

REVIEW

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Gnss-denied unmanned aerial vehicle navigation: analyzing computational complexity, sensor fusion, and localization methodologies

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Abstract

Navigation without Global Navigation Satellite Systems (GNSS) poses a significant challenge in aerospace engineering, particularly in the environments where satellite signals are obstructed or unavailable. This paper offers an in-depth review of various methods, sensors, and algorithms for Unmanned Aerial Vehicle (UAV) localization in outdoor environments where GNSS signals are unavailable or denied. A key contribution of this study is the establishment of a critical classification system that divides GNSS-denied navigation techniques into two primary categories: absolute and relative localization. This classification enhances the understanding of the strengths and weaknesses of different strategies in various operational contexts. Vision-based localization is identified as the most effective approach in GNSS-denied environments. Nonetheless, it's clear that no single-sensor-based localization algorithm can fulfill all the needs of a comprehensive navigation system in outdoor environments. Therefore, it's vital to implement a hybrid strategy that merges various algorithms and sensors for effective outcomes. This detailed analysis emphasizes the challenges and possible solutions for achieving reliable and effective outdoor UAV localization in environments where GNSS is unreliable or unavailable. This multi-faceted analysis, highlights the complexities and potential pathways for achieving efficient and dependable outdoor UAV localization in GNSS-denied environments.

Keywords UAV localization, GNSS-denied navigation, Absolute localization, Relative localization, Visual sensors, Non-visual sensors, Terrain aided algorithm, Digital map, Multi-modal sensor fusion framework, Multiple localization techniques, Computational complexity

Introduction

Global Navigation Satellite Systems (GNSS), such as Global Positioning System (GPS), Global'naya Navigatsionnaya Sputnikovaya Sistema (GLONASS), Galileo satellite navigation system (Galileo), BeiDou Navigation Satellite System (BDS), play a critical role in enhancing

transportation efficiency and operations in various sectors, especially Unmanned Aerial Vehicles (UAVs) (Li et al., 2020). While GNSS plays a key role in the providing precise location and navigation information for UAVs, it faces significant hurdles due to environmental and technical issues. These challenges underline the importance of developing advanced autonomous navigation solutions for UAVs to achieve effective self-localization (Materak, 2023; Yan et al., 2023; Marut et al., 2023; She et al., 2020).

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Advancements in UAV navigation: a historical overview

UAV navigation evolved from a simple Radio Detection and Ranging (RADAR) system and visual guidance in the 1940 s, to the current sophisticated technologies. The introduction of the H2S RADAR system in 1942 and the subsequent advancement of Doppler RADAR post-World War II represented pivotal moments in UAV operations, significantly reducing manual control dependence and enhancing UAV autonomy (Khawaja et al., 2024; Galati & Galati, 2016; Chandrasekar et al., 2023). In the 1950 s, Terrain Referenced Navigation (TRN) became a key technology, improving UAV navigation by matching measured terrain elevations with existing elevation maps. This period marked the transition from analog to digital systems. The introduction of Terrain Contour Matching (TERCOM) (Baker & Clem, 1977; Golden, 1980) in the 1970 s represented a significant advancement in navigation precision using Digital Elevation Maps (DEM). Innovations, including Sandia Inertial Terrain-Aided Navigation (SITAN) (Hollowell, 1990) and the Digital Scene Matching Area Correlator (DSMAC) (Carr & Sobek, 1980), emerged in later decades. These technologies improved accuracy through real-time adjustments and better alignment with terrain images, marking significant advancements in the development of TRN technology (Cottrill & Gu, 2024; Zhao et al., 2024; Gambrych et al., 2023). Despite significant progress, the full adoption of TRN and similar terrain-aided navigation techniques was limited by the challenges in sensor technology, data storage, signal processing, and computing power. Until the 1990 s, these challenges often made complete UAV navigation impractical, necessitating operators to rely on manual visual guidance (Wang et al., 2024), (Forsyth, 2024). This issue prompted continuous efforts in research to overcome these barriers (Ding & Cheng, 2022).

The progress made in GNSS and advanced sensor technologies during the 1990s marked a significant leap forward in autonomous navigation capabilities. Flight Management Systems (FMS) (Liden, 1994) and Electronic Flight Instrument Systems (EFIS) (Ford C. Eng & MRAeS, 1985) expanded UAV navigational capabilities, enhancing operational efficiency and precision (Strauss & Scott, 2024). However, reliance on GNSS satellite networks exposes UAVs to risks from interferences such as atmospheric conditions, urban canyon effects, and security threats like spoofing and jamming, compromising operational effectiveness (Pany et al., 2022). This underscores the need for robust navigation solutions to ensure efficient UAV navigation in complex environments, thus improving overall mission success.

Recent progress in UAV navigation is integrating advanced sensor technologies such as Light

Detection and Ranging (LiDAR), cameras (Yin et al., 2023; Abdelkader et al., 2024, 2025) and Inertial Measurement Units (IMUs), along with sophisticated Simultaneous Localization and Mapping (SLAM) algorithms (Gao et al., 2024). These developments have notably enhanced the precision and autonomy of UAV flights indoors, aiming at dependable navigation without GNSS (El-Sheimy & Li, 2021; Guo et al., 2024; Liu et al., 2024). The objective is to achieve similar levels of accuracy in outdoor environments where GNSS availability is limited. The adaptation of indoor navigation technologies to outdoor applications faces challenges due to weather fluctuations and the varied terrains encountered in outdoor UAV navigation. Current research and development efforts are focused on improving approaches that ensure reliable and consistent UAV navigation in diverse environments (Brommer et al., 2024; Cui et al., 2024).

Literature analysis & landscape

This survey comprehensively analyses the UAV localization in GNSS-denied environments, covering advancements and future directions. By analyzing 132 recent research papers, this work provides an overview of current strategies, technologies, and trends. Significant contributions from IEEE Xplore, ScienceDirect, MDPI, ACM Digital Library, and arXiv are highlighted, with journal articles representing 70% of the literature (Fig. 1.a). The remaining sources include conference proceedings (20%) and other publications (10%). The survey widely covers UAV localization studies, from theoretical work to practical experiments. Figure 1.b shows that 54.8% of the methodologies emphasize real-world experimentation, underlining the importance of empirical studies. Simulations account for 42.2% of research, reflecting a balanced approach between practical and theoretical development in the field.

Contribution

Our comprehensive survey, based on a detailed review of research papers, offers a deep understanding of the current state and future directions of outdoor UAV localization in GNSS-denied environment. The key contributions of this review are highlighted below:

- We provide a new global categorization/architecture all types of localization techniques. Specifically, we categorized localization techniques into *Absolute Localization (AL)*, with respect to the global Earth coordinate frame, and *Relative Localization (RL)*, with respect to a locally defined coordinate frame, as illustrated in Fig. 2. This structured approach facilitates the analysis of problems and solutions discussed

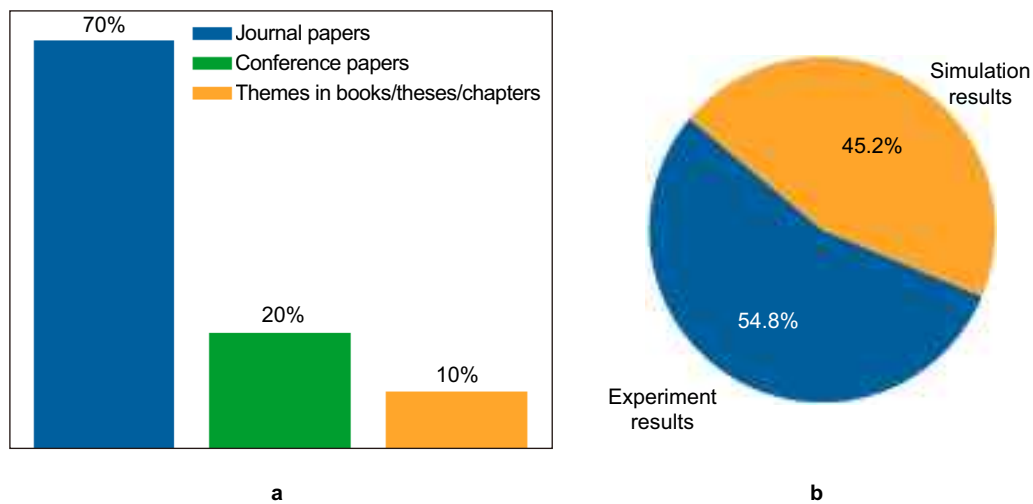


Fig. 1 **a:** Percentage distribution of papers by type. **b:** Percentage distribution of papers by experiment or simulation methodologies

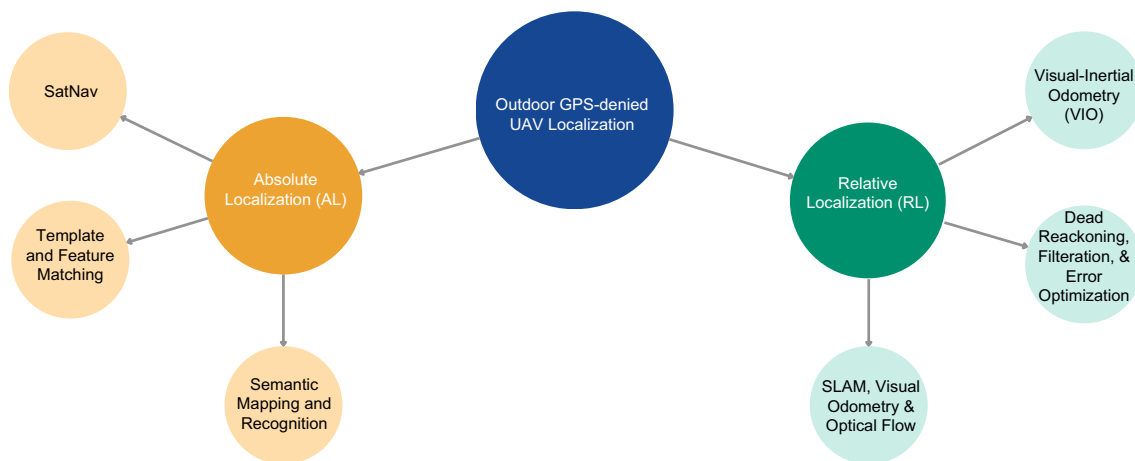


Fig. 2 Classification of UAV localization methods

in the research literature and ensures a holistic coverage of the domain.

- Emphasizing the significance of sensor fusion, specifically *multi-modal sensor fusion*, which incorporates techniques like SLAM, Visual Odometry (VO), and Visual-Inertial Odometry (VIO) to enhance accuracy and reliability.
- *Multiple Localization Techniques:* Our survey explores UAV localization methods, including Inertial Navigation System (INS), vision, LiDAR, and terrain-aided navigation, highlighting TERCOM, SITAN, and DSMAC navigation models, which utilize terrain and visual matching, along with algorithms such as the Kalman Filter (KF) and

Artificial Intelligence (AI)-based approaches to enhance accuracy and robustness.

- *Navigating Implementation Hurdles and Regulatory Requirements:* We address the multifaceted challenges in deploying UAV localization solutions, focusing on system complexity, energy management system, security, and compliance with regulatory standards.

