

Kilometer-Scale GNSS-Denied UAV Navigation via Heightmap Gradients: A Winning System from the SPRIN-D Challenge



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Abstract

We present a fully onboard UAV system developed for the SPRIN-D Fully Autonomous Flight Challenge, which required **9 km long-range** waypoint navigation **below 25 m AGL** (Above Ground Level) **without GNSS** or **prior mapping**. The system integrates perception, mapping, planning, and control with a lightweight drift-correction method that matches LiDAR-derived local heightmaps to a prior geodata heightmap via gradient-template matching and fuses the evidence with odometry in a clustered particle filter. Deployed during the competition, the system **executed kilometer-scale flights** across **urban, forest, and open-field terrain** and reduced drift substantially relative to raw odometry, while running in real time on CPU-only hardware. We describe the system architecture, the localization pipeline, and the competition evaluation, and we report practical insights from field deployment that inform the design of GNSS-denied UAV autonomy.

System architecture

The task of GNSS-denied long-range navigation requires integration of perception, localization, planning, and control into a reliable onboard system. The feedback control is based on Visual-Inertial Odometry (VIO) [1] and MRS UAV System [2]. Drift of the odometry is then corrected by global localization. The onboard lidar data are processed into a local volumetric map with an integrated planner for collision avoidance. The task execution (including waypoint detection) is commanded by the state machine. The presence of a mission waypoint (equipped with a small red flag and black box with a waypoint number, see Fig. 6) was verified by a vision-based detector.

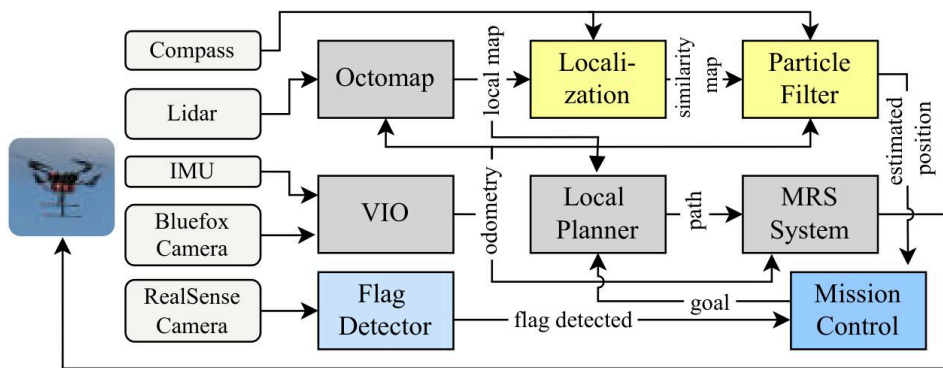


Fig. 1: System overview. Sensor inputs from LiDAR, cameras, IMU, and compass feed modules for visual-inertial odometry, obstacle mapping, and flag detection. A similarity-based localization module fuses odometry with prior geodata in a particle filter. Mission control coordinates planning and control for waypoint-based flight

Hardware

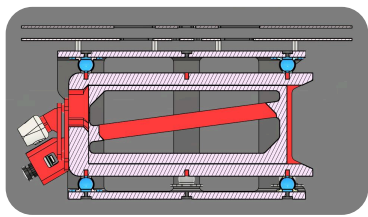


Fig. 2: Vibration-dampening system. The VIO camera and IMU are attached to the 3D printed battery mount (red) and isolated from the rest of the UAV frame via soft 3D printed silent blocks.



Fig. 3: Overview of the UAV platform and integrated sensor suite. The multirotor airframe carries a Livox Mid-360 LiDAR for mapping and localization, an Intel RealSense D435 depth camera for short-range obstacle perception, IMU ICM42688 coupled with VIO camera Bluefox2, and an onboard Intel NUC computer.

Heightmap-Based Localization

Operating in previously unvisited areas eliminated the possibility of loop closures, requiring a fully onboard, CPU-only system capable of executing real-time drift correction against publicly available prior geodata. The key component of our system is the lightweight GNSS-denied global localization, which matches the local heightmap to a prior heightmap of the terrain and obstacles. The global position was then estimated by the clustered Bayesian (particle) filter.

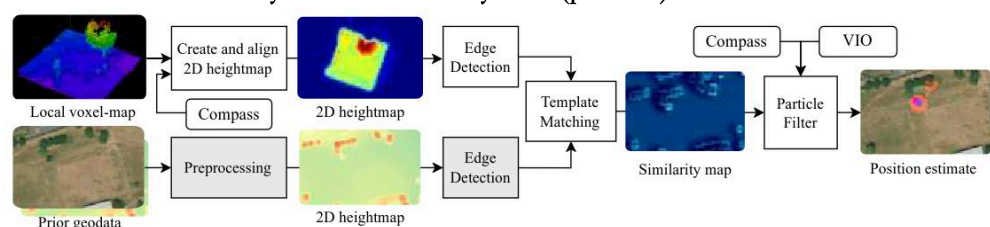


Fig. 4: Overview of the proposed GNSS-denied localization pipeline. The local 3D voxel map is aligned to North using compass measurements, projected to a 2D heightmap and matched against prior heightmap data obtained from available remote sensing geodata.

