BAŞKENT UNIVERSITY
INSTITUTE OF SCIENCE
DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING
MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONICS ENGINEERING

ANALYSIS OF GPS AND IMU SYSTEM PERFORMANCE IN UNMANNED AERIAL VEHICLES (UAVS): FEATURES, ADVANTAGES, AND LIMITATIONS

BY

MUAMMER ERBAŞ

MASTER OF SCIENCE THESIS

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ADVISOR

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This study, which was prepared by Muammer ERBAŞ, for the program of Electrical and Electronics Engineering, has been approved in partial fulfillment of the requirements for the degree of MASTER OF SCIENCE in Institute of Science and Engineering Department by the following committee.

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Tez Başlığı: Analysis Of Gps And Imu System Performance In Unmanned Aerial Vehicles (Uavs): Features, Advantages, And Limitations

Yukarıda başlığı belirtilen Yüksek Lisans tez çalışmamın; Giriş, Ana Bölümler ve Sonuç Bölümünden oluşan, toplam 99 sayfalık kısmına ilişkin, 23 / 07 / 2025 tarihinde tez danışmanım tarafından iThenticate adlı intihal tespit programından aşağıda belirtilen filtrelemeler uygulanarak alınmış olan orijinallik raporuna göre, tezimin benzerlik oranı % 4'tür. Uygulanan filtrelemeler:

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ONAY

Tarih: 14 / 08 / 2025

Advisor

Assistant Prof. Dr. Gülşah DEMİRHAN AYDIN

I dedicate this thesis to Gazi Mustafa Kemal Atatürk, who entrusted the Republic to us with his unwavering belief in science, progress, and the youth.

Muammer ERBAŞ

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ABSTRACT

Muammer ERBAŞ

ANALYSIS OF GPS AND IMU SYSTEM PERFORMANCE IN UNMANNED AERIAL VEHICLES (UAVS): FEATURES, ADVANTAGES, AND LIMITATIONS

Başkent University Institue of Science
Department of Electrical-Electronics Engineering

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This thesis presents a performance evaluation of Global Positioning System (GPS) and Micro-Electro-Mechanical Systems-based Inertial Measurement Unit (MEMS-based IMU) technologies in Unmanned Aerial Vehicles (UAVs), based on experimental analysis of the built-in GPS and IMU sensors of the DJI and an externally integrated MPU6050 IMU module. Tests were conducted under open-sky, semi-obstructed, and Global Navigation Satellite System (GNSS)-denied indoor conditions to assess sensor reliability and environmental adaptability. Sensor data were post-processed using Kalman filter-based fusion to enhance positioning accuracy and continuity. A loosely coupled aided Inertial Navigation System (INS) was implemented to mitigate the limitations of standalone GPS and IMU systems. Results showed that fusion reduced positional error by 50–75% during temporary GPS outages and decreased orientation drift by ~75% compared to the standalone MPU6050 without GPS correction. For attitude estimation, Kalman filtering improved pitch stability by up to 80% and roll stability by up to 75% over raw IMU data. While GPS performs well in open areas, it degrades under obstruction due to signal loss and multipath effects. MEMS-based IMUs enable continuous motion tracking but suffer from drift, bias instability, and thermal sensitivity, whereas their fusion significantly improved robustness during short-term GPS outages. The comparison between the onboard IMU and MPU6050 revealed that low-cost inertial sensors require precise calibration and advanced filtering. The study highlights the need for adaptive fusion frameworks and the future integration of multi-constellation GNSS, vision-based odometry, and machine learning for reliable UAV navigation in GPS-denied environments.

KEYWORDS: UAVs, GPS, MEMS-based IMU, Sensor Fusion, System Performance

ÖZET

Muammer ERBAŞ

İNSANSIZ HAVA ARAÇLARINDA (İHA) GPS VE IMU SİSTEM PERFORMANSININ ANALİZİ: ÖZELLİKLER, AVANTAJLAR VE SINIRLAMALAR

Başkent Üniversitesi Fen Bilimleri Enstitüsü

Elektrik-Elektronik Mühendisliği Anabilim Dalı

2025

Bu tez, insansız hava araçlarında (İHA) Küresel Konumlama Sistemi (GPS) ve Mikro-Elektro-Mekanik Sistem (MEMS) tabanlı Ataletsel Ölçüm Birimi (IMU) teknolojilerinin performans değerlendirmesini, DJI'ın dahili GPS ve IMU sensörleri ile harici entegre MPU6050 IMU modülü üzerinde yapılan deneysel analizlere dayandırmaktadır. Sensör güvenilirliği ve çevresel uyarlanabilirlik, açık hava, yarı kapalı ve GNSS sinyalinin bulunmadığı kapalı alan koşullarında test edilmiştir. Sensör verileri, konum doğruluğu ve sürekliliği artırmak için Kalman filtre tabanlı füzyonla işlenmiştir. Bağımsız GPS ve IMU sistemlerinin sınırlamalarını azaltmak amacıyla gevşek bağlı destekli Ataletsel Seyrüsefer Sistemi (INS) uygulanmıştır. Sonuçlar, füzyonun geçici GPS kesintilerinde konum hatasını %50–75, yalnız çalışan MPU6050'e kıyasla yönelim sapmasını yaklaşık %75 azalttığını göstermektedir. Kalman filtreleme, pitch kararlılığını %80, roll kararlılığını ise %75 iyileştirmiştir. GPS açık alanlarda yüksek doğruluk sağlasa da sinyal kaybı ve çok yollu etkilerle engelli ortamlarda performansı düşer. MEMS tabanlı IMU'lar hareket takibi sağlasa da sapma, bias kararsızlığı ve sıcaklık hassasiyeti sorunları yaşar; füzyon ise kısa süreli GPS kesintilerinde sağlamlığı artırmıştır. Dahili IMU ile MPU6050 karşılaştırması, düşük maliyetli sensörlerin hassas kalibrasyon ve gelişmiş filtreleme gerektirdiğini göstermiştir. Çalışma, uyarlanabilir füzyon algoritmalarının geliştirilmesi ve GPS olmayan ortamlarda güvenilir İHA seyrüseferi için çok takımyıldızlı GNSS, görüntü tabanlı odometri ve makine öğrenmesi teknolojilerinin entegrasyonunu önermektedir.

ANAHTAR KELİMELER: İHA, GPS, MEMS tabanlı IMU, Sensör Füzyonu, Sistem Performansı

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LIST OF SYMBOLS AND ABBREVIATIONS

a	accelaration
AI	artificial ıntelligence
AKF	adaptive kalman filter
c	speed of light
DGPS	differential gps
DUT	device under test
EKF	extended kalman filter
f	frequency
f0	transmitted signal frequency
GDOP	geometric dilution of precision
GNSS	global navigation satellite systems
GPS	global positioning system
IMU	inertial measurement unit
INS	inertial navigation system
IP	ingress protection
LiDAR	laser imaging detection and ranging
MEMS	micro-electro-mechanical systems
ML	machine learning
PF	particle filters
PSD	power spectral density
Q	process noise covariance
R	measurement noise covariance
RTC	real time clock
RTK	real time kinematic
SNR	signal-to-noise ratio
TEC	total electron content
UAVs	unmanned aerial vehicles
UKF	unscented kalman filter
UWB	ultra-wideband
v	velocity
w	angular velocity
σ	standard deviation of sensor measurements (precision)
τ	latency

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have revolutionized numerous industries, including defense, agriculture, logistics, disaster response, and infrastructure inspection. Their ability to operate autonomously and perform missions in diverse environments has made them indispensable tools in modern applications. A fundamental requirement for UAVs is precise navigation and stable orientation control, both of which rely heavily on accurate positioning and motion tracking systems [1-6].

To achieve reliable navigation, UAVs integrate Global Positioning System (GPS) and Inertial Measurement Unit (IMU) technologies, each playing a complementary role in ensuring accurate trajectory tracking and flight stability. GPS provides absolute positional data by receiving signals from satellite constellations, offering high accuracy in open environments. However, its performance is often compromised by factors such as signal blockages, multipath errors, atmospheric disturbances, and vulnerability to jamming or spoofing attacks [7-11].

On the other hand, IMUs measure motion and orientation using accelerometers and gyroscopes, providing high-frequency data that is crucial for real-time UAV control. Unlike GPS, IMUs operate independently of external signals, making them highly reliable for short-term motion tracking and attitude estimation. They play a critical role in stabilizing UAV flight, compensating for disturbances, and supporting precise maneuvering during dynamic operations [12-16]. When combined, GPS and IMU systems complement each other, enabling UAVs to maintain accurate and stable navigation across diverse operational scenarios.

1.1. Problem Statement

UAVs have become indispensable in both military and civilian applications, ranging from reconnaissance and surveillance to disaster management and precision agriculture. However, their operational effectiveness heavily depends on accurate navigation and positioning systems, which are typically based on GPS and IMU technologies. While GPS provides precise global positioning, it is highly susceptible to signal degradation or complete loss due to environmental obstructions, such as urban canyons, dense forests, or indoor environments [17-20]. Moreover, GPS signals are vulnerable to intentional jamming and spoofing attacks, particularly in military operations, which can lead to critical mission failures [21].

IMU sensors, on the other hand, offer self-contained navigation by measuring acceleration and angular velocity. However, they suffer from cumulative errors over time due to sensor drift, resulting in inaccurate positioning during prolonged operations. Additionally, IMUs are affected by environmental factors such as temperature variations and vibrations, which can further degrade accuracy [22-25]. The challenge lies in achieving a balance between GPS and IMU integration to ensure reliable and continuous navigation, even in GPS-denied or degraded environments [26].

Beyond the limitations of GPS and IMU, UAVs also face challenges in sensor synchronization, real-time data fusion, and computational efficiency. The latency in processing GPS and IMU data can introduce errors in fast-moving UAVs, particularly in high-speed or maneuver-intensive applications. Furthermore, power consumption is a critical factor, as IMU-based navigation requires significant processing power to compensate for drift, impacting the UAV's flight endurance.

Literature review revealed that studies specifically addressing this problem are limited, with most existing works focusing on high-end systems or simulation-based analyses. In contrast, this study conducts real flight tests using a DJI drone equipped with its onboard IMU and an externally mounted MPU6050 IMU, collecting synchronized data from both sensors. By analyzing and comparing the performance of GPS and IMU systems under real operating conditions, the research aims to provide insights into optimizing sensor fusion techniques, enhancing UAV navigation reliability, and improving robustness in military and other critical applications.

1.2. Literature Review

UAVs rely on GPS and IMU technologies for navigation and control. While GPS provides accurate absolute positioning, it is highly susceptible to signal degradation, multipath errors, and intentional jamming, making it unreliable in urban canyons, dense forests, or military applications with GPS-denied environments. On the other hand, IMU systems offer high-frequency motion and orientation data, but sensor drift due to accumulated bias over time degrades long-term positioning accuracy [13, 27, 28, 29].

To address these challenges, Kalman filtering-based sensor fusion has emerged as a dominant technique in the literature, allowing UAVs to leverage the strengths of both GPS and IMU while compensating for their respective weaknesses. The Extended Kalman Filter (EKF), which can handle the nonlinearities of UAV motion, is widely used for integrating GPS and IMU data. By continuously updating position estimates based on real-time sensor readings and system dynamics, EKF significantly improves UAV localization accuracy, even in environments with temporary GPS outages [30-33].

In addition to EKF, other Kalman filter variants, such as Unscented Kalman Filter (UKF) and Adaptive Kalman Filter (AKF), have been explored to improve UAV navigation performance in highly dynamic environments. These adaptive models adjust filter parameters based on noise characteristics, making them more resilient to sudden disturbances or varying sensor accuracies [34-36].

Recent advancements in low-cost Micro-Electro-Mechanical Systems (MEMS) based IMUs and high-precision GPS receivers have further enhanced the feasibility of Kalman filter-based sensor fusion for UAVs. Furthermore, machine learning techniques, including deep neural networks and reinforcement learning, are being integrated with Kalman filtering to optimize UAV navigation, particularly in GPS-denied conditions [19, 37, 38, 39].

The literature underscores the importance of hybrid sensor fusion techniques, where Kalman filtering remains a fundamental method for combining GPS absolute positioning with IMU high-frequency motion tracking. The ability to predict and correct positional errors in real time makes Kalman filter-based sensor fusion an essential approach for UAVs used in applications such as military surveillance, autonomous flight, and precision mapping [40-43]. Future research directions include enhancing real-time processing efficiency, reducing computational load, and integrating multi-sensor frameworks (e.g., LiDAR, vision-based navigation) for robust UAV localization.

1.3. Motivation

In this thesis, a comprehensive analysis of GPS and IMU systems in UAV applications has been presented, focusing on their individual characteristics, advantages, and limitations to overcome the problems of standalone GPS, such as low update rate and signal loss, and the drift errors inherent in IMU-based navigation. Additionally, advanced integration techniques have been explored to enhance UAV performance, ensuring high-precision navigation in complex operational scenarios.

As part of this study, a comprehensive data acquisition and processing system has been developed, as illustrated in Figure 1. The DJI UAV serves as the main platform, utilizing its internal GPS and IMU sensors to collect positioning, motion, and orientation data. Additionally, a low-cost external IMU sensor (MPU-6050) has been mounted on the drone to obtain supplementary inertial measurements. The external IMU data are recorded onto a Micro SD card module, with precise timestamping provided by a Real Time Clock (RTC) module to ensure accurate synchronization.

The collected data are processed using filtering techniques, including Kalman filtering, to reduce sensor noise and improve data stability. This stage enables a clearer comparison between the GPS and IMU data, and between internal and external sensor performances. A detailed analysis is then conducted to examine drift, offset, and overall sensor accuracy in UAV navigation.

A key motivation of this work is to demonstrate that low-cost IMU sensors, when properly calibrated and combined with effective filtering techniques, can be successfully employed in critical UAV applications, potentially reducing system costs without compromising performance. The final aim of this workflow is to support sensor fusion-based navigation, improve UAV flight stability, and enhance positioning accuracy. The results have been visualized through graphical representations and performance evaluations to demonstrate the benefits and limitations of the integrated system.

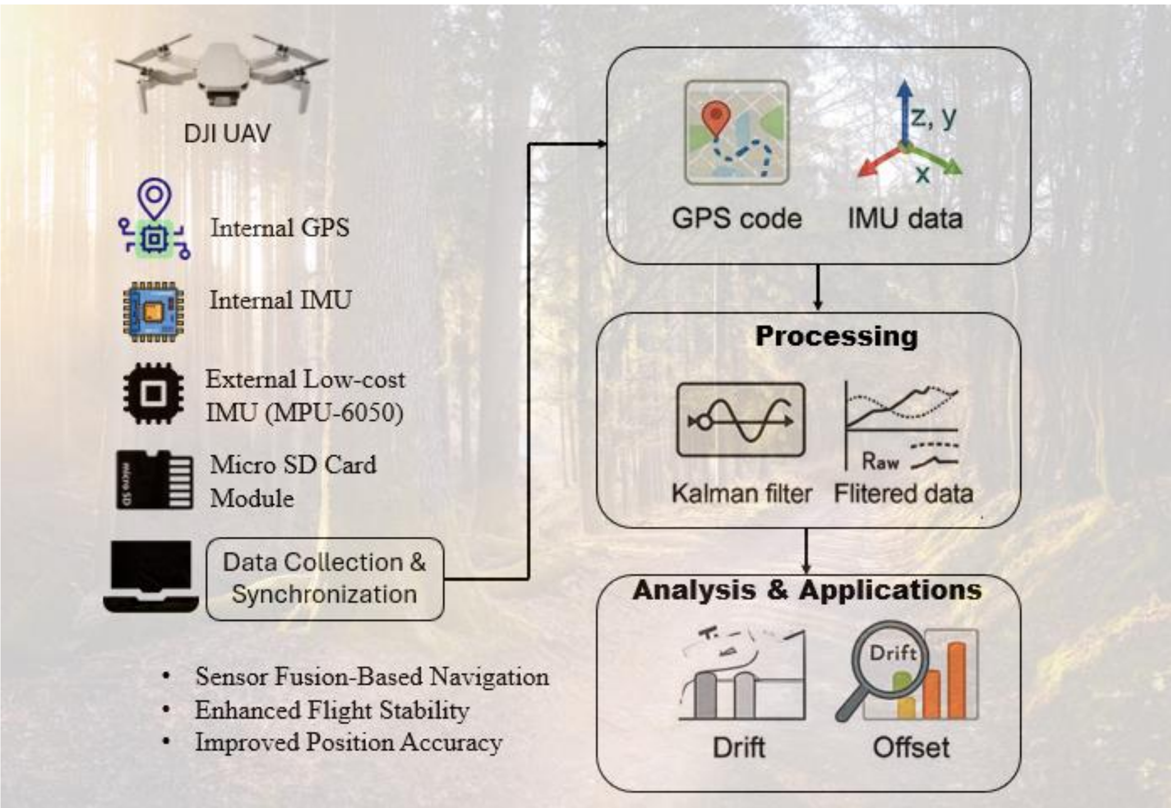

Figure 1.1. Overall System Architecture for GPS and IMU Data Acquisition, Processing, and Analysis in UAVs

The system's performance was evaluated under various test conditions to assess the robustness of the UAV and its onboard sensors. Both open-space and enclosed-space experiments were conducted to analyze GPS and IMU accuracy under different spatial constraints. Additionally, temperature and relative humidity conditioning tests were performed to evaluate sensor reliability under varying atmospheric conditions. To ensure robust navigation and precise positioning in real-world applications, it is essential to examine UAV behavior across diverse environmental scenarios. Environmental factors such as wind, rain, and temperature fluctuations can significantly impact sensor accuracy and flight stability. Consequently, testing under simulated weather conditions provides critical insights into the resilience of UAV systems and supports the development of more effective control algorithms and sensor fusion strategies.

In addition to these experimental evaluations, this study has discussed future research directions, including adaptive sensor fusion algorithms, AI-driven navigation enhancements, and the potential of multi-sensor integration, such as Laser Imaging Detection and Ranging (LiDAR), vision-based navigation, and 5G positioning. By addressing these aspects, this research has aimed to contribute to the development of more robust, precise, and resilient UAV navigation systems, particularly in challenging operational environments.

1.4. Research Objectives & Aim

The primary aim of this study is to evaluate and compare the performance of GPS and IMU systems in unmanned aerial vehicles (UAVs), focusing on their accuracy, advantages, and limitations under various operational conditions. The research particularly emphasizes military applications, where precise navigation and positioning are critical for mission success.

To achieve the stated aim, this study is designed to address the following key objectives:

- Assessing the accuracy and reliability of GPS-based positioning in UAVs through tests conducted in both open and enclosed spaces.
- Investigating the impact of temperature and relative humidity on GPS and IMU performance through controlled environmental tests.
- Evaluating system robustness under various weather conditions, such as changes in wind speed, atmospheric pressure, humidity, and simulated rainfall.
- Integrating the MPU6050 IMU sensor with an Arduino Uno-based data logging system to enable real-time data collection and comparative analysis.
- Exploring the advantages and limitations of using an external IMU sensor, especially in GPS-denied environments where inertial navigation is critical.

By addressing these objectives, this study aims to provide a comprehensive evaluation of GPS and IMU systems, contributing to advancements in UAV navigation technologies across various applications, such as defense, aerospace, and agriculture.

1.5. Thesis Structure

This thesis is organized into six main chapters, along with supplementary sections such as the abstract, acknowledgments, and references. Chapter 1, titled "Introduction," introduces the research problem, reviews relevant literature, defines the research objectives, and outlines the structure of the thesis. Chapter 2, "Fundamentals of GPS and IMU Systems," delves into the foundational principles of UAV navigation systems, focusing on GPS and IMU technologies. It also introduces sensor fusion techniques and discusses the specific requirements and challenges of UAV navigation. In Chapter 3, "Performance Analysis of GPS and IMU in UAVs," the experimental methodology is presented, covering performance metrics, factors influencing GPS and IMU accuracy, and the experimental setup. This chapter includes tests conducted in both open-space and enclosed-space, as well as environmental conditioning experiments. It evaluates the system's performance under actual weather conditions, such as wind observed during outdoor flights, and under simulated conditions, including controlled rainfall exposure in a laboratory setting. Chapter 4, "Advantages and Limitations of GPS and IMU in UAVs," explores the benefits and limitations of GPS and IMU systems based on the experimental results. It examines performance variations in different environments, IMU drift over time, and the impact of environmental conditions, while also discussing sensor fusion as a method to enhance UAV navigation accuracy. Chapter 5, "Results and Discussion," provides an analysis and interpretation of the experimental study results, focusing on the effects of environmental factors on GPS and IMU performance. It includes a comparative analysis of standalone GPS, IMU, and sensor fusion approaches, along with key findings and their implications for UAV navigation. Finally, Chapter 6, "Conclusion," summarizes the main findings of the study, highlights the contributions of the research, and suggests potential directions for future work in UAV navigation and sensor integration.

2. FUNDAMENTALS OF GPS AND IMU SYSTEMS

UAVs rely on advanced navigation systems to achieve precise positioning, motion estimation, and trajectory planning. Among these systems, the GPS and IMU play a crucial role in determining the UAV’s location, velocity, and orientation [19, 43, 44, 45].

GPS is a satellite-based navigation system that provides accurate positioning information by calculating the time delay between signals received from multiple satellites. On the other hand, an IMU consists of accelerometers and gyroscopes that measure linear acceleration and angular velocity, enabling the estimation of movement and orientation changes [18,19,20, 45, 46].

This chapter presents the fundamental principles of GPS and IMU systems used in UAV applications. It begins with an overview of UAV navigation systems, followed by a detailed explanation of the basic principles of GPS and IMU technology, sensor fusion methods, and the key requirements for UAV navigation.

2.1. Overview of Navigation Systems in UAVs

Navigation systems are essential for the operation of UAVs, ensuring precise positioning, stability, and control. These systems use various sensors and technologies to determine the UAV’s position, orientation, and movement. Among the most commonly used navigation systems in UAVs are the GPS and the IMU [46, 47].

GPS provides absolute positioning by receiving signals from multiple satellites and determining the UAV’s location through trilateration. It is widely used due to its accuracy, but can be affected by signal loss or interference. On the other hand, IMU consists of accelerometers and gyroscopes that measure acceleration and angular velocity, enabling short-term navigation independently of external signals. However, IMU data tends to drift over time and requires correction through sensor fusion techniques [41, 43, 44, 45, 48].

To enhance navigation performance, UAVs often integrate GPS and IMU data using filtering algorithms, such as Kalman filtering. This improves accuracy and reliability, compensating for the limitations of each individual system [40, 49, 50, 51]. Additionally, some UAVs employ supplementary navigation aids, including magnetometers, barometers, and vision-based navigation systems, to further refine their positioning capabilities.

Overall, UAV navigation systems combine multiple technologies to ensure reliable and accurate operation in various environments. Continuous advancements in sensor technology and data processing methods are crucial for enhancing UAV autonomy and performance.

2.2. Global Positioning System (GPS) Basics

GPS is a satellite-based navigation system that provides precise location and time information to users worldwide. It is a fundamental component in UAV navigation, enabling accurate positioning and autonomous flight operations [52-54]. The fundamental working principle of the GPS, including trilateration and the role of satellites and the control segment, is illustrated in Figure 2.1.

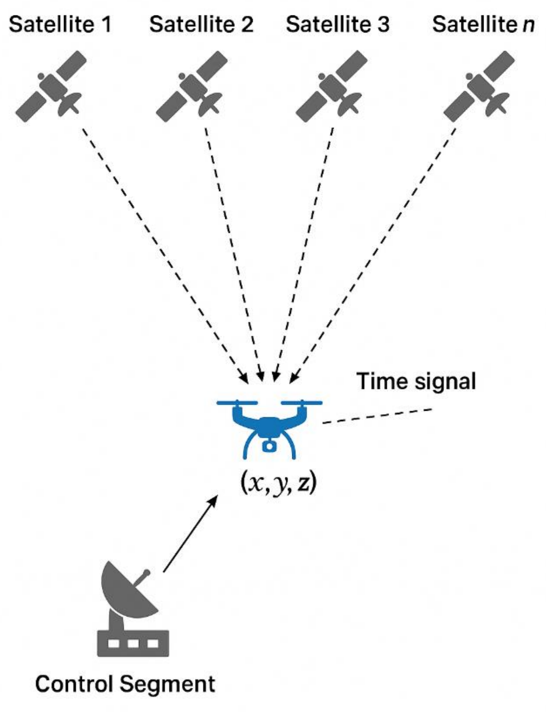

Figure 2.1. Basic Working Principle of the GPS

GPS operates using a network of satellites that transmit signals to GPS receivers on the ground. By measuring the time, it takes for signals to travel from multiple satellites to the receiver, the system calculates the receiver's exact position through a process called trilateration. A minimum of four satellites is required to determine a three-dimensional position, including latitude, longitude, and altitude [52]. The trilateration process follows the equation 2.1:

$$(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = \left(c.(t - t_i)\right)^2 \tag{2.1}$$

Where (x_i, y_i, z_i) are the satellite coordinates, c is the speed of light, and t-t_i represents the time delay between the satellite and the receiver.

