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Visual Navigation System for Small Unmanned Aerial Vehicles*

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Abstract

This article presents a visual navigation system for small Unmanned Aerial Vehicles (UAVs) designed to operate in environments where GNSS signals may be unreliable or disrupted due to a range of factors, including jamming systems, adverse weather conditions, or environmental obstacles. The primary goal of this work is to enable UAVs to autonomously continue their missions under GNSS interference, ensuring reliable navigation in challenging conditions. The proposed solution combines map-based and map-less navigation methods, utilizing ORB and LoFTR algorithms to enhance positioning accuracy through visual feature matching. The study introduces the development of a PROXY component, which facilitates seamless switching between GNSS and visual navigation modes, preserving mission continuity without interruption. Simulations demonstrate the system's ability to maintain acceptable localization accuracy despite GNSS signal disruption. This solution provides an adaptable alternative for UAV navigation in GNSS-compromised environments, enhancing UAV capabilities for autonomous operation in varied and challenging scenarios.

Keywords: UAV, visual navigation, GNSS interference, ORB algorithm, LoFTR algorithm, PROXY component, autonomous flight, localization accuracy

Introduction

In recent years, Unmanned Aerial Vehicles (UAVs) have become crucial tools in fields such as environmental monitoring, agriculture, military reconnaissance, and infrastructure inspection. These vehicles typically rely on the Global Navigation Satellite System (GNSS) for precise localization and navigation, enabling them to autonomously follow pre-defined routes. However, as UAVs increasingly operate in complex and contested environments, vulnerabilities in GNSS-reliant navigation systems have become apparent. GNSS signals are often subject to interference from various sources, including intentional jamming, adverse atmospheric conditions, and natural obstacles like dense vegetation or urban structures [1]. Such interference can lead to mission interruptions, forced landings, or, in extreme cases, total UAV loss.

The navigation system of an autopilot functions by processing signals from either an operator's commands or real-time coordinates from GNSS systems, allowing it to autonomously execute missions and adjust its direction based on the latest positional data. In the absence of these signals, however, UAVs are unable to orient themselves toward designated waypoints, which frequently necessitates an emergency landing to prevent potential loss or misdirection. This dependency on external signals makes UAVs particularly susceptible to failure in GNSS-denied environments, where maintaining accurate localization is essential for mission continuity.

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To mitigate these risks, alternative navigation solutions are required to allow UAVs to operate autonomously even when GNSS input is unavailable. Visual navigation, which leverages onboard cameras and computer vision algorithms, offers a promising approach by enabling UAVs to use environmental features for localization [4]. Visual navigation acts as a fallback system, ensuring that UAVs can continue to operate effectively even when GNSS signals are unavailable or unreliable. The effectiveness of visual navigation has been extensively explored in numerous publications, with a variety of approaches proposed to address the limitations of GNSS dependency. For instance, studies have investigated combining computer vision with inertial measurement units (IMUs) for enhanced resilience to signal loss [5], while other research has focused on feature-matching algorithms that maintain positioning accuracy in GNSS-denied settings.

Visual navigation methods are broadly categorized into three types: map-based, map-less, and Simultaneous Localization and Mapping (SLAM).

- Map-based approaches use preloaded maps or satellite imagery to compare real-time visual input with stored data, allowing the UAV to estimate its position by matching landmarks or terrain features. This method offers high precision in known environments but requires up-to-date and detailed maps, which may not always be accessible, especially in remote or dynamically changing areas.
- Map-less approaches avoid reliance on pre-existing maps, instead using real-time environmental data to estimate relative positioning. Techniques include feature recognition, where UAVs track objects or shapes in their surroundings, and optical flow, which measures changes in object position over time to infer motion. While adaptable to unknown environments, map-less methods may struggle with accuracy in complex settings where identifiable features are sparse or frequently changing.
- Simultaneous Localization and Mapping (SLAM) combines real-time mapping and localization, enabling UAVs to construct a map of their surroundings while identifying their position within it [6]. SLAM is especially beneficial in dynamic or unknown environments, but its computational demands can be prohibitive for small UAVs with limited onboard resources, as it requires continuous processing of sensor data from sources like cameras and LiDAR.

