Fine-registered Object LiDAR-inertial Odometry for a Solid-state LiDAR system

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Abstract

We propose the LiDAR-inertial odometry with object measurements for the solid-state LiDAR system with narrow field-of-view. Although the geometric feature has been used for the precise localization with LiDAR, the measurement vanishing can lead to the localization failure in the limited field-of-view. To address this problem, objects that are sufficiently present in a man-made environment can be used as localization measurements, but accurate registration is needed to formulate them due to partial observations. The point clouds in the object are registered and the processed measurements are coupled with the geometric measurements in the estimator. The effectiveness of the object measurements is verified through a virtual environment simulator, and the proposed algorithm shows superior localization performance compared to the case of geometric measurement alone.

Keywords: Localization, LiDAR-inertial odometry, semantic perception, point cloud registration

1. Introduction

LiDAR has superior performance in sensing the spatial information from the environment with the accurate distance measurements from ray-casting and is used in many applications such as object perception, tracking, and localization based on map-matching or odometry. Especially in the field of localization, a framework for pose estimation with whole point cloud data has been developed, which is represented by iterative closest point (ICP) and its variants [1]. On the other hand, in the last decade, the use of 3D LiDAR has led to the demand for lightweight computation and mapping, and has been used as a necessary block in the task of simultaneous localization and mapping (SLAM). To meet the above two conditions, an effective and efficient approach to extract and match feature points based on geometric information among the entire point cloud was proposed, called LiDAR odometry and mapping (LOAM) [2]. It provided a breakthrough in LiDAR localization in terms of a real-time operation and accuracy. Since then, LOAM-based LiDAR localization studies have been proposed, and in particular, tight coupling with IMU has been studied for robust application in real-world problems [3]. This has led to significant performance improvements such as mitigating the distortion problem of point clouds due to motion, robust association between features, and accurate initialization of estimators from inertial navigation system (INS).

Although LiDAR can be used as a useful sensor for robotic systems, the inherently complex structure of spinning LiDAR leads to high prices. Therefore, solid-state LiDAR with simple structures are being developed for commercialization. However, solid-state LiDAR has a narrow field of view (FoV), which introduces measurement vanishing into currently existing geometric LiDAR localization algorithms. This does not provide sufficient constraints on the estimated state variables and leads to pose drift and divergence. To address this issue, we propose an approach that additionally uses object measurements in addition to geometric measurements. Object measurements can be effectively obtained and utilized for LiDAR systems that are typically operated in man-made environments.

Recently, object perception has been the main agenda in robotics and computer vision with rapid performance improvement. Autonomous systems require high-level perception as an essential building block for manipulation, exploration, and autonomous driving. In LiDAR systems, data-driven object detectors provide an object bounding box (Bbox) [4] that can be utilized to formulate object measurements. However, LiDAR measurements have a measurement characteristic called L-shape, and there are inevitably unobserved parts of the object. These parts are implicitly estimated based on a prior model within the trained neural network, which cannot provide accurate information about each observed object. To tackle this problem, we aim to perform precise registration by utilizing the point cloud inside the obtained object, and the obtained relative pose is used as a measurement for the localization algorithm. In addition, the obtained object measurements also provide semantic information, which can play an important role in autonomous systems.

2. LiDAR localization with object feature

Geometric feature-based LiDAR-inertial odometry (LIO) starts by using both planes and edges as measurements, but plane features are dominant with robustness to data association in the current. In our algorithm, we also construct a plane-based LIO that combines geometric and statistical information to extract the plane and perform data association.

