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Fusion of Optical Flow and Dead Reckoning Algorithms for UAV Navigation Without GPS

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ABSTRACT: The article presents an innovative navigation system for unmanned aerial vehicles (UAVs) operating in environments with limited or unavailable GPS signal. The developed solution integrates dead reckoning navigation methods with advanced computer vision algorithms utilizing optical flow analysis, enabling precise drone positioning. The research includes implementation of data fusion algorithms from inertial measurement units (IMU) and analysis of image sequences from a downward-facing camera. Experimental results from tests conducted in both simulated environments and on real flight platforms are presented. The study demonstrates that the application of optical flow techniques significantly improves dead reckoning navigation accuracy in GPS-denied conditions, reducing the accumulating position error. The proposed system offers a promising solution for UAV operations in challenging navigation conditions, such as urban areas, indoor environments, or regions with electromagnetic interference.

1 INTRODUCTION

In recent years, there has been a dynamic development of Unmanned Aerial Vehicles (UAVs), which have found wide application in areas such as environmental monitoring, infrastructure inspection, search and rescue operations, and precision agriculture. A key component enabling the autonomous operation of UAVs is the navigation system, which allows for the determination of the vehicle's current position and orientation in space. In most contemporary UAV systems, the Global Positioning System (GPS) is utilized due to its availability, accuracy, and ease of integration with other control system components [1].

However, in many operational scenarios—such as missions conducted in dense forests, narrow urban streets, tunnels, indoor environments, or under conditions of electromagnetic interference (e.g., due to intentional GPS jamming)—the availability of satellite signals is limited or entirely absent [2]. In such cases, the development of alternative localization methods becomes essential to maintain the navigational functionality of UAVs in GPS-denied environments.

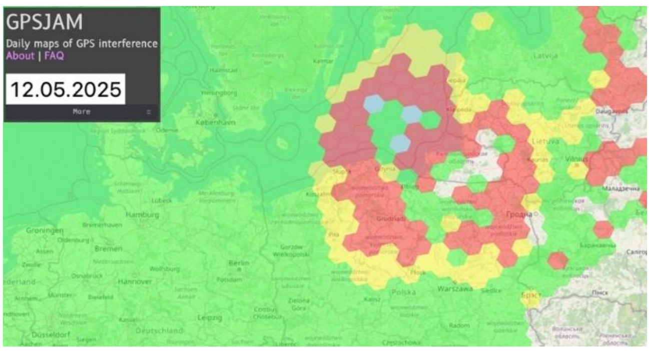

Figure 1. GPS signal interference in the vicinity of the Kaliningrad region (source: https://gpsjam.org)

One alternative approach involves the use of optical flow, which enables the estimation of the UAV's relative motion with respect to its surroundings based on the analysis of image sequences captured by onboard cameras [3]. Another approach is inertial navigation based on dead reckoning, which estimates the current position by integrating data from accelerometers and gyroscopes without relying on external signals [4]. Both approaches, however, have inherent limitations: optical flow is susceptible to errors in homogeneous or poorly textured environments, while dead reckoning suffers from cumulative position drift over time.

The aim of this study is to propose and evaluate a fusion method combining optical flow and dead reckoning navigation to improve the accuracy and robustness of UAV navigation in GPS-denied environments. Integrating these two approaches allows for mutual compensation of their respective weaknesses, resulting in a more stable and accurate position estimation. The following sections present a review of related work on GPS-independent localization methods, a description of the implemented algorithms, and the results of simulation-based and field experiments.

2 SURVEY OF ALTERNATIVE UAV NAVIGATION APPROACHES

In response to the growing need for reliable UAV navigation in environments where access to GPS signals is limited or entirely unavailable, several alternative localization methods have been proposed in the literature. Particular attention has been given to systems based on the fusion of data from optical and inertial sources, such as cameras and Inertial Measurement Units (IMUs). This chapter presents previous approaches that utilize optical flow and dead reckoning independently, as well as studies that integrate both techniques within GPS-independent localization systems.

