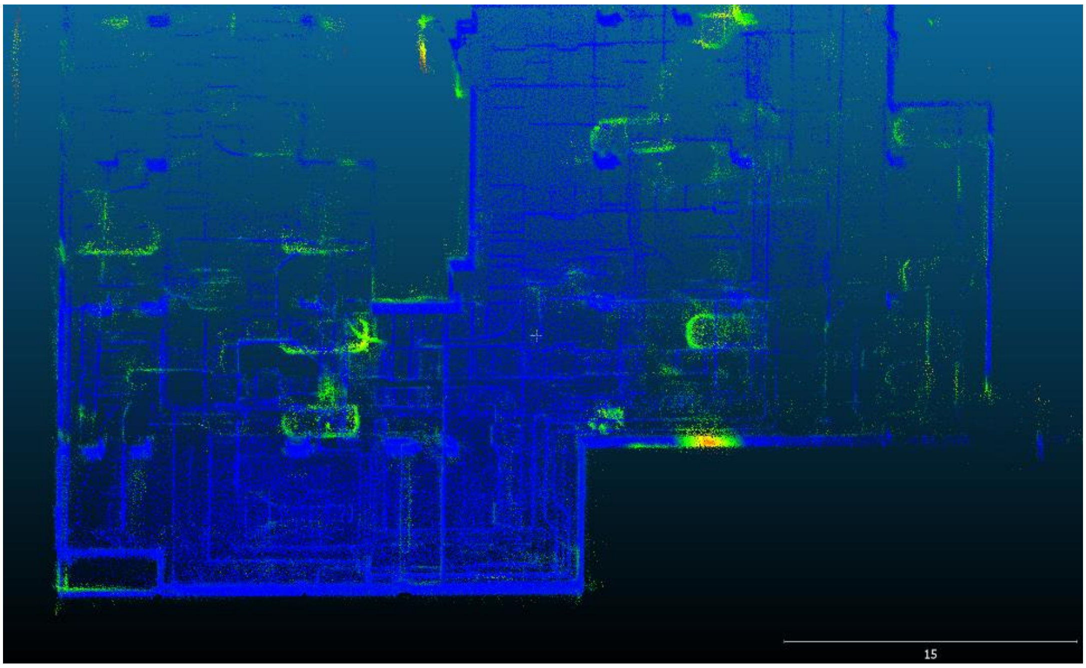


Figure 6. Point cloud matching results. Blue color denotes points that coincide with the reference map. Points marked with different colors, from green to red, show the differences between the two maps. Points with green color stem from smaller discrepancies deriving from the presence of cars and operator station; red color indicates lack of points in the reference map.

4. CONCLUSIONS

Making a comparison and matching the point clouds prove the utility of the one gathered with the LeGO-LOAM algorithm. Even though the sensor mounted on the robot provides lower accuracy than geodetic scanners due to the size reduction of the measuring device and shrinking the acquisition time, it offers satisfying outcomes that represent the environment.

Using a LiDAR with the accuracy of 3 cm yielded 5 cm accuracy of mapping, which shows that the impact of the mapping algorithm worsens accuracy, but not substantially. The map obtained from LeGO-LOAM can be further processed for other tasks and the robot's localization estimated from the map is reliable. Analysed LiDAR-based SLAM method can be applied in a space with poor lightning conditions and implemented in vast, interior areas.

The availability limitations of the empty parking lot influenced the findings. Changing occurrences of the cars between two measurements had an impact on fitted point percentage results in chosen range.

Accurate maps can be further applied for autonomous driving, path planning or semantic segmentation. Future works involving gathering point clouds in an unknown environment can be based on LeGO-LOAM method.

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