Paper structure

This paper is organized into several sections for a thorough exploration of UAV localization in GNSS-denied environments:

- Sect. 2: Related surveys
- Sect. 3: Challenges in UAV localization in GNSS-denied environments.
- Sect. 4: Comprehensive classification of UAV localization methods within GNSS-denied environments. The structure of this section is designed as follows:
 - Sect. 4.1: Absolute Localization (AL)
 - * Sect. 4.1.1: Template and feature matching for UAV localization
 - * Sect. 4.1.2: Semantic mapping and place recognition
 - Sect. 4.2: Relative Localization (RL)
 - *Sect. 4.2.1: Dead reckoning, filtration, and error optimization
 - *Sect. 4.2.2: Visual odometry and optical flow
 - *Sect. 4.2.3: SLAM
- Sect. 5: Discussion and future directions
- Sect. 6: Conclusion

Related surveys

In this section, we provide a detailed analysis of 12 surveys published between 2020 and 2024, focusing on UAV localization and navigation techniques in GNSS-denied environments. The papers, outlined in Table 1 and Table 2, examine key advancements in non-GNSS navigation techniques, the sensors utilized, and the challenges encountered in UAV localization.

Several papers provide comprehensive classifications of UAV localization methods in GNSS-denied environments, systematically organizing them according to distinct technological approaches. For instance, Ali et al. (2022) categorize UAV navigation into three primary vision-based techniques: correlation-extreme approaches, feature detection methods, and deep learning models. Likewise, Lu et al. (2022) divide vision-based localization into two categories: Relative Vision Localization (RVL) and Absolute Vision Localization (AVL), each focusing on different ways of leveraging visual data for UAV navigation. Raković et al. (2021) take a more comprehensive approach, classifying UAV navigation methods into five categories: Satellite Navigation, INS, Terrestrial Navigation, Geomagnetic Navigation, and Vision Navigation Systems. Additionally, Couturier and Akhloufi (2021) further refine the classification of absolute visual localization in GNSS-denied environments

into three subcategories: template matching, feature points matching, and deep learning.

A key trend emerging from recent surveys is the pivotal role of multi-sensor fusion techniques in advancing UAV localization in GNSS-denied environments. Yin et al. (2023), Tong et al. (2023) provide comprehensive reviews on SLAM systems and collaborative visual positioning, respectively, emphasizing the integration of sensors such as visual-inertial, LiDAR-inertial, and LiDAR-visual combinations. This multi-sensor fusion is critical for the robust and accurate UAV localization, particularly in large-area group positioning. However, despite the potential of these approaches, significant challenges remain, including real-time processing, system reliability in dynamic environments, and hardware compatibility across diverse localization methods.

Vision-based techniques remain pivotal, as demonstrated by studies such as Ali et al. (2022) and Lu et al. (2022). Their studies delve into techniques such as feature extraction, optical flow enhanced by deep learning, and Visual SLAM (VSLAM) for environmental mapping. While these methods, particularly those relying on algorithms like the Extended Kalman Filter (EKF), have shown promise in navigation prediction, their performance is highly susceptible to environmental factors such as low visibility. This limitation underscores the need for the continued integration of AI and deep learning models, which can significantly enhance the adaptability and robustness of vision-based approaches. Furthermore, Dissanayaka et al. (2023) stress the importance of Visual LiDAR Odometry and Mapping (VLOAM) for improving navigation reliability, especially in scenarios where GNSS signals are degraded. Their research highlights that VLOAM ensures compliance with safety standards and increases operational robustness, as evidenced by numerical simulations.

AI-driven approaches are increasingly prominent in UAV navigation, as demonstrated by studies such as Ghasemieh and Kashef (2024), which explore the application of deep learning to VO for enhanced navigation and surveillance in GNSS-denied environments. A central focus of their work is the development of explainable AI models, addressing critical challenges such as the robustness of optical flow and the need for improved processing speeds. These models emphasize transparency and interpretability, ensuring their effective integration into UAV autonomy systems. Rezwan and Choi (2022) offer a comprehensive review of AI technologies in UAV navigation, categorizing them into mathematical, optimization and model-based learning approaches. Their research highlights the utility of algorithms such as Convolutional Neural Networks (CNNs) for image recognition, Recurrent Neural Networks (RNNs) for temporal data analysis,

Table 1 Comparative analysis of previous UAV navigation survey papers (Part 1)

| No. | Paper Title, Authors, Year | Technologies | Sensors | Limitations |
|-----|---|--|---|--|
| 1 | Towards explainable artificial intelligence in deep vision-based odometry, Alireza Ghasemieh et al., 2024 Ghasemieh and Kashef (2024) | Deep Learning, Visual Odometry | Cameras, IMU data, potentially including depth sensors | Based on visual odometry with AI, without mentioning other techniques |
| 2 | An overview of simultaneous localization and mapping: towards multi-sensor fusion, Jun Yin et al., 2024 Yin et al. (2023) | Visual-inertial, LiDAR-inertial, LiDAR-visual, LiDAR-visual-inertial, and other multi-sensor fusion systems | Various heterogeneous sensors | Does not address alternative methods beyond SLAM for UAV localization, such as terrain-aided navigation. |
| 3 | Review of Navigation Methods for UAV-Based Parcel Delivery, Dissanayaka et al. (2023) | Satellite-based navigation, inertial navigation, vision-based navigation, and sensor fusion-based navigation | Camera, Visual, LiDAR, IMU, Multi-sensor | Does not cover all UAV navigation scenarios, excludes detailed terrain-aided navigation algorithms. |
| 4 | Autonomous Underwater Vehicle Navigation: A Review, Zhang et al. (2023) | Dead Reckoning, Signal-Based Navigation, and Map-Matching Navigation | Sensors: Camera, Sonar, Inertial Sensors, Multi-beam Echosounder, Wide-swath bathymetry | Underwater focus, limiting applicability to aerial UAV navigation |
| 5 | Multi UAV Collaborative Absolute Vision Positioning and Navigation: A Survey and Discussion, Tong et al. (2023) | Collaborative visual positioning, distributed collaborative measurement fusion | Visual sensors in UAV clusters | Does not encompass terrain UAV localization methods as TERCOM and DSMAC. |
| 6 | A Review of Navigation Algorithms for Unmanned Aerial Vehicles, Ali et al. (2022) | Outdoor vision-based UAV navigation; correlation-extreme approach, key point matching, and NN | Visual sensors | Focus on vision-based navigation, excluding non-visual methods. |
| 7 | Vision-based localization methods under GPS-denied conditions, Lu et al. (2022) | Relative Vision Localization (RVL), Absolute Vision Localization (AVL) | Visual sensors | Excludes non-visual terrain-relative navigation. |

Table 2 Comparative analysis of previous UAV navigation survey papers (Part 2)

| No. | Paper Title, Authors, Year | Technologies | Sensors | Limitations |
|-----|--|---|---|---|
| 8 | Artificial Intelligence Approaches for UAV Navigation: Recent Advances and Future Challenges, Rezwan and Choi (2022) | Outdoor Navigation: Inertia-based, Signal-based and Vision-based | Camera, gyroscopes, accelerometers, and altimeter | Focus on AI methods for UAV localization, excluding others. |
| 9 | A Survey on Radio Frequency based Precise Localisation Technology for UAV in GPS-denied Environment, Yang et al., 2021 Yang and Yang (2021) | RF based UAV Localisation Systems (Wi-Fi, Bluetooth, Zigbee, RFID, UWB), Classical Localisation Mechanisms (RSS, AOA, TOF/TOA, TDOA, Fingerprint) | Transmitters & Receivers | Focuses exclusively on RF-based localization techniques; overlooking non-RF sensor-based methods. |
| 10 | State of the Art in Vision-Based Localization Techniques for Autonomous Navigation Systems, Alkendi et al. (2021) | Odometry techniques: Single-based approaches, Hybrid approaches | visual sensors, RADAR odometry, laser-based odometry and IMUs | Focuses on VO, Visual-Inertial Odometry (VIO) methods; excludes other localization methods. |
| 11 | A review on absolute visual localization for UAV, Couturier et al., 2021 Couturier and Akhloufi (2021) | Absolute visual localization: template matching, feature points matching, deep learning, visual odometry | Cameras, potentially including specialized imaging hardware | The survey is dedicated to absolute visual localization methods and does not extensively cover other localization technologies. |
| 12 | UAV Positioning and Navigation-Review, Rakovic et al., 2020 Raković et al. (2021) | Satellite, Geomagnetic, Inertial (Kalman Filter, Markov Model), Terrestrial, Vision Navigation Systems | GPS, GLONASS, GALILEO, INS, cameras & geomagnetic sensors | It lacks detailed exploration of Artificial Intelligence (AI) and ML technologies for enhanced UAV navigation accuracy and adaptability. |
| 13 | Our work: GNSS-Denied Unmanned Aerial Vehicle Navigation: Analyzing Computational Complexity, Sensor Fusion, and Localization Methodologies | Absolute localization and Relative localization | Visual Sensors & Non-Visual Sensors | Focus on outdoor localization, overlooking indoor environments and additional navigation layers such as path planning and obstacle avoidance |

Reinforcement Learning (RL) for adaptive decision-making, and Genetic Algorithms (GAs) for optimizing route planning. Together, these AI-driven techniques are transforming UAV autonomy by providing robust, adaptive solutions to complex navigation challenges.

Several surveys specifically address UAV localization in GNSS-denied environments, emphasizing the importance of TRN methods. Raković et al. (2021) comprehensively review positioning and navigation techniques, covering Satellite Navigation, INS, Terrestrial Navigation, Geomagnetic Navigation, and Vision Navigation Systems, with a particular focus on TRN methods like TERCOM and DSMAC. These techniques have significant potential in improving localization accuracy in GNSS-denied outdoor settings. The successful application of TRN methods in Autonomous Underwater Vehicles (AUVs) (Zhang et al., 2023) also highlights their versatility and precision in environments where GNSS signals are unavailable. However, their widespread adoption in UAV systems is hindered by the need for highly detailed environmental maps and substantial computational resources. Further research is required to adapt and optimize these methods specifically for UAVs operating in GNSS-denied scenarios, addressing the challenges they present.

Non-visual localization methods have also gained prominence, Yang and Yang (2021) explored Radio Frequency (RF)-based technologies for UAV localization in GNSS-denied environments. Unlike vision-based approaches, RF-based localization utilizes signals such as Wi-Fi, Bluetooth, Zigbee, RFID, and Ultra-Wide-Band (UWB) to determine position. These signals are paired with classical localization mechanisms, including Received Signal Strength (RSS), Angle of Arrival (AOA), Time of Flight/Time of Arrival (TOF/TOA), Time Difference of Arrival (TDOA), and fingerprinting. UWB,

in particular, has demonstrated high accuracy and low latency, making it effective in complex environments where visual data may be unreliable. However, challenges remain, such as the requirement for additional anchor nodes and the inherent variability in communication conditions, which can affect the reliability of RF-based localization techniques. These surveys examine UAV localization strategies in GNSS-denied environments, focusing on evolving methodologies like vision-based navigation, AI-driven techniques, and multi-sensor fusion. Table 3 highlights key algorithms. However, many surveys lack a holistic analysis covering the full range of technologies, such as TERCOM, DSMAC, and other advanced methods.

Our survey provides a comprehensive review on UAV localization in GNSS-deprived environments, that addresses the gaps identified in prior research. It introduces absolute and relative localization as essential frameworks for understanding the various UAV positioning methods. In contrast to previous surveys, which offer limited insights into UAV localization without GNSS, ours provides an extensive outlook on TRN methods, including TERCOM, SITAN, and DSMAC, alongside AI and vision-based navigation applications. Moreover, our methodology integrates various multi-modal sensors and localization strategies, enriching the landscape of UAV navigation solutions.

