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Multi-sensor Data Fusion for Autonomous Unmanned Aerial Vehicle Navigation in GPS Denied Environments

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ABSTRACT Although the Global Positioning System (GPS) is a cornerstone of modern navigation, its accuracy can diminish in urban areas, indoors, and intentionally jammed locations. This poses significant challenges for Unmanned Aerial Vehicles (UAVs) operating autonomously in these "GPS-denied" environments. In this context, multi-sensor data fusion (MSDF) is suggested as a viable technique, as it integrates inputs from various sensors to create a more robust and reliable navigation solution. In this paper, a system has been developed that enables an AUAV flying along a predetermined route to reliably detect both fixed and moving obstacles in challenging environments where GPS signals are weak or absent, and to perform effective avoidance maneuvers to prevent potential collisions, offering superior situational awareness and operational efficiency. The results obtained demonstrate that the AUAV can navigate safely and accurately in complex and continuously changing environments. The findings reveal that the proposed system has the ability to reliably detect both stationary and moving obstacles in challenging environments where GPS signals are absent or weak, and to perform effective avoidance maneuvers to prevent potential collisions in real time.

KEYWORDS Data fusion; Extended Kalman filter; multi-sensor; obstacle avoidance; optical flow; UAV.

I. INTRODUCTION

UNMANNED Aerial Vehicles (UAVs) have an intense impact on various industries, including disaster control, monitoring, farming, and transportation. UAVs use a Global Positioning System (GPS) for navigational purposes. Nevertheless, depending solely on GPS signals limits their capability in an environment where the signals are feeble or non-existent. This environment is called GPS-denied and has many obstacles that impede UAV flight [1]. Multi-sensor data fusion (MSDF) has been proposed as a solution to address these issues [2, 3]. These are referred to as GPS environments that are denied; their range can range from a high-rise cityscape to a remote and barren locale in which the ground itself poses a problem [4, 5]. In all of these instances, GPS navigation may be impossible or dangerous because the signal is low or lacking. This issue not only adversely affects the performance and versatility of Unmanned Aerial Vehicles (UAVs), but also increases their susceptibility and damage to the operational area. Consequently, the capacity to control independently, without relying on GPS receivers is invaluable. This is particularly important in environments in which GPS signals are unavailable.

The term MSDF is used to combine information from multiple sensors to obtain a more accurate, reliable, and complete set of data than that of individual sensors. Combining the benefits of various sensors can result in a high degree of situational awareness and operational efficiency for GPS-disabled UAVs.

MSDF approaches can be described at three different levels: low-level, mid-level, and high-level integration. Low-level fusion, also known as data fusion, is the direct combination of raw data from various sensors. Middle, or average-level fusion combines traits that are separated from the sensor information, which are then added to the data to improve the recognition of patterns or attributes that are difficult to understand in the raw data. The high level of fusion, or decision-level fusion, combines separate readings from sensors intended to measure different aspects of a problem, resulting in a reliable method of addressing complex issues when the real world is not entirely clear.

A wide range of sensors are used for UAVs navigation, including Inertial Navigation Systems (INS), Light Detection and Ranging (LiDAR), radar, and visual cameras. Every sensor addresses the shortcomings of another sensor, which results in a complex environment that guarantees precise guidance without the need for GPS.

The obstacles are located in the fact that although it is obvious that the MSDF has a bright future, there are multiple difficulties in executing the system during UAVs' flight in GPS-disabled and deep-rooted environments. These obstacles include noise and errors in the sensors, computational complexity, and the dynamic nature of frequently altered outdoor environments. These issues cannot be resolved without additional research that focuses on important areas, such as advanced sensors for fusion, machine-learning-based methods for pattern recognition, and lightweight, energy-efficient sensors. Current research concentrates on the concept of the MSDF in the domain of UAV travel in GPS-disabled environments. This was performed to highlight the importance, methodology, and issues. The reminder of this paper is organized as follows. The first part of the section explores various sensor systems and their contributions to UAV navigation with a relevant literature review. Subsequently, the proposed system is introduced, detailing its design and functionality. The third section presents a comprehensive validation of the system through simulations and real-world testing. Finally, the article is presented in the concluding section.

II. SENSOR SYSTEMS EMPLOYED IN UAV NAVIGATION

In the UAV world, many sensors are used for various applications, including navigation, obstacle avoidance, target tracking, altitude sensing, and speed tracking. Inertial sensors, including accelerometers and gyroscopes, form the backbone of UAV navigation systems by providing crucial data on the linear acceleration and rotational movement of a drones, respectively. These sensors enable UAVs to maintain stability and orientation, particularly in environments in which external navigation aids may be unreliable or unavailable. The strength of inertial sensors lies in their ability to function independently of external references, making them indispensable for initial flight stabilization and situations in which GPS signals are weak or obstructed. However, their primary limitation is the accumulation of errors over time, which is a phenomenon known as drifting. Without external correction, the accuracy of inertial navigation systems degrades rapidly, limiting their utility in long-duration missions.