The main components of GPS include the space segment, the control segment, and the user segment. The space segment consists of satellites orbiting the Earth, continuously transmitting signals. The control segment includes ground-based monitoring stations that track satellites, update their positions, and maintain system accuracy. The user segment consists of GPS receivers found in UAVs and other devices, which process satellite signals to determine location and velocity [3, 52, 55].

GPS accuracy can be affected by several error sources, including atmospheric delays, multipath interference, and clock or orbital errors. Signals passing through the ionosphere and troposphere may experience delays, impacting accuracy [53]. The ionospheric delay can be estimated using the formula given in the equation 2.2:

$$\Delta T_{ion} = 40.3\ x\ \frac{TEC}{f^2} \tag{2.2}$$

Where TEC is the Total Electron Content, and f is the signal frequency.

Multipath interference occurs when signals reflect off surfaces before reaching the receiver, leading to positioning errors. Small inaccuracies in satellite clocks or orbits can also introduce errors in position calculations. To mitigate these errors, techniques such as Differential GPS (DGPS) and Real-Time Kinematic (RTK) positioning are used to enhance accuracy [41, 45, 52].

In addition to position determination, GPS can also be used to estimate velocity based on the Doppler effect. The velocity of a moving receiver can be computed as in equation 2.3:

$$v = \frac{\Delta f \cdot c}{f_0} \tag{2.3}$$

Where Δf is the frequency shift due to Doppler effect, c is the speed of light, and f_0 is the transmitted signal frequency.

GPS plays a vital role in UAV operations, enabling precise navigation, waypoint-based flight, and autonomous mission execution. It allows UAVs to maintain stable flight paths, return to home when needed, and execute complex flight maneuvers with high accuracy. As UAV applications continue to expand, advancements in GPS technology, including multi-frequency signals and integration with other sensors, will further improve navigation reliability and robustness [41, 45, 52, 53, 55, 56].

2.3. Inertial Measurement Unit (IMU) Basics

An IMU is a critical sensor suite in UAV navigation systems responsible for providing continuous estimates of a vehicle's orientation, velocity, and acceleration in three-dimensional space. Typically composed of accelerometers and gyroscopes and in advanced configurations magnetometers an IMU functions independently of external signals enabling short-term dead reckoning navigation and attitude stabilization [57, 58].

The accelerometers within an IMU measure linear accelerations along the x, y, and z axes, governed by Newton's second law given in equation 2.4:

$$a = \frac{F}{m} \tag{2.4}$$

Where a is acceleration, F is the applied force, and m is mass. These measurements allow the estimation of translational motion, although integration over time introduces cumulative drift.

Gyroscopes, on the other hand, measure angular velocity w, which can be integrated over time to determine orientation, and its equation is given in 2.5:

$$\theta(t) = \int_{0}^{t} w(\tau)d\tau \tag{2.5}$$

This process provides crucial information for attitude control, especially during dynamic maneuvers. However, the accuracy of gyroscopic integration is sensitive to sensor biases and noise, which accumulate over time [59].

IMUs operate in various configurations, such as 3-axis, 6-axis (3 accelerometers + 3 gyroscopes), and 9-axis (3 accelerometers + 3 gyroscopes + 3 magnetometers), with the latter offering enhanced orientation data by accounting for magnetic field effects. These IMUs are often embedded within MEMS technology, making them compact and lightweight, which is ideal for UAV platforms [57]. The data provided by IMUs are typically referenced in the body frame of the UAV and require transformation into a global reference frame (e.g., using direction cosine matrices or quaternions) for integration with other navigation systems [49].

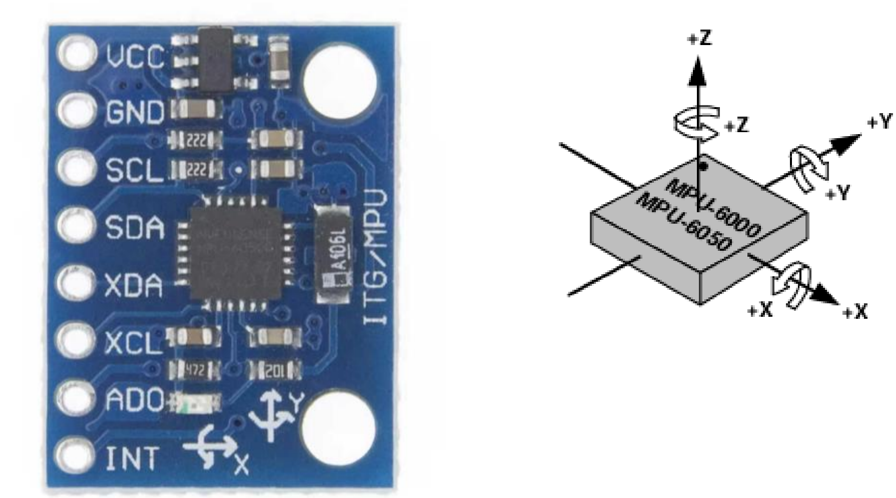

Figure 2.2. Pin Configuration and Axis Orientation of the MPU-6050 [60, 61]

Figure 2.2 illustrates the internal pin layout (left) and axis orientation (right) of the MPU-6050 IMU, commonly used in Arduino-compatible breakout boards. The MPU-6050 integrates a 3-axis accelerometer and a 3-axis gyroscope in a single QFN package. While the chip itself has 24 pins, Arduino breakout boards typically expose only the essential ones, such as VCC, GND, SCL, and SDA, simplifying integration with microcontrollers like the Arduino Uno. The axis orientation diagram (right) shows the positive directions for linear acceleration and angular velocity measurements. These axes (+X, +Y, +Z) and their rotational polarities are critical for correctly mounting the module and interpreting motion data during UAV experiments. Positive angular velocity follows the right-hand rule, corresponding to counterclockwise rotation about each axis.

While standalone IMUs cannot provide absolute positioning, their high update rate and independence from external infrastructure make them indispensable for short-term motion estimation and sensor fusion with GPS and other systems [47, 49].

2.4. Sensor Fusion Techniques

IMUs and GPS are widely employed in UAV navigation systems due to their complementary characteristics. While GPS offers absolute position information with high long-term accuracy, its data update rate is relatively low and susceptible to signal loss, especially in urban or obstructed environments [50]. On the other hand, IMUs provide high-frequency measurements of acceleration and angular velocity, enabling precise short-term motion tracking, but they suffer from drift and cumulative errors over time. The process of sensor fusion aims to integrate these two data sources in a manner that preserves the advantages of each, ultimately providing a more robust and reliable estimate of the UAV's state [42, 50].

A commonly adopted approach for sensor fusion is based on Kalman filtering, a recursive estimation algorithm that continuously updates predictions of a system's state based on a combination of prior knowledge and incoming sensor measurements [62]. The prediction phase of the Kalman filter involves estimating the current state $\hat{X}_{k|k-1}$ using the previous state estimate $\hat{x}_{k-1|k-1}$, the system dynamics F_k, the control input u_k, and the process noise w_k, as represented by equation 2.6:

$$\hat{X}_{k|k-1} = F_k \, \hat{x}_{k-1|k-1} + B_k u_k + w_k \tag{2.6}$$

Here, F_k is the state transition matrix, which models how the system evolves from one time step to the next and B_k represents the control input matrix that maps external inputs to state changes.

Simultaneously, the filter predicts the error covariance by using equation 2.7:

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \tag{2.7}$$

where, Q_k represents the process noise covariance, capturing uncertainties in the model dynamics. In the update phase, the filter incorporates actual sensor measurements to refine the predicted estimate. First, the Kalman gain is calculated by using the equation 2.8 to determine the optimal balance between the prediction and measurement:

$$K_k = P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + R_k \right)^{-1} \tag{2.8}$$

In this context, H_k is the measurement matrix, which maps the predicted state into the measurement space, and R_k is the measurement noise covariance, representing sensor inaccuracies. The measurement vector z_k which may include data from GPS or other sources, is then used to update the state estimate by using the equation 2.9:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(z_k - H_k \hat{x}_{k|k-1} \right) \tag{2.9}$$

Finally, the error covariance is updated as given in equation 2.10:

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \tag{2.10}$$

This cycle is repeated in real-time, allowing continuous refinement of UAV state estimates such as position, velocity, and orientation.

For nonlinear systems, which are common in UAV dynamics, extensions such as the EKF and UKF are employed. The EKF linearizes nonlinear models using Jacobian matrices, whereas the UKF utilizes sigma points to propagate uncertainties through nonlinear transformations. In scenarios involving highly non-Gaussian or multi-modal distributions, Particle Filters (PF) provide greater flexibility, although this comes at the cost of increased computational complexity [63].

As shown in Table 2.1, various sensor fusion methods differ in terms of accuracy, computational cost, and real-time applicability. The selection of a suitable method depends on the UAV's mission requirements and onboard processing capabilities [64].

Table 2.1. Comparison of Sensor Fusion Methods for GPS/IMU Integration

Method	Advantages	Limitations
Kalman Filter	Provides optimal estimation by modelling probabilistic uncertainty. Works well in sensor fusion.	Requires accurate system modelling 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, labelled 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.

Fusion architectures can be categorized as either loosely coupled or tightly coupled. In loosely coupled systems, the outputs of GPS and IMU are processed independently and then combined at a higher level. In contrast, tightly coupled systems integrate raw measurements from both sensors directly within the estimation algorithm. Tightly coupled approaches, particularly those based on EKF, have demonstrated greater robustness in degraded or GPS-denied environments [51, 65]. For example, such systems have been shown to reduce positional errors from approximately 5 meters (when using GPS alone) to below 1 meter, while also mitigating the cumulative drift error inherent in standalone IMU data.

In summary, sensor fusion techniques based on Kalman filtering form the backbone of UAV navigation systems. They ensure more accurate and reliable estimates of position and motion by leveraging the complementary characteristics of GPS and IMU sensors [51, 65, 66].

2.5. UAV Navigation Requirements and Challenges

Reliable navigation is one of the most fundamental requirements for UAVs, directly influencing flight stability, mission success, and autonomous functionality. A UAV must be capable of continuously determining its position, velocity, and orientation with sufficient accuracy and speed to respond effectively to dynamic flight conditions. In this context, several key performance requirements come to the forefront [67]. Precision is vital in tasks such as mapping, surveillance, and target tracking, where even small deviations in location data can lead to significant errors. Equally important is the need for real-time processing, as navigation data must be delivered with minimal latency to enable fast and accurate control decisions, especially in autonomous or high-speed operations [68, 69].

However, meeting these requirements in practice presents several challenges. GPS, while widely used for global positioning, is vulnerable to signal loss, multipath interference, and atmospheric disturbances, particularly in enclosed, urban, or densely vegetated environments. In such situations, IMUs serve as an essential backup, but they are also prone to drift and accumulated error over time. This creates a trade-off between short-term responsiveness and long-term reliability [3, 48, 70, 71]. For example, a UAV might rely on GPS data to provide fast response times in open environments. GPS is highly accurate in wide-open spaces, but its performance deteriorates in areas with signal loss or interference, such as tunnels or urban canyons. In such cases, short-term responsiveness is compromised because the GPS signal is unavailable. To compensate for this, the UAV can use an IMU, which tracks motion and orientation accurately in the short term, but it suffers from drift over time. For example, during a long-duration flight, even a small error in the IMU data can accumulate, leading to significant deviations in position and negatively impacting long-term reliability.

Additionally, navigation systems must be designed with hardware constraints in mind, as weight, size, and power consumption are critical limiting factors, especially for small UAVs. For example, a high-precision IMU may consume more power and occupy more space, which could reduce the UAV's flight time. Similarly, a high-resolution GPS antenna might increase the UAV's weight and reduce its energy efficiency, which is particularly problematic for small platforms. Therefore, optimizing the weight and power consumption of sensors is crucial, particularly for mini-UAVs [71, 72].

As autonomy becomes more prevalent, systems must also incorporate intelligent sensor fusion and adaptive algorithms to compensate for individual sensor limitations without relying on constant human supervision. For example, when GPS signals are lost, the UAV can continue its flight using IMU data. However, as IMU accuracy deteriorates over time, sensor fusion algorithms can combine GPS and IMU data to provide a more accurate position estimate. Adaptive algorithms, such as Kalman filters, help minimize the errors from both sensors and improve data accuracy. This approach balances short-term responsiveness with long-term reliability [70, 71, 73, 74].

Ultimately, developing a navigation system for UAVs involves more than just selecting accurate sensors. It requires a delicate balance between performance, resilience, and resource constraints. For example, high-precision sensors typically consume more power, while low-power sensors may offer reduced accuracy. Optimizing the sensors and utilizing sensor fusion techniques are crucial for enhancing overall system efficiency. Approaches like combining GPS and IMU data through sensor fusion provide an ideal solution to achieve this balance [74-77].

3. PERFORMANCE ANALYSIS OF GPS AND IMU IN UAVs

The accurate navigation and positioning of UAVs rely heavily on onboard sensor systems, particularly the GPS and the IMU. While GPS provides absolute positioning by receiving satellite signals, IMU delivers relative motion data through measurements of acceleration and angular velocity[43, 48, 78]. Each system has distinct advantages and limitations depending on operational conditions such as environment, motion dynamics, and signal availability. Therefore, a detailed performance analysis of these two systems is essential to understand their individual and complementary roles in UAV applications.

This section presents a comprehensive examination of GPS and IMU performance through both theoretical metrics and experimental results. Key performance indicators such as accuracy, precision, drift, and responsiveness are discussed.

Table 3.1. Key Performance Differences Between GPS and IMU Systems Commonly Used in UAV Navigation [3, 4, 43, 45]

Feature / Criterion	GPS	IMU
Type of Positioning	Absolute (Global) position	Relative motion (acceleration and angular velocity) measurement
Accuracy	Medium to high (1–10 meters)	High short-term accuracy, but drifts over time
Data Update Rate	Low (1–10 Hz)	High (100 Hz and above)
Environmental Effects	Satellite signal quality, atmospheric conditions, obstructions	Vibrations, temperature changes, calibration errors
Operational Environment	Requires open sky	Works in both indoor and outdoor settings
Noise and Error Types	Multipath effects, signal loss	Drift and sensor noise
Typical Use	Absolute position determination	Orientation, velocity, and acceleration estimation
Power Consumption	Moderate	Low to moderate

Table 3.1 provides a comparative summary of the key characteristics and performance criteria of GPS and IMU systems commonly used in UAV navigation.

Due to their differing operational principles and environmental sensitivities, both sensors offer unique advantages. Therefore, UAV navigation solutions typically integrate both to leverage their complementary strengths.

Additionally, environmental and technical factors that influence sensor reliability are identified. The subsequent experimental evaluations, conducted under varying spatial and atmospheric conditions, enable a comparative assessment of GPS and IMU data to highlight the strengths, weaknesses, and potential for sensor fusion in UAV navigation systems.

3.1. Performance Metrics

The evaluation of GPS and IMU performance in UAVs relies on well-defined metrics that quantify how effectively each sensor contributes to navigation and control under various flight conditions. These metrics include accuracy, precision, latency, drift, update rate, and noise characteristics, each offering unique insight into system performance [78, 79]. The performance metrics utilized in this study are derived from standard definitions widely adopted in the fields of signal processing, inertial navigation, and control systems. These include commonly accepted formulations for position error, standard deviation, latency, drift rate, and sampling frequency, which are essential for evaluating sensor behavior in UAV applications [43, 47, 80, 81].

To ensure a rigorous understanding, these indicators can be described both qualitatively and quantitatively using mathematical expressions where applicable.

Accuracy refers to the degree of closeness between a sensor's measurement and the actual or true value. In UAV applications, the positioning error for GPS can be computed as the Euclidean distance between the measured coordinates (x, y, z) and the ground truth coordinates (x_{true}, y_{true}, z_{true}):

$$Position\ Error = \sqrt{(x - x_{true})^2 + (y - y_{true})^2 + (z - z_{true})^2} \tag{3.1}$$

Equation 3.1 provides a scalar value representing spatial deviation and is particularly useful for evaluating GPS accuracy during hovering or waypoint navigation tasks.

Precision, on the other hand, reflects the sensor's consistency across repeated measurements. A common method to quantify precision is through the standard deviation of a set of readings, as expressed in Equation 3.2.

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2} \tag{3.2}$$

Here, x_i represents individual sensor readings, n is the number of samples, and μ is the sample mean. A smaller σ indicates higher precision. In inertial systems, even if measurements are not accurate due to drift, consistent output (i.e., high precision) enables error modeling and sensor fusion.

Latency is defined as the time delay between the occurrence of a physical event and its recognition by the sensor. Although not always expressed with a fixed formula, latency τ can be measured as shown in Equation 3.3.

$$\tau = t_{measured} - t_{event} \tag{3.3}$$

Where, t_{event} is the timestamp of the actual event (e.g., movement initiation), and $t_{measured}$ is the sensor's response time. Low latency is critical in closed-loop UAV systems for maintaining stability and control.

Drift is a cumulative error characteristic of IMUs, resulting from the integration of sensor noise and biases over time. Angular drift rate, for example, can be expressed as described by Equation 3.4.

$$Drift\ Rate = \frac{\Delta\theta}{\Delta t} \tag{3.4}$$

Where $\Delta\theta$ represents the deviation in orientation and Δt is the elapsed time. High drift rates lead to poor long-term estimation unless corrected using external references such as GPS.

Update rate, or sampling frequency, determines how frequently the sensor outputs data. IMUs typically operate at high rates (≥100 Hz), allowing them to capture high-frequency dynamics. In contrast, GPS modules generally update at lower frequencies (1–10 Hz), making them less responsive to rapid maneuvers.

Sensor noise introduces random fluctuations in the measured signal, which can be modeled as white Gaussian noise in many cases. In signal processing, noise characteristics are often analyzed in terms of power spectral density (PSD), but for simpler UAV applications, filtering techniques such as moving averages or Kalman filters are commonly employed to suppress high-frequency noise components [82].

3.2. Factors Affecting GPS Performance

The effectiveness of GPS systems in UAV applications is shaped by a range of environmental and technical conditions that directly influence the accuracy, availability, and reliability of positional data. Since GPS relies on satellite signals to compute absolute location, even minor disruptions in signal quality or geometry can significantly impact navigation outcomes, particularly during dynamic or long-duration UAV missions [3, 7, 54].

One of the most influential factors is satellite geometry, which refers to the spatial distribution of visible satellites in the sky relative to the GPS receiver. A well-distributed arrangement across the sky reduces the geometric dilution of precision (GDOP) and improves positional accuracy. On the other hand, a configuration where satellites are clustered within a narrow area of the sky increases uncertainty in the calculated position. This issue becomes more prominent during low-altitude flights or in environments with obstructed sky views [79, 83].

Another critical factor is atmospheric interference. As GPS signals pass through the ionosphere and troposphere, they experience delays that distort timing and lead to position calculation errors. Ionospheric delays vary with solar activity and are frequency-dependent, while tropospheric delays are influenced by meteorological parameters such as temperature, pressure, and humidity. If uncorrected, these delays can introduce errors ranging from a few centimeters to several meters [84].

Multipath propagation is also a significant source of error, especially in urban or cluttered environments. This phenomenon occurs when GPS signals reflect off nearby surfaces like buildings or terrain before reaching the receiver, causing delayed versions of the signal to be processed. As a result, the estimated position may deviate from the actual location, which negatively affects tasks that require high accuracy, such as autonomous landing or precision waypoint following [3, 85]. In addition to passive signal errors, active interference such as GPS spoofing can also mislead UAVs, as shown in Figure 3.1.

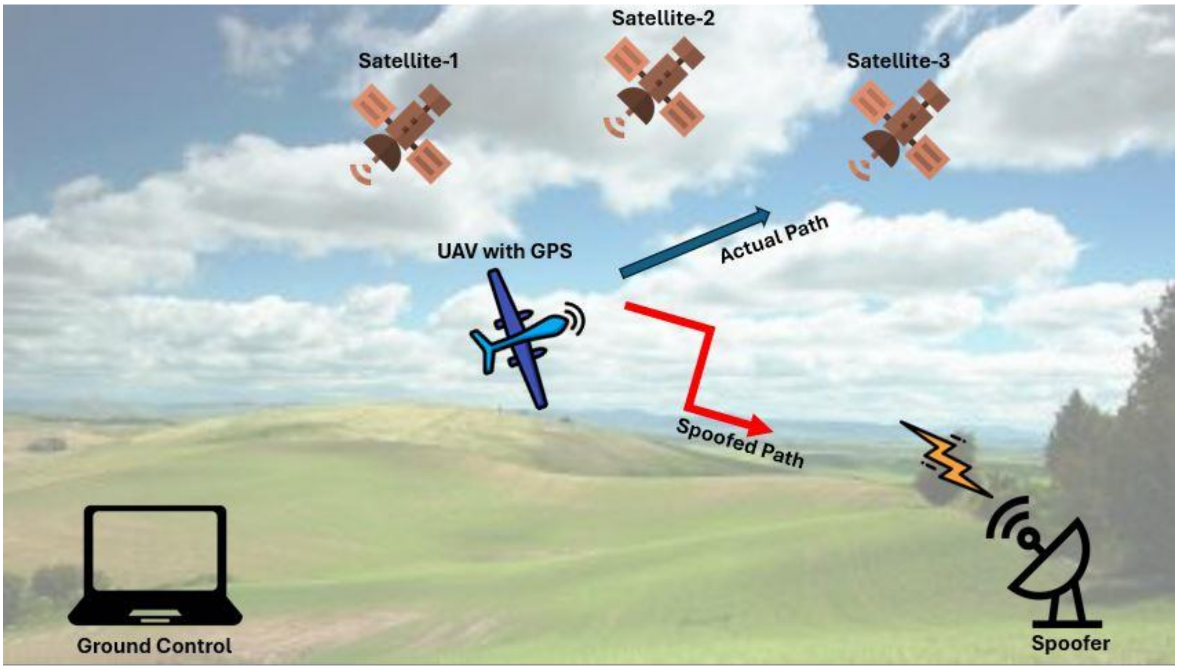

Figure 3.1. A Conceptual Illustration of a GPS Spoofing Attack on a UAV

Beyond environmental influences, the internal design and performance of the GPS receiver itself play an essential role. Components such as the antenna type, signal tracking algorithms, and built-in error correction mechanisms determine how effectively the receiver operates in challenging signal environments [86]. High-grade receivers typically offer better resistance to noise and faster reacquisition after signal loss, while low-cost modules may struggle to maintain consistent performance.

GPS signal availability also decreases in environments where the line of sight to satellites is partially obstructed. Obstacles such as buildings, dense vegetation, or even parts of the UAV itself can block or weaken incoming signals [84-86]. This disruption may result in intermittent reception or complete signal loss. Under such conditions, navigation performance degrades significantly, and UAVs may have to rely on inertial navigation systems (INS) or data fusion techniques to maintain mission continuity.

3.3. Factors Affecting IMU Performance

IMUs play a vital role in UAV navigation, but their accuracy is affected by various internal and external factors. Sensor noise and bias instability are among the main challenges. Accelerometers and gyroscopes inherently produce random noise and slowly drifting biases due to manufacturing tolerances and electronic imperfections. These errors accumulate over time and can significantly degrade navigation accuracy if not properly compensated [87].

Environmental conditions, especially temperature changes, also impact IMU performance. Temperature variations influence the mechanical and electrical properties of the sensors, causing shifts in bias and sensitivity. Although some IMUs include temperature compensation, low-cost MEMS sensors frequently used in UAVs remain sensitive to thermal effects, which can lead to increased measurement errors during flight [4, 87, 88, 89].

