



**UNMANNED
SYSTEMS LAB**

SSRR 2022

IEEE International Symposium on Safety, Security, and Rescue Robotics



TEXAS A&M UNIVERSITY

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Online Multi Camera-IMU Calibration

Jacob Hartzler and Srikanth Saripalli

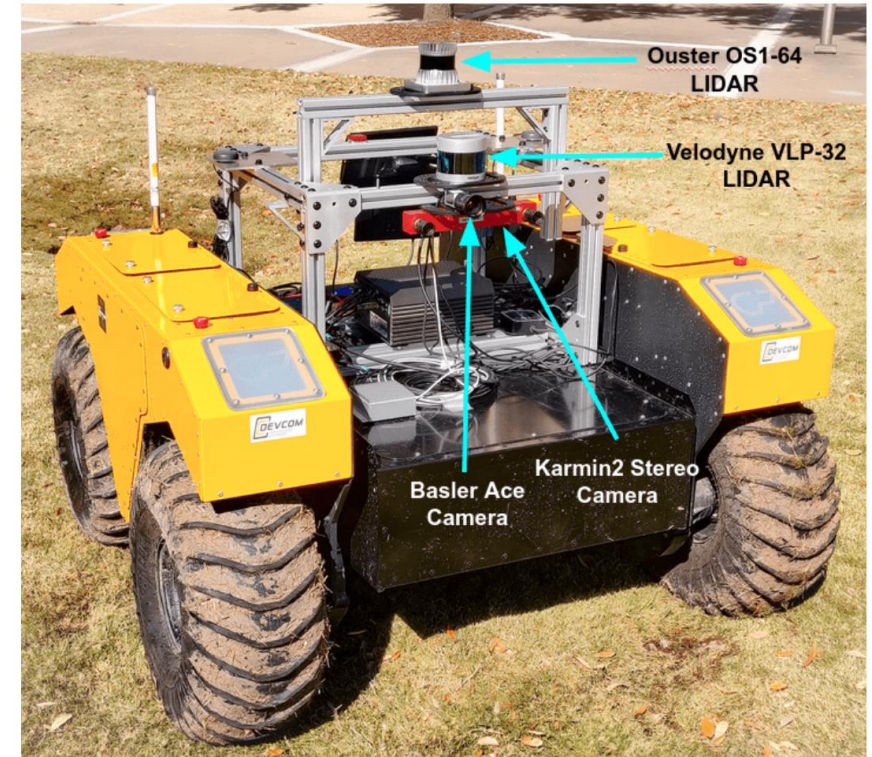
IEEE International Symposium on Safety, Security, and Rescue Robotics 2022

Presentation Outline

- Motivation
- Estimator Design
- Simulation Results
- Experimental Results
- Future Work / Conclusions

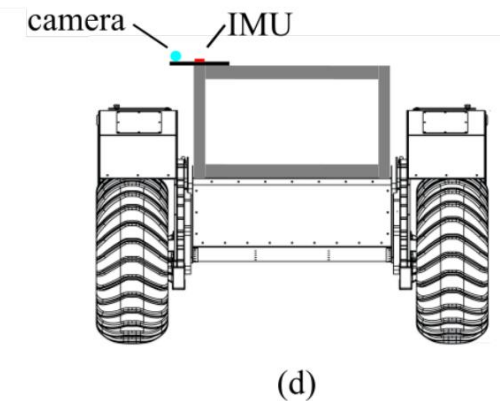
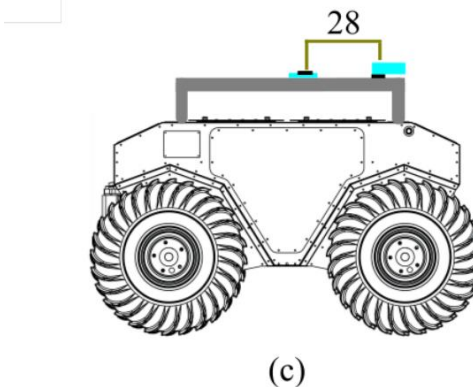
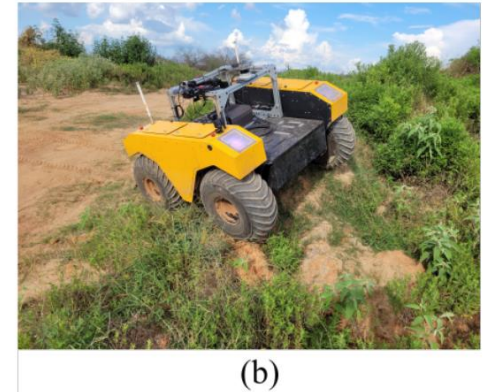
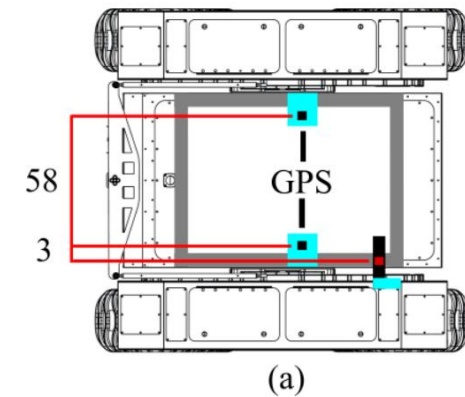
The Need for Calibration

- Mobile robotic systems rely on proprioceptive and exteroceptive sensors
- Accurate sensor integration requires good intrinsic and extrinsic calibration
- Poor calibrations often lead to visual-inertial odometry and SLAM divergences
- Therefore, it is necessary for mobile robotic systems to have highly accurate calibrations throughout the use lifecycle



The Challenges of Calibration

- It is difficult to achieve good, consistent sensor calibrations
- High-accuracy calibration devices are costly and time-consuming
- Batch processes are cheap, but cannot handle calibration changes
- Therefore, accurate, online processes for calibrating IMU-camera systems are desirable



Example Challenging Scenario

- Shocks and vibrations impact initial calibrations
- There are drastic lighting differences based on FOV
- Returning to calibration environment would be time consuming and costly

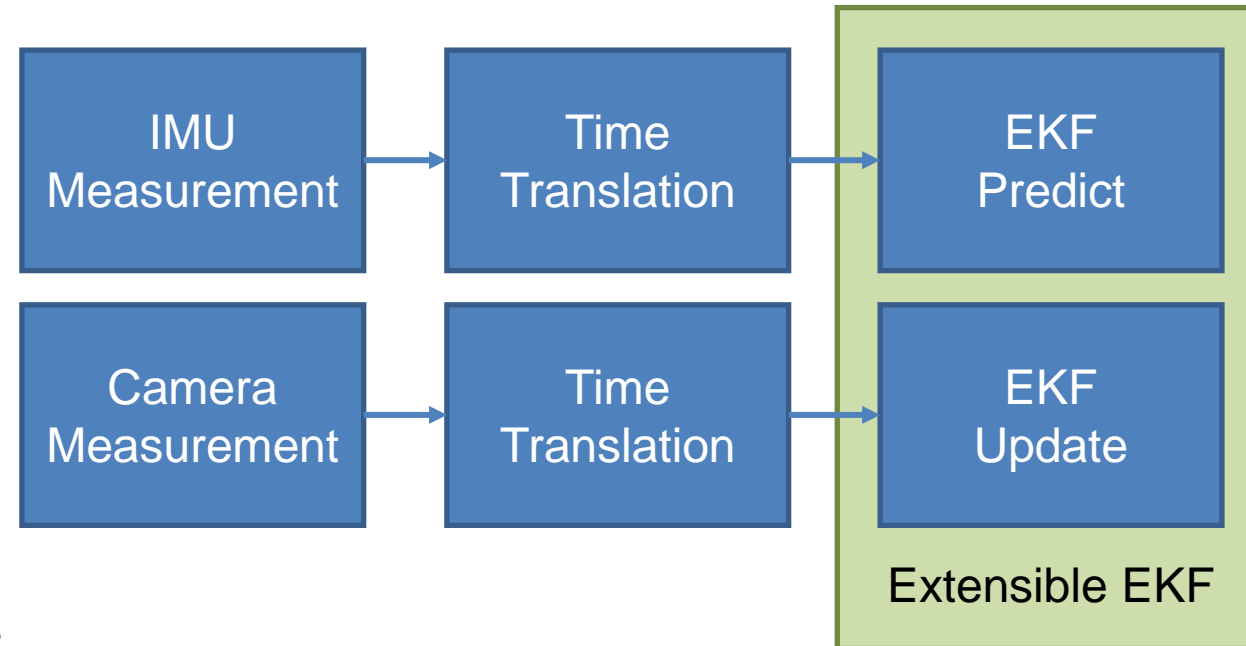


Problem Statement

- Create an online multi-camera IMU calibration filter
- Design camera count flexibility into the filter
- Utilize high-accuracy, generic fiducial markers for detection
 - Trades robustness for additional accuracy
- Handle time translation, where closed-loop corrections are not possible

