



Learning and Optimization for Reliable Robot Motion Estimation

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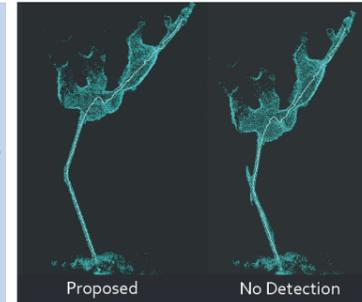
1 Self-supervised Learning of LiDAR Odom (ICRA 2021)

- Efficient utilization of data
- Geometric losses ONLY during training
- No labelled or GT data
- Self-sup. network training
- Various experiments



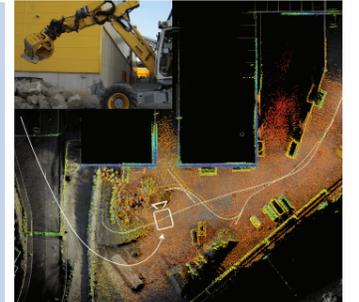
2 Learning-based Localizability Estimation (IROS 2022)

- Env.-Degeneracy → loc. failure
- Estimation on raw sensor meas.
- Underlying opt. not considered
- Generalization across envs/sensors
- NN-based estimation approach
- Only trained on simulated data

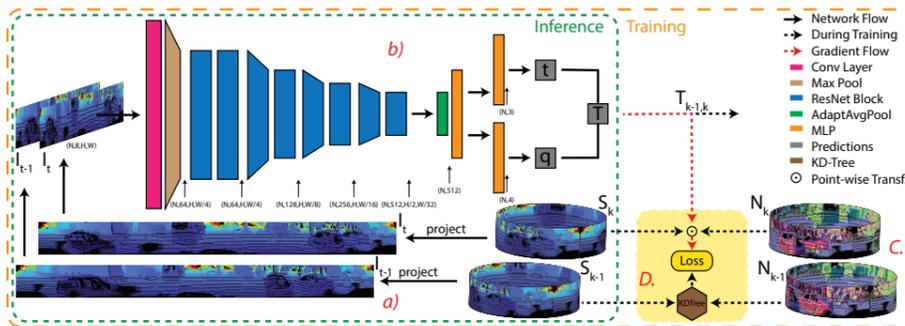


3 Graph-based Multi-sensor Fusion (ICRA 2022)

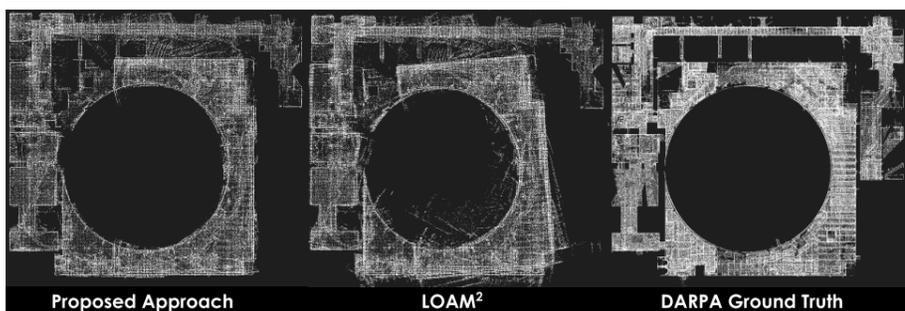
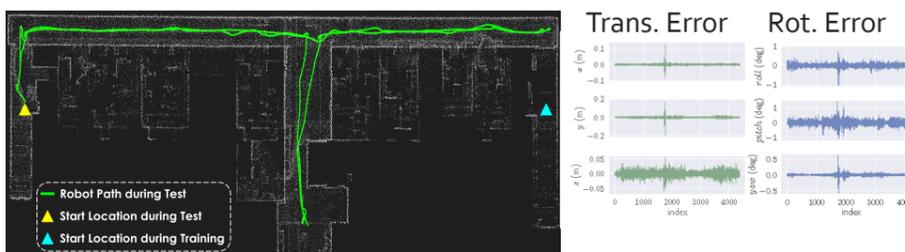
- Fast-update rates for control
- Global accuracy for construction
- Smooth & consistent estimates
- Flexible (delay, meas. types)
- Opt.-based prediction-update loop
- Dual-graph design → switching