The obtained plane measurements are processed in an Extended Kalman filter with sliding window to take the advantage of the fixed-lag smoother. The state to be estimated has the form of an error state variable as

$$\delta x = \left[\delta\theta^T\ \delta p^T\ \delta v^T\ \delta b_a^T\ \delta b_g^T\ \delta\theta_1^T\ \delta p_1^T, \dots, \delta\theta_N^T, \delta p_N^T\ \right]^T. \quad (1)$$

Each element is, in order, an error representation of the attitude, position, velocity, accelerometer bias, gyro bias, and attitude and position at the current point in time. N is the size of the sliding window. The system model for the state variables is as follows.

$$\dot{\delta x} = F\delta x + \omega. \quad (2)$$

F is the Jacobian of the state transition model and ω is the process noise. In our system, this is done by the IMU. Accordingly, the equation for the discretized covariance propagation is expressed as

$$P_k = \Phi P_{k-1}\Phi^T + Q. \quad (3)$$

P_k and P_{k-1} are the covariances at time k and $k-1$, Φ is F discretized through integration, and Q is the covariance of discretized ω. The measure model is then as follows.

$$z_k = Hx_k + v. \quad (4)$$

z_k is the measurement obtained via lidar, which in our system includes geometric and object measurements. H is the Jacobian of the measurement model and v is the measurement noise. The Kalman gain is

$$K = PH^T(HPH^T + R)^{-1}. \quad (5)$$

The measurement update equation about state is shown below.

$$\delta x = K\big(z - h(\hat{x})\big). \quad (6)$$

$h(\hat{x})$ is the nonlinear mapping function from state to measurement. The covariance is updated as follows.

$$P^+ = (I - KH)P^-(I - KH)^\mathrm{T} + KRK^T \quad (7)$$

P^+ and P^- mean posteriori covariance and priori covariance, respectively. The object measurement used in Eq. (4) is obtained by ICP and is the solution of the optimization problem in (8).

$$(\mathrm{R}, \mathrm{t})^* = \arg\min_{(R,t)} \Sigma\|p_i - (Rq_i + t)\|. \quad (8)$$

p_i and q_i are the i-th pair of points in point sets that are associated by distance.

3. Results

To validate the localization performance of the proposed algorithm, the sensor data is corrected in CARLA, a virtual environment simulator based on the Unreal engine. The virtual environment used in the simulation is shown in Figure 1. In the configured virtual environment, a solid-state LiDAR with a FoV of 45 degrees and an IMU are attached to the ego-vehicle, and an example of the point cloud data obtained is shown in Figure 2. Considering the MEMS IMU performance, the accelerometer error and gyroscope error are introduced into the raw data, respectively. The sensor specifications are listed in Table 1. For object measurements, semantic

Figure 1. The virtual environment in simulator.

