Vision and Autonomous Navigation of Micro Air Vehicles

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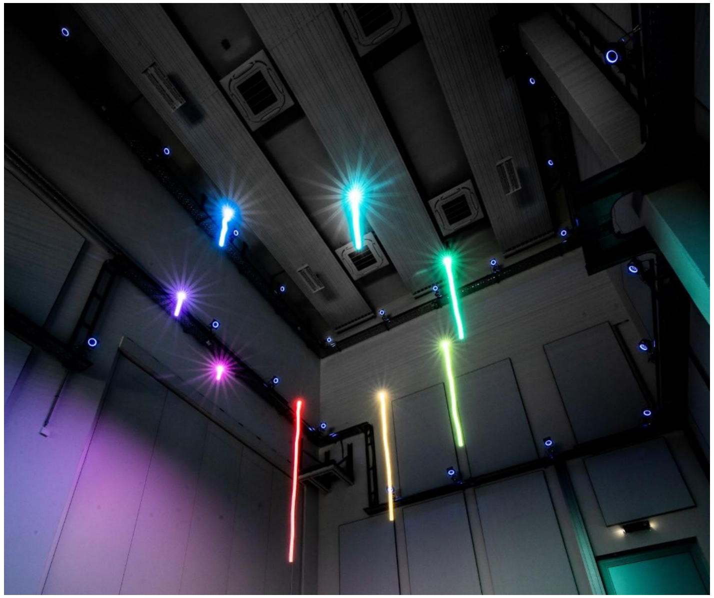


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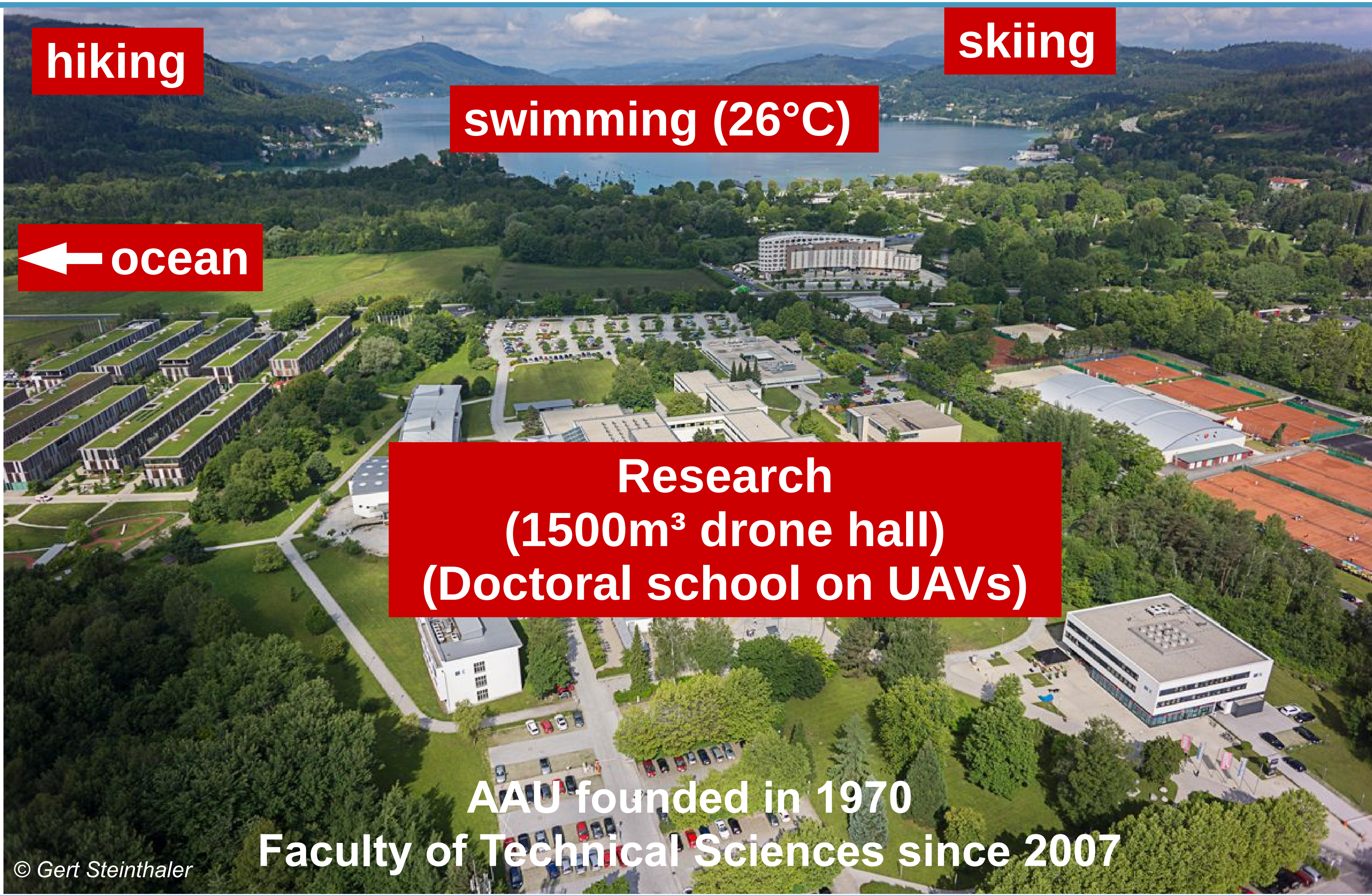
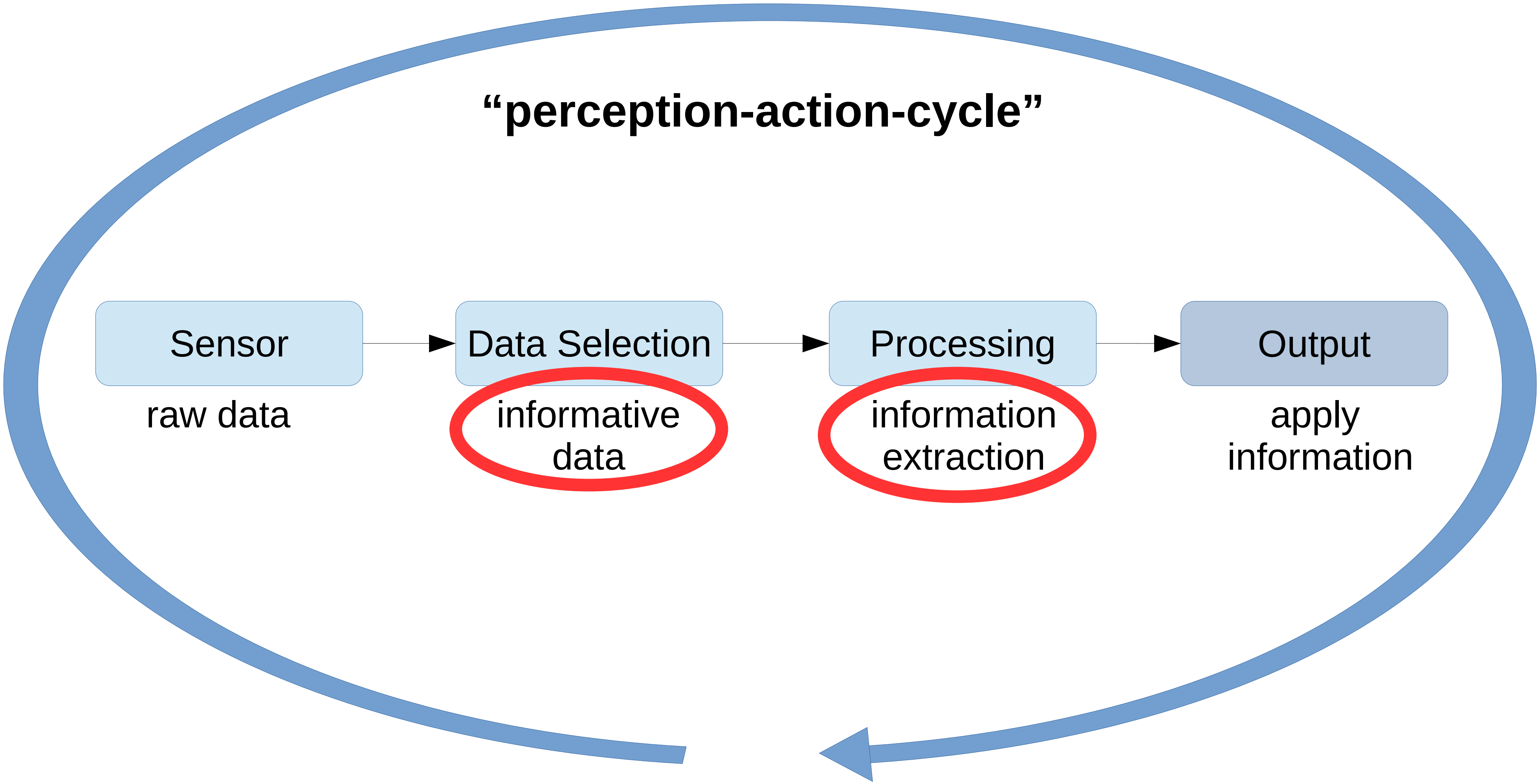
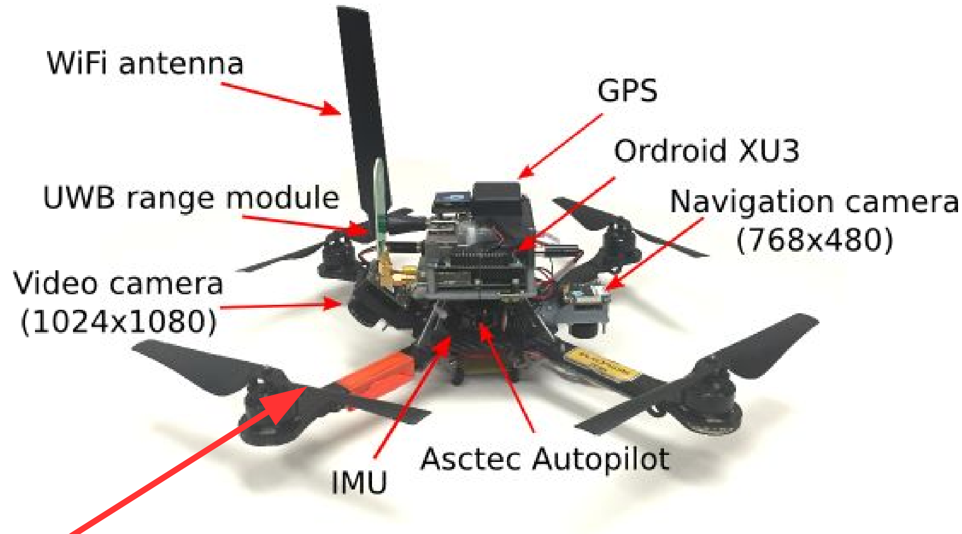


Robot Navigation is... Use of Information

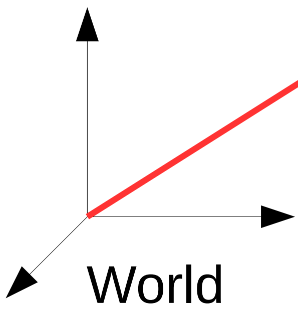


The Problem: Where am I?



