Open Source Tools for Deployment of GPS-Denied Autonomous UAVs in Real-World Applications

Fernando Cladera*, Yuwei Wu*, Xu Liu, Yuezhan Tao, Ian D. Miller, CJ Taylor, and Vijay Kumar

***Abstract*— Despite the widespread use of Autonomous Unmanned Aerial Vehicles (UAVs) in various outdoor applications, their deployment in indoor and GPS-denied environments—such as under dense forest canopies—continues to pose significant challenges. Robust trajectory planning, accurate state estimation, and effective obstacle avoidance are crucial to successful mission completion in these complex, dynamic, and unstructured settings. In this work, we present our open source autonomy stack for aerial robots operating in GPS-denied environments. We specifically focus on two critical components: (1) compensation for inaccurate state estimation and (2) trajectory planning in uncertain scenarios. Using these techniques, our systems are capable of executing long-range missions in challenging environments. We hope that the tools and methodologies introduced in this study will accelerate the adoption and safe deployment of UAVs in GPS-denied conditions.**

I. Introduction

Simulators with realistic physics engines such as Gazebo[1] and Unity[2] have become powerful tools for the verification and design of UAVs. These tools can help at every stage of the process, from tuning low-level control loops to high-level behavior design. Even for learning-based systems, recent work shows that learning models trained in simulations can generalize to real-world applications with the right sensor abstractions [1]. However, simulators are not suitable for long-range missions and repeatable behavior in real-world applications. Uncertainties from UAV model discrepancies, aerodynamic forces, and sensor noise are difficult to identify, isolate, and model within simulated models and therefore can affect UAV performance.

In addition, UAVs consist of multiple interconnected subsystems whose behavior is difficult to analyze in real-world deployments. Traditional approaches focus on the uncertainty in one or a few of these submodules, trying to keep margins for safe operation. For example, uncertainties and disturbances of the control subsystem are usually validated in laboratory environments with ground-truth positions by motion capture systems, which provide bounds on errors. However, in real-world deployments, tracking errors will influence the state estimation, leading to potentially unsafe UAV operations [2].

Therefore, UAVs operating in real-world GPS-denied environments must be resilient to these uncertainties. In this work, we present our open source autonomy stack for UAVs without GPS. We focus on our approaches for deploying robots in real-world missions, considering the uncertainty in the state estimation and planning modules. Experiments [3] demonstrate that our approaches increase the accuracy and safety of the system when performing long-range missions in complex GPS-denied environments.

*Both authors contributed equally. All authors are within the GRASP Laboratory, University of Pennsylvania, PA, 19104, USA {fclad, yuweiwu, liuxu, yztao, iandm, cjtaylor, kumar}@seas.upenn.edu

[1]https://staging.gazebosim.org/

[2]https://unity.com/

Fig. 1: Platforms used in our deployments. Top: The Falcon 4 has a total weight of 4.2 kg, can fly for more than 30 minutes, and performs autonomous flights greater than 1 km under dense forest canopies. Bottom: the Falcon 250 has a total weight of 1.3 kg and performs missions in indoor cluttered environments. Both platforms run all estimation, path planning, navigation, and control algorithms onboard.

II. Deploying Flying Robots in Real-World Scenarios

A. Autonomy Stack

We presented an open source software stack for GPS-denied UAVs in [3], [4]. Our stack is composed of the following elements:

- State estimator: We use MSCKF for our Stereo Visual Inertial Odometry (VIO) [5], FasterLIO [6] for LiDAR Inertial Odometry (LIO), and an off-the-shelf solution for monocular VIO from ModalAI [7].
- Mapper: We construct an occupancy grid by combining data from various depth sensors with odometry.
- Planner: Discussed in detail in Sec. III.
- Controller: a high-level position controller runs on the onboard computer, and a low-level attitude controller runs on a Pixhawk 4 flight controller.

B. Experiments

We deployed our system on two different platforms (Fig. 1) targeting under-canopy and indoor flight, respectively. Both platforms are powered by an Intel i7-10710U processor with 32 GB of RAM. The main difference between the platforms lies in the perception stack:

1) Falcon 4: This platform is equipped with an Ouster OS64-U 3D LiDAR and an Open Vision Computer (OVC) 3 [8] which provides synchronized IMU and stereo cameras. We have used both LiDAR and VIO for state estimation.