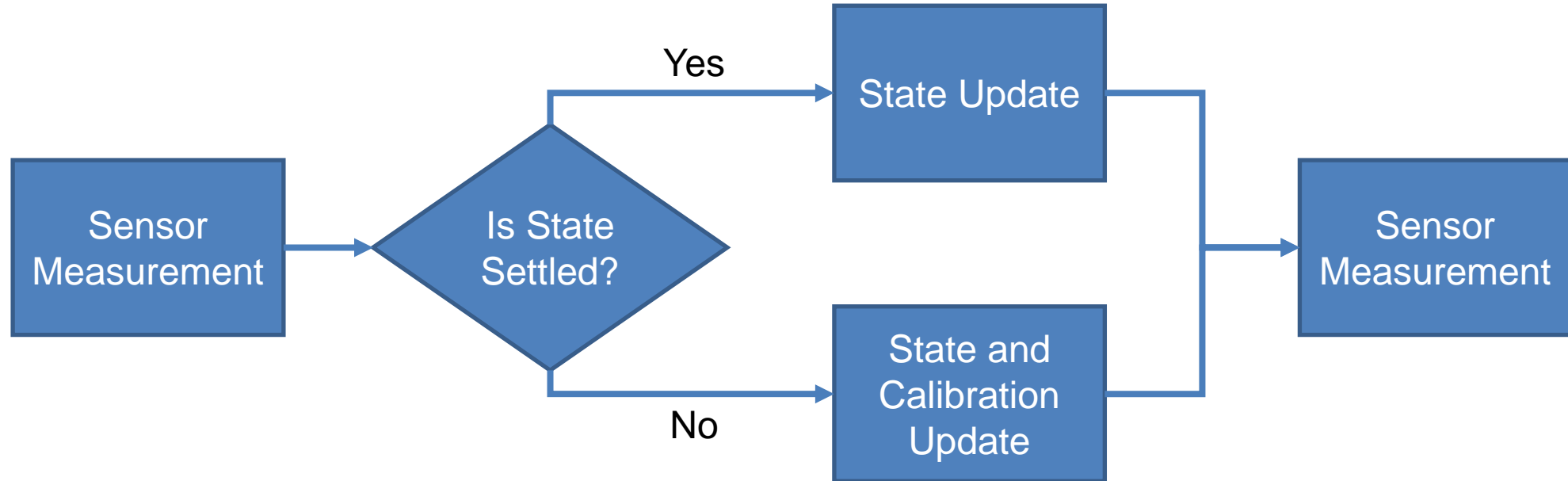
Filter Design

- Body States
 - Position, Velocity, Orientation ...
- IMU States
 - Extrinsic Offsets, Intrinsic Biases
- Camera States
 - Extrinsic Offsets
- Time Translation
 - Time offset and skew parameters



Settle-Detection

- Monitoring EKF states for settle criteria
- Consider a state settled when uncertainty is sufficiently reduced
- Once settled, we modify the update equations to not adjust calibrations
 - With higher rates and number of sensors, this can improve performance

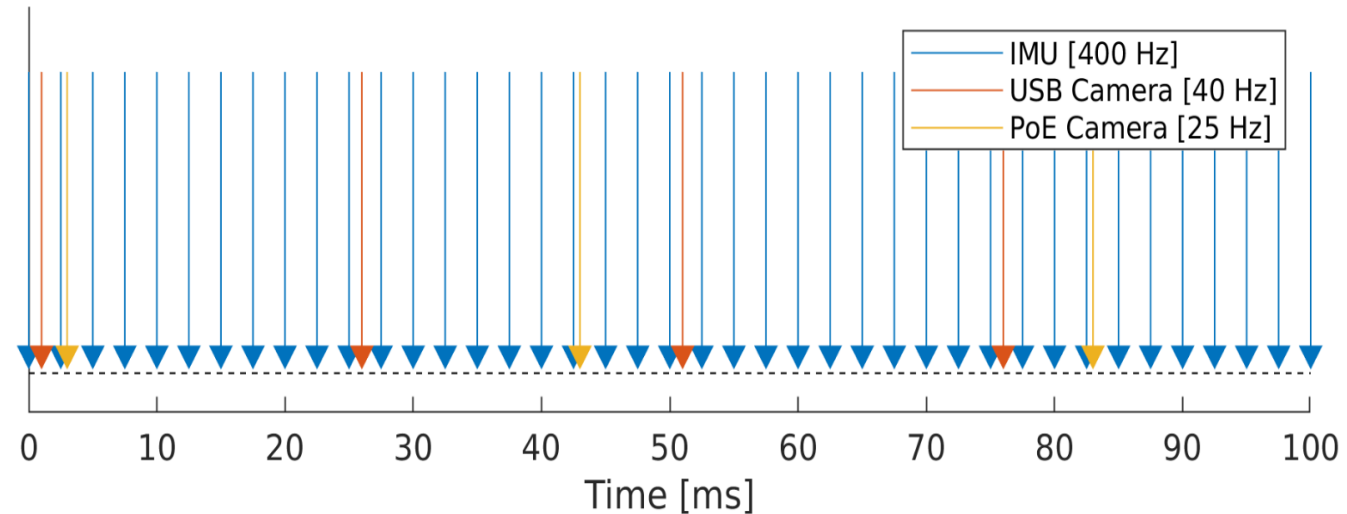


Shift-Detection

- Monitor EKF states for shift criteria using just residuals
- Using a sliding-window t-test, we test residuals for changes in calibrations
- When a shift in calibration is detected, reinstate the full update equation

Sensor Timing and Rates

- IMU
 - 400 Hz VectorNav VN 300
- Cameras
 - 40 Hz USB 3.0 Basler Ace
 - 25 Hz PoE Pointgrey Blackfly
- Resulting Measurement Stream
 - Non-synchronized measurements
 - Varying network delays (10-100 ms)



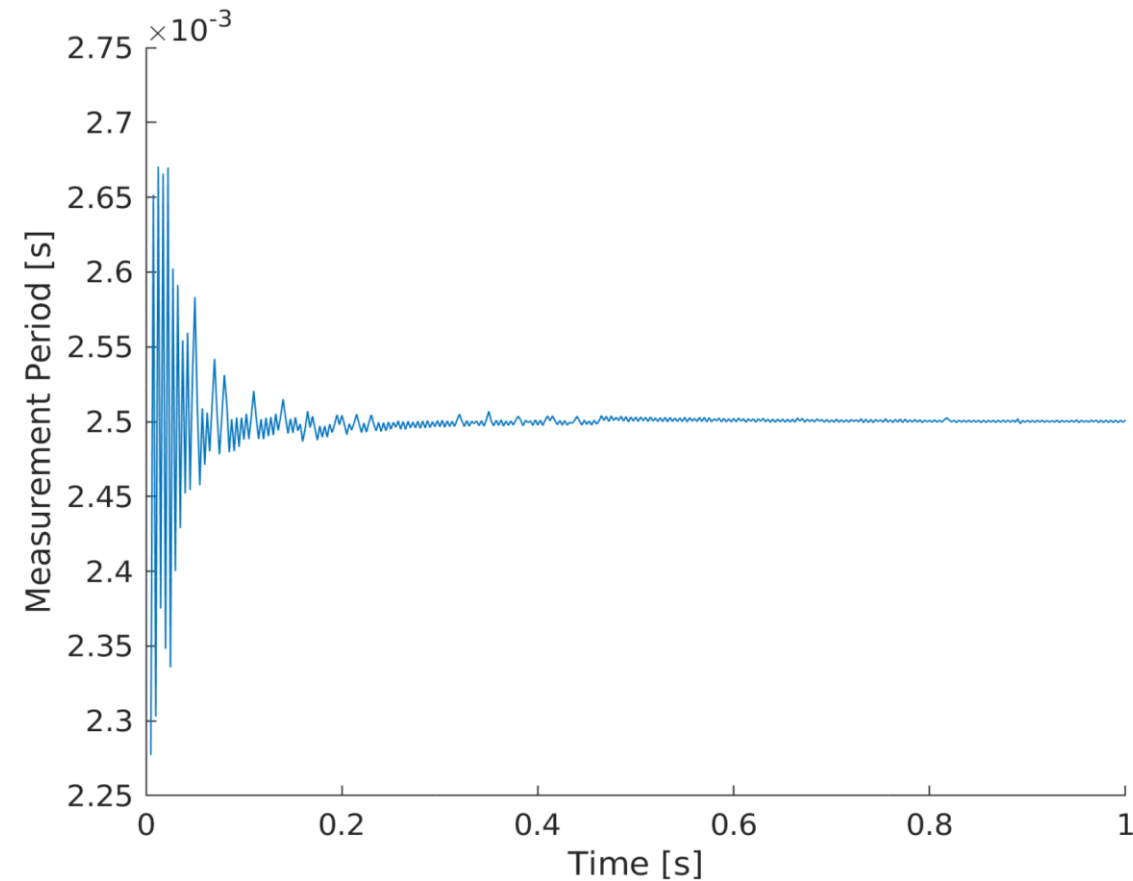
Time Translation Filter

- Many sensors are not PTP capable
- Local sensor clocks are consistent
- Network delays vary and are difficult to predict
- A one-way filter was used to pre-process measurement time
- Adjusted measurement time was then fed into filter
- Simple measurement model allows for linear filter updates

$$t_{filter} = \alpha t_{sensor} + \beta$$

Time Translation Results

- Implemented for USB Sensors
- Converged quickly for high-rate sensors
- Reduced measurement jitter
- Corrects for simultaneous packets



