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Review Article

Review of GPS and IMU System Performance in Unmanned Aerial Vehicles (UAVs)

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Abstract

This paper reviews the pivotal role of Global Positioning System and Inertial Measurement Unit technologies in the navigation and control of Unmanned Aerial Vehicles. The Global Positioning System offers precise global positioning, while the Inertial Measurement Unit provides high-frequency motion and orientation data. However, Global Positioning System signal interruptions and Inertial Measurement Unit drift pose challenges, particularly in dynamic or Global Positioning system-denied environments. This review explores the integration of the Global Positioning System and low-cost Inertial Measurement Unit systems through advanced sensor fusion techniques, such as Kalman filtering and machine learning, to enhance navigation reliability. Future directions, including advancements in hardware, adaptive algorithms, and swarm navigation, are discussed to address operational challenges and unlock the potential of Unmanned Aerial Vehicles in diverse applications.

Keywords: UAVs, GPS, MEMS-based IMU, sensor fusion, positioning accuracy, system performance, navigation

İnsansız Hava Araçlarında (İHA) GPS ve IMU Sistem Performansının İncelenmesi

Özet

Bu makale, İnsansız Hava Araçlarının navigasyon ve kontrolünde Küresel Konumlama Sistemi ve Ataletsel Ölçüm Birimi teknolojilerinin kritik rolünü incelemektedir. Küresel Konumlama Sistemi, hassas küresel konumlama sağlarken, Ataletsel Ölçüm Birimi yüksek frekanslı hareket ve yönelim verileri sunar. Ancak, Küresel Konumlama Sistemi sinyal kesintileri ve Ataletsel Ölçüm Birimi kayması, özellikle dinamik görevlerde veya Küresel Konumlama Sistemi erişiminin olmadığı ortamlarda zorluklar yaratmaktadır. Bu inceleme, navigasyon güvenilirliğini artırmak için Kalman filtresi ve makine öğrenimi gibi ileri seviye sensör füzyon teknikleri kullanılarak Küresel Konumlama Sistemi ve düşük maliyetli Ataletsel Ölçüm Birimi sistemlerinin entegrasyonunu ele almaktadır. Çalışmada ayrıca donanım gelişmeleri, uyarlanabilir algoritmalar ve sürü navigasyonu gibi gelecekteki yönelimler ele alınarak operasyonel zorlukların üstesinden gelinmesi ve İnsansız Hava Araçlarının çeşitli uygulamalardaki potansiyelinin açığa çıkarılması hedeflenmektedir.

Anahtar Kelimeler: İnsansız hava araçları, GPS, MEMS tabanlı IMU, sensör füzyonu, konum doğruluğu, sistem performansı, navigasyon

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1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are utilized in diverse fields such as military, agriculture, logistics, surveillance, and disaster management, where precise navigation and stable orientation control are essential. For UAVs to operate effectively, they rely heavily on accurate positioning and orientation data. This is achieved by integrating a Global Positioning System (GPS) and an Inertial Measurement Unit (IMU), each serving a complementary role in tracking a UAV's position and orientation [1, 2].

However, GPS performance is often hindered by environmental factors, such as signal multipath and satellite obstructions, which can lead to latency or inaccuracies [3]. On the other hand, the IMU system provides high-frequency orientation and motion data but is susceptible to long-term drift, which degrades positional accuracy over time [4]. To address these challenges, sensor fusion techniques have emerged as a popular approach for integrating GPS and IMU data, allowing UAVs to leverage the strengths of each system while mitigating their respective weaknesses [5].

To establish a strong foundation for this study, a thorough literature review was conducted using various academic platforms (e.g., Google Scholar, Web of Science, ScholarOne, ScienceDirect) to analyze existing research on GPS and IMU systems in UAVs. A total of 67 sources, including books and articles, were examined, out of which 42 were deemed relevant and cited in this paper. This review focuses on identifying key methodologies, advancements, and issues related to the integration of GPS and IMU systems and their performance enhancement. By examining various studies, the paper aims to provide a comprehensive understanding of current trends and future research directions in GPS/IMU sensor fusion. The key terms associated with this study include but are not limited to, UAV navigation, GPS accuracy, GPS spoofing, IMU drift, GPS advantages, IMU sensor advantages, sensor fusion, Kalman Filter, machine learning approaches in UAV navigation, and positioning algorithms.

This paper provides a detailed analysis of the GPS and IMU systems used in UAVs, examining the individual characteristics of each system, their benefits, limitations, and the potential of sensor fusion to enhance UAV performance. This review paper is structured as follows: section 2 provides a technical background about GPS and IMU systems in UAVs, section 3 presents an integration of GPS and IMU systems, section 4 explores sensor fusion techniques in UAVs, section 5 discusses open challenges in GPS/IMU integration, section 6 highlights future directions, and section 7 gives concluding points about the topic.

2. TECHNICAL BACKGROUND: GPS AND IMU SYSTEMS IN UAVS

2.1 Overview of GPS and IMU Systems in UAVs

UAVs rely heavily on GPS and IMU systems for accurate navigation, stability, and control. Each system contributes uniquely.

GPS provides absolute positional data by triangulating signals from satellites, offering global coverage and high accuracy, especially in open environments. Its precision can be further enhanced by techniques like Real-Time Kinematic (RTK) positioning and Differential GPS (DGPS). However, its performance is hindered by environmental factors such as multipath errors, signal obstructions, and susceptibility to jamming and spoofing, which can compromise its reliability.

IMU measures orientation, velocity, and acceleration through sensors like accelerometers and gyroscopes, providing high-frequency data essential for motion tracking. While it offers valuable measurements, it faces challenges such as drift over time and sensitivity to environmental noise, which can affect accuracy over extended periods.

Figure 1 illustrates the complementary roles of GPS and IMU in UAV navigation, highlighting their combined strengths.

