Evaluation of LeGO-LOAM: Lightweight and Ground-Optimized LiDAR Odometry and Mapping

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***Abstract*—LeGO-LOAM, a lightweight and ground-optimized LiDAR odometry and mapping method, is able to do six degree-of-freedom pose estimation for real time with ground vehicles [2]. This project will evaluate the LeGO-LOAM which reduced computational expense while keeping similar accuracy compared to LOAM method. The whole LeGO-LOAM system is implemented in Robot Operating System. The data used for evaluation is raw data (with Velodyne LiDAR data and IMU) from KITTI odometry benchmark dataset, KAIST Dataset, and UTBM Dataset. We compared the mapping and odometry results of these data, and analysis the relative motion and mapping error in this report.**

I. Introduction

Great efforts have been made to achieve real-time 6 degree-of-freedom simultaneous localization and mapping (SLAM). Both visual-based methods and LiDAR-based methods are widely used in this field. Compared to visual-based methods, LiDAR-based methods can function independent of the light intensity and provide more detailed information with a higher resolution. In addition, mapping with LiDARs can provide high frequency range measurements where errors are relatively constant irrespective of the distances measured.

LOAM, a low-drift and real-time lidar odometry and mapping method, is proposed in [4] and [5]. LOAM achieves both low-drift and low-computational complexity in real-time. It can do mapping in real time because it matches and registers the point cloud at a lower frequency while performing odometry at a high frequency. LOAM performs point feature to edge/plane scan-matching to find correspondences between scans. Features are extracted by calculating the roughness of a point in its local region. The points with high and low roughness values are selected as edge features and planar features respectively.

LeGO-LOAM: lightweight and ground-optimized lidar odometry and mapping method is proposed by Tixiao Shan and Brendan Englot [2]. In this project, we will evaluate the performance of the LeGO-LOAM and use LOAM as the baseline. The system overview of LeGO-LOAM is shown in Fig. 1. First, a single scan point cloud for segmentation is used and then project it onto the range image for segmentation. Then, the features extracted from the previous module are used to find the transformation associated with the last scan. These features are further processed in the LiDAR map and registered to the global point cloud map. Finally, the transform integral module combines the attitude estimation results of lidar odometry and LiDAR mapping, and outputs the final pose estimate. The Lidar based SLAM technology normally was not advantage in the loop closure detection, such as LOAM. However, in LeGO-LOAM, we are able to perform the loop closure detection by only using Lidar. In addition, LeGO-LOAM could perform a better accuracy for some data and increase the time efficiency .

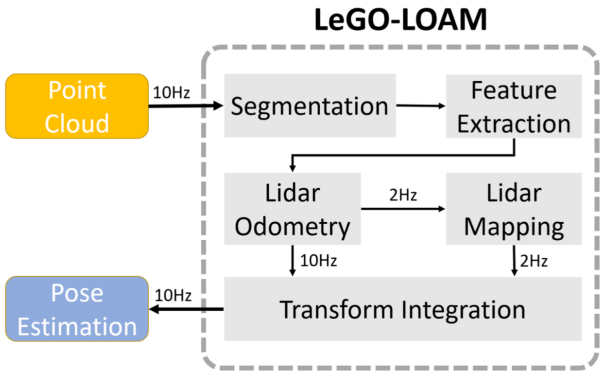


Fig. 1: LeGO-LOAM system overview. First apply point cloud segmentation to filter out noise. Then do feature extraction to obtain distinctive planar and edge features. Lidar Odometry estimates the sensor motion between two scans. Lidar Mapping algorithm takes the projected point cloud from lidar odometry, And transforms the point cloud into map coordinates.

II. Methodology

A. LIDAR Segmentation Step

LiDAR segmentation step improves processing efficiency and feature extraction accuracy. With image projection algorithm and point cloud segmentation method, small objects in a noisy environment is filtered out and ground points are segmented.

1) Image Projection: Point Cloud is first projected onto the range image. The resolution of the projected distance image comes from the horizontal and vertical angular resolution of the LiDAR device. Each valid point in the point cloud is now

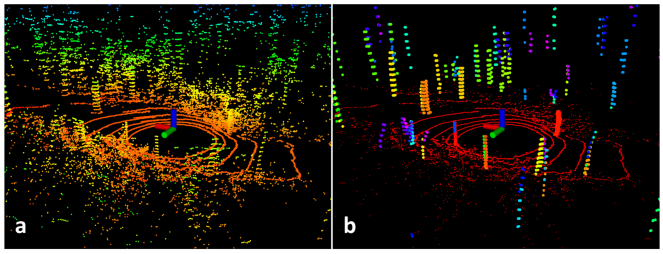


Fig. 2: Visualization of (a) original point cloud and (b) result of point cloud segmentation. The red points are ground points. The other points are other segmented clusters. This segmentation step filtered out small objects in the noisy environment.

represented by a unique pixel in the range image, and the value is the Euclidean distance. A ground plane estimate is performed prior to segmentation. After this process, points that may represent the ground are marked as ground points and not used for segmentation.