Monte Carlo Simulations

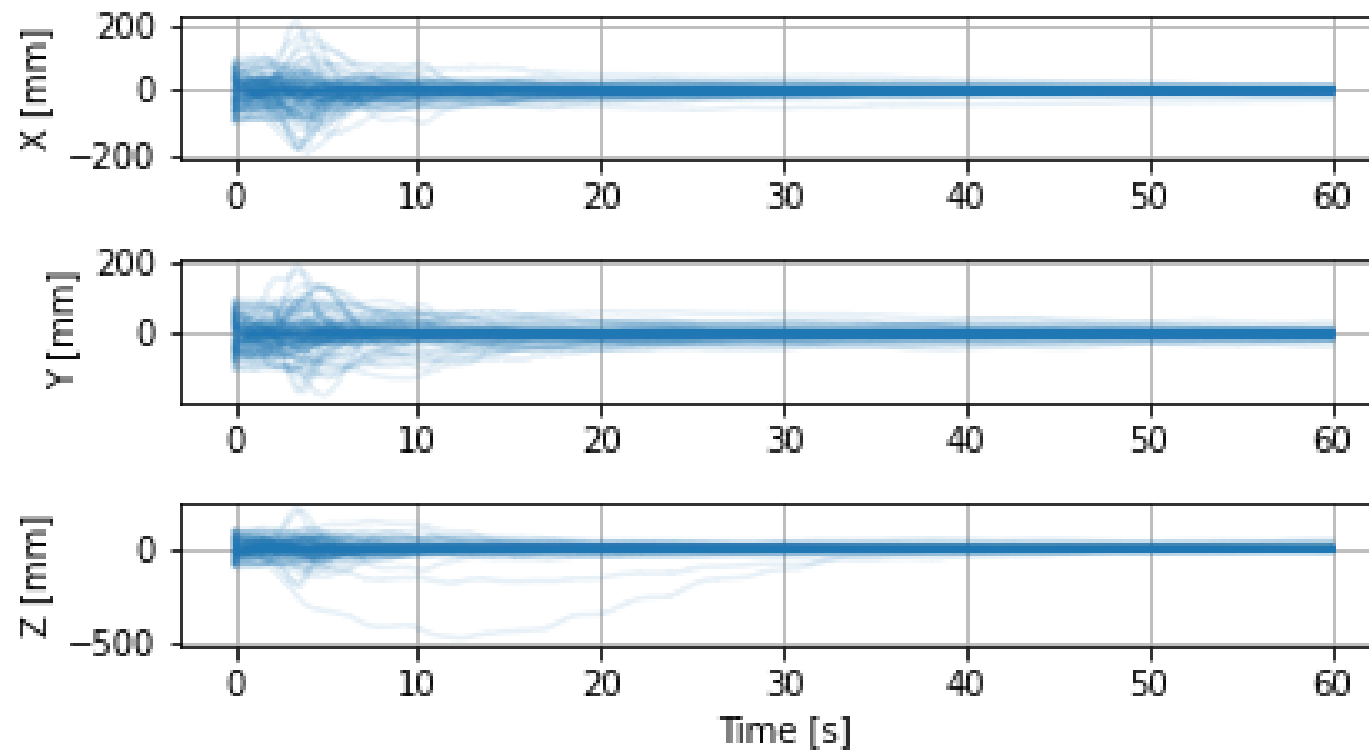
- Monte Carlo Simulation
 - Parallelized for faster processing
 - Random draws for
 - Initial intrinsic and extrinsic errors
 - Sinusoidal sensor motion errors
 - Target measurement errors
 - Shifts in extrinsic calibration parameters
 - 1000 runs for convergence testing

Monte Carlo Results

- Sensor Calibrations
 - Showed consistent and timely convergence
- Settle and Shift Detection
 - Showed ability to detect and react to settling and shifts
 - Consistent convergence after shifts in sensor calibrations