Position
Velocity
Attitude

robust, at high rate, with high precision



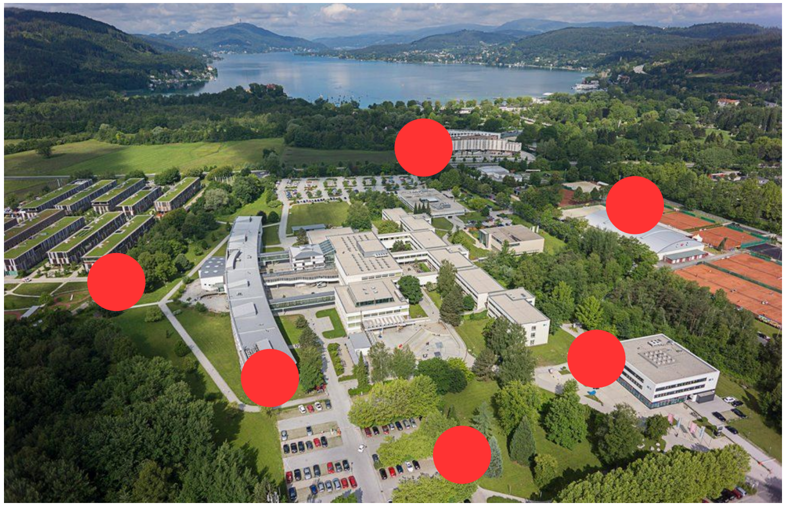
Is more information always better?

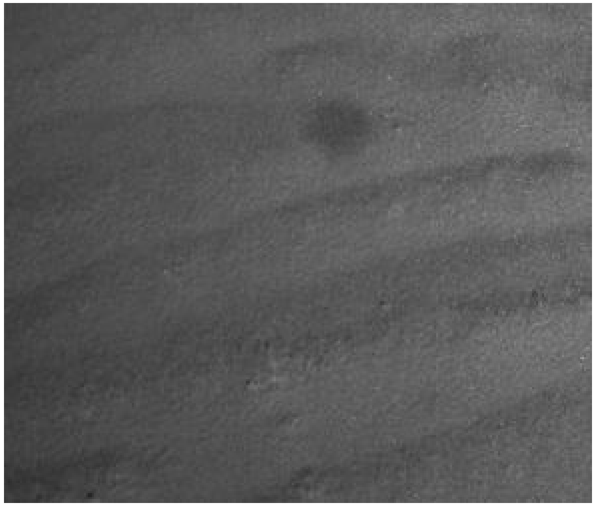
"More data is confusing – at least until there is enough of it"

More Information in Vision Based Localization

- A VGA image has >300k pixels!
  - Data selection: Only take informative areas (high contrast) for localization
  - And if there is no contrast?

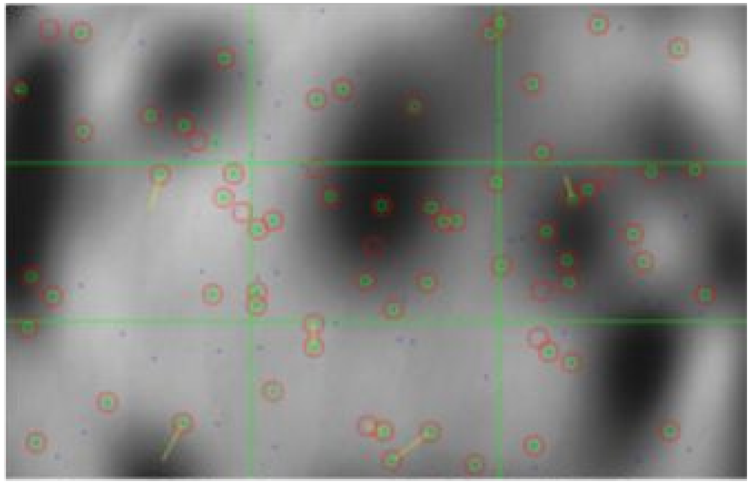
- Information selection in images has a long, and continuing, history





desert

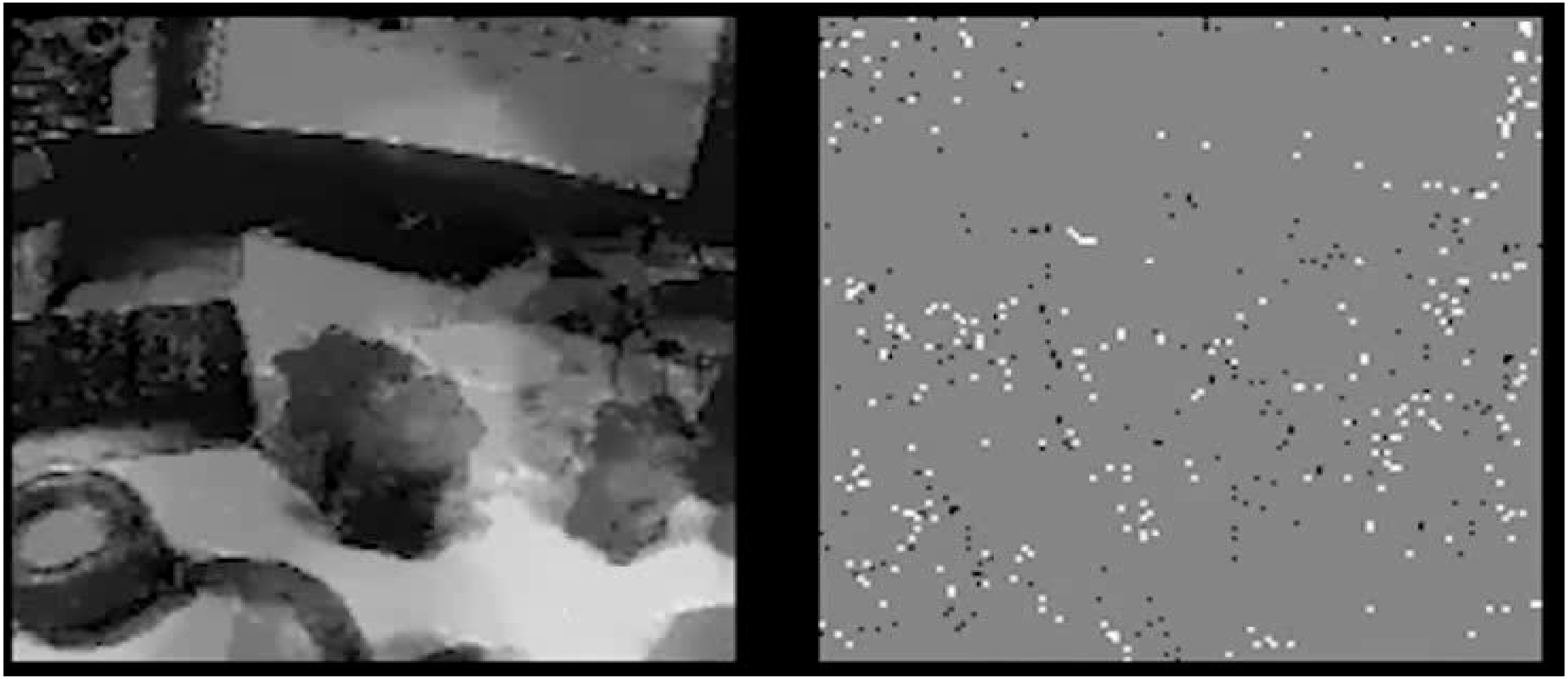
man made structures



no clear identification

Motivation for Dense Image Information

Image reconstruction from event camera stream



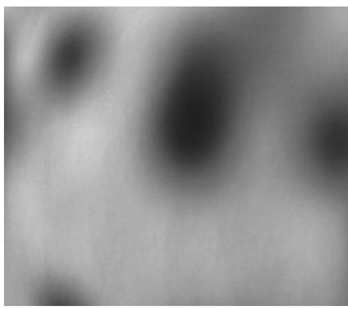
interpolated information | raw data

[Pock et al.]

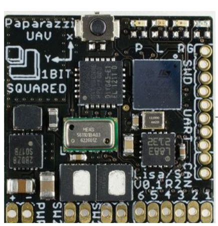
Estimator using Dense Image Information

- Setup
  - Tightly coupled filter based approach (towards real-time)
  - Sensors: one camera, one IMU (3D acceleration, 3D gyro)

Sensors



camera



IMU
(acc, gyro)

Processing

EKF Framework

Core state: $x_{core} = [p_w, v_w, q_w, \mathbf{b_a}, \mathbf{b_\omega}, \mathbf{p_{ci}}, \mathbf{q_{ci}}]$

localization **intr.** **extr.**

Measurement: $z = h(x) = I_{im}$ (pixel intensities)

Full state: $x = [x_{core}\ \boldsymbol{\rho_{im}}\ \mathbf{I_{im}}]$

pixel depths (a.k.a. local map!)