Challenges in UAV localization in GNSS-denied environments

A single GNSS unit is pivotal for UAV navigation, providing an accuracy of 5–10 ms, which is primarily used for mission planning and execution (Zhou et al., 2024; Dang et al., 2023). Nonetheless, its shortcomings in terms of accuracy, reliability, availability, integrity, and safety underscore the need for alternative navigation strategies

Table 3 Comparative overview of algorithms for UAV localization in GNSS-denied environments

| Category | Algorithms/Methods | Explanation |
|---|---|---|
| Probabilistic Localization Algorithms (PLA) | Kalman Filter, Extended Kalman Filter, Particle Filter, Adaptive Kalman Filter, Fuzzy Logic Systems, Bayesian Estimators | The use of probability theory and optimization. |
| Feature-Based Localization Algorithms (FBLA) | TERCOM, DSMAC, SLAM, V-SLAM, ORB-SLAM | The use of matching features or landmarks in the environment. |
| Optical Localization Algorithms (OLA) | Optical Flow, VO, SfM, Stereo Vision | The use of visual data from cameras to determine how a robot moves relative to its environment. |
| Artificial Intelligence-Based Localization (AI) | Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Multi-Layer Perceptrons (MLP) | The use of machine learning models for localization. |
| Dead Reckoning Localization (DRL) | Dead Reckoning, INS, Step Counting, Magnetometer-Based Dead Reckoning, Accelerometer-Based Dead Reckoning, Gyroscope-Based Dead Reckoning | The use of algorithms that estimate position based on movement from a known point and assumed kinematics. |

in the situations where GNSS signals face compromise (Alpern, 2023; Rao et al., 2023). This section outlines five principal challenges faced in accurately localizing UAVs: signal issues, technical limitations and regulatory factors (Deraz et al., 2023; Gao et al., 2023).

Sensor signal issues

In GNSS-denied environments, UAVs depend on a variety of visual and non-visual sensor technologies, including RADAR, barometers, cameras, and LiDAR, to navigate and localize effectively (Zhang et al., 2023; Boroujeni et al., 2024). Both visual and non-visual sensors have distinct strengths and limitations, which can significantly impact their performance across varying environmental conditions.

- *Cameras (Visual Odometry)*: VO systems, like those using the Intel RealSense D435 camera, estimate a UAV's position by analyzing sequential images. Cameras are cost-effective and provide high-resolution data, making them ideal for detailed mapping and navigation. However, their performance is significantly impacted by lighting conditions and environmental factors, such as low visibility during night-time operations or in foggy environments (Tahir et al., 2024).
- *Barometers*: Barometers, like the Bosch BMP388, are utilized to determine altitude based on atmospheric pressure. However, these sensors require frequent recalibration due to environmental pressure changes, which can lead to inaccuracies. Moreover, dynamic weather conditions, such as rapid temperature fluctuations, can cause glitches in barometric readings, affecting altitude measurements (Zibaei & Borth, 2024; Ahmad & Akram, 2024).
- *Radar altimeters*: Radar altimeters, exemplified by the Honeywell KRA 405B, provide precise altitude measurements by analyzing RADAR signal reflections from the ground. Radar is particularly reliable in various weather conditions and can penetrate through obstacles like fog. However, RADAR altimeters can be susceptible to physical barriers, such as large objects obstructing the signal path, or electronic interference from other devices, which may degrade their accuracy (Gong et al., 2023b).
- *Acoustic sensors (Sonar)*: Acoustic sensors, such as the Tritech Micron Sonar, are crucial in environments where visual or RADAR data might be unreliable, like underwater or densely vegetated areas. Sonar systems emit sound waves and analyze the returning echoes to determine distance and detect obstacles. These sensors are less affected by lighting conditions or atmospheric interferences, but they have limited

range and suffer from signal scattering in complex environments (Nagla & Yadav, 2024).

- *Inertial measurement units (IMUs)*: IMUs, such as the Bosch BMI160, are essential for real-time navigation by providing data on acceleration and rotational rates. They are highly robust and operate well in various environmental conditions. However, IMUs suffer from drift, which needs other sensors to correct these errors and maintain accurate navigation (Chen & Pan, 2024).
- *Intermittent GNSS*: Systems like the u-blox NEO-M8N GPS module can be used to temporarily regain GPS signals in environments where GPS is intermittently available. These systems are particularly useful for correcting drift in inertial navigation systems and improving overall localization accuracy during brief moments when the UAV can reconnect to GNSS (Moore et al., 2022).
- *LiDAR*: LiDAR systems, such as the Velodyne VLP-16, are widely used for creating detailed 3D maps by emitting laser pulses and measuring their reflection times. While LiDAR is highly accurate in optimal conditions, its performance can degrade in adverse weather, such as fog or rain, where laser pulses may scatter, reducing the sensor's effectiveness. Additionally, high-power laser applications in LiDAR can suffer from thermal distortions, impacting beam quality and overall mapping accuracy (Matyja et al., 2024).

Technical limitations

Navigating UAVs in GNSS-denied environments outdoors introduces several technical challenges for autonomous operations:

- *Dependency on terrain features*: UAV localization in GNSS-denied environments often relies on TRN methods, such as TERCOM and SITAN. These systems depend heavily on distinct terrain features. However, in the areas with uniform or featureless landscapes, or where the terrain database is outdated, these methods struggle, limiting their utility in varied or dynamic environments (Zhang et al., 2024; Ge et al., 2024; Gao et al., 2023a).
- *Initial positioning accuracy*: Establishing a UAV's initial position without GNSS is a significant challenge. TRN systems, including TERCOM and SITAN, require accurate initial positioning to effectively match the UAV's observed terrain with pre-stored maps. Inaccuracies in this initial step can lead to compounded errors in subsequent navigation tasks (Wang et al., 2024).

- *Inertial measurement unit drift*: IMUs provide inertial data for navigation by estimating velocity, orientation, and gravitational forces. Despite their utility, IMUs suffer from drift, where small errors accumulate over time, leading to increasing errors. This drift necessitates frequent calibrations, a task complicated without GPS or other external reference points (Elk-holy et al., 2023; Sivamani & Gudipalli, 2024).
- *Vision-based navigation system limitations*: Vision-based navigation, which uses cameras and computer vision algorithms to interpret environmental features, faces challenges in adverse weather, low-light, or low-visibility conditions. These limitations can degrade the quality of visual data essential for navigation, impacting the UAV's ability to accurately perceive and interact with its surroundings (Rani et al., 2024).
- *Computational and sensor limitations*: Navigating UAVs in GNSS-denied environments demands significant computational resources to analyze the data from IMUs, vision-based systems, LiDAR, RADAR altimeters, and to implement AI and TRN techniques. The limited processing power and memory onboard UAVs pose challenges in utilizing advanced navigation strategies such as SLAM, sensor fusion, or AI for enhanced effectiveness (Wang et al., 2023; Peng et al., 2020).
- *Malicious threats*: Even in GNSS-denied environments, UAV navigation systems face vulnerabilities such as signal jamming (Almomani et al., 2022), electromagnetic interference, and spoofing of alternative navigation sensors (e.g., LiDAR or RF-based systems) (Zhang et al., 2023; Alhafnawi et al., 2023). These threats can significantly impair the performance of sensor-based localization systems, compromising UAV safety and security. To mitigate these risks, it is crucial to employ robust encryption, secure communication protocols, and advanced anomaly detection systems that can defend against sensor spoofing and signal interference (Allouch et al., 2021; Gonzalez-Jorge et al., 2024; Eshmawi et al., 2024; Fang et al., 2024; Hou et al., 2023).

Regulatory factors

Navigating regulatory landscapes for UAV localization in GNSS-denied areas requires adherence to guidelines from authorities like the Federal Aviation Administration (FAA) in the United States, European Aviation Safety Agency (EASA) in the European Union, and Civil Aviation Authorities worldwide. Regulations prioritize reliability, accuracy, integration, and availability of alternative navigation systems like LiDAR or RADAR for precise

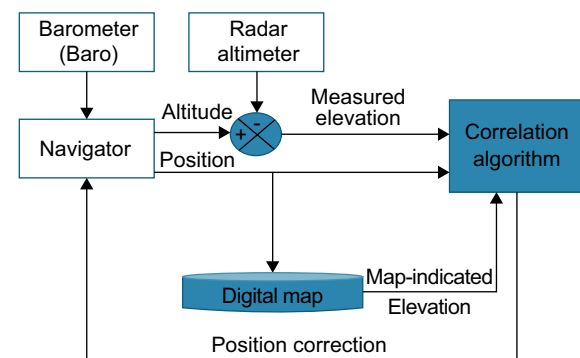


Fig. 3 TERCOM algorithm integration for UAV localization in GNSS-denied environments

UAV localization on maps while addressing operational limits and risk mitigation without GNSS. Collaboration among developers, regulators, and stakeholders is crucial to update regulations in line with technological advancements and operational needs (Gallo & Barrientos, 2022; Zenz, 2024).

Classification of UAV localization methods in GNSS-denied environments

The section summarizes UAV localization techniques in non-GNSS outdoor environments, offering an overview that highlights the methods used for UAV localization in these challenging scenarios.

Absolute localization (AL)

Absolute Localization techniques play a vital role in determining a UAV's specific location in relation to the global Earth coordinate system. While traditional satellite navigation systems like GPS, GLONASS, or GALILEO are widely utilized, they are beyond the scope of our current discussion. Instead, our focus shifts to alternative AL methods, with a particular emphasis on TRN, also known as TAN or Terrain-Based Navigation (TBN). TRN exploits the terrain profile directly below the aircraft based on sensor data and matches it with an onboard digital elevation model. AL methods also include Template and Feature Matching (TFM) and Semantic Mapping and Recognition (SMR), which rely on advanced sensors and technologies to achieve accurate geolocation, especially in environments where GNSS signals may be unreliable.

Template and feature matching for UAV localization

Template and Feature Matching methods are crucial for UAV localization in GNSS-denied environments, utilizing sensor data to match predefined templates or features for precise navigation. Sophisticated systems like TERCOM, SITAN, and DSMAC enhance localization

by comparing real-time terrain or scene data with pre-stored maps, such as DEM, ensuring reliable navigation in challenging conditions.

TERCOM, SITAN and DSMAC The TERCOM system is an application of TFM, comparing real-time RADAR altimetry data with pre-existing Digital Terrain Elevation Data (DTED) or DEM. As illustrated in Fig. 3, TERCOM integrates inputs from both RADAR and barometric altimeters, correlating the measured elevation data with digital maps to correct the UAV's position (Raković et al., 2021). This technique excels in regions with distinct terrain features, where the difference between the measured and map-indicated elevations allows for precise localization. However, TERCOM's effectiveness decreases in flatter regions lacking significant terrain contours. To overcome this limitation, the SITAN system, an evolved version of TERCOM, introduces real-time updates to terrain data, allowing UAVs to dynamically adjust to environmental changes during flight. This adaptability makes SITAN highly reliable in more complex and variable terrains. In addition, SITAN integrates advanced filtering techniques, such as the Kalman Filter (KF) and its variants, further enhancing its precision and robustness in both structured and unpredictable environments. Conversely, the DSMAC system depicted in Figure 4 improves localization accuracy by matching observed terrain with stored visual images. This approach offers a distinct advantage in areas with minimal topographic variation, as it relies on visual terrain characteristics rather than elevation data. While TERCOM and SITAN are most effective in regions with significant terrain variations, DSMAC excels in environments where visual cues are more reliable (AbdulMajuid et al., 2021; Gupta et al., 2022; Jurevičius et al., 2019).



