UNIVERSITY OF
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URBANA-CHAMPAIGN

Studying the impact of adding inertial constraints in two-view reconstruction

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AE 598 Final Project
April 30, 2024

Project Objective

We study the impact of adding inertial constraints (e.g., IMU factors) for optimizing two-view reconstruction

- Two-view reconstruction as covered in class only uses monocular visual data and suffers from a scale ambiguity
- Inertial Measurement Units (IMUs) provide measurements of acceleration and angular velocity that can resolve this ambiguity and potentially improve accuracy
- We wish to combine IMU and vision data, analyzing how IMU factors affect our two-view reconstruction

Project Agenda

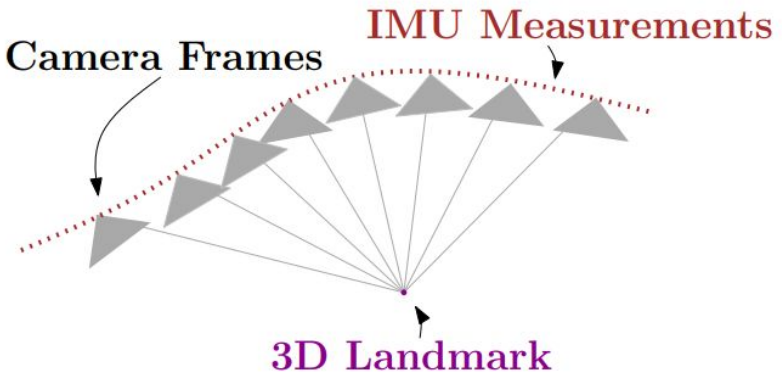
Completed Tasks:

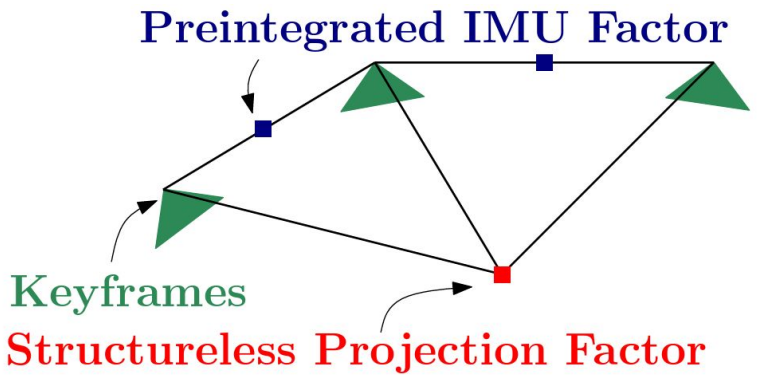
- Adapted our SfM code to work with VO/VIO datasets
- Implemented IMU preintegration “from scratch”
- Integrated IMU factors into the two-view reconstruction optimization
- Analyzed the two-view reconstruction with and without IMU factors, in terms of reprojection error

IMU Pre-Integration

- **IMU sensors capture at frequencies much higher than cameras**

- **IMU pre-integration combines many inertial measurements between two keyframes into a single relative motion constraint**



