On-line Calibration Monitoring and Tracking

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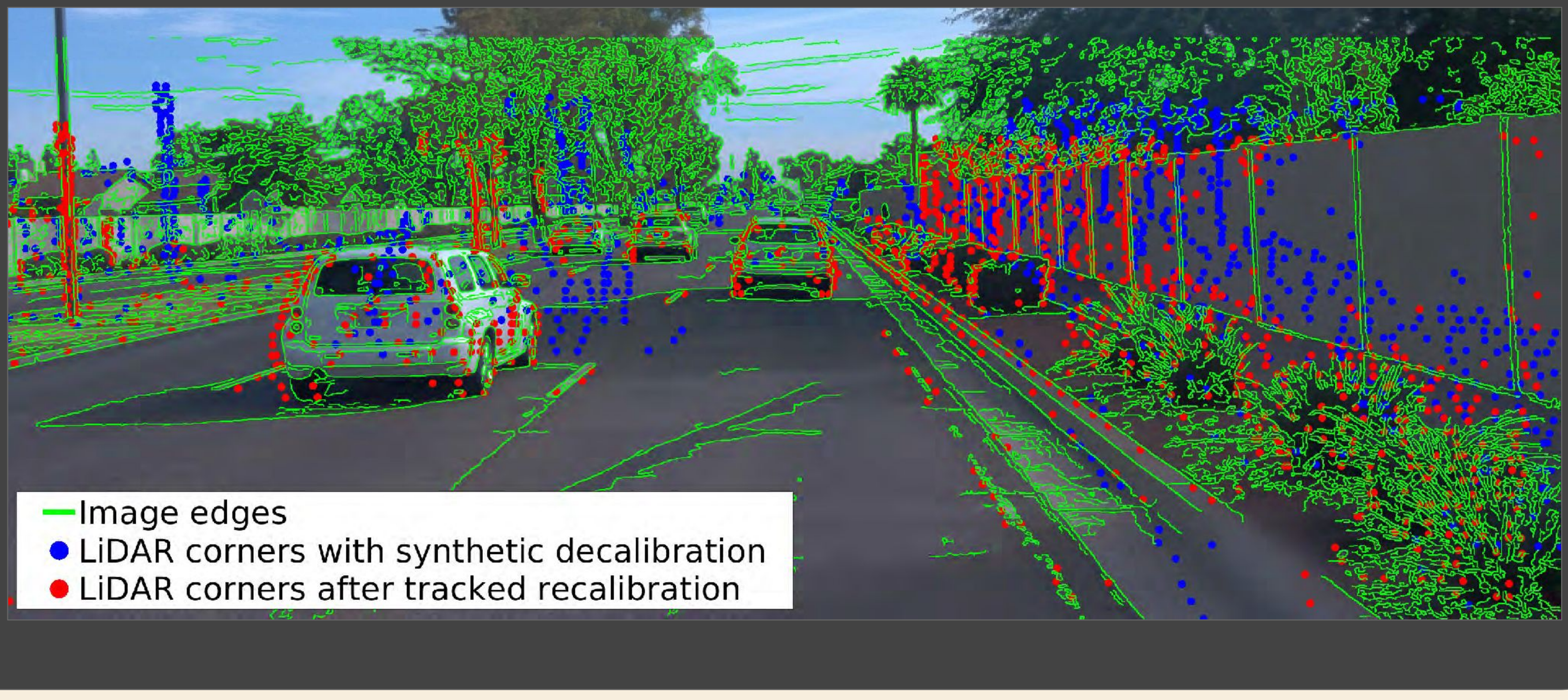
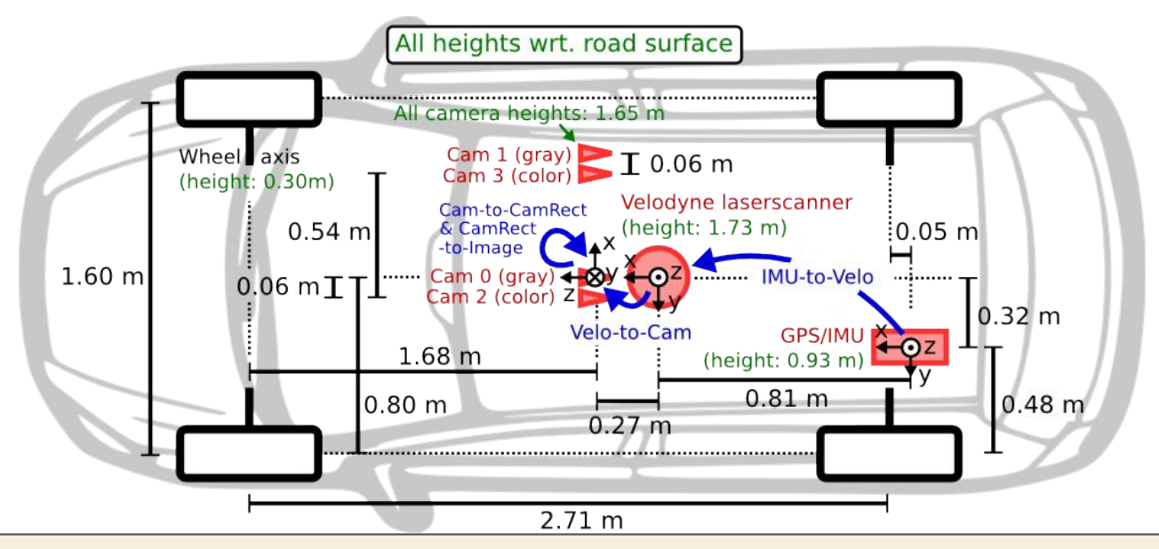