Mechanical vibrations and shocks are other important factors. UAVs are subject to constant vibrations that may excite resonances in sensor housings, resulting in transient errors in acceleration and angular velocity measurements [89, 90]. Moreover, improper mounting or misalignment of the IMU relative to the UAV's coordinate system introduces systematic errors and amplifies noise due to mechanical coupling.

Over time, sensor performance can deteriorate due to aging effects like material fatigue and environmental exposure. External influences such as humidity, pressure fluctuations, and electromagnetic interference further contribute to measurement inaccuracies, especially in challenging operating environments [48, 89, 90, 91].

Finally, the IMU's sampling rate and data processing algorithms significantly affect the quality of the output data. Inadequate sampling may cause signal distortion, while insufficient filtering can leave noise unmitigated. Therefore, advanced filtering and sensor fusion techniques, including Kalman filtering, are applied to improve measurement accuracy and reliability [51, 81, 92, 93, 94].

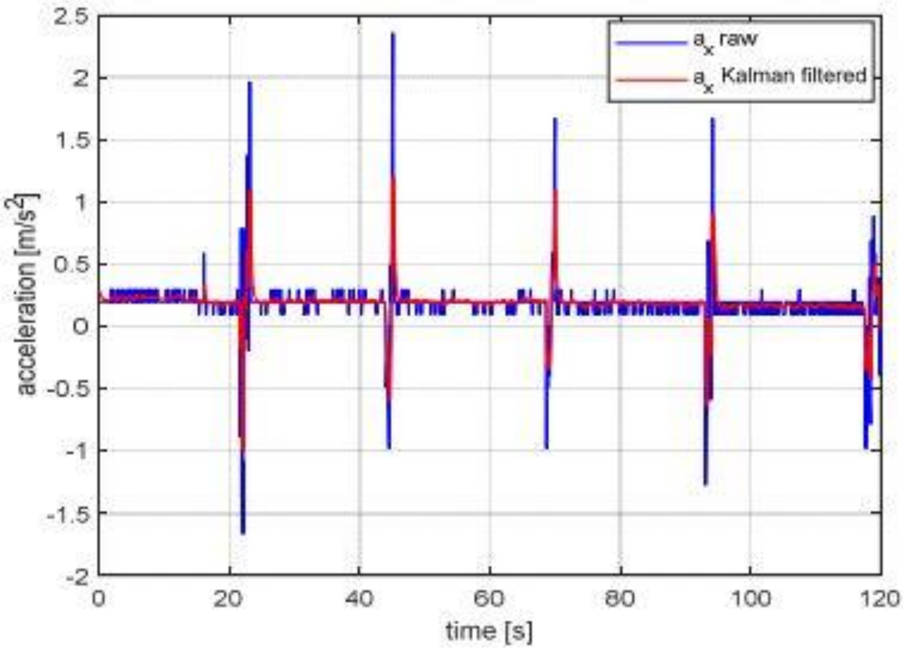

Figure 3.2. Example of Raw IMU Acceleration Data and its Variability [95]

Figure 3.2 illustrates the noisy nature of raw x-axis acceleration data (blue) obtained from a low-cost IMU, where sudden spikes and random fluctuations are clearly visible, reflecting the effects of sensor noise, bias instability, and possible external disturbances. The red line shows a smoothed version for reference, emphasizing how these imperfections underscore the need for filtering and compensation methods in precision navigation applications.

3.4. Experimental Setup and Data Collection

This section details the experimental framework developed to systematically evaluate and contrast the performance characteristics, inherent advantages, and limitations of GPS and IMU systems within UAVs. The DJI UAV platform was selected for this purpose, enabling simultaneous acquisition of both internal and external sensor datasets to facilitate comprehensive comparative analyses.

An external IMU, based on the widely utilized and cost-effective MPU6050 MEMS sensor, was rigidly affixed to the UAV airframe. The MPU6050 was chosen due to its prevalent application in consumer electronics and its suitability for assessing performance disparities between low-cost MEMS sensors and the proprietary commercial-grade sensors embedded in UAVs. This external sensing module was interfaced with an Arduino Uno microcontroller, supplemented by a DS3231 RTC module to ensure precise temporal synchronization, and a microSD card interface for reliable onboard data logging. The entire assembly was powered via a 9V battery source and mechanically secured to minimize the influence of mechanical vibrations on sensor outputs.

The complete external sensor assembly was integrated onto the UAV platform using the DJI, as illustrated in Figure 3.3, which provides a detailed visual of the experimental hardware configuration.

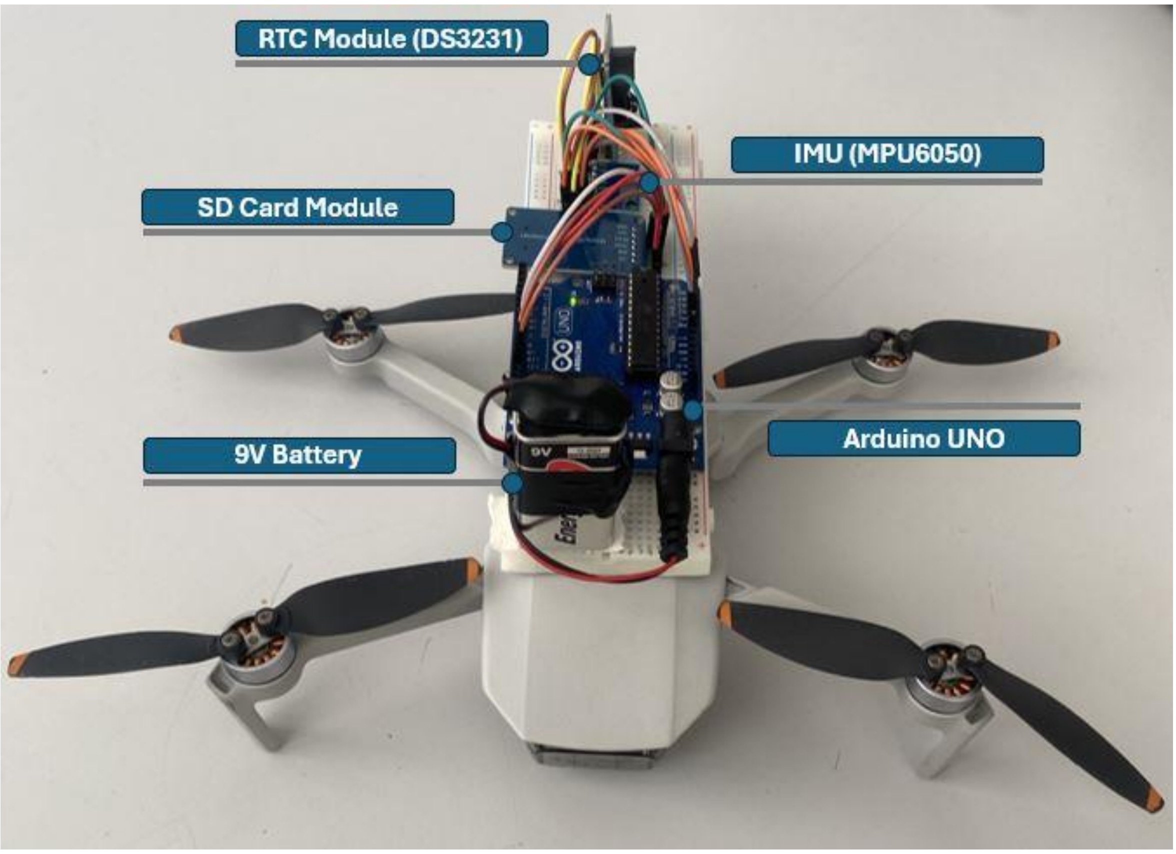

Figure 3.3. Experimental hardware setup mounted on the DJI UAV

Concurrently, onboard GPS and IMU data from the DJI were recorded using Air Data UAV software. Although detailed technical specifications for the UAV's integrated IMU remain undisclosed, these internal sensor readings served as a critical benchmark against which the external MPU6050 data were evaluated, particularly in terms of measurement accuracy, signal stability, and noise characteristics. GPS parameters logged included geospatial coordinates (latitude, longitude, altitude), velocity vectors, and satellite constellation metrics, while IMU data encompassed tri-axial accelerometer and gyroscope signals.

The raw data collected from both the internal and external sensors were processed using a Kalman filter to reduce noise and improve measurement accuracy. Subsequently, sensor fusion techniques were applied to integrate GPS and IMU data, enhancing the overall navigation performance and providing a more reliable dataset for analysis.

The dual-sensor acquisition methodology facilitated a rigorous comparative assessment of the UAV’s native sensor suite against the external MEMS-based IMU. Sensor performance was scrutinized under a variety of operational and environmental conditions, including temperature and relative humidity tests conducted in accordance with the MIL-STD-810 standard, wind exposure, operation in both open and enclosed spaces, and water splash resistance conforming to IPX2 standards of the Ingress Protection (IP) rating system, which specifies protection against vertically dripping water. These conditions were selected to replicate realistic and standardized environmental stresses encountered in typical UAV missions, thereby enhancing the relevance and robustness of the experimental findings.

3.4.1. Open and enclosed space testing

The operational environment plays a critical role in the performance of navigation and inertial sensing systems in UAVs. In particular, GPS signal quality and IMU stability can vary significantly depending on spatial constraints such as satellite visibility, electromagnetic interference, and the availability of open sky. To systematically evaluate the influence of such spatial factors, this study includes test scenarios in both open-field and enclosed environments. These contrasting conditions allow for an in-depth assessment of the positional accuracy, sensor drift, and noise characteristics of both the internal (DJI built-in sensors) and external (MPU6050-based) sensor suites.

The open-field flight tests were conducted in a wide, unobstructed outdoor area located in the Alacaatlı neighborhood of Ankara, Turkiye. The test location consisted of an unobstructed outdoor area free from high-rise buildings, dense vegetation, or significant electromagnetic interference sources. This setting provided an ideal environment for consistent satellite visibility and minimal multipath signal reflection, ensuring optimal GPS signal reception during flight.

During the tests, ambient environmental conditions were stable, with air temperature ranging between 22°C and 25°C, relative humidity between 20–25%, and an average wind speed of approximately 18 km/h. These nominal conditions provided a reliable baseline for evaluating sensor performance in open-air scenarios, serving as a reference for comparison with enclosed and environmentally conditioned test environments.

Enclosed space tests were carried out in an indoor facility with no direct satellite visibility, thereby simulating GPS-denied or GPS-degraded conditions. The structure was built with reinforced concrete and steel elements, which effectively blocked GNSS signals and introduced potential sources of electromagnetic interference. Lighting and temperature conditions were maintained constant throughout the experiments. This setting was selected to assess the standalone performance of IMU-based inertial navigation when GPS input was unavailable or unreliable.

The figures from Figure 3.4 to Figure 3.7b illustrate the raw sensor outputs obtained from the external MPU6050 sensor mounted on the UAV. The Figure 3.4 presents unfiltered accelerometer data along the X, Y, and Z axes. The data reveals the presence of high-frequency noise components, particularly along the X-axis, which are likely attributed to drone vibrations and mechanical disturbances occurring during flight. As expected, the gravitational component is most prominent on the Z-axis due to the sensor's orientation relative to the Earth’s surface.

As shown in Figure 3.4, the raw acceleration measurements from the external IMU (MPU6050) clearly exhibit these high-frequency fluctuations, which are typical characteristics of unfiltered inertial data.

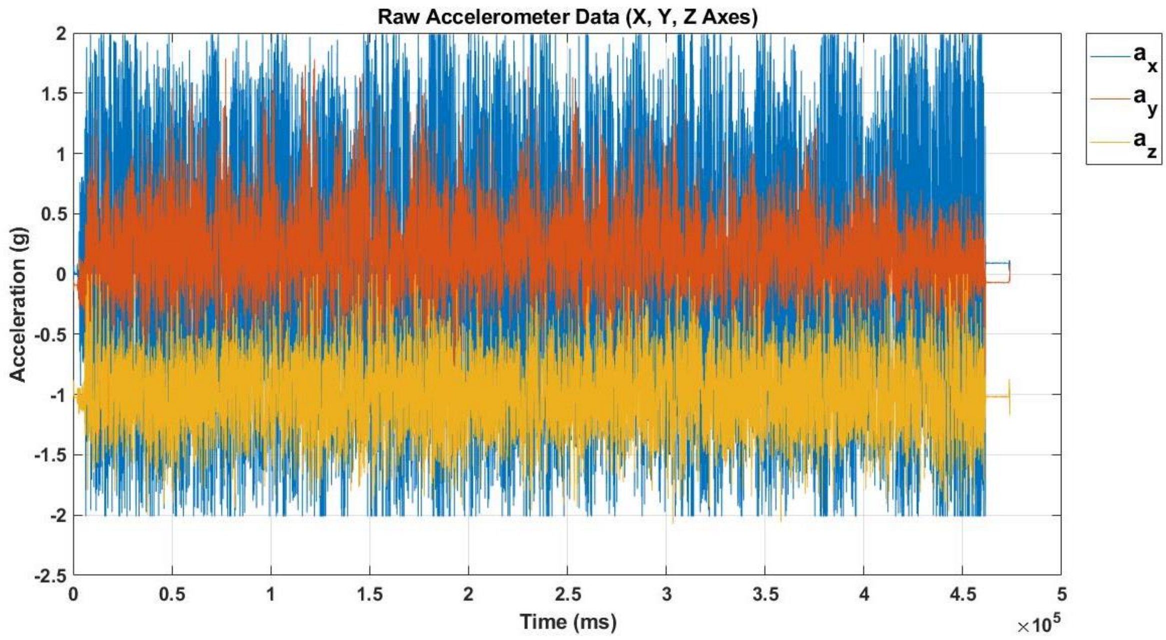

Figure 3.4. Unfiltered Acceleration Measurements in X, Y, and Z Axes from External IMU

The Figure 3.5 presents the unfiltered gyroscope data along the X, Y, and Z axes, recorded from the external MPU6050 sensor. These measurements offer valuable insight into the angular velocity variations captured by the MPU6050 sensor mounted on the UAV during open-space flight. As illustrated in Figure 3.5, the unfiltered gyroscope measurements display significant noise and fluctuations, especially in the X and Y axes, which are likely caused by rapid attitude changes and mechanical vibrations during flight maneuvers. Additionally, observable drift in some axes reflects the cumulative nature of integration errors commonly encountered in low-cost MEMS gyroscopes. These raw outputs highlight the limitations of relying solely on gyroscope data without filtering or sensor fusion techniques, particularly in scenarios requiring long-term stability and accuracy in orientation estimation.

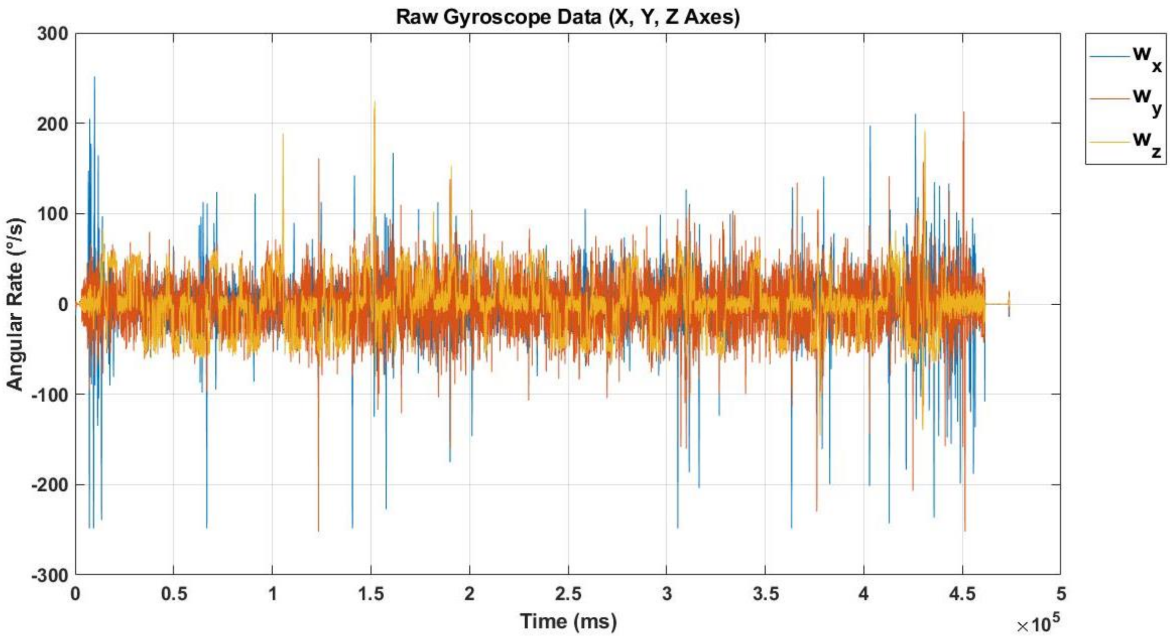

Figure 3.5. Unfiltered Gyroscope Measurements in X, Y, and Z Axes from External IMU

Following the analysis of raw inertial data, the orientation estimation process was carried out in MATLAB using the collected accelerometer and gyroscope signals. Built-in computational routines and custom scripts were utilized to derive the pitch and roll angles from the multi-axis sensor measurements. These calculations were based on the standard trigonometric relations applied to the sensor outputs, although explicit formula-based computation was not directly implemented. The data were acquired during open-space tests, where environmental interferences such as magnetic distortions or dynamic accelerations were minimized.

Figure 3.6 presents the raw pitch and roll angle estimations recorded under open-space conditions. Specifically, Figure 3.6a illustrates the data obtained from the external MPU6050 IMU mounted on the UAV, while Figure 3.6b displays the measurements collected from the internal IMU of the DJI. These figures facilitate a direct comparison between the unfiltered orientation data produced by the external sensor and the filtered output generated by the DJI onboard system.

Following the experimental flights conducted under open-air conditions, the pitch and roll angle data obtained from both the external (MPU6050) and internal (DJI) IMU sensors were analyzed to evaluate attitude estimation performance.

As shown in Figure 3.6a, the raw, unfiltered pitch and roll data captured by the external MPU6050 sensor mounted on the UAV exhibits significant high-frequency noise and broad angular variations, often exceeding ±70°, which do not correspond to the UAV's actual flight behavior. This pronounced noise and instability are likely caused by several factors, including:

- mechanical vibrations transferred from the UAV to the sensor housing,
- the inherent temperature sensitivity of the MPU6050,
- and the absence of any onboard filtering or sensor fusion processes.

In contrast, Figure 3.6b presents the pitch and roll angles obtained from the DJI built-in IMU, which demonstrate relatively stable behavior, with angles predominantly contained within a ±20° range. Although minor high-frequency oscillations are observed, they remain within acceptable limits for consumer-grade UAVs, indicating effective onboard calibration, digital filtering, and sensor fusion mechanisms. The smooth orientation transitions reflected in this data are consistent with the UAV's expected motion profile in an open and interference-free environment.

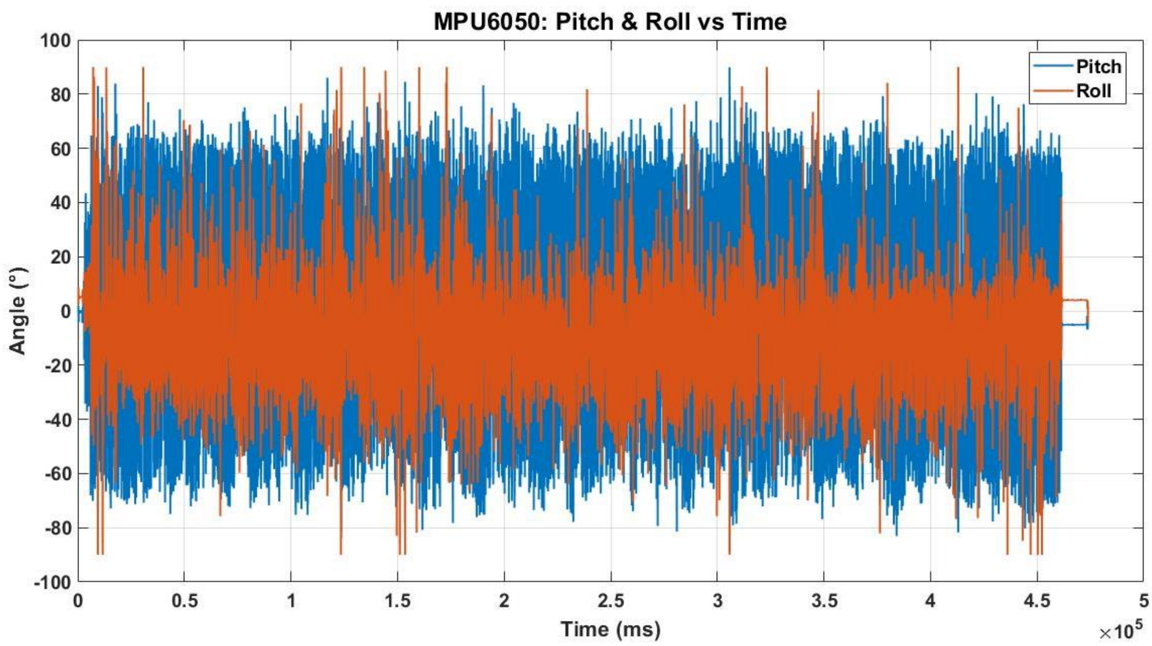

Figure 3.6a. Pitch and Roll Angle vs Time for MPU6050 External IMU (Open Space) – Raw Data

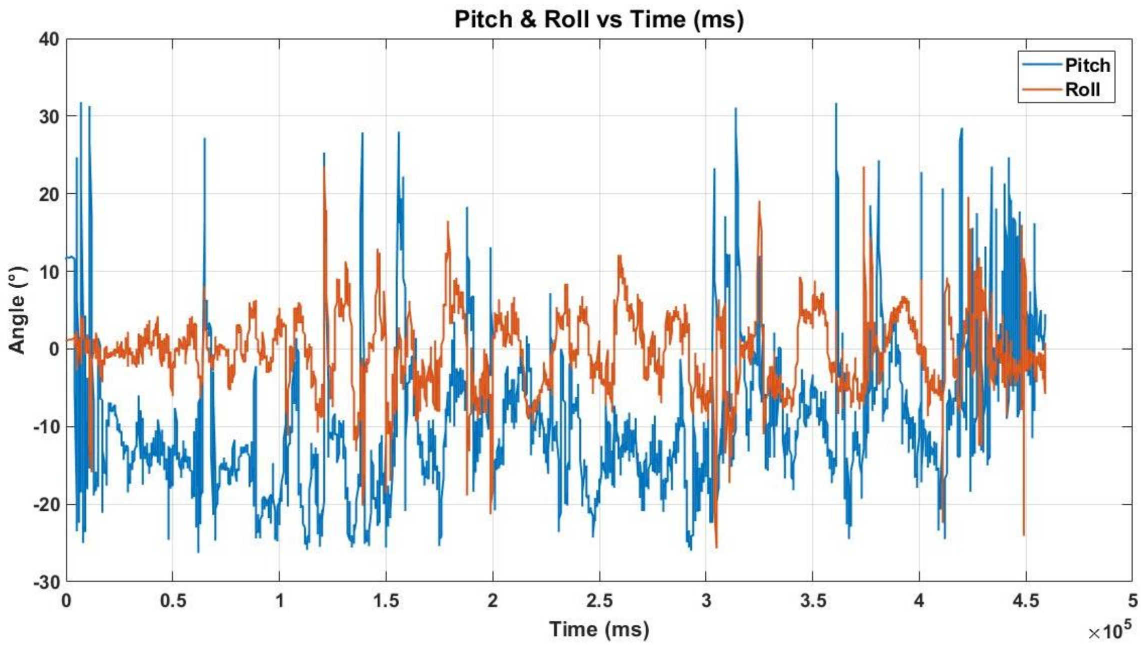

Figure 3.6b. Pitch and Roll Angle vs Time for DJI Internal IMU (Open Space)

Following the open-air evaluations, additional test flights were conducted within an enclosed environment characterized by significant structural reflections, limited GNSS reception, and increased electromagnetic interference. This setting was intended to simulate challenging indoor operational scenarios commonly encountered by UAV platforms.

