A Filter-Based LiDAR-Inertial Odometry

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Abstract— **This report summarizes Megvii-3D team's approach to IROS 2021 The HILTI SLAM Challenge. The system carries out LiDAR-Inertial Odometry by taking pointclouds from two LiDARs together with IMU measurements. Our method includes motion compensation, nearest search, state estimation and mapping. The state estimation is achieved by a filter-based IEKF estimator implemented in FAST-LIO2[1], with some functional adaptions and parameter tuning. We consider the pose of IMU frame in our state vector. The IMU bias are also calibrated online.**

I. Summary of the Approach

Our approach using two LiDAR sensors and IMU Ouster to estimate the state and simultaneously build a high-precision map of the surrounding environment. The Ouster LiDAR has a large FOV and dense measurements while Livox LiDAR has a limited FOV and a long-distance detection range, which is a good complement to Ouster. With the measurements from all individual sensors, our algorithm is robust enough in aggressive, degenerated scenarios, and is able to run in real-time on PC.

Since the timestamps of the two LiDARs are not completely synchronized, pointclouds from Livox are rearranged according to their timestamps to align with the Ouster. To estimate the states, we use an iterated extended Kalman filter. The states include the position, velocity and attitude of IMU in the global frame, and IMU bias. After synchronizing the pointclouds, the IMU measurements received during this scan are used for state propagation (the prediction phase of the filter). The high-rate IMU measurements can effectively compensate for the motion distortion in a LiDAR scan. Meanwhile, pointclouds from Livox are transformed into Ouster Frame. We only select planar features as LOAM[2] to reduce computation.

For each LiDAR feature point, the closest plane is defined by its K nearby feature points in the map and is fitted by PCA[3]. The residual is then defined as the distance between the feature point's coordinate estimated in global frame and the closest plane. In the update phase, combining the prior and residuals, an iterative extended Kalman filter is carried out to compute the optimal state. Plane features in current scan are transformed to global frame and added to global map which is maintained by an incremental KD-tree[4]. To maintain the sparseness of the map, only planar feature that is far away from its K nearest points in map is allowed to insert into global map. Thanks to the global map, no loop closure is needed.

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II. Parameters Setting

Identical parameters were used throughout all sequences. The two drone sequences used Ouster LiDAR only since the device moved in a small room. Adding Livox LiDAR did not improve the accuracy and it may introduce errors due to inaccurate extrinsic. The details for parameter setting are demonstrated in Table 1.

TABLE I
PARAMETER SETTINGS

Parameter	Value
Voxel Filter size	0.3
Map grid size	0.3
Num. to fit plane	6
Point to plane distance Thresh	0.1

III. Processing Time Hardware

All the datasets were processed on a local device with Intel Core i5 CPU@1.6GHz×8 and 16GB memory. The time used to evaluate each sequence is summarized in Table 2.

TABLE II
PROCESSING TIME FOR EACH EVALUATION SEQUENCE

Sequences	Processing Time [Sec]
uzh_tracking_area_run2	0.0349
IC_Office_1	0.0320
Office_Mitte_1	0.0331
Parking_1	0.0529
Basement_1	0.0299
Basement_3	0.0315
Basement_4	0.0266
Lab_Survey_2	0.0252
Construction_Site_1	0.0426
Construction_Site_2	0.0417
Campus_1	0.0372
Campus_2	0.0386

IV. Conclusion Further Developments

In this report, we present our solution based on FAST-LIO2 applied to IROS2021 The HILTI SLAM Challenge. Although it shows a decent result on the evaluation, we still believe there are many other promising strategies to further advance the behaviors of the system as a whole, such as fusing measurement from camera to achieve robust and accurate state estimation. Also, the estimator can be replaced by MSCKF[5] to gain better performance.

References

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