

# Visual-Inertial Based Navigation in GPS - Restricted Environments

Localization, state estimation, control and path-planning

## Overview

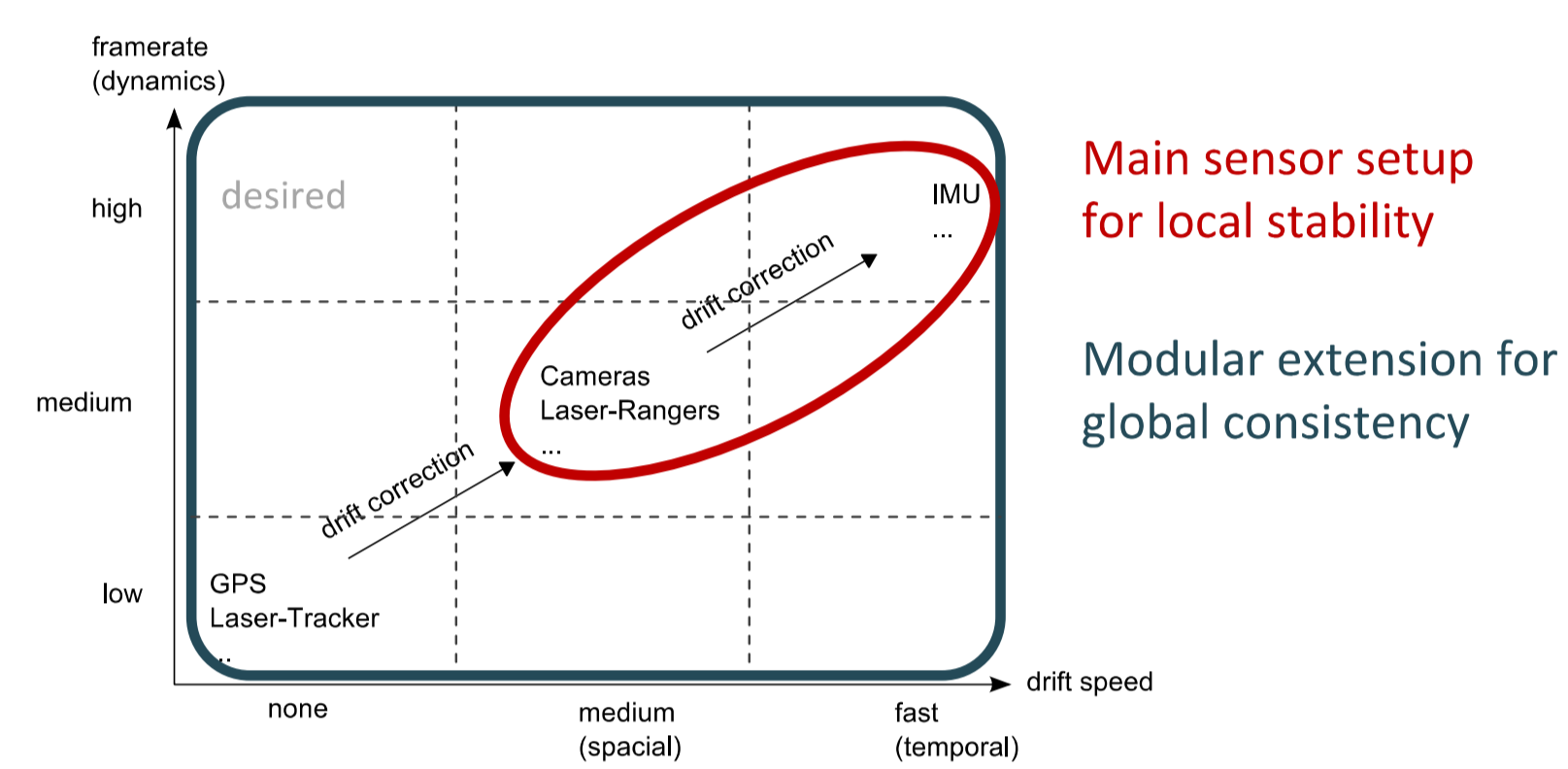


Automation of take-off and landing relies on accurate knowledge of variables, such as the position, velocity and orientation of the vehicle. While GPS is a popular sensor choice in open spaces, it suffers from accuracy issues in urban environments. The wealth of information captured, their low weight and high frame-rate make cameras a very attractive choice as onboard sensor.