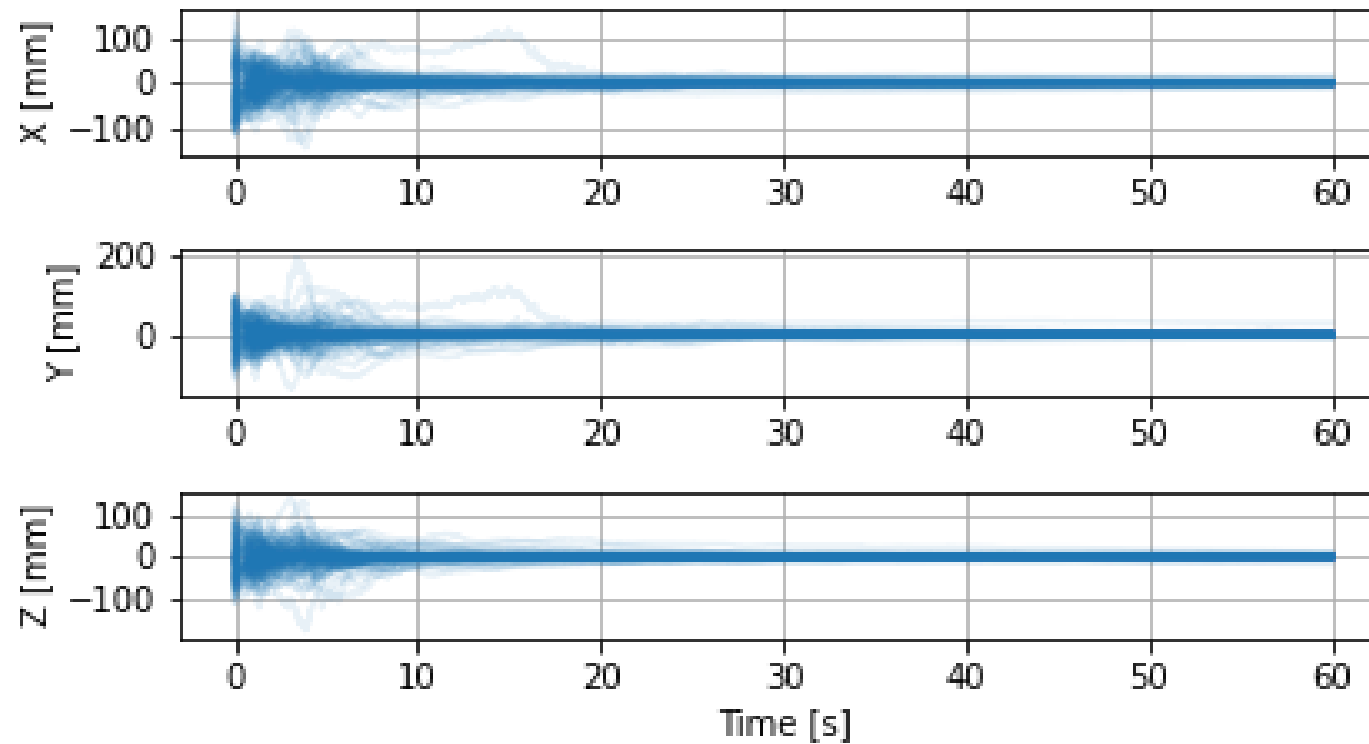
Monte-Carlo Results

IMU Positional Offset Error



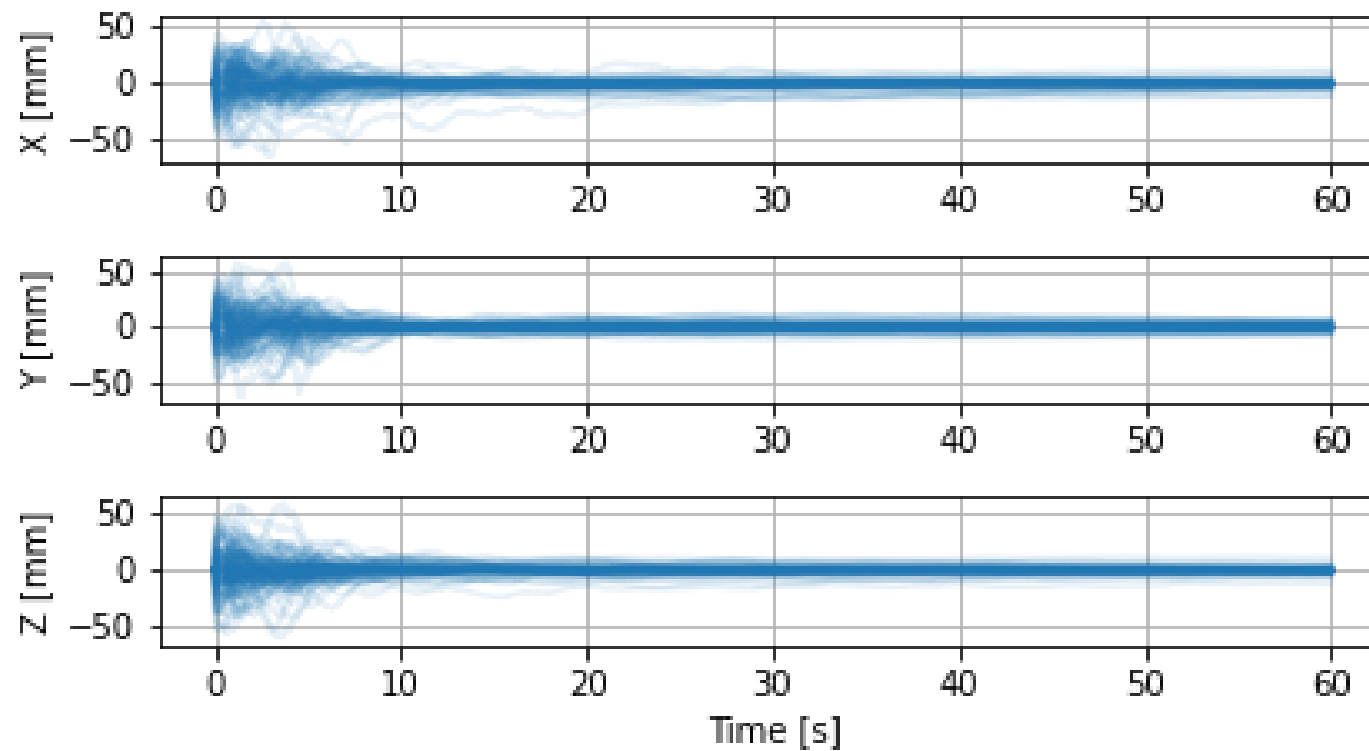
Monte-Carlo Results

IMU Angular Offset Error



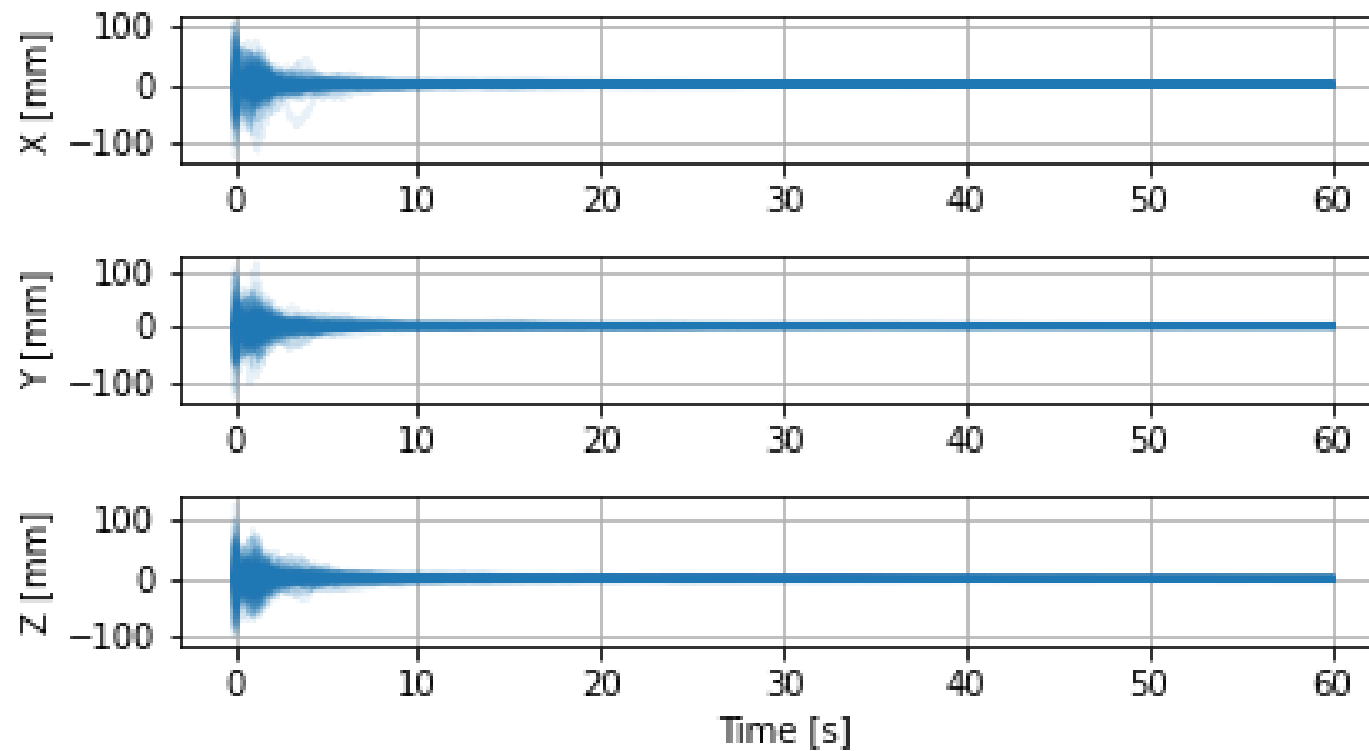
Monte-Carlo Results

IMU Accelerometer Bias Error



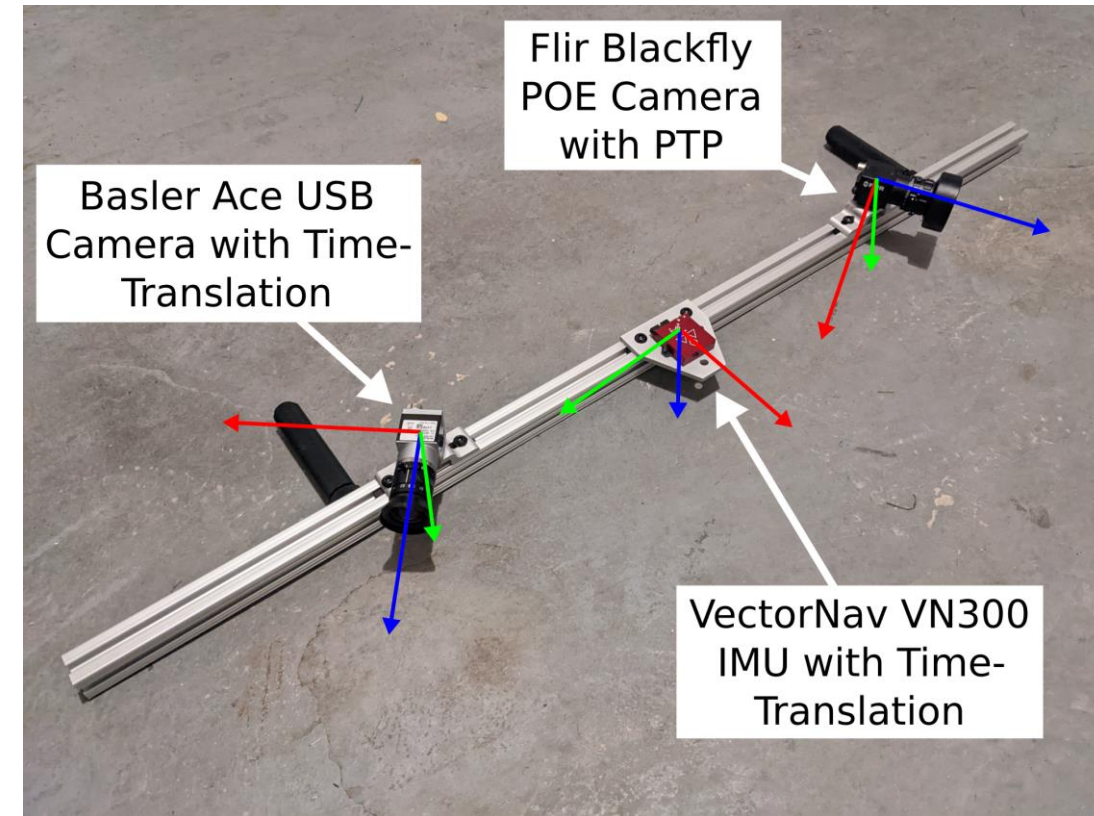
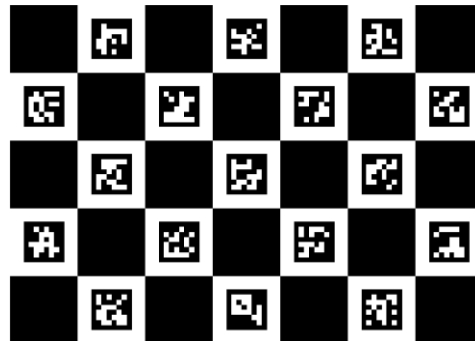
Monte-Carlo Results

IMU Gyroscope Bias Error



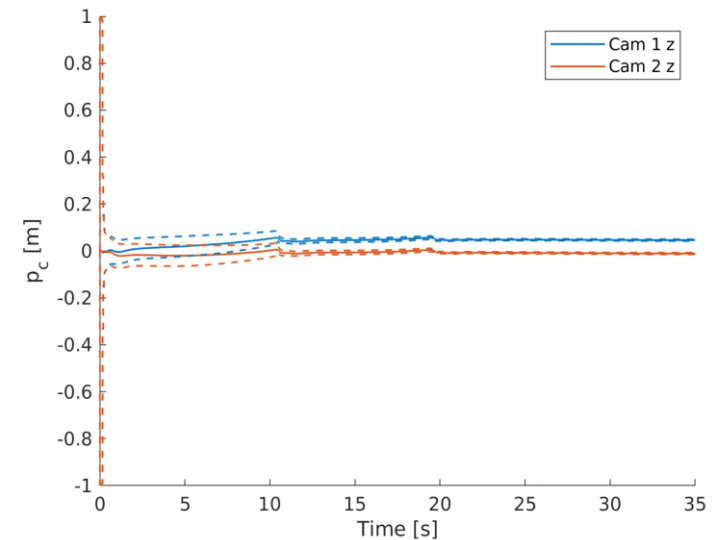
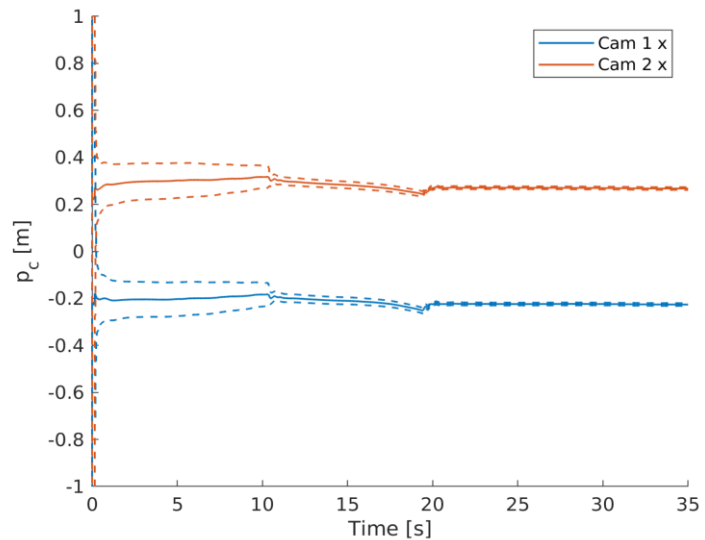
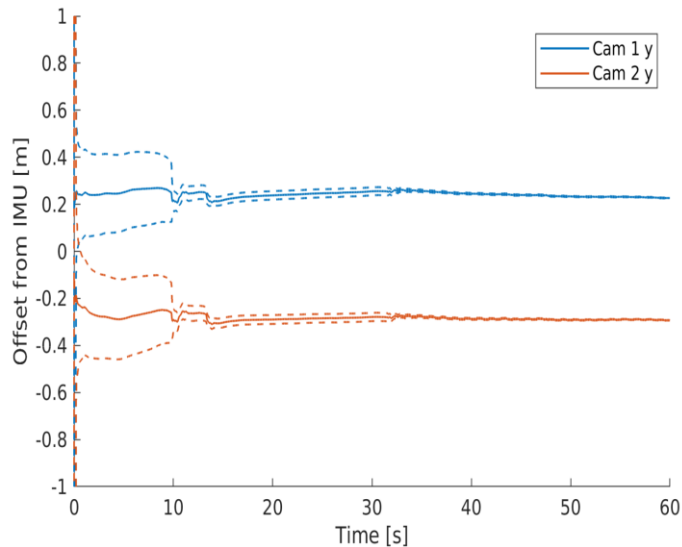
Experimental Setup