Fig. 4 TERCOM vs DSMAC

Recent advances in template and feature matching

Recent advancements in TFM techniques for UAV localization have increasingly focused on integrating advanced imaging technologies, neural network algorithms, and sensor fusion methods, particularly in GPS-denied environments. A key trend is the growing use of sensor fusion to enhance both the robustness and precision of TFM systems. For example, He et al. (2020) introduced a hybrid approach combining GNSS and LiDAR-SLAM, using GNSS for broad-area coverage and LiDAR-SLAM for precise pose estimation, which is especially beneficial in GNSS-denied environments. There are also substantial advancements in vision-based systems, particularly for large-scale mapping. Mughal et al. (2021) developed a system that relies on pre-stored orthomosaic maps for UAV localization, while Hosseini et al. (2020) proposed an automatic localization system that combines high-resolution images with elevation models, greatly improving real-time localization accuracy in GPS-denied environments.

Another important advancement is using deep learning techniques to enhance feature extraction and matching processes. Kinnari et al. (2023) introduced the LSVL method, which integrates high-resolution UAV imagery with satellite data to ensure reliable localization, even across diverse terrains and under challenging seasonal variations. Likewise, Cao et al. (2023) combined template matching and CNNs, achieving greater accuracy in GPS-independent UAV localization. These methods exemplify how deep learning is improving the precision and adaptability of UAV navigation in complex environments.

Recent advancements have increasingly focused on improving real-time processing capabilities in UAV localization systems. For example, Lee et al. (2020) introduced the Advanced Precision Terrain-Aided Navigation (APTAN) system, which integrates INS, GNSS, and TRN technologies, along with an interferometric RADAR altimeter and LiDAR, to enable reliable real-time navigation without GPS. This highlights the growing emphasis on real-time functionality in TFM systems. Nevertheless, challenges in scalability and generalization remain. While many TFM methods work well in controlled settings, they can struggle in unfamiliar or highly variable environments. To address this, Lindstrom et al. (2022) utilized Synthetic Aperture Radar (SAR) images processed with the Range-Doppler Algorithm, enhancing the robustness of UAV localization under challenging conditions. Additionally, Wang and Somani (2020) introduced a triplet-ranking Siamese deep CNN model for matching aerial images with pre-stored DEMs, achieving high accuracy in diverse operational scenarios.

Hybrid approaches are also being explored, like dead reckoning with terrain image processing to improve

localization accuracy in new environments. Van Kirk et al. (2022) combined traditional image processing techniques such as Scale-Invariant Feature Transform (SIFT) with dead reckoning. Similarly, Kinnari et al. (2022) developed a season-invariant visual localization system using Monte-Carlo localization and CNNs to maintain the performance of the system in different seasons.

In summary, significant advancements in Template and Feature Matching for UAV localization have been achieved, with notable progress in areas such as sensor fusion, deep learning, and real-time processing. However, overcoming the challenges of scalability and generalization remains essential for ensuring these systems can reliably function in diverse environments and operational scenarios. Table 5 provides an overview on the current state of the art in this critical area.

Semantic mapping and place recognition

Semantic Mapping and Place Recognition (PR) are much interconnected and enhancing global localization capabilities in autonomous systems. Semantic Mapping focuses on creating a detailed and structured representation of the environment by processing the data from sensors such as cameras and LiDARs. With advanced algorithms, particularly those rooted in artificial intelligence, this data is transformed into meaningful labels (e.g., “tree,” “building,” “road”) and organized spatially to capture the relationships between elements. The primary goal of Semantic Mapping is to provide a contextual framework that enables systems to interpret their surroundings at a higher level. In contrast, PR is the overarching framework that identifies and correlates places based on sensory data. PR operationalizes the structured data provided by Semantic Mapping to recognize and localize specific locations. While Semantic Mapping builds detailed environmental models, PR applies this enriched information to solve practical localization challenges. PR methodologies are divided into distinct branches: appearance-based PR relying on visual features; geometric-based PR using spatial relationships; semantic-based PR leveraging semantic labels and spatial relationships; and semantic-structural PR, a hybrid approach combining semantic and geometric data. These methodologies benefit from the structured and context-rich data generated through Semantic Mapping.

The significant contributions of various studies in this field are comprehensively outlined in Table 6, showcasing the advancements in methodologies, applications, and innovations within Semantic Mapping and PR.

- Bui et al. (2023) introduce an appearance-based PR approach for UAV localization, utilizing cross-view image comparison where UAV-captured ground

photos are matched with satellite imagery. This method employs a Transformer-based architecture, specifically a Vision Transformer, to match ground-level UAV photos with satellite imagery. It enhances the image tokens to significantly improve localization accuracy. The use of Recall@1, a metric evaluating the system’s ability to identify the correct item as the top result, underscores the method’s precision. By adopting sophisticated deep learning strategies, the approach underscores the potential of visual data for precise geo-localization, shifting from conventional sensors and reliance on GPS.

- Ouyang et al. (2023) presents a novel semantic-based PR approach for aircraft positioning in GNSS/GPS-denied environments, harnessing a semantic vector map-based framework. It utilizes a downward-facing monocular camera, an altimeter, and a compass in conjunction with open-source Vector Maps (VMAPs). The core of the methodology involves a coarse-to-fine building vector matching technique combined with an improved particle filter algorithm, aiming to minimize localization errors. This approach underscores the significance of semantic targets in improving localization precision. Nevertheless, challenges persist in the regions lacking clear semantic features, particularly at lower altitudes.
- Wang et al. (2023) proposed a semantic-based PR approach through the Weight-Adaptive Multi-Feature Fusion Network (WAMF-FPI) for UAV image localization. This method employs a fusion network integrating multiple features to enhance localization accuracy, particularly to improve spatial and scale information handling. It introduces a unique Hanning loss to prioritize central area accuracy. By restoring feature maps to the original satellite image resolution and employing a novel weighting mechanism, they significantly improved localization accuracy. The model demonstrates the improved performance on the UL14 dataset, showcasing its potential for precise navigation in challenging environments. This work harnesses deep learning strategies, offering an innovative solution for UAV localization without traditional satellite navigation systems. This underscores the critical need to address spatial and multi-scale challenges in UAV localization.
- Wang et al. (2022) propose a geometric-based PR approach that integrates geomagnetic data with INS to achieve accurate aircraft positioning in GNSS-denied environments. This method utilizes geomagnetic field information, aligning it with an a priori geomagnetic reference map and applying an INS to correct errors over long distances. The system lever-

ages a geomagnetic triangle matching algorithm integrated with SLAM techniques to enhance localization accuracy. This approach addresses the challenges in geomagnetic navigation by improving adaptability and accuracy in complex magnetic environments.

- Allik et al. (2022) contributed an appearance-based PR approach using machine learning with a twin network architecture for scene recognition from NADIR imagers. This method demonstrates effectiveness in sparse terrains, where traditional localization techniques may struggle due to limited features. By leveraging machine learning for high-altitude systems, their approach highlights the potential of visual-based recognition in GNSS-denied conditions, showcasing its adaptability and precision in challenging environments..
- The paper (Liu et al., 2024) introduces the Semantic-aware Graph Convolutional Network (SeGCN) as a Semantic-Structural PR approach for UAV geolocalization, particularly in GNSS-denied environments. It addresses the challenge of cross-view geolocalization by utilizing both semantic information (e.g., object categories) and structural relationships (e.g., spatial geometry) of objects from UAV and satellite images. SeGCN uses a graph convolutional network that infers potential semantic features through cross-attention of image contexts and explores the structural information of objects. This approach has demonstrated superior accuracy in localization and navigation tasks over traditional methods, confirmed by experiments on University-1652 and SUES-200 benchmarks and real UAV datasets. SeGCN represents a significant advancement in UAV navigation and localization under GNSS-denied conditions by effectively matching UAV-captured images to maps using semantic and structural insights.

Relative localization (RL)

RL is designed to ascertain a UAV's location using a local coordinate frame, making it highly effective in the environments lacking GPS, such as indoor and outdoor spaces. RL employs diverse strategies, including Dead Reckoning, Filtration & Error Optimization; SLAM; Visual Odometry & Optical Flow; and Visual-Inertial Odometry, to offer adaptable and precise localization solutions where absolute localization is not available.

Dead reckoning, filtration, and error optimization

This strategy calculates the UAV's current position based on previous positions and movements, adjusting for errors and uncertainties with filtering or/and optimization techniques. This subsection highlights key

advancements and collaborative efforts that have significantly enhanced the accuracy of UAV navigation in GPS-denied scenarios (Gallo & Barrientos, 2022; Ye et al., 2023; Zheng et al., 2023; Ouyang et al., 2020; AbdulMajid et al., 2021; El Sabbagh et al., 2023; Taghizadeh & Safabakhsh, 2023). Some recent works are presented in Table 4.

Recent advancements in this field have shown a significant progress in minimizing errors and enhancing long-term positioning accuracy. Gallo and Barrientos (2022) developed the algorithms aiming at reducing attitude error and position drift in low SWaP UAVs, highlighting how computationally efficient methods can address the limitations of lightweight platforms. Similarly, Ye et al. (Xiaoyu et al., 2024) combined Error State Right-Invariant Extended Kalman Filtering (ES-RIKF) with LSTM networks, achieving drift-free state estimation in fixed-wing UAVs by integrating traditional filtering with machine learning for error correction over time.

Multi-UAV collaborations have also contributed to advancements in relative localization. Zheng et al. (2023) integrated multi-UAV ranging with IMU data to improve localization accuracy during low-altitude flights. Their method demonstrated that the collaborative data sharing between multiple UAVs can effectively reduce localization errors. Ouyang et al. (2020) employed cooperative navigation using RSSI measurements and Kalman filters, enhancing accuracy in RSS-based localization through shared data between UAVs.

Neural network-based approaches have also emerged as effective tools for GPS-denied navigation. AbdulMajid et al. (2021) employed RNNs to estimate position and velocity reliably, while El Sabbagh et al. (2023) utilized cascaded neural networks to predict velocity and position errors during GPS signal loss. These neural models enable learning and adapting over time, providing robust navigation solutions in environments where traditional methods might struggle. Also, Taghizadeh and Safabakhsh (2023) introduced an integrated INS/GNSS system that incorporates an attention-based hierarchical LSTM model. Their approach achieved exceptional long-term accuracy in position and velocity predictions, demonstrating the potential of advanced machine learning models to address complex navigation challenges in the environments with extended GNSS outages.