The criticality of these data for the path planning and control modules underscores the need for accurate and reliable navigational inputs [6]. However, the reliance on GPS, while prevalent owing to its accuracy and ubiquity, is fraught with challenges, such as signal disruption in dense urban environments or intentional jamming [7]. These limitations have propelled research into alternative navigation methods and the enhancement of sensor technologies.

Although uncommon, INS, which uses accelerometers and gyroscopes as a fall-back to GPS, provides measures of motion, position, and direction independent of any external signals from outside [8]. In terms of their usefulness, the drift error contained in the INS proves corrective as an integral requirement over extended GPS non-availability, thus showcasing a significant disadvantage [9].

The establishment of micro-electromechanical systems (MEMS) technology is a vital step forward for low-cost, high-performance IMUs and other sensors [10] These developments play a critical role in providing UAVs with better navigation capabilities to ensure their successful operation in challenging environments.

The INS can deliver instant position, velocity, and orientation without any external reference. Groves [11] includes a comprehensive account of INS, focusing on their autonomy from external signals as a significant benefit. However, the INS's Achilles' heel lies in drift, which has been characteristically termed as error accumulation over time, as evident by [12]. In his work, [11] made a comprehensive description of an INS capable of providing instantaneous location, speed, and orientation without any external signals.

Satellite navigation systems, such as the Global Positioning System (GPS), GLONASS (Globalnaya Navigatsionnaya Sputnikovaya Sistema or Global Navigation Satellite System), and so-called Galileo (the European Global Navigation Satellite System (GNSS)), provide global coverage and have become ubiquitous in UAVs navigation. These systems offer precise positional information by triangulating signals from a constellation of satellites, thereby enabling UAVs to perform tasks that require high positional accuracy, such as surveying and targeted payload delivery. The principal strength of satellite navigation systems is their ability to provide accurate real-time location data over vast geographical areas. However, their effectiveness is constrained by their dependence on the unobstructed lines of sight from satellites. In urban canyons, dense forests, or indoors, satellite signals can be blocked or reflected, leading to significant inaccuracies or loss of positioning capability.

Atmospheric conditions, including ionospheric and tropospheric delays, can adversely affect the accuracy of the GPS data. In their studies [13], the impact of ionospheric disturbances on GPS signals was examined, and dual-frequency GPS receivers were proposed for correcting ionospheric errors. Furthermore, [14] we investigated the effects of tropospheric delays on GPS accuracy, suggesting the incorporation of real-time weather data into GPS algorithms to adjust for atmospheric conditions, thereby improving the positioning accuracy.

Signal blockage, primarily in urban canyons and heavily forested areas, poses a significant challenge for UAV navigation. García et al. [15] discussed the impact of signal blockage on GPS reliability and proposed the use of auxiliary sensors, including IMUs and barometers, to compensate for GPS signal loss. Their research showed that a sensor-fusion approach can significantly enhance the navigation accuracy in environments where GPS signals are obstructed.

Optical sensors, including cameras and LiDAR systems, offer rich environmental data by capturing detailed visual and topographic information. Both visible and infrared cameras, are versatile tools for navigation, object detection, and environmental monitoring, providing both real-time imagery and the basis for photogrammetry. LiDAR sensors, on the other hand, emit laser pulses to measure distances to objects, creating precise three-dimensional maps of the UAV's surroundings. The strength of optical sensors lies in their ability to generate high-resolution data that is invaluable for obstacle avoidance, terrain following, and detailed environmental analysis. However, their performance is heavily influenced by environmental conditions; for example, cameras may be less effective in low light or adverse weather conditions, while LiDAR systems can struggle with reflective surfaces or atmospheric obscurants such as fog.

In addition, the primary sensor types, UAVs often incorporate additional sensing technologies such as radar and ultrasonic sensors to enhance their navigational capabilities. Radar systems, particularly Synthetic Aperture Radar (SAR), can penetrate cloud cover and provide all-weather and, day, night operational capabilities, making them valuable for surveillance and earth observation missions. Ultrasonic sensors that emit high-frequency sound waves for detecting nearby objects are particularly useful for close-range obstacle detection and avoidance. Although these sensors significantly augment UAV navigation by filling the gaps left by optical and satellite systems, they also have limitations. Radar systems can be bulky and power-intensive, whereas ultrasonic sensors have a limited range and are susceptible to interference from environmental noise.

To overcome the limitations of individual navigation systems, researchers have proposed sensor fusion techniques. Sensor fusion involves integrating data from multiple sources, such as IMUs, cameras, LiDAR, and radar, to achieve more accurate and reliable navigation outcomes. The Kalman Filter (KF) and the Particle Filter (PF) are among the most widely used algorithms for this purpose.