Training exercises and simulations have also been conducted to prepare UAV operators and systems for GNSS-denied scenarios, proving essential for evaluating the efficacy of navigation algorithms and identifying areas for improvement in achieving reliable localization and mission continuity.

In response to these challenges, this study presents a hybrid visual navigation solution that combines map-based and map-less approaches to achieve reliable localization in GNSS-compromised environments. The system integrates two complementary algorithms: ORB (Oriented FAST and Rotated BRIEF), which provides rapid feature detection, and LoFTR (Local Feature Matching with Transformers), which offers accurate positioning relative to satellite imagery. Together, these algorithms mitigate each other's limitations, with ORB delivering fast position estimates and LoFTR providing recalibration when GNSS signals are unavailable. Additionally, the system includes a PROXY component that automatically switches the UAV to visual navigation upon GNSS signal loss, enabling seamless transitions and preserving mission continuity.

This work demonstrates that the proposed navigation system achieves acceptable localization accuracy in the absence of GNSS, offering a feasible alternative for UAV operations in environments with compromised GNSS availability. This solution enhances UAV autonomy in challenging conditions, providing resilience against various types of GNSS disruptions and ensuring reliable performance in GNSS-denied environments.

System Architecture and Methodology

The proposed visual navigation system aims to maintain reliable localization for small UAVs in GNSS-denied environments by integrating map-based and map-less visual navigation methods. The system architecture leverages onboard computer vision algorithms, enhanced by a PROXY component, to switch between GNSS and visual navigation modes when necessary. This section provides an in-depth examination of the architecture, highlighting each key component and its role in achieving seamless navigation continuity.

The system consists of three main components:

- Autopilot Module: The UAV's autopilot module is designed to execute mission plans based on real-time positional data. When GNSS data is available, the autopilot utilizes it to navigate toward predefined waypoints. In GNSS-denied conditions, however, the autopilot relies on input from the PROXY component, which dynamically provides positional data generated from visual navigation, allowing the

UAV to continue the mission without interruption.

- PROXY Component: The PROXY component functions as an intermediary between the GNSS system and the visual navigation module. Continuously monitoring GNSS signal quality, the PROXY automatically switches to visual navigation input upon detecting signal degradation. This seamless transition between data sources maintains mission continuity without manual intervention. Additionally, the PROXY formats visual navigation data to mimic GNSS output, ensuring compatibility with the autopilot's data requirements and eliminating the need for extensive system modifications.
- Visual Navigation Module: The Visual Navigation Module employs two complementary algorithms - ORB (Oriented FAST and Rotated BRIEF) and LoFTR (Local Feature Matching with Transformers) [6] - to generate accurate positional information in real time. ORB provides efficient feature detection, identifying and tracking visual landmarks that allow the UAV to estimate relative movements. The data flow of the ORB algorithm within the visual navigation system is illustrated in Fig. 1. However, as ORB may accumulate drift over time, it is periodically recalibrated using LoFTR, which enhances accuracy by matching real-time UAV images with satellite or map-based imagery. LoFTR's transformer-based architecture bypasses traditional keypoint detection, enabling effective positioning even in varying environmental conditions. The processes of the ORB and satellite-based algorithms used for visual navigation are illustrated in a simplified schematic in Fig. 2.

