

Universitat de Girona

# **Robust LiDAR-Inertial Localization with Prior** Maps in GNSS-Challenged Environments







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### **Motivation**

Autonomous robots require accurate localization in GPS-denied environments like indoors or urban canyons. GNSS-INS systems are prone to failure in these conditions, while real-time SLAM often drift without loop closures

Map-based localization offers a stable and accurate alternative, but it faces several key challenges:

- Real-time performance and Scalability: Handling high-resolution 3D maps and computing scan-to-map registration efficiently.
- **Drift correction**: Fusing local motion estimation with global map constraints while preserving consistency.
- Dynamic environments: Removing or mitigating the effect of moving objects during scan matching.
- Localization failures in feature-sparse or unmapped transition zones.

## **Contribution**

This thesis presents a robust and real-time localization framework for GNSS-denied environments by fusing LiDAR-Inertial Odometry (FAST-LIO2) with multithreaded NDT-based map matching using a sliding-window factor graph. It introduces a scalable submap management strategy and integrates dynamic object removal via deep learning, enabling consistent pose estimation even in dynamic, degraded, or feature-sparse areas. The system achieves centimeter- to decimeter-level accuracy across diverse datasets, maintaining low-latency performance suitable for realworld autonomous navigation. Extensive evaluations show that the proposed method not only surpasses standalone odometry and SLAM baselines but also outperforms recent state-of-the-art map-based localization approaches in accuracy, robustness, and scalability.

## Methodology

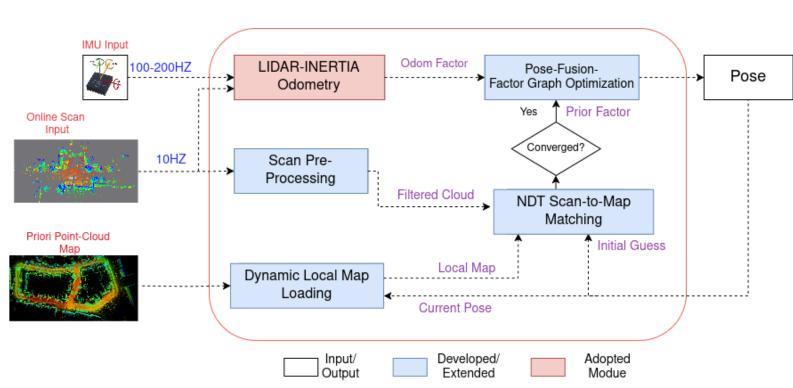
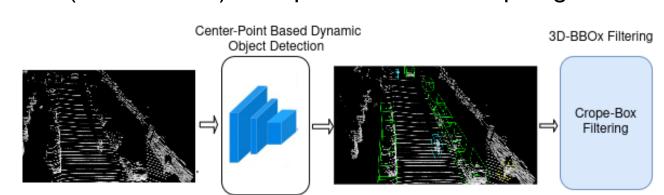


Figure 1: Complete Diagram of The Localization System

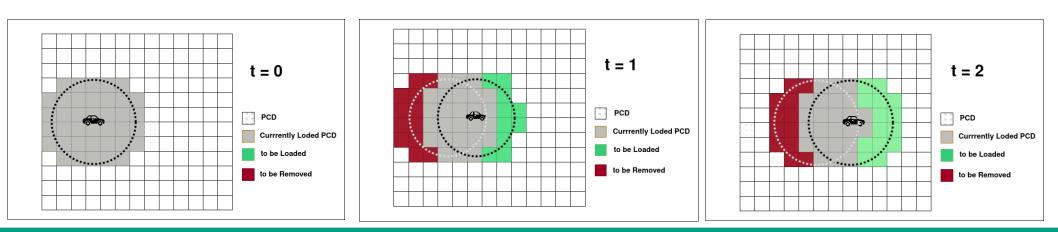
### **Scan Pre-Processing**

Dynamic objects are removed from LiDAR scans using a deep learning-based 3D detector (CenterPoint) to improve scan-to-map alignment.



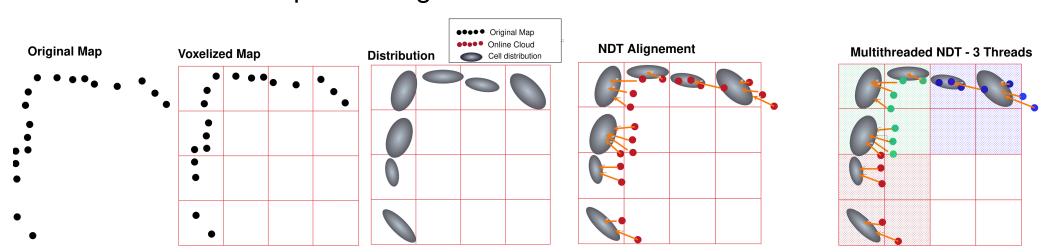
### **Local Map Loading**

loads only relevant submaps based on the robot's estimated position



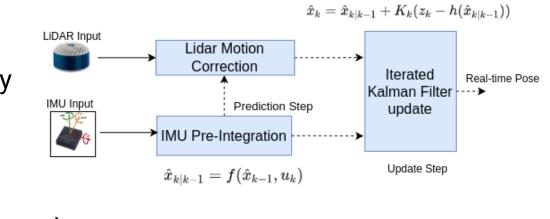
### **Scan-to-Map Matching**

multithreaded implementation of the Normal Distributions Transform (NDT) used to accelerate scan-to-map matching



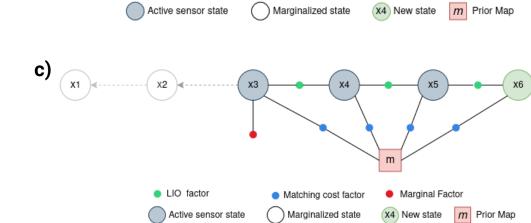
### **Local Motion Estimation**

FAST-LIO2 based LiDAR-Inertial Odometry for real-time local pose estimation.