EK, as discussed by Welch and Bishop [16], provides a means of fusing data in a linear, Gaussian error context, making it suitable for combining the INS and GPS data. However, in GPS-denied environments, the focus shifts towards integrating INS with Visual Odometry (VO) or Simultaneous Localization and Mapping (SLAM). In these scenarios, the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) are adapted to handle the nonlinearities associated with these technologies [17].

The PF offers an alternative approach that is particularly advantageous for dealing with non-Gaussian noise and nonlinear systems [18]. They have been effectively used in SLAM applications, allowing for robust estimation of the position and orientation in complex environments [19].

Recent advancements have also seen the incorporation of deep learning techniques in sensor fusion, aiming to leverage the pattern recognition capabilities of neural networks to further enhance the navigation accuracy in GPS-denied environments [20].

The integration of sensor fusion methods has become a powerful solution for addressing the limitations of individual sensors, thereby increasing the accuracy and reliability of navigation. By combining data from various sensors with different spatial resolutions, such as combining GPS and INS, the combination can correct INS drift while still providing a complete picture of the location, which guarantees the continued ability to navigate GPS-disabled environments [21].

Advances in algorithmic approaches to data processing, particularly the implementation of EK and PF, have demonstrated the potential of UAVs to have more accurate and robust navigation systems [22]. These algorithms have a superior capacity to deal with the nonlinearity and uncertainty present in sensor data; they provide more refined estimates of the state of a vehicle.

The MSDF is an active area of research for enabling navigation of UAVs in environments where GPS signals are unavailable or unreliable. When GPS is unavailable, UAVs must rely on alternative sensors and data fusion algorithms to estimate their position and orientation [23]. The sensors commonly used for this application include cameras, laser rangefinders, radar, and IMUs comprising accelerometers and gyroscopes.

Data fusion combines data from multiple sensors to achieve better accuracy and robustness than that of any individual sensor [2]. For UAVs, the tight integration of IMU outputs with other proprioceptive and exteroceptive sensors can enable the accurate state estimation required for waypoint following and obstacle avoidance. Seliquini [24] developed an EKF framework to fuse IMU, magnetometer, GPS, and barometric sensor data, demonstrating an improved navigation performance in GPS-denied areas. Vision-aided inertial navigation is an active research direction that uses cameras to provide velocity and orientation constraints. For example, Weiss and Siegwart [25] combined an IMU with a monocular camera to estimate the metric scale and achieve an accurate state estimation.

Laser rangefinders and radar are useful for obstacle detection, mapping, and localization. Laser scan matching against an a priori map can enable localization in the absence of GPS [26]. Radar provides direct position measurements and can characterize the dynamics of moving obstacles. The fusion of radar and onboard sensors can enhance the situational awareness. The MSDF remains an open challenge owing to computational complexity, scale, synchronization, calibration, and registration issues across different modalities [3].

VO and SLAM represent a paradigm shift in navigation technology, by leveraging visual information from the environment. Scaramuzza and Fraundorfer [27] described VO as the process of estimating the ego-motion of a robot by analyzing the changes in images taken from its on-board cameras. In contrast, SLAM not only tracks the UAV’s location but also builds a map of the environment simultaneously [28]. Although VO and SLAM offer solutions to the drift problem inherent in INS, they are still challenging. Both technologies require significant computational resources and are sensitive to environmental conditions such as lighting and texture [29].

Deep learning techniques have also been integrated into sensor fusion to take advantage of the pattern recognition capabilities of neural networks and improve GPS-denied navigation precision, as demonstrated in [3].

The adoption of sensor fusion methodologies has been recognized as an effective countermeasure to the drawbacks experienced by single sensors, increasing navigation accuracy and reliability. By blending information from different sensors, such as combining GPS with INS, sensor fusion can rectify INS drift using GPS data or vice versa, ensuring continued navigation capacity in GPS-denied environments [21].

In data analysis, research advancements in algorithmic techniques for data processing, such as the application of EK and PF, have the potential to make UAV navigation systems more robust and precise. The aforementioned algorithms cope well with the nonlinear dynamics and uncertainties usually detected in sensor readings, thereby yielding enhanced information on the vehicle state.

Furthermore, the importance of external infrastructure, such as ground-based beacons and satellite-based augmentation systems, in improving UAV navigation is highly significant [30]. These systems provide supplementary points for navigation, such that an increase in precision and reliability can occur.

III. PROPOSED UNMANNED AERIAL VEHICLE SYSTEM

In this paper, an UAV that enables it to operate independently is presented. Fig. 1 illustrates the block diagram of the system, offering a detailed view of the essential components and their interconnections that allow the UAV to function without human intervention. This system generally comprises UAV propulsion systems, guidance, navigation and control systems, communication modules, sensors, and power supply units.