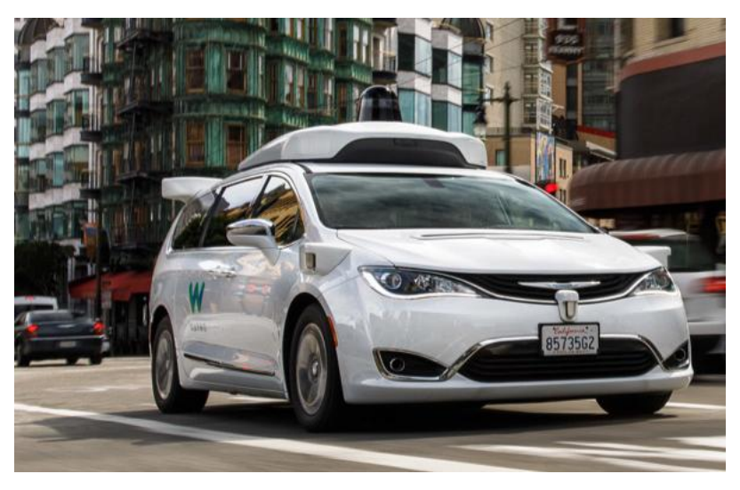
On-line calibration may considerably improve efficiency of downstream perception methods and/or detect inconsistencies that would otherwise lead to autonomous system failure.