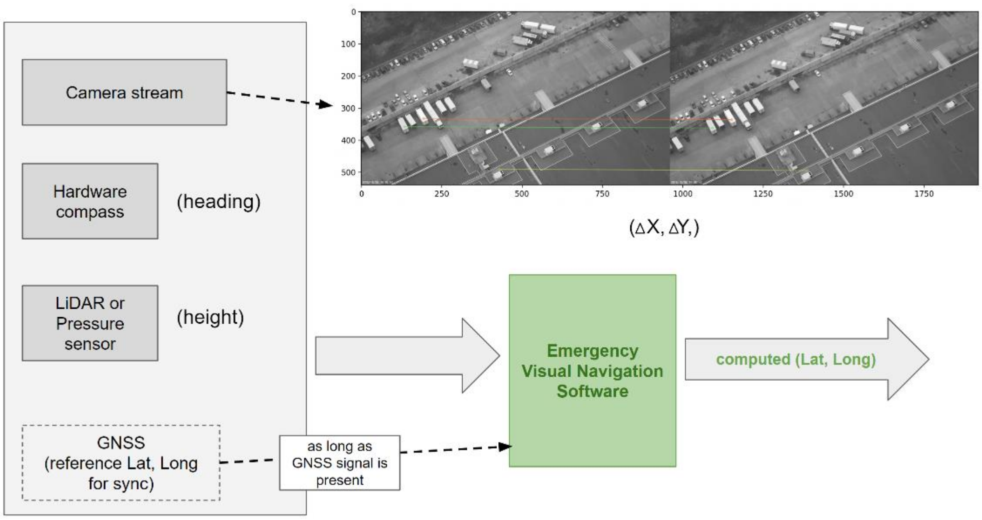

Fig. 1 Data flow representation of the ORB algorithm for UAV visual navigation.

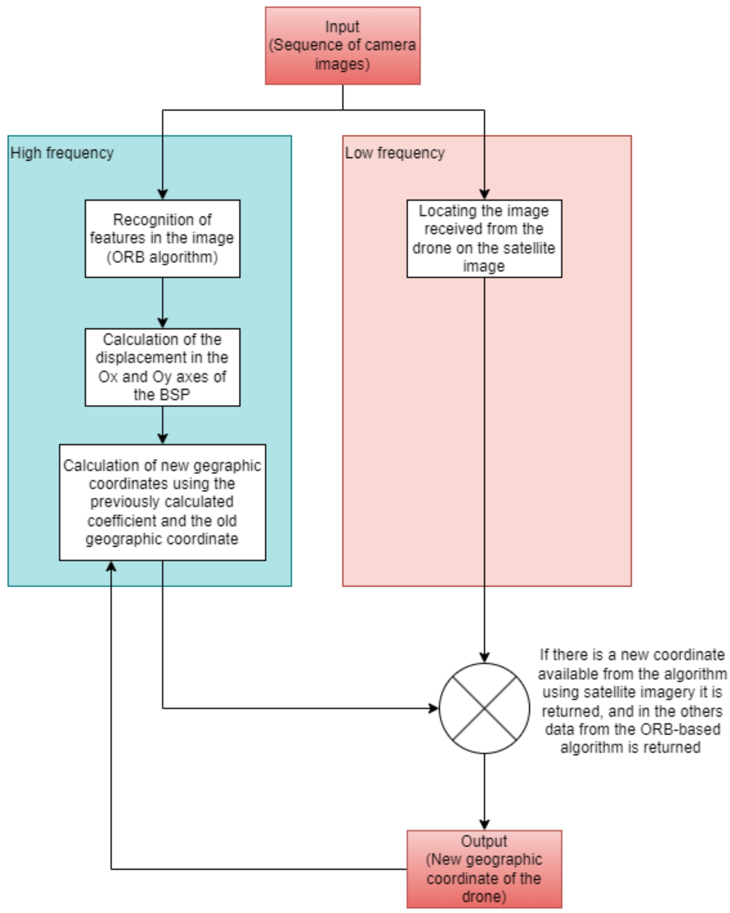

Fig. 2 Schematic representation of the ORB and satellite-based algorithms for UAV visual navigation.