2) Point Cloud Segmentation: Point cloud segmentation is performed to discard points that may represent unreliable features after ground separation. This split method is applied to range images to group points into multiple clusters and assign a unique label to each cluster. In order to perform fast and reliable feature extraction using segmented point clouds, we omit clusters of less than 30 points. Applying segmentation to a point cloud can improve processing efficiency and feature extraction accuracy. The visualization of point cloud segmentation is shown in Fig. 2.

B. Algorithm for feature Association

The current position of the robot $(z, roll, pitch)$ could be localized from the ground feature. Similarly to the LOAM[4], we will match the point cloud in each scan to update the position of robot (x, y, yaw).

In this algorithm, we will use GTSAM C++ base which is used for smoothing and mapping in the robotic and computer vision area. Comparing with the g2o (A General Framework for Graph Optimization) which uses sparse matrix to solve nonlinear optimization problems, GTSAM would use factor graphs and Bayes networks to maximize the posterior probability.

There are two parts of this algorithm: 1) Feature point extraction and 2) Feature point matching.

1) Feature point extraction: For the most point cloud $\mathcal{P}_k$ extracted from LiDARs, many 3D LiDARs naturally generate unevenly distributed points in $\mathcal{P}_k$. For this project, we choose the LiDAR with the horizontal and vertical angular resolution of $0.2°$ and $2°$ respectively. The resolution of the projected range image is 1800 by 16. To improve the efficiency and reduce the complicity of calculation, instead of extracting features from raw point clouds, we extract features from ground points and segmented points. Let S be the set of continuous points of p_i from the same row of the range image. Half of the points in S are on either side of p_i. For this project, the magnitude of S would be set as 10. Using the range values

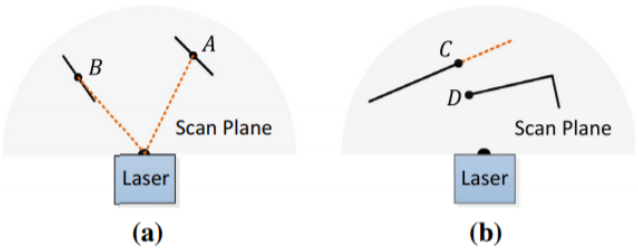


Fig. 3: a) The solid line segments represent local surface patches. The point A is on a surface that has an angle to the laser beam (the orange dot line segment). The point B is on a surface patch that roughly parallel to the laser beam. We decide to treat point B as unreliable laser and do not select since it does not have enough feature information. b) The solid line segments are observable objects by the laser. The point C is on the boundary of an occluded region which is the orange dot line segment. It could be detected as an edge point. However, if LiDAR scan at a different angle, the occluded region can change and be observable. Therefore, we don't choose point D as a salient edge point or select it as a feature point

computed during segmentation, we can evaluate the roughness of point p_i is S,

$$c = \frac{1}{|S| \cdot \|r_i\|} \| \sum_{j \in S, j \neq i} (r_j - r_i) \| \tag{1}$$

In order to evenly extract features from all directions, we will divide the range image horizontally into several equal sub-image based on their roughness c. We will use a threshold c_{th} to distinguish different type of features. The points in a scan are sorted based on the c values, then feature points are selected with the c larger than c_{th} called edge points, and the c smaller then c_{th} called planar features points. Then n_{F_c} edge feature points with maximum c, which do not belong to the ground, are selected from each row in the sub-image. n_{F_p} planar feature points with the minimum c, which may be labeled as either ground or segmented points, are selected in the same way, such as figure 3. From all sub-images, we define F_e and F_p to be the set of all edges and planar features from all sub-images. We then extract n_{F_e} edge features with the maximum c, which does not belong to the ground, such as figure 4.

When selecting the feature point, we need to choose the best point. we need to avoid points whose surrounded points are selected or points on local planar surfaces that are roughly parallel to the laser beams. From Fig.3a, the solid line A and B represent the local planar surface that is parallel to each other. We consider these points are normally unreliable. In addition, we also want to avoid the points which are on the boundary of occluded regions (such as Fig.3b).

In the summary, we would choose the feature points as edge points starting from the maximum c value, and the feature points as planar points starting from the minimum c value.

There are three standards for us to determine the reliability of the points, as follows:

- The number of selected edge points or planar points cannot exceed the maximum of the sub region
- None of its surrounding point is already selected
- It cannot be on a surface patch whose normal is within 10° to the laser beam, or on boundary of an occluded region.

2) Finding feature point correspondence: The odometry algorithm estimates motion of the LiDAR within a sweep. For the time t_k to be the starting time of a sweep k. At the end of sweep k-1, the point cloud perceived during the sweep, $\mathcal{P}_{k-1}$, is projected to time stamp t_k which illustrated in the figure 5. We define the projected point cloud as $\overline{\mathcal{P}}_{k-1}$. During the next sweep k, $\overline{\mathcal{P}}_{k-1}$ is used together with the newly received point cloud, $\mathcal{P}_{k-1}$, to estimate the motion of the LiDAR.