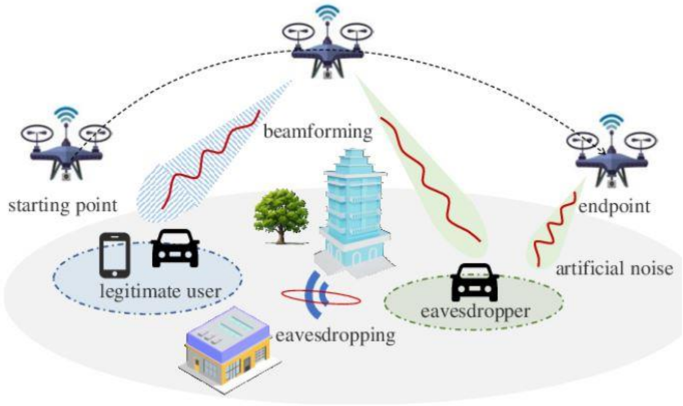

Figure 1. UAV-enabled secure communication networks [6]

This section provides a detailed exploration of the features, advantages, and limitations of GPS and IMU technologies as applied to UAVs, supported by recent studies and technical resources.

GPS technology for UAVs relies on a constellation of satellites that transmit signals to GPS receivers on the UAV. These receivers calculate their position by measuring the time delay from multiple satellite signals and triangulating their location. This system plays a critical role in ensuring reliable and precise navigation for UAVs. GPS enables real-time positioning, allowing UAVs to determine their exact coordinates, which is essential for navigation and following predefined flight paths [7]. Its global coverage ensures accessibility in diverse and remote environments where terrestrial navigation may not be available [8]. Additionally, GPS data helps determine both altitude and speed, which are critical for stable flight control. This is particularly valuable in applications that demand accurate altitude management, like surveying or mapping [7, 9].

Advanced GPS options such as DGPS and RTK positioning enhance precision by providing real-time corrections. These methods are particularly valuable in operations where even small positioning errors could impact results, such as aerial inspections and precision agriculture [7-9]. The integration of GPS in UAVs provides a wide array of benefits, making it an indispensable tool for both commercial and research applications. These advantages significantly enhance the performance and usability of UAVs in various fields such as agriculture, surveying, infrastructure inspection, and environmental monitoring.GPS also contributes to enhanced autonomy, enabling UAVs to follow predefined flight paths independently with high accuracy and efficiency. This capability is especially useful in applications like land surveying, precision agriculture, and infrastructure assessment, where repeated and precise flights are necessary. Autonomous navigation reduces the need for manual intervention and increases the potential for large-scale data collection [10, 11].

Another key advantage of GPS is cost efficiency. GPS receivers are relatively affordable and can be integrated into small UAV systems without significantly increasing the overall cost. This makes GPS a cost-effective solution for UAVs, particularly for commercial applications where minimizing operational costs is a priority. With the availability of low-cost GPS receivers that provide accurate positioning, UAV systems can deliver precise navigation without the need for expensive alternatives like ground-based systems [10, 12]. Finally, GPS enables real-time monitoring and control, allowing UAV operators to continuously track the UAV's location, which is essential for mission control and safety. This capability is crucial in applications where continuous monitoring of UAVs is required, such as in disaster response scenarios or during long-distance flights. The real-time data allows for in-flight adjustments, ensuring the UAV stays on course and responds to dynamic environmental conditions or unexpected obstacles, thus enhancing mission safety and success [10, 11].

Despite its widespread use and critical role in UAV navigation, GPS technology has certain limitations that can impact UAV performance, particularly under specific environmental and operational conditions. One such limitation is signal interference and multipath errors, where GPS signals can be blocked, reflected, or attenuated by obstacles like buildings, trees, and mountains. These multipath errors can reduce GPS accuracy, especially in urban or forested areas where signal reflections may mislead the receiver. In these environments, UAVs can experience significant positioning errors due to these distorted signals [11].

Another limitation arises from low accuracy in dynamic conditions, where rapid movement during high-speed UAV flight can introduce errors in GPS measurements due to Doppler shifts. Furthermore, GPS receivers may struggle to update positions quickly enough, leading to inaccuracies. This issue is particularly noticeable in fast-moving UAVs, such as those used in aerial photography or surveying, where precise real-time positioning is critical. Additionally, environmental factors like ionospheric and tropospheric delays can interfere with GPS signal transmission, reducing the accuracy and reliability of GPS readings. These atmospheric effects are especially relevant for UAVs operating at high altitudes or in extreme weather conditions, where signal degradation may occur more frequently.

GPS performance is also dependent on the availability and visibility of satellite constellations. In regions with limited satellite visibility, such as polar areas or dense urban landscapes, GPS performance can degrade significantly, leading to less reliable positioning data for UAVs operating in these challenging environments. Lastly, GPS signals are vulnerable to intentional jamming and spoofing, which poses a significant security risk for UAV operations, especially in applications requiring high reliability, such as military or critical commercial operations. The risk of signal interference can jeopardize mission success and UAV safety in sensitive or hostile environments [11, 13]. Figure 2 illustrates a spoofing scenario.

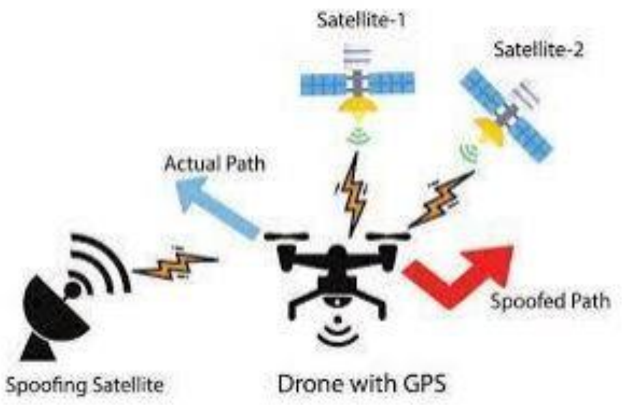

Figure 2. Spoofer tries to deviate UAV from the main trajectory [14]

To mitigate some of the limitations of GPS, various enhancements and complementary technologies are being employed in UAVs to improve accuracy and reliability, especially in challenging environments. These advancements help address the issues of signal interference, multipath errors, and limited accuracy. One such enhancement is RTK GPS, which improves the precision of GPS data by using ground-based reference stations to provide real-time corrections. This method achieves centimeter-level accuracy, making it crucial for precision tasks such as surveying and agriculture, where high positional accuracy is paramount. RTK GPS has become a standard for tasks that require extreme precision, as it can correct errors in real-time, reducing the dependency on satellite visibility [15].