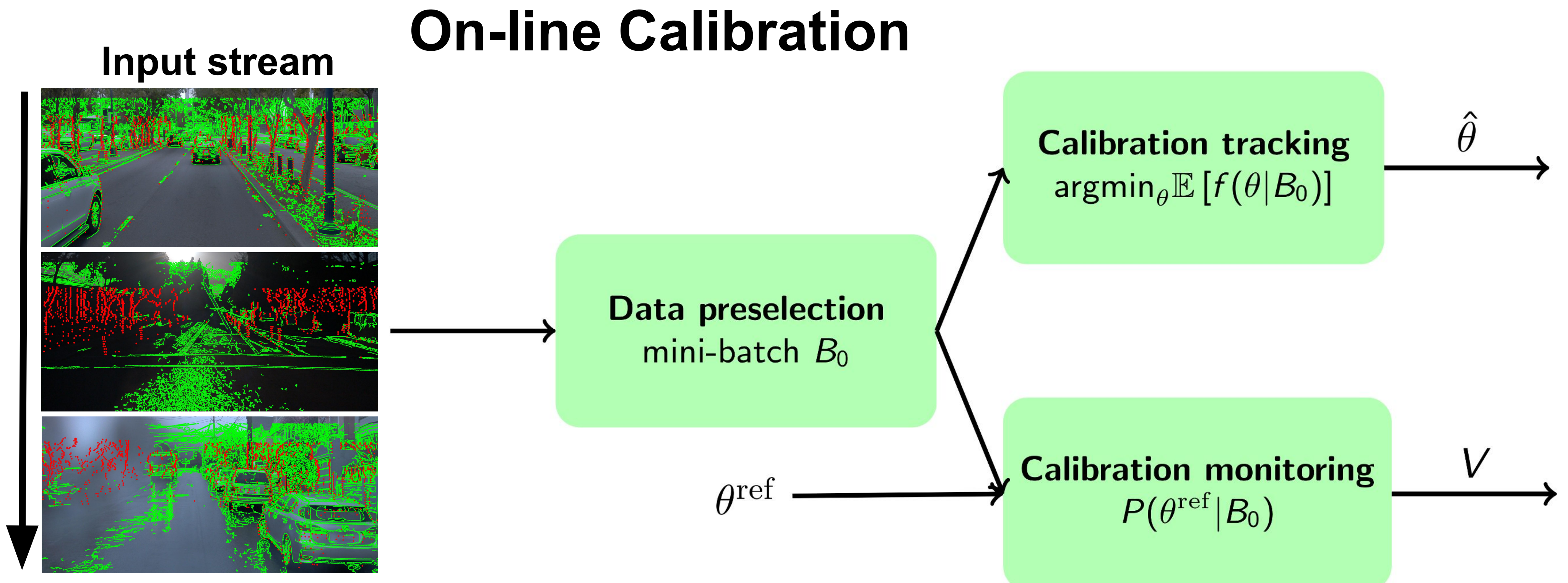
Problem Introduction

- Off-line calibration provides high precision of parameters at the cost of time-consuming and hard setup All data D → $\text{argmin}_\theta f(\theta|D)$
  ➥ But: Parameters may change during system's operation due to vehicle twisting, thermal dilations or moving parts
- We propose **on-line** methods for **calibration tracking** (refinement) and **monitoring** (miscalibration detection)