C. LeGO Lidar Odometry Algorithm

The LiDAR odometry module estimates the sensor motion between the two consecutive scans. The transformation between two scans is found by performing point-to-edge and point-to-plane scan-matching. We need to find the corresponding features for the points in the current point cloud and previous point clouds.

In order to improve feature matching efficiency and matching accuracy. In the project, we will make some improvement for the LeGO-LOAM based on LOAM algorithm as shown in Algorithm 1.

1) Label Matching: Since each feature point is labeled after segmentation, we could only find correspondences that have the same label from the points from the previous scan. For planar feature points, only points that are labeled as ground points in the previous point cloud are used for computing correspondence distances. For edge feature points, the corresponding edge line points are found from the previously segmented clusters. This label matching method would improve the matching accuracy by only considering the points with the same category to prevent crossover mistakes. This process could filter out the outliers and accurately locate the potential candidates for computing correspondence distance.

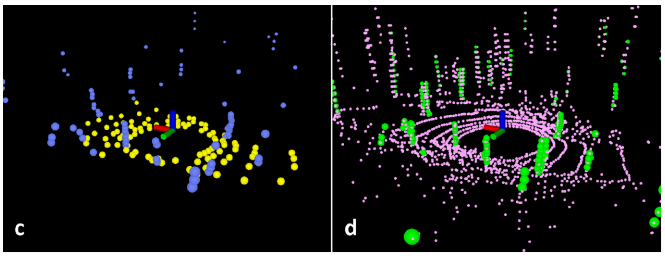


Fig. 4: From the plot (d), the pink point and green point represent the edge and planar feature with out filtering. In (c), the blue point and yellow point represent the number of sharpest and flattest points of edge and planar feature in F_e and F_p

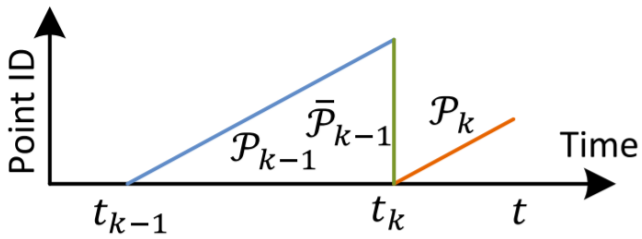


Fig. 5: Project point cloud to the end of a sweep. The blue colored line segment represents the point cloud perceived during sweep k, $\mathcal{P}_{k-1}$. At the end of sweep k-1, $\mathcal{P}_{k-1}$ is projected to time stamp t_k to obtain $\overline{\mathcal{P}}_{k-1}$ (the green colored line segment). Then, during sweep k, $\overline{\mathcal{P}}_{k-1}$ and the newly perceived point cloud $\mathcal{P}_k$ (the orange colored line segment) are used together to estimate the lidar motion (Color figure online)

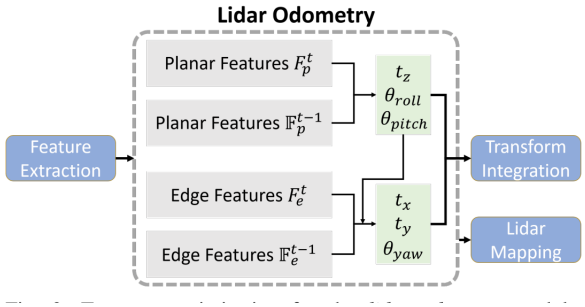


Fig. 6: Two-step optimization for LeGO LiDAR odometry. $[t_z, \theta_{roll}, \theta_{pitch}]$ is first obtained and optimized by matching the planar features extracted from ground points. $[t_x, t_y, \theta_{yaw}]$ are then estimated using the extracted edge features while considering other states as constraints.

2) Two-step L-M Optimization: In LOAM, the distances between the edge and planar feature points from the current scan and the corresponding feature points from the previous scan are computed respectively as equation (2) and (3). $\overline{X}$ denotes the edge or planar feature points in one scan. $\widetilde{X}$ denotes the edge or planar feature points in the consecutive scan. (j, l) describes the correspondences for edge feature points, and (j, l, m) describes the correspondences for planar feature points. Then the distances for the edge and planar feature points are compiled into a single distance vector as a nonlinear equation (4), which could be optimized by the Levenberg-Marquardt method as equation (5) by minimizing d toward zero, where J is the Jacobian matrix of the nonlinear function f.

$$d_{\varepsilon} = \frac{|(\widetilde{X}_{k+1,i} - \overline{X}_{k,j}) \times (\widetilde{X}_{k+1,i} - \overline{X}_{k,l})|}{|\widetilde{X}_{k,j} - \overline{X}_{k,l}|} \tag{2}$$

$$d_{\mathcal{H}} = \frac{|(\widetilde{X}_{k+1,i} - \overline{X}_{k,j})(\overline{X}_{k,j} - \overline{X}_{k,l}) \times (\overline{X}_{k,j} - \overline{X}_{k,m})|}{|(\overline{X}_{k,j} - \overline{X}_{k,l}) \times (\overline{X}_{k,j} - \overline{X}_{k,m})|} \tag{3}$$