To enhance the system's accuracy and stability, an Extended Kalman Filter (EKF) is employed for multi-sensor data fusion [3]. The EKF combines visual data from ORB and LoFTR algorithms with IMU (Inertial Measurement Unit) readings, reducing the impact of positional drift and correcting discrepancies across different data sources. This fusion approach provides a smoothed, reliable estimate of the UAV's position, ensuring robust performance even in complex environments where GNSS signals may be completely absent.

The PROXY component is crucial for managing dynamic switching between GNSS and visual navigation modes. By continuously assessing GNSS signal quality, the PROXY can detect signal loss and activate the visual navigation module, thus maintaining mission continuity. Designed to mimic the structure of GNSS data, the PROXY enables the autopilot to process data received from the visual processing module as though it were standard GNSS input, facilitating seamless integration without requiring changes to the UAV's native control system.

For small UAVs with limited onboard computational resources, the combination of ORB and LoFTR was chosen to balance accuracy with processing efficiency. ORB allows rapid feature detection, which is particularly suitable for real-time navigation, while LoFTR is used intermittently for recalibration against satellite imagery, reducing the computational load. This setup enables the UAV to operate effectively within the hardware constraints of lightweight UAV platforms, while still achieving high localization accuracy.

Extensive simulations were conducted to validate the system's performance under various environmental conditions, including urban and rural settings, as well as scenarios involving simulated GNSS interference. These tests were based on recordings from flights conducted exclusively on sunny days, under ideal weather conditions, with no atmospheric disturbances. The entire testing area was well illuminated by sunlight, ensuring optimal visibility for the visual navigation system. The flights were performed at an altitude of 90 meters above sea level, maintaining consistent conditions across all test scenarios. Such conditions were maintained during flights in both urban and rural environments. The simulations evaluated the effectiveness of the PROXY component in managing transitions, the accuracy of EKF-based sensor fusion, and the overall stability of the navigation system. The results demonstrate that the proposed system achieves an acceptable level of localization accuracy across a variety of challenging conditions, proving its resilience and suitability for UAV missions in GNSS-denied environments.

To validate the system's performance, simulations were conducted by repeatedly running the proposed algorithms and analyzing the results. Each simulation represented a UAV flight where GNSS signals were lost at a specific point, and the UAV's position was subsequently calculated using the visual navigation algorithm. At every program step, the UAV's current position, as read from the GNSS, was compared with the position estimated by the algorithm. This approach enabled the collection of metrics such as the average deviation and maximum deviation from the actual position.

After multiple test runs, these average and maximum deviations were analyzed. The system was considered to achieve an acceptable level of localization when the average deviation remained below 20 meters over consecutive simulations. Simplifying further, if the average displacement error across a series of simulations was less than 20 meters, the system was deemed to have reached a satisfactory performance level for the given test conditions.

Results and Performance Analysis

The proposed visual navigation system was rigorously tested in two distinct environments: an urban setting and a field environment with forested areas. These environments were selected to evaluate the system's adaptability to varying feature densities and visual conditions, providing insights into how well the system maintains localization accuracy in GNSS-compromised scenarios.

- Urban Environment: Characterized by a high density of unique features, the urban environment allowed for effective performance of the ORB algorithm, which provided reliable relative positioning by consistently identifying and tracking distinct visual landmarks. The urban setting also included obstacles such as buildings and narrow corridors, which posed potential interference sources but did not impede ORB's feature-matching capabilities. The ORB algorithm's performance in this environment demonstrated its suitability for high-density, feature-rich settings.
- Field Environment with Forested Areas: This environment included a mix of open fields and densely forested sections, presenting challenges in feature recognition due to the repetitive and less distinctive visual patterns found in natural surroundings. Here, ORB encountered difficulties in distinguishing and recognizing unique landmarks, leading to positional drift over time. The algorithm's limitations in this setting highlighted its reduced effectiveness in environments with sparse or repetitive features, where visual similarity between objects affects ORB's tracking accuracy.