Visual odometry and optical flow

VO and Optical Flow are essential for UAV localization in GNSS-denied environments by estimating displacement and orientation using sequential image data. VO focuses on pose estimation without mapping, offering a lightweight solution for real-time motion tracking, while SLAM integrates localization with mapping

Table 4 Literature summary of dead reckoning, filtration, & error optimization

| Authors | Sensors | | | Algorithms | | | | | | | Implementation | | Description of results | |
|--|---------|-------|-------|------------|-----------|--------------|-----|-----|------|-----|----------------|------------|------------------------|--|
| | IMU | RADAR | LiDAR | Camera | Barometer | Magnetometer | DRL | PLA | FBLA | OLA | AI | Simulation | | Experiment |
| Ye et al. Xiaoyu et al. (2024) | ✓ | | | ✓ | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ | | - Using the ES-RIKF and the ES-EKF, along with integrating an LSTM prediction network into the state estimation system, the approach enhances accuracy during periods when GNSS is unavailable. Results demonstrate that ES-RIKF outperforms ES-EKF with faster convergence, a maximum positioning error of 30 meters over a 130-second GNSS denial period, and minimal three-axis position disturbances. |
| Zheng et al. (2023) | ✓ | | | | | | ✓ | ✓ | | | | ✓ | | - Developed a fusion localization method based on multi-UAV collaboration and IMU for GNSS-denied scenarios. This method includes UAV coordinate correction, pre-processing of ranging data, and unscented Kalman filter (UKF) application. The method reduced positioning error by 21.4% compared to EKF and performed better at low altitudes. |
| El Sabbagh et al. (2023) | ✓ | | | | | | ✓ | | | | ✓ | ✓ | ✓ | - Cascaded neural networks is proposed to estimate velocity and position errors during GPS signal blockage to handle the time dependency and non-linearity modeling for different GPS outage periods. Using the proposed CNFNN during GPS outages enhances the position estimation accuracy by 30%, 44%, and 80% for 10, 25, and 50 s GPS outages. On the other hand, the estimated position accuracy of MEMS IMU is enhanced by 94%, 98%, and 99% |

Table 4 (continued)

| Authors | Sensors | | | Algorithms | | | | | | | Implementation | | Description of results | |
|----------------------------------|---------|-------|-------|------------|-----------|--------------|-----|-----|------|-----|----------------|------------|------------------------|--|
| | IMU | RADAR | LIDAR | Camera | Barometer | Magnetometer | DRL | PLA | FBLA | OLA | AI | Simulation | | Experiment |
| Taghizadeh and Safabakhsh (2023) | ✓ | | | | | | ✓ | ✓ | | | ✓ | | ✓ | - Examined Attention-based Hierarchical Long Short-Term Memory (AHLSTM) model improvement on INS/GNSS integrated navigation systems during GNSS outages. The results indicate a remarkable 70% improvement in long-term position and velocity prediction compared to similar methods. |
| Gallo and Barrientos (2022) | ✓ | | | | | ✓ | ✓ | ✓ | | ✓ | | ✓ | | - Inertial navigation algorithm for GNSS-Denied conditions, evaluated with Monte Carlo simulations. The vertical position estimation error is independent of the quality of all sensors and depends exclusively on ionospheric effects, and the pressure offset change since the time the GNSS signals are lost. |
| AbdulMajuid et al. (2021) | ✓ | | | ✓ | | ✓ | ✓ | | | | ✓ | ✓ | | - RNN used for GPS-denied navigation with median MPE of 35m in validation, as low as 2.7m in some cases. The MPE in 90% of the validation flights is bounded below 166 meters. |
| Ouyang et al. (2020) | ✓ | | | | | | ✓ | ✓ | | | | ✓ | | - Localizing 20 UAVs in a GNSS-denied environment using a hybrid centralized-distributed scheme and a multi-sensor fusion algorithm (AV-ECKF) that relies on RF ranging measurements and other sensors. AV-ECKF is more accurate and stable than EKF, with 85% confidence in achieving a 5-meter estimation error. |

for simultaneous navigation and map construction. To enhance accuracy, Visual-Inertial Odometry (VIO) combines camera data with inertial sensors like accelerometers and gyroscopes, improving performance in GPS-limited settings (Li et al., 2021; Xu et al., 2023). These techniques collectively enable UAVs to navigate in challenging environments effectively. Table 7 highlights key developments in VIO and Optical Flow, emphasizing their roles in enhancing localization accuracy.

Wang et al. (2023) developed a stereo visual-inertial method for UAV navigation in complex bridge environments, significantly improving navigation accuracy in diverse conditions. Addressing similar challenges, Luo et al. (2023) introduced a monocular VIO system enhanced with point-line fusion and backend adaptive optimization, resulting in a 33.8% improvement in positioning accuracy. This advancement underscores the importance of advanced optimization techniques in enhancing navigation reliability in GNSS-denied environments. Similarly, Gallo and Barrientos (2023) proposed a semi-direct visual navigation method that integrates INS outputs with visual estimations, effectively mitigating the position drift during GNSS outages and improving localization stability.

Further advancing UAV localization capabilities, Ellingson et al. (2020) explored the navigation for fixed-wing UAS in GPS-denied settings using monocular cameras and IMUs. Their system achieved less than 2.5% accumulated error over the distance traveled, emphasizing the effectiveness of monocular camera systems in delivering accurate pose estimation. Complementing these efforts, Lu et al. (2022) introduced a hybrid mapping strategy for micro-aerial vehicles, merging 3D motion planning with robust localization techniques. This approach proved highly effective in dynamic and GPS-denied scenarios, highlighting the critical role of hybrid strategies in real-time UAV operations. In this context, Allak et al. (2020) tested VIO algorithms in Mars-like environments, achieving an RMSE of 1.52 ms over a 113-meter trajectory. This demonstrates the adaptability and resilience of VIO techniques in environments with minimal navigational cues. Additionally, Kim et al. (2022) developed an optical sensor fusion method that combines a Feature Point Threshold Filter (FPTF) algorithm with INS data, demonstrating superior performance in low-altitude UAV navigation. While Benjumea et al. (2021) achieved sub-10 cm localization accuracy for high-precision infrastructure inspection by merging stereo camera data with a robotic total station.

Incorporating advanced machine learning techniques, Deraz et al. (2023) integrated optical flow with a deep learning-based LSTM model, significantly reducing velocity errors during GNSS signal loss. This work

demonstrates the transformative potential of AI in enhancing UAV navigation systems, particularly in challenging scenarios with signal disruptions.

SLAM

Simultaneous Localization and Mapping is essential for relative localization in UAVs, enabling them to create real-time maps of unknown environments while simultaneously determining their position within those maps (Zhang et al., 2022). This dual capability is especially critical in regions where reliable maps are unavailable, significantly boosting UAV navigation and autonomy in GNSS-denied or map-scarce environments.

A key component of SLAM is VO, which estimates displacement and orientation by analyzing sequential image data, providing the motion estimates necessary for SLAM to generate globally consistent trajectories and detailed environmental maps. Building on this foundation, VIO enhances accuracy and robustness by integrating visual data with inertial measurements from accelerometers and gyroscopes. This fusion not only compensates for motion blur but also improves performance in dynamic and GNSS-limited environments, making it indispensable for UAV operations in complex scenarios. Recent advancements in SLAM, VO, and VIO have further refined their efficiency and adaptability, incorporating innovations such as multi-sensor fusion, event-based cameras, and deep learning, which collectively address the challenges of localization and mapping in unstructured and dynamic environments. These developments continue to empower UAVs to navigate and operate autonomously in diverse and demanding settings. Recent advancements in UAV SLAM have introduced noteworthy innovations, contributing to the enhanced performance of UAVs in various challenging settings, as some recent works are presented in Table 8.

Wan et al. (2022) introduced a terrain-aided SLAM algorithm for planetary UAV localization. By integrating VO in frame-to-frame motion estimation and geo-referencing UAV images using DEMs, their approach significantly reduces localization errors in featureless planetary landscapes. The method achieves robust and accurate localization with Local Bundle Adjustment (LBA), which fuses the relative pose estimates from VO with absolute geo-referencing results. This combined approach outperforms traditional SLAM methods like ORB-SLAM2 and ORB-SLAM3, highlighting the adaptability of SLAM technology for planetary exploration. Such advancements demonstrate the potential of extending UAV capabilities beyond Earth, making SLAM a critical tool in environments where the conventional navigation methods are ineffective.

Additionally, LiDAR-based SLAM solutions have also gained attention, particularly for their ability to perform in low-visibility conditions. Ho et al. (2021) addressed the limitations of visual odometry by utilizing 2D LiDAR-based SLAM for UAV navigation in GPS-denied environments. Their study demonstrates how optimizing key parameters, such as loop closure thresholds and search radii, can significantly enhance SLAM performance. With MATLAB simulations, Ho et al. achieved a 45% increase in processing speed, underscoring the potential for LiDAR-based systems to provide accurate trajectory mapping even in environments where visual cues are insufficient.

These advancements highlight SLAM's pivotal role in enhancing UAV autonomy and navigation in GPS-denied environments. The integration of advanced sensors like LiDAR and AI algorithms (Al-Iqubaydhi et al., 2024) enhances SLAM's effectiveness, driving more precise and adaptable processes. For example, Jensen and Budge (2023) developed an innovative localization system for small UAVs operating in GPS-denied environments. By combining camera and LiDAR sensors with Error-State Extended Kalman Filtering (ESEKF) and camera-to-LiDAR sensor fusion, their system achieved an average localization error of 3.2 ms, demonstrating the effectiveness of sensor fusion. These innovations in sensor technologies and algorithmic optimizations position SLAM as a cornerstone for reliable UAV operations, particularly in the most challenging settings (Chiang et al., 2023).

A major development is the integration of SLAM with computer vision algorithms, as demonstrated by Ngo et al. (2022), who developed a UAV platform for autonomous search and rescue missions. Their approach effectively merges real-time localization with environmental mapping, showcasing the practical application of SLAM in complex and dynamic settings. This integration not only proves the feasibility of SLAM in high-stakes operations but also emphasizes its growing importance in enabling UAVs to operate without reliance on GNSS.

Discussion and future direction

Discussion

Analysing 132 research papers, we explored the integration of diverse sensors and algorithms to improve UAV localization in GPS-denied environments. These efforts focus on terrain or map feature extraction, advanced scene recognition techniques, multi-sensor fusion, and implementing sophisticated localization methods.

Absolute localization methods, such as TERCOM, SITAN, and DSMAC, rely on pre-mapped terrain data like DEMs and external sensors, including RADAR, LiDAR, and barometers. These systems use this data to accurately match the UAV's position with distinct terrain

features, ensuring precise navigation even in GPS-denied environments. For instance, TERCOM matches barometric and RADAR readings to terrain profiles but may lack the precision needed for more advanced tasks. To overcome these limitations, SITAN was developed, integrating advanced filtering techniques such as the EKF and UKF to enhance accuracy. Additionally, an enhanced DSMAC takes precision by leveraging high-resolution satellite imagery and detailed terrain maps to match specific ground features more effectively. Despite their strengths, AL methods struggle in environments with sparse or uniform features (e.g., deserts or open water), where few distinctive features are available to match pre-mapped data (see Sect. 4.1). In contrast, RL methods rely on real-time data from onboard sensors, such as cameras for visual odometry or LiDAR for SLAM, excelling at lower altitudes where they can capture detailed environmental features. Techniques like SLAM, which integrate visual-inertial odometry and optical flow, enable the UAV to map unfamiliar environments in real-time while simultaneously determining its position. RL methods are highly adaptable, performing effectively in dynamic environments where pre-mapped data may be unavailable or outdated (see Sect. 4.2).