Algorithm 1 LeGO Feature Extraction and Lidar Odometry

input: Segmented Point Clouds from last scan $\overline{P}k$ with EDGE and PLANAR labels and from current scan P_{k+1}; Pose transformation T_{k+1} P
output: $\overline{P}_{k+1}$; optimized T_{k+1}
if at the beginning of the sweep **then**
  $T_{k+1} \leftarrow 0$
end if
Find edge and planar feature points in P_{k+1} and store as ε_{k+1} and $\mathcal{H}_{k+1}$
for $i \leq MaxIteration$ **do**
  for $\forall$ point $\in \mathcal{H}_{k+1}$ **do**
    find correspondences with PLANAR labelled points and compute distances as equation (3)
  end for
  Update $[t_z, \theta_{roll}, \theta_{pitch}]$ by performing L-M Optimization
  for $\forall$ point $\in \varepsilon_{k+1}$ **do**
    find correspondences with EDGE labelled points and compute distances as equation (2)
  end for
  Update $[t_x, t_y, \theta_{yaw}]$ by performing L-M Optimization with $[t_z, \theta_{roll}, \theta_{pitch}]$ as constraints, get T_{k+1}.
  if at the end of the sweep **then**
    Project P_{k+1} and get $\overline{P}_{k+1}$
    return $T_{k+1}, \overline{P}_{k+1}$
  else
    return T_{k+1}
  end if
end for

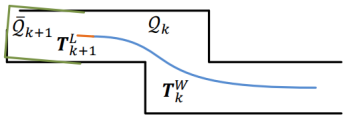


Fig. 7: Mapping Process

$$f(T_{k+1}) = d \tag{4}$$

$$T_{k+1} = T_{k+1} - (J^T J + \lambda diag(J^T J))^{-1} J^T d \tag{5}$$

However, this method is computationally intensive because all six states are considered together. LeGO-LOAM proposed a two-step L-M Optimization as shown in Figure 6. The optimal pose transformation T is found in two steps: First, $[t_z, \theta_{roll}, \theta_{pitch}]$ are estimated by matching the planar features and their correspondences in the previous scan. Second, $[t_x, t_y, \theta_{yaw}]$ are then estimated using the edge features and their correspondences in the previous scan while applying $[t_z, \theta_{roll}, \theta_{pitch}]$ as constraints. Therefore, LeGO-LOAM reduces the 6D transformation optimization process to two steps of 3D optimization process, which is much more efficient than LOAM and similar accuracy can be maintained.

D. LeGO-LiDAR Mapping Algorithm

1) Mapping: It can be recalled that the LiDAR mapping algorithm runs at a lower frequency than the Lidar odometry. LiDAR mapping algorithm take the outputs of Lidar odometry (LiDAR pose transformation T_{k+1}, and reprojected the point cloud $\overline{P}_{k+1}$) at the end of sweep $k+1$. The mapping algorithm then matches $\overline{P}_{k+1}$ from Lidar coordinates to world coordinates, as shown in Figure 7. $\mathcal{Q}_k$ are the current point cloud on the map, T^W_k is the Lidar pose transformation and the end of sweep k. The mapping algorithm extends T^W_k for one more step T^W_{k+1} as shown in Figure 8.

To extract the feature points on the map, the process is the same as Section II-B1. To find the correspondences between the current map cloud and $\overline{Q}_{k+1}$, instead of those points in a 10m cube region in Q_k that intersect with $\overline{Q}_{k+1}$ being extracted in LOAM, points in a 100m cube region in the history of key frame point clouds are extracted. A covariance matrix, and its eigenvalues and eigenvectors of surrounding points could be computed. If the points are distributed on an edge line, one eigenvalue would be significantly greater than others; if the points are distributed on a planar patch, one eigenvalue would be significantly smaller than others.

2) Loop Closure: Another main difference between LeGO-LOAM and LOAM is that it has the ability to detect loop closure. Loop closure detection runs at a lower frequency and is feature-pose based. Since the history of the keyframe point clouds is stored, it grants the algorithm to perform loop closure and better mapping. The detection returns true if two point cloud frames are separated by time duration, within the searching region, and edge and planar feature points are close to each other.

3) Transform Integration: Integration of the pose transforms is demonstrated in Figure 8. The blue region represents the pose transformation output from LiDAR mapping algorithm generated once per sweep at a lower frequency. The orange region represents the transform output from the Lidar odometry algorithm at a higher frequency. The LiDAR pose transformation in the world coordinates is computed by combining two transformations at the same frequency as the LiDAR odometry.

III. Results

Both LOAM and LeGO-LOAM are operating in Robot Operating System (ROS). The data used for evaluation is raw data (with Velodyne LiDAR data and IMU) from KITTI, KAIST dataset [1], and UTBM dataset [3]. We evaluated both LOAM and LeGO-LOAM on KITTI, LOAM on KAIST, and LeGO-LOAM on UTBM.