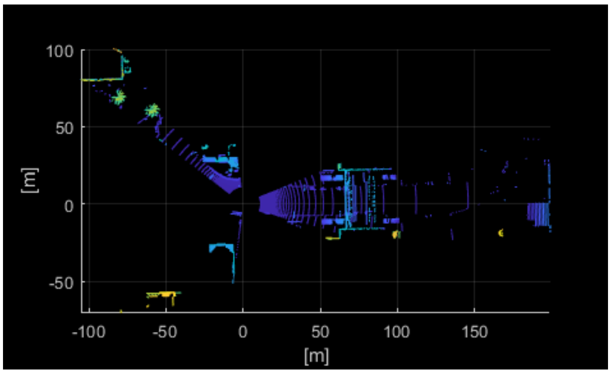

Figure 2. The example of a point cloud data

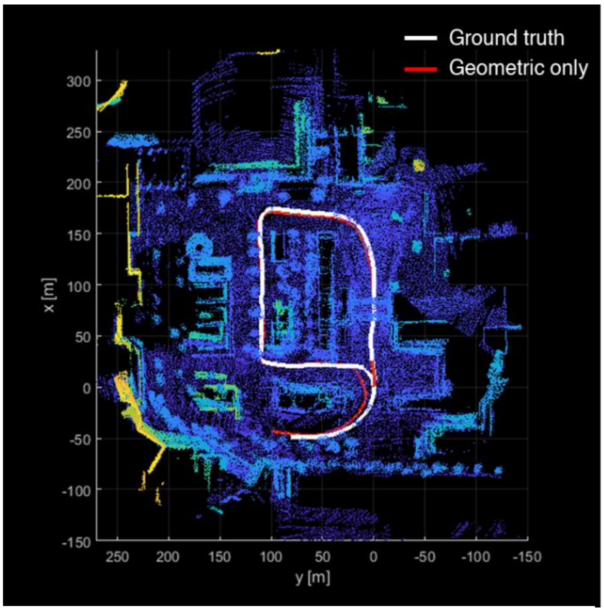

Figure 3. The trajectory of geometric only LIO

labels provided by CARLA [5] are used, and a static vehicle is formulated as a measurement.

The sliding window size of the estimator is set to 10, and the maximum iteration number of ICP is set to 20. To use stable object measurements, convergence is determined by the final loss value of ICP, and outliers are removed by Mahalanobis distance with the covariance of the measurements obtained by the estimator. For comparison, LIO using only geometric measures is used.

Table 1. IMU specification.

	Accelerometer	Gyroscope
Noise density	$0.14\mathrm{mg}/\sqrt{Hz}$	$0.0035°/s/\sqrt{Hz}$
Turn-on bias	0.005g	$0.2°/s$

The vehicle moves the virtual map under these conditions, and the estimated trajectories from the proposed method and the compared method are shown in Figure 3 and Figure 4, respectively. The proposed result is closer to the true trajectory compared to the comparison using only geometric measurements. This indicates that when geometric measurements are lost due to the narrow FoV of solid-state LiDAR in certain segments, object measurements can lead to a robust navigation estimate. Finally, the quantitative error of the two results is presented in Table 2 using the root-mean-square-error (RMSE) metric, and it can be seen that the estimation error is also superior using the proposed object measurements.

Table 2. Position RMSE results

Position	Geometric only	Proposed
RMSE [m]	7.2702	**5.9435**

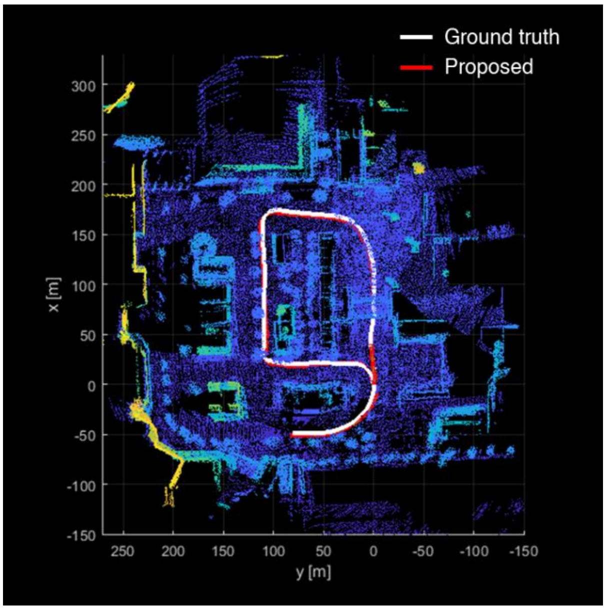

Figure 4. The trajectory of proposed LIO

4. Conclusion

We have proposed the LIO algorithm with object measurement to address the geometric measurement vanishing due to the narrow FoV of a solid-state LiDAR. Observed objects are fine-registered by ICP to formulate relative pose measurements, which are coupled with geometric measurements to update the measurements of the EKF. The proposed algorithm has been validated using a sensor dataset obtained in a virtual urban environment, and an improved localization error is presented compared to the case using geometric measurements alone. The proposed algorithm can be developed into a precise localization algorithm by mapping with object state and loop closure.

Acknowledgment

This research was supported by the National Research Foundation of Korea funded by the Ministry of Science and ICT, the Republic of Korea, under Grant NRF-2022R1A2C2012166.

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