- IMU
 - VectorNav VN300
 - GPS-aided INS solution as truth
- Cameras
 - Gig-E Flir Blackfly S
 - USB 3.0 Basler Ace
- Target
 - ChArUco Board

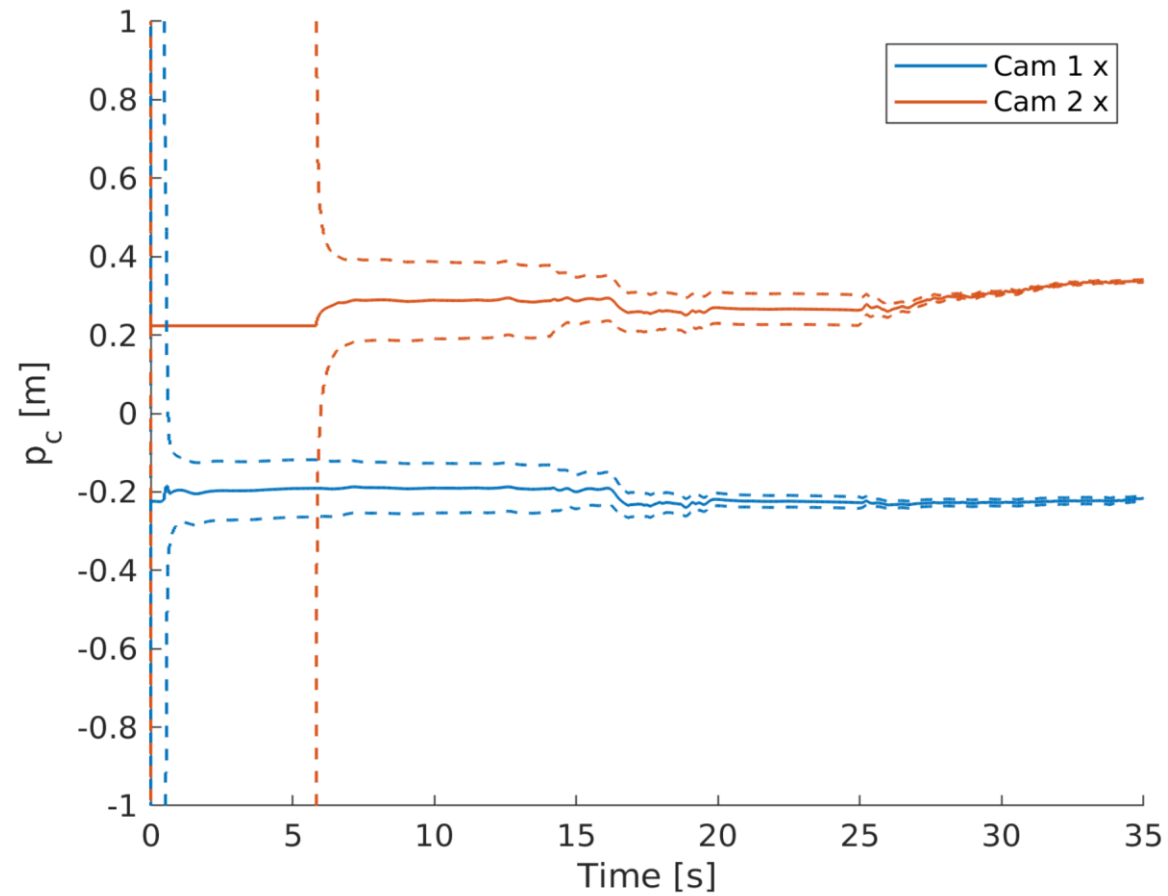


Experimental Results

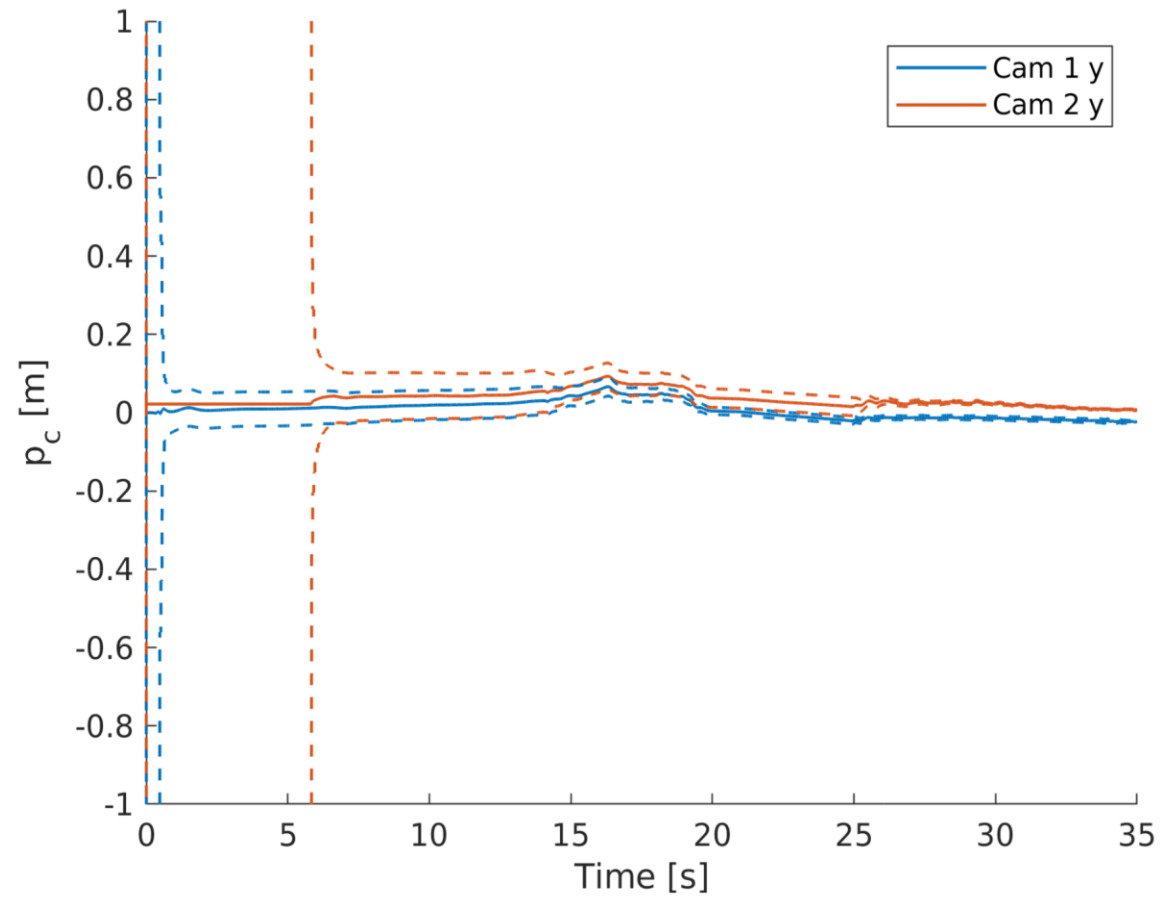
- Overlapping Fields of View
 - Convergence for extrinsic and intrinsic parameters