2) Falcon 250: This platform is equipped with an Intel Realsense D435i as its main perception sensor, coupled with a ModalAI VOXL for state estimation.

In both platforms, the state estimation is the subsystem that incurs most of the uncertainties. We summarize odometry drifts in Tab. I.

Platform / Environment	**State Estimation**	**Distance**	**Drift**
Falcon 4 / Forest	Stereo VIO	1.1 km	0.92%
Falcon 4 / Forest	LIO	1 km	0.05%
Falcon 250 / Indoor	Monocular VIO	85 m	3.97%
Falcon 250 / Outdoor	Monocular VIO	714 m	1.56%

TABLE I: Onboard state estimation drift without semantic SLAM. Indoor flight is more challenging with clutter and fewer textured objects.

III. Model Uncertainty and Safety

A. Semantic SLAM

Semantic representations offer significant advantages over purely geometric ones, such as robustness to environmental variations and invariance to viewpoint changes [9]. Semantics can be used in loop closure or graph optimization approaches to reduce drift of the state estimation through Semantic SLAM [3], [10].

We observe a significant reduction in drift when implementing semantic SLAM. For example, in complex forest environments with the Falcon 4, we reduced the odometry drift by 60.5% in the long-range flight mission, on a trajectory of 1.1 km. The use of LiDAR enables more accurate LiDAR inertial odometry but at the expense of carrying heavy-weight sensors and reducing the autonomy of the platform. For example, the LiDAR weighs 619 g, while the OVC only weighs 122 g. Therefore, VIO with Semantic SLAM is an efficient approach for long-range autonomy in size, weight, and power (SWaP) restricted platforms.

B. Planning Under Uncertainty

Due to the noise in the sensor data and the approximations in the SLAM algorithms, there exist uncertainties in robot perception (i.e. potential discrepancies between the estimated state and the true state of the robot and environment). Actively accounting for and reducing such uncertainties is critical for robotic exploration and mapping tasks [11].

With the states and maps provided, the robot can generate trajectories, but it may be necessary to consider all the errors and uncertainties to ensure the safety for real-world deployment. Some previous work models uncertainty or noise

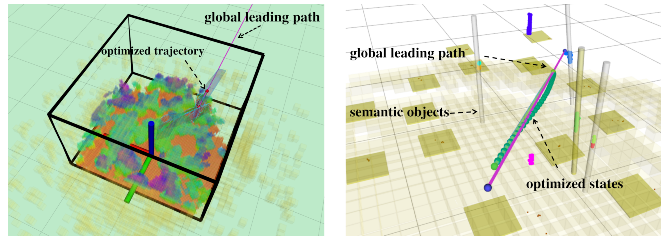

Fig. 2: Hierarchical planning pipeline. Left: Traditionally, both global and local maps are over-inflated to cover bounded noises and uncertainty. Right: The uncertainty-aware local planner incorporates semantic objects, such as cylinders and planes, avoiding map over-inflation. This helps navigate narrow corridors safely.

and analyzes reachabilities [12] or develops probabilistic collision avoidance constraints [13] to generate safe but more conservative trajectories. As illustrated in Fig. 2, our previous work [3] proposed a hierarchical planning framework where high-level planning usually involves task-specific route or behavior planning, while low-level planning considers dynamic feasibility to generate trajectories to track. To address noise and uncertainties, we initially employed bounded ranges to inflate global and local maps with different resolutions, which is a reliable but conservative method for navigating cluttered outdoor environments. Inflating the global map is particularly bad: As the global map is coarsely discretized compared to the local map [3], small corridors can become obstructed after conservative inflation. To address these issues, we incorporate the uncertainty models of the measurement of semantic objects [11] with trajectory optimization to avoid over-inflation.

We deploy a similar planning pipeline on the Falcon 250 platform which has a limited Field of View. We predict the unseen areas for robust and reliable trajectory planning [14]. We incorporate learning-based occupancy grid prediction and semantic object detection to help with high-level goal selection and behavior planning. We also consider the potential information of the unknown environment to actively yaw the robot toward unseen areas, providing safe and non-conservative trajectories.

For both platforms, while the planners are complete in theory, in practice, due to sensor noise and estimation errors, the approximations can cause the algorithm to fail to find solutions even if solutions exist. However, the rate at which safe solutions are found is higher compared to traditional approaches.