Another approach is DGPS, which enhances GPS accuracy by using ground stations that transmit correction signals. DGPS is widely used in applications where sub-meter accuracy is required. By correcting signal errors and reducing positional drift, DGPS ensures that UAVs can maintain accurate positioning even over long-duration flights. This technology has been applied in fields such as precision farming and infrastructure inspection, where minor positional errors can lead to significant operational consequences. Additionally, UAVs sometimes use augmented GPS systems such as Wide Area Augmentation System (WAAS) or European Geostationary Navigation Overlay Service (EGNOS) to enhance the accuracy, integrity, and availability of GPS signals. These systems provide corrections that improve GPS performance, particularly in regions with limited satellite coverage. By reducing the impact of atmospheric and signal-related errors, these augmentation systems make GPS navigation more reliable in remote or challenging environments [8].

GPS technology plays a critical role in UAV performance, providing essential data for autonomous navigation and real-time location tracking. Despite its limitations, particularly in terms of signal reliability and susceptibility to environmental interference, advancements in GPS technology—coupled with the integration of systems like IMUs—are enhancing UAV capabilities across a broad spectrum of applications. Future improvements in GPS technology, along with the development of robust sensor fusion methods, are expected to further expand the operational effectiveness of UAVs in complex environments [3,8].

IMU systems are crucial in UAVs for ensuring stable navigation, orientation, and flight control. By providing real-time data on acceleration and angular velocity, IMUs enable UAVs to maintain stability and correct for disturbances autonomously. MEMS, which stands for Micro Electromechanical Systems, enables the integration of microelectronic circuits and mechanical structures on a single chip, facilitating monolithic integration. This technology has revolutionized sensor design, making it possible to sense the physical and chemical aspects of the external environment with high precision. Over recent decades, MEMS has become a leading choice in sensor development, particularly for applications in UAVs, where IMU sensors play a critical role. MEMS-based IMUs offer several advantages over traditional sensors, including smaller size and lower cost, enhanced sensitivity, and the ability to be batch-fabricated on wafers with integrated circuits. These attributes make MEMS ideal for UAV applications, where weight, space, and power efficiency are crucial, allowing for improved navigation, control, and stability [16, 17].

An IMU is a sensor module that measures an object's velocity, orientation, and gravitational forces. Most UAV IMUs consist of an accelerometer, a gyroscope, and sometimes a magnetometer. Each component of the IMU contributes uniquely to flight control and stability, which are mentioned below in detail; respectively.

An accelerometer in a UAV's IMU measures linear acceleration across three axes (x, y, and z). It detects the rate of velocity change due to forces such as gravity, allowing the UAV to assess tilt, altitude shifts, and motion. This data is critical for stabilizing the UAV, particularly when hovering or performing controlled maneuvers. MEMS (Micro-Electro-Mechanical Systems) technology is commonly used in UAV accelerometers due to its small size, low weight, and high sensitivity, which is ideal for compact UAV designs. By continuously analyzing acceleration data, the accelerometer assists in maintaining a stable flight path [17]. Accelerometers offer specific advantages, such as high-frequency stability data, which helps the flight controller quickly adjust for minor shifts, maintaining flight stability. They also provide continuous data on the UAV's tilt and altitude, which is crucial for operations that require precision, like mapping or surveying. However, accelerometers can be susceptible to issues such as noise and drift over time, which may impact long-duration flights. Techniques like Kalman filtering are often used to mitigate these issues, especially when accelerometer data is fused with gyroscope and GPS inputs to enhance accuracy [12, 17].

The gyroscope measures the UAV's angular velocity along three rotational axes: roll, pitch, and yaw. By detecting rotational movement, the gyroscope plays a critical role in maintaining orientation, allowing the UAV to make real-time corrections during dynamic maneuvers. This is particularly essential in environments with strong wind or when the UAV performs quick directional changes. In UAVs, MEMS-based gyroscopes are widely used, as they are compact, responsive, and integrate well with accelerometer data for precise movement tracking [17]. Gyroscopes play a critical role in maintaining the UAV's fixed orientation, ensuring stabilized video capture and smooth flight transitions. Additionally, they enable the flight controller to make rapid adjustments during sudden environmental changes or high-speed operations, enhancing overall flight performance and reliability. The main limitation of gyroscopes is their potential for drift, especially over long flights. Integrating gyroscope data with accelerometer and magnetometer readings in sensor fusion algorithms reduces this drift, allowing for improved reliability and accuracy in UAV navigation systems [12, 17].

Magnetometer measures magnetic field strength and direction, often used to provide heading information when GPS signals are weak or unavailable. This feature is particularly valuable for UAVs flying in dense urban areas or remote locations with limited satellite visibility. Magnetometers help maintain heading information, especially when GPS data is unreliable or obstructed by tall structures or dense foliage [17].

Figure 3 shows the classical configuration of IMU sensors.

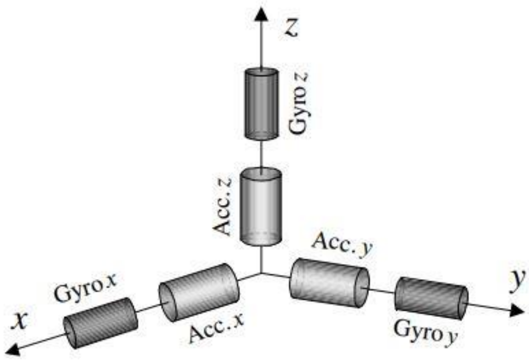

Figure 3. Classical configuration of IMU sensors [18]

Together, these sensors enable UAVs to detect and respond to dynamic changes in flight conditions. When combined with GPS data, IMU data allows UAVs to navigate smoothly and avoid obstacles even in environments with poor GPS signal quality. The integration of IMU sensors helps ensure that UAVs can perform in areas where GPS signals are intermittent, making the system more robust in challenging environments [12, 18, 19].