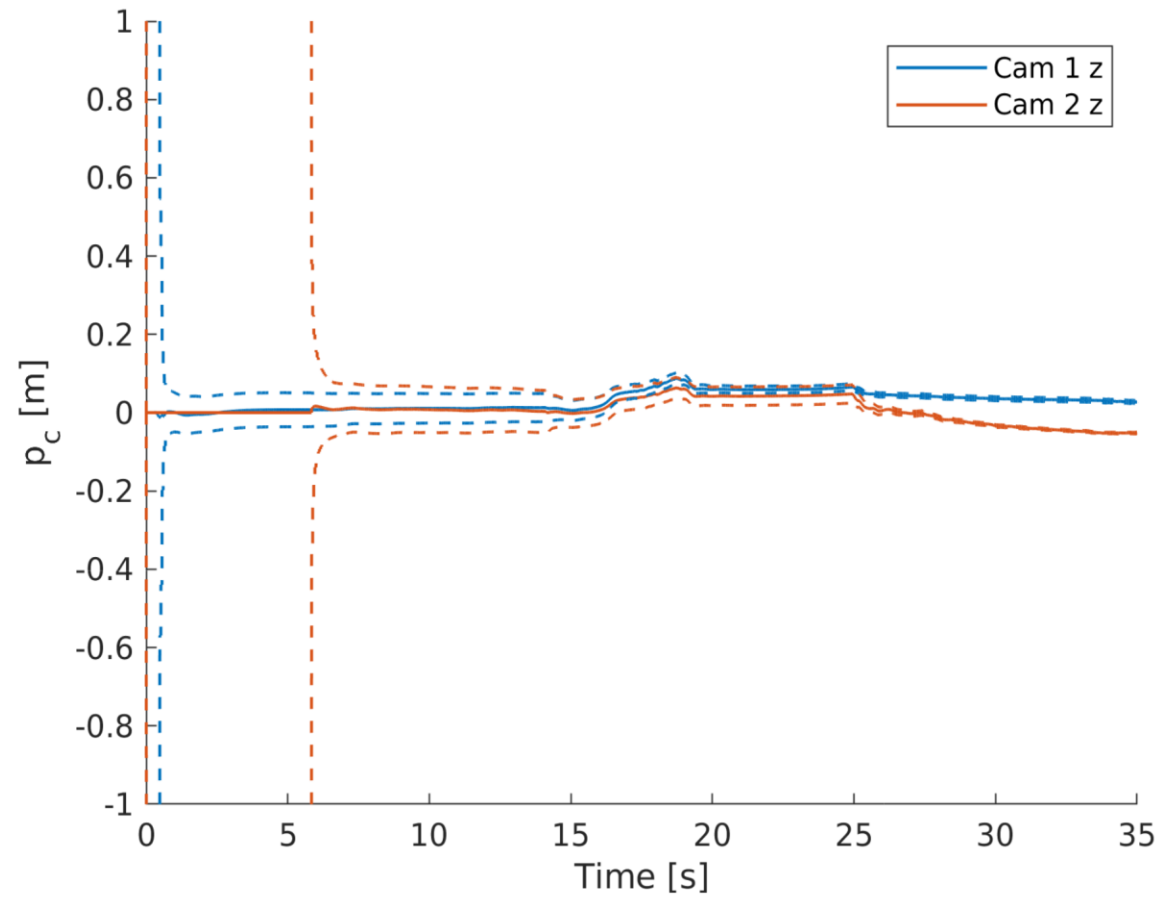
Experimental Results



Experimental Results

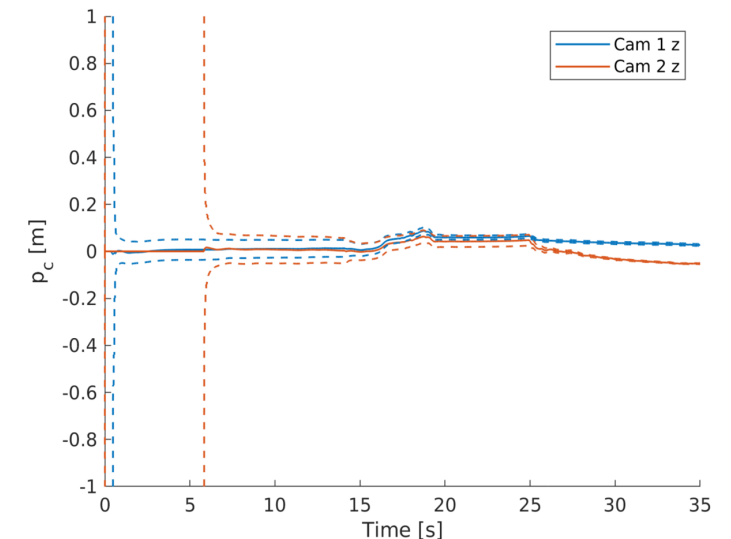
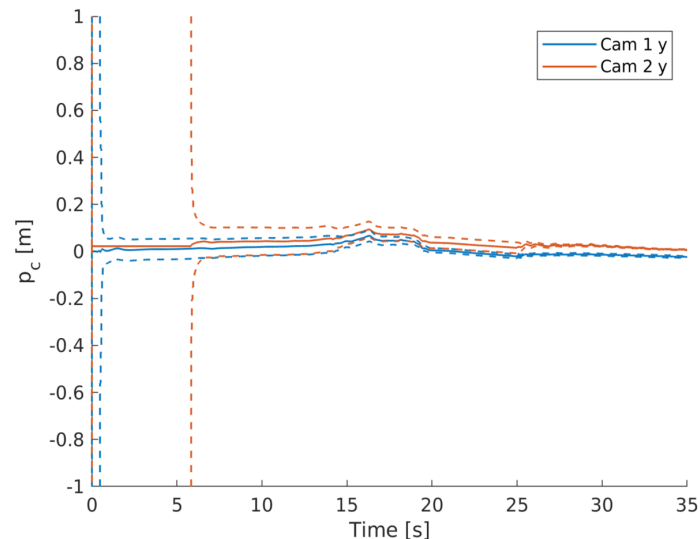
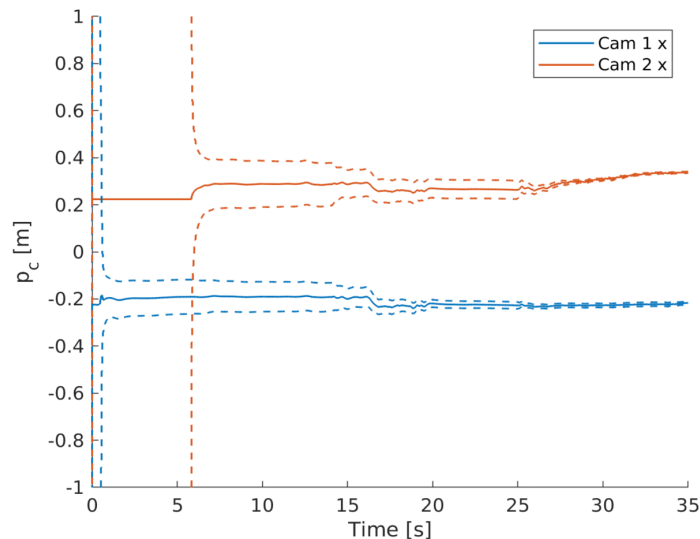


Experimental Results

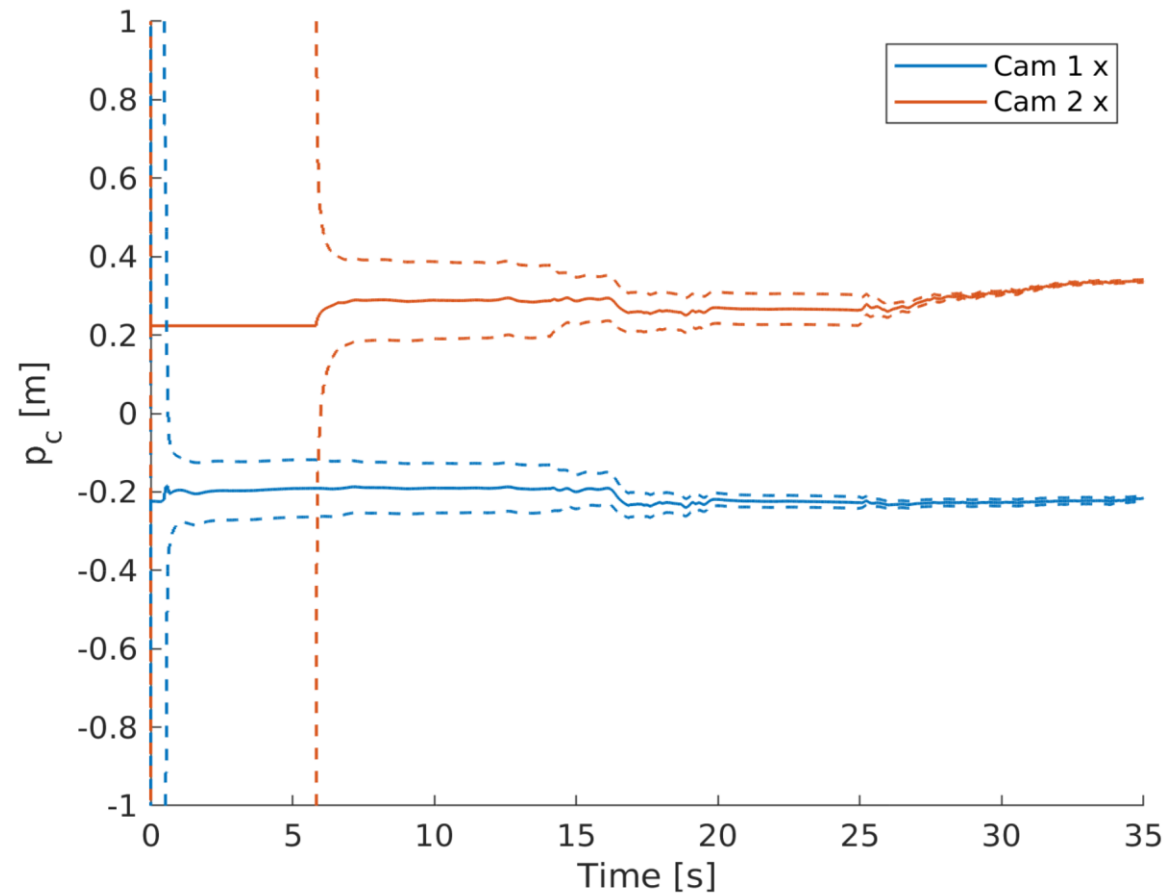


Experimental Results

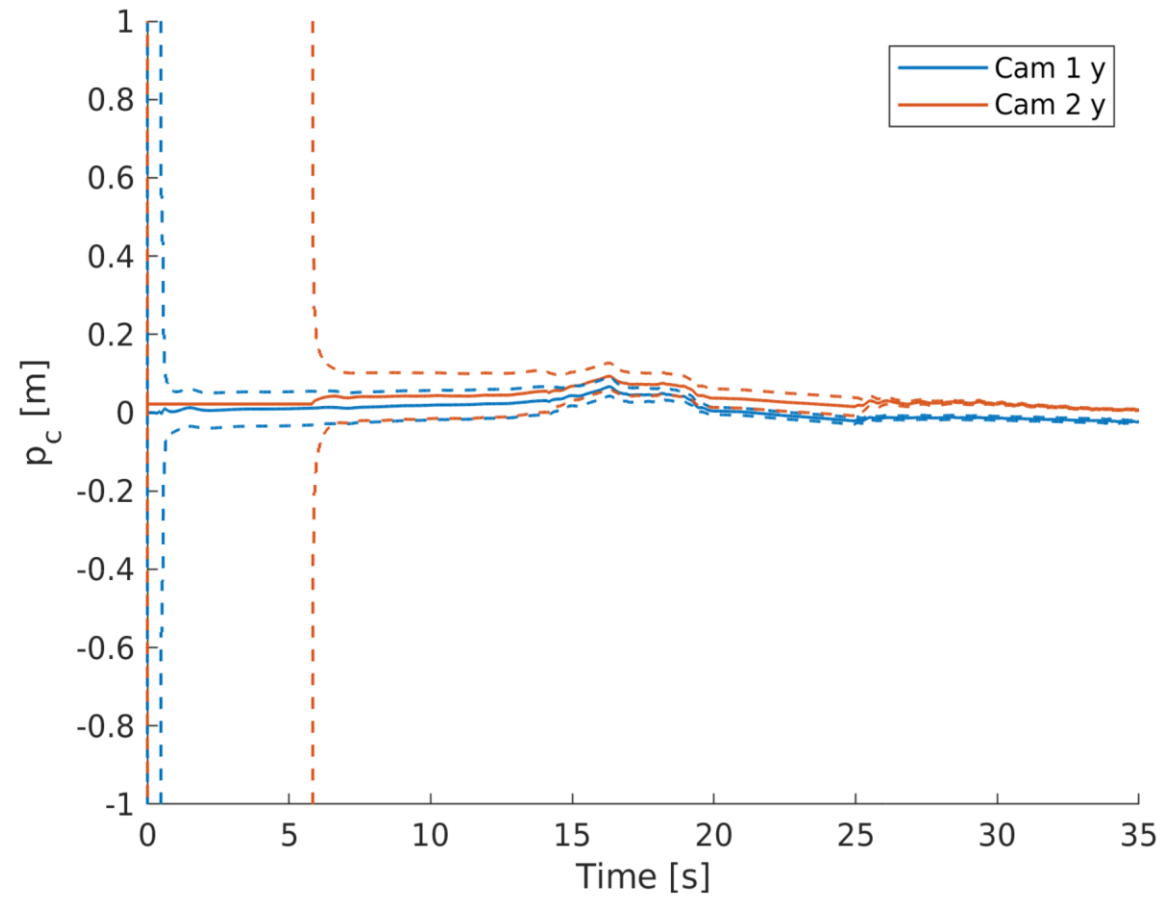
- Non-Overlapping Fields of View
 - Separate parameter convergence as targets becomes visible
 - Allows for large angular motions while still utilizing fiducial markers