2.1 *Optical Flow in UAV Navigation*

Optical flow is a technique for estimating a vector field that describes the motion of image points between consecutive frames. It is commonly used in mobile robotics to estimate both velocity and direction of movement within an environment. Classical algorithms such as the Horn–Schunck and Lucas–Kanade methods enable accurate optical flow estimation in well-textured scenes [5].

In the context of UAVs, Santos-Victor and Sandini demonstrated that optical flow can be effectively employed for docking manoeuvres and navigation within enclosed spaces [6]. More recent studies, such as those by Kendall and Cipolla, have applied deep learning techniques to improve flow estimation accuracy under challenging lighting conditions and in environments with low texture [7].

Although optical flow provides valuable information about relative motion, its accuracy is highly dependent on image quality, and it may result in significant errors in homogeneous or poorly lit environments. Therefore, it is often combined with other sources of information to enhance robustness and reliability.

2.2 *Inertial Navigation and the Dead Reckoning Method*

Dead reckoning is a method for estimating the current position based on the previous state and information about the traversed path, typically obtained from inertial sensors such as accelerometers and gyroscopes. These solutions are characterized by high-frequency measurements and independence from external sources of information [8]. However, the primary limitation of this method lies in the accumulation of error over time, due to its recursive nature—inferring the current state solely from the last known state.

Classical inertial navigation systems (INS) have been thoroughly described by Titterton and Weston, who emphasized the necessity of incorporating auxiliary data sources to compensate for inertial drift [9]. In the case of UAVs, dead reckoning remains effective only for short durations without correction from external positioning systems.

2.3 *Fusion of Optical Flow and Dead Reckoning*

One of the most promising approaches to GPS-denied UAV localization involves the integration of visual and inertial data, commonly referred to as Visual-Inertial Odometry (VIO). Mourikis and Roumeliotis proposed the Multi-State Constraint Kalman Filter (MSCKF), which enables real-time trajectory estimation of UAVs while accounting for measurement uncertainties [10].

Weiss et al. developed a lightweight VIO system for micro-UAVs, capable of real-time operation with minimal computational overhead—an important consideration for onboard applications [11]. Similarly, Badino et al. demonstrated that combining optical flow with IMU data enhances the robustness of the system against sudden lighting changes and temporary loss of visual features [12].

More recent approaches leverage deep neural networks to estimate position based on sequences of images and inertial data. The work by Zhan et al. introduces DeepVO—a recurrent network that learns temporal dependencies between visual and inertial observations [13]. Although such methods achieve high accuracy, their implementation requires substantial computational resources and access to extensive training datasets.

A review of the literature indicates that the fusion of optical flow and inertial data represents a promising solution to the challenge of UAV navigation in GPS-denied environments. Key challenges include drift mitigation, robustness to visual disturbances, and real-time operation on platforms with limited resources. In the following sections, the proposed system architecture is presented, along with the results of its validation in both simulated and real-world environments.

3 METHOD FOR ESTIMATING UAV POSITION

3.1 *Estimating UAV Velocity Using Optical Flow*

To estimate the velocity of the UAV relative to the ground, optical flow analysis was applied to images captured by a downward-facing onboard camera. The method is based on the Farnebäck algorithm [14], which allows for efficient computation of pixel displacement vectors between two consecutive image frames.

The approach proposed by Farnebäck [14] estimates dense optical flow by approximating image intensity using a quadratic function within local neighbourhoods. It is assumed that the displacement of points in the image between two frames results primarily from the movement of the camera relative to the environment. The optical *flow* $v=(v_x, v_y)$ is estimated as a displacement vector for each pixel between frames I_t i I_{t+1}. The resulting flow field is decomposed into horizontal and vertical components $u(x, y)$ and $v(x, y)$, and the average flow magnitude is then computed as:

$$\bar{v} = \frac{1}{N}\sum_{x,y}\sqrt{u(x,y)^2 + v(x,y)^2} \tag{1}$$

where N is the number of pixels in the image.