In UAVs, stability and control are paramount for ensuring reliable operation under varying flight conditions. IMUs, which typically combine accelerometers, gyroscopes, and sometimes magnetometers, are critical for enhancing the stability and control of UAVs by providing real-time measurements of the vehicle’s orientation and motion. The integration of IMUs with other navigation systems, such as GPS, significantly improves UAV performance, particularly in environments with weak or unreliable GPS signals, such as urban canyons or dense forests.

IMUs provide high-frequency data that is essential for maintaining the UAV’s attitude (pitch, roll, and yaw) and velocity (acceleration and angular velocity). These measurements enable the flight control system to make rapid adjustments to stabilize the UAV in response to external disturbances or aerodynamic forces. The accelerometer in an IMU measures linear acceleration, while the gyroscope records angular velocity, allowing the UAV to maintain its desired orientation with high precision. This capability is especially critical in applications such as aerial mapping, surveillance, and search-and-rescue missions, where precise control and stability are crucial for mission success.

When GPS data is lost or degraded, the IMU continues to provide continuous measurements of the UAV’s position and orientation, ensuring uninterrupted operation. Studies have shown that IMU-based systems can significantly enhance UAV performance by compensating for GPS signal loss or interference, which is particularly important in precision applications such as surveying and infrastructure inspection [8].

Additionally, the small size and low weight of MEMS-based IMUs make them ideal for UAV applications, where minimizing payload is critical. These advantages, combined with the ability to integrate IMU systems with GPS, result in improved UAV stability, reliability, and control, enabling successful operations across a wide range of demanding tasks [8, 20].

While IMUs offer significant advantages in UAVs, such as providing high-frequency data on motion and orientation, they also have several limitations that must be addressed for optimal performance in various UAV applications. These limitations stem from factors such as sensor drift, bias accumulation, and sensitivity to environmental conditions.

One of the primary limitations of IMU systems is the inherent drift that occurs over time due to sensor inaccuracies. Gyroscopes, which measure angular velocity, are prone to drift, meaning that small errors in the measurement can accumulate, leading to larger deviations in the UAV's estimated position and orientation. Over time, this drift can result in significant errors in navigation and control, particularly in long-duration flights where frequent corrections are required [21].

Another limitation of IMUs is the sensitivity of accelerometers and gyroscopes to temperature fluctuations and other environmental factors. These sensors can experience varying degrees of error under different temperature conditions, which can lead to biases in the measurements. As MEMS-based sensors are more compact and cost-effective, they tend to be more susceptible to environmental variations compared to larger, more precise sensors [16]. This challenge can be particularly problematic in UAV applications that operate in harsh or rapidly changing environments, where temperature variations are common.

Additionally, while the integration of IMU and GPS data via sensor fusion techniques such as Kalman filtering has been shown to improve accuracy, the reliability of the GPS signal itself can be a limiting factor. IMUs can maintain accurate orientation and motion data when GPS signals are unavailable, but they cannot provide the positional accuracy required for many UAV tasks, such as surveying or mapping, without the aid of external navigation systems. This issue emphasizes the importance of robust sensor fusion techniques that combine IMU data with reliable positioning systems to enhance overall UAV performance.

Despite these limitations, advancements in IMU technology and sensor fusion methods continue to improve the performance of UAV systems. Ongoing research focuses on reducing the impact of drift, enhancing temperature stability, and optimizing sensor fusion algorithms to further improve the accuracy and reliability of IMU-based navigation systems for UAVs.

IMU systems have become an integral part of UAV navigation due to their ability to provide real-time data on orientation, velocity, and acceleration. However, the performance of IMUs can be limited by factors such as sensor drift, noise, and sensitivity to environmental conditions. Recent advancements in IMU technology have addressed these limitations, improving the accuracy, reliability, and overall performance of UAV systems.

One significant enhancement is the integration of advanced sensor fusion algorithms, such as Kalman filtering, which combines IMU data with other navigational sensors like GPS and magnetometers. This fusion allows UAVs to compensate for the drift and bias that are inherent in standalone IMU systems. The combination of GPS and IMU data can significantly reduce errors in UAV positioning and orientation, even in GPS-denied environments, improving system stability and precision for tasks such as surveying and agriculture [8].

Another key enhancement in IMU systems is the use of high-precision MEMS sensors. MEMS-based accelerometers and gyroscopes offer smaller sizes, lower costs, and better integration with other systems, which is particularly advantageous for UAV applications where payload weight and space are critical. These sensors can now achieve higher accuracy and stability compared to earlier MEMS models, making them more suitable for precise control in UAV flight dynamics. Additionally, MEMS sensors are often designed to be more resilient to environmental factors, such as temperature and humidity, thus enhancing their performance in varying conditions [16].

Furthermore, the development of error correction techniques has greatly improved the performance of IMU systems in UAVs. Recent advancements in bias correction, drift compensation, and noise filtering are essential for extending the operational time of IMUs without significant performance degradation. These error correction techniques can significantly mitigate the impact of environmental noise and sensor imperfections, ensuring that UAVs can maintain high accuracy during extended flights [22].

The fusion of IMU data with external reference systems, such as RTK GPS or DGPS, has become another essential enhancement. RTK and DGPS systems provide real-time corrections to GPS data, achieving centimeter-level accuracy, and when combined with IMU data, they allow for even more precise UAV navigation, particularly in critical applications such as surveying, infrastructure inspection, and precision farming [3, 8].

These enhancements in IMU technology and integration with other systems have made UAVs more robust, accurate, and reliable, enabling their use in a wide range of applications, from autonomous delivery to disaster response. Figure 4 depicts sample IMU sensor placement and orientation of the quadrotor.