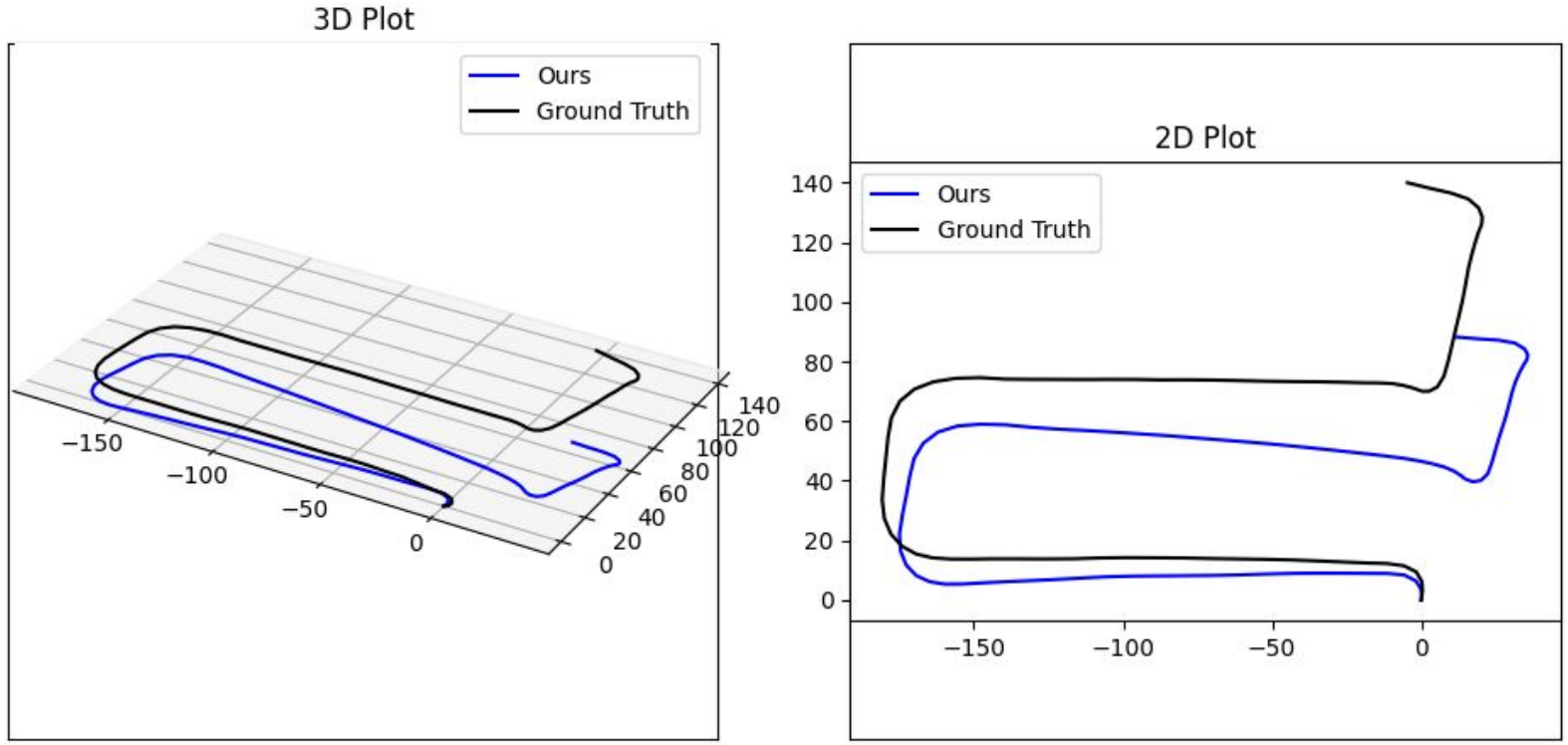


Forster, Christian, et al. ***"IMU preintegration on manifold for efficient visual-inertial maximum-a-posteriori estimation,"*** RSS. 2015.