To convert pixel displacement into real-world units (meters), known camera parameters are used: focal length f in millimetres, flight altitude h and the image diagonal length d_{px}. If the camera's field of view corresponds to that of a pinhole camera with focal length f, the physical length of the image diagonal on the ground d_m is given by:

$$\mathrm{d_m} = 2h \cdot \tan\left(\frac{\theta}{2}\right) \tag{2}$$

where θ is the camera's field of view in radians. The final scaling factor from pixels to meters allows the computation of real-world velocity as:

$$\mathrm{v_{real}} = \bar{v} s f_{FPS} \tag{3}$$

where f_{FPS} is the frame rate of the video stream (frames per second).

3.2 *Integration of Velocity and Orientation in Position Estimation*

The integration process is based on continuously updating the UAV's position $P(t)$ using its previous state and the currently estimated velocity and flight direction:

$$\mathrm{P}(\mathrm{t}+\Delta\mathrm{t}) = P(t) + V(t)\Delta t \tag{4}$$

where $V(t)$ is the velocity estimated from optical flow using the Farnebäck method, Δt is the time interval between successive measurements, and $P(t)$ represents the UAV's position in the geographic coordinate system (latitude, longitude, altitude).

The displacement d over time Δt is computed based on the current speed $V(t)$ and the heading angle $\theta(t)$, which can be obtained from onboard IMU and magnetometer sensors:

$$d = |\mathrm{V}(\mathrm{t})|\Delta t \tag{5}$$

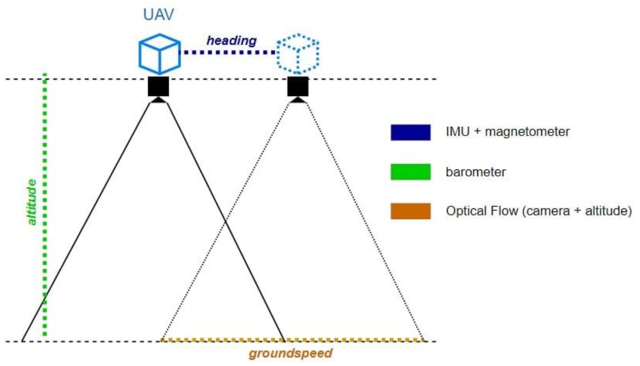

Figure 2. Diagram of data flow used for determining UAV motion parameters (own work).

The new geographic position is calculated using spherical formulas that solve the direct geodesic problem, given a distance and a bearing:

$$\phi_2 = \arcsin\left(\sin(\phi_1)\cos\left(\frac{d}{R}\right) + \cos(\phi_1)\sin\left(\frac{d}{R}\right)\cos(\theta)\right) \tag{6}$$

$$\lambda_2 = \lambda_1 + \mathrm{arctan2}\left(\sin(\theta)\sin\left(\frac{d}{R}\right)\cos(\phi_1),\ \cos\left(\frac{d}{R}\right) - \sin(\phi_1)\sin(\phi_2)\right) \tag{7}$$

where ϕ and λ denote geographic latitude and longitude, respectively, d is the ground distance travelled by the UAV, and R is the Earth's radius.

The main advantage of the proposed approach lies in its resilience to temporary GNSS signal loss. The system maintains continuity in position estimation by relying on motion information from independent sources, such as a downward-facing camera and inertial sensors. As a result, it enables navigation in environments with limited satellite visibility, such as urban canyons, tunnels, or indoor spaces. Additionally, velocity estimation based on optical flow contributes to smoother trajectory estimation, eliminating the abrupt positional jumps typically associated with weak or degraded GPS signals.