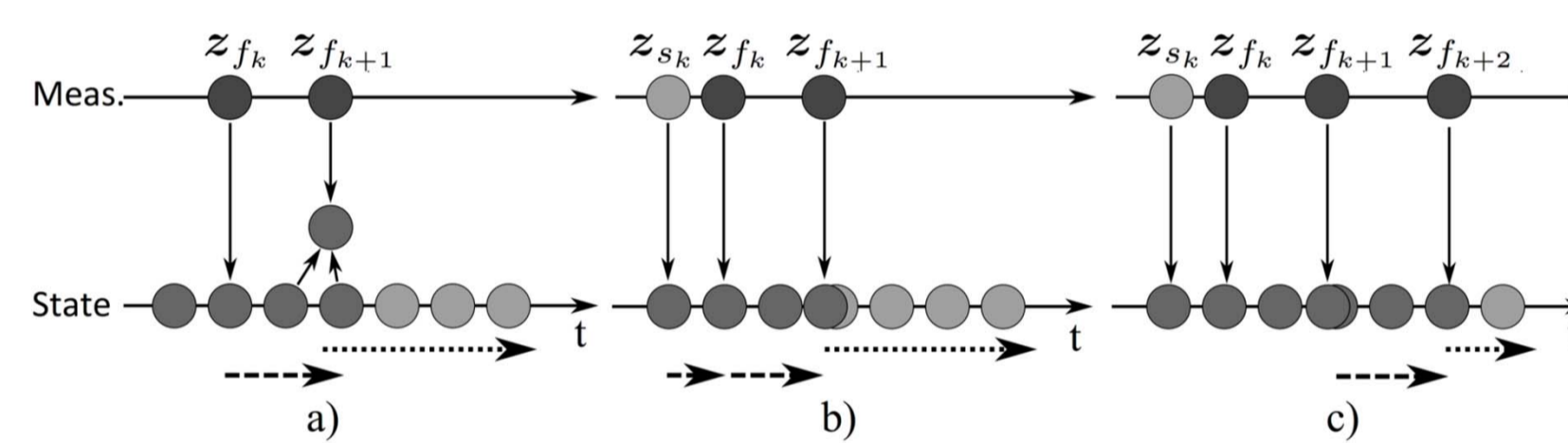
To ease development and testing, we use a multi-rotor Micro Aerial Vehicle (MAV) as experimental platform. We focus on enabling autonomous flights with MAVs, solely using an onboard camera as the only exteroceptive sensor. As vision cues alone are not enough to ensure robust flight performance, fusing cues from an Inertial Measurement Unit (IMU) is key in enabling autonomous flights using solely onboard sensors, thanks to their complementary nature.

## State Estimation and Calibration

For successful control of the MAV, accurate state estimation is key. We developed a versatile framework, using an Extended Kalman Filter (EKF) to fuse visual information with inertial measurements from the onboard sensor suite. Not only are sensor calibration states essential for consistent state estimation throughout an entire flight, but also handling of delays and different rates of the sensors' measurements are vital. Due to using a monocular camera, arbitrarily scaled position-measurements are also handled.



The graph above shows a classification of different sensors with respect to their update rate and drift. Temporal drift refers to drift over time, while spatial drift only occurs when the vehicle does not maintain its current position. The scheme below shows how measurements from different sensors are applied.