On-line Calibration



Input stream

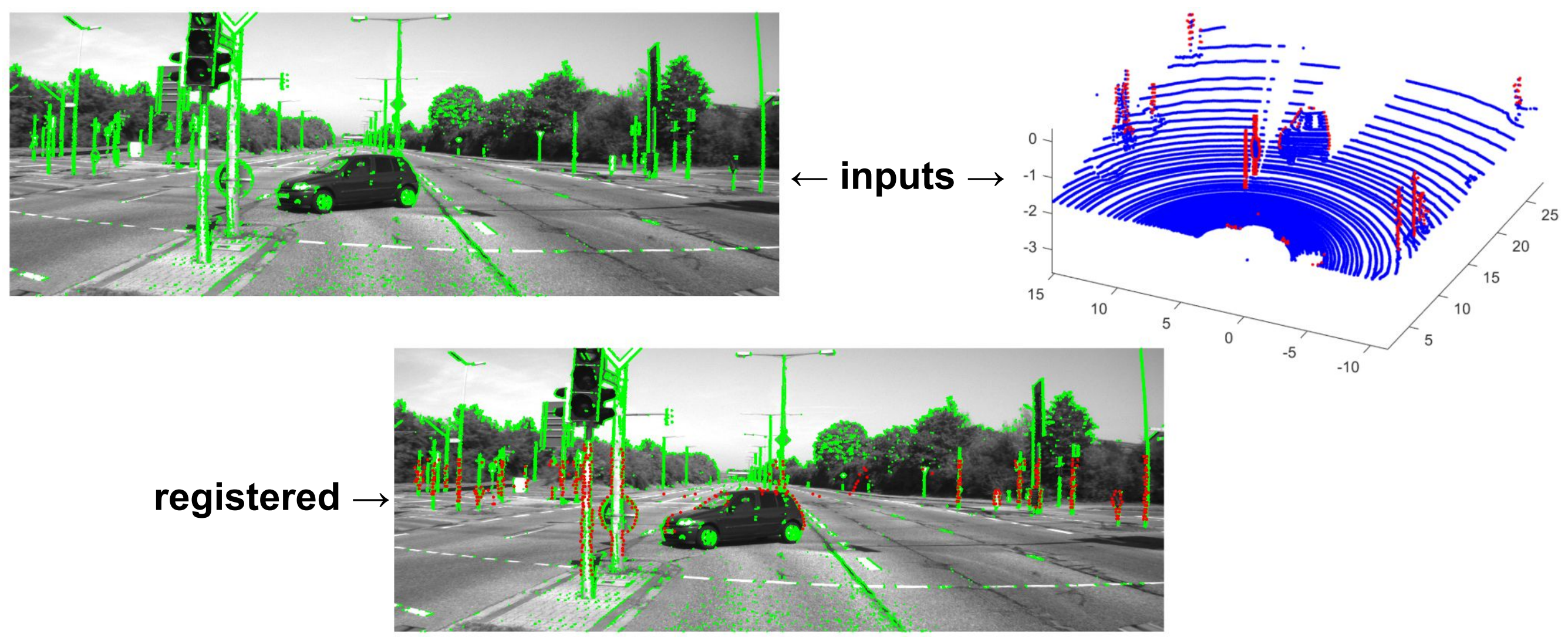
Data preselection
mini-batch B_0

Calibration tracking
$\text{argmin}_\theta \mathbb{E}\left[f(\theta|B_0)\right]$ → $\hat{\theta}$

θ^{ref} → **Calibration monitoring**
$P(\theta^{\text{ref}}|B_0)$ → V

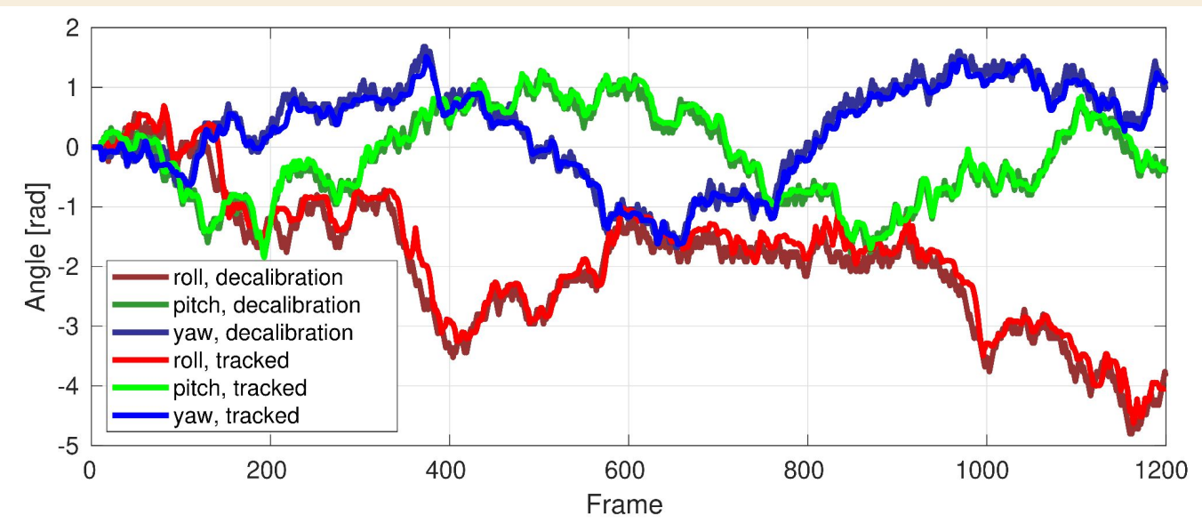
Methods

- Local optimization of alignment between low-level features from a camera-LiDAR pair, with FoV overlap
- Kernel correlation [1] (robust, w/o 1-to-1 matching)