Pre-Integration: Our implementation shows significant drift

We compare our IMU pre-integration implementation to the ground truth on KITTI

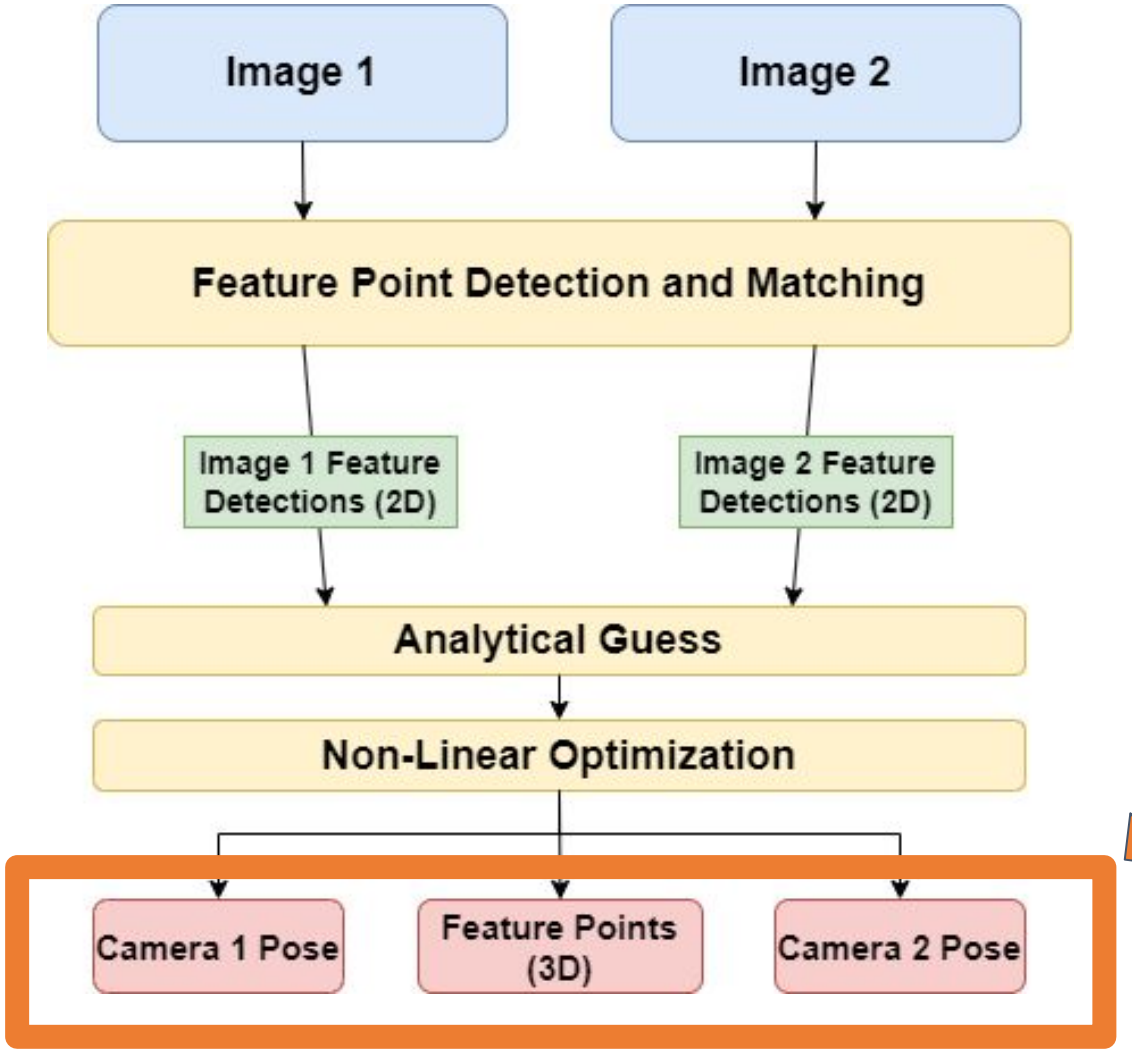
Our implementation shows the correct general shape but significant drift



A plot of the ground truth as well as our estimated IMU trajectories (unit: meter)
KITTI seq 0022, 09/26/2011