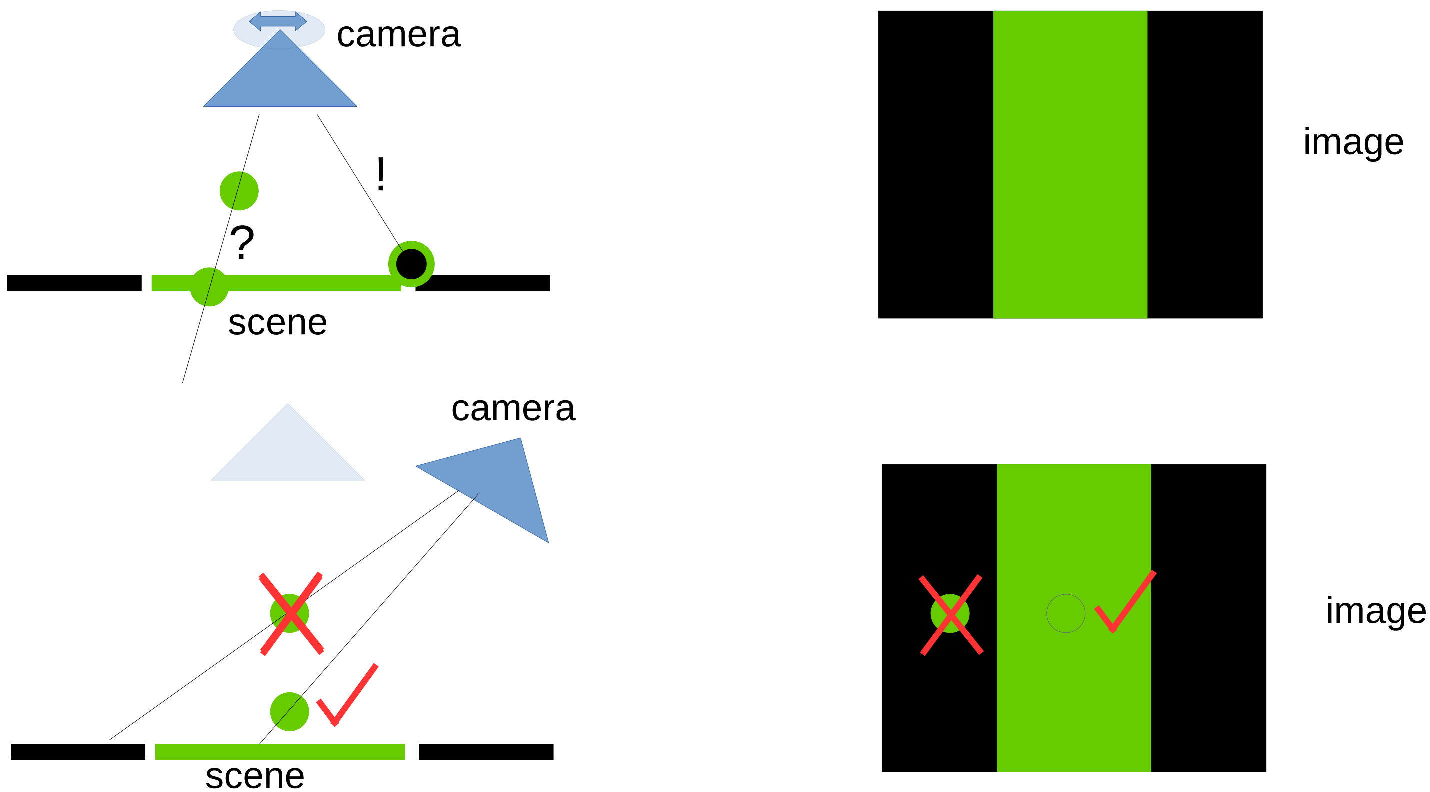
Output

[A. Hardt-Stremayr and S. Weiss, "Towards Fully Dense Direct Filter-Based Monocular Visual-Inertial Odometry", International Conference on Robotics and Automation (ICRA), May 2019]

Fully Dense VIO Information Propagation

- As with other approaches:
  corners and edges have most information, homogeneous areas have none?

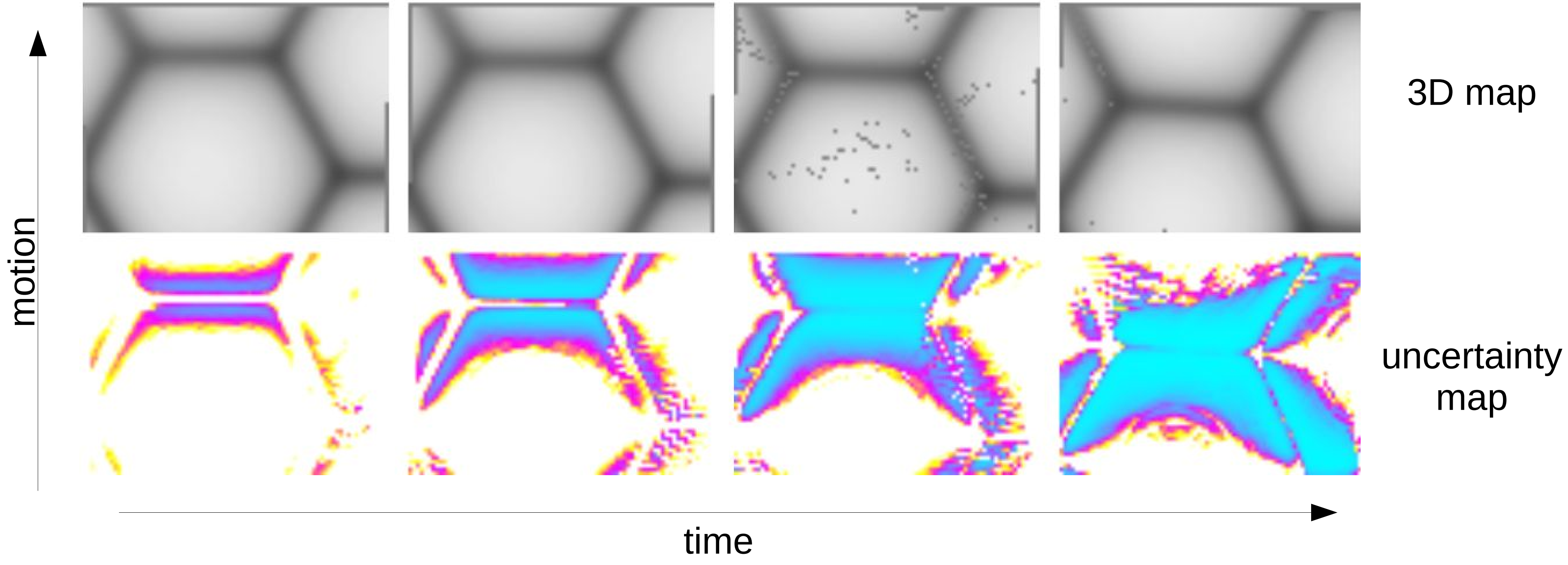
- Paradigm shift for fully dense approach:
  Inherent information propagation from informative regions



[A. Hardt-Stremayr and S. Weiss, “Towards Fully Dense Direct Filter-Based Monocular Visual-Inertial Odometry”, International Conference on Robotics and Automation (ICRA), May 2019]

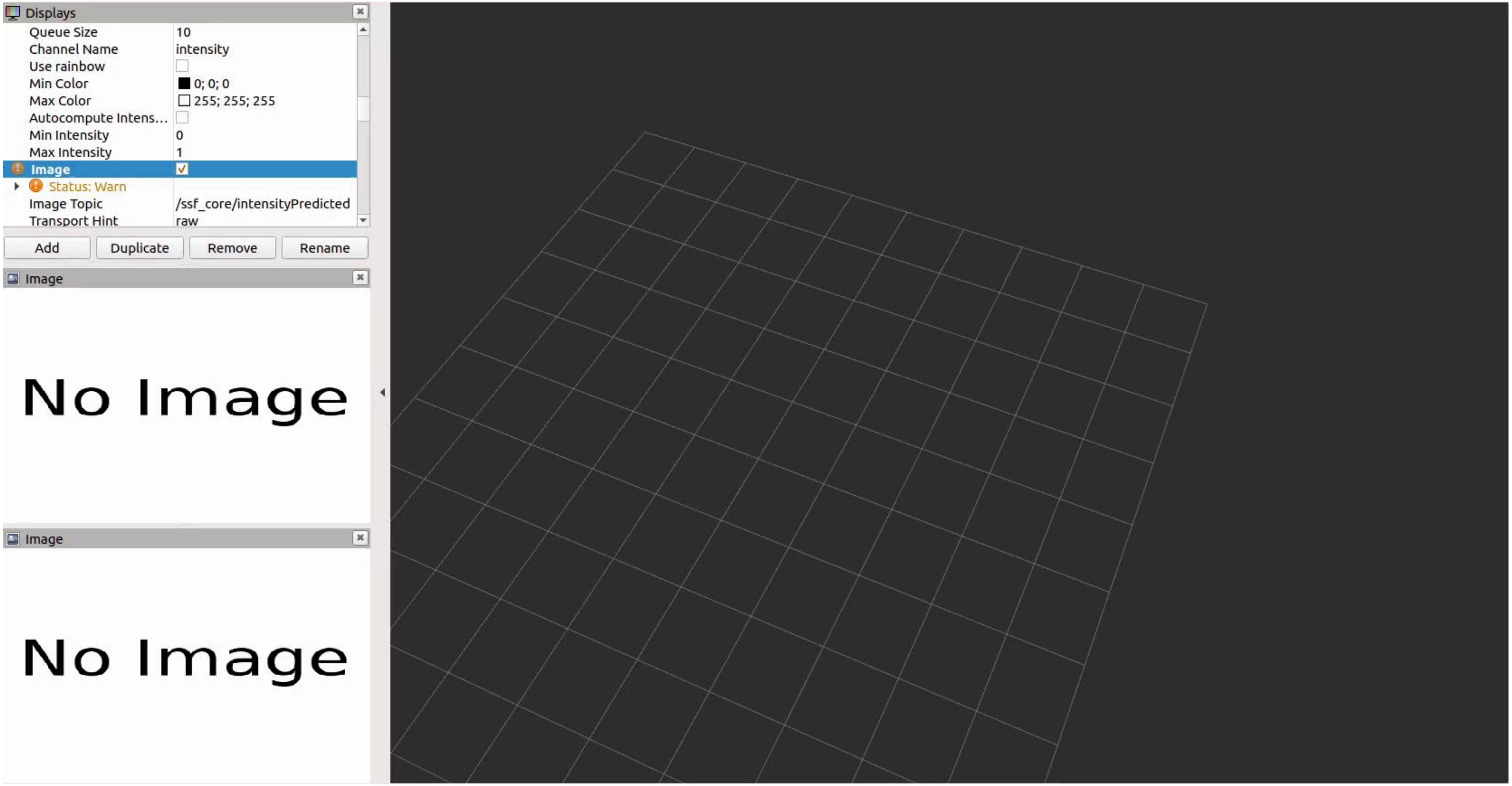
Fully Dense VIO Information Propagation

- Uncertainty information per pixel leads to:
  - Probabilistically consistent information propagation
  - Inherent map *with uncertainty*
  - Probabilistically consistent link to motion states