4 EXPERIMENTAL ENVIRONMENT

The experiments were conducted in a simulated environment, where sensor data (camera images and IMU measurements) were previously recorded during real-world UAV flights and subsequently processed locally on a computer. The objective was to evaluate the trajectory estimation system under GNSS-denied conditions.

The block diagram in Figure 3 illustrates the overall processing pipeline. The system takes as input video frames and corresponding samples from the Inertial Measurement Unit (IMU), which include altitude and orientation data. These inputs are then passed to the optical flow processing module, which estimates the horizontal ground-relative velocity (groundspeed). The resulting velocities are subsequently used by the dead reckoning module to determine the UAV's position in geographic coordinates, based on current speed and orientation.

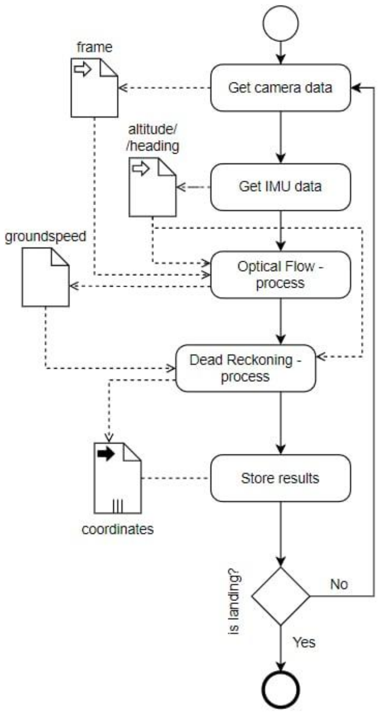

Figure 3. Diagram illustrating the operation of the software prototype developed for experimental purposes (own work).

For the experimental validation, the industrial UAV platform Yuneec H520 was used. This hexacopter is equipped with a high-resolution camera (E90, 4K) and was chosen for its stable flight performance, precise trajectory control, and full access to sensor logs, including:

- downward-facing video recordings from the onboard camera,
- IMU data: accelerations, angular velocities, and magnetometer readings,
- barometric altitude readings,
- telemetry and navigation data (including GPS, which was used for reference only).

The Yuneec H520 platform allows for data export in standard formats and ensures proper time synchronization of onboard sensors, making it a suitable testbed for evaluating alternative GNSS-independent navigation algorithms.

5 EXPERIMENTAL RESULTS

5.1 *Experiment No. 1*

The test flight was conducted over flat, open terrain with sparse vegetation (individual trees not exceeding 30 meters in height) and good visual texture. The mission duration was 129 seconds, consisting of 3885 frames, with an average flight altitude of 61 meters. Weather conditions were sunny with light wind.

Table 1. Position error metrics compared to GNSS (Experiment 1)

Mean error (MAE) [m]	RMSE [m]	Maximum error [m]
17,82	19,80	33,65

Table 2. Velocity error metrics compared to GNSS (Experiment 1)

Mean error (MAE) [m/s]	RMSE [m/s]	Maximum error [m/s]
0,25	0,32	1,36

The obtained results indicate high effectiveness of the proposed navigation method in open-space conditions. The estimated position trajectory without the use of GNSS shows a moderate mean error (17.82 m) and a relatively low maximum error (33.65 m), which can be considered acceptable given the absence of satellite-based positioning. The nature of the error suggests a stable, systematic drift caused by motion integration through dead reckoning without external position correction.

Velocity estimation using optical flow demonstrated very good agreement with GPS data. The low mean error of 0.25 m/s and a maximum deviation of 1.36 m/s confirm the validity of the applied algorithm in a well-textured environment with stable lighting conditions. Minor discrepancies may have resulted from brief overflights of taller vegetation or transitions over less distinct surfaces (e.g., uniform greenery).