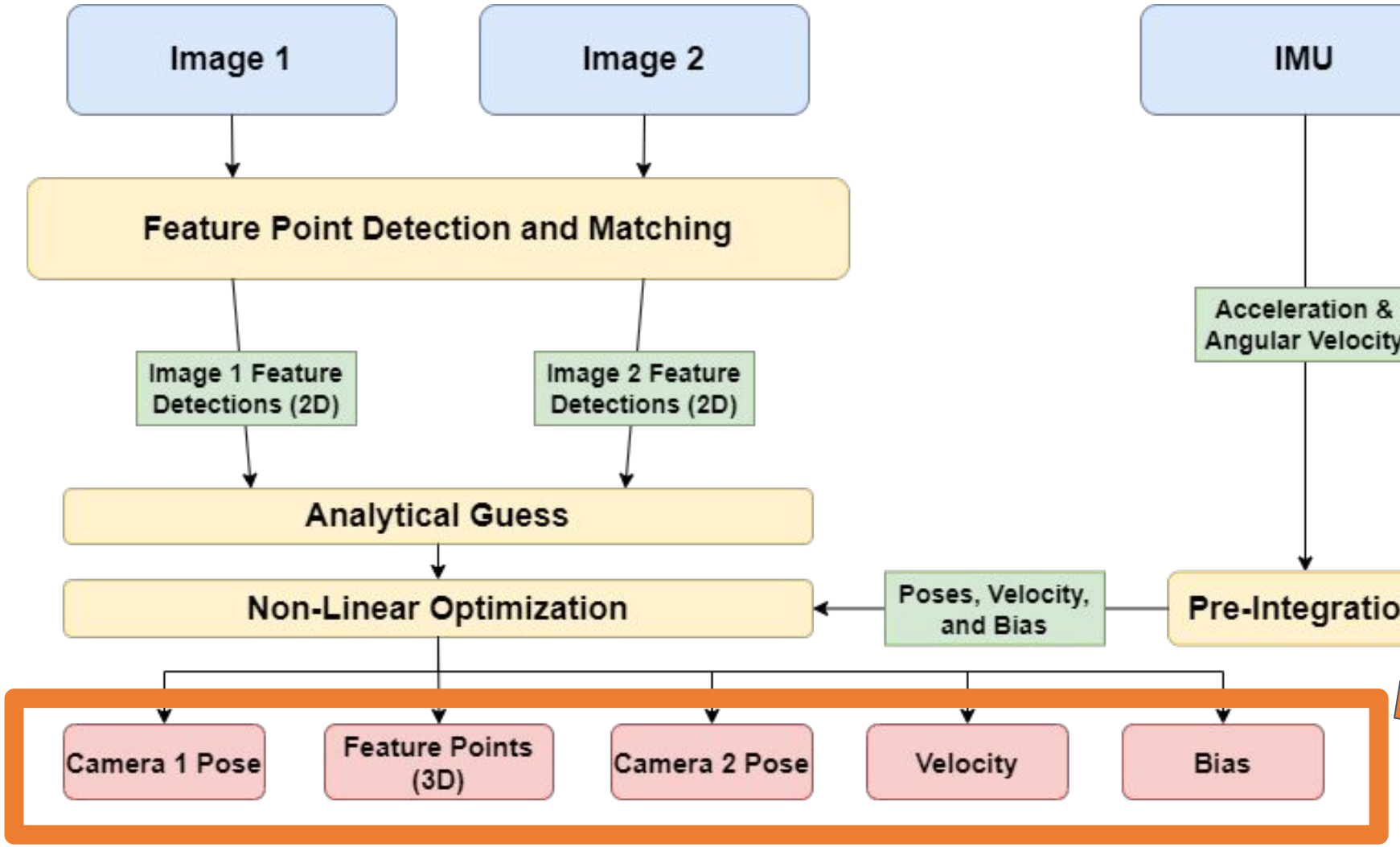
A. Geiger, et al. ***"Are we ready for autonomous driving? The KITTI vision benchmark suite,"*** CVPR. 2012.

Optimization Formulation (Visual-Only)



Pose and point locations estimated up to scale by minimizing reprojection error

Optimization Formulation (Visual + Inertial)



Pose and point locations estimated (with scale) using additional factors from IMU

Results (Reprojection Error)

Method	Image 0 Reprojection Error (Pixels)	Image 1 Reprojection Error (Pixels)
Analytical Guess	0.073 ± 0.272	0.071 ± 0.259
Non-Linear (Visual-Only)	**0.031 ± 0.032**	**0.031 ± 0.031**
Non-Linear (Visual-Inertial)	0.043 ± 0.041	0.043 ± 0.040