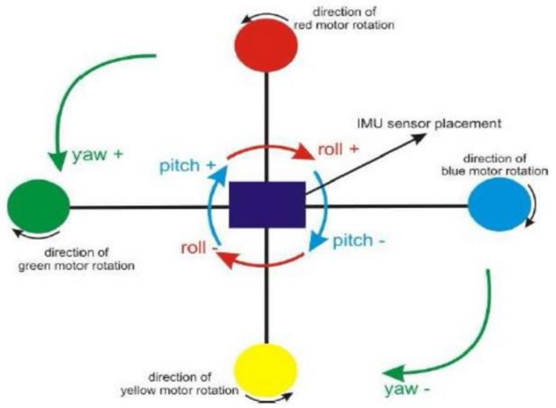

Figure 4. IMU sensor placement and orientation of the quadrotor [23]

2.2 Comparative Analysis of GPS and IMU Systems

GPS and IMU systems are critical for UAV navigation, providing complementary capabilities. GPS offers long-term positional accuracy, global coverage, and support for real-time corrections via methods such as RTK and DGPS, making it indispensable for tasks like surveying, mapping, and waypoint navigation. IMU, on the other hand, provides high-frequency orientation and motion data, enabling stability and control in dynamic environments. Its independence from external signals allows reliable performance in GPS-denied areas like urban canyons or dense forests.

However, both systems also have their limitations. GPS is susceptible to signal loss or degradation due to environmental obstructions such as buildings and trees, as well as atmospheric interference. Additionally, it is vulnerable to intentional disruptions like jamming and spoofing. IMU, meanwhile, experiences drift over time due to sensor biases and noise, leading to reduced accuracy during extended operations. It is also sensitive to environmental conditions such as temperature changes.

So, integrating these two systems has its benefits. Combining GPS and IMU mitigates individual limitations, ensuring both absolute and relative accuracy. GPS corrects IMU drift, while IMU compensates for temporary GPS outages, enabling robust navigation even in challenging environments.

3. INTEGRATION of GPS and IMU SYSTEMS

The integration of GPS and IMU systems enhances UAV navigation by addressing the limitations of each. GPS corrects long-term drift in IMUs, while IMUs provide continuous data during GPS signal loss. Advanced fusion algorithms, such as Kalman filtering, ensure seamless integration, enabling UAVs to navigate accurately even in challenging environments.

GPS provides highly accurate absolute positioning but is susceptible to signal interruptions or degradation due to environmental factors such as buildings, trees, or poor satellite geometry. IMUs, on the other hand, are not affected by external factors and provide continuous measurements of orientation and relative movement. Integration of the two systems helps mitigate GPS signal loss or errors, significantly improving overall accuracy and reliability. This is particularly beneficial in GPS-denied environments or when GPS signals are weak or unavailable, such as urban canyons or indoors [17, 24].

IMUs, particularly MEMS-based units, offer real-time orientation data that can fill in gaps during GPS outages, such as when passing through tunnels or dense urban environments. IMUs track motion continuously, making it possible to maintain a stable and continuous navigation solution, even in the absence of GPS. This is crucial for applications requiring uninterrupted movement tracking, such as autonomous vehicles and robotics [25].

While IMUs excel in providing short-term stability, they suffer from drift over time due to sensor biases and noise. GPS, when available, provides a reliable external reference to correct this drift. By applying sensor fusion algorithms, such as Kalman filters, GPS and IMU data can be combined to minimize drift and improve long-term positioning accuracy. The correction of IMU drift through GPS significantly enhances system performance over extended periods [21, 26]

GPS signals can be weak or unavailable in certain environments, such as indoors or in GPS-denied areas. IMUs, however, are independent of external signals and can operate in these conditions, providing continuous navigation data. The fusion of IMU data with GPS ensures that, even when GPS signals are temporarily lost, the system continues to function effectively by relying on the IMU's motion data. This combination enhances the versatility of navigation systems across a variety of challenging environments, as noted in several studies [10, 26].

The integration of GPS and IMU enhances the resilience of navigation systems. When GPS is available, it provides accurate absolute positioning, while IMU data can fill in when GPS is unavailable, maintaining continuous and reliable navigation. This redundancy is particularly beneficial for autonomous driving, UAVs, and robotics, where safe and accurate operation is essential. Robustness to system failures and signal degradation is a key advantage of GPS/IMU integration [24].

While high-end GPS systems can be costly, MEMS IMUs offer a more affordable solution for orientation and motion tracking. Integrating low-cost IMUs with GPS provides a scalable and economical approach to improve system performance without the need for expensive equipment. This makes GPS/IMU integration accessible for a wide range of applications, from consumer-grade UAVs to industrial autonomous systems [16, 19].

In summary, the integration of GPS and IMU systems offers a versatile, accurate, and cost-effective solution that overcomes the limitations of each technology. By complementing each other's strengths and compensating for weaknesses, the combination of GPS and IMU is essential for reliable and continuous navigation in dynamic and GPS-challenged environments [10, 27, 28].

Each of the GPS and IMU systems has significant limitations. GPS provides high accuracy in open areas, but its signal can be lost or degraded in challenging environments such as urban canyons or mountainous regions. On the other hand, IMU sensors offer internal data when GPS signals are unavailable, but they suffer from drift over time, leading to reduced accuracy. Both systems, when used individually, have limited reliability and precision. To overcome these standalone limitations, UAVs often use GPS-IMU sensor fusion techniques, such as Kalman filtering, which combines the strengths of both systems. This integration allows UAVs to maintain accurate, real-time navigation data, compensating for GPS signal loss and IMU drift, especially in challenging environments.

4. SENSOR FUSION TECHNIQUES in UAVs

Sensor fusion in UAVs involves combining data from multiple sensors, primarily GPS and IMU, to enhance navigation accuracy, reliability, and performance. This process mitigates the limitations of standalone systems by leveraging their complementary strengths. Under sub-headings 4.1 to 4.3, the following topics will be discussed in order: Kalman filter-based fusion (4.1), complementary filtering (4.2), and machine learning approaches (4.3).

