FrankenPharos: Lidar-Inertial SLAM

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Abstract

Our proposed solution combines point cloud registration with inertial estimation, forming a factor graph which optimizes the pose and IMU biases simultaneously. We developed an accurate point cloud de-skewing method that benefits from bias estimation. The robustness of our approach has been validated with the datasets from the Hilti SLAM Challenge.

1. Approach Summary

For solving the specific problem of this challenge, we propose an optimization-based approach that tightly fuses LiDAR and inertial sensor data in an online manner. LiDAR provides accurate depth information of the environment but cannot capture high dynamic motions while IMU provides high frame-rate but noisy acceleration and angular velocity measurements. These two kind of sensors are complementary and can assist each other. Specifically, LiDAR measurements can enable the computation of 3D poses, enabling online estimation of IMU parameters, while the IMU measurements can be integrated to provide a good prior for Iterative Closest Point (ICP) registration even in the presence of highly dynamic motions.

In our approach a scan-to-map point cloud registration method is accompanied by IMU-based propagation. We made use of the open-source point cloud library libpointmatcher [4] to perform ICP registration. First, the most up-to-date map point cloud is rendered, and correspondence search is performed in a KD-tree. With data associations available, the point-to-plane cost function is formed based on [3] and solved as a least-squares optimization problem. Furthermore, to deal with intrinsic problems of point-cloud based data (structure-less environments) an active degeneracy awareness system is deployed [5].

The pre-integration factors [2] are computed from the IMU measurements which are provided at 400hz. We made use of the pre-integration factor from [2] Based on the pre-integration factor and the previous state, the current state is predicted as a prior to use scan-to-map ICP [4] to do point cloud registration. The ICP refined pose is then added as a prior for the current state to do a window-based factor graph optimization using GTSAM [1]. Finally the pre-integration factor is re-propagated with the updated biases.

The Lidars carried by the Challenge's sensor payloads are subject to motion distortion, which can have a negative effect on point cloud registration. To ameliorate its effect, we developed a point cloud de-skewing algorithm that performs forward IMU propagation with the most recent IMU biases, and linearly interpolates in-between IMU-propagated poses.

Our solution for this challenge does not perform offline trajectory optimization or loop detection, it estimates the trajectory and map in one session, in *open loop*. As shown in **??**, it can produce accurate maps in challenging conditions.

2. Parameters

Our approach is generic and we used the same set of parameters for all the datasets. The parameters are listed in Table 1 below.

Table 1. Key parameters.

Parameter	Value
Normal estimation radius	0.10m
Map Rendering Time	0.1s
ICP Translation Gradient	0.001m
ICP Rotation Gradient	0.0005 deg
X-ICP Threshold - Normal alignment	30 deg
X-ICP Threshold - Min. contributions	50 deg
Map resolution	5cm

3. Computation Time Analysis

Despite being highly crucial in autonomous operation, in the HILTI SLAM challenge the competing systems are not required to run real-time and being real-time applicable does not provide additional points to the competing teams. As a consequence, we tuned our customized solution to provide more accurate output at the expense of more resources.

All the evaluations were done on a laptop with Intel Core i7 12780H @ 3.6GHZ and 32GB RAM. The average computation time per optimization step for each dataset is provided in Table 2.

Table 2. Average Computation Time

Sequences	Average Computation Time(Sec)
Site 1	0.2
Site 2	0.07
Site 3	0.1

4. Conclusion

We propose an optimization-based ICP degeneracy-aware LiDAR-inertial odometry in 2023 HILTI SLAM challenge. Our solution has been proved accurate and robust on the evaluation datasets, with an ATE in the range of 1 to 3cm.

Our system was able to provide very accurate trajectories and maps, but struggled the most in challenging situations where it clearly held information on how to solve a problem, but due to the separation of the estimation problem into 12-DOF optimization (comprising the IMU Preintegration factors), and 6-DOF point cloud registration, it didn't produce smooth or gravity-aligned trajectories, which would bear higher consistency.