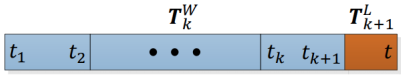


Fig. 8: Illustration of Transformation Integration

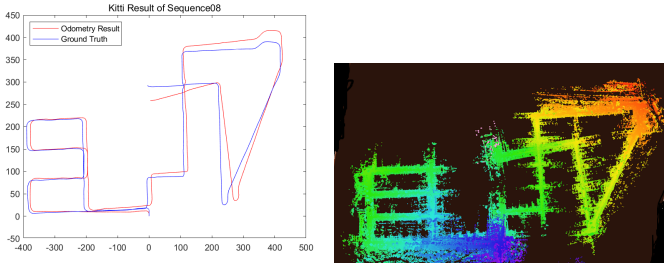
A. KITTI Sequence Data Test

1) Odometry Result of LeGO-LOAM: We perform the quantitative test on LeGO-LOAM by using the Kitti dataset. With difference sequences from the Kitti dataset, we could compare the odometry with the ground truth.

To evaluate the performance of odometry, the predicted pose published by *TransformFusion* are printed in the terminal and saved into a .txt file, while the ground truth data are provided by KITTI dataset.

Then, the odometry results of Kitti data sequence 08 and 00 are shown in Fig. 9 and 10, respectively. The figures and the error calculation are operated in a MATLAB file. As the figures show, the odometry result is very similar to the ground truth, with only a small drift.

Video of LeGO-LOAM on Kitti sequence 00 and sequence 08 are available at youtu.be/z3yXCRAMC18, and youtu.be/nJ74Uk6m10U.



(a) LeGO-LOAM Odometry compared with ground truth (b) LeGO-LOAM Mapping result

Fig. 9: The (a) Odometry and (b) Mapping result for LeGO-LOAM in Kitti sequence 08.

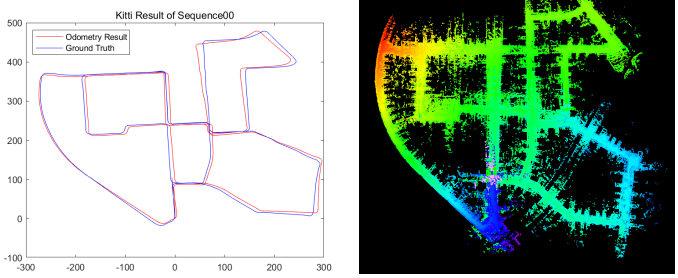
To evaluate the odometry result, the position error is defined in Eq. 6:

$$e_t = \sqrt{(x_t - x_t^{GT})^2 + (y_t - y_t^{GT})^2 + (z_t - z_t^{GT})^2} \quad (6)$$

where (x_t, y_t, z_t) and $(x_t^{GT}, y_t^{GT}, z_t^{GT})$ are the LeGO-LOAM evaluation and ground truth pose at time t. The position error for Sequence 05, 00, and 08 are shown in Fig. 11 (a)-(c), respectively. The average position error is 6.41 m, 7.3 m and 18.68 m for Sequence 05, 00, and 08, respectively, which is quite satisfying when compared with the field size of around 400 m $\times$ 400 m.

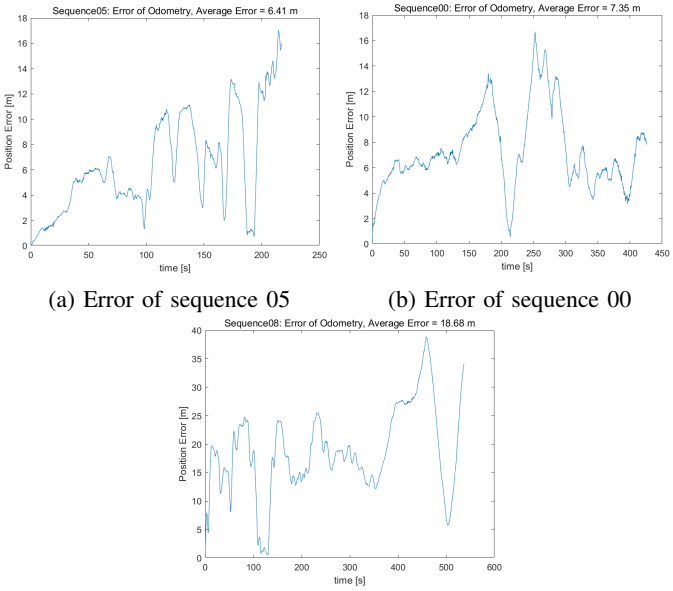
The position error for Sequence 00 is larger than that of Sequence 05. It agrees with the theory since its reason is that Sequence 00 has a more sharp turn. The sharp turn breaks the assumption that there is no drift over a short period of time for the transform integration step. In Sequence 08, there are even sharper and more corners in the trajectory, and, thus, the position error is even much higher than that of Sequence 00.

In addition, for Sequence 00, the position error significantly decreases at time 220s, which corresponds to the road between (0m, 20m) and (0m, 30m). This is a loop closure, so it is reasonable that the odometry error drops significantly.