[Hardt-Stremayr and Weiss, “Monocular Visual-Inertial Odometry in Low-Textured Environments with Smooth Gradients: A Fully Dense Direct Filtering Approach”, ICRA 2020]

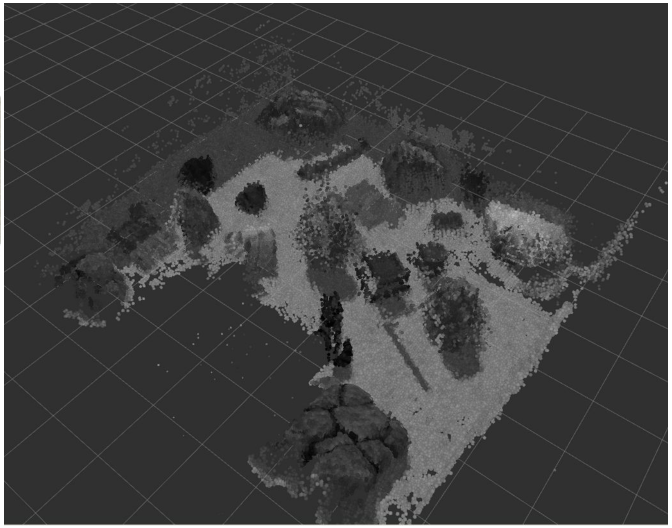
Fully Dense VIO

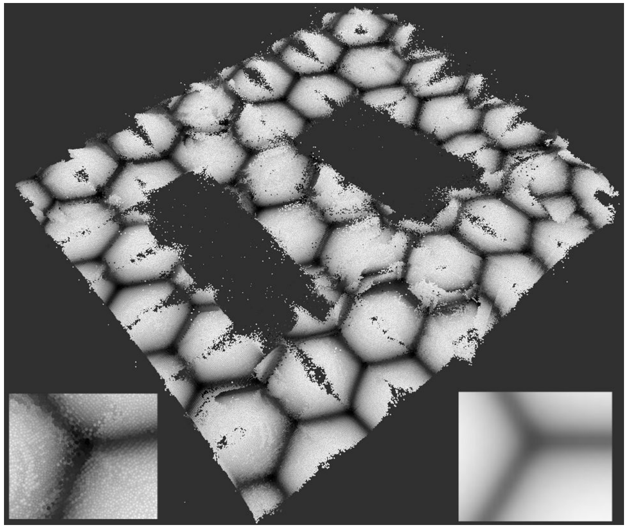


[Hardt-Stremayr and Weiss, “Monocular Visual-Inertial Odometry in Low-Textured Environments with Smooth Gradients: A Fully Dense Direct Filtering Approach”, ICRA 2020]

Fully Dense VIO (back-up)

- Fully Dense Direct Filter for Low-Textured Environments with Smooth Gradients
  - Tightly coupled filter frame takes all pixels into account
  - Predicts core state as well as depth for each pixel (building dense 3D map of environment)
  - Works in low-textured environments with smooth gradients





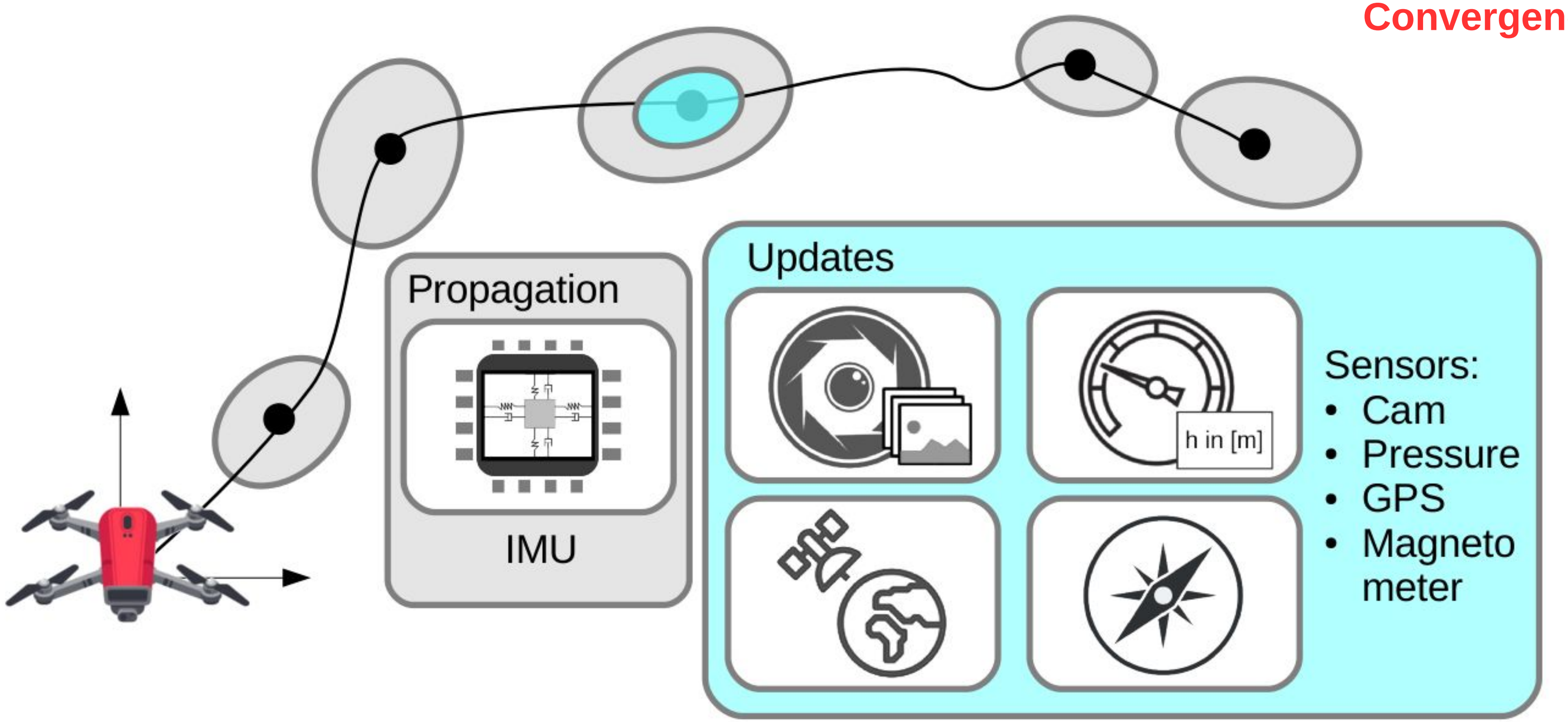
[Hardt-Stremayr and Weiss, “Monocular Visual-Inertial Odometry in Low-Textured Environments with Smooth Gradients: A Fully Dense Direct Filtering Approach”, ICRA 2020]

Multi-Sensor State Estimation

- We use a set of sensors to estimate the state of UAVs
  - IMU data for state dynamics
  - Sensors for update: Camera, GPS, Pressure, Magnetometer, etc.

