MA-LIO: Multiple Asynchronous LiDAR-Inertial Odometry with Time-dependent Point-wise Uncertainty

Reference

[1] M. Helmberger, K. Morin, B. Berner, N. Kumar, G. Cioffi, and D. Scaramuzza, "The hilti slam challenge dataset," IEEE Robot. and Automat. Lett., vol. 7, no. 3, pp. 7518–7525, 2022.

[2] L. Hsu, N. Kubo, W. Wen, W. Chen, Z. Liu, T. Suzuki, and J. Meguro, "Urbannav: An open-sourced multisensory dataset for benchmarking positioning algorithms designed for urban areas," in ION GNSS+, 2021, pp. 226–256.

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Summary

Continous-time interpolation for multiple asynchronous LiDAR
- Tackling field-of-view discrepancies in LiDAR

Point-wise Uncertainty based on range and acquisition time
- Reflecting the ambiguity resulting from measurement

Localization weight based on the distribution of normal vector
- Balancing prior and measurement residual, providing automatic adjustments in challenging environments

Compatibilty with any LiDAR type and scanning patterns
- Validation across three datasets (Hilti 2021, UrbanNav and City)

Visit the Link!

SCAN ME

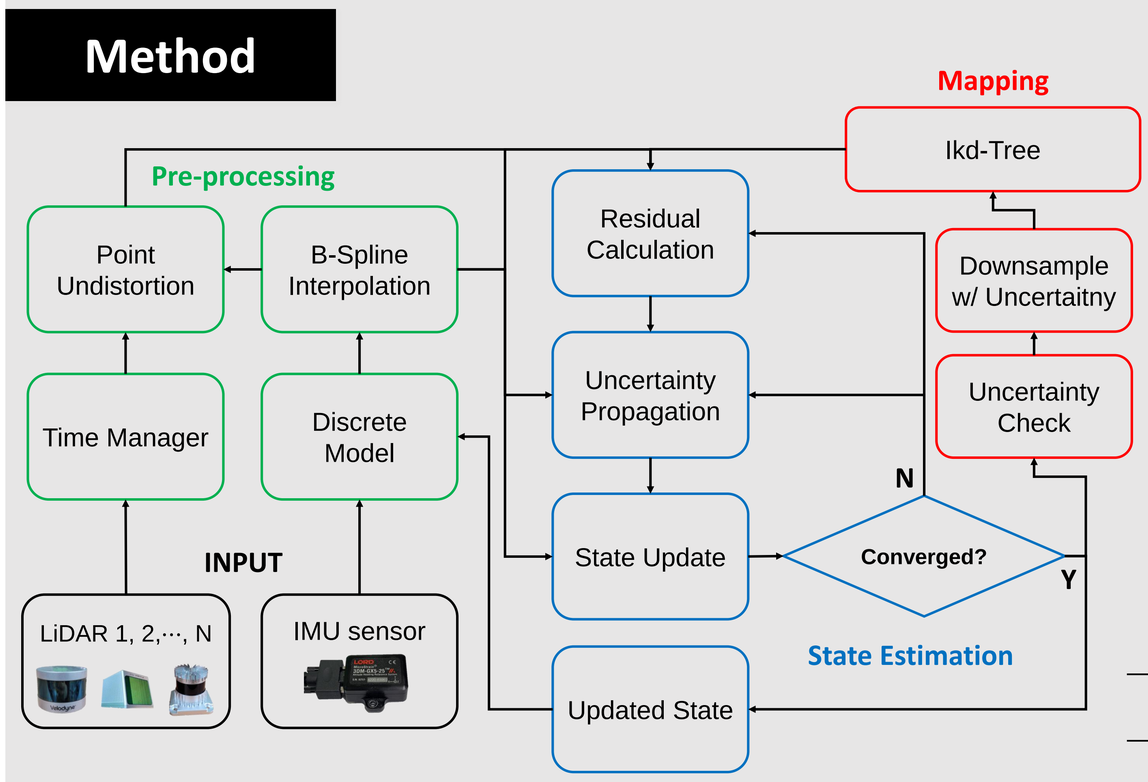
Link for MA-LIO Github Repository!

If you scan the QR, you can find ..

- Source code of MA-LIO
- Dataset link for City dataset (Consist of 2 Livox and 1 Ouster)
- Link for Paper and Results (Youtube)

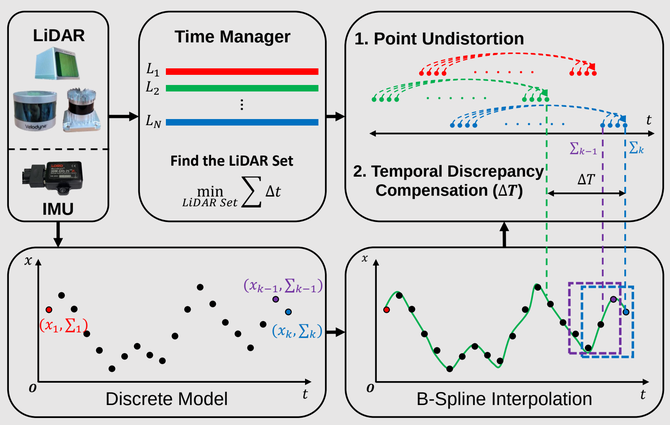
Feel free to scan, and enjoy our project.