A key factor in the performance of AL and RL techniques lies in the types of features each method utilizes. AL methods predominantly rely on elevation-based features, detected by sensors such as RADAR, barometers, or LiDAR, which are particularly effective for capturing large-scale terrain changes. In contrast, RL methods focus on visual features, captured by cameras or other imaging sensors, to detect finer and localized details in the UAV's immediate surroundings. For instance, in feature-sparse environments at low altitudes, AL methods can improve localization accuracy by increasing altitude to detect more prominent terrain features. Conversely, in urban settings with high visual complexity, RL methods prove more effective by utilizing detailed visual cues such as building edges, textures, and obstacles for precise navigation.

The performance of both AL and RL methods is highly dependent on environmental conditions and the availability of sensor data. A hybrid approach that combines both AL and RL can offer a more reliable and robust localization solution, allowing UAVs to adapt to diverse environmental challenges and ensuring consistent performance in various conditions. This hybrid model ensures that UAVs can capitalize on both terrain-based and real-time data-driven localization techniques, which enhances overall navigation accuracy, particularly in GPS-denied environments. Integrating AL and RL techniques in a sensor fusion framework is an advanced

solution to UAV navigation challenges in GPS-denied environments (see Table 9).

For both absolute and relative navigation, the key challenges in real-time processing lie in optimizing algorithmic efficiency and harnessing high-performance computational resources to ensure reliable operation. This includes effective sensor integration, low-latency processing, and maintaining robust performance in dynamic environments. The main implementation obstacles are summarized below:

- *Computational complexity* Integrating multiple sensors such as LiDAR, RADAR, cameras, and IMUs presents computational challenges due to the need to process large volumes of heterogeneous data in real-time. The sensor type directly influences the processing load; for instance, Visual SLAM systems, which use camera data, can operate at high frequencies (e.g., 250 Hz) when leveraging GPU-enabled hardware. Meanwhile, LiDAR typically produces larger raw data streams due to denser point clouds. However, modern LiDAR-based odometry and SLAM solutions (e.g. LIO-SAM Shan et al. (2020), Fast-LIO2 Xu et al. (2021)) efficiently use geometric feature extraction, sub-sampling, or scan matching to run in real-time often avoiding the need for computationally heavy Bundle Adjustment. Consequently, although LiDAR data volume can be high, well-optimized pipelines can achieve performance on par with, or even surpass, purely visual methods. Managing these diverse data streams efficiently (whether visual or LiDAR) requires advanced algorithms such as deep learning models, Kalman filters, or other recursive methods to achieve reliable multi-modal sensor fusion in real-time applications. Commonly used in research, algorithms such as the EKF, UKF, and RLS offer varying trade-offs between accuracy and computational complexity:
 - *Extended kalman filter* offers a balance between accuracy and computational efficiency, making it a widely-used choice for many real-time applications. However, the EKF can introduce errors in highly non-linear environments, as highlighted in studies such as Refs. Ye et al. (2023) and Ouyang et al. (2020). This limitation often results in divergence in system state estimation, especially when initial conditions are poorly defined or system dynamics exhibit significant non-linearity.
 - *Unscented kalman filter* improves accuracy by avoiding the need for linearization, unlike the EKF. For example, a study by Zheng et al. (2023) demonstrated that in a multi-UAV collaboration using
- fusion localization in partial GNSS-denied scenarios, the UKF significantly outperformed the EKF. This approach utilized sensors like IMUs and distance measurement modules, including time-of-flight (TOF) and received signal strength indicator (RSSI), for UAV localization. The simulation results showed a 21.4% reduction in positioning error, demonstrating clear improvements in both accuracy and robustness. However, the UKF typically increases computational complexity due to the generation of sigma points required for non-linear transformations.
- *Recursive least squares (RLS)* is highly effective in environments with dynamically changing parameters due to its ability to continuously update its estimates. This adaptability makes it particularly valuable for real-time applications, though it comes with higher computational demands. For example, in the study by Benjumea et al. (2021), RLS was used for UAV sensor fusion, significantly improving real-time adaptability and reducing sensitivity to sensor noise. In GPS-denied environments, the integration of RLS enabled the UAV to maintain a positional error of less than 2 ms over 100 s of GPS signal loss, achieving a 15-20% improvement in localization accuracy compared to standard Kalman Filters by better adapting to rapidly changing flight dynamics.
- *Real-time processing capabilities* Real-time processing is critical for UAV operations in environments where GPS is unavailable. It ensures the timely and accurate handling of sensor data, requiring the integration of optimized algorithms with high-performance hardware. The following factors are essential for achieving real-time performance:
 - *Hardware acceleration* Utilizing specialized hardware, such as Graphics Processing Units (GPUs) and Field Programmable Gate Arrays (FPGAs), can significantly reduce processing latency. GPUs excel at parallel processing tasks, making them ideal for managing the large datasets produced by sensors like LiDAR and cameras. For instance, the VINS-MONO (visual inertial SLAM using monocular camera and an IMU) algorithm has a GPU accelerated version (pjrambo, 2025) that can run on NVIDIA Jetson edge devices to achieve a real-time performance. Another stere-based visual inertial SLAM is the Isaac ROS Visual SLAM software package developed by NVIDIA (Corporation, 2025), which is GPU-accelerated and can provide pose estimation at frequency up to 250 Hz.

- *Algorithm optimization* Customizing sensor fusion algorithms for specific hardware architectures can significantly boost processing speed. Techniques such as down sampling sensor data, using approximation methods, and optimizing matrix operations are essential for maintaining real-time performance. For example, the ES-RIEKF framework (Ye et al., 2023) achieves attitude convergence in less than 25 s during flight, outperforming traditional EKF by reducing oscillations. Similarly, integrating enhanced visual odometry with LSTM-based drift correction (Deraz et al., 2023) reduces forward velocity error by 63.01% after 30 s and 54.33% after 113 s of GNSS signal loss, demonstrating the direct impact of algorithm optimization on UAV localization in GPS-denied scenarios
- *Latency management* Ensuring low-latency communication between sensors and processing units is crucial for real-time operations. High-bandwidth communication protocols and the strategic placement of processing units to minimize data transmission distances are essential. For example, in the study (Deraz et al., 2023), a micro-FMCW RADAR attached to a 3DR Solo quadcopter achieves real-time RADAR target detection in just 1.3 ms, allowing near-instantaneous sensor feedback. Low latency is especially vital for maintaining precise localization and rapid response to dynamic conditions, which is crucial for successful missions in GPS-denied environments and other challenging scenarios.

Experimental methods

Simulation and quasi-experimental strategies for UAV localization in GPS-denied environments are well-documented, as highlighted in previous sections and particularly in Tables 5 to 8. However, despite the existence of diverse approaches, practical implementations remain limited, and their real-world applications and effectiveness are still underexplored, particularly concerning execution time, computational delays, and other specific details. Herein, we present relevant experimental implementations for UAV localization in environments lacking GPS support.

1. Experiment at Hong Kong University of Science and Technology (HKUST) using VINS-Mono (Qin et al., 2018):

- *Description:* The experiment conducted at the HKUST utilized the VINS-Mono, a Visual-Inertial Navigation System combining monocular

camera input with inertial measurement data. VINS-Mono, and its successor VINS-Fusion, are typically suited for indoor environments, where they excel in scenarios with rich visual features and controlled conditions. However, this experiment aimed to assess the system's performance in a large-scale outdoor environment. Data collection for this outdoor test conducted at a rate of 20 Hz for visual data and 200 Hz for IMU measurements, covering a path length of 2.5 km under normal walking conditions. In another larger-scale test, data was collected at a rate of 25 Hz for visual data and 200 Hz for IMU measurements, covering a path length of 5.62 km over 1 h and 34 min. The results were notable, showing nearly zero drift in the entire path, with the estimated trajectory closely aligning with Google Maps. This suggests that VINS-Mono can maintain accurate localization over extended periods and distances, even in challenging outdoor scenarios, despite not being primarily designed for them. Notably, VINS-Mono has been succeeded by VINS-Fusion, a more flexible system that builds on its predecessor's capabilities for enhanced applicability across various environments.

- *Strengths:* VINS-Mono is highly effective in environments with rich visual features, providing accurate pose estimation with minimal drift over extended distances. It excels in urban or well-lit environments where visual data is reliable.
- *Limitations:* The reliance on visual data makes VINS-Mono less effective in environments with poor lighting, low visibility, or sparse visual features, such as forests, deserts, or during night operations. It may also struggle in dynamic lighting conditions.

2. Development and testing of the PO-MSCKF algorithm (Xueyu et al., 2024):

- *Description:* Xueyu et al. introduced and rigorously tested the Pose-Only Multi State Constrained Kalman Filter (PO-MSCKF) algorithm, which enhances traditional VIO systems. The key innovation of PO-MSCKF is its focus on eliminating the need for 3D feature reconstruction by using the Pose-Only (PO) theory. This approach simplifies the algorithm, reducing computational costs while maintaining model consistency. Comprehensive experiments were conducted in various environments, including indoor, outdoor, and

Table 5 Literature summary of absolute localization - template and feature matching

| Authors | Sensors | | Algorithms | | | | | | | | Implementation | | Description of results | |
|-------------------------|---------|-------|------------|--------|-----------|--------------|-----|-----|------|-----|----------------|------------|--|------------|
| | IMU | Radar | LiDAR | Camera | Barometer | Magnetometer | | | | | | Simulation | | Experiment |
| | | | | | | | DRL | PLA | FBLA | OLA | AI | | | |
| He et al. (2020) | ✓ | | ✓ | | | | | ✓ | ✓ | ✓ | | ✓ | Experimental results demonstrate high accuracy, with average position errors around 0.03 meters and rotational errors of 0.0120 rad for yaw and 0.0445 rad for pitch, indicating effective drift error correction and reliable pose estimation without high-cost inertial devices. | |
| Kinnari et al. (2023) | ✓ | | | ✓ | | ✓ | | ✓ | ✓ | ✓ | | ✓ | Large-scale map matching method together with a point mass filter, achieving 12.6–18.7 m error with a map size of 100 km ² in real-time operation. | |
| Cao et al. (2023) | | ✓ | | ✓ | | | | ✓ | | ✓ | | ✓ | Template matching with CNN for UAV visual localization, shows enhanced feature extraction and accuracy. | |
| Zhang et al. (2022) | ✓ | | | ✓ | | | | ✓ | ✓ | ✓ | | ✓ | DNN to extract scene features for position matching and optical flow estimation. This method can correct the position drift of IMU | |
| Van Kirk et al. (2022) | ✓ | | | ✓ | | | ✓ | | ✓ | | | ✓ | Proposed a system combining dead reckoning and terrain imaging for UAV navigation in GPS-denied environments. Utilizes image processing for location estimation and ground speed calculation. Validated through both simulations and physical tests. | |
| Lindstrom et al. (2022) | ✓ | ✓ | | | | | | ✓ | | | | ✓ | SAR-image-based method for matching; errors estimated within 3 meters of truth in both simulated and real data. | |
| Kinnari et al. (2022) | ✓ | | | ✓ | | | | ✓ | ✓ | ✓ | | ✓ | Season-invariant visual localization in GNSS-denied environments. Achieved mean localization errors of 26.5m, 29.1m, and 30.6m in real UAV data after approximately 2 km of travel. | |
| White et al. (2021) | | ✓ | | | | | | ✓ | | ✓ | | ✓ | Utilized SAR images and CNNs for GPS-denied navigation. Tested on both simulated and real data, showing effective navigational error estimation in UAVs. | |
| Mughal et al. (2021) | | | | ✓ | | | | ✓ | | | | ✓ | Developed a deep learning-based image matching system for UAV localization. Achieved matching accuracy of 91.04% and GPS localization error with an average of 3.708 m ² and a maximum of 33.164 m ² . | |