The system can be divided into four blocks: namely obstacle avoidance, navigation sensors, trajectory planning and guidance, and control units. Each block represents a distinct subsystem or component that plays a vital role in UAV's functionality of the UAV, from ensuring stable flight to processing the data collected during its mission. Understanding this diagram is crucial for understanding how various hardware elements contribute to UAV' capabilities.

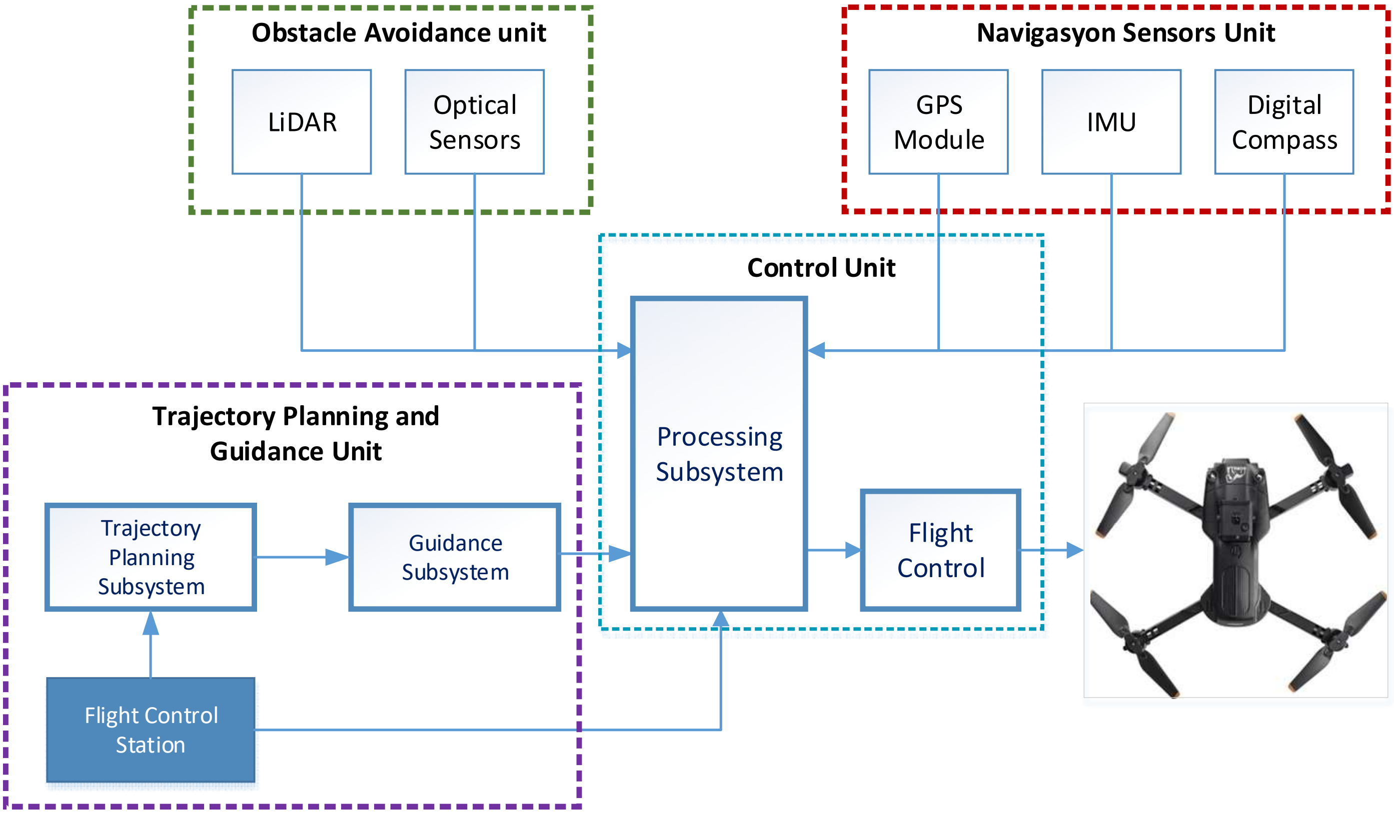


Figure 1. The block diagram of the proposed system.

A. OBSTACLE AVOIDANCE UNIT

The first line of defense against potential collisions for a UAV is its Obstacle Avoidance Unit. This unit is crucial for ensuring the safety of UAV's and the environment in which they operate. It is equipped with an array of sensors designed to detect both dynamic (moving) and static (stationary) obstacles that may lie on UAV's path of the UAV. These sensors include a Light Detection and Ranging (LiDAR) and an Optical Sensor (OF).

The Obstacle Avoidance Unit follows a set of waypoints for the UAV by using a look-ahead point. It utilizes data from LiDAR, OF, and predefined threshold values for altitude and acceleration set by the system operator to prevent the UAV from colliding with obstacles or from crashing. Consequently, the system calculates the pattern length, look-ahead point, desired course, yaw, speed, and altitude based on the UAV position, set of waypoints, and look-ahead distance; detects the nearest obstacle from the current UAV position; and compares it to both thresholds.