(a) LeGO-LOAM Odometry compared with ground truth (b) LeGO-LOAM Mapping result

Fig. 10: The (a) Odometry and (b) Mapping result for LeGO-LOAM in Kitti sequence 00. Loop closure property is observed at the trajectory between around (0m, 20m) and (0m and 30m).



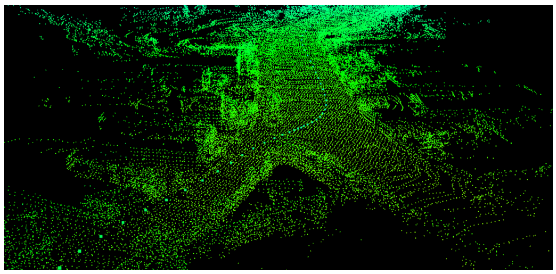
(a) Error of sequence 05 (b) Error of sequence 00

(c) Error of sequence 08

Fig. 11: LeGO-LOAM Odometry position error for (a) Kitti Sequence 05 (b) Kitti Sequence 00, and (c) Kitti Sequence 08 of KITTI. In (a), the error increases at each turning corner in the trajectory. In (b), the error drops significantly at time around $t = 220$s since there is a loop closure. (c) has the highest error since it has more and sharper corners in the trajectory.

2) Mapping Result: The mapping results for KITTI data of sequence 00 are shown in figure 10(b). The darker the color is, the altitude (z) is smaller, which has been verified by the ground truth data. The overall mapping quality is satisfying. For example, Fig. 12 shows a comparison of a scene in the data set. While the mapping result clearly shows the outline of the Y-type crossroad and the surrounding building, while details of objects are lost. It is acceptable because it is a trade-off between the efficiency of the algorithm and details of mapping.

3) Comparison with LOAM: In order to evaluate the different performance of LOAM and LeGO-LOAM, we choose



(a)

(b)

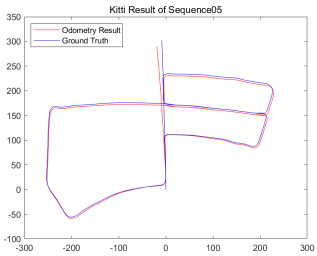
Fig. 12: (a) Mapping result (b) camera data for a scene in KITTI data are shown. The mapping result clearly shows the outline of the Y-type crossing and the surrounding building, while details of objects are lost.

Iteration time[ms]	LeGO-LOAM	LOAM
Map time	70.0	207.8
Odometry time	104.0	114.0
Scan time	103.9	113.9
Transform time	N/A	113.8
Feature time	104.0	N/A

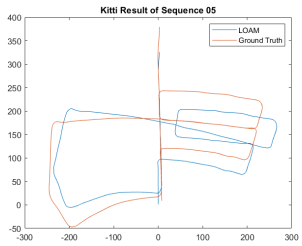
TABLE I: Iteration time comparison for Kitti sequence 05

sequence 05 from Kitti data set to compare the odometry and matching result. We first test the LeGO-LOAM in this environment. From Fig. 13 (a), we can see that the odometry of the LeGO-LOAM matches very well with the ground truth. However, for the LOAM in Fig. 13 (b), there is a drift of about 20 degree compared with the ground truth. From Fig. 14, it proves that LeGO-LOAM has a much better performance on the odometry that it only has 10% error rate than the LOAM. In addition, from Fig. 13 (d), for the LOAM algorithm, there are a lot of noise points around the road which appears as the purple points. Without point cloud segmentation, the unreliable edge and planar features would be extract from the data set. The LeGO-LOAM has a better performance since it successfully maps the whole area without the influence of noise objects such as trees and grass.

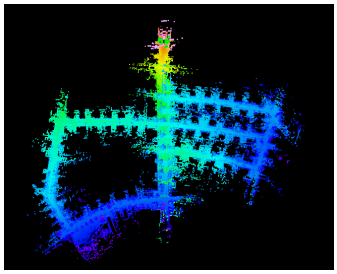
4) Iteration time comparison: The result of iteration time is shown in Table I. We run tests on LeGO-LOAM and LOAM by using KITTI dataset 05 on the same computer. Both of the data run in 10% running time. For LeGo-LOAM and LOAM, they both contain 4 modules. Since LeGO-LOAM uses the two-step L-M optimization method, the running time of each iteration was reduced at least 10% for each module and for the map time. Especially, The run time of mapping is reduced by more than 60% when LeGO-LOAM is used.



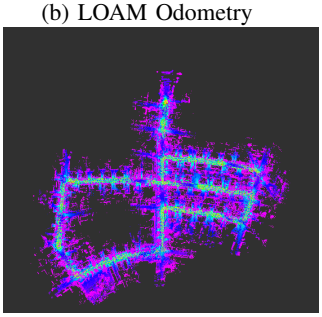
(a) LeGO-LOAM Odometry



(b) LOAM Odometry

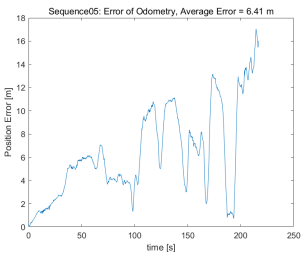


(c) LeGO-LOAM Mapping

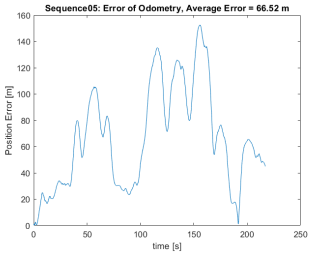


(d) LOAM Mapping

Fig. 13: Compariing odometry result of (a) LeGO-LOAM and ground truth, (b) LOAM and ground truth, and Mapping result for (c) LeGO-LOAM and (d) LOAM of KITTI Sequence 05. LeGO-LOAM has a much better performance on the odometry and mapping.