Real-world deployment

The final round of the challenge took place at the Erding Airbase in Germany. The GNSS-denied flights in diverse (forest, urban, and open; see Figs. 5, 6) and previously unvisited environments made the competition a good stress test for robotic solutions. The experiment showing the ability to correct odometry drift in real-world conditions is shown in Fig. 7 and 8. The results achieved during the competition are illustrated in Fig. 9, 10 and summarized in the Table 1.



Fig. 5: The test area on Erding airbase in Germany consisted of urban, forest and open field environments.



Fig. 6: The organizers made the conditions even more challenging by artificial smoke or sprayed water.



Fig. 7: Competing against nine teams from European countries, our solution secured first place in the challenge.

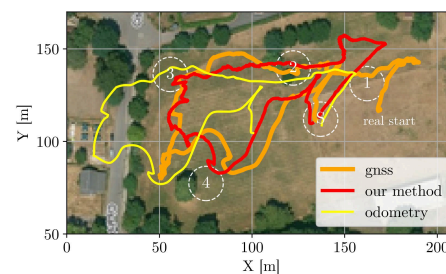


Fig. 7 & 8: Flight ID 61 (precompetition test). The starting (and landing) position is marked with S and the waypoints are numbered in the respective order. During this experiment, the localization method was initialized (waypoint S) 32 m off the starting position (see "real start" in the map). Despite the initial error, the localization method successfully relocalized by the end of the test flight.

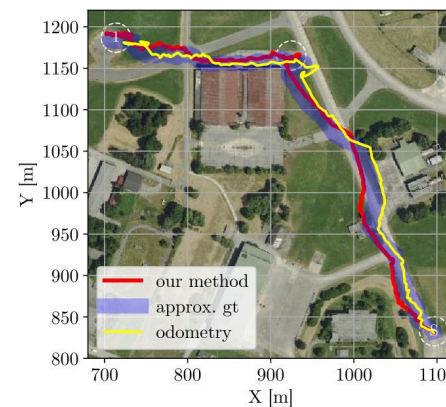


Fig. 9 & 10: Comparison of flight trajectories (ID 208, 232) during the SPRIN-D competition. The results highlight the reduced drift of our method compared to raw odometry across different environments.

Flight ID	Length [m]	Time [s]	RMSE _{odom} [m]	RMSE _{method} [m]	Waypoints detected	Area	Termination
60*	830	606	8	5	-	forest/open field	test finished
61*	495	343	36	13	-	forest/open field	test finished
205 [†]	939	622	31	10	1/1	urban	test finished
206 [†]	1023	621	27	6	2/2	urban	SW issue
208 [†]	872	500	14	11	1/1	urban/open field	low battery
232 [†]	1256	1021	53	7	1/2	forest	failsafe - HW issue
239 [†]	1371	977	8	9	4/4	forest	low battery
242 [†]	939	622	9	11	2/3	urban/open field	low battery

Table 1: Summary of the real-world experiments. a) ID of the flight, b) flight time, c) flight length, d) RMSE of the odometry and our proposed method compared to GNSS ground truth(*)/approximate ground truth(†) (both rounded to meters), e) number of waypoints with flag successfully detected, f) type of the environment and g) termination of the mission are reported.

Our system executed multiple kilometer-scale fully autonomous flights during the challenge finals. In mixed urban and forest areas, the drift correction method effectively reduced the odometry drift. Over completely open, featureless terrain, the system relied heavily on raw odometry and magnetometer heading. Main limitation: the maximum flight speed (the effective mission range) was constrained by the computational limits of the local voxel-based mapper and planner.

Lessons learned

- **Robotics system performance is bounded by its weakest component.** Our system was limited by the speed of the onboard mapping, which limited the effective range of the system.
- **Environmental Magnetic Interference:** We observed severe magnetometer offsets over reinforced concrete. Heading must be actively corrected by structural features.
- **Design for Rapid Maintenance:** Hardware must be modular to allow for fast design iterations and quick field repairs. During the challenge, our team had to replace a broken UAV arm within a strict 30-minute window after a crash caused by hardware failure.
- **Hardware Isolation is Critical:** VIO performance is dependent on mechanical damping. Direct mounting without vibration absorption renders the IMU data noisy and barely usable.

Supported by



[1] P. Geneva et al., "OpenVINS: A research platform for visual-inertial estimation," in Proc. of the IEEE International Conference on Robotics and Automation, Paris, France, 2020.

[2] T. Baca et al., "The MRS UAV System: Pushing the Frontiers of Reproducible Research, Real-world Deployment, and Education with Autonomous Unmanned Aerial Vehicles," Journal of Intelligent & Robotic Systems, vol. 102, no. 26, pp. 1–28, 05 2021.

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Video from the experiments and details about the method



Realistic UAV simulator used for development and testing