Method

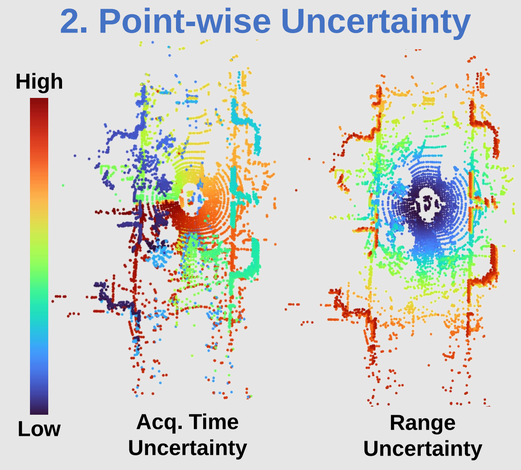


The Pipeline of MA-LIO

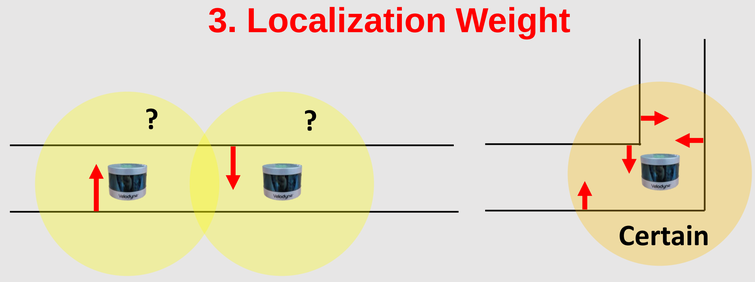
1. B-spline Interpolation



2. Point-wise Uncertainty



3. Localization Weight



Case 1: 2D Degenerate Environment Case 2: 2D Environment

4. Iterated Error State Kalman Filter

Localization weight Measurement model

$$\min_{\tilde{\mathbf{x}}_i^{\kappa}} \left(\|\mathbf{x}_i \boxminus \hat{\mathbf{x}}_i\|^2_{\hat{\Sigma}_i} + w_l \sum_{L=P,S} \sum_{j=1}^{m} \|\mathbf{z}_{L_j}^{\kappa} + \mathbf{H}_{L_j}^{\kappa} \tilde{\mathbf{x}}_i^{\kappa}\|^2_{\mathbf{R}_{L_j}} \right)$$

B-spline Interpolation Point-wise Uncertainty

Results

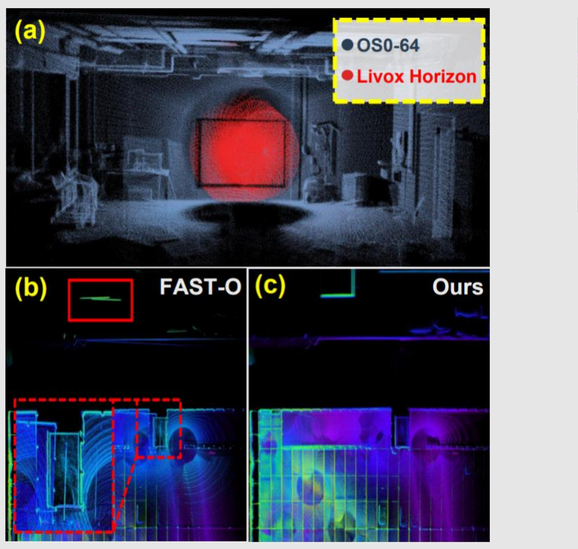
TABLE I: APE for Hilti SLAM Dataset 2021

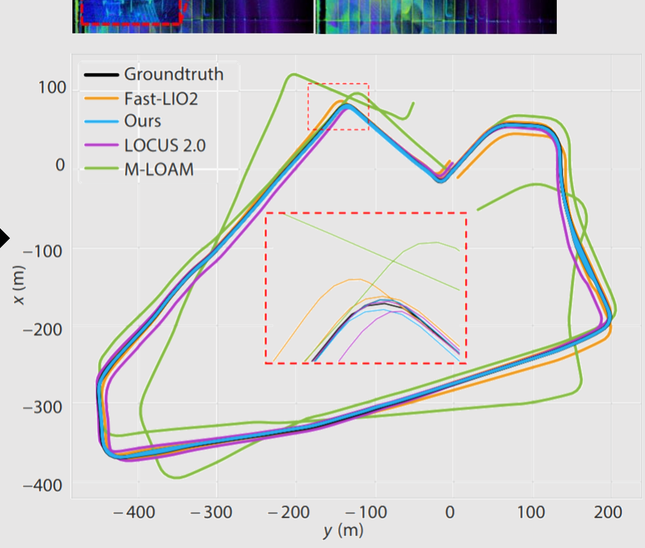
	Ours	Fast-H	Fast-O	M-LOAM	LOCUS 2.0
Basement	**0.036**	0.709	*0.046*	0.115	0.120
Campus	**0.046**	0.063	*0.063*	0.386	0.087
Construct	**0.063**	0.200	*0.088*	2.647	0.290
LAB	**0.024**	Err	*0.026*	0.064	0.040
UZH	**0.177**	0.233	0.184	0.276	*0.177*