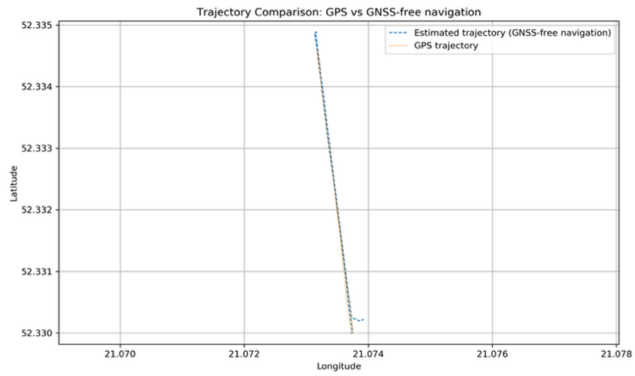

Figure 3. Experiment 1: Trajectory comparison – GPS vs estimated (GNSS-free navigation)

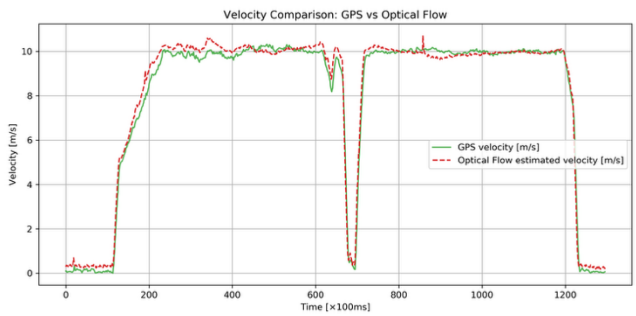

Figure 4. Experiment 1: Velocity over time – Optical Flow vs GPS

5.2 *Scenario No. 2*

The test flight was conducted over flat, open terrain with isolated trees up to a maximum height of 30 meters and good visual texture. The mission duration was 120 seconds, comprising 3619 frames, with an average flight altitude of 120 meters. Weather conditions were sunny with light wind.

Table 3. Position error metrics relative to GNSS (experiment 2)

Mean error (MAE) [m]	RMSE [m]	Maximum error [m]
38,67	47,10	85,67

Table 4. Velocity error metrics relative to GNSS (experiment 2)

Mean error (MAE) [m/s]	RMSE [m/s]	Maximum error [m/s]
1,16	1,22	2,51

Compared to the previous scenario, both position and velocity estimation errors are noticeably higher. The average position error exceeds 38 meters, with a maximum error over 85 meters, indicating a significant deviation of the estimated trajectory relative to the GNSS reference. The most probable factor contributing to this accuracy degradation is the increased flight altitude. At 120 meters, ground texture becomes significantly less distinct in the camera image, which negatively affects the quality of optical flow calculations. In addition, suboptimal camera alignment relative to the flight direction may have introduced distortions in the motion vector field.

Velocity estimation errors are also more pronounced—an average difference of 1.16 m/s and a maximum deviation of 2.51 m/s. This confirms that for flights at higher altitudes, or when the camera is not properly aligned, a drop in estimation quality should be expected. Such conditions highlight the importance of future work focused on error compensation and adaptive calibration of input parameters.

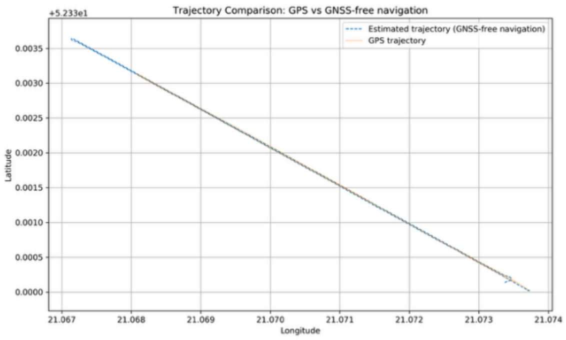

Figure 5. Experiment 2: Trajectory comparison – GPS vs estimated (GNSS-free navigation)