4.1 Kalman Filter-Based Fusion

The Kalman Filter (KF) has been extensively used in GPS/IMU integration due to its ability to combine measurements from multiple sensors in a statistically optimal manner. This algorithm operates by predicting the state of a system and then updating this prediction based on new measurements, minimizing the influence of noise and uncertainties. For GPS and IMU systems, the Kalman Filter has historically proven effective in addressing their complementary strengths and weaknesses. The filter enables the fusion of GPS and IMU data, allowing GPS to correct IMU drift and IMU to interpolate GPS measurements during signal loss [29, 30]. Mathematically, the Kalman Filter follows a recursive estimation process consisting of two main steps: prediction and update [31]. In the prediction step, the system's state is estimated using the process model, defined as in (1):

$$\hat{X}_{k|k-1} = F_k\, \hat{x}_{k-1|k-1} + B_k u_k + w_k \tag{1}$$

where $\hat{X}_{k|k-1}$ is the predicted state vector at time k, F_k is the state transition matrix, B_k is the matrix representing the effect of control input on the system, u_k is the external control input, and w_k represents the process noise.

The corresponding error covariance is updated as in (2):

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \tag{2}$$

where $P_{k|k-1}$ is the predicted error covariance, $P_{k\_1|k-1}$ is the updated error covariance from the previous step, Q_k is the process noise covariance matrix, which accounts for uncertainties in the system model.

During the update step, the Kalman Gain is computed as in (3):

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \tag{3}$$

where K_k is the Kalman Gain, which determines how much the measurement should influence the state estimate, H_k is the measurement matrix that maps the system state to the observed measurements, and R_k is the measurement noise covariance matrix, representing uncertainties in sensor measurements.

The state estimate is then corrected as in (4):

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (z_k - H_k \hat{x}_{k|k-1}) \tag{4}$$

where z_k is the actual measurement at time k, and the term $(z_k - H_k \hat{x}_{k|k-1})$ represents the measurement residual (innovation), which quantifies the difference between the predicted and observed values.

Finally, the updated error covariance is computed as in (5):

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \tag{5}$$

where I is the identity matrix. This equation ensures that the uncertainty in the estimated state is minimized as new data is processed.

In earlier applications, Kalman Filter-based fusion methods predominantly relied on the Standard Kalman Filter (SKF) for linear systems. However, as UAV navigation evolved to involve increasingly complex and nonlinear dynamics, the Extended Kalman Filter (EKF) emerged as the preferred approach. The EKF linearizes nonlinear functions around the current state estimate, offering a highly effective solution for UAV applications. Additionally, adaptive variants of the Kalman Filter were developed to manage time-varying noise levels, addressing challenges caused by environmental factors or changes in UAV velocity. Unlike the standard KF, the EKF can handle nonlinearities by linearizing the system dynamics around the current estimate using a first-order Taylor expansion. The nonlinear state-space model is given in (6) and (7):

$$x_k = f(x_{k-1}, u_k) + w_k \tag{6}$$

$$z_k = h(x_k) + v_k \tag{7}$$

where $f\, and\, h$ are nonlinear functions describing the system dynamics and measurements, respectively. The EKF approximates these equations by computing the Jacobians of *f(x)* and *h(x),* which are used in place of F_k and H_k in the standard Kalman equations. This approach allows the filter to handle complex UAV motion models, including those involving attitude estimation and high-speed maneuvers.

In addition to improving accuracy, Kalman Filter-based fusion demonstrated resilience in GPS-denied environments. For instance, during temporary GPS outages, the filter's predictive step relied solely on IMU measurements to estimate the UAV's position. Though prone to increased drift during prolonged outages, this approach significantly improved operational reliability in challenging conditions such as urban canyons or under dense foliage [32]. In Figure 5, advanced work illustrated how tightly coupled GPS/IMU integration, leveraging Kalman Filtering, could further mitigate the limitations of standalone systems by processing raw satellite signals and IMU data simultaneously, rather than relying on processed GPS outputs [10].

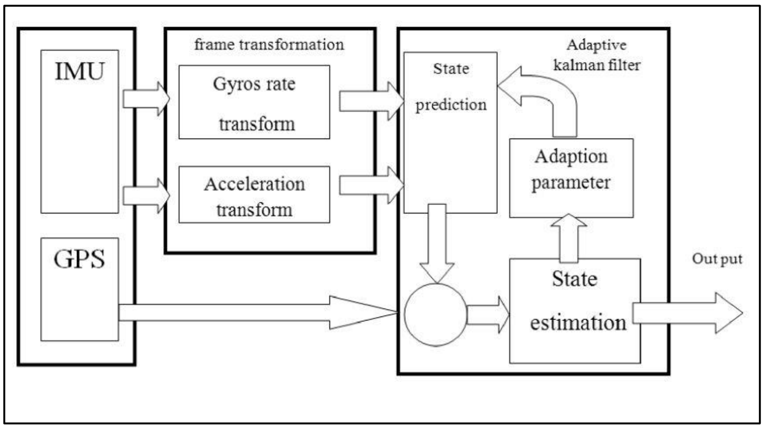

Figure 5. System implementation diagram [33]

Despite these advantages, the Kalman Filter has limitations. Its performance depended on accurate modeling of system dynamics and noise covariance matrices, which often required manual tuning. This tuning process was time-consuming and sensitive to sensor quality, particularly in low-cost UAV applications. Modern advancements have shifted focus toward machine learning-based fusion methods, but the Kalman Filter remains a benchmark in sensor fusion, particularly for its computational efficiency and real-time applicability in resource-constrained UAV platforms.

4.2 Complementary Filtering

Complementary Filtering has been widely used as a lightweight and effective method for fusing GPS and IMU data, especially in resource-constrained UAV systems. Unlike the computationally intensive Kalman Filter, the Complementary Filter operates on a straightforward principle, combining high-frequency data from IMUs with low-frequency, long-term accurate data from GPS to produce a reliable and stable navigation solution. This method assumes that the errors in each data source are complementary short-term inaccuracies in GPS data are corrected by IMU measurements, while long-term drift in IMU data is mitigated using GPS corrections [11].

Historically, Complementary Filters have been applied in scenarios where computational simplicity and low power consumption were critical. For UAVs, these filters proved particularly useful for attitude estimation, where gyroscope data from the IMU provided rapid orientation changes, and accelerometer or GPS measurements ensured long-term stability. Complementary Filters were well-suited for small UAVs due to their ease of implementation and low demand on processing resources [10].