Figure 3.7 presents the raw pitch and roll angle estimations obtained under these enclosed-space conditions. Specifically, Figure 3.7a shows the data acquired from the external IMU (MPU6050) mounted on the UAV, while Figure 3.7b displays the measurements obtained from the internal IMU of the DJI. These figures enable a comparative assessment of orientation performance under constrained environmental conditions between the raw external sensor outputs and the internally processed measurements of the DJI.

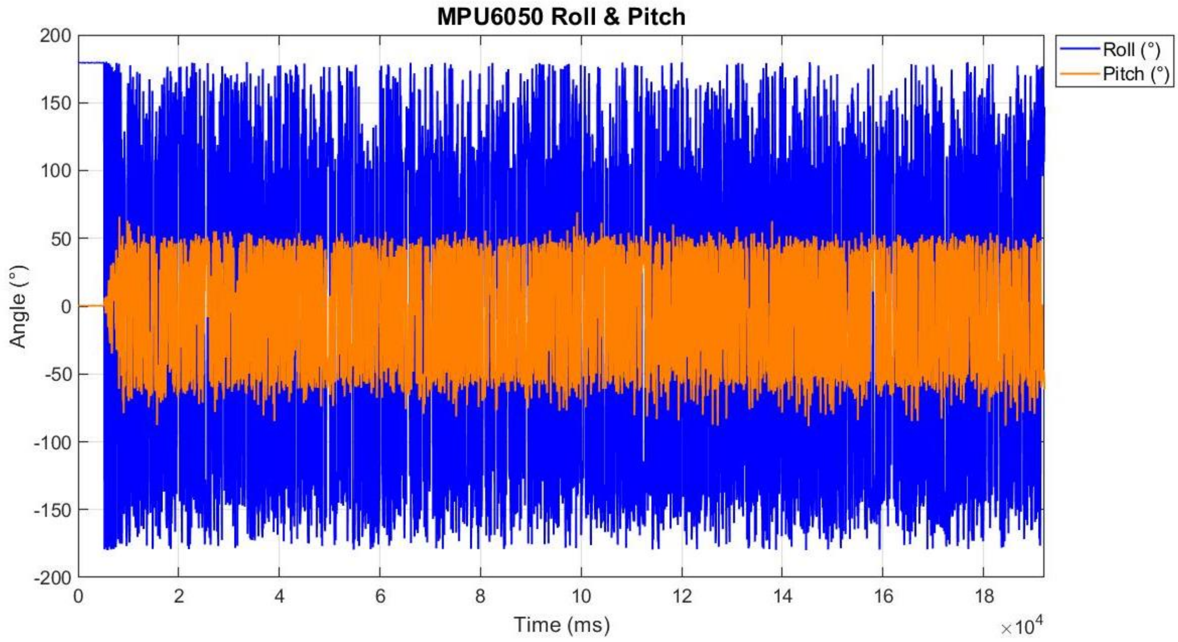

Figure 3.7a. Pitch and Roll Angle vs Time for MPU6050 External IMU (Enclosed Space) – Raw Data

The roll and pitch angles fluctuate within extreme ranges, frequently exceeding ±150°, which are physically implausible given the UAV's constrained movement within the test environment. The worsening signal integrity can be attributed to:

- Amplified mechanical vibrations due to confined airflows,
- Increased magnetic and electromagnetic interference impacting gyroscopic accuracy,
- Further temperature-induced sensor drift,
- And continuous absence of real-time filtering or correction mechanisms.

On the other hand, as depicted in Figure 3.7b, the DJI internal IMU maintains relatively stable roll and pitch estimations even in these adverse conditions.

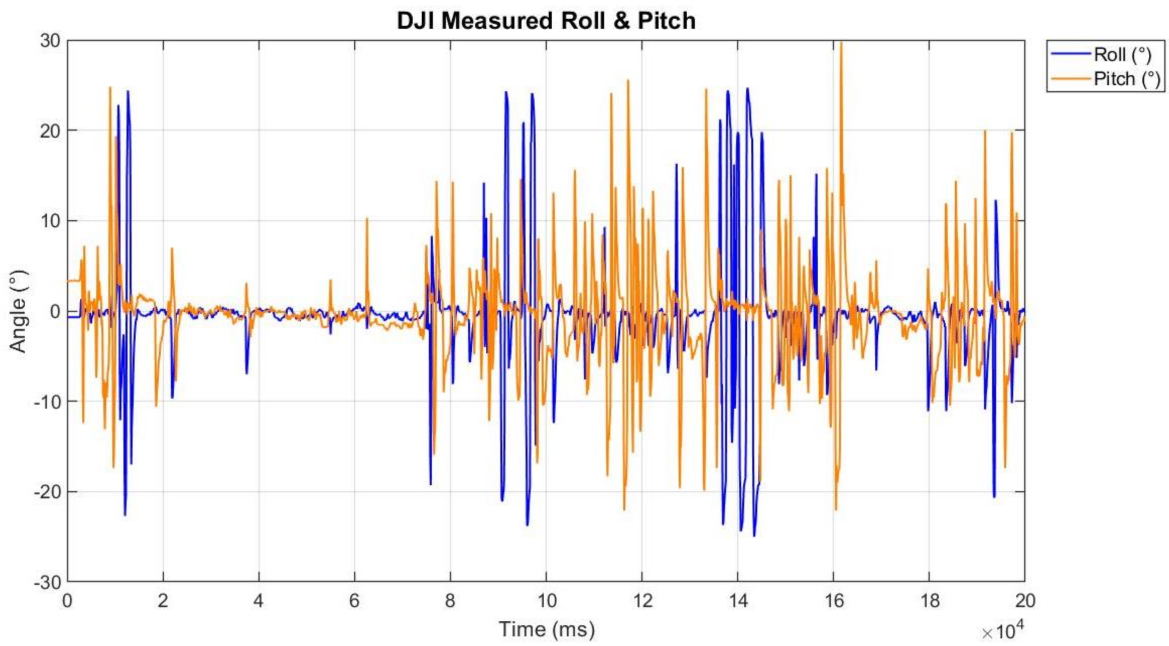

Figure 3.7b. Pitch and Roll Angle vs Time for DJI Internal IMU (Enclosed Space)

While occasional deviations beyond ±20° are observed due to temporary disturbances, the onboard fusion algorithms continue to provide acceptable attitude stability.

To further verify the impact of indoor interference on global positioning capabilities, satellite count and GPS level data were monitored, as shown in Figure 3.8. Both parameters remained nearly zero throughout the entire flight, confirming the expected signal obstruction within the enclosed space. This emphasizes the necessity of reliable inertial-based navigation when GNSS signals are compromised or unavailable.

After presenting the inertial sensor data, the analysis proceeds with the evaluation of positional accuracy and flight trajectory based on the integrated GPS measurements. In this context, an initial overview of the UAV's flight path is provided to offer visual insight into the experimental environment and flight pattern.

Figure 3.8. UAV Trajectory Visualization Recorded by the Onboard Flight Control Interface (Airdata UAV) during Open-Space Flight Experiment

Fig. 3.8 illustrates the UAV’s trajectory during the open-space flight test, as recorded by the onboard flight control system interface (AirData UAV). This representation offers a general visual reference of the mission area and executed flight pattern.

Subsequently, Figure 3.9 presents the processed 2D GPS trajectory, reconstructed from the raw GPS log data collected during the same flight. This trajectory plot reflects the actual data used for post-processing, sensor fusion, and error evaluation in the following sections.

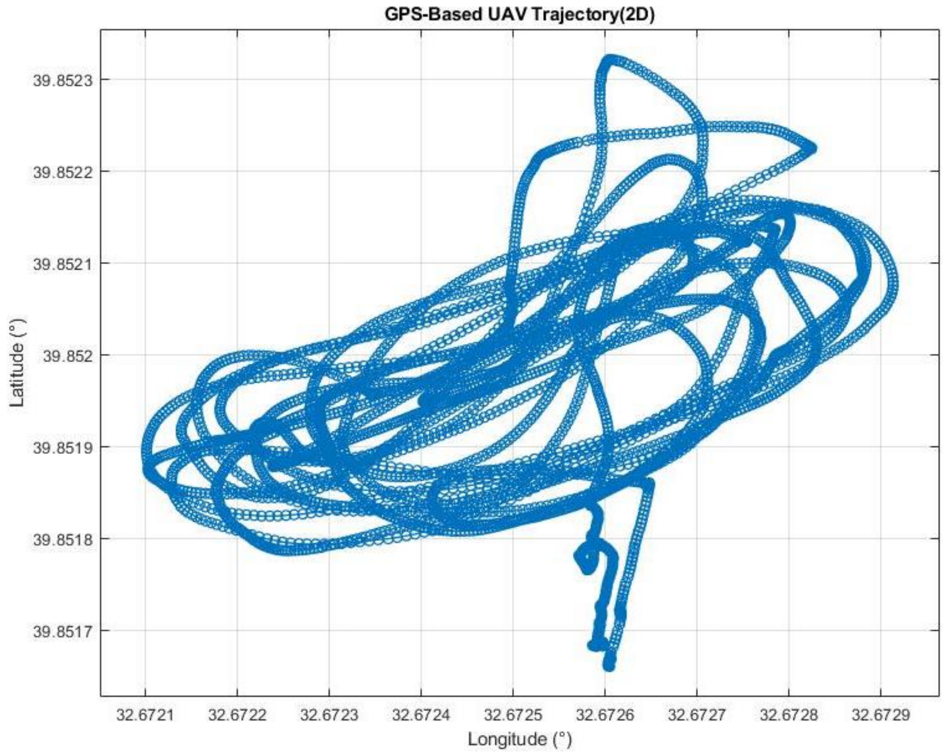

Figure 3.9. Processed 2D GPS Trajectory Reconstructed from Raw GPS Log Data Collected during Open-Space Flight Test

After trajectory evaluation, the analysis proceeds with the comparison of velocity profiles obtained from both GPS and IMU data, providing insight into dynamic performance.

The velocity components recorded by the GPS receiver are presented to analyze the UAV's translational motion along each axis. Figure 3.10 displays the raw GPS-based velocity profiles for X, Y, and Z directions during the open-space flight test. These measurements serve as a reference for evaluating the IMU-based velocity estimation performance.

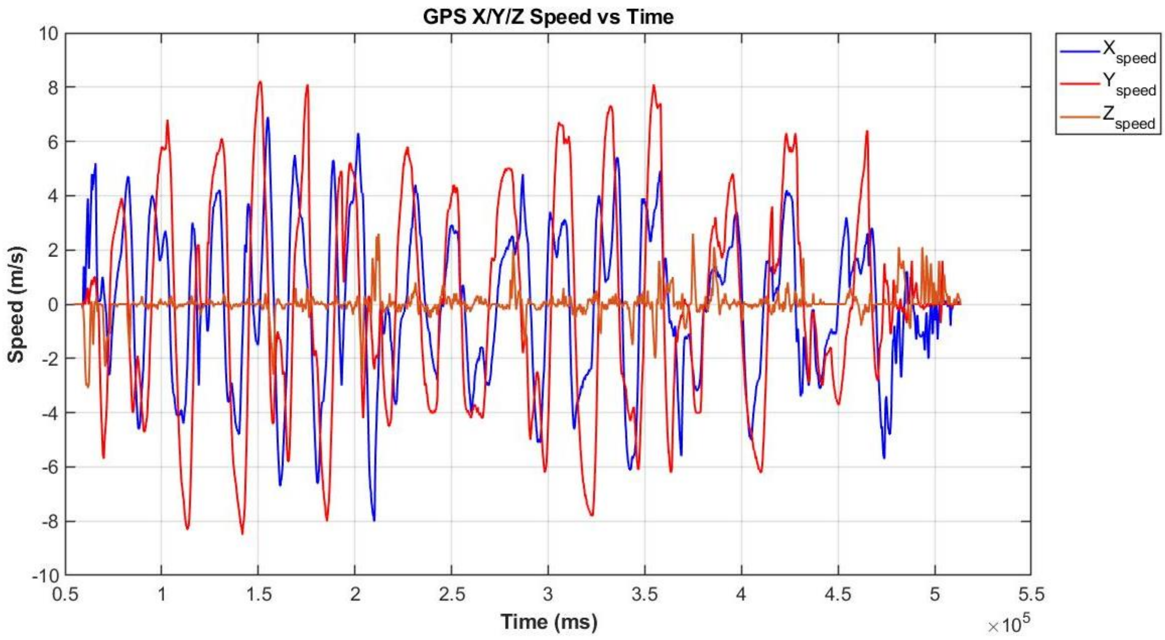

Figure 3.10. Raw GPS-Based Velocity Profiles in X, Y, and Z Directions during Open-Space Flight

Following the GPS-based analysis, the raw velocity profiles along the X, Y, and Z axes were estimated through direct numerical integration of the accelerometer measurements (AccelX, AccelY, and AccelZ) obtained from the MPU6050 sensor. These calculations were performed without applying any bias correction, filtering, or compensation mechanisms.

As depicted in Figure 3.11, the resulting unfiltered velocity estimates are subject to substantial integration drift, particularly along the Z-axis, where the accumulated error rapidly increases due to inherent sensor bias and low-frequency noise. This phenomenon is a well-known limitation of low-cost MEMS-based IMUs, where even minor offset errors in acceleration can lead to exponentially growing velocity errors over time.

The observed drift underscores the critical importance of applying advanced signal processing techniques, such as high-pass filtering, bias compensation, and sensor fusion algorithms like the Kalman filter, in order to obtain reliable and physically meaningful inertial velocity estimates that are suitable for navigation and control applications.

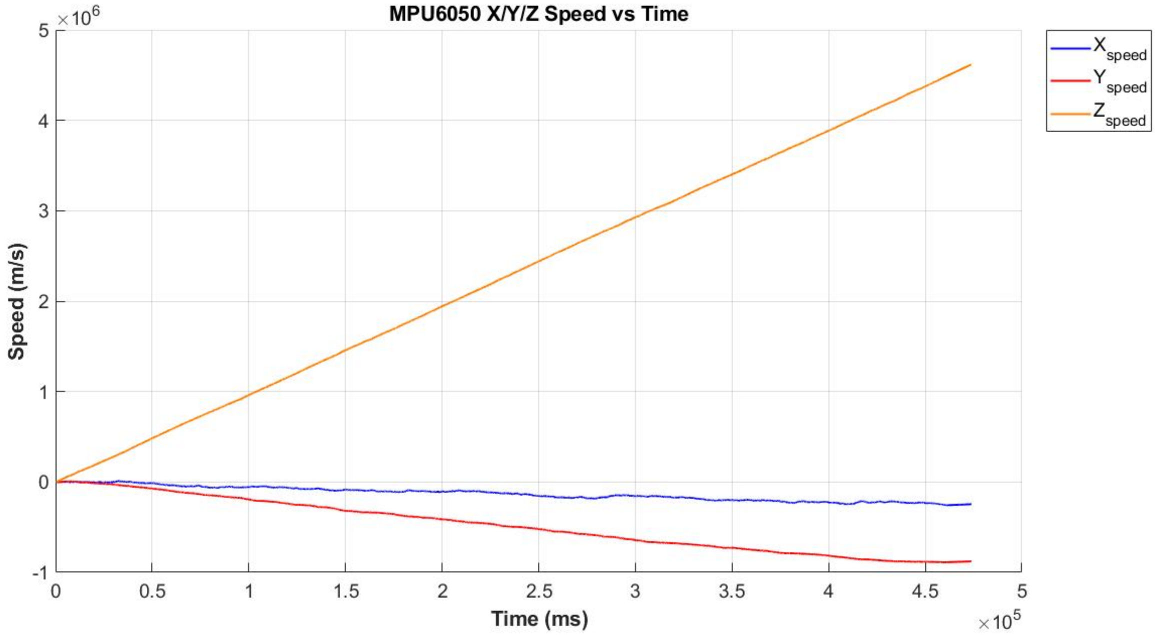

Figure 3.11. Estimated Velocity Components in X, Y, and Z Directions Derived from Raw MPU6050 Accelerometer Data during Open-Space Flight

To further assess the reliability and accuracy of the GPS measurements obtained during the flight tests, additional signal integrity parameters were evaluated. Specifically, the number of visible satellites and the corresponding GPS signal quality levels were monitored throughout the experimental flights. These parameters are critical for determining the precision and consistency of GPS-based position and velocity estimations, particularly under dynamic or obstructed conditions.

As shown in Figure 3.12, the number of satellites varied based on the surrounding environment. In open-field scenarios, satellite visibility remained high and relatively stable, whereas in partially obstructed regions, a noticeable decline was observed. Such reductions in satellite availability can significantly degrade positional accuracy and cause increased uncertainty in GPS-derived data.

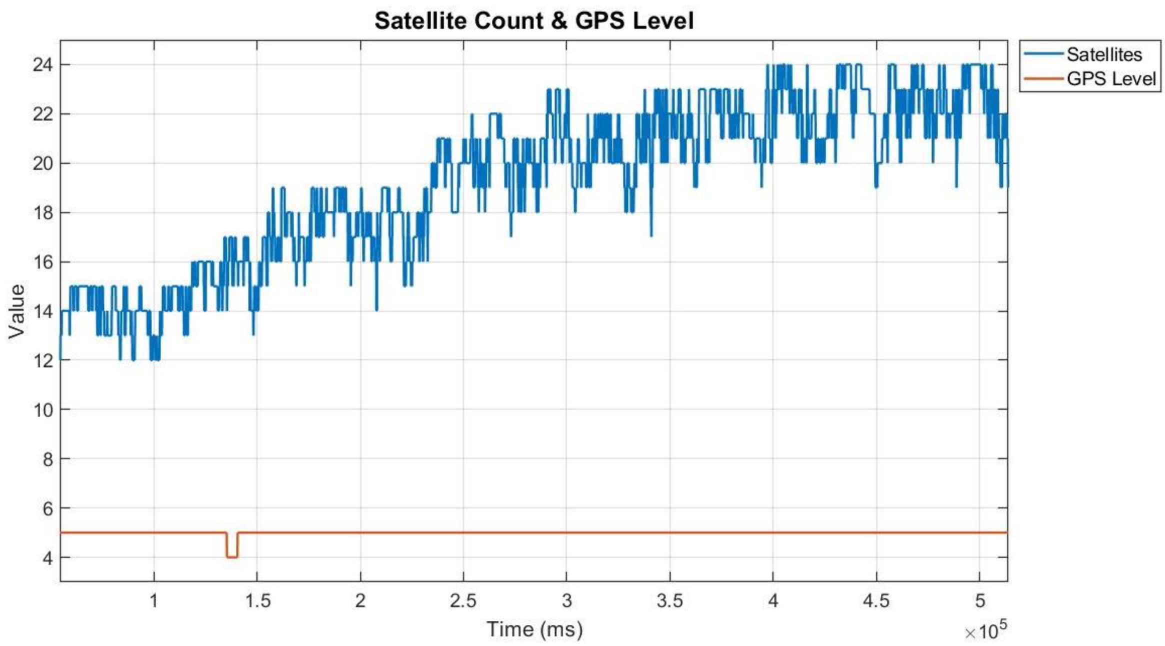

Figure 3.12. Satellite Count and GPS Signal Level Over Time during Open-Space Flight

Figure 3.13, on the other hand, illustrates the conditions during a fully indoor flight segment, where both the satellite count and signal quality dropped to zero for the entire duration. This complete signal loss reflects the inability of the GPS receiver to establish communication with any satellites due to full environmental blockage, rendering GPS-based positioning unavailable.

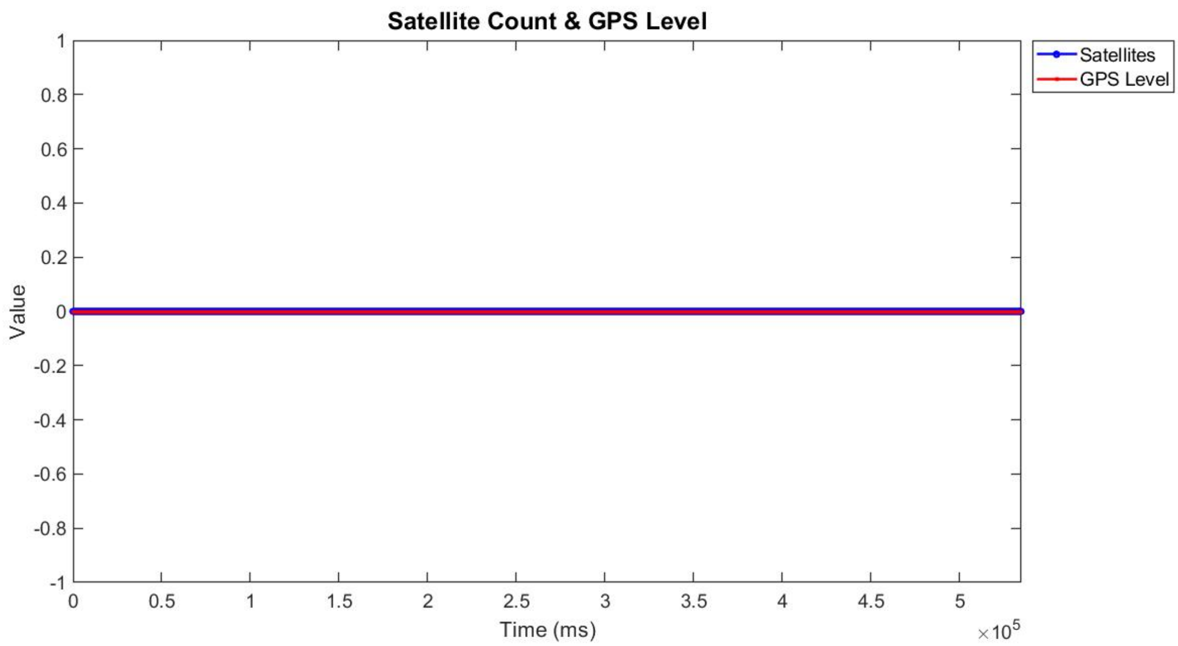

Figure 3.13. Satellite Count and GPS Signal Level during Enclosed-Space

Together, these two figures offer critical insight into the dependency of GPS performance on environmental visibility and signal strength. This analysis helps contextualize the limitations observed in the GPS-based velocity profiles presented earlier, and emphasizes the need for sensor fusion methods to ensure robust navigation in GPS-denied environments.

3.4.2. Temperature and relative humidity conditioning tests

In this section, the impact of high temperature and humidity on the performance of onboard inertial sensors is examined through environmental conditioning and flight testing. The UAV platform, along with its internal and external IMU sensors, was subjected to a controlled environment of 43°C temperature and 75% relative humidity for one hour, based on the environmental guidelines defined in MIL-STD-810G, Method 520.3, which outlines procedures for evaluating combined environmental stressors.

Following the conditioning process, indoor flight tests were conducted in an enclosed space to eliminate external variables such as wind or GPS interference, thereby isolating the effects of temperature and humidity exposure. During these tests, pitch and roll angles were recorded using both the external MPU6050 IMU and the DJI internal IMU. The collected data were then analyzed to evaluate the consistency and reliability of attitude estimation under thermally and hygroscopically stressed conditions.

This procedure provides valuable insight into the environmental resilience of inertial navigation sensors and demonstrates the necessity of robust sensor designs for UAV applications operating in challenging climates.

As shown in Figure 3.14, the UAV system, including the externally mounted MPU6050 IMU module, was placed inside the environmental conditioning chamber during the pre-conditioning phase. This procedure was conducted using the environmental test chamber located at the Turkish Standards Institution (TSE), which complies with standardized temperature and humidity control requirements for pre-operational testing of electronic systems. Following the one-hour exposure to elevated temperature and humidity, the system was removed from the chamber and subsequently operated in an enclosed indoor environment. This setup enabled the assessment of inertial sensor behavior under post-conditioning conditions, without interference from external atmospheric variables.

Figure 3.14. UAV and Externally Mounted MPU6050 IMU Module during Pre-Conditioning Phase Inside the Environmental Test Chamber

Following the pre-conditioning phase illustrated in Figure 3.14, the raw accelerometer and gyroscope outputs recorded from the MPU6050 module were analyzed to evaluate the direct effects of elevated temperature and humidity on the sensor's motion measurements. Figures 3.15 and 3.16 present the unfiltered time-domain responses of the accelerometer and gyroscope axes, respectively, under indoor post-conditioning conditions.