B. NAVIGATION SENSORS UNIT

For a UAV to effectively navigate its position, orientation, and velocity must be known at all times. This occur when the Navigation Sensors Unit comes into play. This unit is equipped with sensors, such as a GPS module, Inertial Measurement Unit (IMU), and Digital Compass (DC).

The GPS module provides precise location data by communicating with satellites, thereby allowing the UAV to determine its exact global position. An IMU, which typically consists of accelerometers and gyroscopes, tracks the UAV's movements and orientation and provide data on its acceleration, rotation, and direction. The DC, much like a traditional compass, offers information on the heading of the UAV, further aiding navigation.

C. TRAJECTORY PLANNING AND GUIDANCE UNIT

Once the UAV knows where it is and what obstacles it should avoid, it must plan its path to its destination. This is the role of the Trajectory Planning and Guidance Unit. This unit involves both hardware and software components, including a control station and various trajectory planning and guidance subsystems.

Trajectory planning can be classified as either offline or online (real-time) path planners. Offline path planners calculate drone routes before launching. Consequently, these path planners require information about the environment prior to travel. Information regarding obstacles and no-fly zones is accessible to these path planners, resulting in accurate paths. One benefit of offline path planners is that they have the ability to utilize models of drone behavior to ensure that the path is possible. However, these algorithms lack the ability to dynamically adapt to environmental changes. Moving obstacles, such as birds, wind, and other aircraft, may deviate from the original path, and a competent path planner must be able to re-compute a new path to avoid these obstacles [31].

Online path planners utilize sensor data to recognize obstacles and respond to environmental changes. However, online path planners are often incapable of ensuring that paths that are near the optimal length are generated. Some online path planners use feasible initial path and alter their paths when dynamic obstacles are encountered. Other online path planners use probability functions to create paths to obtain new information about the environment. Depending on the specific scenario, an approach may be superior. For instance, in applications that involve drones delivering goods, the first approach facilitates a shorter flight path than the second one. However, because it is impossible to use predefined paths in tracking applications with a target, the path planner must create a path.

Several studies have attempted to reduce the three-dimensional planning issue to two -dimensions. By limiting the motion of a drone to a horizontal plane (at a specific elevation), the complexity of the problem can be significantly reduced, and the proposed methods for other ground vehicles can be directly applied to drones [32]. However, there are numerous benefits to using the vertical motion of drones. A unique benefit of this method is the avoidance of obstacles and maneuvers.

In this study, the drone path planning problem refers to creating a minimum cost (considering the total path length, flight time, flight altitude and drone speed) and a collision-free path between the starting and target points. Online planning of paths for UAV in a 2D/3D environment that navigates through stationary polygonal obstacles was considered. $O = \{O_1, O_2, \ldots, O_n\}$, which begins at the designated starting position and ends at the target position [33]. The environment was a constructed rural area with solid and rectangular obstacles. In addition, it's assumed that the knowledge of the entire or partial environment, such as the configurations, dimensions, and locations of obstacles, is already known and generated during each microsecond according to sensors such as LiDAR and, cameras. The resultant path must be collision-free and consists of waypoints $W = \{W_0, \ldots, W_n\}$, which are defined by the positions $W_i = \{x_i, y_i\}$ in R^2 or $W_i = \{x_i, y_i, z_i\}$ in R^3, where i = 0,..., n. Piece-wise linear segments connect $P_{current}$ to P_{target}. Once the UAV begins its mission by following a planned 2D/3D path, the environment may be altered to include pop-ups or previously unknown obstacles along the path. UAV are equipped with sensors that have a limited detection range, and this information is then used to deduce information about the environment, such as popups or previously unknown obstacles. The information gathered from the sensors must be used to plan new motion to avoid collisions with nearby obstacles.

The control station is typically operated by a human who can manually guide the UAV if necessary. However, the majority of trajectory planning is performed autonomously by the UAV's on-board systems. These systems analyze the data from the Obstacle Avoidance and Navigation Sensors Units to plot a safe and efficient course to the UAV's destination, taking into account factors such as wind speed, no-fly zones, and UAV capabilities.

D. CONTROL UNIT

The core of a UAV system is the Control Unit. This unit is tasked with processing all the data gathered by the UAV's sensors, executing fusion algorithms, and determining the position and orientation necessary for navigation. It comprises processing, navigation, and Flight Control subsystems.

- **PROCESSING SUBSYSTEM**

At the core of the system is the MSDF algorithm, which integrates pre-processed data from all sensors to estimate the UAV's position, velocity, and orientation. The MSDF algorithm combines information from different sensors to produce a more accurate and legitimate estimate of a vehicle's condition. EK, PF, and EKF commonly use data fusion in environments with well-documented noise and errors associated with the sensor data. These data can be modelled as Gaussian distributions. Particle filters are more versatile and can handle problems that are not Gaussian or nonlinear, making them ideal for complex UAV navigational tasks. Sensor weighting algorithms facilitate the alteration of the importance of each sensor's data based on the current environmental situation and the performance of the sensor.