The mathematical foundation of Complementary Filtering lies in the use of frequency-domain filtering. High-pass filters are applied to IMU gyroscope data to capture rapid changes, while low-pass filters smooth GPS position data to remove high-frequency noise. These filtered components are then combined to produce an accurate and stable estimate of the UAV's state. This simple structure made Complementary Filters particularly attractive for earlier UAV applications where high-cost or high-performance processing units were unavailable.

However, the performance of Complementary Filters depends on the accurate tuning of the filter gains, which balance the contributions of GPS and IMU data. Early implementations often relied on fixed gain values, which could lead to suboptimal performance in dynamic environments where noise characteristics varied over time. Recent advancements have addressed this limitation by introducing adaptive gain mechanisms that adjust filter parameters based on the operating conditions. For example, adaptive filters have been used to dynamically weigh GPS input more heavily in stable conditions and rely on IMU data during GPS outages.

Despite these advancements, Complementary Filters are not without limitations. Unlike Kalman Filters, they do not provide probabilistic estimates of uncertainty, making them less robust in situations with highly variable noise or extreme sensor errors. Moreover, they cannot handle the intricate coupling of sensor states in tightly integrated navigation systems. As UAV applications demand increasingly complex maneuvers and higher levels of precision, Complementary Filtering is often used in tandem with more advanced algorithms, such as Extended Kalman Filters, to enhance overall performance [24].

Nevertheless, Complementary Filters remain a popular choice for low-cost UAVs and other systems where computational efficiency and simplicity outweigh the need for more sophisticated data fusion techniques. Their continued relevance lies in their adaptability and effectiveness for lightweight sensor fusion, particularly in emerging applications where basic yet reliable navigation solutions are required.

4.3 Machine Learning Approaches

Machine learning (ML) has emerged as a transformative approach for sensor fusion in GPS/IMU integration, offering innovative solutions to address challenges in UAV navigation. Unlike traditional methods such as Kalman or Complementary Filtering, ML-based approaches can learn complex patterns and nonlinear relationships directly from data, enabling adaptive and robust performance even in highly dynamic environments. This capability has made ML increasingly popular in scenarios where traditional algorithms struggle, such as GPS-denied environments, abrupt maneuvers, or varying sensor noise characteristics [34, 35].

Machine learning techniques applied to GPS/IMU integration typically fall into two categories: supervised learning and reinforcement learning. Supervised learning involves training models on labeled datasets to predict navigation states, such as position, orientation, or velocity. For example, neural networks have been utilized to estimate position and correct IMU drift based on historical GPS/IMU data. Reinforcement learning, on the other hand, can optimize decision-making by learning from interactions with the environment, making it useful for dynamic or GPS-denied scenarios.

Deep learning models, such as Long Short-Term Memory (LSTM) networks, have been shown to effectively capture temporal dependencies in sensor data, outperforming traditional algorithms in dynamic conditions [36]. Other architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Gated Recurrent Units (GRUs) have also demonstrated strong performance in capturing spatial and temporal patterns in sensor data, depending on the specific characteristics of the data and the application.

LSTM networks are especially effective when working with time-series data, where long-range temporal dependencies are crucial. For instance, in applications like UAV attitude estimation, LSTMs can model the sequential nature of sensor measurements and predict future sensor states with higher accuracy, even in the presence of noise or complex environmental conditions. The ability of LSTMs to maintain the memory of past data points through their gating mechanisms allows them to outperform traditional methods, such as Kalman filters, in dynamic and non-linear scenarios [37, 38].

On the other hand, CNNs are typically applied to problems involving spatial data, such as images or video frames. CNNs are capable of identifying hierarchical spatial features in sensor data, making them particularly useful in multi-modal sensor fusion, where data from sources like cameras, LiDAR, or thermal sensors must be combined [39]. When paired with temporal models like LSTMs, CNNs can extract both spatial and temporal features, which is beneficial for tasks such as object detection, scene recognition, and path planning in autonomous systems.

RNNs, along with their more efficient variants, GRUs, are another powerful class of models for sequential data processing. Unlike traditional feedforward networks, RNNs and GRUs maintain an internal state that helps capture the temporal dependencies between data points in sequences. GRUs are particularly effective in reducing computational complexity compared to LSTMs while still handling sequential data well. These models are well-suited for continuous data streams, such as those generated by IMU or GPS sensors, where real-time processing is essential [40].

One of the key advantages of ML approaches is their ability to incorporate a wide variety of input features beyond GPS and IMU data, such as barometric altitude, magnetometer readings, and environmental context (e.g., visual data from cameras). This multimodal integration allows for richer and more accurate navigation solutions. Additionally, ML models can adapt to sensor degradation or failures, making them particularly valuable for long-term UAV operations [35].

Despite their advantages, ML-based methods face challenges, particularly in the context of UAV navigation. First, the reliance on large-labeled datasets for training can be a barrier, as collecting and annotating high-quality GPS/IMU data under various environmental conditions is resource-intensive. Second, the computational demands of ML models, especially deep learning, can strain the limited processing power and battery life of UAVs [41, 42]. Researchers have explored lightweight ML architectures and edge computing solutions to address these constraints. Lastly, the generalization of ML models across different UAV platforms and environments remains a challenge, as models trained in one scenario may perform poorly in others. Techniques such as domain adaptation and online learning have been proposed to improve robustness [21, 34, 41].

Looking ahead, the integration of ML with traditional methods, such as hybrid models combining neural networks with Kalman Filters, offers promising directions for UAV navigation. These hybrid systems leverage the strengths of both approaches, using ML to capture complex dynamics and traditional methods to ensure reliability and interpretability. As UAV applications expand, ML-based approaches are expected to play an increasingly critical role in achieving autonomous, efficient, and adaptive navigation.

To help readers compare the various sensor fusion methods discussed in this section, Table 1 provides a concise overview of their advantages and limitations. It summarizes the key characteristics of each method, highlighting factors such as computational efficiency, adaptability, and suitability for different UAV navigation scenarios.