- Sensor output given at different rates with unknown delays

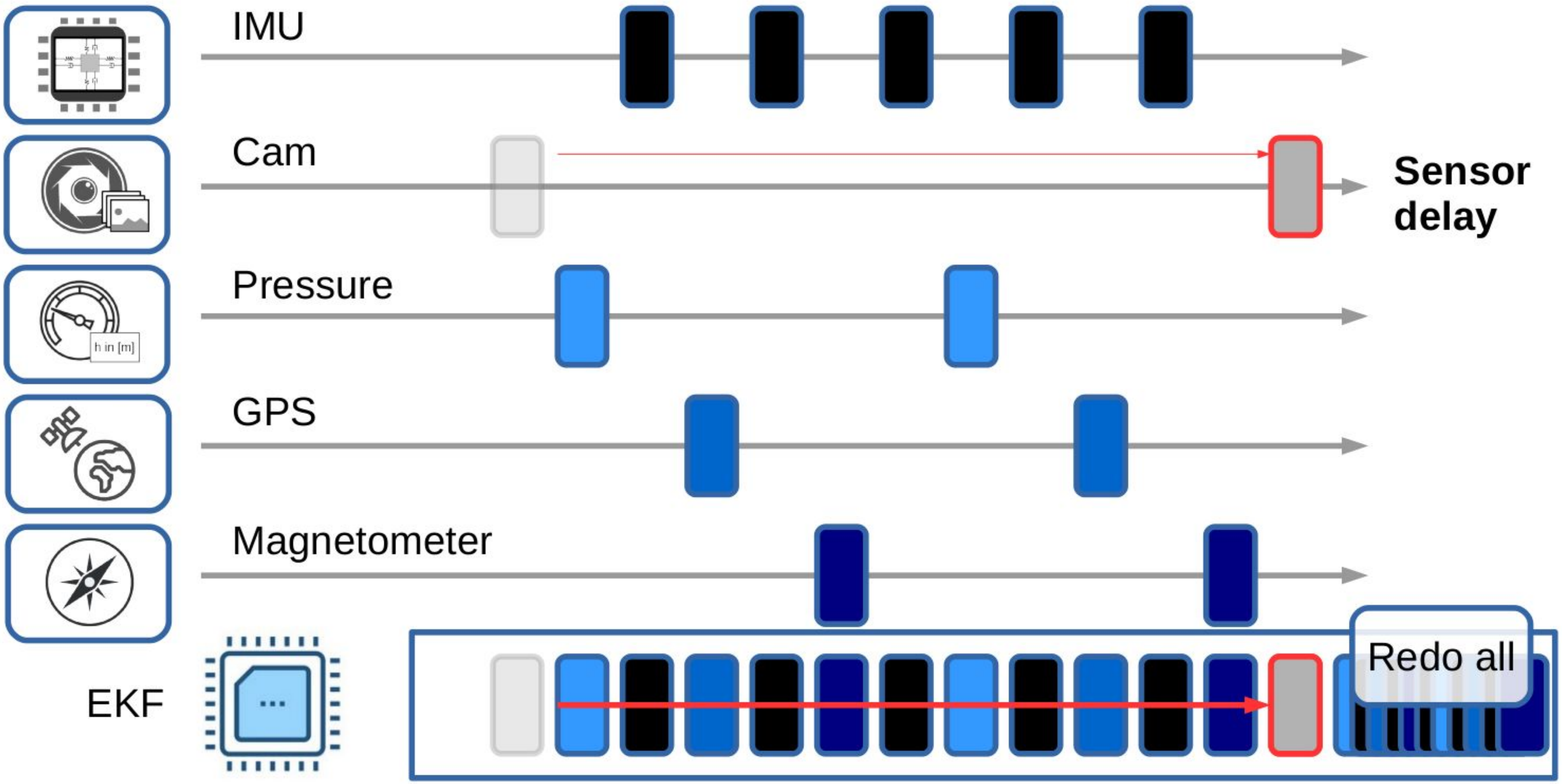
Delays?
Self-Calibration?
Observability?
Convergence?



[Allak et al. "Covariance Pre-Integration for Delayed Measurements in Multi Sensor Fusion", IROS19.]

Out of Sequence Updates

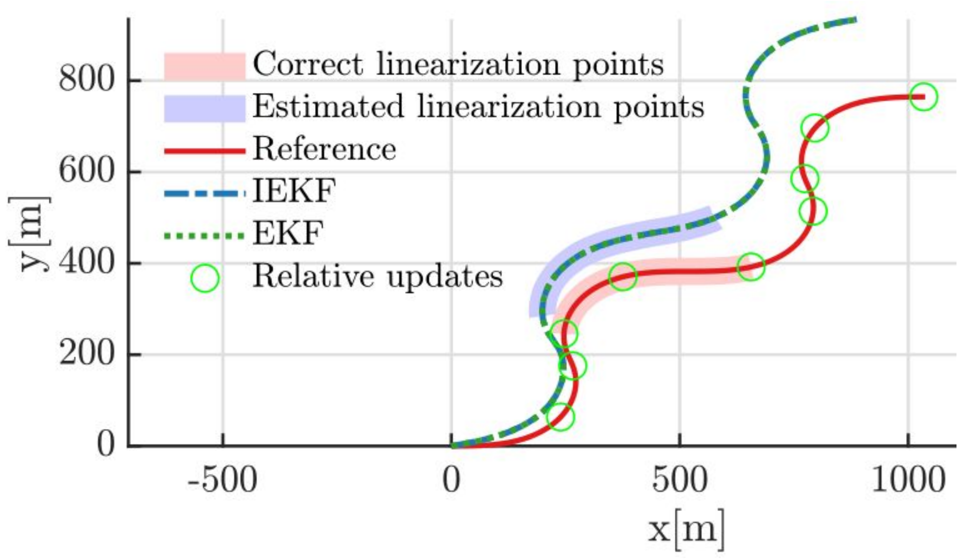
- Delays require re-computations of previous measurements
- Re-computation of uncertainties leads to computation spike

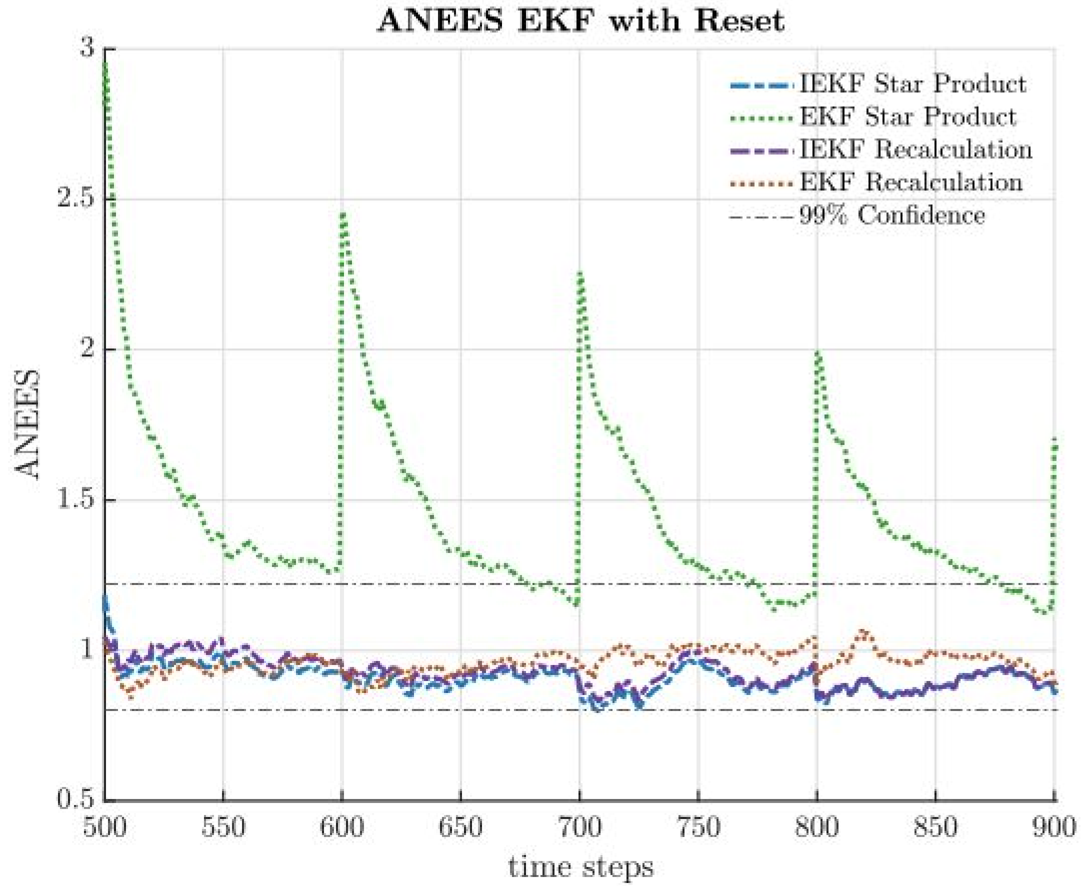


[Allak et al. “Covariance Pre-Integration for Delayed Measurements in Multi Sensor Fusion”, IROS19.]
[Allak et al. “Consistent Covariance Pre-Integration for Invariant Filters with Delayed Measurements”, IROS20]

Covariance Pre-Integration ...a scattering theory approach

- Merge scattering theory with invariant Kalman filters
  - Use covariance pre-integration for fast propagation
  - Formulation as invariant filter for independence on linearization points
  - Result: fast and consistent estimator