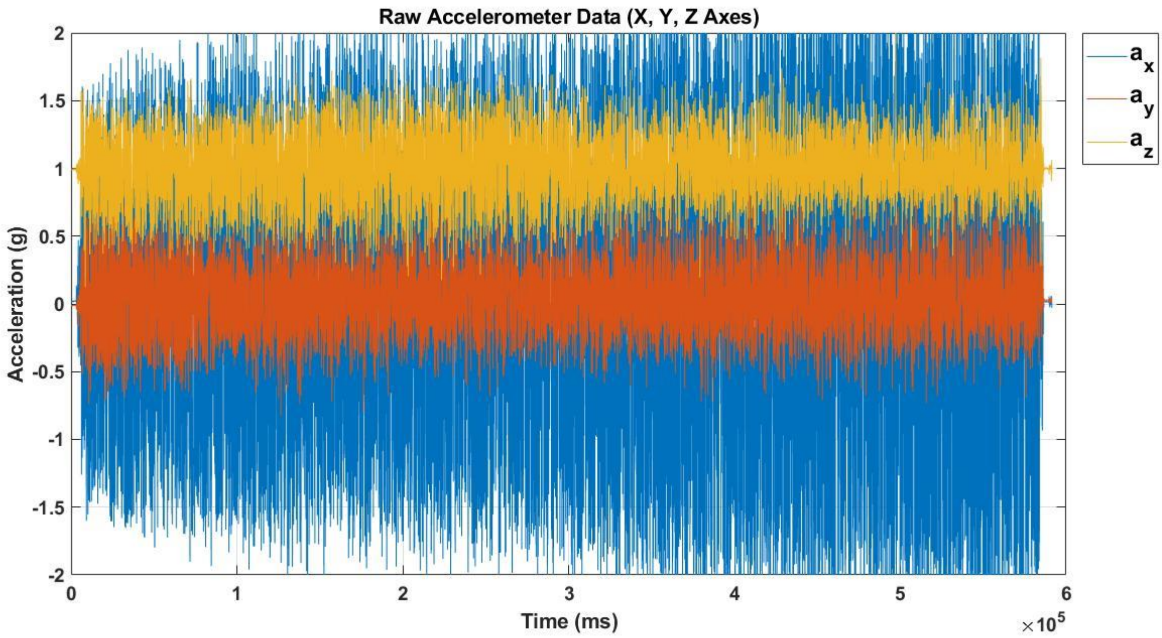

Figure 3.15. Raw Accelerometer Data from MPU6050 after Conditioning

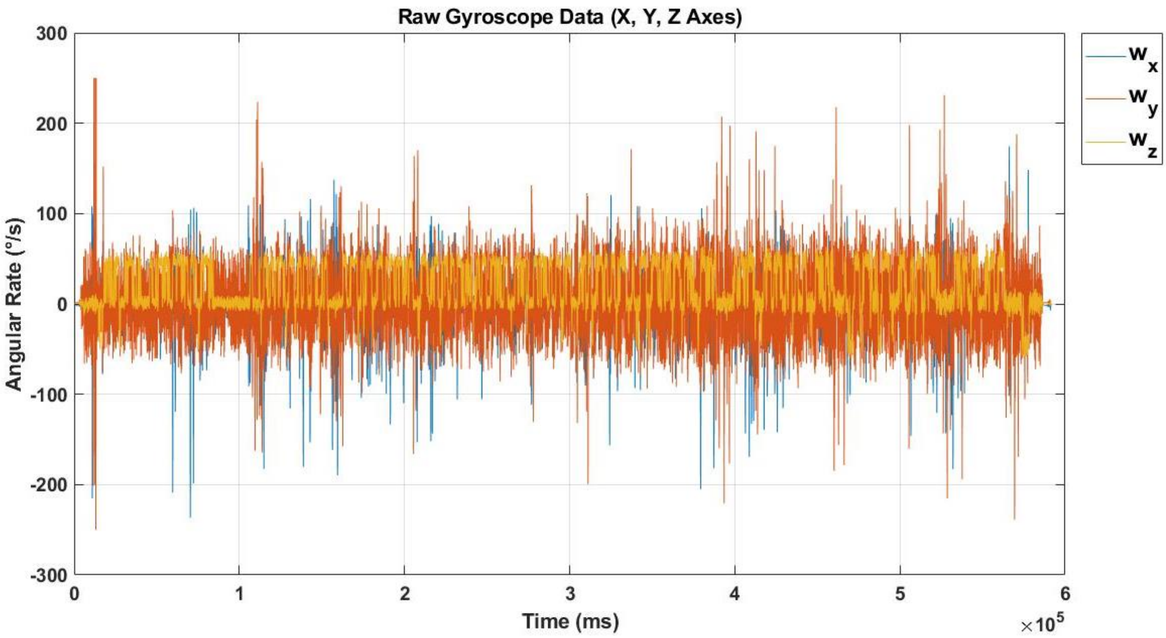

Figure 3.16. Raw Gyroscope Data from MPU6050 after Conditioning

Following the pre-conditioning process, the attitude estimations derived from both the integrated DJI IMU and the externally mounted MPU6050 module were individually analyzed to assess their behavior under post-exposure conditions. Figure 3.17 presents the time series of roll and pitch angles measured directly by the DJI system, while Figure 3.18

illustrates the corresponding roll and pitch outputs computed from the raw accelerometer and gyroscope data of the MPU6050. These comparative plots provide a basis for evaluating the consistency and stability of each sensor's attitude measurements when subjected to identical thermal and humidity stress.

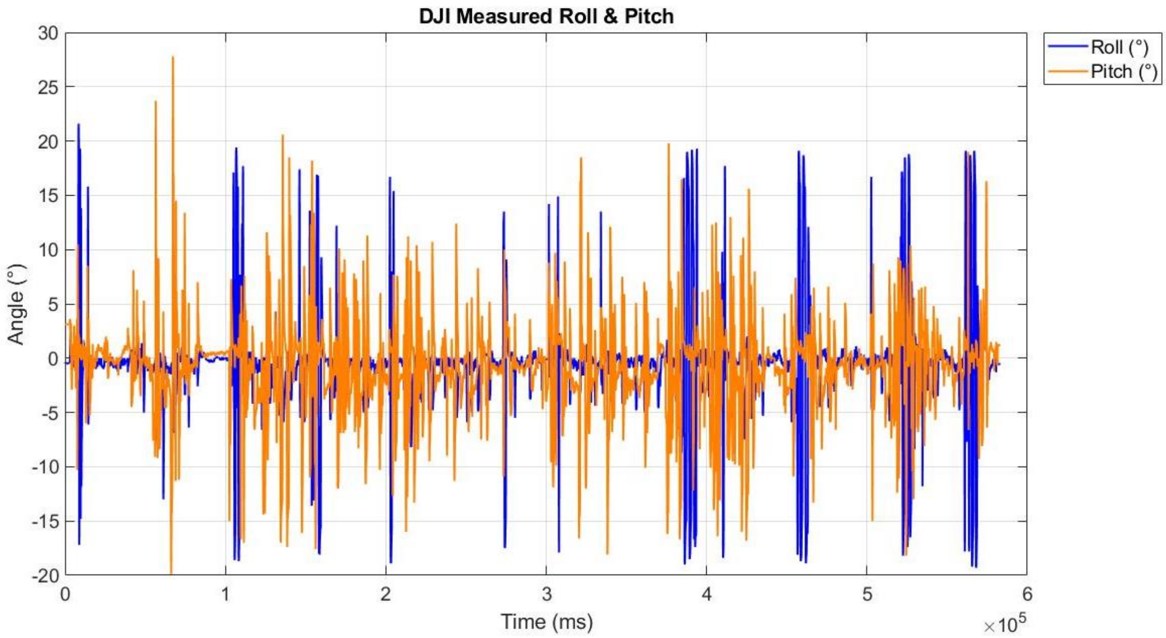

Figure 3.17. Post-Conditioning Roll and Pitch Angles Measured by the DJI IMU System during Enclosed-Space Flight

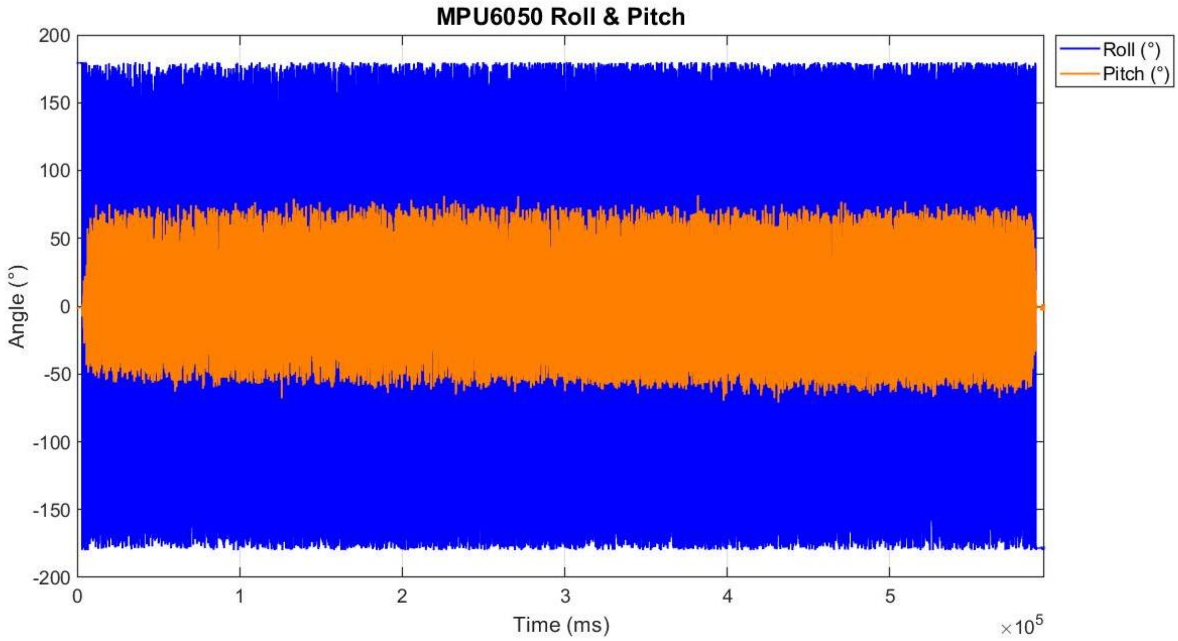

Figure 3.18. Post-Conditioning Roll and Pitch Angles (Raw Data) Measured by the MPU6050 IMU Module during Enclosed-Space Flight

The roll and pitch responses obtained from both the DJI integrated IMU and the externally mounted MPU6050 module, following exposure to elevated temperature and humidity, reveal notable performance differences that reflect the impact of environmental stress on inertial sensor behavior.

As shown in Figure 3.17, the DJI IMU demonstrates stable and consistent attitude measurements in both roll and pitch axes throughout the indoor test phase. The data remain within a bounded amplitude range, indicating the presence of effective internal filtering and compensation mechanisms that help mitigate the effects of temperature and humidity. This robustness is particularly important for UAV operations that require reliable orientation estimation under varying environmental conditions.

In contrast, Figure 3.18 illustrates the raw, unfiltered outputs of the MPU6050 module. The roll and pitch angles exhibit considerable fluctuations and high-frequency noise, which point to a heightened sensitivity to thermal influences and bias instability. It is essential to emphasize that these measurements were collected without the use of any filtering or sensor fusion techniques. Therefore, the observed inconsistencies in the MPU6050 data reflect the sensor’s baseline behavior and do not yet represent its performance potential when enhanced through algorithms such as the Kalman filter or complementary filter.

Since the tests were conducted in a controlled indoor environment, external disturbances such as wind, lighting variability, or electromagnetic interference were effectively eliminated. This ensures that the variations, particularly in the MPU6050 measurements, can be primarily attributed to internal sensor limitations and the residual impact of environmental conditioning.

The comparison of these raw data sets serves as a valuable reference for the discussions in Sections 4.4.2 and 5.2.1. It also underscores the importance of implementing advanced post-processing strategies when employing low-cost IMUs in UAV navigation systems.

3.4.3. Testing Under Simulated Rainfall Conditions

To assess the performance of inertial sensors under adverse environmental conditions, a controlled rainfall simulation was conducted within an indoor IPX2-certified test chamber. This experiment aimed to evaluate the robustness of both low-cost and high-performance

IMUs under mild vertical water exposure, simulating light rain falling at an angle of approximately 15° from the vertical.

The experimental setup included a programmable water dispersal grid positioned above the test area to ensure uniform water distribution. A DJI drone, serving as the Device Under Test (DUT), was positioned directly beneath the simulated rainfall within the chamber. The drone remained mostly stationary during testing, though limited manual movements in forward–backward and lateral directions were applied to observe sensor behavior under both static and low-dynamic conditions.

Approximately 4.5 minutes of data were recorded from both the internal IMU and an externally mounted IMU. The test was conducted at a controlled laboratory temperature of 23 °C, with environmental parameters monitored throughout the experiment. All procedures were carried out at the Turkish Standards Institution (TSE), using a certified IPX2 test chamber compliant with IEC 60529 standards. This setup (Figure 3.19) enabled a realistic evaluation of the IMUs' performance under light rain conditions, focusing on their resistance to water ingress and environmental disturbances.

Figure 3.19. Indoor IPX2-Compliant Rainfall Simulation Setup Used for Testing the IMU Performance under Controlled Water Exposure

Following the rainfall test, raw data from the MPU6050 sensor were logged and analyzed. The graphs below show the unprocessed accelerometer and gyroscope signals collected during the test period.

Figure 3.20 presents the raw accelerometer data obtained from the MPU6050 sensor during the rainfall simulation test. Significant and continuous variations are observed across all three axes (X, Y, and Z), which correspond to the platform's translational movements combined with mechanical disturbances caused by the impact of falling water droplets.

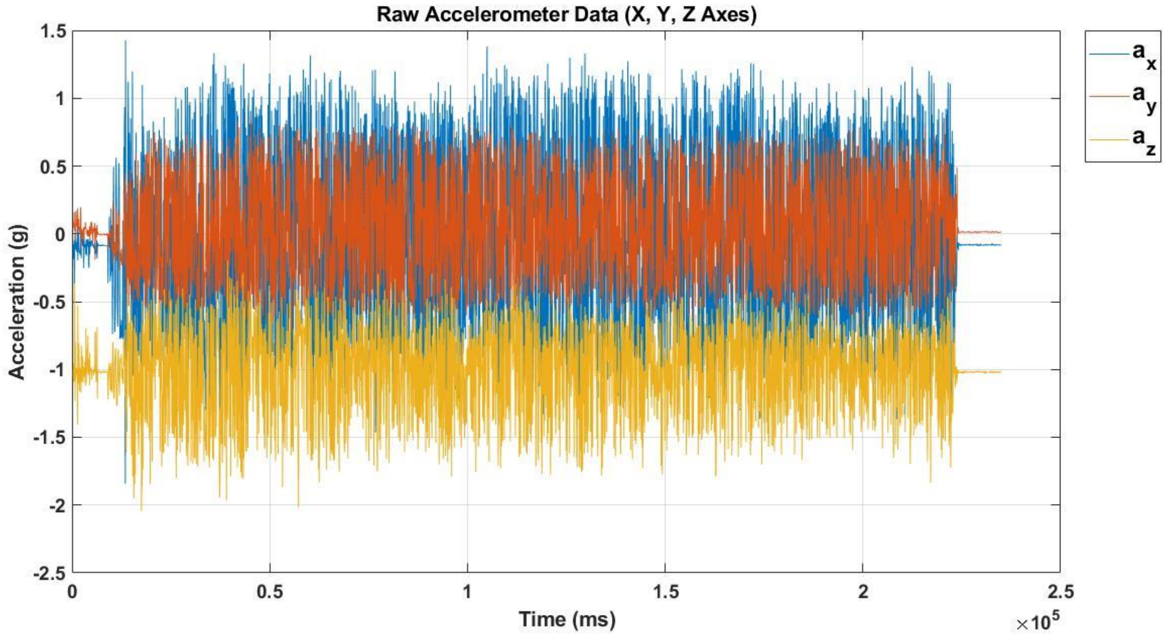

Figure 3.20. Raw Accelerometer Data (X, Y, Z Axes) From MPU6050 during IPX2 Exposure

Figure 3.21 illustrates the raw gyroscope data recorded simultaneously from the MPU6050 sensor during the rainfall simulation test. The gyroscope outputs exhibit pronounced angular velocity variations, especially at the initial and final phases of the test sequence. These fluctuations correspond to pitch and roll dynamics associated with simulated flight maneuvers, whereas the relatively stable middle section reflects periods of steady orientation under light rainfall conditions.

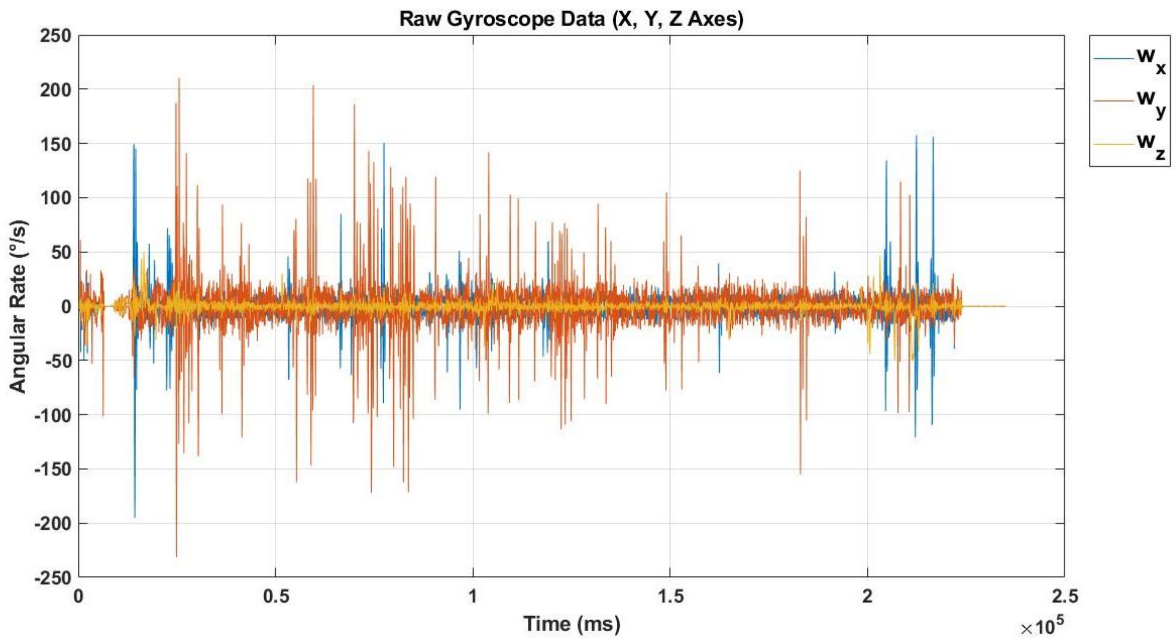

Figure 3.21. Raw Gyroscope Data (X, Y, Z Axes) From MPU6050 during IPX2 Exposure

Following the presentation of the raw accelerometer data and the gyroscope data, Figure 3.22 displays the raw pitch and roll angles computed from these datasets. These angle estimations reveal the instantaneous orientation of the system throughout the rainfall simulation test. The observed fluctuations, particularly during the initial and final phases, indicate significant dynamic activity, whereas the comparatively stable midsection corresponds to periods of steady motion under light rainfall exposure. This visualization provides a more intuitive interpretation of the system's angular behavior and complements the raw sensor readings by highlighting orientation trends during the experiment.

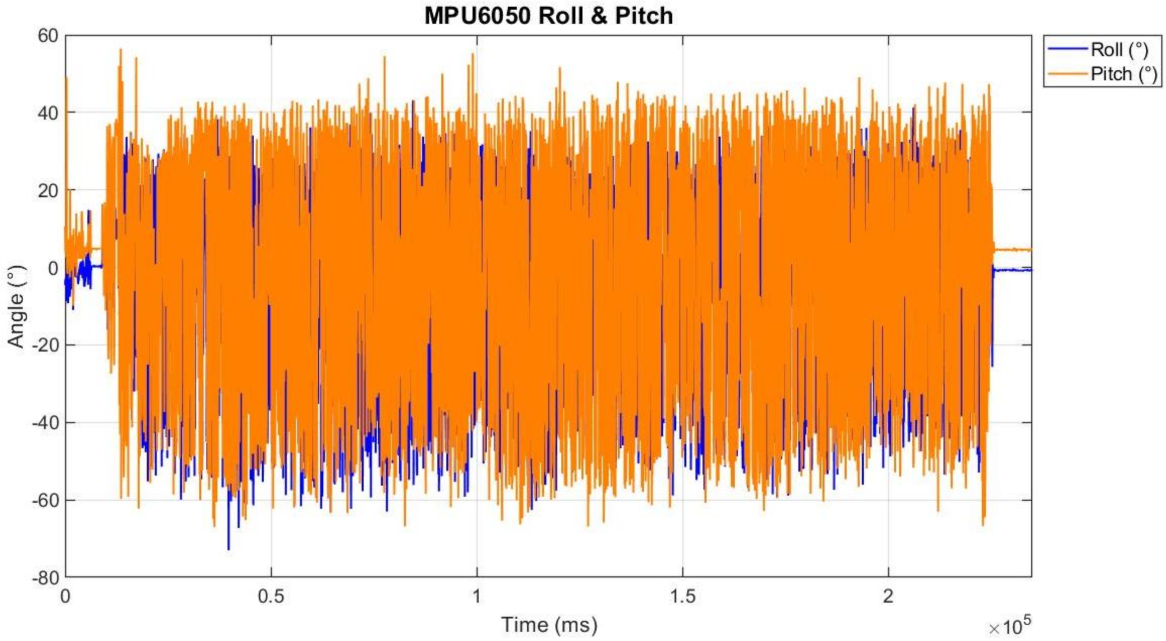

Figure 3.22. Raw Pitch and Roll Angles Estimated from MPU6050 Sensor Data during the Simulated Rainfall Test

To enable a comparative evaluation of the UAV's angular motion sensing capabilities, the subsequent analysis focuses on the pitch and roll angle data obtained from the DJI internal IMU system. By examining the onboard estimation results under identical test conditions, it becomes possible to assess the performance consistency between the external and internal sensors and to determine the degree of alignment in attitude tracking during the simulated rainfall scenario, as illustrated in Figure 3.23.

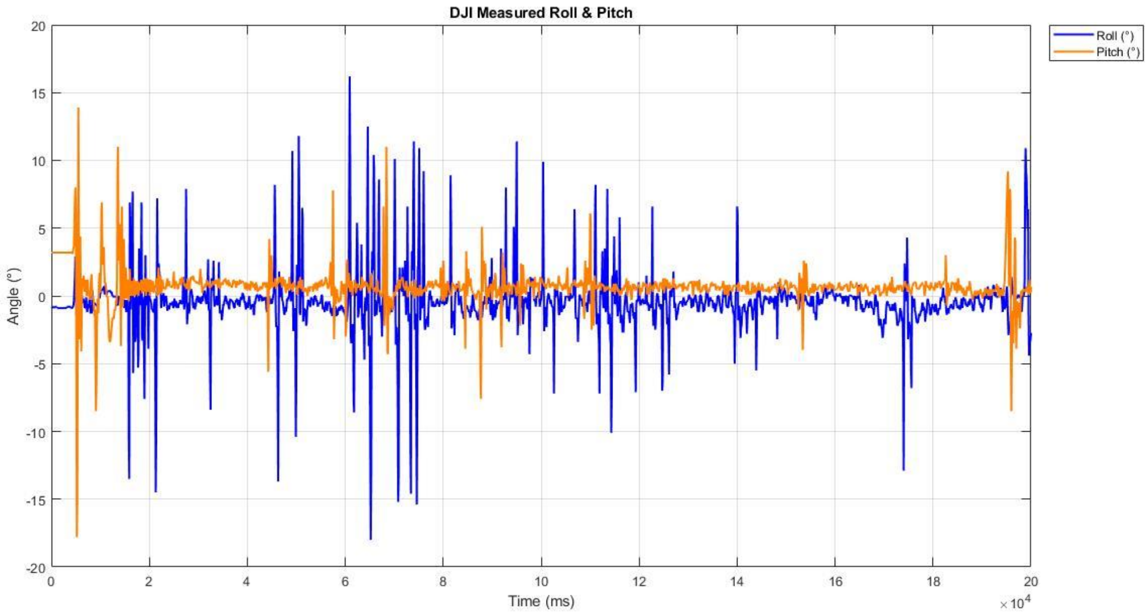

Figure 3.23. Internally Estimated Pitch and Roll Angles Obtained from the DJI Onboard IMU during the Simulated Rainfall Test

3.5. Comparison of GPS and IMU Data

This section presents a comprehensive comparison of the navigation data obtained from the GPS receiver and the IMUs used during the experimental studies. The evaluation includes both the internal IMU integrated into the DJI and the externally mounted MPU6050 sensor. Each system was subjected to identical test conditions, which included open-air environments, enclosed spaces, temperature and relative humidity conditioning tests, and a simulated rainfall scenario designed to assess sensor robustness. The comparative analysis focuses on key performance metrics such as measurement accuracy, signal noise levels, dynamic response, and overall stability. The following subsections refer to the relevant figures to support the discussion and to highlight the differences in behavior and reliability between the two sensing systems. The analysis begins with the examination of raw acceleration and angular rate data obtained from the external IMU under open-air flight conditions.