(a) LeGO-LOAM



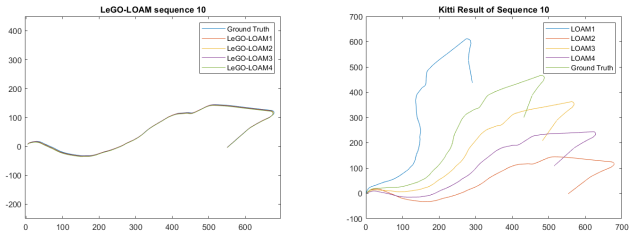
(b) LOAM

Fig. 14: Odometry position error for sequence 05 of Kitti data set(a) LeGO-LOAM , (b)LOAM

5) Accuracy comparison: In order to test the accuracy of LeGO-LOAM and LOAM algorithm. We run the test in KITTI dataset sequence 10 in 10% run time for four times. Fig. 15 (b) shows when the LOAM is applied in this dataset, there is a rotational error around 22 degree for each time and the relative translational error is more than 30m by calculation, which is much larger than around 10 m error for LeGO-LOAM. When LeGO-LOAM is applied to the dataset, as Fig. 15 (a), the transnational and rotational errors are much smaller and all of the results match the ground truth very better.

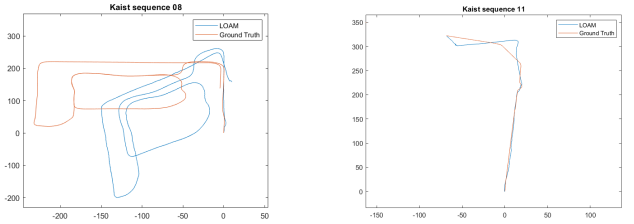
B. KAIST Urban Dataset

We also tested LeGO-LOAM and LOAM algorithm on KAIST data set. This data set provides LiDAR and stereo images with various position sensors targeting at a highly complex urban environment. For KAIST data set, it has right



(a) LeGO-LOAM (b) LOAM

Fig. 15: Path produced by LeGO-LOAM and LOAM for 4 trials at KITTI data sequence 10



(a) LOAM with KAIST urban 08 (b) LOAM with KAIST urban 11

Fig. 16: Odometry result for KAIST dataset urban 08 and 11 by using LOAM

and left LiDARs, and we use the left one of them to test the performance. We tried serval ways for LeGO-LOAM. However, due to the synchronization issue of time in ROS, LeGO-LOAM was not able to output the odometry data and failed to run KAIST. However, from LOAM, we can still analysis its characterise of odometry tracking.

1) Odometry Result: From the previous test, we found that the odometry for the LOAM algorithm has a large degree of drift and a poor performance on loop closure. We decided to verify it by testing on KAIST data set. From Fig. 16, by comparing the translational and rotational difference between the final pose and the initial pose, we can see that LOAM was only able to match the ground truth for the KAIST data when the map has few turns for the robot. On Fig. 16 (a), it proves that LOAM algorithm was not able to perform on loop closure. The test on the KAIST prove the limitation we found on Kitti data set.

C. EU Long-term Dataset with Multiple Sensors for Autonomous Driving (UTBM) [3]

To evaluate the performance of LeGO-LOAM on long-term and roundabout trajectory, we also test the algorithm on the UTBM data set. UTBM is a newly released data (at 2018) which provides a suburb (for roundabout data) of Montbeliard in France. The vehicle speed was limited by the local traffic rules. The roundabout data we use is about 4.2 km and contain 10 roundabouts with various sizes. The time of the recorded data is about 12 minutes.

1) Odometry Result: To analyze the UTBM data, we installed multiple message packages to output the robot pose. From Fig. 17, (a) provides a comparison of between the odometry result and the ground truth. It shows that the LeGO-LOAM is not able to match the ground truth correctly when roundabout exists.

From Fig. 17 (b), by running the program multiple times, even LeGO-LOAM could perform loop closure, we found that there exists a large drift of the odometry comparing with the last result. The roundabout trajectory test result indicates that the LeGO-LOAM would not perform well on odometry matching for the roundabout map. While the translational error is not large (around 20 m), the rotational error is significantly large around the roundabout. The special character of roundabout map would influence the tracking result and limit the function of loop closure.

Meanwhile, it is observed that the evaluation results are not the same for different trials. The reasons are the following: the assumption for no drift over a short period is not held and it is broken at different time stamps for different trials, the effect of drift, thus, is different for different trials; only edge and plane information are not sufficient for stable performance for data association and loop closure in a complicated environment.