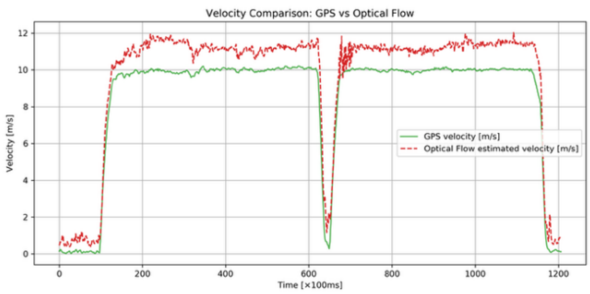

Figure 6. Experiment 2: Velocity over time – Optical Flow vs GPS

5.3 *Scenario No. 3*

The test flight was conducted partially over flat, open terrain with good visual texture, and partially over densely forested areas. The mission lasted 190 seconds and included 5712 frames, with an average flight altitude of 60 meters. Weather conditions were sunny with light wind.

Table 5. Position error metrics relative to GNSS (experiment 3)

Mean error (MAE) [m]	RMSE [m]	Maximum error [m]
59,84	74,44	116,40

Table 6. Velocity error metrics relative to GNSS (experiment 3)

Mean error (MAE) [m/s]	RMSE [m/s]	Maximum error [m/s]
0,97	1,78	6,07

The results of the experiment show a significant increase in estimation errors in the second half of the flight. The primary cause is not directly related to the forested terrain itself, but rather to the fact that the tree canopies were much closer to the camera than assumed based on the flight altitude obtained from the magnetometer.

As a result, the optical flow was incorrectly scaled, leading to an overestimation of speed and, consequently, a substantial trajectory deviation. This phenomenon is clearly visible in the velocity plot (Fig. 8), where sudden spikes in speed appear during the middle segment of the mission. Future improvements should include consideration of relative height above the observed surface, for instance by integrating additional depth sensors or analysing scene structure.

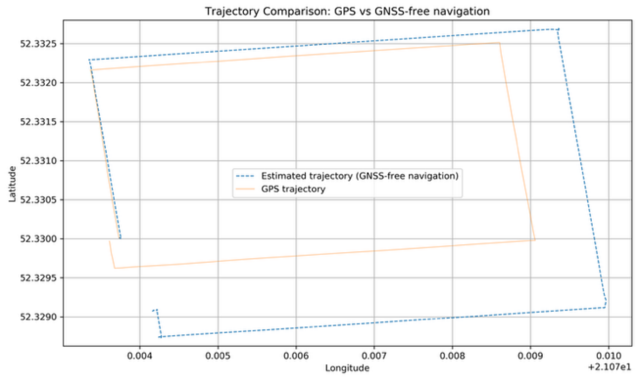

Figure 7. Experiment 3: Trajectory comparison – GPS vs estimated (GNSS-free navigation)

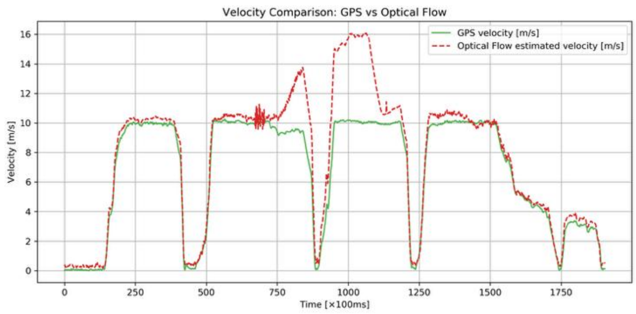

Figure 8. Experiment 3: Velocity over time – Optical Flow vs GPS

5.4 *Scenario No. 4*

The test flight was conducted over flat, open terrain with sparse vegetation (individual trees up to 30 meters in height) and good visual texture. The mission lasted 138 seconds and consisted of 4,143 frames, with an average flight altitude of 119 meters. Weather conditions were sunny with light wind.