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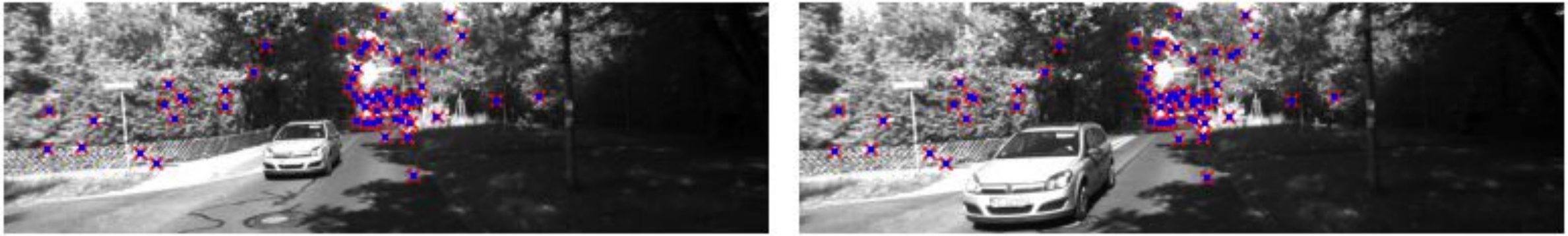

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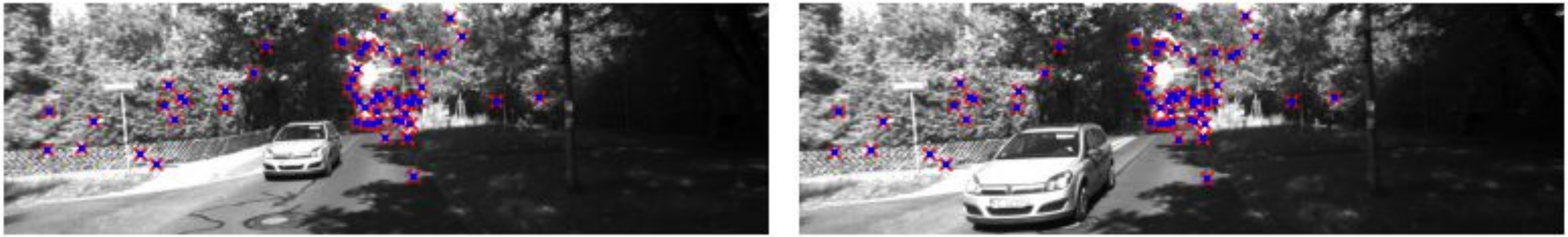

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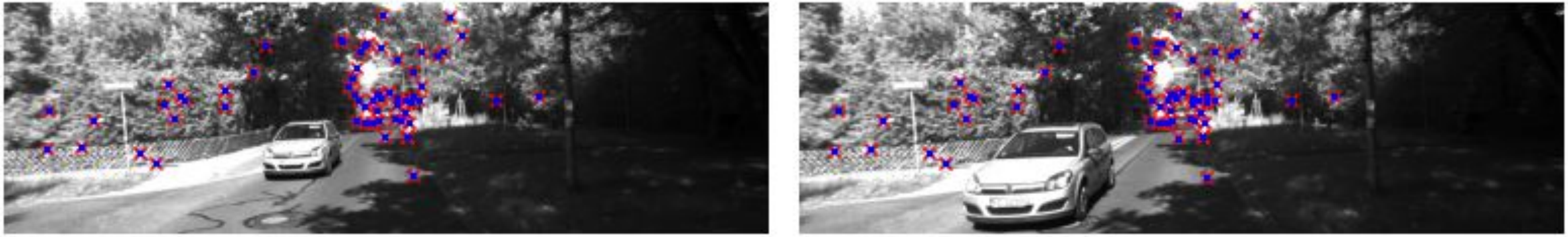

Summary & Key Takeaways

- Integrating inertial data is hard!
- Addition of IMU data in optimization leads to a slight drop in reprojection error as compared to visual-only optimization
- Post-optimization (both visual-only and visual-inertial) results show lower error than the initial guess with regards to reprojection error