

Tightly Coupled LiDAR-IMU-Odometry Fusion with Continuous-Time Trajectory Representation for Robust Ego-Vehicle Localization

Naoki Akai^{1), 2)} Yasuhiro Akagi^{1), 3)} Takayuki Morikawa^{1), 3)}

*1) Institute of Innovation for Future Society, Nagoya University
1 Furo, Chikusa, Nagoya, Aichi, 464-8601, Japan (E-mail: akai@nagoya-u.jp)*

*2) LOCT, Co., Ltd.
Yomogidai, Meito, Nagoya, Aichi, 465-0091, Japan*

*3) XXADE, Co., Ltd.
1-11-20, Nishiki, Naka, Nagoya, Aichi, 460-0003, Japan*

KEY WORDS: LiDAR, IMU, Odometry, Sensor Fusion, Continuous-Time

Accurate and robust ego-pose estimation is essential for autonomous driving and mobile robotic systems. LiDAR-Inertial odometry (LIO) has been widely used because it can estimate vehicle motion without relying on external motion measurements. However, its accuracy may deteriorate in geometrically degenerate environments, such as long corridors, where LiDAR measurements provide insufficient constraints. Wheel odometry can provide complementary motion information in such situations. In conventional discrete-time formulations, however, IMU and wheel-odometry measurements are typically integrated between consecutive states and converted into relative-motion constraints. This representation does not directly exploit their original measurement characteristics and makes it difficult to incorporate individual velocity measurements at their actual timestamps.

This work proposes a tightly coupled LiDAR-IMU-odometry fusion framework based on a continuous-time trajectory representation. The vehicle trajectory is represented using cumulative B-splines on the $SO(3)$ manifold, allowing the pose and its temporal derivatives to be evaluated at arbitrary timestamps. Angular velocity, linear velocity, and acceleration are analytically derived from the trajectory. Consequently, IMU measurements can be directly compared with the angular velocity and acceleration derived from the trajectory, while odometry measurements can be directly incorporated as angular- and linear-velocity observations at their original timestamps. This approach preserves the distinct measurement models of the sensors and eliminates the need to convert IMU and odometry measurements into common relative-pose constraints.

The estimated state consists of the cumulative B-spline control points together with biases for the IMU and odometry measurements and scale factors for the odometry. Several residuals are jointly optimized using the Gauss-Newton method: prior and bias random-walk residuals, a smoothness residual for stabilizing the continuous-time trajectory, point-to-plane LiDAR scan-matching residuals, IMU residuals, and odometry velocity residuals. The optimization is performed in two stages. First, newly generated control points are refined using IMU and odometry measurements. LiDAR measurements are subsequently added for full optimization. Old control points are marginalized, and the aligned LiDAR scans are inserted into a hashed-voxel local map.

The proposed method was evaluated on the M3DGR and HeLiPR datasets. For M3DGR, LiDAR, IMU, and wheel-odometry measurements were used, and the proposed method was compared with FAST-LIO2 and Ground-Fusion++. The experiments included visual challenges, LiDAR degeneracy, wheel slippage, and GNSS-denied conditions. FAST-LIO2 and the proposed LIO configuration without wheel odometry failed on the Corridor01 sequence because of severe LiDAR degeneracy. In contrast, the proposed LiDAR-IMU-odometry configuration successfully estimated the trajectory with an APE RMSE of 0.90 m, demonstrating that wheel odometry can provide effective complementary constraints when LiDAR-based estimation becomes degenerate. Across the other sequences, the proposed method achieved estimation accuracy comparable to or better than existing approaches.

The experiments also revealed limitations of continuously incorporating wheel odometry. In non-degenerate environments, the LiDAR-IMU-only configuration sometimes achieved higher accuracy than the configuration using wheel odometry. Furthermore, removing the Huber loss from the odometry residual substantially degraded accuracy on the Wheel-float01 sequence and caused estimation failure on Grass01, indicating that unreliable wheel-odometry measurements can negatively affect the overall optimization. These results suggest that odometry should be incorporated selectively according to its reliability and the observability of the LiDAR measurements.

Experiments on the HeLiPR autonomous-driving dataset further evaluated the effectiveness of odometry fusion over long trajectories. Synthetic odometry measurements were generated from the ground-truth trajectory with Gaussian noise to emulate short-term velocity estimates obtainable from vehicle motion sensors. Incorporating these measurements reduced the ATE RMSE from 88.05 to 79.93 m on KAIST05, from 357.89 to 302.35 m on Bridge01, and from 26.60 to 25.91 m on DCC06. The corresponding 2D trajectory errors were also reduced for all sequences.

In summary, the proposed continuous-time formulation provides a unified framework for tightly coupling LiDAR, IMU, and odometry measurements while directly respecting their native measurement spaces. The experimental results demonstrate that odometry fusion substantially improves localization robustness in LiDAR-degenerate environments and can also improve accuracy in long-duration autonomous-driving scenarios when reliable odometry is available. Future work will focus on detecting LiDAR degeneracy and its degenerate directions so that odometry constraints can be selectively incorporated only when they are expected to improve estimation accuracy.