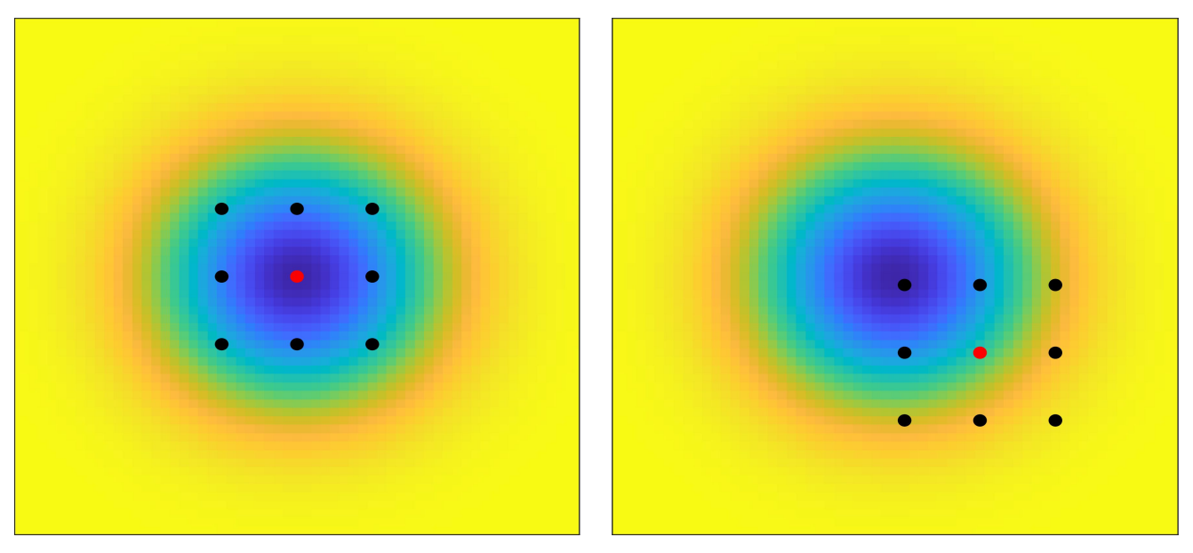


OCaMo Tracking

- Stochastic gradient-based optimization with adaptive learning rate (based on [2])
- It utilizes filtering with adaptive memory to lower the variance of the random loss function and so increases the precision



LTO Monitoring



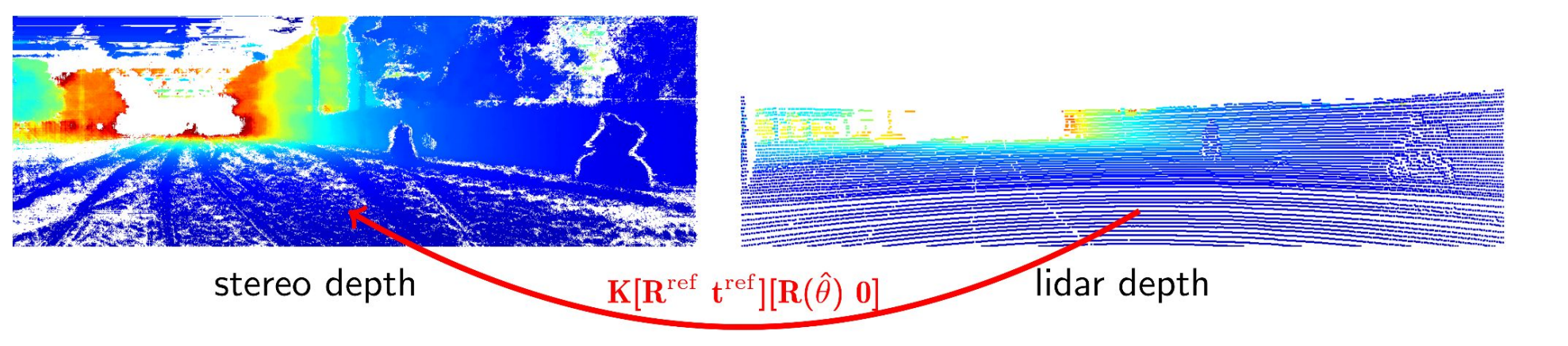
- As the loss is a random function (not comparable across mini-batches), we adapt a grid-based stochastic minimum-confirmation method from [3]
- It uses a proxy measure that estimates the fraction of grid evaluations with higher (worse) loss than in the reference (see the red dot)
  ➥ Upon this measure, we learn the probability distribution $P(\theta^{\text{ref}}|B_0)$

Results

Tracking

Experiment A

- LiDAR projection depth should be consistent with stereo (tested on KITTI sequence)
- OCaMo compensates the effect of synthetic decalibration in the MAE sense



MAE [m]	without decalibration	per-frame rotational decalibration drift of ±0.02°	±0.04°	±0.08°
uncompensated	0.715 (±0.15)	0.952 (±0.27)	1.465 (±0.58)	2.706 (±1.37)
OCaMo	0.700 (±0.15)	0.703 (±0.15)	0.712 (±0.15)	0.749 (±0.17)