Table 1. Comparison of sensor fusion methods for GPS/IMU integration

Method	Advantages	Limitations
Kalman Filter	Provides optimal estimation by modeling probabilistic uncertainty. Works well in sensor fusion.	Requires accurate system modeling and fine-tuning of noise covariance. Sensitive to poor system models.
Extended Kalman Filter (EKF)	Effectively addresses nonlinearities by linearizing the system based on the current state.	Computationally expensive and performance degrades with large nonlinearities in the system model.
Complementary Filter	Simple and computationally efficient, making it suitable for lightweight UAVs and real-time applications.	Struggles with highly dynamic conditions, especially with rapid changes in motion or acceleration. Does not provide uncertainty estimates.
Machine Learning (ML)	Can adapt to complex and dynamic environments, effectively incorporating multiple data sources.	Requires large-labeled datasets, is computationally intensive, and may not generalize well across platforms.
Deep Learning (LSTM, CNN, RNN, GRU)	Adapts to dynamic and complex environments, efficiently combining multiple data sources.	Requires large datasets, high computational power, and may have difficulty with real-time processing due to slow inference times.

5. OPEN CHALLENGES in GPS/IMU INTEGRATION

One of the most significant challenges in UAV navigation is mitigating the impact of GPS signal loss or degradation. UAVs frequently operate in environments where GPS signals are obstructed, such as urban canyons, dense forests, or underwater. Intentional interference, including jamming and spoofing, further exacerbates GPS reliability issues [13]. While IMU systems can temporarily compensate during GPS outages, their drift errors accumulate over time, reducing navigational accuracy. Addressing these issues requires advancements in anti-jamming capabilities, the adoption of alternative positioning systems such as GLONASS or Galileo, and the development of enhanced sensor fusion techniques to ensure uninterrupted navigation [7, 13, 27].

Low-cost IMUs, commonly used in consumer UAVs, present additional challenges due to significant errors stemming from sensor noise and temperature sensitivity. These limitations hinder precise navigation during extended GPS outages. Advanced calibration methods, high-performance MEMS-based IMUs, and machine learning models that predict and correct sensor-specific errors could mitigate long-term drift and improve reliability [12, 19].

The computational demands of GPS/IMU integration, particularly with advanced techniques like Extended Kalman Filters or machine learning-based fusion methods, strain the limited processing power of UAV platforms. This issue is especially pronounced in small UAVs where weight and power efficiency are critical. Optimized algorithms that balance computational efficiency with navigational accuracy, such as lightweight neural networks and adaptive filters, are essential to enable real-time processing in resource-constrained systems [7, 9, 34].

UAVs also face dynamic and unpredictable environments, such as disaster zones or crowded airspaces, which require navigation systems capable of adapting to rapid changes in motion, obstacles, and environmental conditions. Adaptive frameworks that adjust parameters in real-time based on operational contexts are critical for ensuring reliability under such conditions [2,15]. Swarm operations introduce further complexity, necessitating precise relative positioning among UAVs. GPS inaccuracies and IMU drift pose challenges to synchronized swarm behaviors, making decentralized fusion algorithms and robust inter-UAV communication protocols essential [14].

Integrating GPS/IMU systems with emerging technologies such as Light Detection and Ranging (LiDAR), cameras, and 5G-based positioning systems holds great promise for enhancing UAV navigation. However, incorporating additional sensors increases the complexity of data fusion, requiring advanced algorithms capable of managing diverse data streams with varying levels of uncertainty and frequency. Developing hybrid techniques that integrate these modalities seamlessly without imposing significant computational overhead will be crucial [24, 27].

Energy constraints represent another significant hurdle, particularly for long-duration UAV missions. The continuous operation of GPS and IMU sensors, combined with real-time processing requirements, places a heavy burden on battery life. Innovations in low-power hardware design and energy-efficient computational techniques are critical to extending operational endurance [7, 40].

As UAV operations expand, GPS/IMU integration systems must also align with evolving regulatory and safety requirements. Reliable performance in GPS-denied conditions and robust fail-safe mechanisms will be essential for compliance and the safe integration of UAVs into shared airspace, particularly in urban and commercial settings [13, 23].

6. FUTURE DIRECTIONS

Future research in GPS/IMU integration will likely focus on developing hybrid sensor fusion frameworks that combine traditional methods with machine learning techniques. These frameworks could provide greater adaptability to diverse operating environments by leveraging the strengths of deterministic models like Kalman Filters and data-driven approaches to improve robustness and accuracy.

Advancements in hardware, particularly in low-power, high-precision MEMS-based IMUs, will play a pivotal role. Emerging IMUs with higher sensitivity and reduced drift, coupled with miniaturized multiconstellation GNSS receivers, could significantly enhance UAV navigation reliability. Additionally, novel positioning technologies such as 5G and visual odometry may further improve performance, especially in GPS-degraded or denied environments.

The increasing demand for UAV swarm operations will drive innovations in decentralized navigation systems. Real-time inter-UAV communication and collaborative sensor fusion will be critical for precise relative positioning and coordinated flight paths, enabling applications ranging from disaster response to large-scale agricultural monitoring.

Computational and energy efficiency will remain key areas of focus. Lightweight algorithms, edge computing, and energy-efficient hardware are essential for extending UAV operational durations without compromising accuracy. Future systems may also incorporate self-learning capabilities, allowing UAVs to adapt to new environments and sensor degradation over time.

By addressing these challenges and pursuing these advancements, GPS/IMU integration will continue to evolve, supporting the growing complexity and demands of modern UAV applications while unlocking new possibilities in navigation and autonomous operation.

7. CONCLUSION

This review highlighted the essential roles, advantages, and limitations of GPS and IMU systems in UAV navigation. The complementary nature of GPS and IMU systems has led to the development of sensor fusion techniques that significantly enhance the accuracy and reliability of UAV navigation. While GPS provides long-term absolute positioning, IMUs offer high-frequency orientation data, allowing UAVs to navigate effectively. However, challenges such as IMU drift, GPS signal loss, sensor fusion complexity, and environmental sensitivity can affect the overall performance of these systems. Sensor fusion techniques, including Kalman Filtering, Complementary Filtering, and machine learning-based methods, offer promising solutions to address the limitations of standalone GPS and IMU systems. Advances in AI and sensor technology are expected to drive further improvements in UAV navigation systems, making them more resilient to environmental factors and adaptable to a broader range of applications.

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