Data fusion for UAVs involves a combination of data from multiple sources, including a GPS module, IMU module, and DC, which is more accurate, reliable, and comprehensive than the information available from any single sensor. By taking advantage of the strengths of each sensor and addressing their individual weaknesses, the MSDF amplifies the quality of navigational data, which in turn increases the efficiency and safety of UAVs. Raw data from each sensor underwent pre-processing to enhance the quality and compatibility of the fusion. This includes noise reduction, calibration, scaling, and conversion of the data into a common format. Pre-processing is crucial for removing sensor biases and ensuring that data from different sensors can be effectively combined. The functional block diagram of MSDF for the UAV is presented in Fig. 2.

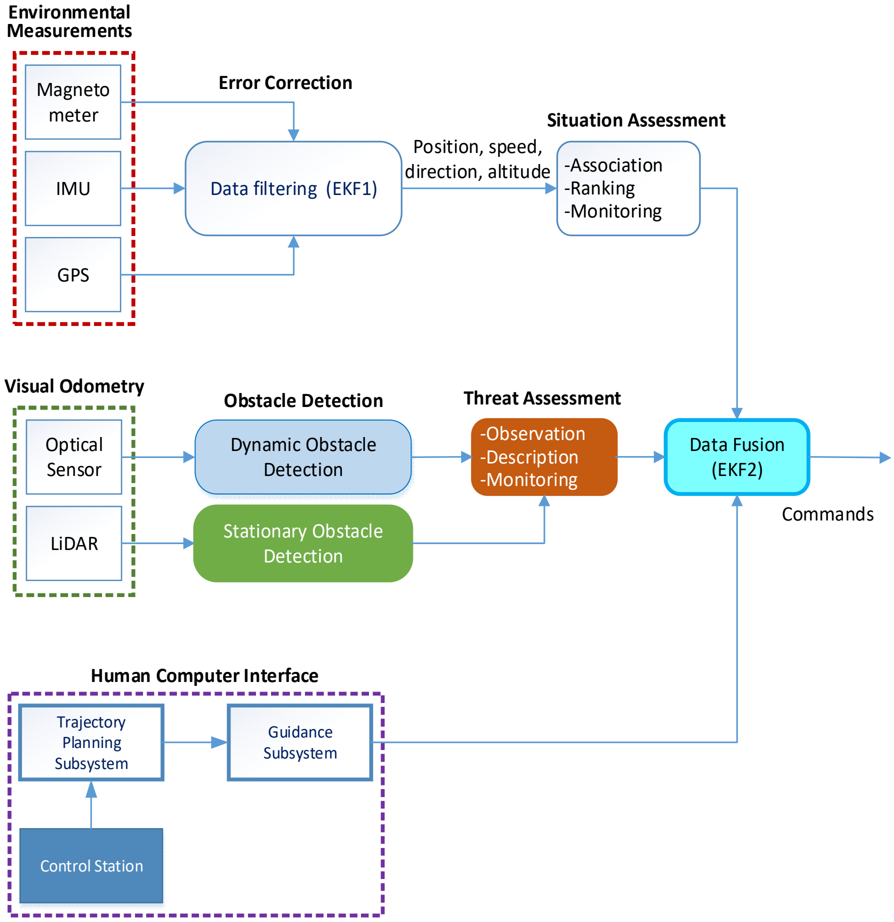


Figure 2. The block diagram of the proposed system.

In the proposed system, sensor data are refined and integrated using the EKF algorithm to derive the UAV's real-time position and orientation. UAV's motion, of the UAV, characterized by six degrees of freedom, is represented by its state $\bar{X}$, which includes the position vector $\bar{P}_{et}^{t}$, spatial velocity vector $\bar{V}_{et}^{t}$, orientation quaternion $\bar{q}$, and gyroscope rotation vector $\bar{b}_{\omega}^{t}$ in the spatial coordinate system. This can be described as follows [34]:

$$\bar{X}=[\bar{P}_{et}^{t} \quad \bar{V}_{et}^{t} \quad \bar{q} \quad \bar{b}_{\omega}^{t}\ ], \tag{1}$$

where $\bar{P}_{et}^{t}, \bar{V}_{et}^{t}, \bar{q}$ and $\bar{b}_{\omega}^{t}$ are acquired as follows:

$$\begin{cases} \bar{P}_{et}^{t} = [P_x^t \quad P_y^t \quad P_z^t] \\ \bar{V}_{et}^{t} = [V_x^t \quad V_y^t \quad V_z^t] \\ \bar{q} = [q_0 \quad q_1 \quad q_2 \quad q_3] \\ \bar{b}_{\omega}^{t} = [b_{\omega x}^t \quad b_{\omega y}^t \quad b_{\omega z}^t] \end{cases}. \tag{2}$$