Table 5 (continued)

| Authors | Sensors | | | Algorithms | | | | | | | Implementation | | Description of results | |
|------------------------|---------|-------|-------|------------|-----------|--------------|-----|-----|------|-----|----------------|------------|------------------------|--|
| | IMU | Radar | LiDAR | Camera | Barometer | Magnetometer | DRL | PLA | FBLA | OLA | AI | Simulation | | Experiment |
| | | | | | | | | | | | | | | |
| Hosseini et al. (2020) | | | | ✓ | | | | | ✓ | | | ✓ | | - Based on GIS data, elevation models, and georeferenced images for UAV localization, the accuracy within a 5 m horizontal difference using aerial and satellite reference data. |
| Lee et al. (2020) | ✓ | ✓ | ✓ | | ✓ | | ✓ | ✓ | ✓ | | | ✓ | | The AP-TAN method attained a navigation accuracy of around 3.1 m CEP at 1.5 km altitude and 5.9 m CEP at 5.1 km altitude. |
| Wang and Somani (2020) | | | | ✓ | | | | | ✓ | | ✓ | | ✓ | High accuracy in Aerial-DEM matching using a triplet-ranking Siamese deep CNN model for real-time UAS navigation in GPS-denied environments. Aerial-DEM matching accuracy as high as 0.96078m. |

Table 7 Summarizing literature on RL: visual-inertial odometry & optical flow

| Authors | Sensors | | Algorithms | | | | | | | Implementation | | Description of results | | |
|-----------------------------|---------|-------|------------|--------|-----------|--------------|-----|-----|------|----------------|----|------------------------|------------|---|
| | IMU | RADAR | LIDAR | Camera | Barometer | Magnetometer | DRL | PLA | FBLA | OLA | AI | | Simulation | Experiment |
| Wang et al. (2023) | ✓ | | ✓ | ✓ | | | ✓ | | ✓ | ✓ | | ✓ | ✓ | Developed a stereo visual-inertial method (FMC-SVIL) with RMSEs of 0.416m (sunny) and 0.340m (cloudy), utilizing Apriltag detection and pose graph optimization for precise UAV navigation. |
| Luo et al. (2023) | ✓ | | | ✓ | | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | Proposed using VINS-MONO, leading to a 32.3% improvement on the EuRoc dataset over PL-VINS, and in challenging real-world scenarios with variable illumination, weak texture, and complex environments, achieving a 33.8% enhancement. |
| Gallo and Barrientos (2023) | ✓ | | | ✓ | | | ✓ | ✓ | | | ✓ | ✓ | | A Semi-Direct Visual Odometry (SVO)-based Inertially Assisted Visual Navigation System (IA-VNS). Results for Scenario 1: mean (max) 0.521 (1.321) degrees, std 0.151 degrees. |
| Lu et al. (2022) | ✓ | | ✓ | ✓ | ✓ | | ✓ | | ✓ | ✓ | | ✓ | ✓ | Hybrid mapping strategy that integrates a matching algorithm with 3D motion planning. The final drift is around 13% of the total traveled distance. |
| Allak et al. (2020) | ✓ | | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | Conducting AVI-NAV experiment for UAV navigation in Mars-like environments. Achieves robust pose estimation with an RMSE of 1.52 m on a 113 m trajectory using vision-based techniques. |
| Ellingson et al. (2020) | ✓ | | | ✓ | | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | Monocular camera and IMU-based odometry-like estimator for fixed-wing UAV navigation in GPS-denied environments. Total accumulated error is demonstrated as less than 1% of the distance traveled. After initialization errors were removed, the filter was accurate, ultimately accumulating an error of approximately 2.5% of the distance traveled. |
| Deraz et al. (2023) | ✓ | ✓ | | ✓ | ✓ | ✓ | | | ✓ | ✓ | ✓ | | ✓ | Forward velocity of the vehicle is calculated using both RADAR height estimate and enhanced visual odometry. VO is implemented using optical flow and deep learning-based techniques. can improve the average forward and lateral velocities errors for the flight to 63.01 % in 30sec, 62.26% in 60 sec, 58.76% in 90 sec and 54.33% in 113 sec during the GNSS signal outage. |

Table 7 (continued)

| Authors | Sensors | | | | Algorithms | | | | | Implementation | | Description of results |
|------------------------|---------|-------|-------|--------|------------|--------------|-----|-----|------|----------------|----|--|
| | IMU | RADAR | LiDAR | Camera | Barometer | Magnetometer | DRL | PLA | FBLA | OLA | AI | |
| Kim et al. (2022) | ✓ | | | ✓ | | | | ✓ | | ✓ | ✓ | Modified FPTF algorithm for enhanced optical-flow-based UAV navigation. Fuses data from INS and optical flow sensor. Evaluated through Gazebo simulations and experimental flight tests in varying flight conditions. Employed EKF and Extended Recursive Least Squares (ERLS) for UAV positional accuracy. ERLS aligned 3D camera data with a global reference from a robotic total station, and EKF integrated this data for precise UAV state estimation, achieving an error below 10 cm against total station measurements. |
| Benjumea et al. (2021) | ✓ | | | ✓ | | | | ✓ | | ✓ | ✓ | |

Table 8 Literature summary of relative visual localization - SLAM

| Authors | Sensors | | | | | Algorithms | | | | | | Implementation | | Description of results |
|-------------------|---------|-------|-------|--------|-----------|--------------|-----|-----|------|-----|----|----------------|------------|---|
| | IMU | RADAR | LIDAR | Camera | Barometer | Magnetometer | DRL | PLA | FBLA | OLA | AI | Simulation | Experiment | |
| | | | | | | | | | | | | | | |
| Wan et al. (2022) | ✓ | | ✓ | ✓ | | | | ✓ | | | | ✓ | ✓ | - Proposed a terrain-aided SLAM algorithm for planetary UAV navigation in GPS-denied environments. Achieved an average localization error of 0.45 m in simulations over a 33.8 km flight, outperforming ORB-SLAM2 and ORB-SLAM3. Processing speed of 12 Hz ensures real-time performance. |
| Ngo et al. (2022) | ✓ | | ✓ | ✓ | | | | ✓ | | | | ✓ | ✓ | - Development of UAVs for autonomous search and rescue in GPS-denied environments. Utilized SLAM for mapping and computer vision for victim detection. Demonstrated in simulations and flight tests. |
| Ho et al. (2021) | | | ✓ | | | | | ✓ | | | | ✓ | | - Utilized LiDAR-based SLAM for 2-D UAV navigation in GPS-denied environment. Achieved up to 45% increase in processing speed and accurate trajectory mapping in MATLAB simulation. |

Table 9 Pros and cons of localization techniques

| Localization type | Technique | Pros | Cons |
|-------------------|--|---|---|
| AL | Template and feature matching | Achieves high precision in environments with distinct terrains, utilizing detailed feature comparison. | Loses effectiveness in uniform landscapes with a lack of distinct features. |
| | Semantic mapping and recognition | Offers in-depth insights into the environment, utilizing semantic information to enhance accuracy and awareness. | Demands extensive computational resources, posing challenges for real-time application. |
| RL | Dead reckoning, filtration, & error optimization | Provides reliable continuous tracking crucial for GPS-independent navigation through IMU data integration and error correction. | Tends to accumulate errors over time, requiring periodic recalibration or adjustments. |
| | SLAM | Enables mapping and localization in unknown environments, offering a comprehensive solution for exploration in GNSS-denied areas. | Requires sophisticated algorithms and extensive computational resources, making implementation challenging on constrained UAVs. |
| | Visual odometry & optical flow | Performs effectively in dynamic environments by providing accurate motion estimation through visual data analysis. | Suffers from degraded performance under poor lighting, rapid movements, or in featureless environments. |
| | Visual-inertial odometry | Enhances robustness of localization by combining visual data with inertial measurements, improving accuracy and stability. | Necessitates complex integration and precise calibration, presenting significant technical challenges. |

large-depth scenarios, using multiple datasets such as EuRoc, Kitti, and NUDT.

- *EuRoc datasets* (Burri et al., 2016): These datasets are commonly used in the research community for testing visual-inertial odometry algorithms. The EuRoc datasets were collected using a micro-aerial vehicle (MAV) and include 20 Hz stereo images, 200 Hz IMU data, and ground truth data.
- *Kitti datasets* (Rosten et al., 2010): The Kitti datasets were collected using a land vehicle equipped with sensors, including cameras and IMUs. The datasets include 10 Hz images, 200 Hz IMU data, and ground truth, making them suitable for testing algorithms in urban and highway environments.
- *NUDT datasets*: The NUDT datasets consist of sequences from both UAV and land vehicle experiments. The UAV data were collected at an altitude of about 180 ms, covering a distance of 2.8 km, while the land vehicle data covered a distance of 4.5 km. These datasets provide challenging sequences for visual-inertial odometry testing, especially in large-depth environments.

The results of the PO-MSCKF algorithm demonstrated exceptional performance in various

challenging scenarios. In the EuRoc dataset, particularly in the difficult MH05 sequence of the Machine Hall environment, PO-MSCKF achieved an RMSE of 0.28 ms, highlighting its robustness in complex indoor settings. In the Kitti datasets, which consist of urban and highway environments with varying depths, the algorithm consistently outperformed other state-of-the-art methods, achieving RMSE values ranging from 9.17 ms in Kitti08 to 14.01 ms in Kitti10. The algorithm's robustness was further validated in the NUDT dataset, which included experiments in large-depth environments. Here, PO-MSCKF achieved an RMSE of 10.69 ms in the land vehicle experiment and 25.47 ms in the UAV experiment, proving its ability to maintain high accuracy even in conditions where traditional methods struggled, particularly in altitude estimation.

- *Strengths*: PO-MSCKF is particularly effective in environments with varied depth, such as those found in the Kitti datasets. The algorithm addresses some of the common limitations of standard VIO systems by avoiding the need for 3D feature reconstruction, thus improving accuracy in pose estimation and enhancing computational efficiency.

- *Limitations:* While PO-MSCKF excels in structured environments, it may face challenges in unstructured or visually featureless environments. Additionally, the algorithm might struggle in dynamic or rapidly changing environments, where the traditional limitations of VIO systems could still persist.