The LoFTR algorithm was employed to recalibrate positioning in both environments, counteracting the drift accumulated by ORB, especially in the forested sections of the field environment. LoFTR's transformer-based feature matching enabled it to bypass the limitations of keypoint detection, matching UAV imagery with satellite or preloaded map-based images to maintain accurate localization [8]. This recalibration process proved effective at restoring positional accuracy, particularly in the field environment where ORB alone struggled. The satellite-based algorithm successfully identified the UAV's position, as indicated in Fig. 3, with a red marker showing the UAV's detected location on the satellite image.

Fig. 3 Satellite image showing UAV position detected by the satellite-based algorithm (red marker).

The PROXY Component played a vital role in the system's adaptability, managing dynamic transitions between GNSS and visual navigation modes. By continuously monitoring GNSS signal quality, the PROXY automatically redirected the autopilot to visual navigation input upon detecting GNSS degradation, ensuring uninterrupted mission execution. This seamless transition allowed the UAV to maintain its designated route without requiring manual intervention, with the PROXY formatting visual data as GNSS-compatible input to integrate smoothly with the autopilot’s existing control systems.

The Extended Kalman Filter (EKF) further improved stability by fusing data from the ORB and LoFTR algorithms with IMU readings. This sensor fusion approach minimized drift and corrected discrepancies, providing a continuous and reliable trajectory for the UAV across both environments. The EKF’s role in combining multiple data sources was instrumental in enhancing system robustness, particularly in scenarios with intermittent GNSS availability or limited visual feature density.

A comparative simulation of successive versions of the ORB algorithm, with and without the satellite element, is presented in Fig. 4. The results show that enhancements to the ORB algorithm alone provided only slight improvements in accuracy, which varied depending on terrain conditions. In contrast, the addition of the satellite-based module significantly improved the accuracy of UAV positioning, reducing the error margin substantially.