Approach

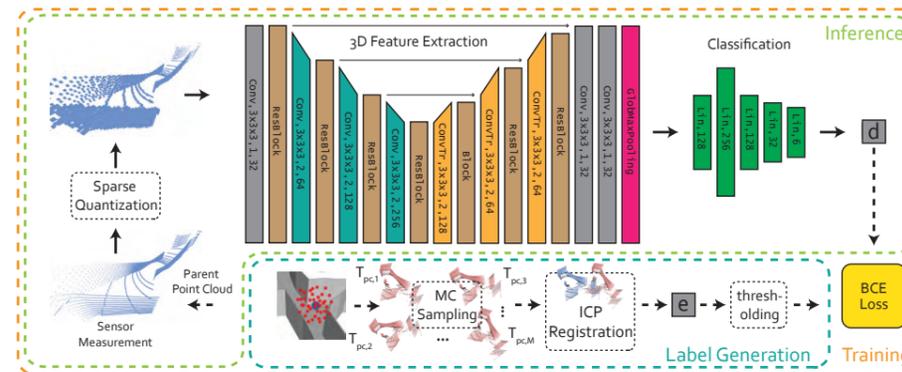


Results

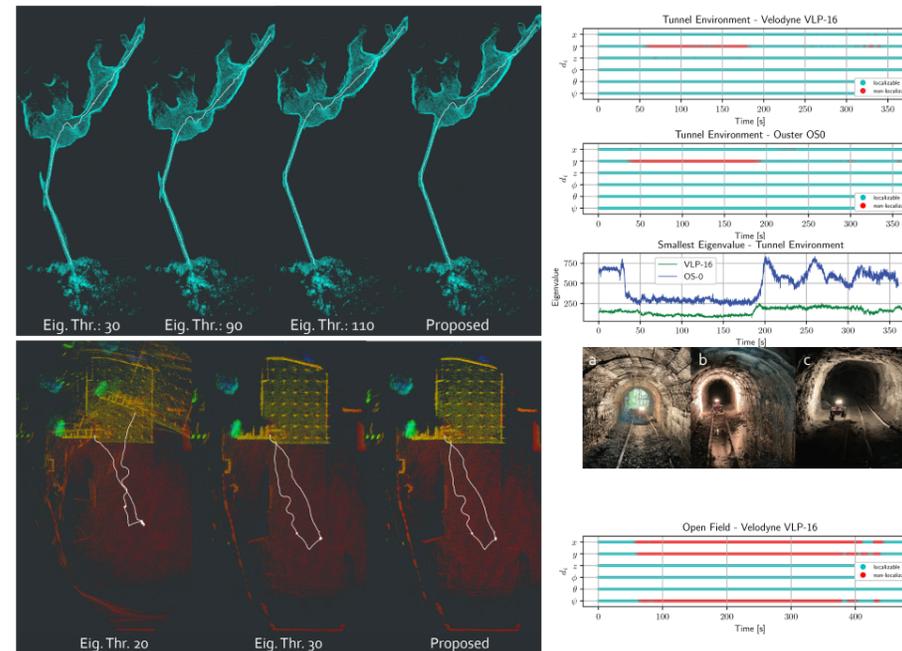


KITTI Ablation Study	Training 00-06		Test 07-10	
	t_{rel}	r_{rel}	t_{rel}	r_{rel}
p2pl + pl2pl	3.41	1.44	8.30	3.45
p2pl	6.47	2.72	8.90	4.00

Approach



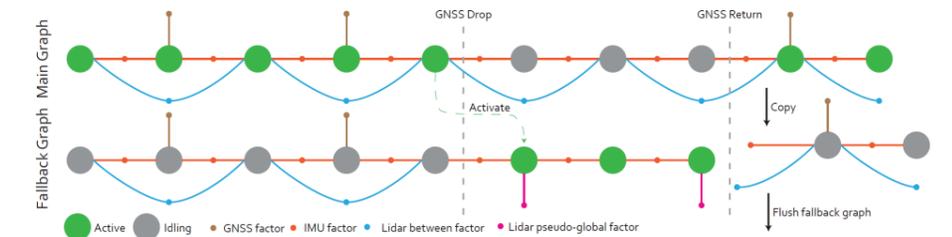
Results



Method

State: ${}^I \mathbf{x} \triangleq [\mathbf{R}_{WI}, {}_W \mathbf{P}_{WI}, {}_W \mathbf{v}_{WI}, {}^I \mathbf{b}^g, {}^I \mathbf{b}^a] \in \text{SO}(3) \times \mathbb{R}^{12}$
 $\mathbf{T}_{WO} \in \text{SE}(3)$
 ${}^B \mathbf{x} \triangleq [\mathbf{R}_{OB}, {}_O \mathbf{P}_{OB}, {}_O \mathbf{v}_{OB}] \in \text{SO}(3) \times \mathbb{R}^6$

MAP estimation ${}^I \mathcal{X}_i^* = \arg \max_{{}^I \mathcal{X}_i} p({}^I \mathcal{X}_i | \mathcal{Z}_i) \propto p({}^I \mathcal{X}_0) p({}^I \mathcal{Z}_i | {}^I \mathcal{X}_i)$



Results