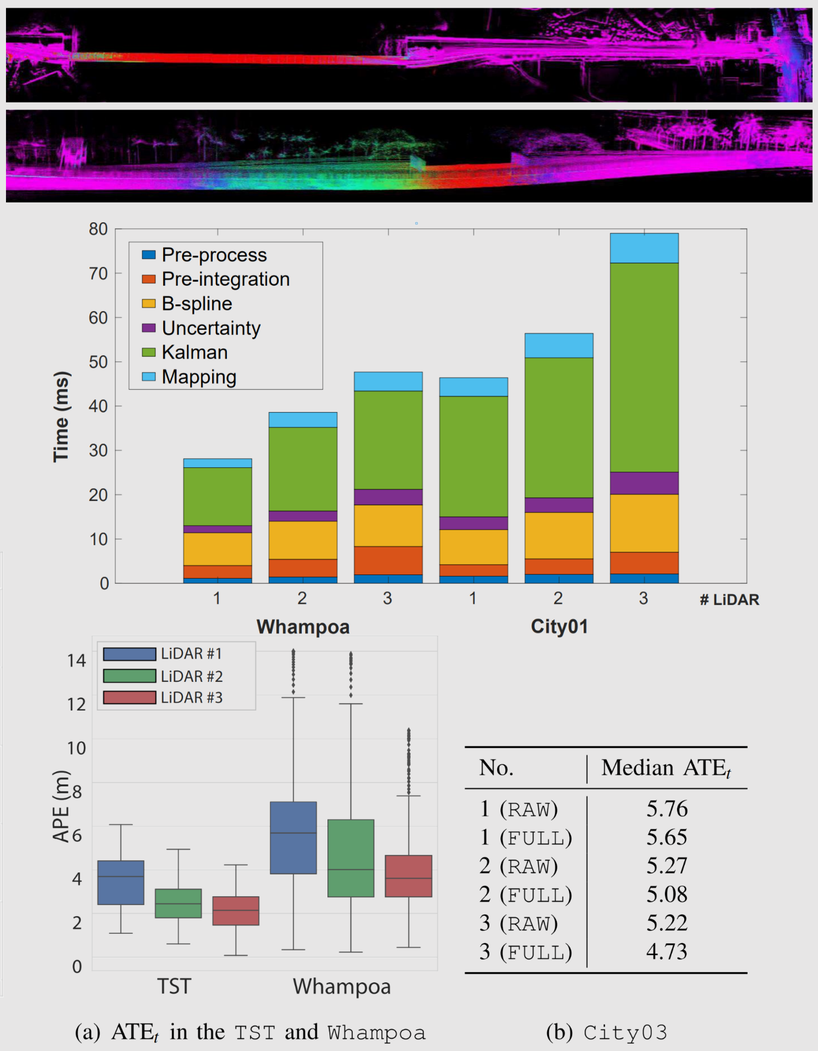
The best results are in **bold** and the second-best's are in *italic*.

TABLE II: UrbanNav and Our Dataset Evaluation

		Fast-LIO2	M-LOAM	LOCUS 2.0	Ours
Mongok	APE	*5.917*	25.899	6.846	**2.579**
	RPE	0.188	0.632	*0.174*	**0.167**
Whampoa	APE	*7.066*	31.482	18.124	**4.236**
	RPE	0.390	0.710	*0.339*	**0.207**
TST	APE	*8.783*	53.682	33.292	**2.342**
	RPE	*0.494*	2.177	0.841	**0.351**
City01	APE	*9.970*	33.907	23.998	**6.538**
	RPE	*0.292*	0.955	0.609	**0.266**
City02	APE	*35.308*	72.382	58.211	***6.707***
	RPE	*0.608*	3.665	1.531	**0.565**
City03	APE	*6.951*	33.801	21.753	**5.470**
	RPE	*0.996*	1.310	1.159	**0.565**







(a) ATE_t in the TST and Whampoa

No.	Median ATE_t
1 (RAW)	5.76
1 (FULL)	5.65
2 (RAW)	5.27
2 (FULL)	5.08
3 (RAW)	5.22
3 (FULL)	4.73

(b) City03

Conclusion

- **A framework for multiple asynchronous LiDAR-inertial systems** that mitigates **temporal discrepancies** and **frame change ambiguities**.
- Presenting **point-wise uncertainty propagation** based on **acquisition time** and **range**, and **localization weight** based on **normal vector**.
- **Surpassing** the **state-of-the-art** in **accuracy, robustness**, and suggesting **the importance of multiple LiDAR attachment**.