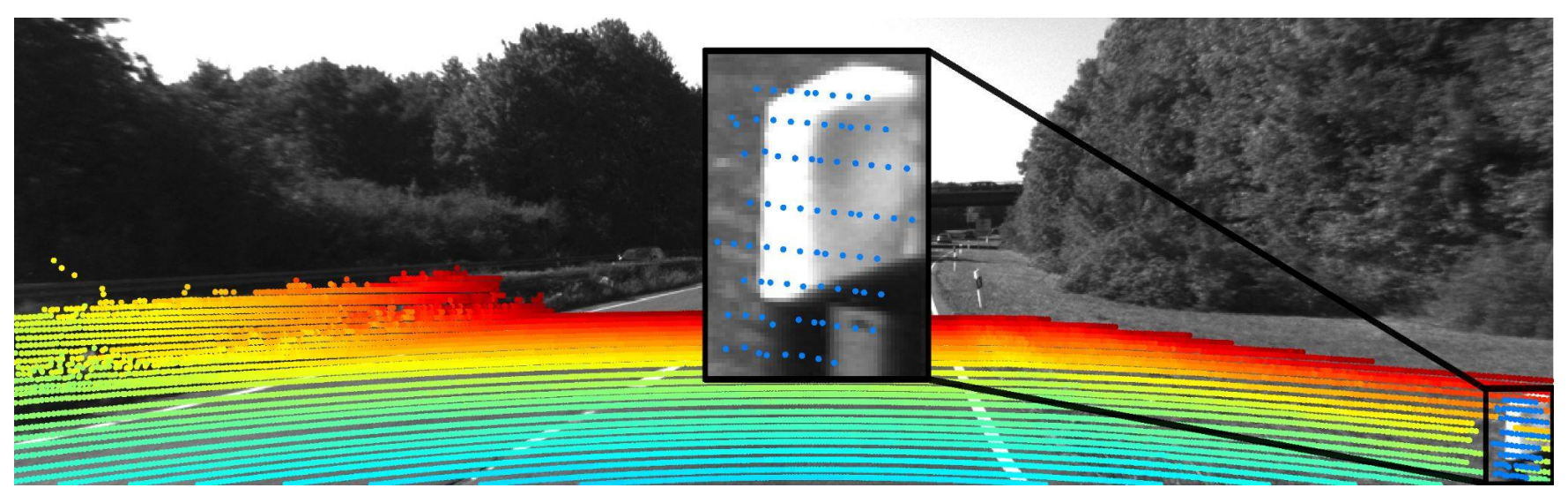
Experiment B

	Preselection	MAE [°] Roll	Pitch	Yaw
LTβ [3]	w/o	0.3365	0.3152	0.1064
	80 %	0.2687	0.2015	0.0681
OCaMo	w/o	0.2155	0.1212	0.0579
	80 %	0.1571	0.0851	**0.0347**

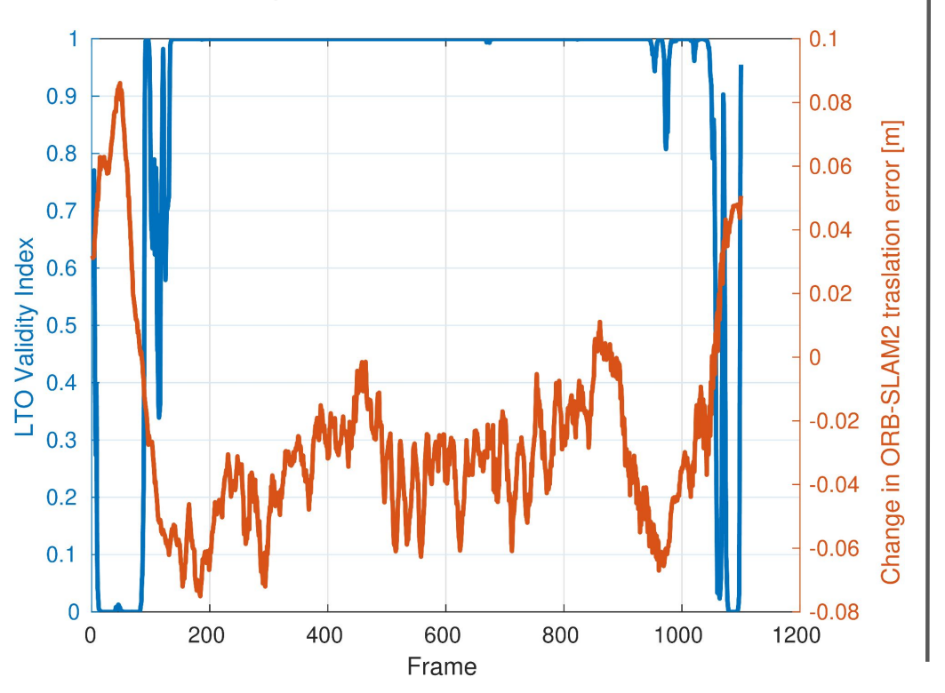
- We simulated decalibration drift of ±0.03°/frame on 545 sequences of 1,500 frames each (using Waymo dataset [4])
- OCaMo with preselection achieved MAE of 0.0347° in yaw