## State Estimation and Calibration

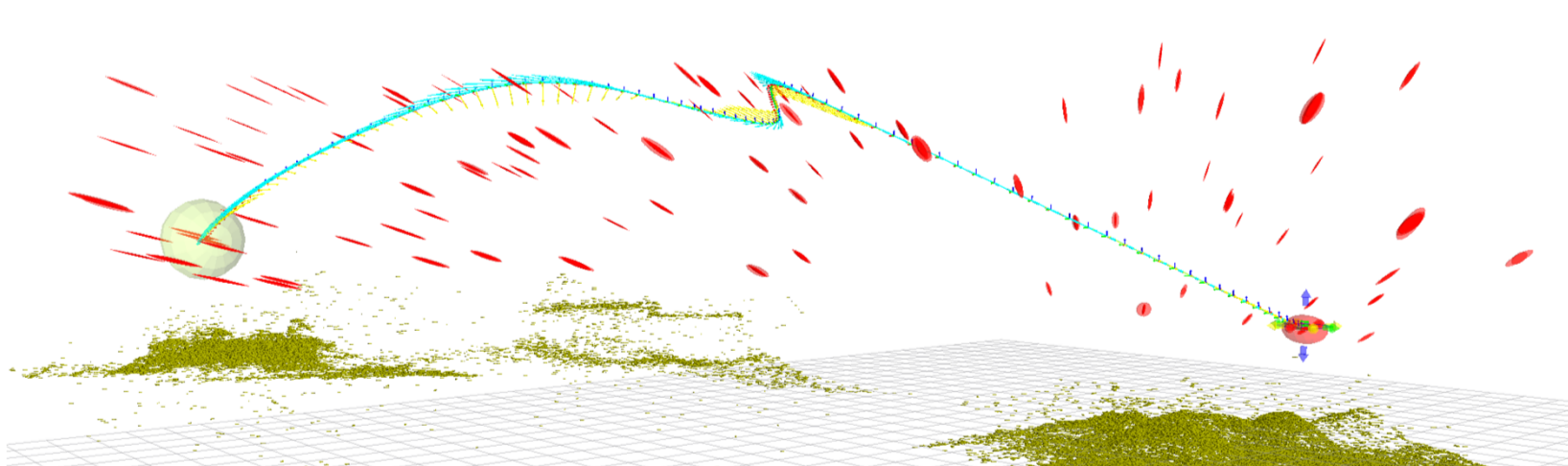


Outdoor experiments with GPS ground truth (red) for verification: After a short initialization phase at the start, vision-based navigation (blue) was switched on for successful completion of a more than 350m-long trajectory (top) and a flight up to 70 m altitude. The comparison of the estimated trajectory with GPS indicates a very low position and yaw drift of our real-time and onboard visual SLAM and state estimation framework.

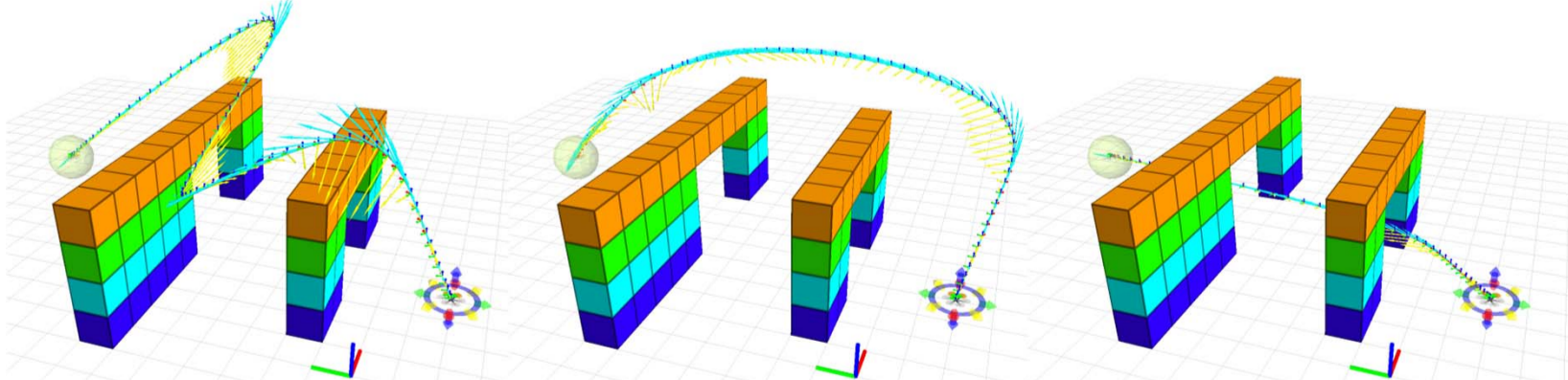


## Motion and Uncertainty Aware ...

Our state estimation framework incorporates states whose observability is only maintained as long as the MAV undergoes certain excitation. We developed a path-planning method, accounting for both the dynamics of the MAV, and the state estimation framework. Paths are planned such that the vehicle remains in an observable mode, while circumnavigating areas where localization becomes too uncertain, as shown below. The dots denote visual landmarks, and the red ellipsoids denote the uncertainty of intermediate points that the planner has considered during the optimization phase.