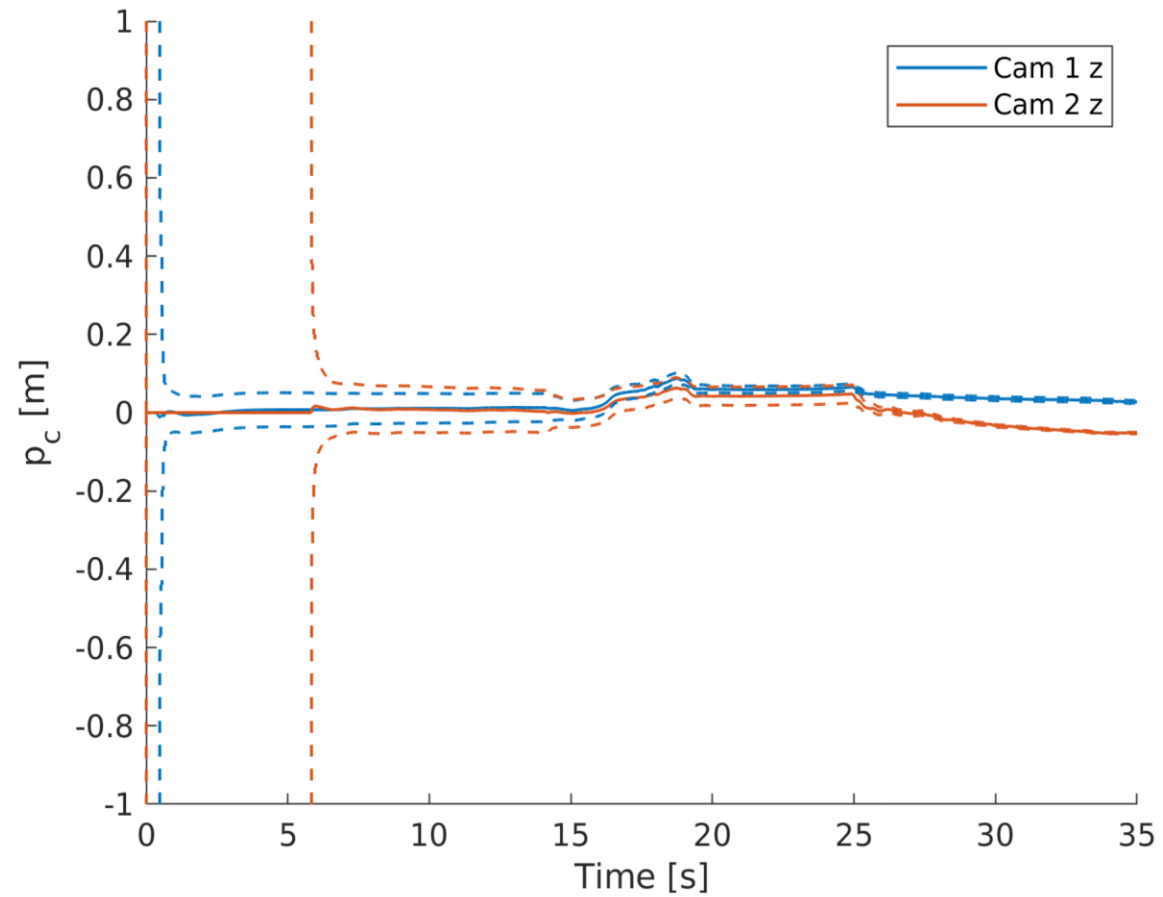
Experimental Results



Experimental Results



Experimental Results



Contributions

- Extended online IMU-camera calibration framework for multiple cameras
- Derived Jacobians and update equations for quaternion-based fiducial measurement and update
- Included time-translation filters for non-PTP sensors
- Provided open-sourced EKF simulation and ROS node implementation

Current Work

- Multi-IMU Inertial Odometry
 - Using multiple, low-cost IMUs to improve localization performance
 - Using higher-order states for rotation estimates
 - Online extrinsic and intrinsic IMU calibration

Future Work

- Integrating Multi-IMU calibration work into filter
- Using feature detection and tracking over fiducials
- Additionally testing of time translation/calibration
- High-fidelity Monte-Carlo simulation
 - Procedurally-Generated environments/images
 - Timing delays and stutters

Open-Sourced Code

- Code repository is available online
- Monte Carlo Simulation
 - Python
 - Multithreaded
 - Faster than real-time
- ROS Node
 - C++ and ROS Kinetic
 - Real-Time (Measurement Limited)
- <https://github.com/unmannedlab/multi-cam-imu-cal>

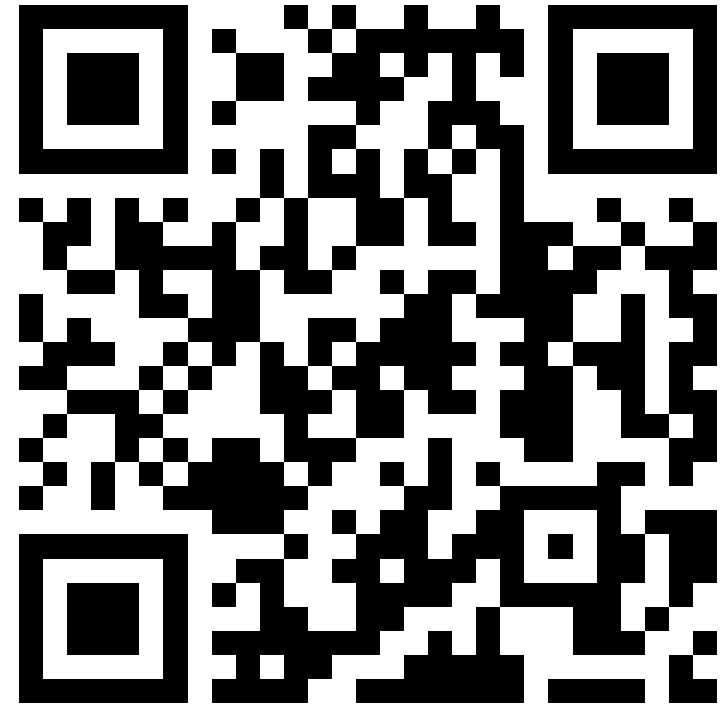
Presentation References

1. Chustz, G., & Saripalli, S. (2021). ROOAD: RELLIS Off-road Odometry Analysis Dataset. *ArXiv*. <http://arxiv.org/abs/2109.08228>
2. Mishra, S., Osteen, P. R., Pandey, G., & Saripalli, S. (2020). Experimental evaluation of 3D-LIDAR camera extrinsic calibration. *IEEE International Conference on Intelligent Robots and Systems*, 9020–9026. <https://doi.org/10.1109/IROS45743.2020.9340911>
3. Jiang, P., Osteen, P., Wigness M., and Saripalli S., (2020). RELLIS-3D: A Multi-modal Dataset for Off-Road Robotics.