Given the presence of ambient noise from the four elements in the space motion velocity vector and the attitude representation when the sensor collects data, it is essential to first perform noise reduction processing. This can be described as follows:

$$\begin{cases} \hat{V}_{et}^{t} = D_b^t f^{-b} + \bar{g}^{-t} + D_b^t \bar{\delta}_a^b \\ \hat{g} = \frac{1}{2}\Omega\, \bar{q}\left(\bar{\omega}_{ib}^{b} - \bar{b}_{\omega}^{b} + \bar{\delta}_{\omega}^{b}\right)^{t} \end{cases}, \tag{3}$$

where, $\bar{\delta}_a^b$ represents the environmental noise detected by the acceleration sensor, $\bar{f}^{b}$ denotes the specific force measurement value, $\bar{\delta}_{\omega}^{b}$ is the environmental noise measured by the gyroscope, $\bar{b}_{\omega}^{b}$ is the gyroscope's measured value, and $\bar{\omega}_{ib}^{b}$ is the gyroscope's measurement deviation correction value. The UAV state representation equation in Equation (1) can be transformed into;

$$\bar{X} = [\bar{P}_{et}^{t} \quad \hat{V}_{et}^{t} \quad \hat{q} \quad \bar{P}_{\omega}^{t}] \tag{4}$$

Setting $\bar{\delta} = [\bar{\delta}_{\omega}^{bt} \quad \bar{\delta}_{a}^{bt} \quad \bar{\delta}_{b}^{bt}]$ as the system noise, Equation (4) can be simplified as:

$$\bar{X} = f(\bar{X}, \bar{U}, \bar{\delta})\,. \tag{5}$$

Owing to the nonlinear characteristics of the UAV multi-sensor fusion localization system, Equation (5) requires linearization. The Taylor series expansion is utilized and represented by the Jacobian matrix [34].

$$\begin{cases} F = \dfrac{\partial f(\bar{X},\bar{U},\bar{\delta})}{\partial \bar{X}}\Bigg|_{\substack{\bar{X} = \hat{X}_{k-1} \\ \bar{\delta} = 0}} \\ G = \dfrac{\partial f(\bar{X},\bar{U},\bar{\delta})}{\partial \bar{\delta}}\Bigg|_{\substack{\bar{X} = \hat{X}_{k-1} \\ \bar{\delta} = 0}}, \\ H = \dfrac{\partial f(\bar{X})}{\partial \bar{X}}\Bigg|_{\bar{X} = \hat{X}_{k,k-1}} \end{cases} \tag{6}$$

where F is the external force vector, G is the acceleration vector, and H is the horizontal direction vector.

The motion state is represented by the position vector $\bar{P}_{et}^{t}$ in the spatial coordinate system, velocity vector $\bar{V}_{et}^{t}$, four components of attitude representation $\bar{q}$, and gyro rotation vector $\bar{b}_{\omega}^{t}$. The EKF algorithm was employed for the state estimation, yielding a covariance matrix that was utilized to adjust the state parameters.

- **FLIGHT CONTROL**

The Flight Control (FC) obtains the coordinates of the target point and waypoints as an input parameter and then outputs the UAV's movement towards the target position. The target coordinate data type is confined to a two-dimensional Cartesian map; the x-axis represents the east-west position relative to the UAV, and the y-axis represents the north-south position. By using the Waypoint Tracker, the UAV can follow a series of waypoints according to the forward point. Based on the UAV position, waypoints, and forward distance, the forward view point, desired route, desired yaw, speed, and altitude were calculated. A flow chart of the FC is shown in Fig. 3.

