

FIELD EVALUATION OF ROBOTIC UNDER-CANOPY DRONES IN BOREAL FOREST

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Abstract

Drones are increasingly used in forestry to capture high-resolution remote sensing data. Although operations above the forest canopy are already highly automated, autonomous flying under the canopy remains challenging due to poor Global Navigation Satellite System (GNSS) signals and the need to avoid collisions with trees and branches. Recently, various methods for GNSS-free autonomous flying in obstacle-rich environments have been proposed in the literature. These methods typically rely on either a stereo camera or a LiDAR,

combined with an inertial measurement unit (IMU), to obtain a pose estimate using a SLAM or an odometry estimation algorithm. The obstacles are detected in real-time from depth images or point clouds, and the trajectories are planned to be collision-free, utilizing either local 3D grid maps or neural networks directly mapping the depth images to motion primitives. However, the methods proposed in the literature have typically been validated only by individual flights in a specific forest environment with non-specified forest characteristics, making it difficult to evaluate the

performance in other types of forest based on the test flights reported in the original articles. In this study, the performance of three state-of-the-art approaches for autonomous GNSS-denied under-canopy flying was compared in Nordic Boreal Forest environments. The study aimed to evaluate the reliability of the path planning methods and identify situations that lead to navigation problems, with the ultimate goal of determining the most suitable approach for a robotic drone platform in future boreal forest research and remote sensing studies.

Methods

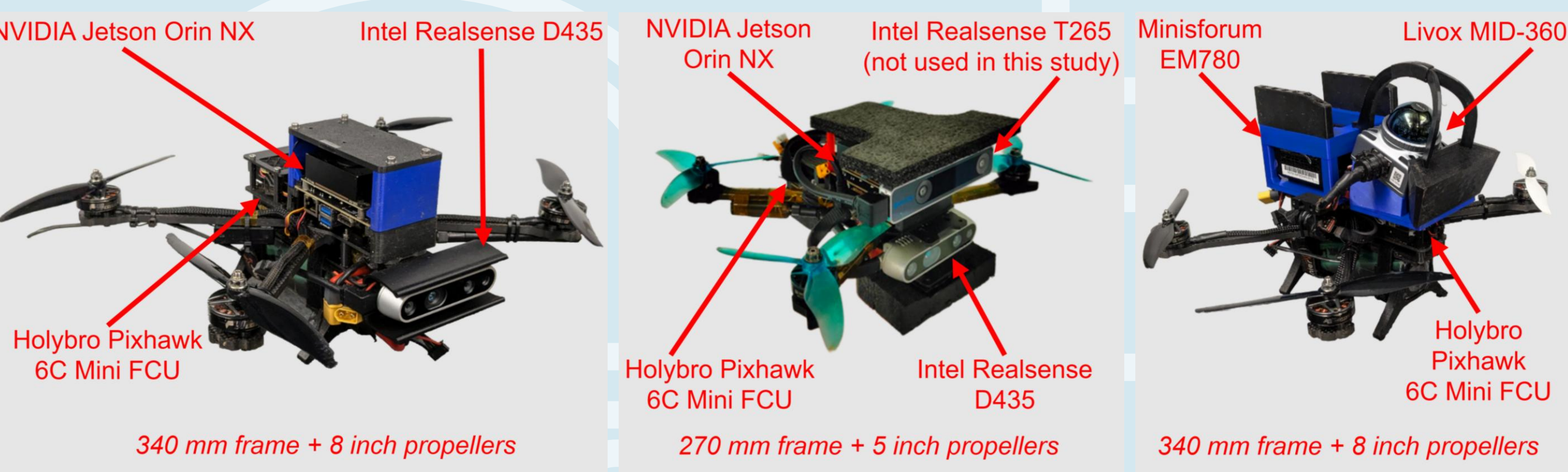
Three prototype drone platforms were built to run three different state-of-the-art methods:

(I) A prototype running EGO-Planner-v2 [1] based on traditional iterative trajectory planning within a local 3D grid map formed with a stereo camera. The local pose estimate was obtained with VINS-Fusion [2][3].

(II) A stereo camera prototype replacing the distinct mapping and planning subtasks with a deep neural network directly mapping the depth images to safe actions. The algorithm was based on ORACLE [4] and SeVAE [5], further enhanced with an additional safety layer and image filtering, and re-training [6] based on the initial flight tests. The pose estimate was obtained with VINS-Fusion.

(III) A prototype with a LiDAR running an IPC algorithm [7] which combines the path planning within a local 3D grid map and control with Model Predictive control. Based on the initial flight tests, the algorithm was further enhanced with an updated heuristics function [8]. The pose estimate was obtained with the LTA-OM LiDAR SLAM algorithm [9].

The methods were evaluated in two challenging boreal forest sites located in Paloheinä, Helsinki, Finland. In both test sites, 15 test flights were conducted with all three systems. The goal was set to 60 m forward from the takeoff location, and the target flight speed was set to 1 m/s.



▲ The custom drones built for the tests, (I) (left), (II) (middle), and (III) (right).
▼ Views from the takeoff locations of the test sites A (left) and B (right). The test site A consisted mainly younger Norway spruces with a higher density (~2200 trees/ha) and more low-hanging dry branches, whereas the test site B (~1600 trees/ha) had older trees but more understory vegetation (leafless season).



Results

Method	Flight Success Rate	Avg. Odom. vel.	Avg. takeoff-to-goal vel.
(I)	10 / 15	0.91 m/s	0.83 m/s
(II)	15 / 15	0.90 m/s	0.82 m/s
(III)	14 / 15	0.75 m/s	0.70 m/s

▲ Flight results in the first test site (A). ▼ Flight results in the second test site (B). The flights were evaluated based on the success rate, average velocity estimated by the odometry, and the average linear velocity towards the goal.

Method	Flight Success Rate	Avg. Odom. vel.	Avg. takeoff-to-goal vel.
(I)	13 / 15	0.90 m/s	0.80 m/s
(II)	12 / 15	0.96 m/s	0.92 m/s
(III)	13 / 15	0.68 m/s	0.60 m/s

In terms of flight velocity and success rates, the deep learning -based prototype (II) demonstrated the best overall performance. However, the performance of the systems varied between the test environments. Whereas the stereo camera-based traditional mapping and planning method (I) struggled with vertical thin branches in test site A, it performed best in test site B in terms of success rate and actual flight speed.

Prototype (II) performed perfectly at the test site A but experienced most failures at the test site B, potentially indicating issues with avoiding obstacles that differed significantly from those used in training of the neural network.

Unlike the camera-based prototypes, the LiDAR prototype (III) did not have any problems with detecting the thin branches. However, it was the only prototype that detected the dry leaves blown from the ground by the propeller airflow as obstacles, leading to unstable flight and a few failures. Furthermore, the system was consistently flying notably slower than the specified target velocity.

Note regarding the limitations of the study

Due to the available hardware during the development and training process, the deep learning-based prototype (II) had a slightly smaller size than the two other prototypes. Since the test forests had sufficient free space for all drones and the nature of the reasons for failures (sensor or algorithmic limitations), this is not expected to have a notable impact on the success rates. However, the smaller size probably gave a slight advantage in terms of time to reach the final goal (and consequently the takeoff-to-goal velocity), since the smaller size allows going through narrower gaps, leading to more direct paths towards the goal.

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