3. *Steerable-laser terrain-referenced navigation system* (Carroll & Canciani, 2021):

- *Description:* The study by Carroll & Canciani (2021) investigated a steerable-laser TRN system designed specifically for GPS-denied environments. Mounted on an aircraft, the system utilized a steerable laser altimeter capable of measuring terrain profiles at various slant angles, representing a significant advancement over traditional nadir-only systems, which capture data directly beneath the aircraft in a vertical orientation. The experiment was conducted under two distinct flight scenarios: a flat terrain profile over California and a mountainous terrain profile. The steerable-laser TRN system demonstrated substantial improvements in navigation accuracy, particularly in complex terrains. In flat terrain, optimal laser steering led to a remarkable reduction in RMSE values, decreasing from 29.1 ms (East) and 30.7 ms (North) to 10.8 ms (East) and 7.9 ms (North). In mountainous terrain, the enhancements were more significant, with RMSE values reduced to 1.2 ms (East) and 1.0 ms (North). These results indicate that the system can enhance navigation accuracy by up to 20 times compared to traditional nadir-only systems.
- *Strengths:* The system is particularly effective in complex terrains, such as mountainous regions, where traditional TRN systems might struggle. By optimizing the laser steering, the system significantly enhances navigation accuracy, reducing RMSE values dramatically in such environments. Moreover, the steerable-laser TRN system does not depend on external signals, making it highly reliable in GPS-denied or contested environments. The ability to adjust the laser's angle to target specific terrain features optimizes the amount of navigational information collected, significantly improving overall system performance.
- *Limitations:* While the system's performance in complex terrains is impressive, its complexity and potential cost may limit its application to smaller UAVs or budget-conscious projects. Additionally, the requirement for specialized hardware and pre-

cise calibration can increase operational overhead. Furthermore, the system's reliance on laser technology may pose challenges in adverse weather conditions, such as fog or heavy rain, where laser measurements could be disrupted. This limitation might necessitate the use of complementary sensors or techniques to ensure reliable operation under all conditions.

4. *Novel positioning method for UAVs in GNSS-denied environments* (Cui et al., 2024):

- *Description:* Cui et al. proposed a novel positioning method for UAVs in GNSS-denied environments using a Mechanical Antenna (MA). The system comprises a rotating permanent magnet-based MA installed on the UAV, which generates a Low-Frequency (LF) magnetic signal. This signal is received by a 3D magnetic field sensor at a ground base station. The positioning algorithm employed is based on Particle Swarm Optimization (PSO), which calculates the UAV's position relative to the base station. The LF bands offer high propagation stability and strong anti-interference capabilities, making this method particularly effective in challenging environments such as dense forests or underground areas. Experimental results showed that the system achieved a mean positioning error of 0.43 ms within a range of 549 ms. The experiments also demonstrated that the system maintained a stable signal propagation and was resilient to environmental interferences, making it a robust alternative for accurate UAV positioning in scenarios where GNSS signals are unreliable or unavailable.
- *Strengths:* This method is highly effective in environments where traditional GNSS signals are unreliable, such as dense forests or underground areas. The LF magnetic signal generated by the MA ensures stable and interference-resistant communication. The PSO algorithm enhances the system's accuracy and efficiency in position calculation, making it suitable for a wide range of industrial applications. The system's positioning accuracy of 0.43 ms is a significant achievement, highlighting its potential for precise navigation in GNSS-denied environments.
- *Limitations:* The reliance on ground-based infrastructure, such as the 3D magnetic field sensor and base station, limits the system's flexibility and scalability for large-scale or remote operations. The system also requires precise calibration and maintenance of the ground station to ensure accu-

racy. Additionally, the effective range of 549 ms may not be sufficient for all applications, particularly those requiring long-range positioning.

5. *Long-range GPS-denied aerial navigation with LiDAR localization* (Hemann et al., 2016):

- **Description:** Hemann et al. presented a method for long-range GPS-denied aerial navigation using LiDAR localization, validated on two helicopter flights covering distances of 196 km and 218 km. The system achieved a final position error of 27.2 ms, representing 0.012% of the total distance traveled, demonstrating a significant improvement in drift-free navigation over long distances. The method integrates LiDAR measurements with an error-state KF, which uses intermittent global corrections to maintain an accurate state estimate. The LiDAR system provided 42,000 measurements per second, and the method was tested using 10 m resolution DEMs from the U.S. Geological Survey's (USGS). The system exhibited robustness in challenging environments, such as dense vegetation or low terrain variability, demonstrating the feasibility of long-distance GPS-denied navigation using advanced sensor fusion techniques.
- **Strengths:** The LiDAR-based system is highly effective for long-range navigation, offering minimal drift over extended distances. It performs well in different environments, including those with limited visual features, and is less affected by lighting conditions. The system's ability to maintain a small position error (within 27.2 ms over 218 km) demonstrates its robustness in challenging conditions.
- **Limitations:** The system's reliance on accurate and up-to-date DEMs can limit its effectiveness in rapidly changing environments. While LiDAR systems are more expensive and required higher computational resources-potentially restricting their use in smaller UAVs or cost-sensitive applications-we acknowledge that recent developments (e.g., Livox Mid 360, Unitree L1, Intel Realsense L515) offer more compact, lightweight, and energy-efficient LiDAR sensors with lower price. Nevertheless, challenges remain, especially when operating in featureless or uniformly flat terrains (e.g., flying over water or regions with minimal height variation), where both LiDAR and DEM-based matching can struggle to maintain accuracy due to the lack of distinct features. As such, additional sensing modalities (e.g. RGB/thermal cameras) or complementary algorithms may still be

necessary to ensure robust performance in these environments.

The experimental results reveal multiple strategies for UAV localization in GPS-denied environments, with different systems excelling in specific conditions. Some systems perform best in structured and visually rich settings, while others are more effective in complex terrains where traditional methods fall short. It is noted that achieving centimeter-level accuracy is typically feasible only in optimal, feature-rich settings. However, outdoor environments often introduce additional challenges that can impact performance.

Implications for different UAV types and altitudes

One important practical consideration in selecting a non-GNSS navigation strategy is the type of UAV platform and its typical flight altitude.

Fixed-wing UAVs often fly at higher altitudes and maintain faster and more stable flight profiles. As a result, techniques leveraging coarse or large-scale terrain matching-such as TERCOM and DSMAC-can be more suitable for these platforms. Their reliance on broader and consistent terrain features aligns well with the altitude ranges and speed envelopes that many fixed-wing aircraft maintain. On the other hand, rotorcrafts (e.g., quadcopters), which typically operate at lower altitudes and hover or fly slowly, benefit more from SLAM-based methods or visual odometry. These techniques rely on local and detailed features in the immediate environment, which rotorcraft can capture effectively due to their proximity to the ground and slower, more agile flight dynamics.

Consequently, the operational envelope (e.g., flight altitude, speed) and vehicle type (fixed-wing vs. rotorcraft) become important design considerations when deciding on sensor payload and navigation algorithms. Fixed-wing UAVs may allocate more onboard resources for terrain-based correlation (using DEMs, RADAR altimetry, etc.), while rotorcraft often favor real-time vision or LiDAR-based SLAM pipelines.

Going forward, system designers should continue to tailor navigation algorithms to the primary use cases of each UAV platform, ensuring that processing power, sensor selection, and algorithmic complexity match the flight regimes. Balancing these trade-offs can optimize performance and reliability in diverse GNSS-denied conditions.

Future directions

The advancement of autonomous localization technologies, encompassing both absolute and relative localization, is crucial for the future of UAV operations, particularly in GNSS-denied environments. As these

technologies evolve, several key areas offer substantial opportunities for innovation, enhancing UAV capabilities in challenging conditions:

- *Advanced multi-modal sensor fusion:* Integrating data from various sensors into a unified framework is crucial to overcoming individual sensor limitations. By synthesizing information from sources such as cameras, LiDAR, RADAR, and IMUs, UAVs can achieve a comprehensive understanding of their environment, significantly improving navigation accuracy in GPS-denied scenarios.
- *Deep learning and AI integration:* The integration of deep learning and AI for advanced data analysis and predictive modeling is poised to transform UAV localization. These technologies empower UAVs to navigate autonomously through complex environments with higher precision by continually learning from and adapting to their surroundings. Future research will likely center on developing more advanced AI models capable of addressing the variability and unpredictability inherent in real-world scenarios, ultimately improving the accuracy, reliability, and efficiency of UAV localization systems in GPS-denied environments.
- *Enhancing real-time processing capabilities:* Real-time processing is crucial for UAVs, especially in GPS-denied environments where timely decision-making based on sensor data is essential for safe navigation. To optimize performance, UAVs should leverage advanced computing platforms to reduce processing latency and fine-tune sensor fusion algorithms for specific hardware architectures using techniques such as data downsampling and optimized matrix operations. Additionally, maintaining low-latency communication between sensors and processing units through high-bandwidth protocols and strategic positioning is vital to minimize data transmission delays.
- *Addressing implementation barriers:* Implementing multi-modal sensor fusion frameworks in UAVs presents several practical challenges essential for reliable operation. Achieving the full potential of UAV localization in GPS-denied environments necessitates ongoing advancements focused on:
 - *Sensor calibration:* Future efforts must ensure accurate calibration, as it is crucial for reliable data fusion. Calibration errors can lead to significant inaccuracies in UAV positioning and orientation, particularly in GPS-denied environments where alternative navigational aids are unavailable.
 - *Data synchronization:* Efforts must focus on improving synchronization mechanisms, as sensors often operate at different sampling rates and experience varying latencies. Advanced time-stamping and interpolation techniques will be critical to aligning data streams effectively.
 - *Environmental adaptation:* Sensor systems must be developed to adapt to environmental factors like fog or low light. Future solutions should enable adaptive weighting of sensor inputs based on their reliability under specific conditions to maintain consistent performance.
 - *Software integration:* Further work is required to develop middleware that efficiently manages data flow between sensors, fusion algorithms, and UAV control systems, ensuring seamless software integration.
 - *Power efficiency:* Efforts should focus on energy-efficient algorithms and hardware to manage the increased power demands from sensor fusion, which is particularly critical for battery-powered UAVs.
 - *Scalability:* Future sensor fusion frameworks should be designed to integrate additional sensors and adapt to various UAV platforms without requiring significant reconfiguration, ensuring scalability.

Conclusion

This paper presents a comprehensive review of key developments in UAV navigation, with a particular focus on operations in environments where GNSS is unavailable. Our analysis highlights key innovations in sensor technologies, including IMUs, barometers, and the strategic fusion of cameras, RADAR, and LiDAR. These advancements have collectively reduced the dependency on GNSS, allowing UAVs to operate more effectively in challenging environments. A key component of these innovations is the integration of VIO and SLAM, both essential for improving UAV localization accuracy. VIO combines visual data with inertial measurements, allowing for precise navigation even when GNSS signals are unreliable. Meanwhile, SLAM enhances this capability by simultaneously mapping unknown environments and tracking the UAV's position, enabling seamless interaction with dynamic surroundings.

Furthermore, our survey emphasized the transformative potential of AI-driven Semantic Mapping and Recognition technologies, which enable UAVs to autonomously recognize and categorize environmental features, significantly improving decision-making and operational efficiency. These improvements become even more impactful when integrated with absolute methods such

as terrain-aided navigation techniques like TERCOM and DSMAC, offering a powerful synergy. AI improves the UAV's ability to interpret complex terrains, while terrain-based techniques ensure precise positioning, providing reliable path finding even in the most challenging conditions without GNSS signals. By combining AI's real-time scene analysis with terrain elevation data, these methods enhance the robustness of UAV navigation in GNSS-denied environments.

In conclusion, this survey provides a comprehensive overview of the current advancements in UAV navigation in GNSS-denied environments, highlighting both significant achievements and areas ripe for further research. The collaborative efforts of the international research community are crucial in overcoming the challenges of GNSS-independent navigation, ultimately aiming to equip UAVs for safe and efficient operation in diverse environments. As the field continues to evolve, the integration of cutting-edge sensors, advanced algorithms, and innovative localization techniques will be instrumental in shaping the future of autonomous UAV navigation, making airspace more navigable and accessible than ever before.

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Author contributions

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Competing interests

The authors declare no Conflict of interest.

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