Monitoring

Experiment A



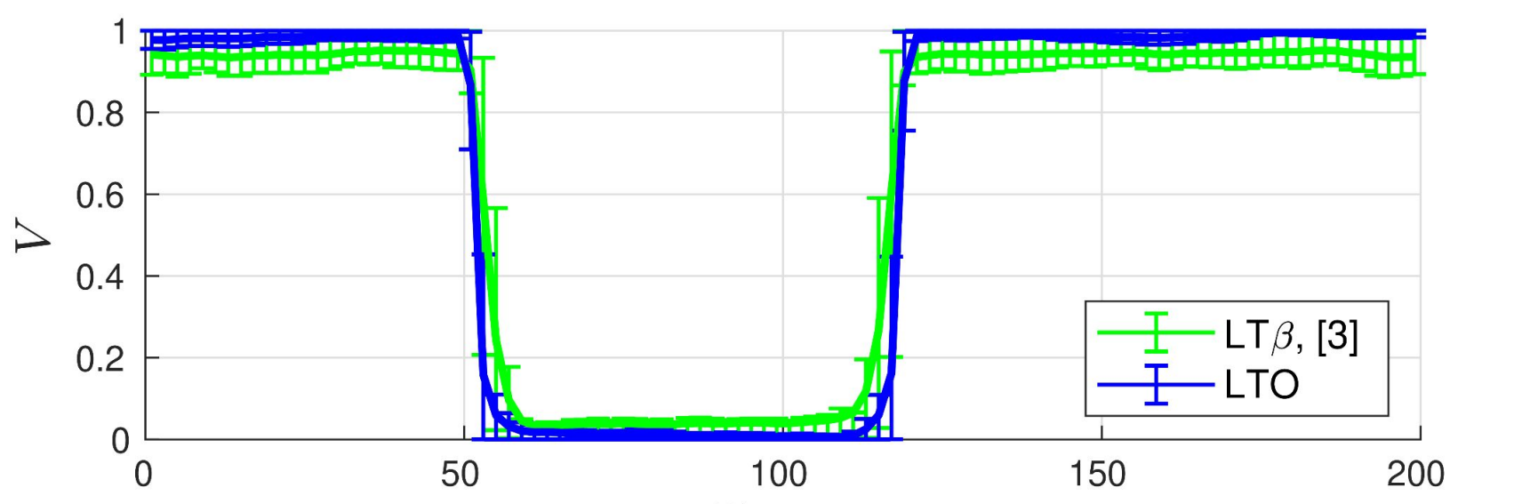
- One of the KITTI sequences exhibits some dynamic decalibration
- LTO monitoring has a high correlation of -0.77 with ORB-SLAM2 translation error on the sequence