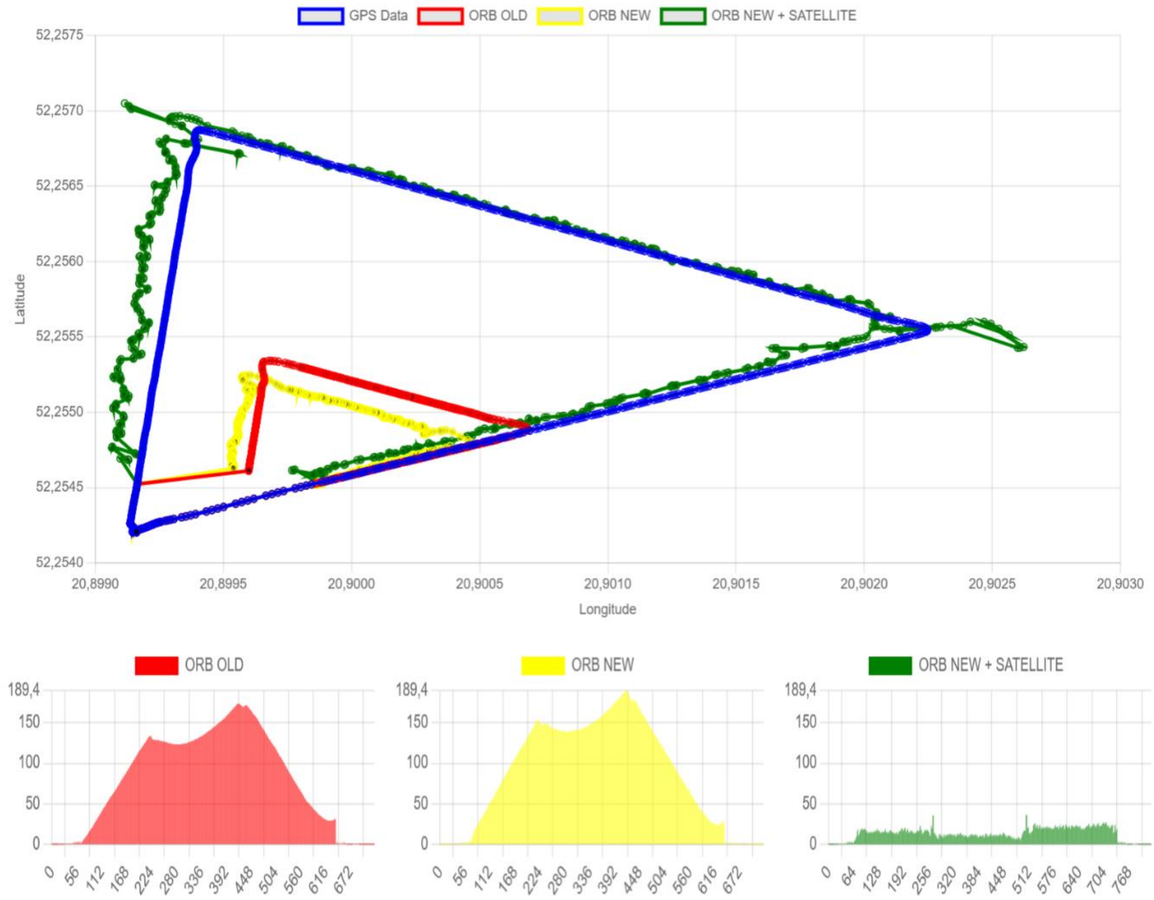

Fig. 4 Simulation comparing the ORB algorithm's performance with and without satellite-based correction, demonstrating a significant improvement in positioning accuracy with the addition of the satellite module.

Overall, the results demonstrate that the proposed visual navigation system successfully maintains localization accuracy across diverse conditions. The combination of ORB and LoFTR algorithms, managed by the PROXY component and enhanced by EKF-based sensor fusion, allows the UAV to navigate reliably in environments with compromised GNSS. The system shows resilience and adaptability, proving its effectiveness for UAV missions in both urban and field settings with forested areas.

Discussion

The evaluation of the visual navigation system in both urban and field environments has demonstrated its potential to enable reliable UAV operations in GNSS-compromised scenarios. The combined use of ORB and LoFTR algorithms, managed by the PROXY component and stabilized through EKF-based sensor fusion, provided robust localization and allowed the UAV to autonomously maintain its mission path under various conditions. Nevertheless, the tests also highlighted specific areas where system performance could be further optimized.

One of the main findings is that while the ORB algorithm proved effective in urban settings with high feature density, it encountered challenges in field environments with forested areas. In these natural surroundings, ORB struggled to identify distinct landmarks, leading to accumulated positional drift. The LoFTR algorithm compensated for these limitations by recalibrating the UAV's position against satellite or preloaded map-based images, which improved localization accuracy. However, the dependency on LoFTR for recalibration suggests a potential area for enhancement in ORB's feature recognition capabilities, particularly for environments with limited visual variety.

Another key insight from the simulation tests is the need for enhanced image stabilization. The current approach utilizes a basic transformation algorithm based on IMU data to counteract UAV motion, but this method proved insufficient, as it could not achieve the desired level of image stability. The simple nature of the transformation algorithm was unable to correct for rapid UAV movements, leading to residual image instability. This limitation suggests the need for a more advanced stabilization solution, such as mounting the camera on a gimbal. Implementing a gimbal would allow for mechanical stabilization of the camera, isolating it from abrupt UAV movements and thereby improving the accuracy of both the ORB and LoFTR algorithms by providing a steadier image input.

However, using a gimbal presents additional challenges, especially for small UAVs. The added weight and cost of a gimbal increase the overall payload, which in turn reduces the drone's flight time—a critical factor for UAV missions where maximizing operational duration is essential. Therefore, while a gimbal could substantially improve image stabilization, future work should also investigate the feasibility of advanced algorithmic stabilization as an alternative. Such an algorithm, if effectively implemented, could provide sufficient image stability without the drawbacks of added weight and cost, aligning with the goal of minimizing payload and operational expenses.