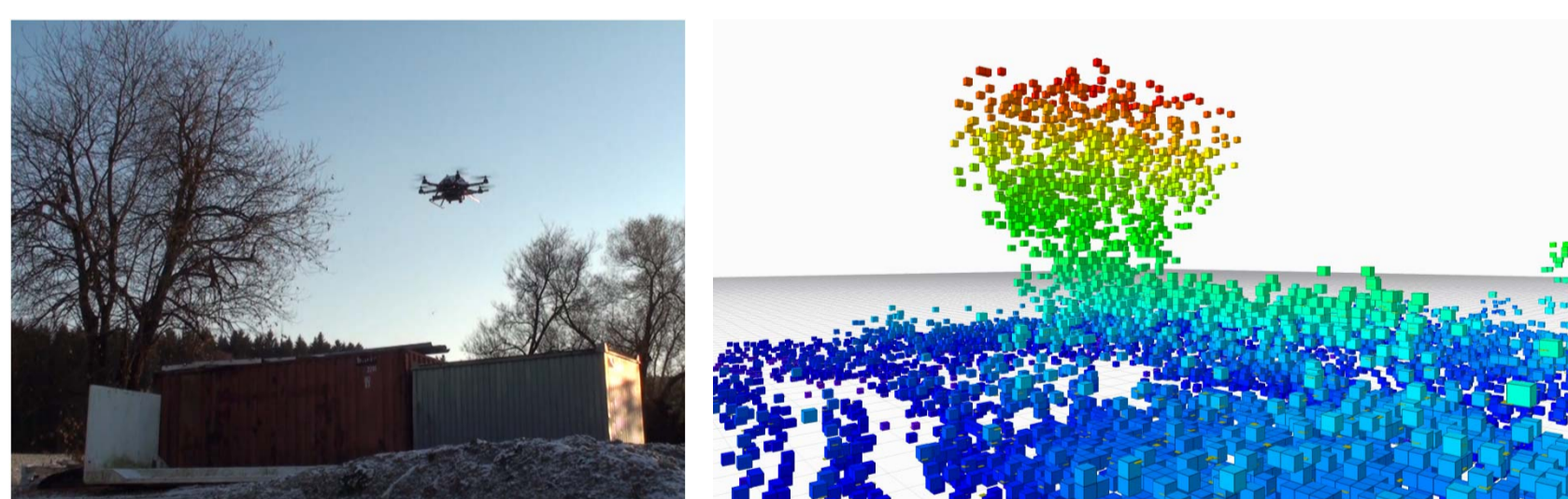


Obstacles can also be incorporated and successfully circumnavigated. The figure shows the first path, an intermediate path and the final path.