2) Mapping Result: We compare the mapping result from both the side view, Fig. 18 (a), and the top view, Fig. 18 (b). The UTBM roundabout map provides an aggressive test to challenge the mapping ability of the algorithm. From the side view, the LeGO-LOAM successfully captures the side trees and road feature. It also successfully labels the elevation of the whole area. However, there is still unclear area during the roundabout location. From the left corner of the Fig. 18 (b), there are only edge features on the one-side of roundabout area. This proves that the roundabout feature still influences the mapping ability of LeGO-LOAM. The algorithm would filter out some useful points as noise and influence the accuracy of mapping result.

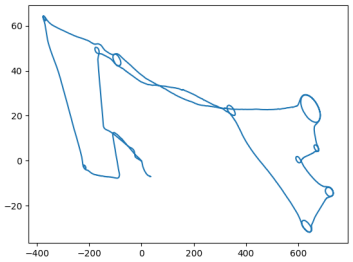
IV. Challenges

While evaluating the algorithm, we found there are a few challenges exist for the Lego-algorithm.

The first challenge occurs when we run the KITTI data set. When the vehicle drives at crossroads, the algorithm would return a wrong transformation where there is a shift exist for the mapping. This behavior appears at sharp turns also. We believe this happened because of the wrong transformations that if IMU data is not aligned with the Velodyne axis. After the test, for the data set without using IMU, it indeed performs much less drift but still unable to eliminate the drift. In the next step, the team would try to re-calibrate the IMU data and try to solve this issue.

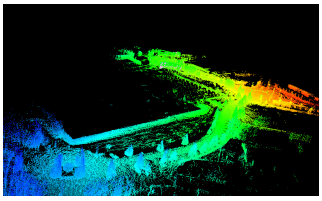
Another challenge is that although LeGO-LOAM is a high-efficiency algorithm, it only has 10 Hz for the point cloud and pose estimation. Considering that the data within one minute is around 4 GB, the algorithm is of high demanding for the processor when implemented on board. This issue would limit the reliability of a single scan and may lose information for a fast speed vehicle.

(a) LeGO-LOAM Trail 1

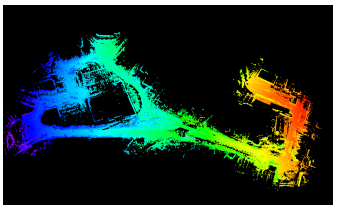


(b) LeGO-LOAM Trail2

Fig. 17: Odometry result for UTBM dataset: roundabout 20190418 by using LeGO-LOAM



(a) LeGO-LOAM side



(b) LeGO-LOAM top

Fig. 18: Mapping result for UTBM dataset: roundabout 20190418 by using LeGO-LOAM

Furthermore, the algorithm does not distinguish between moving and static objects. When the features on a moving object are taken for localization, the performance of the algorithm is negatively affected. It is part of the reason for the error in odometry estimation. It also explains why the loop closure does not improve the odometry estimation sometimes.

In addition, understanding and debugging for the whole system framework and different datasets in ROS is challenging for us. The delay and asynchronous communication between nodes affected the performance of the algorithm. For example, it is observed that the odometry result for the same data input is not completely identical on different computers and different trials.

V. Conclusion

LeGO-LOAM efficiently and accurately utilizes LiDAR point cloud data for SLAM problem. It takes point cloud data as input and outputs the 6-DOF pose for odometry and mapping. The odometry and the mapping results verified the performance of LeGO-LOAM and are consistent with the theory of LeGO-LOAM.

LeGO-LOAM involves segmentation, feature extraction, LiDAR odometry, LiDAR mapping, and transformation integration steps. Compared with typical LOAM algorithm, LeGO-LOAM is more computationally efficient. It extracts two kinds of features, plane, and edge, based the criterion of smoothness from point cloud data, and significantly reduces the amount of data for the association. The computation for matching of selected feature points is further reduced since the matching is operated only with groups of features with the same label. Then, a two-step L-M optimization efficiently estimates $(t_x, \theta_{roll}, \theta_{pitch})$ from plane features first, and (t_y, t_z, θ_{yaw}) from edge features next for LiDAR odometry. Finally, mapping is operated at a lower frequency and integrated with odometry result. In addition, the ability to detect loop closure enables LeGO-LOAM to do long distance mapping and odometry.

The evaluation result on KITTI data set illustrates that position estimation error for odometry is acceptable (around 10 m) and that mapping result can provide concise but adequate information of the environment. By comparing with LOAM, LeGO-LOAM provides a better accuracy on mapping and odometry tracking (both rotational and translational), and more efficient since filtering the unreliable point cloud. It is also observed that the loop closure reduces the error in odometry for LeGO-LOAM, and LOAM does not have loop closure ability. However, when the drift is large within a short time (such as sharp turn), the performance of LeGO-LOAM is negatively affected. In addition, from the test on UTBM, LeGO-LOAM also have a limited mapping and tracking ability for the roundabout trajectory.

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