Experiment B

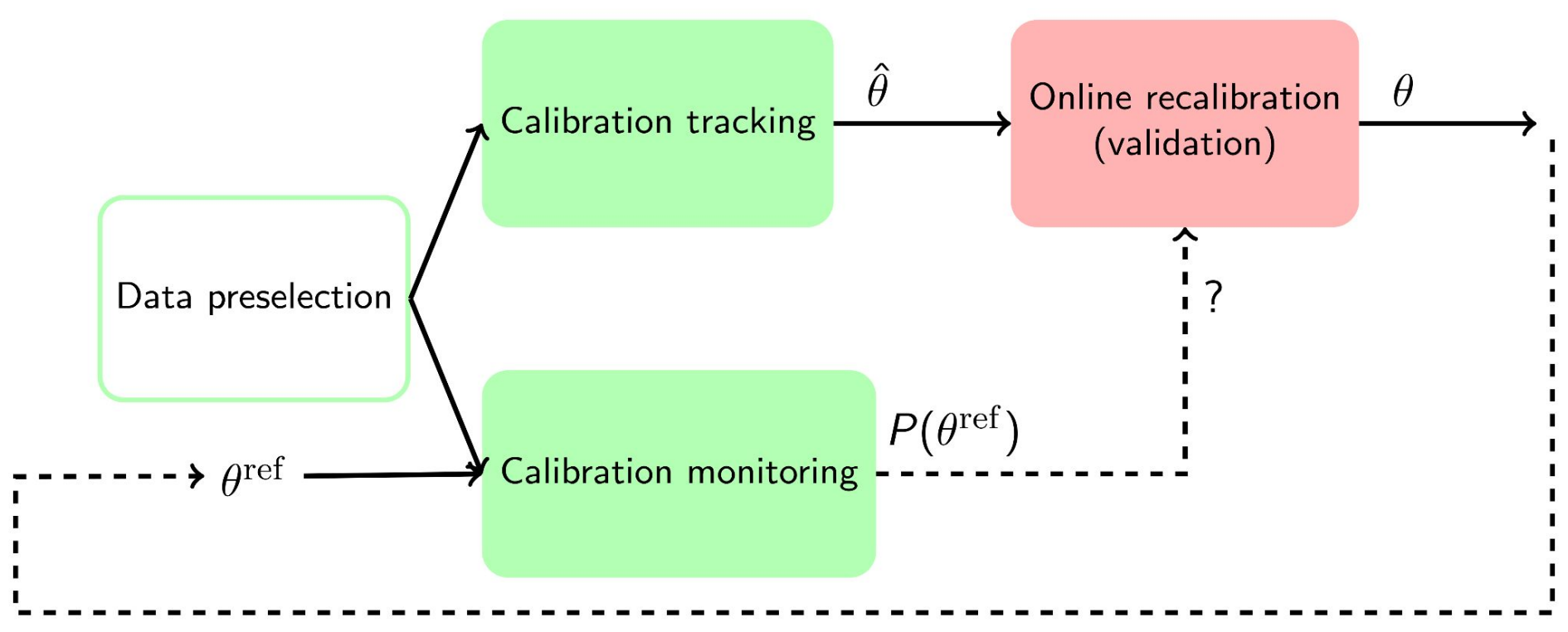
- Simulating abrupt decalibration between frames 50 and 110 on 545 sequences from the Waymo dataset [4]
- LTO monitoring outperforms LTβ [3]
- Data preselection improves accuracy of both methods

	Presel.	Accuracy [%]
LTβ [3]	w/o	95.64
	80 %	96.78
	60 %	97.25
LTO	w/o	98.94
	80 %	99.31
	60 %	99.45



Ongoing and Published Work

- Could we use the monitoring as a validation technique for tracking to create a precise and reliable recalibration method?
- Could the frame preselection binary classifier be replaced with an informativeness metric per degree of freedom?
- The proposed monitoring was extended to camera-to-camera [5]



Data preselection

Calibration tracking → $\hat{\theta}$ → Online recalibration (validation) → θ

θ^{ref} → Calibration monitoring → $P(\theta^{\text{ref}})$ → ?

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[1] Y. Tsin and T. Kanade, "A correlation-based approach to robust point set registration". ECCV, 2004, pp. 558–569.
[2] T. Schaul, S. Zhang, and Y. LeCun, "No More Pesky Learning Rates". ICML, 2013, vol. 28(3), pp. 343–351.
[3] J. Levinson and S. Thrun, "Automatic Online Calibration of Cameras and Lasers". In: Proceedings Robotics: Science and Systems Conference, 2013, art. no. 29.
[4] P. Sun, H. Kretzschmar, X. Dotiwalla et al., "Scalability in perception for autonomous driving: Waymo open dataset". CVPR, 2020, pp. 2446–2454.
[5] J. Moravec and R. Šára, "High-recall calibration monitoring for stereo cameras". In: Pattern Analysis and Applications, 2024, vol. 27, art. no. 41.