Table 7. Position error metrics relative to GNSS (experiment 4)

Mean error (MAE) [m]	RMSE [m]	Maximum error [m]
11,17	12,34	20,81

Table 8. Velocity error metrics relative to GNSS (experiment 4)

Mean error (MAE) [m]	RMSE [m]	Maximum error [m]
0,46	0,65	2,92

Despite the relatively high flight altitude (119 m), the system demonstrated very good accuracy in both position and velocity estimation. The average position error was only 11.17 meters, and the maximum deviation did not exceed 21 meters. The velocity estimated via the optical flow method closely matched the GPS data, with an average error below 0.5 m/s.

These results suggest that, given sufficient visual texture and uniform terrain, the system can operate reliably even at higher altitudes. A key factor was the homogeneous and well-defined surface structure (e.g., fields, roads, low vegetation), which enabled stable optical flow analysis and minimized disturbances in metric scaling.

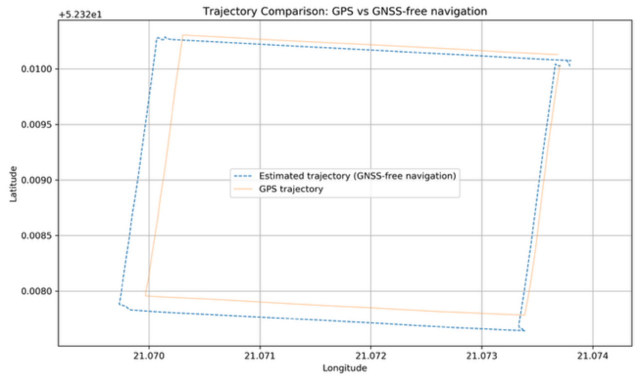

Figure 9. Experiment 4: Trajectory comparison – GPS vs estimated (GNSS-free navigation)

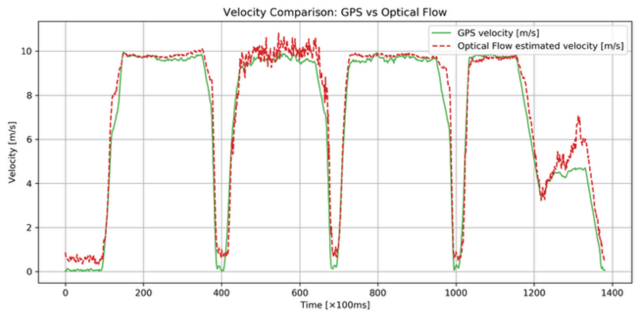

Figure 10. Experiment 4: Velocity over time – Optical Flow vs GPS

6 CONCLUSION

This work presented a prototype navigation system for an unmanned aerial vehicle (UAV) designed to estimate its position in environments where GNSS signals are unavailable. The proposed method relies on optical flow analysis from a nadir-facing camera and a simplified fusion with spatial orientation data. The implemented model was evaluated in a simulated environment using real flight data, and the results indicate that it is possible to maintain consistent trajectory and velocity estimation even under challenging observational conditions.

The key advantages of the presented approach include its resilience to temporary GNSS signal loss and the smoothness of the estimated trajectory—enabled by velocity estimation derived from optical flow. The method is characterized by low computational complexity, making it suitable for on-board implementation in resource-constrained UAV platforms.

The observed limitations—particularly positional drift over time, sensitivity to heterogeneous terrain structure, and distortion caused by objects such as trees or buildings—highlight the need for further development. Specifically, errors resulting from inaccurate estimation of the UAV's height above ground can be mitigated using additional sensors such as laser rangefinders. Alternatively, more advanced fusion with classical inertial navigation methods could be implemented, incorporating airspeed measurements and inertial sensor data.

The results obtained in this study provide a promising foundation for future work toward a lightweight, GNSS-independent positioning system, intended for use in environments with limited satellite visibility.

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