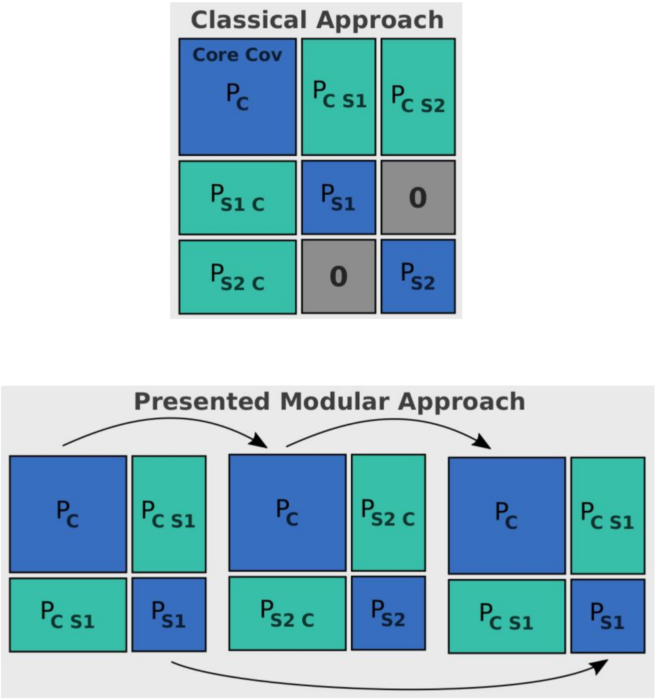


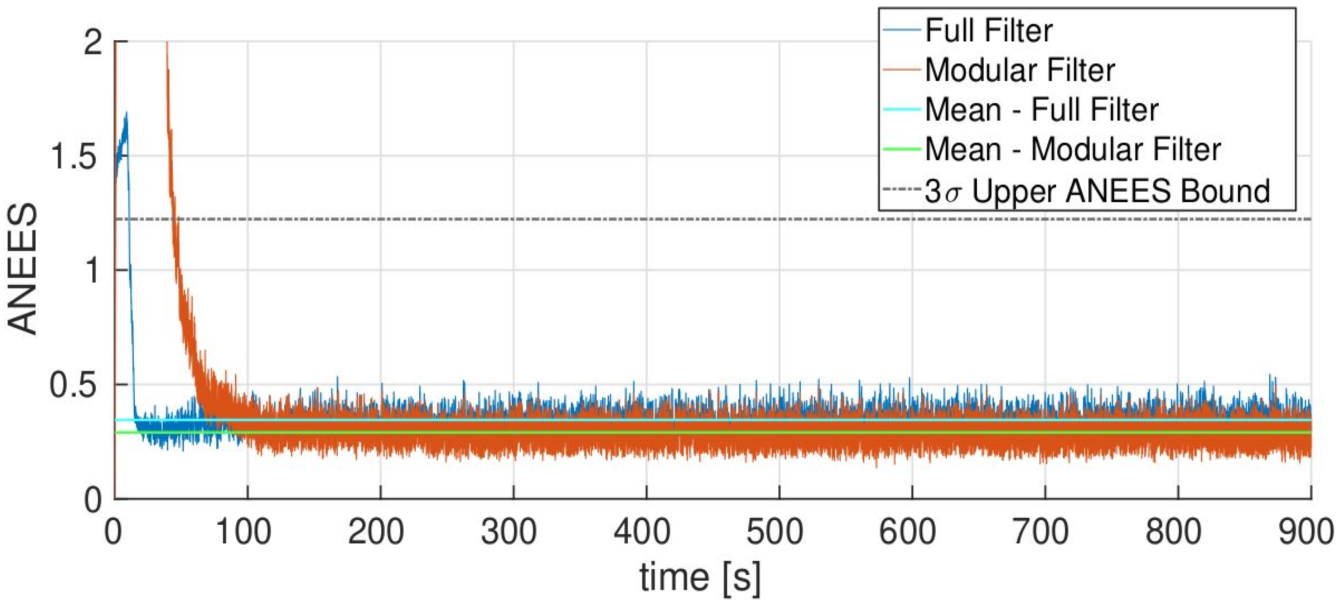


[Allak et al. “Consistent Covariance Pre-Integration for Invariant Filters with Delayed Measurements”, IROS20]

MaRS: A Modular and Robust Sensor-Fusion Framework

- Combine fast covariance (re-)propagation with the ability to modularly add and remove sensors *during mission time*
- Fully self-calibrating framework of sensor extrinsics





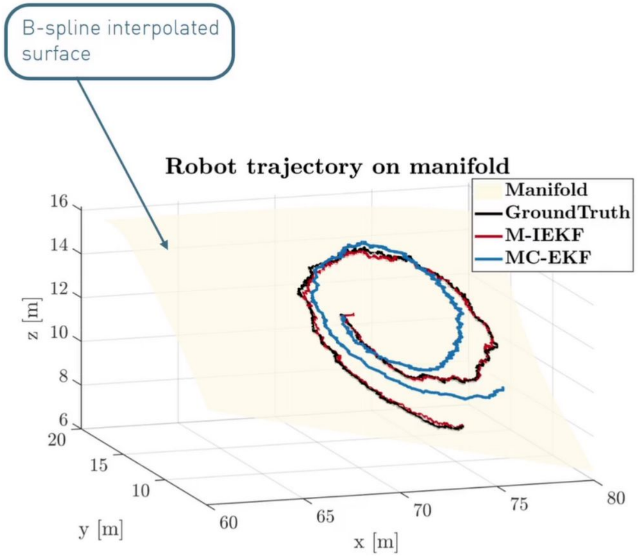
github.com/aau-cns/mars_ros

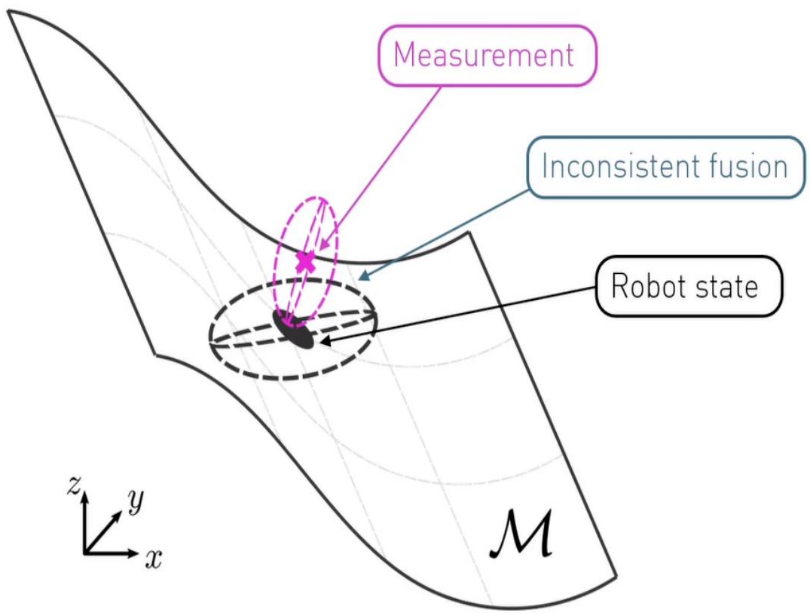
[Brommer, Jung, Weiss “MaRS: A Modular and Robust Sensor-Fusion Framework”, RA-L, November 2020.]

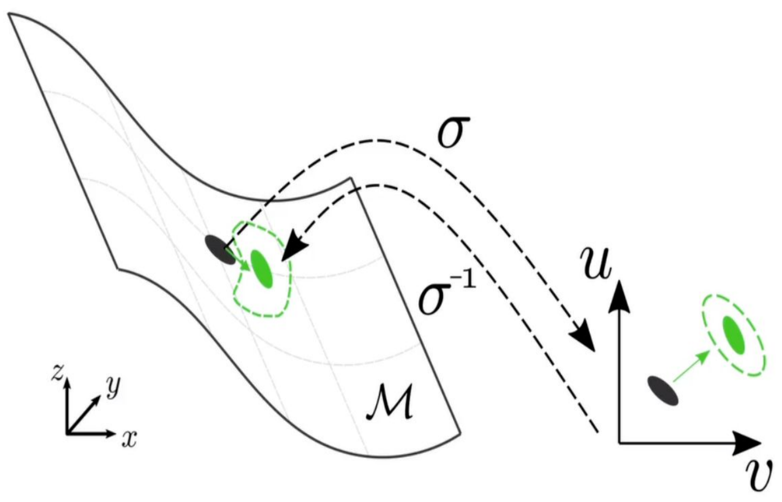
Modular Multi-Sensor Consistency

- Estimators based on geometric observers
  - Invariant, equivariant Kalman Filter
  - Guaranteed convergence

- Manifold constrained estimators
  - Mapping from the manifold to the low-dimensional space via chart
  - Perform consistent estimation on that space



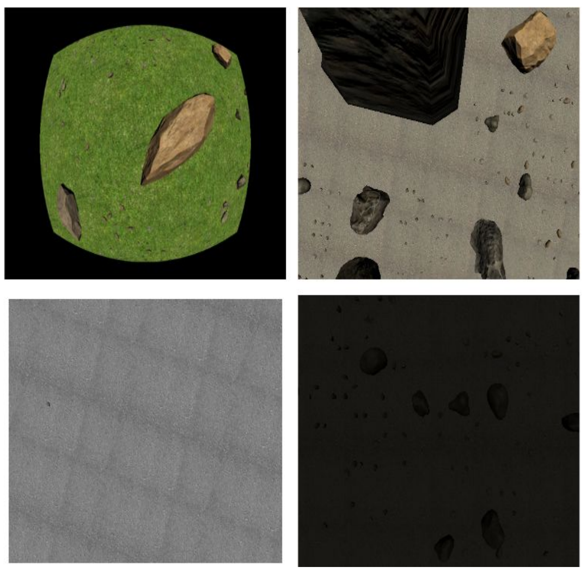




[Starbuck, Fornasier, Weiss, Pradalier. "Consistent State Estimationon Manifolds for Autonomous Metal Structure Inspection", ICRA21]

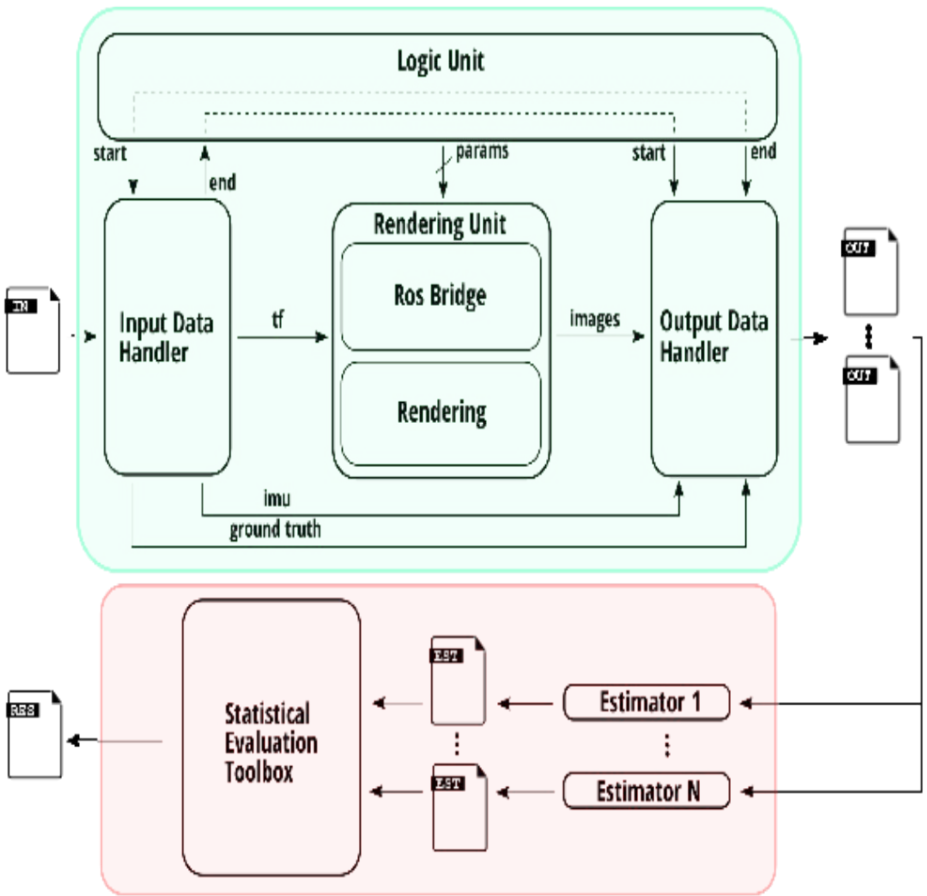
Modular Multi-Sensor Consistency

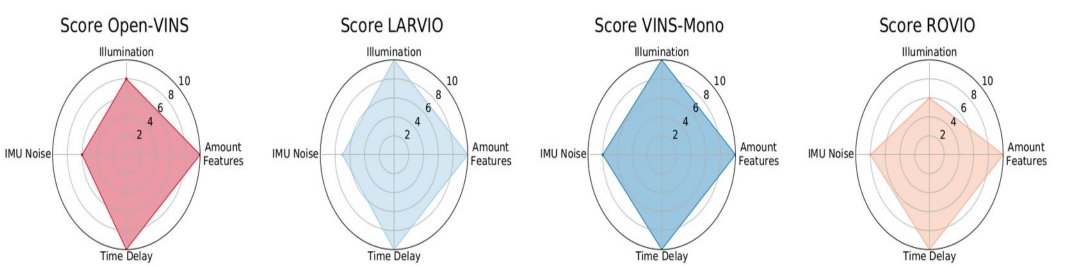
- Statistically relevant consistency and robustness analysis:
  - VINSEval: fully automated (Unity3D & ROS)



