Supplementary Material
GRIL-Calib: Targetless Ground Robot IMU-LiDAR Extrinsic Calibration Method using Ground Plane Motion Constraints

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A. Extrinsic Calibration Performance on the Real-World Scenario

To demonstrate the robustness of our algorithm in real-world scenarios, we experiment with a custom dataset. We use a Velodyne VLP-16 and a Microstain 3DM-GX5-AHRS to acquire a custom dataset, which is described in detail in Fig. 1. In the additional experiment, we utilized CAD assembly drawings provided by Hurim Robot, the manufacturer of the ground robot, as the ground truth (GT) for calibration. We set the initial values of the calibration parameters to $\mathbf{R}_L^I = (-5.0, -5.0, 5.0)$ with the unit in degrees. The initial translation parameters $\mathbf{p}_L^I = (0.6, 0.45, 0.6)$. We initialized all remaining state vectors $\mathbf{t}_f, \mathbf{b}_g, \mathbf{b}_a$ to zeros.

In addition, to experiment with the various ground environments that can be faced in the real world. We additionally conducted experiments on a *Forest 01* sequence acquired from the TIERS lidars dataset [1] which has rough terrain. We utilize the Ouster OS1-64 LiDAR and the ICM 20948 IMU (Built-in IMU). For ground truth, we utilize parameters provided in the Ouster OS1-64's datasheet. For the initial values, $\mathbf{R}_L^I = (-5.0, -5.0, 5.0)$ and set $\mathbf{p}_L^I = (0.0, 0.0, 0.0)$. All remaining state vectors are also zeros. During the experiment, the trajectory produced by our proposed algorithm in *Forest 01* is shown in Fig 2.

The results for *Yonsei 01* are similar to results seen with other public datasets, as table I illustrates. It performs well in comparison to other algorithms since it satisfies the premise that the ground is flat. On the other hand, in the case of *Forest 01*, which was experimented on rough terrain, the rough ground affects the LiDAR ground segmentation results and degrades the performance of the proposed algorithm.

B. Application to IMU-LiDAR Fusion System

We compare the competing extrinsic calibration methods by applying the respective results to IMU-LiDAR fusion system and evaluating the corresponding odometry accuracy. In the experiment, we utilize Faster-LIO [6] as the IMU-LiDAR fusion system. The extrinsic parameters resulting from the M2DGR experiment were used as averages. The experiment uses the *hall 02* sequence since the sequence was not used in M2DGR experiment. The Absolute Pose Error (APE) is depicted from different calibration methods in Fig 3. We observe that the odometry obtained by our *Gril-Calib* outperforms those of other methods. In particular, our Gril-Calib achieves 8.6% improvement from LI-Init and 9.6% improvement from OA-LICalib. This experiment shows the importance of accurate calibration when applied to IMU-LiDAR fusion systems.

Fig. 1: To validate the proposed method, we utilized a ground robot equipped with LiDAR and IMU (**Left**). We acquired data of the ground robot driving in a figure-eight pattern in the indoor environment. Images (**Right**) obtained from a camera attached to the robot platform and not used in the experiment.

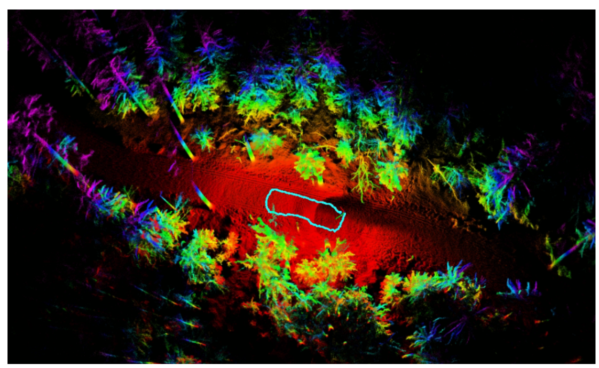

Fig. 2: Visualization of trajectory in *Forest 01* sequence. Rough terrain would affect the LiDAR ground segmentation results, which in turn would also influence our proposed calibration method.

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TABLE I: RMSE result compared to Real-world Scenario

	Custom Dataset		TIERS [1]	
	Yonsei 01 *[0, 150]*		*Forest 01* *[0, 60]*	
	Rotation (°)	Translation (m)	Rotation (°)	Translation (m)
ILC [2]	6.189	0.395	10.843	0.307
FAST-LIO2 [3]	3.722	0.421	4.458	0.087
OA-LICalib [4]	1.265	0.078	**0.098**	0.248
LI-Init [5]	0.391	0.313	0.351	**0.082**
GRIL-Calib (Proposed)	**0.279**	**0.018**	1.588	0.151

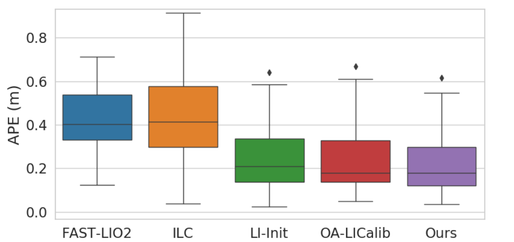

Fig. 3: Evaluation of LiDAR-inertial odometry using different calibration algorithms.

C. Evaluating Performance Time

To evaluate the efficiency, we calculated the computation time of the algorithm using *Lift 04* sequence and illustrated it in Fig 4, which demonstrates that the proposed algorithm outperforms other algorithms not only in accuracy but also in computation time. ILC [2] is dependent on a time-consuming EKF-based method that updates states at each step by using LiDAR scans for NDT scan matching. Furthermore, OA-LICalib [4] uses surface maps for calibration, and the computational cost increases rapidly with the number of surfaces. On the other hand, our *GRIL-Calib*, LI-Init [5], and FAST-LIO2 [3] use the Iterated Error State Kalman Filter, which offers a more effective procedure.

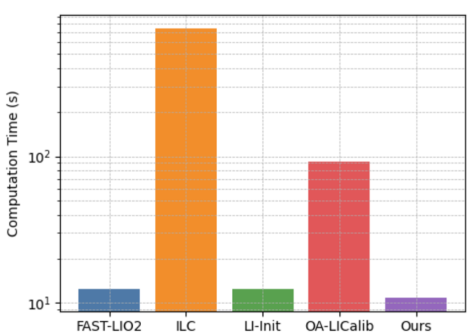

Fig. 4: Time consumption comparison. We evaluate the execution time of the algorithm without the total length of the data.

References

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