The raw accelerometer and gyroscope outputs obtained from the external MPU6050 sensor are presented in Figures 3.4 and 3.5. These plots reveal essential insights into the dynamic response and noise behavior of the inertial system under open-air flight conditions. In Figure 3.4, the acceleration data across the X, Y, and Z axes exhibit substantial high-frequency variations, which are indicative of both the platform's motion and environmental vibrations. The Z-axis measurements are centered around -1 g, which reflects the influence of gravity, whereas the X and Y axes oscillate around 0 g as expected during translational movement. Despite this general consistency, the signal is affected by sporadic spikes and irregularities, suggesting the absence of built-in filtering mechanisms.

Figure 3.5 displays the corresponding gyroscopic measurements from the same sensor. The angular rate data shows a similar noise pattern, with visible fluctuations particularly during maneuvering intervals. The presence of rapid transient changes across all three axes, especially during the initial and final segments of the dataset, indicates sensitivity to dynamic angular motion. Additionally, the baseline of the signal remains centered around zero, implying no persistent drift over the measurement period. However, the amplitude of variation reaches ±200°/s in some instances, highlighting the limited noise suppression in the raw output. These results confirm that the MPU6050 sensor is capable of capturing rapid motion but lacks onboard signal conditioning, which may lead to degraded performance in downstream attitude estimation without post-processing.

Figures 3.6a and 3.6b present the estimated pitch and roll angles during open-space flight as measured by the MPU6050 external IMU and the DJI internal IMU, respectively. The raw data obtained from the MPU6050 sensor in Figure 3.6a reveals large fluctuations in both pitch and roll signals, with angular variations frequently exceeding ±60 degrees. This level of noise is consistent with the unfiltered nature of the data and reflects the sensitivity of the sensor to vibrations, minor body-frame oscillations, and potential bias accumulation. The amplitude and density of these fluctuations indicate that the MPU6050 lacks any embedded stabilization or compensation algorithms, resulting in a high degree of variability in orientation estimates.

In contrast, the internal IMU of the DJI, as shown in Figure 3.6b, produces significantly more stable pitch and roll profiles. The angle estimates remain largely confined within ±20 degrees, with smoother transitions and visibly lower signal noise. This improved performance suggests that the internal IMU system incorporates real-time filtering and sensor fusion algorithms, which enhance the reliability of the orientation data. The comparison highlights the effectiveness of integrated processing in reducing angular estimation errors and improving motion tracking consistency during open-air flight.

Figures 3.7a and 3.7b illustrate the pitch and roll angle estimations obtained from the MPU6050 external IMU and the DJI internal IMU, respectively, during flight in an enclosed environment. In Figure 3.7a, the MPU6050 data presents pronounced fluctuations across both angular channels, with values frequently exceeding ±150 degrees, especially in the roll axis. These extreme variations are unlikely to reflect actual platform orientation and instead indicate significant signal distortion caused by environmental interference, sensor drift, and the absence of external correction sources such as GPS. The enclosed environment likely amplifies magnetic disturbances and inertial noise, further deteriorating the performance of the external IMU.

By contrast, the internal IMU measurements displayed in Figure 3.7b remain relatively stable despite the absence of satellite-based positioning and navigation input. The DJI system maintains pitch and roll values largely within ±20 degrees, with only intermittent disturbances observed in limited intervals. This behavior suggests that the internal IMU is equipped with more advanced onboard processing and filtering techniques capable of sustaining robust orientation tracking even in GPS-denied and electromagnetically degraded environments. The results underscore the vulnerability of low-cost inertial sensors to enclosed conditions and the advantages of integrated systems with sensor fusion and calibration mechanisms.

Figures 3.8 and 3.9 provide a visualization of the UAV's horizontal trajectory during open-space flight, based on GPS data. Figure 3.8 represents the flight path as recorded by the onboard control interface (AirData UAV), offering a practical overview of the UAV's movement across the test area. The trajectory appears continuous and smooth, with clear indications of maneuvering patterns and return-to-home behavior, which confirms that the GPS-based navigation system maintained consistent connectivity and spatial awareness during the test.

In Figure 3.9, the same trajectory is reconstructed from raw GPS log data in two-dimensional latitude and longitude coordinates. The plotted path closely matches the visual output shown in Figure 3.8, verifying the accuracy of the recorded GPS data and the post-processing approach. Minor deviations and clustering effects can be observed in sections with tighter turns, which may reflect transient delays or jitter in GPS signal acquisition. However, the overall path remains coherent and consistent with the intended flight plan. These results confirm that the GPS receiver provided stable and reliable positional information during open-air conditions, serving as a reference dataset for evaluating inertial navigation performance.

Figures 3.10 and 3.11 compare the velocity profiles derived from GPS and IMU data, respectively, during open-space flight. Figure 3.10 illustrates the raw velocity components in the X, Y, and Z directions obtained from GPS measurements. The velocity curves exhibit realistic oscillatory behavior that corresponds to the UAV's translational motion throughout the flight. The variations remain within a reasonable range, typically below 8 m/s, and fluctuate symmetrically around zero, suggesting consistent acceleration and deceleration phases along each axis. The data reflects a physically plausible dynamic profile, aligned with expected movement patterns of a small UAV in open air.

In contrast, the velocity estimation shown in Figure 3.11 is derived through direct integration of raw acceleration data from the MPU6050 IMU, based on the fundamental kinematic relationship expressed in Equation 3.5.

$$v(t) = \int a(t)dt \tag{3.5}$$

where v(t) is the estimated velocity and a(t) represents the measured acceleration along each axis. The resulting curves reveal substantial drift, particularly in the Z-axis, where the velocity increases almost linearly over time and exceeds 4 million meters per second by the end of the dataset. The X and Y components similarly show steady divergence, though at a smaller scale. This unbounded behavior is characteristic of integration errors caused by sensor noise, offset bias, and the absence of correction mechanisms. These findings highlight the limitations of using raw accelerometer data for velocity estimation in the absence of filtering or external reference systems. Unlike GPS-based velocity, which remains bounded and interpretable, IMU-only velocity estimation without compensation results in rapidly accumulating errors that render the data unusable for practical navigation purposes.

Figures 3.12 and 3.13 illustrate the number of visible satellites and the GPS signal level recorded during open-space and enclosed-space flights, respectively. In Figure 3.12, the UAV maintains a strong satellite connection throughout the flight. The number of tracked satellites increases steadily during the initial phase, eventually stabilizing around 22 to 24 satellites. This level of satellite visibility ensures a robust and accurate position fix. However, the recorded GPS signal level remains constant and does not reflect dynamic signal quality, suggesting that the data represents only availability rather than performance metrics.

To quantitatively assess the signal quality, the signal-to-noise ratio (SNR) is often used, as shown in Equation 3.6.

$$SNR = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right)(dB) \tag{3.6}$$

where P_{signal} and P_{noise} represent the signal and noise power, respectively. A higher SNR value corresponds to a clearer and more reliable signal. Although direct SNR measurements are not available in this dataset, the high number of satellites indicates favorable signal conditions.

Despite this, the consistent satellite count supports the validity of the GPS-based trajectory and velocity measurements observed in earlier figures.

In contrast, Figure 3.13 shows a complete loss of GPS functionality during the enclosed-space test. No satellite data or signal level is recorded throughout the experiment, confirming that the structural enclosure effectively blocks GPS signals. This condition creates a representative GPS-denied environment, which is critical for evaluating the standalone performance of INS. The absence of satellite data emphasizes the need for alternative localization strategies, such as IMU-based dead reckoning or sensor fusion, to maintain positional awareness in indoor or obstructed scenarios.

In accordance with MIL-STD-810G Method 520.3 guidelines, the UAV platform and the externally attached MPU6050 IMU module were conditioned for 60 minutes in a controlled environment chamber set to 43°C and 75% relative humidity. This process, illustrated in Figure 3.14, aimed to simulate high-temperature and high-humidity operating conditions prior to the closed-space test scenario [96]. This procedure aimed to evaluate the thermal and hygrometric resilience of both inertial systems prior to enclosed-space operation.

After conditioning, the accelerometer outputs from the raw MPU6050 data (Figure 3.15) displayed an increased noise density, particularly along the Z-axis, where the standard deviation rose from approximately 0.42 g to 0.58 g. Similarly, the gyroscope data (Figure 3.16) exhibited elevated fluctuations, with peak-to-peak angular rate excursions exceeding

±250°/s, especially prominent in the Y-axis. These results indicate that the sensor is sensitive to prolonged exposure under high humidity and elevated temperature.

Attitude estimation was also noticeably affected. As shown in Figure 3.18, the roll and pitch angles derived from the unfiltered MPU6050 data showed wide oscillations, ranging from –180° to +180°, which points to a significant level of drift and instability. In contrast, the DJI internal IMU (Figure 3.17) produced stable orientation estimates, with pitch and roll angles remaining within a narrower ±15° range, reflecting the benefits of internal thermal compensation and calibration.

Overall, the findings suggest that temperature and humidity stress can considerably impair the performance of low-cost MEMS-based IMUs when operating with raw and unprocessed data. Nevertheless, applying appropriate filtering methods such as complementary or Kalman filters is likely to improve the accuracy and reliability of these measurements under adverse environmental conditions.

In the final phase of the comparative evaluation, both inertial systems were tested under a controlled rainfall scenario using an indoor IPX2-compliant simulation rig (Fig. 3.19). This setup was employed to assess the performance stability and waterproof resilience of the sensors under mild water exposure, as would be encountered during light rainfall or wet operational environments.

The raw accelerometer outputs from the MPU6050 sensor (Figure 3.20) displayed persistent noise fluctuations in all three axes, with standard deviations exceeding 0.55 g, indicating limited signal integrity under moisture influence. Additionally, the gyroscope measurements (Figure 3.21) exhibited intermittent spikes surpassing ±200°/s, particularly along the X axis. These disturbances suggest transient water interference or surface-level capacitive disruption affecting the sensor membrane.

The estimated roll and pitch angles derived from the MPU6050 (Figure 3.22) showed substantial instability, with angular swings reaching ±60°, making it difficult to extract meaningful orientation data without post-processing. By contrast, the DJI IMU system (Figure 3.23) preserved its operational integrity, maintaining roll and pitch outputs largely within the ±10° range. The smoother profiles and consistent attitude tracking demonstrate superior moisture shielding and internal error correction mechanisms.

Overall, the data confirm that exposure to water, even in low-pressure conditions, can significantly impair the raw outputs of unprotected MEMS-based IMUs. Implementing signal filtering and sensor fusion techniques would be essential to recover reliable navigation data from such sensors under wet environmental stress.

The comparative evaluation of GPS and IMU data under various test conditions demonstrates that integrated navigation systems provide superior stability, accuracy, and environmental resilience. While raw MPU6050 data exhibited significant noise, drift, and sensitivity to temperature, humidity, and water exposure, the DJI internal IMU maintained consistent, bounded outputs. GPS data was highly reliable in open spaces but unavailable in enclosed areas, underscoring the critical role of inertial navigation in GPS-denied scenarios. These findings reveal the limitations of low-cost IMUs alone and emphasize the need for sensor fusion, error mitigation algorithms, and environmental conditioning for reliable positioning.

Table 3.2 summarizes GPS, internal IMU, external MPU6050 IMU, and sensor fusion performance, showing that Kalman-filtered fusion significantly improves accuracy, stability, and robustness by reducing noise and drift in raw external IMU data.

Table 3.2. Comparison of GPS, Internal IMU, External IMU, and Sensor Fusion Performance

Parameter	**GPS (Built-in)**	**Internal IMU (DJI)**	**External IMU (MPU6050 Raw)**	**Sensor Fusion (Kalman + GPS + MPU6050)**
Signal Availability	High (open sky)	Always available	Always available	Always available
Position Accuracy (Open Sky)	±2–4 m	N/A	N/A	±1 m (**50–75% improvement**)
Position Accuracy (GPS Denied)	No fix	N/A	Unreliable	Improved (limited by IMU drift)
Orientation Stability	N/A	±20° drift max	±60–150° drift	±10–20° (**75% drift reduction**)
Pitch/Roll Stability	N/A	±15–20°	±60° fluctuations	±5–10° pitch, ±8–12° roll (**up to 80% improvement**)
Drift Over Time	N/A	Minimal	Significant	Bounded (periodic GPS correction)
Robustness	Good (open air)	Good (with filtering)	Poor	Improved

4. ADVANTAGES AND LIMITATIONS OF GPS AND IMU IN UAVS

GPS and IMU systems play a critical role in UAV navigation by ensuring positional accuracy and maintaining flight stability. These sensors enable the vehicle to determine its position, velocity, and orientation, allowing for the successful execution of autonomous missions. In the previous chapter, experimental data collected under various environmental and operational conditions were presented and the measurements obtained from GPS and IMU systems were compared in detail. This chapter focuses on interpreting those findings to provide a comprehensive evaluation of the advantages and limitations of each system. The individual performance characteristics of GPS and IMU are discussed first, followed by an analysis of their combined use through sensor fusion. The discussion emphasizes key aspects such as positioning accuracy, resilience to environmental disturbances, and the overall robustness of the navigation system.

4.1. Advantages of GPS in UAV Navigation

GPS provides one of the most effective solutions for absolute positioning in UAV applications. Its ability to deliver real-time location data with global coverage makes it a cornerstone of modern aerial navigation systems [97]. One of the key advantages of GPS is its high positional accuracy in open-sky environments, which allows UAVs to follow predefined trajectories with minimal deviation. This level of accuracy is particularly important for missions that require waypoint tracking, autonomous flight control, or georeferenced data collection such as aerial mapping and surveying [98].

Another significant advantage of GPS is its low computational demand on the onboard system. Since GPS modules typically process signals externally and transmit simple coordinate outputs, they reduce the need for complex onboard calculations, preserving processing resources for other flight control tasks. Additionally, GPS systems are relatively lightweight and easy to integrate into UAV platforms of various sizes, contributing to overall system efficiency and portability [99].

Furthermore, GPS provides consistent and reliable performance under stable atmospheric conditions. The technology is highly mature, with well-established infrastructure including satellite constellations, ground control networks, and correction services that enhance positional accuracy through methods such as DGPS or RTK positioning. These enhancements make GPS especially valuable in applications where centimeter-level precision is necessary [63, 100, 101]

Overall, the strengths of GPS in UAV navigation include global availability, high accuracy in ideal conditions, ease of integration, and low computational load, all of which support reliable autonomous operations in open environments.

4.2. Limitations of GPS in UAVs Based on Experimental Results

Although GPS is widely used in UAV navigation due to its global coverage and relatively high positional accuracy in open-sky conditions, experimental findings from this study reveal significant performance limitations under certain environmental constraints. Specifically, the reliability of GPS-based navigation diminishes considerably in scenarios involving signal obstruction, multipath interference, and environmental factors such as structural enclosures and severe weather. These limitations, observed and quantified through controlled test conditions, highlight the vulnerability of GPS to external disturbances and emphasize the necessity of complementary sensor systems, particularly in critical or safety-sensitive applications.

Two separate open-space experiments were conducted to evaluate the robustness of GPS signals under environmental stress conditions including elevated temperature, high humidity, and controlled water exposure. The following subsections detail the impact of each condition on the GPS signal quality and overall navigational performance.

4.2.1. Environmental conditions and their impact on GPS performance

Experimental data collected during open-space flights revealed that real-world atmospheric conditions have a significant influence on the accuracy and stability of GPS-based navigation systems. Variations in ambient temperature, wind intensity, humidity, and atmospheric clarity directly affected both the quality of satellite signals received and the consistency of positional estimates throughout the tests. For instance, under conditions with high temperature and high humidity, the number of satellites locked by the GPS receiver decreased intermittently, and the GPS fix level fluctuated between levels 2 and 4. These fluctuations were accompanied by increased noise in the velocity measurements and temporary instability in position estimation. As environmental conditions improved, especially when temperature and humidity dropped and wind pressure became moderate, the number of tracked satellites gradually increased. In many of these improved conditions, the satellite count exceeded sixteen, and the GPS fix level stabilized at level 5, which reflects a full three-dimensional position lock with higher confidence.

This sensitivity to environmental variability was particularly observable during the initial segments of the flights. In these early stages, thermal gradients and shifts in wind direction resulted in brief disruptions in signal quality. During such intervals, the velocity components derived from GPS data, particularly along the X and Y axes, exhibited noticeable high-frequency oscillations. These irregular patterns were further associated with short-term position drift, leading to small deviations from the expected trajectory and momentary deterioration in navigational precision. In some cases, the GPS fix level dropped to values indicative of two-dimensional positioning, which significantly reduced vertical accuracy and contributed to transient inaccuracies in the flight path.

In contrast, when the atmospheric conditions remained stable and the sky was clear of obstructions, the GPS system consistently maintained high accuracy and reliability. The satellite count remained consistently high, the GPS fix level stayed at 5, and the recorded velocity data showed smooth, continuous behavior. The estimated trajectory under these conditions closely followed the expected flight path, and the overall navigation performance was significantly improved compared to segments affected by atmospheric disturbances.

Furthermore, data analysis indicated that even minor changes in environmental conditions, such as brief increases in wind or the passage of thin cloud cover, could result in measurable changes in satellite connectivity. These small disturbances did not necessarily cause complete signal loss, but they often led to fluctuations in the number of tracked satellites and minor shifts in GPS quality. Although these changes were temporary, they were sufficient to introduce detectable noise in the velocity profiles and small trajectory deviations, particularly in systems that rely solely on GPS for positioning.

The accumulated findings demonstrate that GPS performance is highly dependent on environmental conditions, especially in outdoor applications involving mobile systems such as unmanned aerial vehicles. The results also reveal that even in the absence of large-scale interference, subtle atmospheric variations can significantly impact the consistency and accuracy of GPS-derived navigation data. Given the vulnerability of standalone GPS systems to such variations, it becomes evident that relying solely on GPS in dynamic outdoor environments is insufficient for applications that require continuous and precise positioning.

To overcome these limitations, the integration of GPS data with inertial measurement units is recommended. Sensor fusion techniques, including the Kalman filter and its adaptive variants, can help mitigate the effects of signal degradation by providing estimated positions during periods of reduced satellite visibility. By leveraging the complementary strengths of GPS and inertial data, it becomes possible to achieve more robust and accurate navigation, even in the presence of fluctuating environmental conditions. This approach not only enhances overall system performance but also improves reliability in mission-critical tasks where consistent positioning is essential.

4.2.2. Impact of enclosed spaces on GPS performance

Experimental tests conducted in fully enclosed indoor environments revealed that GPS performance is severely compromised when line-of-sight access to satellites is obstructed. In such conditions, the GPS receiver was unable to acquire signals from any satellites, resulting in a complete loss of satellite count and a GPS fix level of zero throughout the duration of the test. This outcome confirms the inherent limitation of GPS technology, which relies on direct communication with multiple satellites positioned in orbit. In the absence of a clear sky view, radio signals transmitted by the satellites cannot penetrate physical structures such as reinforced concrete, thick walls, or metallic enclosures, leading to total signal degradation.

The data collected in this scenario, characterized by a flat satellite count of zero and an unchanging GPS level of zero, demonstrates that GPS receivers are entirely ineffective in closed environments. As a consequence, all derived positional and velocity data become unavailable or meaningless. This lack of signal not only impairs absolute positioning but also makes GPS-based velocity estimation and trajectory tracking impossible. In real-world applications, such as unmanned aerial vehicles or mobile robotic systems operating in indoor or transition areas (e.g., tunnels, warehouses, parking structures), this limitation poses a significant challenge to navigation continuity and system reliability.

Given the complete signal loss observed in the indoor test case, it is evident that GPS cannot be solely relied upon for positioning in environments without satellite visibility. This highlights the critical need for auxiliary localization methods, such as INS, visual odometry, or radio-based indoor positioning technologies. Integration of these systems through sensor fusion algorithms becomes essential to maintain navigational accuracy and robustness in GPS-denied environments. These findings further justify the implementation of hybrid localization architectures for autonomous platforms expected to operate across diverse spatial contexts.

4.3. Advantages of IMU in UAV Navigation

IMUs have become indispensable components in modern UAV navigation systems due to their ability to provide continuous, high-frequency measurements of motion dynamics independent of external signals. Unlike GPS, which relies on satellite visibility and can suffer from signal blockages or atmospheric disturbances, IMUs operate autonomously by measuring linear accelerations and angular velocities through onboard accelerometers and gyroscopes. This inherent autonomy makes IMUs particularly valuable in environments where GPS signals are unreliable or entirely unavailable, such as urban canyons, dense forests, tunnels, or indoor spaces [4, 19, 48, 102].

A primary advantage of IMUs is their high update rate, enabling real-time monitoring of UAV attitude, velocity, and position changes with minimal latency. This rapid responsiveness is critical for flight stabilization, precise maneuvering, and control system feedback, particularly during dynamic flight conditions involving sudden accelerations or abrupt directional changes. Additionally, IMUs provide data at significantly higher frequencies than GPS receivers, allowing fine-grained motion tracking essential for closed-loop control systems in UAVs [101, 102].

Another important benefit of IMUs is their ability to function without external references, which allows them to deliver continuous relative motion information even in GPS-denied environments. This capability is vital for mission-critical applications requiring uninterrupted orientation and velocity data, such as search and rescue operations, military reconnaissance, and indoor inspections. Moreover, integrating IMU data with other sensor inputs through sensor fusion algorithms like Kalman filtering greatly enhances overall navigation accuracy and robustness by mitigating sensor noise and inherent limitations [103].

Furthermore, IMUs support improved dead-reckoning performance by estimating position through the integration of acceleration and angular velocity data over time. Although this method is prone to drift and cumulative errors, it remains indispensable for short-term navigation when GPS signals are lost or degraded. Technological advancements, particularly the development of MEMS-based IMUs, have resulted in smaller, lighter, and more cost-effective units, facilitating their widespread adoption across UAV platforms of various sizes and applications [29, 46, 63, 104].

In summary, IMUs offer significant advantages in UAV navigation, including independence from external signals, high-frequency data acquisition, and the provision of continuous, real-time motion information crucial for flight control and stability. When combined with GPS and other navigational aids, IMUs form a fundamental component of robust and accurate navigation systems capable of performing effectively across diverse and challenging operational environments.

4.4. Limitations of IMU in UAVs Based on Experimental Results

Despite their widespread use in UAV navigation systems, low-cost IMUs are inherently prone to several performance limitations, especially under real-world operating conditions. This section presents experimental observations highlighting the primary issues encountered with IMU measurements, including drift, bias accumulation, and sensitivity to environmental factors.

IMUs estimate orientation and motion using accelerometers and gyroscopes. However, these sensors are affected by intrinsic errors such as bias, noise, and scale factor inaccuracies. When measurements are integrated over time, these errors accumulate, resulting in drift and degraded estimation accuracy. Additionally, environmental conditions such as temperature and humidity can further affect sensor stability and reliability.

To evaluate these limitations, experiments were conducted using both the internal IMU of the DJI and an external MPU6050 sensor mounted on the UAV. Data was collected under various conditions, including static and dynamic states, as well as in temperature- and humidity-controlled environments.

The following subsections present detailed findings related to two key issues observed during testing: drift and bias accumulation over time, and the influence of temperature and humidity on IMU performance.