The PROXY component demonstrated significant value by ensuring seamless data source transitions, automatically redirecting the autopilot to visual navigation upon GNSS loss. This functionality enabled the UAV to continue missions uninterrupted, highlighting the PROXY's role in managing mission-critical data transitions. However, the reliance on preloaded map-based imagery for LoFTR's recalibration process presents a limitation in scenarios where such data is unavailable or outdated. Future work could explore adaptive feature recognition or real-time map updating, which would increase the system's versatility in uncharted or dynamically changing environments [9].

Sensor fusion through EKF integration was instrumental in maintaining stable and accurate positioning across test conditions. By combining visual navigation data with IMU readings, the EKF smoothed positional estimates, reducing drift and improving trajectory consistency. Nonetheless, the EKF's performance may be further enhanced by incorporating additional sensors, such as barometric altimeters or magnetometers, to refine altitude and orientation data.

In summary, the proposed system shows considerable promise for enabling UAV autonomy in GNSS-denied environments, particularly in urban and structured settings. Key areas for improvement include enhancing ORB's robustness in natural environments, implementing a gimbal or advanced stabilization algorithm for improved image stability, and exploring alternatives for map-based recalibration to extend LoFTR's applicability. Future research efforts could focus on adapting the system for real-time environmental mapping and optimizing feature recognition algorithms for diverse landscapes, ultimately broadening the range of GNSS-compromised scenarios in which UAVs can operate effectively.

Although SLAM (Simultaneous Localization and Mapping) is a well-known technique for UAV navigation in GNSS-denied environments, it was not included in this study due to the additional hardware requirements, such as LiDAR, which were not available during testing. The computational load associated with SLAM, as mentioned earlier, is based on findings in the literature rather than direct testing. SLAM typically demands high processing power for real-time map generation and localization, which could pose challenges for small UAVs with limited onboard resources.

Future work may explore the integration of SLAM techniques with the proposed system, provided that suitable hardware is available. This comparison would enable a deeper understanding of the trade-offs between the computational complexity and localization accuracy of different approaches.

Conclusions

This study presents a visual navigation system designed to enable small UAVs to operate effectively in GNSS-compromised environments. By integrating the ORB and LoFTR algorithms with an EKF-based sensor fusion approach and a dynamically adaptive PROXY component, the system successfully maintains localization accuracy and mission continuity, even under conditions of limited GNSS availability. The system's performance in both urban and field environments demonstrates its robustness, with ORB proving effective in feature-rich settings and LoFTR compensating for drift in more challenging, feature-sparse areas [7].

One of the primary outcomes of this research is the realization that, while visual navigation provides a viable alternative to GNSS-based localization, certain environments—such as densely forested areas—require additional stabilization measures to optimize image quality for accurate feature detection. Simulation tests highlighted the potential benefits of integrating a gimbal to enhance image stability, though the added weight and cost of such a solution could reduce flight duration, especially for small UAVs. Therefore, a significant future direction would be the exploration of advanced image stabilization algorithms that can achieve adequate stability without increasing payload [2].

Further improvements could also focus on enhancing ORB's feature recognition in natural environments and implementing real-time adaptive mapping solutions to extend LoFTR's functionality in uncharted areas. Additionally, integrating supplementary sensors, such as barometric altimeters or magnetometers, could refine altitude and orientation data, contributing to even greater positional accuracy and stability.

The findings of this research are intended for use by UAV developers, defense agencies, and other organizations involved in autonomous navigation technologies, particularly those operating in environments where GNSS signals may be unreliable or obstructed. This analysis can assist in guiding the design and development of robust navigation systems for small UAVs, as well as in planning mission strategies that account for GNSS-denied conditions.

In summary, the proposed system provides a promising solution for UAV navigation in GNSS-denied conditions, supporting applications where GNSS signals are unreliable or absent. The findings and recommendations from this study lay a foundation for further advancements in autonomous UAV navigation, with a focus on refining both hardware and algorithmic approaches to enhance operational resilience and extend mission capabilities across diverse environments.

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