IV. Conclusion

In this study, we presented two approaches to increasing the safety and reliability of GPS-denied UAVs using uncertainty-aware trajectory generation and semantic information to reduce state estimation drift. These methods enable successful long-range missions in complex, cluttered, and unstructured environments. Our open source stack aims to bridge the gap between academia and industry, fostering widespread adoption, and inspiring further advancements in aerial robotics.

References

[1] A. Loquercio, E. Kaufmann, R. Ranftl, M. Müller, V. Koltun, and D. Scaramuzza, "Learning high-speed flight in the wild," *Science Robotics*, vol. 6, no. 59, p. eabg5810, 2021. [Online]. Available: https://www.science.org/doi/abs/10.1126/scirobotics.abg5810

[2] X. Liu, S. W. Chen, G. V. Nardari, C. Qu, F. C. Ojeda, C. J. Taylor, and V. Kumar, "Challenges and Opportunities for Autonomous Micro-UAVs in Precision Agriculture," *IEEE Micro*, vol. 42, no. 1, pp. 61–68, 2022.

[3] X. Liu, G. V. Nardari, F. C. Ojeda, Y. Tao, A. Zhou, T. Donnelly, C. Qu, S. W. Chen, R. A. F. Romero, C. J. Taylor, and V. Kumar, "Large-Scale Autonomous Flight With Real-Time Semantic SLAM Under Dense Forest Canopy," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 5512–5519, 2022.

[4] F. Cladera, X. Liu, C. Taylor, and V. Kumar, "KR Autonomous Flight: An Open Source Flight Stack for GPS-denied UAVs," in *ROSCon 2022*, 2022.

[5] K. Sun, K. Mohta, B. Pfrommer, M. Watterson, S. Liu, Y. Mulgaonkar, C. J. Taylor, and V. Kumar, "Robust Stereo Visual Inertial Odometry for Fast Autonomous Flight," *IEEE Robotics and Automation Letters*, vol. 3, no. 2, pp. 965–972, 2018.

[6] C. Bai, T. Xiao, Y. Chen, H. Wang, F. Zhang, and X. Gao, "Faster-LIO: Lightweight Tightly Coupled Lidar-Inertial Odometry Using Parallel Sparse Incremental Voxels," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 4861–4868, 2022.

[7] "Flying with VIO," n.d., accessed: 2023-04-15. [Online]. Available: https://docs.modalai.com/flying-with-vio/

[8] M. Quigley, K. Mohta, S. S. Shivakumar, M. Watterson, Y. Mulgaonkar, M. Arguedas, K. Sun, S. Liu, B. Pfrommer, V. Kumar, and C. J. Taylor, "The Open Vision Computer: An Integrated Sensing and Compute System for Mobile Robots," in *2019 International Conference on Robotics and Automation (ICRA)*, 2019, pp. 1834–1840.

[9] I. D. Miller, F. Cladera, T. Smith, C. J. Taylor, and V. Kumar, "Stronger Together: Air-Ground Robotic Collaboration Using Semantics," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 9643–9650, 2022.

[10] S. W. Chen, G. V. Nardari, E. S. Lee, C. Qu, X. Liu, R. A. F. Romero, and V. Kumar, "SLOAM: Semantic lidar odometry and mapping for forest inventory," in *IEEE Robotics and Automation Letters (RA-L)*, 2020.

[11] X. Liu, A. Prabhu, F. Cladera, I. D. Miller, L. Zhou, C. J. Taylor, and V. Kumar, "Active Metric-Semantic Mapping by Multiple Aerial Robots," 2022.

[12] D. Althoff, M. Althoff, and S. Scherer, "Online safety verification of trajectories for unmanned flight with offline computed robust invariant sets," in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2015, pp. 3470–3477.

[13] H. Zhu and J. Alonso-Mora, "B-UAVC: Buffered Uncertainty-Aware Voronoi Cells for Probabilistic Multi-Robot Collision Avoidance," in *2019 International Symposium on Multi-Robot and Multi-Agent Systems (MRS)*, 2019, pp. 162–168.

[14] Y. Tao, Y. Wu, B. Li, F. Cladera, A. Zhou, D. Thakur, and V. Kumar, "SEER: Safe Efficient Exploration for Aerial Robots using Learning to Predict Information Gain," 2023.