4.4.1. Drift and bias accumulation over time

One of the most significant limitations of low-cost IMUs in UAV applications is the accumulation of drift and bias over time. Drift refers to the gradual deviation of estimated orientation angles due to the integration of noisy and biased sensor signals, particularly from gyroscopes. This phenomenon becomes especially prominent in systems that rely solely on inertial data without external correction mechanisms. During static and dynamic tests conducted with the MPU6050 sensor, it was observed that pitch and roll estimations continuously deviated from the initial reference even when the UAV remained stationary. In contrast, the internal IMU of the DJI maintained relatively stable angle estimations over the same time period, highlighting the impact of internal filtering and sensor fusion algorithms. Figure 4.1 clearly illustrates the dramatic impact of Kalman-filtering on MPU6050-derived attitude estimates.

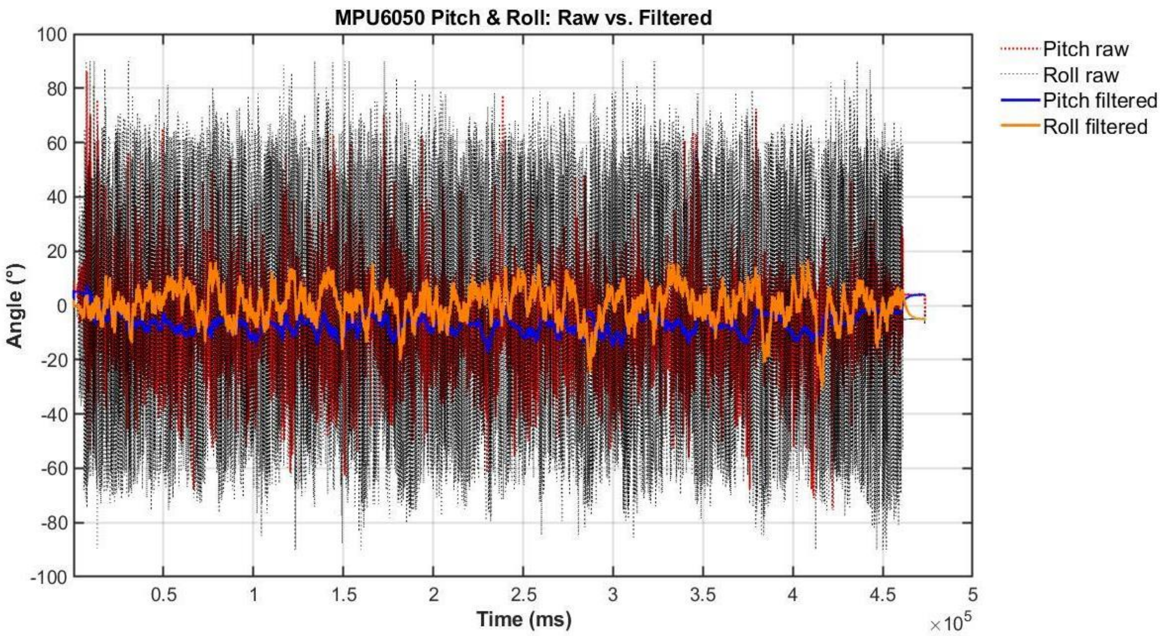

Figure 4.1. Comparison of Filtered and Unfiltered Pitch and Roll Angle Estimations from the MPU6050 During Open-Space Flight

In the unfiltered traces, with pitch in red and roll in black dashed lines, both angles fluctuate widely between –90° and +90°, showing high-frequency noise and integration drift even when the sensor is stationary. These deviations result from gyroscope noise, accelerometer bias, and the accumulation of errors over time. In contrast, the Kalman-filtered signals (solid blue for pitch, solid orange for roll) remain bounded within ±10° to ±20°, effectively suppressing high-frequency artifacts while preserving only the low-frequency components related to actual motion or slow bias drift. Although a small long-term trend is still noticeable over the $5x10^5$ ms observation window, the filtered output is significantly more stable. While the performance still falls short of that achieved by the professional-grade internal IMU of the DJI (Figure 3.6b), the Kalman-filtered results come remarkably close. These findings highlight that even a simple 1-dimensional Kalman filter can dramatically improve data quality from a low-cost sensor, making it suitable for more reliable UAV attitude estimation under certain conditions.

Following the analysis in clear outdoor conditions, it is essential to assess whether the Kalman-filtered MPU6050 can maintain its stability when subjected to environmental stress in an indoor laboratory environment. Figure 4.2 presents the pitch and roll estimations under IPX2 rain simulation conducted in a controlled indoor laboratory setting, offering insights into the sensor's behavior in mild weather disturbances.

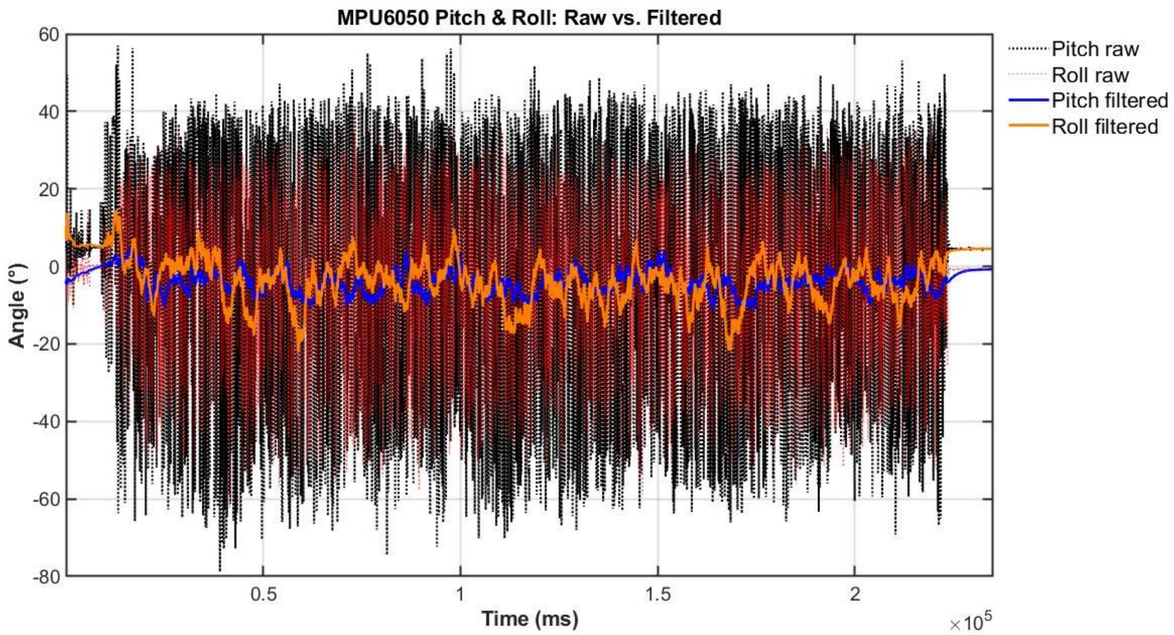

Figure 4.2. Comparison of Filtered and Unfiltered Pitch and Roll Angle Estimations from the MPU6050 under IPX2 Rain Simulation

As shown in Figure 4.2, a comparison between raw measurements and signals processed by a one-dimensional Kalman filter reveals significant differences. In the unfiltered traces, pitch is shown in black and roll in red dashed lines. Both signals exhibit high-frequency noise and long-term divergence exceeding ±60 degrees, even during stationary periods. These deviations are caused by sensor imperfections such as gyroscope drift, accelerometer bias, and numerical integration errors.

In contrast, the Kalman-filtered signals (solid blue for pitch and solid orange for roll) demonstrate markedly improved stability, remaining constrained within approximately ±15 degrees. The filter effectively reduces high-frequency fluctuations while preserving lower-frequency dynamics associated with slow bias changes or actual UAV movements. Although minor long-term drift persists, the filtered output offers substantially enhanced reliability for orientation tracking under challenging conditions.

While the performance of the MPU6050 still falls short of that achieved by high-end UAV inertial measurement units such as the internal sensor of the DJI, which maintains consistently stable pitch and roll estimations even under rainfall conditions (see Figure 3.23), these results demonstrate that appropriate filtering techniques can significantly improve the data quality of low-cost sensors. With sufficient filtering, drift-prone sensors like the MPU6050 can be effectively utilized for short-term or moderately constrained UAV operations.

4.4.2. Impact of temperature and humidity on IMU accuracy

Environmental conditions such as temperature and humidity significantly influence the performance and accuracy of IMUs in UAVs. Variations in these factors can induce sensor bias, noise, and drift, ultimately affecting the reliability of attitude estimations. Therefore, assessing the impact of controlled thermal and humidity exposure on IMU accuracy is essential for understanding sensor behavior in real-world operational environments.

As shown in Figure 4.3, the pitch and roll estimations obtained from the MPU6050 sensor prior to thermal and humidity conditioning exhibit relatively stable performance in a controlled indoor laboratory environment maintained at 23 °C and 35% relative humidity. These baseline measurements serve as a reference for evaluating the effects of environmental stress on sensor performance.

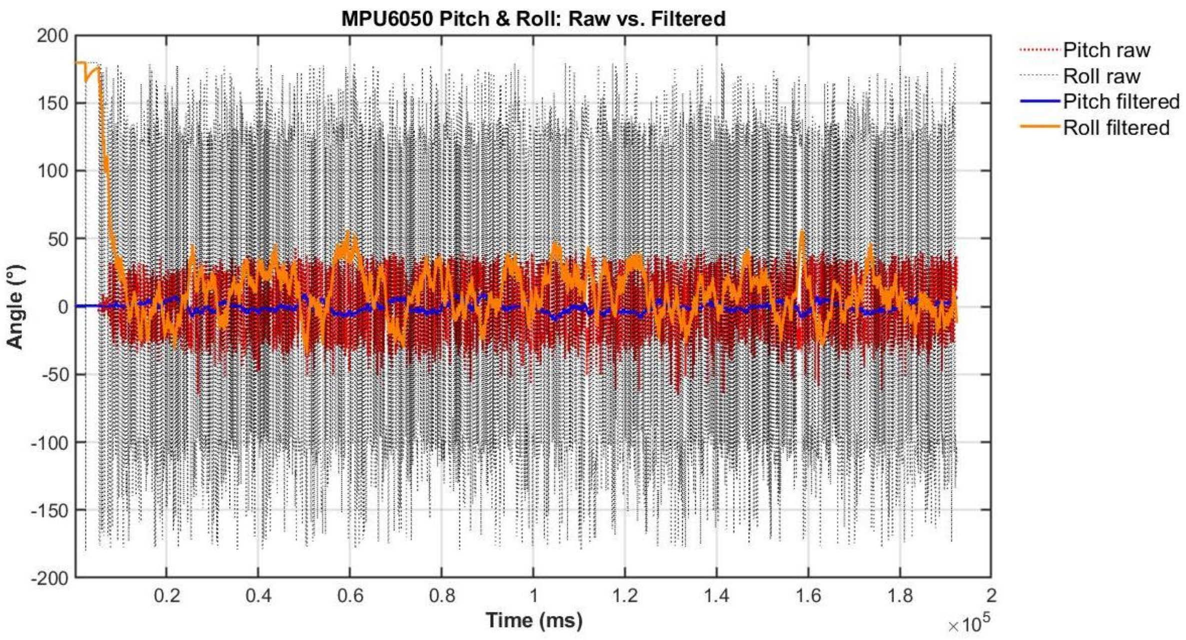

Figure 4.3. Comparison of Filtered and Unfiltered Pitch and Roll Angle Estimations from the MPU6050 under Controlled Laboratory Conditions

Figure 4.4 presents the pitch and roll estimations recorded after subjecting the MPU6050 sensor to thermal and humidity conditioning at 43 °C and 75% relative humidity.

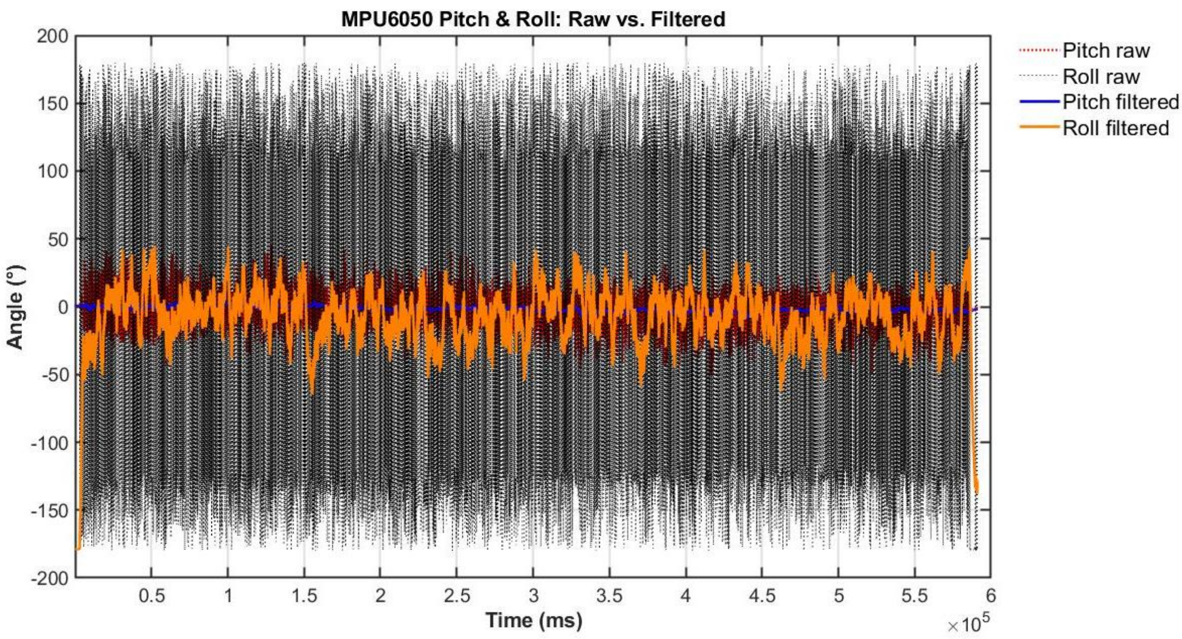

Figure 4.4. Filtered and Unfiltered Pitch and Roll Estimations from the MPU6050 after Thermal and Humidity Exposure (43 °C, 75% RH)

The raw output signals, with pitch in red and roll in black dashed lines, exhibit extreme spikes ranging from approximately ±150° to ±200° during both the baseline laboratory testing (Figure 4.3) and the post-conditioning flight test (Figure 4.4). The conditioning process involved exposing the MPU6050 sensor to 43 °C and 75% relative humidity inside a controlled chamber for approximately one hour. Subsequently, a closed-space flight test was conducted in a laboratory environment under controlled conditions of 23 °C temperature and 35% relative humidity. Following conditioning, an increased density of spikes was observed, indicating hysteresis effects or moisture-induced bias shifts within the sensor.

Analysis of the Kalman-filtered pitch data (blue) during the post-conditioning flight test (Figure 4.4) reveals angle estimations generally contained within ±5°, similar to the results observed under controlled laboratory conditions (Figure 4.3). However, in Figure 4.4, the signal exhibits slightly higher levels of noise and a small positive drift over time. This increased variability can be attributed to thermally induced sensor bias, minor degradation in filter performance, and reduced sensor linearity at elevated temperatures following the 1-hour pre-conditioning period.

Similarly, the Kalman-filtered roll measurements (orange) expand to ±35° during the post-conditioning flight test (Figure 4.4), compared to ±25° observed in the laboratory setting (Figure 4.3). Additionally, transient excursions occur more frequently, reflecting reduced baseline stability.

Although the same one-dimensional Kalman filter effectively suppresses high-frequency noise in both environments, extreme temperature and humidity conditioning degrades the MPU6050's baseline bias stability. As a result, the filtered signal during the post-conditioning flight exhibits larger swings and more pronounced drift. Nevertheless, the data remain within a practically usable ±35° envelope, whereas under ideal laboratory conditions, this envelope narrows to ±25°.

This comparative analysis highlights that while Kalman filtering significantly improves the quality of low-cost IMU data, environmental extremes inevitably widen the effective error bounds. Therefore, these factors must be carefully considered in the design of UAV attitude control systems to ensure reliable operation under diverse environmental conditions.

The DJI data presented in Figure 3.17 further underscores the superior performance of its internal IMU compared to the MPU6050. As shown in Figure 3.17, the DJI pitch and roll angles remain tightly confined within ±5°, exhibiting only occasional spikes up to ±15° during brief disturbances. In contrast, the filtered MPU6050 signals from the laboratory test fluctuate within a much wider ±10° to ±20° band, with raw data swinging dramatically between ±150° and ±200° (Figure 4.3). This comparison highlights the DJI IMU's effective suppression of high-frequency jitter, minimal long-term drift, and overall tighter, drift-free attitude estimates. Although Kalman filtering significantly improves MPU6050 data quality, it cannot fully match the professional-grade stability demonstrated by the DJI sensor. Nevertheless, these results demonstrate that with appropriate filtering, low-cost IMUs like the MPU6050 can approach the performance levels of high-end sensors, making them viable options for certain UAV applications where cost and weight are critical factors.

4.5. GPS-IMU Sensor Fusion: Strengths and Weaknesses

The integration of GPS and IMU sensors through sensor fusion techniques has become a cornerstone in advancing the navigation and attitude estimation performance of UAVs. GPS provides absolute positioning information with high global accuracy but suffers from limitations such as signal blockage, multipath effects, and reduced availability in enclosed or urban environments. In contrast, IMUs offer high-frequency measurement of linear accelerations and angular velocities, enabling rapid dynamic response and continuous attitude updates, but they are prone to drift and cumulative errors over time . By fusing the complementary data from GPS and IMU sensors, it is possible to achieve robust, accurate, and reliable state estimation that overcomes the individual shortcomings of each sensor type [42, 105, 106].

Despite these advantages, sensor fusion introduces challenges including sensor noise disparities, timing and synchronization errors, complex algorithmic requirements, and sensitivity to environmental conditions. Moreover, the selection of appropriate fusion algorithms such as Kalman filters, particle filters, or more advanced nonlinear estimators significantly impacts the overall system performance and computational burden [42, 47, 107]. This section aims to explore both the strengths and the practical limitations of GPS-IMU sensor fusion, supported by experimental findings and recent literature, to provide a comprehensive understanding of its application in UAV systems.

4.5.1. Advantages of sensor fusion

Sensor fusion between GPS and IMU data has become a fundamental component in modern UAV navigation systems. This integration enables the system to exploit the complementary characteristics of both sensors, resulting in improved accuracy, robustness, and reliability under varying operational conditions [42, 47, 62, 108].

One of the primary advantages of sensor fusion is improved positioning accuracy. GPS provides absolute position estimates with high long-term stability, whereas IMUs offer high-frequency measurements of motion dynamics, including acceleration and angular velocity. When fused appropriately, GPS can correct the long-term drift in IMU data, while the IMU can fill in the gaps during periods of poor GPS availability [47, 91, 109].

Second, sensor fusion provides enhanced robustness in environments where GPS signals are denied or degraded. For instance, when GPS signals become temporarily unavailable in tunnels, urban canyons, densely wooded areas, or under intentional interference, the IMU enables the system to continue navigation using dead reckoning. This is achieved by integrating acceleration measurements from the accelerometers to estimate velocity, and then integrating the velocity over time to estimate position. At the same time, gyroscope data is used to track the vehicle's orientation in three dimensions. Although errors accumulate due to sensor drift and measurement noise, sensor fusion algorithms such as the Kalman filter help mitigate these effects. When GPS signals become available again, they can be used to correct the accumulated drift, restoring accurate and stable navigation performance [42, 110, 111].

A further benefit is real-time responsiveness. IMUs typically operate at high sampling rates (e.g., 100–1000 Hz), allowing the system to rapidly detect and respond to changes in orientation or acceleration. This high temporal resolution is critical for real-time attitude control, especially in dynamic flight scenarios where GPS alone would be insufficient due to its slower update rate (e.g., 1–10 Hz) [33, 108].

Additionally, sensor fusion contributes to noise reduction and improved signal reliability. Combining the statistically independent error characteristics of GPS and IMU measurements allows filtering algorithms to isolate and suppress sensor noise. This leads to smoother and more stable estimations of both position and orientation, even in the presence of mechanical vibration or electromagnetic interference [112, 113].

Finally, fusion systems enable greater system autonomy and safety. By continuously cross-validating inputs from both GPS and IMU sensors, anomalies such as sudden signal loss or sensor malfunction can be detected more reliably. This redundancy improves fault tolerance and enhances the overall reliability of the UAV's navigation and control systems [114, 115, 116].

These advantages collectively demonstrate that GPS-IMU sensor fusion plays a critical role in ensuring accurate, responsive, and robust navigation, particularly for UAV applications operating in complex or unpredictable environments.

4.5.2. Challenges in sensor fusion based on experimental findings

While GPS and IMU sensor fusion significantly enhances the accuracy and continuity of UAV navigation, several practical challenges emerged during experimental evaluation that highlight the limitations of low-cost fusion implementations.

First, raw GPS data alone, such as that recorded via Airdata UAV during a stationary hover, produced a wide, unstructured scatter of position points within an approximate 20–30 meter ellipse. This level of spatial noise renders precise station-keeping or trajectory reconstruction nearly impossible. When fused with MPU6050 IMU data via a basic 1-dimensional Kalman filter, the resulting trajectory was dramatically improved, producing a condensed 5×8 meter track that better reflected the UAV's true motion. However, this enhancement comes with trade-offs.

In Figure 4.5, a loosely coupled INS approach was implemented by fusing GPS and IMU data using a Kalman filter. While the IMU alone is insufficient for long-term navigation due to drift, its short-term motion tracking capability significantly improves position estimation when GPS signals are degraded or temporarily unavailable.

One critical limitation is the accumulation of drift during periods of prolonged GPS signal degradation or loss. As shown in Figure 4.5, during GPS dropouts, the fused trajectory begins to deviate from the true path, with the IMU-only integration unable to fully compensate for the absence of external correction. This is especially evident in segments of the Kalman-estimated path where red GPS points are sparse; the blue fusion track gradually veers outward, reflecting accumulated bias and integration error.

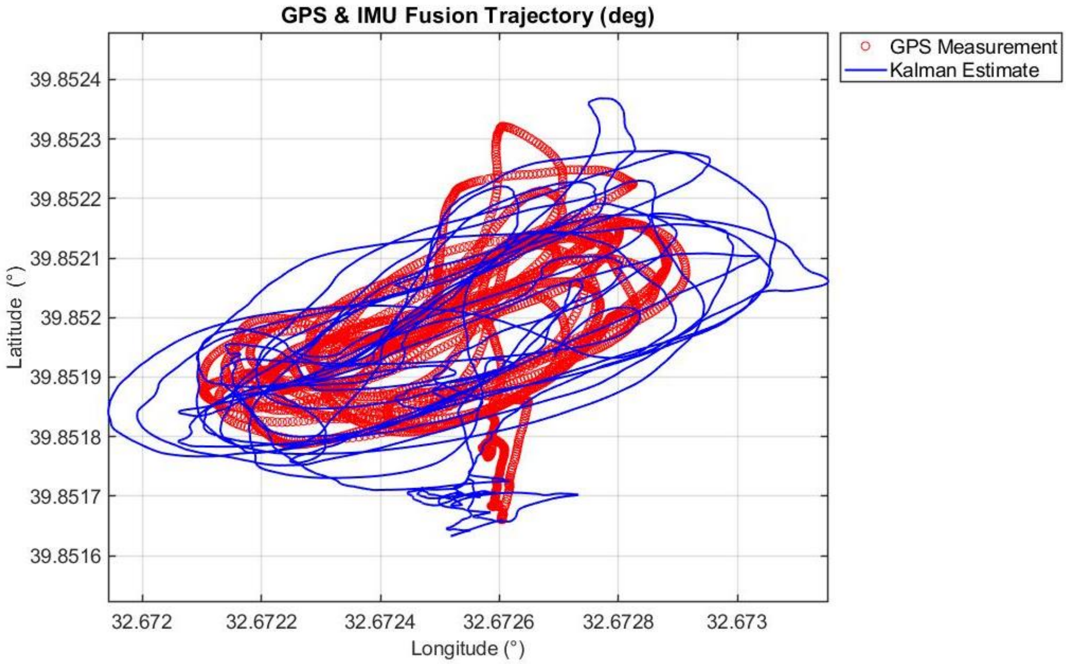

Figure 4.5. GPS & IMU Kalman-Fusion Trajectory

Time synchronization also presents a challenge. GPS updates typically occur at 1–10 Hz, whereas IMU data may be collected at rates up to 50-100 Hz. Without precise timestamp alignment, the fusion algorithm may react too late or too early to real-world events. In the fused trajectory, this manifests as a slight lag in the system's response to rapid GPS fluctuations, resulting in small trajectory mismatches.