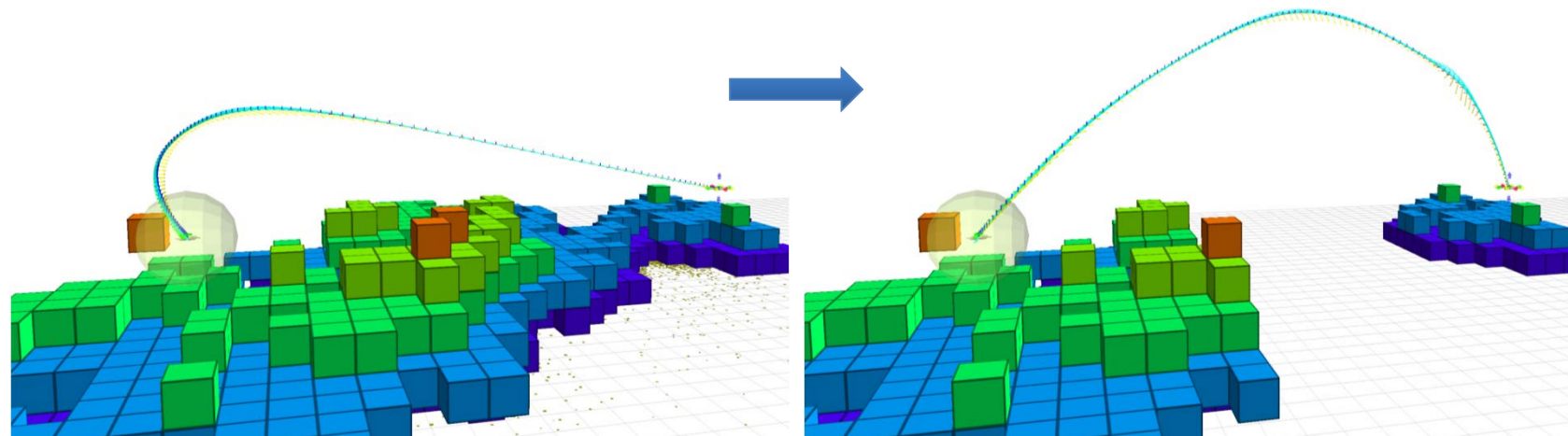


## ... Path-Planning for MAVs

Obstacle maps are created during a flyover prior to the landing maneuver at a safe altitude – just as a pilot would do. Using a statistical model, visual landmarks are inserted into a 3-D occupancy grid, that allows for efficient storage and fast obstacle look-ups. An impression of the real scenario and the reconstructed version is shown below.

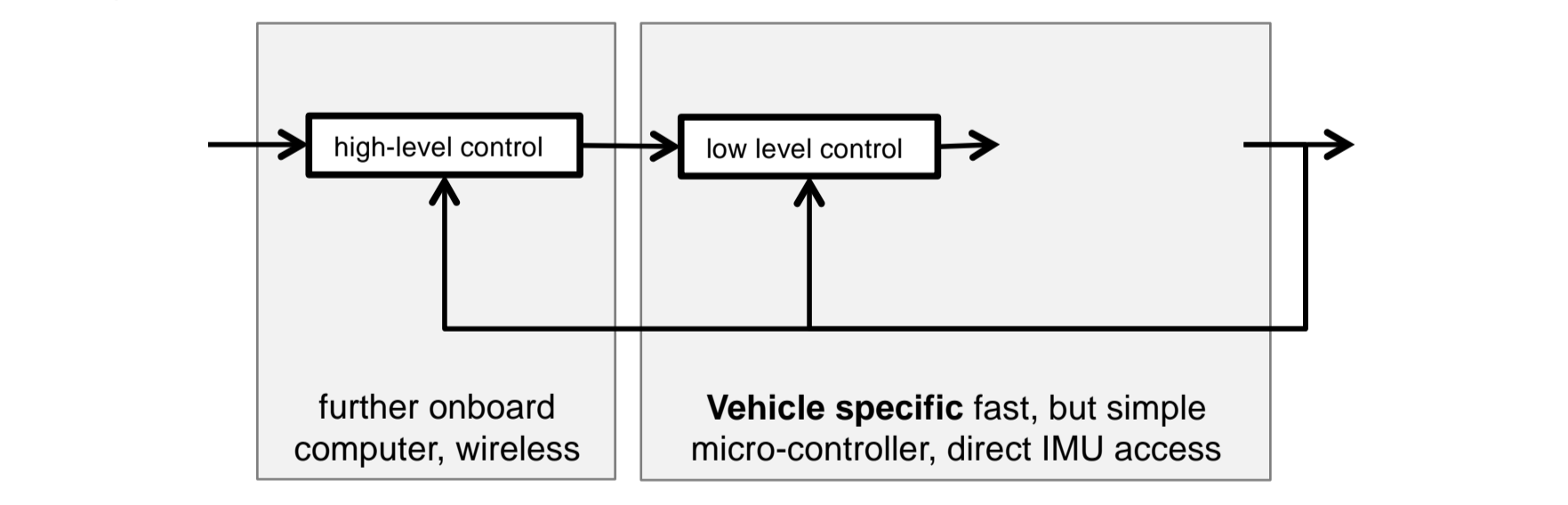


Taking into account the visibility of landmarks yields trajectories that allow the vehicle to safely traverse feature-less areas. On the left, the vehicle can fly a relatively straight path to the goal. In case of feature-less areas (right), the planner increases altitude for more landmarks to become visible.



## Direct Position Control

We developed a powerful, albeit simple position control approach for Micro Aerial Vehicles (MAVs) targeting specifically multi-rotor systems. We show that pitch and roll do not need to be controlled states, but rather just need to be known. This simplifies computation on embedded hardware and allows for higher bandwidth.



Instead of the common approach of having multiple cascaded control loops, the proposed method employs an outer control loop based on dynamic inversion, which directly commands angular rates and thrust. The inner control loop then reduces to a simple proportional controller on the angular rates.