VINS EVAL
Powered by CNS

github.com/aau-cns/vins_eval



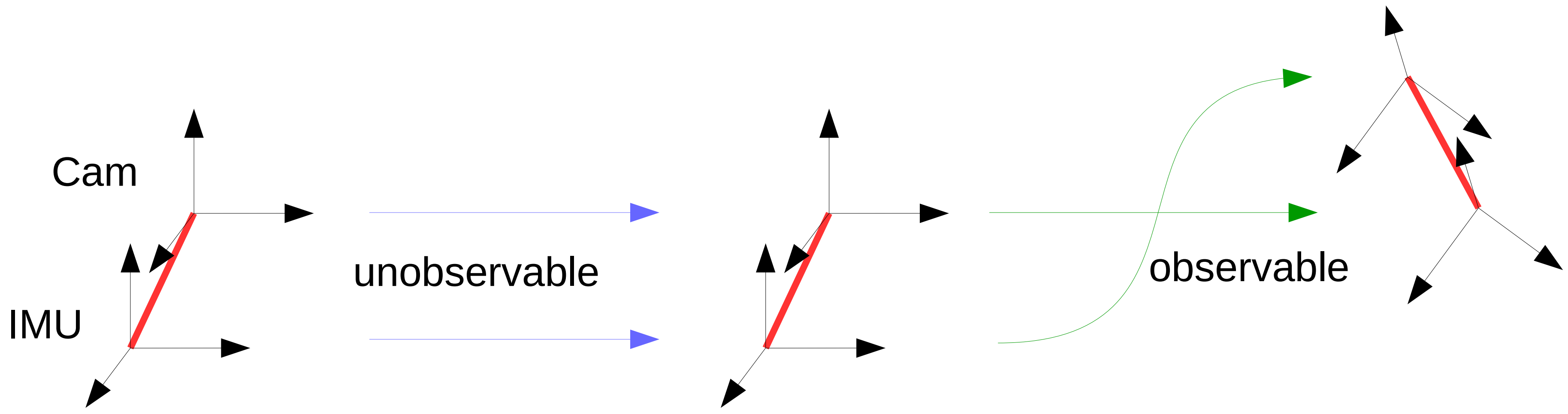


[Fornasier et al. "VINSEval:Evaluation Framework for Unified Testing of Consistency and Robustness of Visual-Inertial Navigation System Algorithms", ICRA21

Decisions for Information Extraction

- Taking all information: What can it be used for?
  → a motivation for system self-calibration

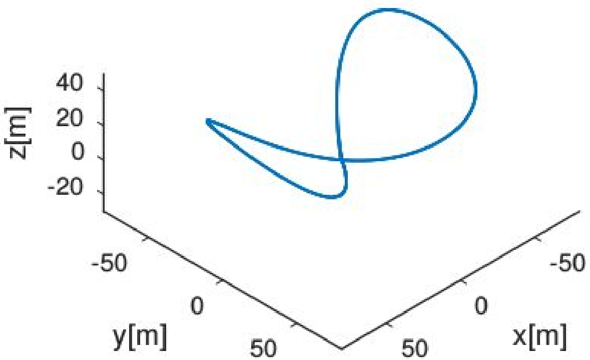
- More sensors introduce more variables (intrinsics, extrinsics)
  - Despite good measurements, system **input** might be insufficient

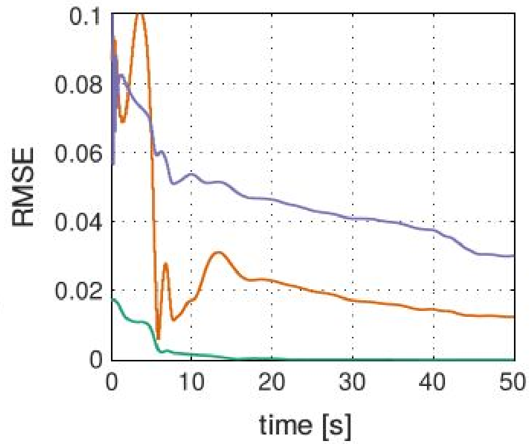


[JA Preiss, K Hausman, GS Sukhatme, S Weiss, "Trajectory Optimization for Self-Calibration and Navigation" Robotics: Science and Systems (RSS), 2017]
[K Hausman, J Preiss, GS Sukhatme, S Weiss, "Observability-aware trajectory optimization for self-calibration with application to uavs", IEEE Robotics and Automation Letters (RA-L), 2 (3), 1770-1777, 2017]
[JA Preiss, K Hausman, GS Sukhatme, S Weiss, "Simultaneous self-calibration and navigation using trajectory optimization" The International Journal of Robotics Research (IJRR), 2018]

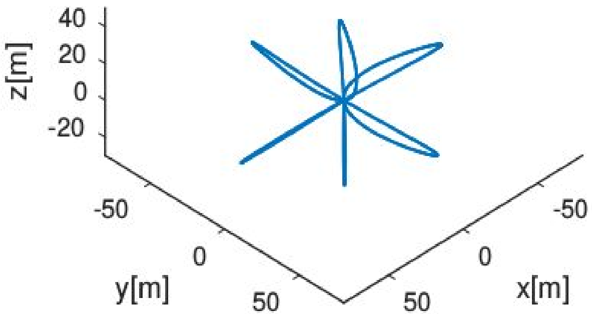
Observability Aware Motion: Fast Convergence

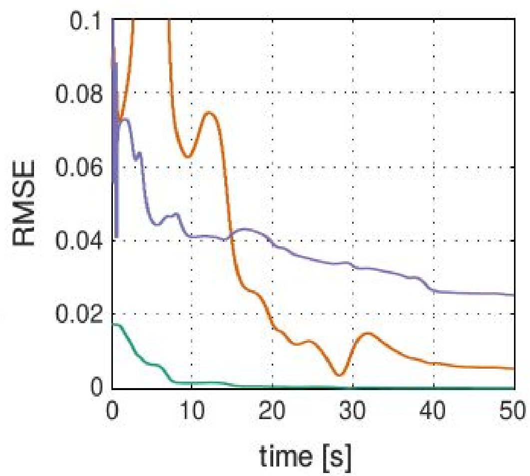
User 1

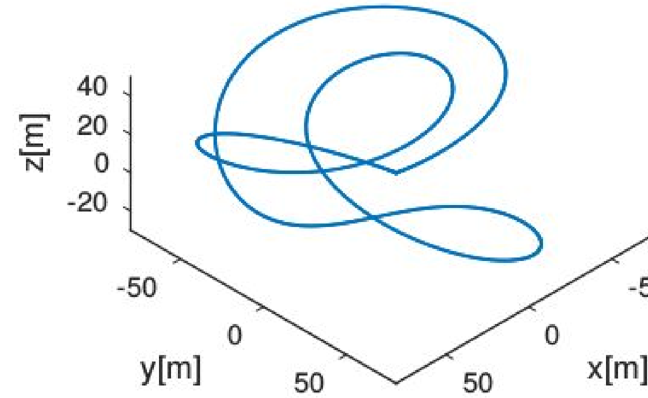


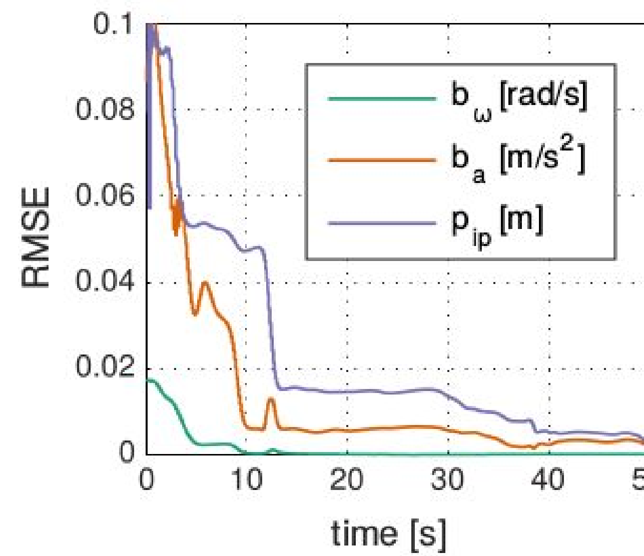


User 2









[Hausman et al., "Observability-Aware Trajectory Optimization for Self-Calibration with Application to UAVs", RA-L/ICRA 2017]
[Preiss et al., "Trajectory Optimization for Self-Calibration and Navigation", RSS 2017]
[Preiss et al., "Simultaneous self-calibration and navigation using trajectory optimization", IJRR 2018]