Questions



Code Repository



Unmanned Systems
Lab Website

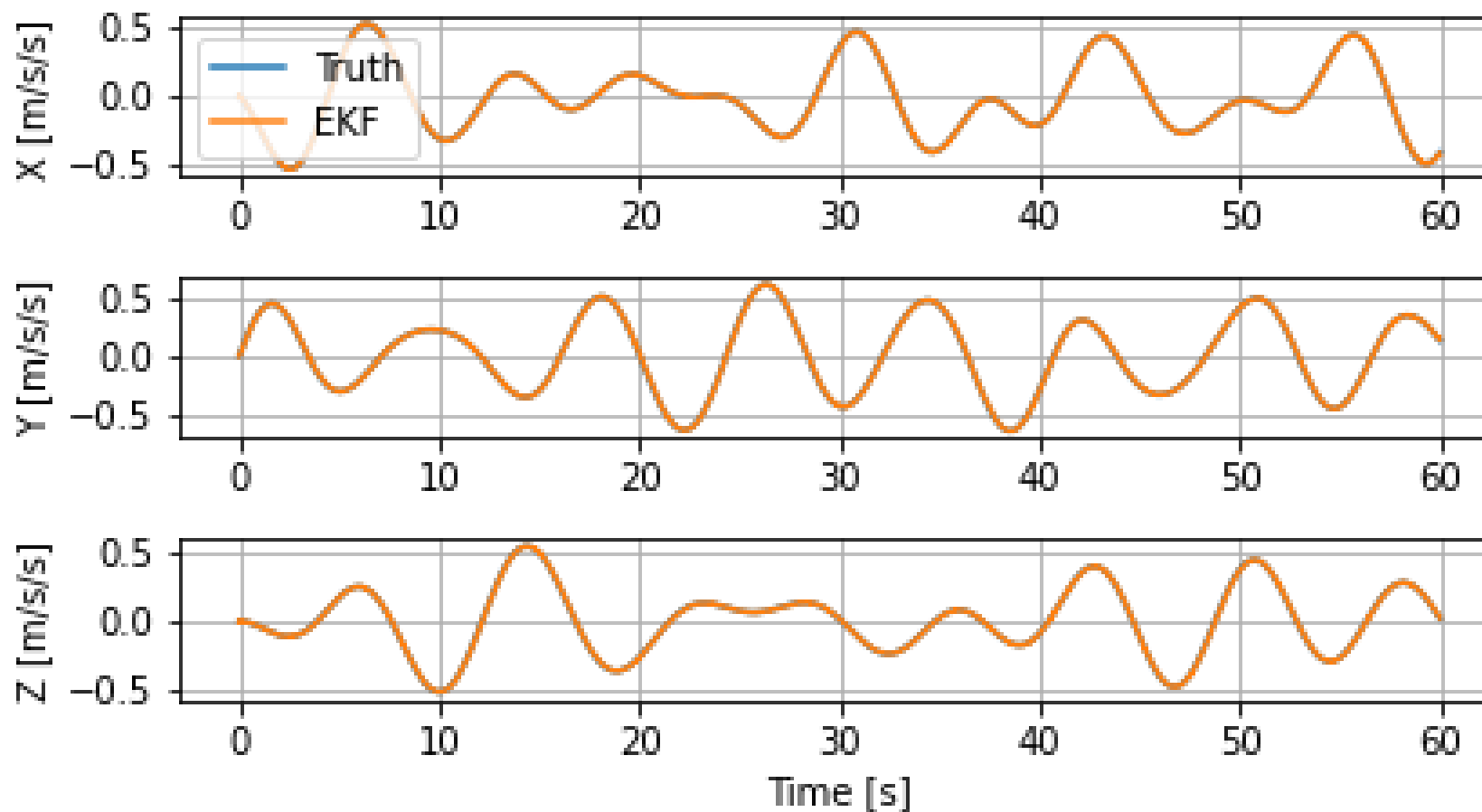


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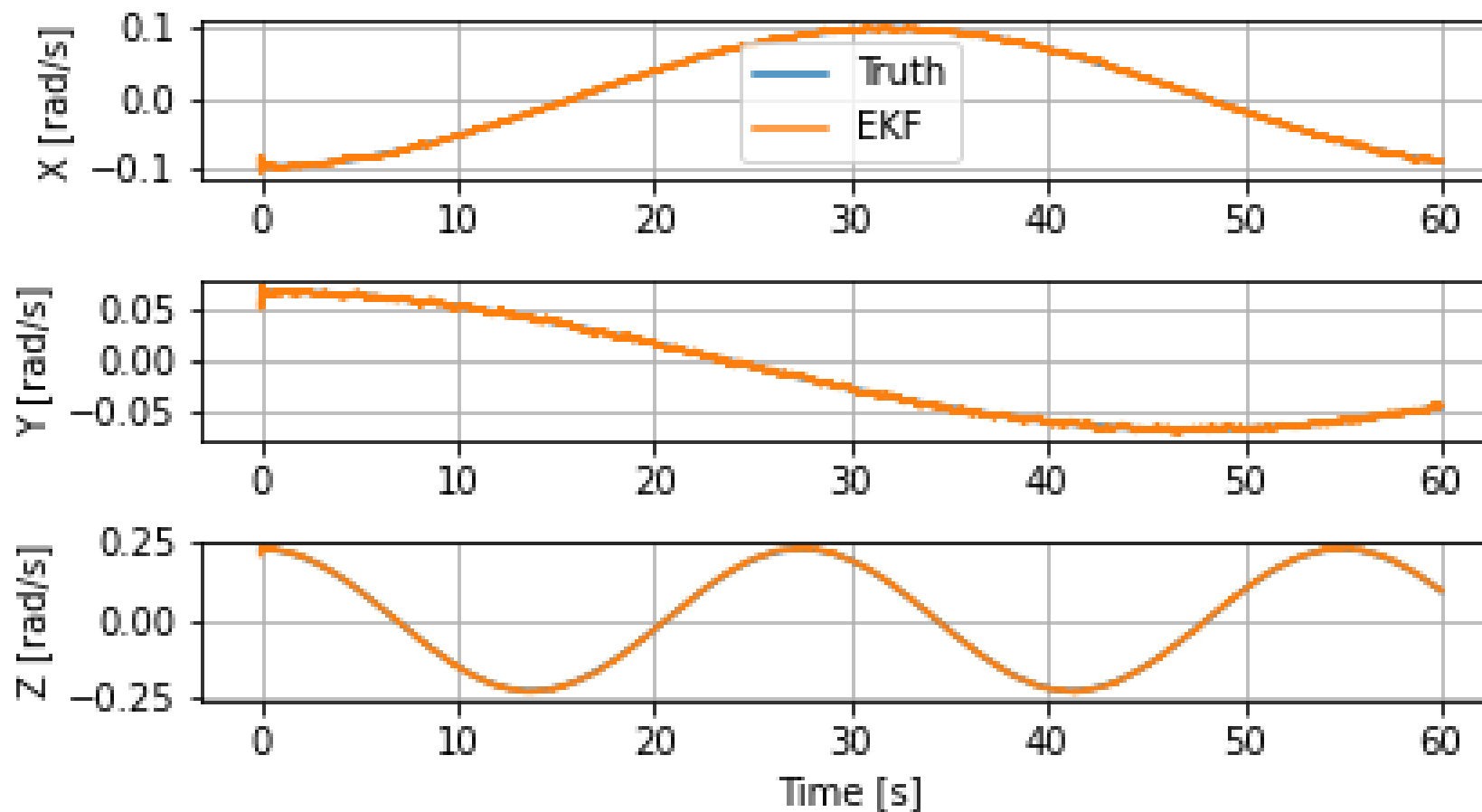
Backup: Single Run Results

Body Acceleration



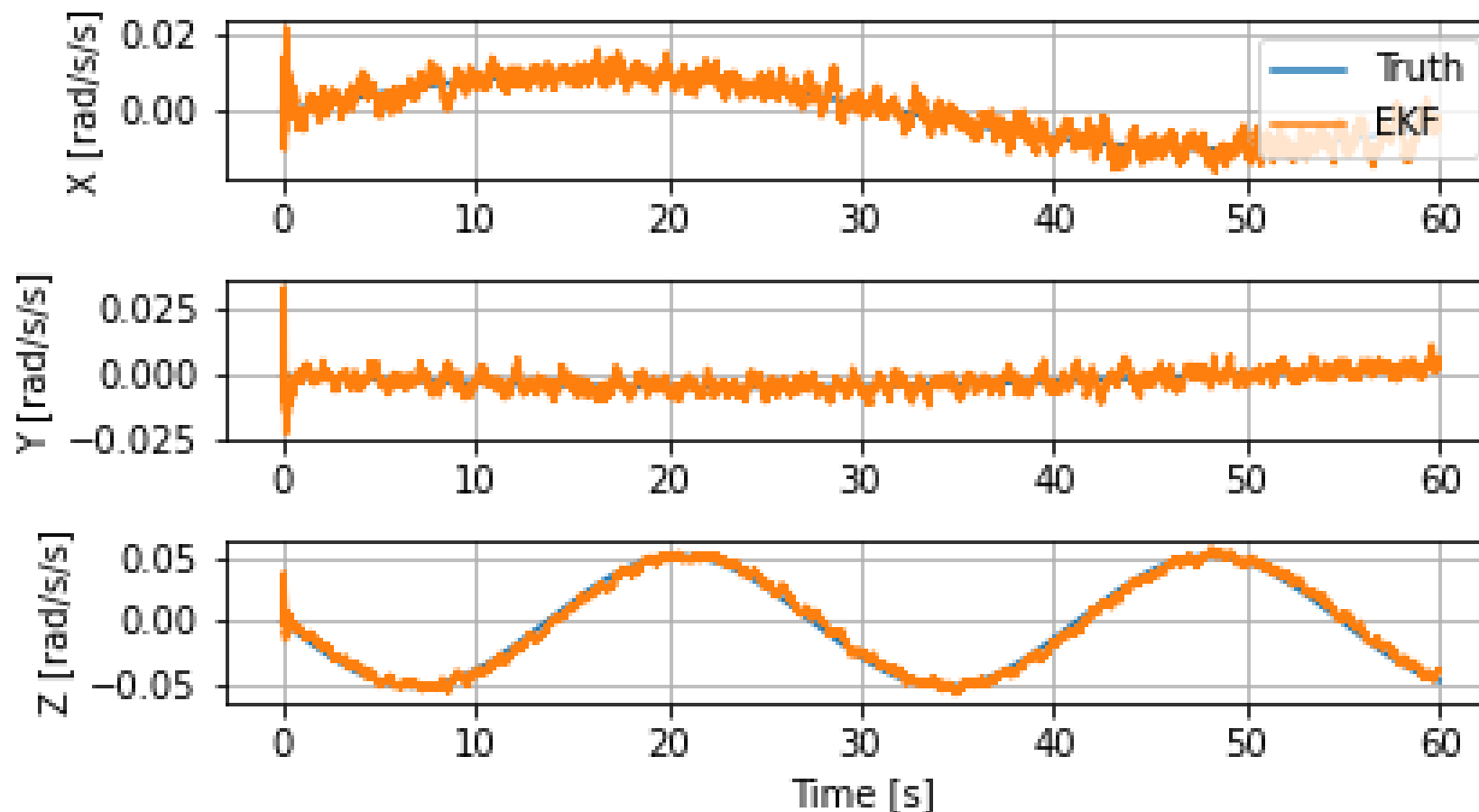
Backup: Single Run Results

Body Angular Rate



Backup: Single Run Results

Body Angular Acceleration



Backup: Single Run Results

IMU Covariance