### **Sliding Window Pose-Graph Optimization**

Odometry poses from FAST-LIO2 are added as relative motion and Scan-to-map corrections from inserted as absolute pose factors.



## b) LIO factor Active sensor state m Prior Map

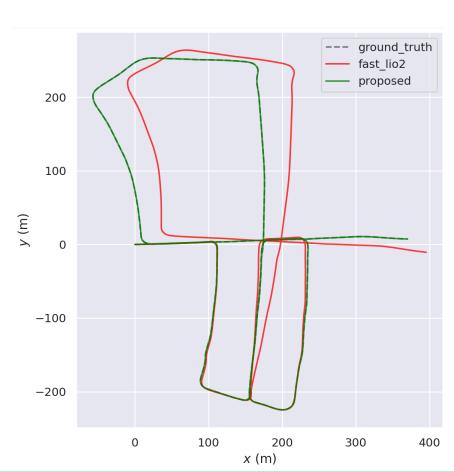
## **Experimental Results**

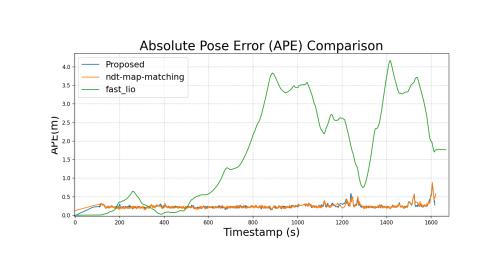
### Comparison with baseline methods: LIO exhibits high drift over time while proposed method acheives both low localization error and high temporal consistency.

N. (1) 1	Metric	Sequence 2			Sequence 3		
Method		Max	RMSE	$\mathbf{Mean}\pm\mathbf{Std}$	Max	RMSE	$\mathbf{Mean}\pm\mathbf{Std}$
Proposed	APE (m) Rot. (deg)	0.44 4.36	$0.11 \\ 1.05$	$0.09 \pm 0.06$ $0.78 \pm 0.70$	0.82 2.02	$0.14 \\ 1.04$	$0.10 \pm 0.09$ $0.73 \pm 0.74$
Map Matching	APE (m) Rot. (deg)	0.25 2.64	0.12 1.39	$0.10 \pm 0.06$ $1.20 \pm 0.72$	0.30 3.24	<b>0.13</b> 1.65	$0.11 \pm 0.06$ $1.37 \pm 0.92$
Fast-LIO2	APE (m) Rot. (deg)	6.99 5.49	3.88 2.68	$3.56 \pm 3.88$ $2.25 \pm 1.46$	4.08 2.75	2.16 1.09	$1.47 \pm 1.15$ $0.96 \pm 0.52$

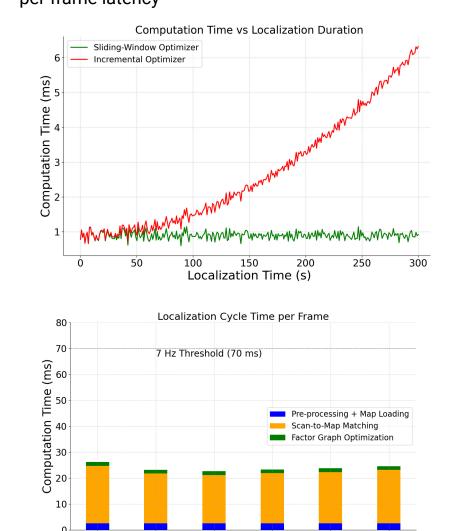
### Benchmarking on Public Dataset: tested on kitti05

Method	Map Correction	Translation Error (m)	Rotation Error (°)
Proposed (Ours)	<b>√</b>	$0.121\pm0.077$	$0.30\pm0.144$
Youngji Kim et al.	✓	$0.15\pm0.14$	$0.34 \pm 0.40$
D. Rozenberszki et al	✓	$\sim$ 2.5 $\pm$ 2.0	_
Xiaohu Lin et al.	✓	$3.18 \pm 5.58$	$1.27 \pm 1.97$
FAST-LIO2	*	$9.18 \pm 3.58$	$5.2\pm1.7$





**Real-time performace:** 23 ms (√ 43 Hz real-time) per frame latency



### **Conclusions and Future Work**

### **Accurate & Drift-Free**

Achieves centimeter-to-sub-decimeter accuracy by fusing FAST-LIO2 and NDT with a sliding-window factor graph, effectively reducing drift without loop closures.

### **Real-Time & Scalable**

Maintains <23 ms latency using multithreaded NDT and dynamic submap loading. Sliding window factor graph optimization remains bounded regardless of trajectory length.

### **Robust to Challenges**

Dynamic object removal improves convergence, and fused graph keeps localization stable even when scan matching fails.

### **Limitations & Future Work**

Assumes a known initial pose and a static map. Future directions include global re-localization, adaptive map updating, and integration of camera/radar for increased robustness.

## References

- [1] Xu, W. et al. "FAST-LIO2: Lightweight LiDAR-Inertial Odometry", IROS 2022
- [2] Rozenberszki, D. et al., LOL: LiDAR-only Odometry and Localization, ICRA 2020
- [3] Kim, Y. et al. "Stereo Camera Localization in 3D LiDAR Maps", IROS 2018
- [4] Lin, X. et al. Autonomous Vehicle Localization with Prior Visual Point Cloud Map Constraints in