5. Acknowledgements

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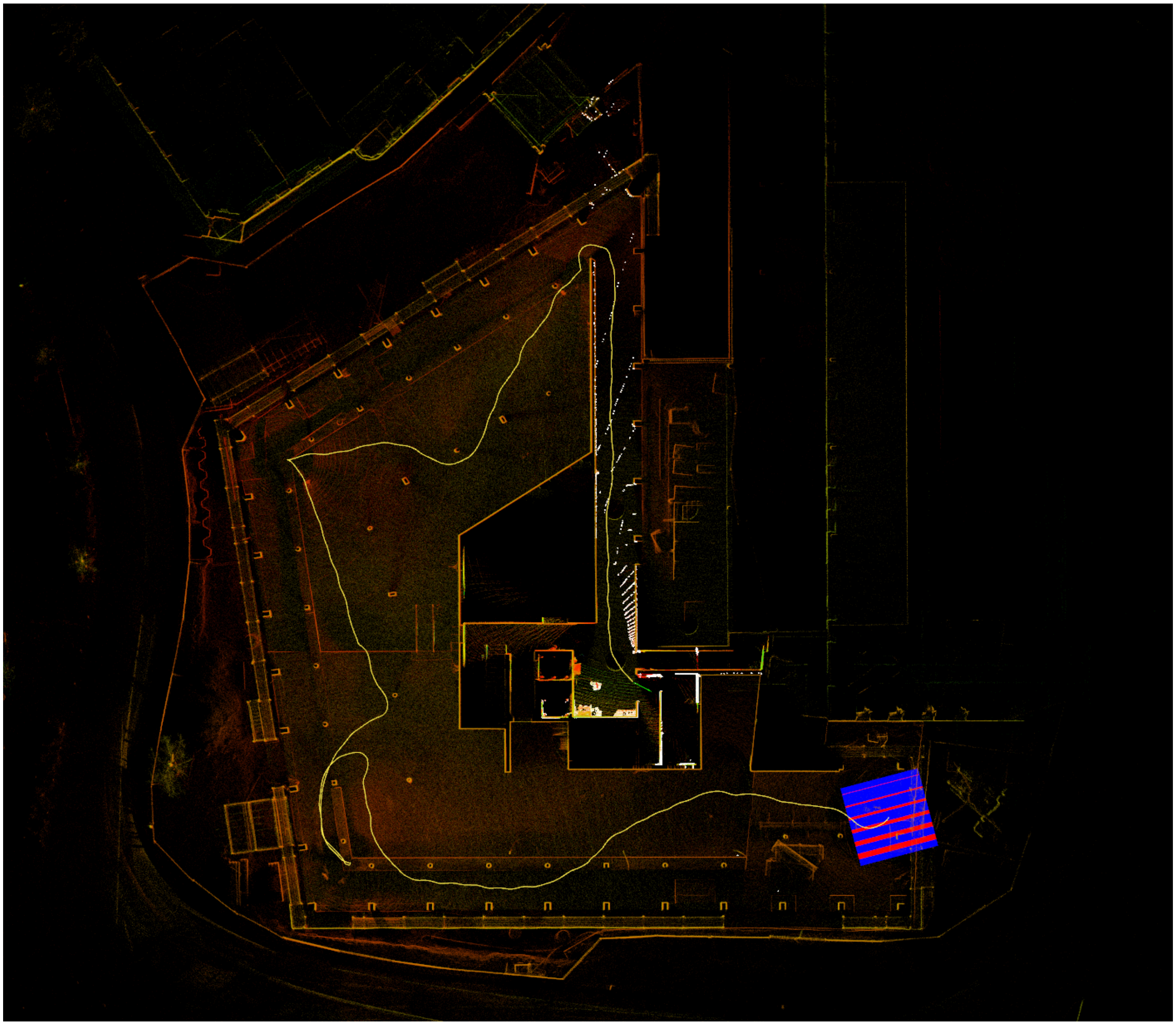

Figure 1. Top view of the scene from Site 1 - Handheld 1

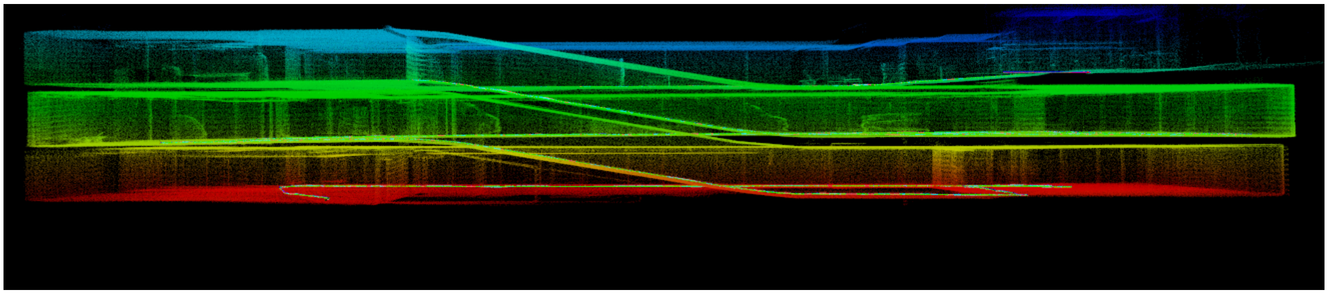

Figure 2. Multi-level scene from Site 2 - Robot 1