The performance of the Kalman filter is strongly influenced by the selection of its parameters, especially the ratio between process noise covariance (Q) and measurement noise covariance (R). When these parameters are not appropriately configured, the filter may smooth the trajectory too heavily, which can obscure actual UAV maneuvers, or fail to smooth sufficiently, resulting in visible jitter. As illustrated in Figure 4.5, this effect can be seen in the filtered blue trajectory, which at times does not fully reflect minor deviations captured by the GPS measurements.

Moreover, the filter model assumes stationary or slowly varying bias and white noise, which does not fully capture real-world sensor imperfections. Nonlinearities, axis misalignment, and temperature-dependent bias drifts persist in the data and subtly degrade accuracy.

Another important limitation emerges in fully enclosed environments where GPS signals are completely absent. During the closed-space tests, efforts to estimate position using only IMU data did not yield consistent or meaningful two-dimensional trajectories. In the absence of external correction, errors from sensor drift accumulate rapidly, rendering extended position tracking impractical. This emphasizes the critical importance of incorporating correction mechanisms such as GPS, visual odometry, or Ultra-Wideband (UWB) systems to ensure reliable navigation performance.

Finally, it should be acknowledged that commercial systems like the DJI utilize advanced multi-sensor fusion frameworks combining GNSS, IMU, magnetometer, and barometer inputs within tightly coupled or extended Kalman filter architectures. These systems demonstrate far superior stability and drift suppression compared to single-sensor, low-cost setups. While the 1D Kalman filter used in this study provided substantial improvements over raw data, its capabilities are inherently limited.

In summary, sensor fusion significantly enhances UAV navigation performance, but its effectiveness depends on proper parameter tuning, robust time synchronization, and environmental context. Fusion systems must be designed with awareness of their operational limits, especially in GPS-denied environments where inertial-only navigation cannot guarantee positional accuracy.

5. RESULTS AND DISCUSSION

This section presents a comprehensive analysis and interpretation of the experimental results obtained during the evaluation of GPS and IMU performance under varying environmental conditions. The findings are discussed in terms of sensor accuracy, stability, and robustness, with emphasis on UAV navigation implications.

Quantitatively, the sensor fusion approach reduced positional errors by 50–75% during temporary GPS outages and decreased orientation drift by approximately 75% compared to standalone MPU6050 data. Pitch stability improved by up to 80% and roll stability by up to 75% after Kalman filtering. GPS maintained an accuracy of ±2–4 meters in open-sky conditions but failed entirely indoors, whereas the internal IMU demonstrated bounded orientation drift within ±20° across all test scenarios.

Comparative insights between standalone sensors and fusion algorithms highlight that raw external IMU data suffers from significant noise and drift, which can be effectively mitigated through Kalman filtering and sensor fusion, thereby enhancing UAV navigation reliability in challenging environments.

5.1. Performance Evaluation of GPS and IMU Under Various Conditions

In this section, the performance of the GPS and IMU systems is evaluated based on experimental data collected under open-space and enclosed environmental conditions. The analysis focuses on positioning accuracy, signal stability, and sensor drift characteristics observed throughout the test flights.

5.1.1. Accuracy of GPS positioning in different environments

The positional accuracy of the GPS module was assessed through a series of flight tests conducted in both open-space and enclosed environments. In open areas with unobstructed sky visibility, the GPS receiver generally maintained stable positioning with relatively low error margins. However, in enclosed or partially obstructed settings, signal reflections, multipath effects, and limited satellite visibility introduced significant deviations. The evaluation focuses on quantifying these variations in terms of absolute positioning error and temporal consistency, providing insight into the reliability of GPS-based navigation in diverse operational conditions.

As illustrated in Figure 3.12, during the open-space test flights, the number of satellites tracked by the GPS receiver progressively increased from approximately 14 to over 22 satellites, indicating strong and stable satellite visibility. The GPS signal quality level remained constant at level 4 throughout the test, further supporting the reliability of the positioning data in unobstructed environments.

In contrast, Figure 3.13 demonstrates the GPS receiver's performance under enclosed conditions, where both the satellite count and GPS level remained at zero for the entire duration of the test. This result confirms that signal reception was completely obstructed, preventing the receiver from obtaining a valid position fix. These observations validate the critical dependence of GPS systems on direct line-of-sight to satellites and highlight the significant degradation in performance when operating in GNSS-denied or structurally confined environments. Compared to the stable and continuous trajectory observed in open-space conditions (Figure 3.9), the complete loss of positional capability in enclosed space underscores the limitations of GPS-based navigation in indoor or obstructed settings.

Furthermore, the reconstructed 2D GPS trajectory obtained during the open-space flight tests, as illustrated in Figure 3.9, demonstrates a coherent and continuous path that aligns with the UAV's intended motion. As previously discussed in Section 3.5, the trajectory exhibited minimal deviation, with minor clustering observed particularly during tighter turns. This behavior may be attributed to brief delays or jitter in GPS signal acquisition. These results further confirm the high positional reliability of the GPS module in open-sky conditions and establish a strong baseline for comparing inertial navigation performance in subsequent analyses.

5.1.2. IMU drift and sensor stability over time

This subsection focuses on evaluating the temporal stability of the IMU by examining sensor drift and bias accumulation during the flight tests conducted in both open and enclosed environments. The analysis is based on pitch and roll angle estimations obtained under real operating conditions, with particular attention to the performance of low-cost IMUs such as the MPU6050.

As illustrated in Figure 3.6a, raw IMU outputs recorded during open-space tests exhibited significant fluctuations over time. These variations were primarily caused by noise in the accelerometer and gyroscope data, as well as integration errors that accumulate in the absence of absolute reference updates. However, after applying Kalman filtering (Figure 4.1), signal stability improved substantially. The filtered outputs demonstrated smoother and more coherent estimates of pitch and roll angles, reducing the impact of short-term noise and improving the overall reliability of the sensor data.

Although some residual drift remained, particularly during extended static phases, the filtered results indicate that even low-cost IMUs can achieve acceptable stability for short-duration or assisted UAV navigation tasks. This finding highlights the effectiveness of computational methods such as Kalman filtering in enhancing the utility of affordable sensors. In this context, the approach presents a viable balance between cost and performance, especially for applications where full-scale INS are not economically feasible.

Additional experiments were conducted to examine the influence of environmental conditions such as humidity and water exposure on IMU behavior. A detailed discussion of these effects and their implications for system robustness is provided in Section 5.2.2.

In conclusion, the analysis confirms that while low-cost IMUs are inherently prone to drift and bias accumulation over time, their performance can be significantly improved through signal filtering. With proper processing, these sensors can support UAV operations in constrained or cost-sensitive environments, offering a practical solution where high-precision inertial systems are not available.

5.2. Impact of Environmental Factors on GPS and IMU Performance

This section evaluates the effects of environmental stressors such as high temperature, elevated humidity, and water exposure on the performance of GPS and IMU systems in UAVs. Following sensor conditioning under challenging conditions and subsequent testing in enclosed environments including an IPX2-certified chamber, the GPS system failed to acquire satellite signals, demonstrating its vulnerability to structural obstructions and moisture. Conversely, the IMU remained functional, allowing for the analysis of its stability and accuracy under these adverse conditions.

The comparison between open and enclosed environments clearly highlights the limitations of GPS navigation in confined or moisture-laden spaces, where satellite visibility is severely restricted or lost entirely. These results underscore the necessity of sensor fusion and alternative navigation strategies in such scenarios.

The following subsections provide a detailed analysis of the individual effects of temperature, humidity, and simulated rainfall on sensor performance, and discuss their implications for UAV navigation system reliability.

5.2.1. Effect of temperature and humidity on sensor accuracy

Environmental factors such as elevated temperature and humidity can substantially impair the performance of inertial sensors by altering their internal mechanical and electronic characteristics. In this study, the MPU6050 IMU was subjected to a conditioning phase involving exposure to 43 °C and 75% relative humidity for one hour. Following this process, a flight test was conducted in a controlled indoor environment to evaluate post-conditioning sensor behavior.

The results revealed a marked deterioration in the sensor’s baseline stability. Compared to standard laboratory conditions, the post-conditioning data exhibited significantly larger fluctuations in pitch and roll estimations, slower recovery from bias shifts, and an increased frequency of transient spikes. These effects suggest that prolonged exposure to heat and moisture caused internal drift, hysteresis, and nonlinearities in the sensor's output characteristics. Notably, roll angle estimations expanded up to ±30°, while pitch values ranged as high as ±15°, indicating a considerable widening of the effective error envelope.

Such deviations are primarily linked to thermal stress, humidity-induced bias instability, and potential changes in the MEMS sensor’s mechanical damping behavior. While Kalman filtering continued to suppress high-frequency noise effectively, it was insufficient to fully compensate for the deeper, environmentally induced bias shifts and structural disturbances. These findings demonstrate that filtering alone cannot restore original precision once the sensor's intrinsic stability has been compromised by environmental stress.

In contrast, the DJI internal IMU maintained consistent performance under the same test conditions. The onboard sensor delivered pitch and roll angle readings that remained tightly confined within a ±5° range, showing minimal drift and jitter. This performance likely results from the integration of temperature compensation mechanisms and sophisticated sensor fusion algorithms, which enhance resilience to environmental variations.

Overall, the findings confirm that elevated temperature and humidity significantly degrade the accuracy of low-cost IMUs by inducing structural and electrical instability. Nonetheless, with appropriate filtering strategies, sensors like the MPU6050 can still deliver practically usable data, approaching the performance of more advanced systems. These results underscore the importance of accounting for environmental effects during sensor selection and UAV system design, particularly for applications expected to operate under harsh or variable atmospheric conditions.

5.2.2. Environmental simulation testing and system robustness

This subsection evaluates the robustness of UAV inertial sensing systems under simulated environmental stress, focusing on moisture exposure tested via an IPX2-certified chamber designed to replicate light rainfall conditions. The analysis centers on pitch and roll angle data acquired simultaneously from the DJI internal IMU and an externally mounted MPU6050 sensor.

Environmental simulation testing reveals significant challenges faced by UAV inertial sensing systems under moisture exposure. Low-cost sensors like the MPU6050 demonstrate marked instability in raw outputs when subjected to water and humidity, resulting in large angular fluctuations and drift. These conditions expose inherent system limitations including insufficient environmental sealing, sensitivity to temperature variations, and susceptibility to noise and bias errors. Such factors complicate the extraction of reliable orientation data without effective mitigation strategies.

Despite these difficulties, advanced signal processing methods such as Kalman filtering significantly enhance data quality by reducing noise and compensating for drift. Although these improvements narrow the performance gap with high-end internal IMUs (e.g., DJI), the system challenges remain non-trivial. External sensor systems often require additional considerations including protective enclosures, rigorous calibration, and sensor fusion to maintain operational reliability under harsh environmental stress.

The findings highlight that ensuring system robustness in UAV navigation involves addressing both hardware vulnerabilities and software limitations. Environmental stressors induce complex error patterns that cannot be fully resolved by filtering alone, necessitating comprehensive design approaches. Balancing cost, weight, and reliability demands careful sensor selection and integration to overcome these system challenges and sustain navigation accuracy.

In conclusion, environmental simulation tests underscore the importance of a holistic strategy combining resilient hardware design, environmental protection, and sophisticated data processing to meet the demands of UAV operation in adverse conditions. While professional-grade internal IMUs offer superior inherent robustness, low-cost sensors remain viable options provided their system-level challenges are effectively managed.

5.3. Comparative Analysis of GPS, IMU, and Sensor Fusion

This section presents a comprehensive performance comparison of GPS, IMU, and their integration through sensor fusion based on data collected during open-space and enclosed flight experiments. The analysis aims to evaluate each system's operational strengths, inherent limitations, and overall suitability for UAV navigation under diverse environmental conditions.

In open-space scenarios, where satellite visibility was unobstructed, the GPS module performed reliably, delivering position estimates with minimal absolute error. As illustrated in Figure 3.12, the number of tracked satellites remained consistently high, reaching over 22 during flight, while the GPS signal quality level was maintained at level 4. The reconstructed trajectory (Figure 3.9) aligned well with the UAV's intended flight path, exhibiting only minor deviations due to signal jitter. However, despite its overall accuracy, raw GPS data demonstrated clear limitations, including low update frequency (~1 Hz), temporal discontinuity, and sensitivity to external disturbances. These characteristics are evident in Figure 4.5, where the red markers indicate sparse and noisy GPS measurements that fluctuate in response to multipath effects or brief signal degradation.

The standalone performance of the external IMU (MPU6050) exhibited a markedly different profile. In both open and enclosed environments, the sensor remained operational, continuously providing inertial data at a frequency of approximately 50 Hz. However, due to the inherent limitations of low-cost MEMS-based sensors, the unfiltered outputs suffered from substantial drift and noise. For instance, the raw pitch and roll signals during open-space tests (Figure 3.6a) exhibited wide fluctuations and angular swings that rendered direct use impractical. Kalman filtering significantly improved the signal quality by reducing high-frequency noise and stabilizing the orientation estimates (Figure 4.1), yet long-term drift persisted in the absence of external correction sources. The problem became more pronounced under elevated temperature and humidity, where bias shifts and nonlinearities increased, further degrading performance (Figure 4.4).

The internal IMU of the DJI clearly demonstrated the advantages of professional-grade systems in terms of environmental resilience and data stability. As shown in Figures 3.6b and 3.23, the integrated IMU maintained pitch and roll angles within ±5° under both open-field and simulated rainfall (IPX2) conditions, delivering highly stable and reliable outputs. In contrast, the raw data from the externally mounted low-cost MPU6050 sensor exhibited greater sensitivity to environmental disturbances. However, upon applying Kalman filtering, the quality of these measurements improved significantly. During open-field tests, the filtered MPU6050 data closely approached the performance of the DJI IMU, offering consistent orientation estimates within the ±10–15° range.

Table 5.1 presents a comparative evaluation of all systems under varying environmental conditions.

Table 5.1. Comparative Evaluation of GPS, IMU, and Sensor Fusion Systems under Varying Environmental Conditions

Test Condition / Parameter	GPS (Built-in)	Internal IMU (DJI)	External IMU (MPU6050)	Sensor Fusion (GPS + MPU6050, Kalman Filter)
Signal Availability (Open Area)	High signal quality; consistent fix	Always available (not signal-dependent)	Always available (not signal-dependent)	Fully operational (requires both GPS and IMU data)
Signal Availability (Enclosed Area)	No fix; signal completely lost	Fully available	Fully available	Degraded performance (relies on last GPS fix and IMU input)

Position Accuracy	±2–4 meters under open sky	Not applicable	Not applicable	±1 meters (temporarily during GPS dropout)
Orientation Stability (open area)	Not applicable (No orientation data)	Stable (–20° to +30° drift under stress)	Drift-prone (±90° long-term drift)	Stable (±10–20° with filtering)
Orientation Stability (Under Rain / Humidity)	Not applicable	Stable (±5–10° even under rain)	Degraded (±60° drift after humidity exposure)	Acceptable (±15° under sensor stress)
Drift Over Time	Not applicable	Minimal (compensated by DJI's onboard algorithms)	Significant drift due to error accumulation	Bounded drift (periodically corrected via GPS updates)
Responsiveness / Update Rate	~1–10 Hz	~50-100 Hz	~50 Hz	Higher responsiveness when synchronization is accurate
Thermal Sensitivity	Slight performance variation	Stable under temperature fluctuations	High sensitivity (drift increases after heating)	Moderately affected (depends on calibration/filtering accuracy)
Use in GPS-Denied Scenarios	Not functional	Functional for orientation only	Functional, but unreliable for position	Temporarily usable; limited by IMU drift
Overall Navigation Reliability	High in open areas; fails in GNSS-denied environments	Reliable for orientation feedback only	Unreliable without correction	Improved robustness in dynamic and partially obstructed areas

Table 5.1 presents a comprehensive comparison of sensor performance based on the experimental setups, data analyses, and interpretative discussions conducted throughout this thesis. The evaluation integrates details from Section 3, which outlines the testing conditions, Section 4, which covers data processing and filtering methodologies, and Section 5, where key findings and comparative analyses are discussed. This holistic synthesis highlights the relative strengths and limitations of standalone GPS, standalone IMU units (both internal and external), and GPS–IMU sensor fusion across varied environmental conditions relevant to UAV navigation.

5.3.1. Effectiveness of sensor fusion in GPS-denied environments

The application of sensor fusion using a one-dimensional Kalman filter effectively mitigated many of the individual shortcomings of GPS and IMU systems. In Figure 4.5, the fused trajectory (blue line) shows a smooth and continuous position estimate, combining the global accuracy of GPS with the high-frequency motion tracking of the IMU. The fusion process successfully filled the temporal gaps between GPS updates, suppressed measurement noise, and maintained trajectory continuity even during transient GPS disturbances. Initial deviations caused by asynchronous sensor initialization were quickly corrected by the filter, demonstrating robust convergence.

Nonetheless, the benefits of fusion were limited to scenarios in which GPS data were available. In enclosed environments where satellite signals were completely absent, sensor fusion could not be performed. The lack of periodic GPS updates prevented the Kalman filter from executing its correction step, resulting in the gradual accumulation of drift in the IMU-only estimates. This limitation emphasizes the structural reliance of conventional fusion architectures on the availability of both sensor inputs.

To maintain navigation capability in fully GPS-denied conditions, alternative methods such as visual-inertial odometry (VIO), simultaneous localization and mapping (SLAM), or ultra-wideband (UWB) ranging systems may be required. These methods can provide external references to constrain IMU drift when GPS is unavailable.

5.3.2. Challenges in sensor fusion implementation

Despite its advantages, implementing sensor fusion presents several technical challenges, especially when using low-cost sensor systems. One of the primary difficulties involves achieving accurate synchronization between the GPS and IMU data streams. While the GPS typically provides updates at a frequency of 1 Hz, the IMU operates at much higher rates, such as 50 Hz. This discrepancy necessitates precise interpolation and alignment of the respective timestamps to ensure coherent data fusion. During the experimental process, it was observed that even small mismatches in the timing of data acquisition, such as the IMU beginning operation slightly earlier than the GPS, led to initial discrepancies in the fused output. These inconsistencies required compensation through post-processing and filtering techniques to restore temporal consistency across the datasets.

Another difficulty is the sensitivity of low-cost IMUs to environmental conditions. As shown in Figure 4.4, thermal and humidity exposure caused bias shifts and hysteresis in the MPU6050 sensor, degrading its reliability. Although the Kalman filter helped suppress some of these effects, its performance deteriorated when sensor drift exceeded expected noise bounds.

Moreover, conventional Kalman filters assume linear system models and Gaussian noise distributions, which may not hold in real-world UAV applications involving aggressive maneuvers or harsh environments. This can limit the filter’s accuracy and convergence behavior.

Finally, the reliability of sensor fusion is highly dependent on proper tuning of the filter parameters (e.g., process noise covariance, measurement noise covariance). Incorrect parameter selection may lead to suboptimal performance or instability.

These challenges must be addressed through careful system design, calibration, and possibly the adoption of more advanced filtering techniques, such as adaptive Kalman filters, EKF, or complementary fusion with additional sensing modalities.

5.4. Key Findings and Implications for UAV Navigation Systems

The experimental studies conducted within the scope of this thesis provided detailed insights into the performance of both the built-in GPS and IMU systems of the DJI drone, as well as the external IMU sensor (MPU6050), under various environmental conditions.

According to the collected data, GPS demonstrated high positioning accuracy in open environments; however, significant deviations and signal losses were observed in environments where the signal was obstructed, such as enclosed spaces and urban structures. This indicates that relying solely on GPS for UAV navigation may lead to reliability issues under challenging conditions.

Conversely, inertial data obtained from both the built-in IMU and the external MPU6050 sensor proved valuable for short-term position estimation but were insufficient for long-term standalone navigation due to cumulative sensor drift. The application of a Kalman filter-based sensor fusion method in this study enabled the stabilization of position estimates during periods of weak or temporarily lost GPS signals by leveraging IMU data, resulting in more continuous and accurate navigation.

Furthermore, comparison of data from the external MPU6050 sensor with that of the drone’s built-in IMU revealed that the performance of the external sensor is highly dependent on the precision of calibration and filtering processes. This suggests that low-cost external IMUs can be effectively integrated into UAV navigation systems, provided that proper calibration and advanced filtering algorithms are applied.

In light of these findings, it can be concluded that the reliability of UAV navigation systems largely depends on the integration of GPS and IMU data through sensor fusion, with system performance being sensitive to environmental conditions, sensor calibration, and filtering algorithm effectiveness. Particularly, during short-term GPS signal weakening or loss, accurate filtering and calibration of IMU data are critical to maintaining navigation accuracy.

In summary, the performance of GPS-IMU integrated navigation in UAVs is inherently linked not only to the quality of sensors and filtering techniques employed but also to the dynamic characteristics of the operational environment. Therefore, developing flexible, environment-aware sensor fusion algorithms capable of dynamically managing sensor calibration is essential to adapt UAVs to diverse mission profiles and environmental conditions.

6. CONCLUSION AND FUTURE ASPECTS

This thesis investigated the performance, advantages, and limitations of GPS and IMU systems used in Unmanned Aerial Vehicles, with a focus on the DJI drone and an external MPU6050 MEMS-based IMU sensor. Comprehensive experimental evaluations were conducted not only across different environmental scenarios such as open fields and indoor environments, but also under varying temperature conditions, IPX2-level rainfall simulation, and environmental conditioning in accordance with MIL-STD-810G standards. These tests enabled a thorough analysis of system performance under diverse climatic and environmental conditions.

The findings clearly showed that the fusion of GPS and IMU data using Kalman filtering significantly enhances navigation accuracy and reliability, particularly under challenging conditions where GPS signals are weak or temporarily unavailable. However, in fully obstructed environments such as enclosed indoor spaces, where GPS signals are completely absent, sensor fusion becomes infeasible due to the lack of positional input. In such cases, the system must rely solely on inertial data, which results in increasing drift and reduced positional accuracy over time. This highlights the importance of developing complementary navigation techniques for GPS-denied environments.

The results also confirmed that GPS provides accurate absolute positioning under optimal conditions but suffers significant degradation in performance in obstructed environments such as urban canyons and indoor areas. In contrast, MEMS-based IMU sensors deliver continuous inertial data but are prone to drift and cumulative errors, limiting their reliability when used independently over extended durations. Sensor fusion effectively mitigates these limitations by combining the complementary strengths of both systems, enabling more robust and uninterrupted UAV navigation, provided that both data sources remain available.

Comparative analysis between the drone’s built-in IMU and the external MPU6050 sensor revealed that the effectiveness of low-cost external MEMS-based IMUs depends heavily on meticulous calibration and advanced filtering techniques. This finding underscores the potential for affordable inertial sensors to be successfully integrated into UAV navigation systems, provided that appropriate data processing methods are implemented.

Despite these promising outcomes, several challenges remain for future research. Developing adaptive and environment-aware sensor fusion algorithms that can dynamically adjust to varying operational conditions and sensor behavior is essential. Moreover, integrating complementary navigation aids such as vision-based systems, LiDAR, multi-constellation GNSS, as well as machine learning and artificial intelligence techniques can further improve positioning accuracy and resilience, especially in GPS-denied scenarios.

Future studies should also focus on improving calibration procedures and reducing drift in low-cost MEMS-based IMUs to enhance their standalone performance. Additionally, implementing robust real-time filtering and fusion algorithms on embedded UAV platforms is necessary to ensure the practical applicability of theoretical advancements.

In conclusion, this thesis provides a solid foundation for enhancing UAV navigation through GPS and MEMS-based IMU integration, demonstrating up to 75% reduction in positional error and up to 80% improvement in attitude stability. These results offer both practical contributions and a strong basis for future innovations in more reliable, adaptable, and versatile autonomous flight systems.

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