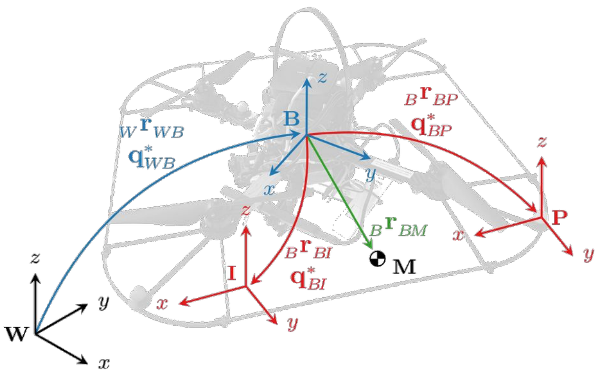
From Motion Generation to Path Generation

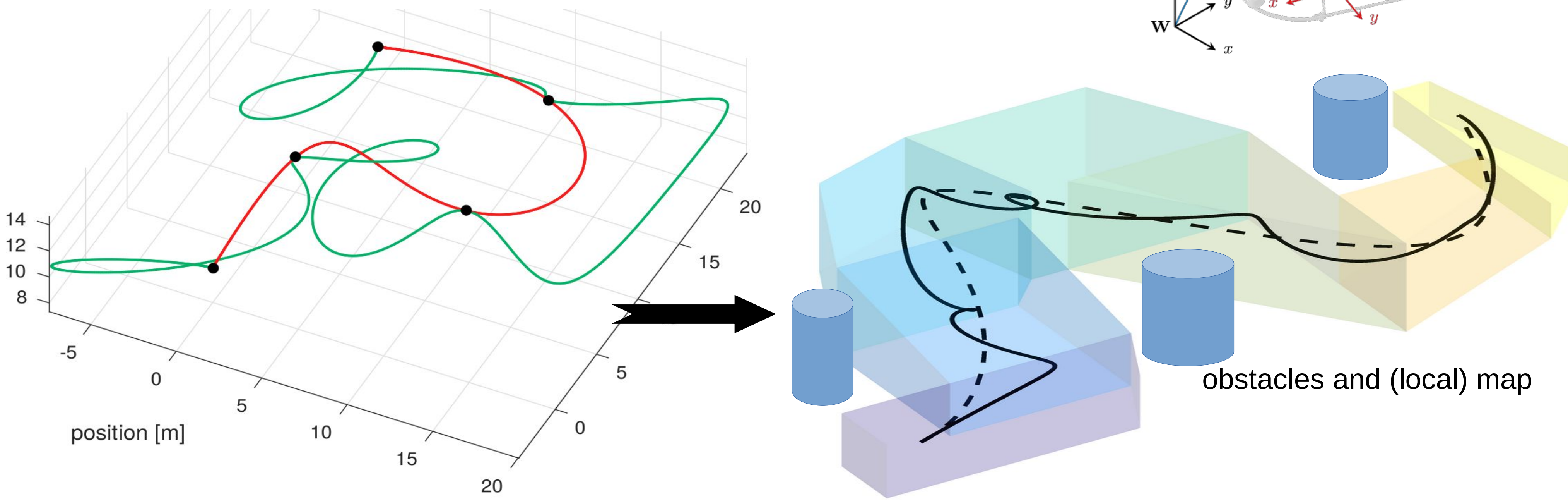
Observability aware motion has (so far) no specific boundaries in space and time

- Problem: obstacles, time to arrival
- Does include dynamic feasibility

Idea: "wiggle" around existing path solutions for best observability

- Collision-free path within feasible volumes (polytopes)
- Maximizes observability/convergence, eliminates unobservable modes





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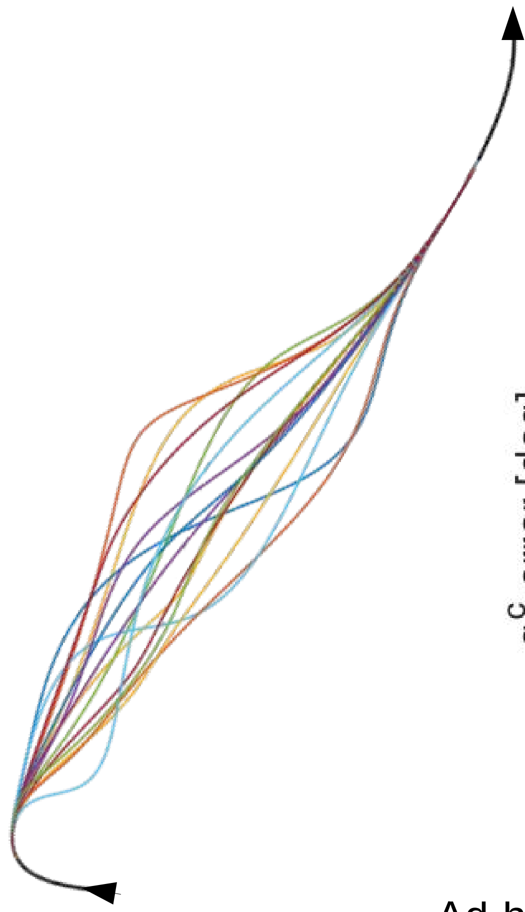
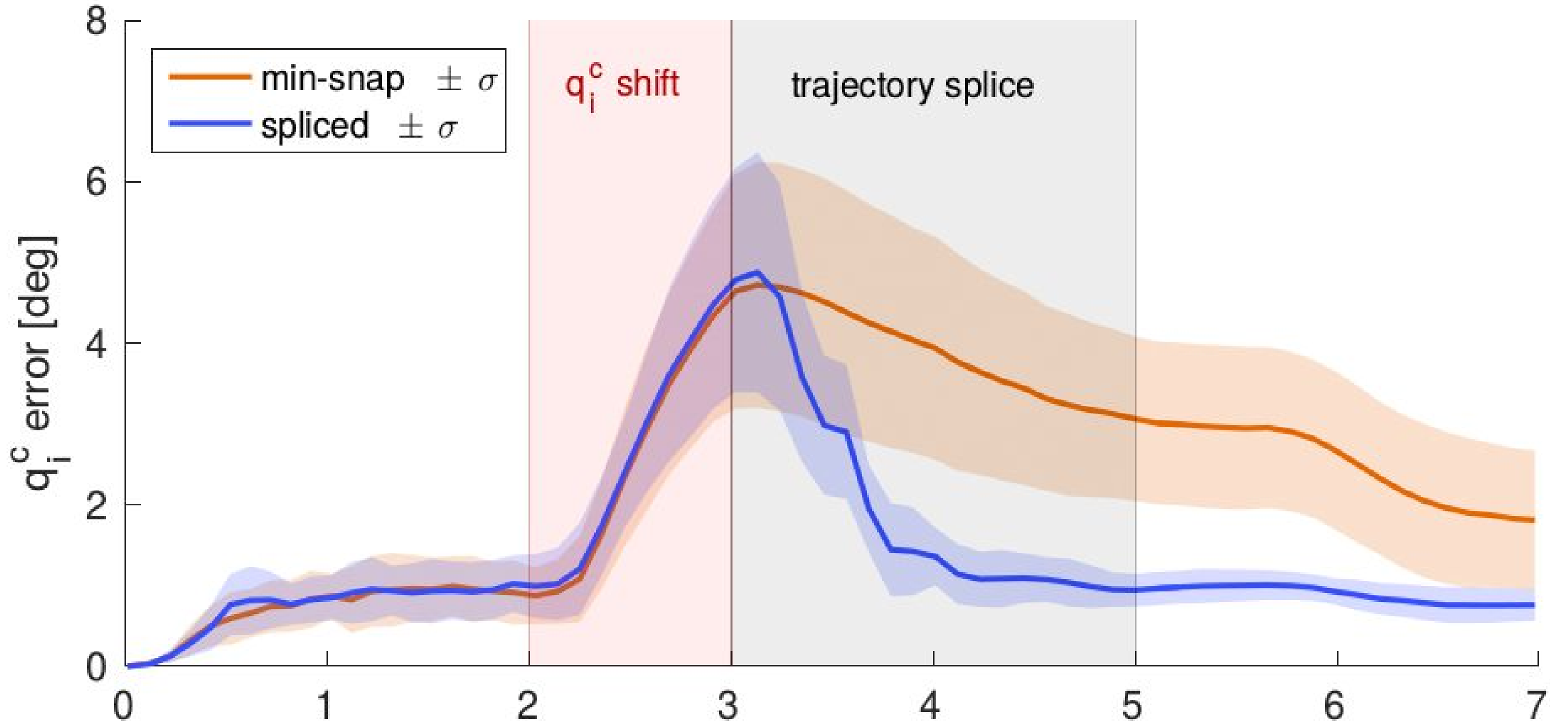
[Preiss et al., "Trajectory Optimization for Self-Calibration and Navigation", RSS 2017]
[Preiss et al., "Simultaneous self-calibration and navigation using trajectory optimization", IJRR 2018]
[Böhm et al., "Filter-Based Online System-Parameter Estimation for Multicopter UAVs", RSS2021]
[Böhm et al., "Combined System Identification and State Estimation for a Quadrotor UAV", ICRA 2021]

Ad-hoc Observability Aware Re-Calibration

- Problem: minimum energy paths yield poor observability
- Idea: Probabilistic state estimators trigger re-calibration
  Select most informative sub-trajectory from bundle





Ad-hoc path adaptation for fast in-flight state re-calibration

[Preiss et al., "Simultaneous self-calibration and navigation using trajectory optimization", IJRR 2018]

Take-Home Messages

- “More data is confusing – at least until there is enough of it”
  - Using all data in images for vision based navigation in low-textured areas
  - “Enough data” allows for system self-calibration improving localization and recovery in challenging situations (self-healing)

- Multiple sensors lead to resilient navigation in challenging situations
  - Sensor delay as major issue in real-time applications (re-computations!)
  - Correct uncertainty estimation as a challenge versus complexity
  - Leveraging geometric properties helps for consistency

- System self-awareness for improved localization
  - Require (observability aware) motion for system self-calibration
  - Correct uncertainty estimation to trigger self-healing motion

Thank you

Visit us at our research Website (incl. people, papers and many videos):

http://sst.aau.at/cns

http://uav.aau.at