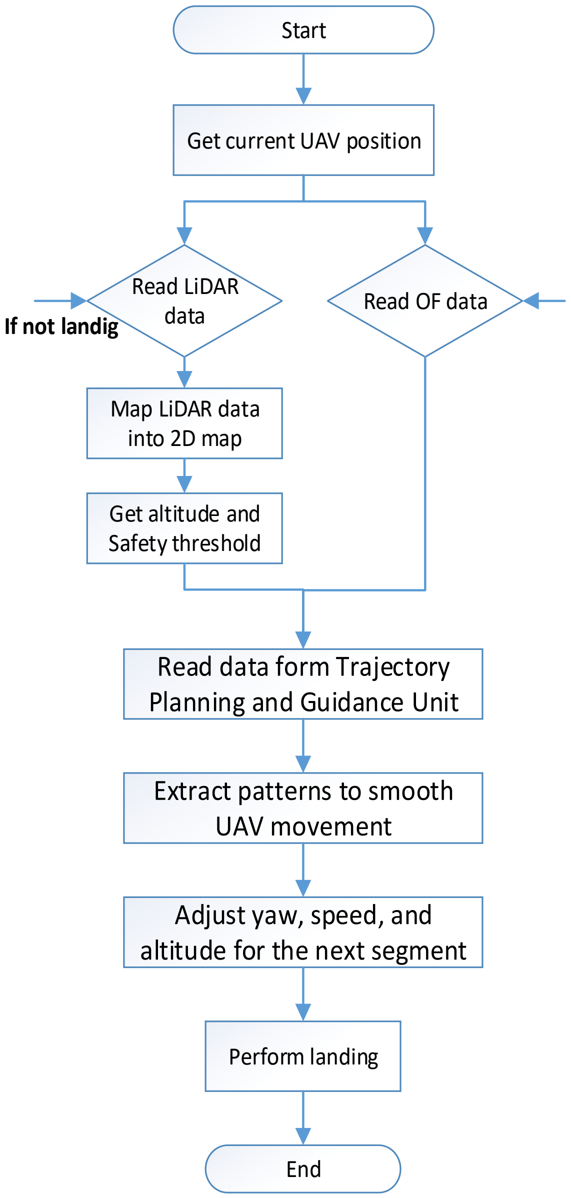


Figure 3. The flow chart of the flight control.

To compute the trajectory plan, the first step is to locate the current position of the UAV (0; 0) on the discretized map, as well as the data regarding the altitude and coordinates of the waypoints. This is performed using a hash map with a key-value pair mechanism, where the key is the node position (NP) associated with the waypoint and UAV, and the data are computed using Equation (7).

$$NP = mr \times x + y \,. \tag{7}$$

The variable mr, is the maximum width of the discretized map, x and y represent the x-axis and y-axis coordinates of the waypoints respectively.

IV. VALIDATION OF THE SYSTEM

The system comprises an extensive collection of software and hardware elements that are, meticulously crafted to fulfil distinct tasks and synergistically enhance the system's overall efficiency. Fig. 4 provides, a detailed visual representation of the UAV, showing both its external architecture and the integrated systems crucial for its operation.

Simulations and real-world tests are conducted to evaluate the effectiveness and efficiency of the proposed system. The tests were meticulously designed to provide a holistic understanding of the system performance under various conditions.

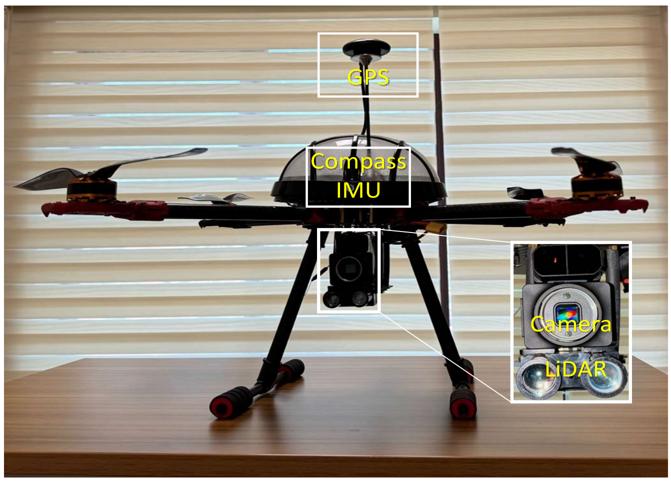


Figure 4. The comprehensive external representation of the UAV.

A. SIMULATION TESTS

The proposed EKF-based multi-sensor data fusion system, and the functionality of the UAV were studied in a real environment. The investigation included a series of tests designed to assess the capabilities of UAV for a variety of key parameters, including waypoint tracking, obstacle avoidance, immunity to signal interference, and general maneuverability. Tests were conducted based on three different scenarios, each carefully designed to reflect the complexity of the real-world environment depicted on the corresponding map. This comprehensive testing approach helps to verify UAV's operational effectiveness and adaptability of UAVs to unforeseen challenges, highlighting their potential applicability in diverse and complex operational environments.

In this study, the time period of the system was 1 s, which is the same as the typical sampling frequency of a GPS module. Consequently, the sampling frequency of the DC was set to 1 s. The IMU typically provides readings at a higher rate; for example, 0. 02 s, and the average of these values within 1 s is incorporated into the system. Measures derived from different sensors used for navigational purposes, including GPS, DC, and IMU, were augmented with noise to represent true values. The test area was based on the existing environment of Gölbaşı district (Ankara, Türkiye).

SCENARIO 1: SIMULATION STUDIES

In Scenario 2, the UAV was tested on a waypoint tracking mission and two obstacle avoidance maneuvers, and the system performance was evaluated when the GPS signal was blocked in two areas.

In the simulation, the UAV trajectory was initiated from the starting point (100 m, 100 m) and embarked on a mission to navigate through three waypoints (100 m, 900 m), (900 m, 900 m), and (900 m, 100 m), aiming for a target point (100 m, 100 m) while avoiding two obstacles (900 m, 300 m) and (100 m, 300 m) in Gölbaşı district.

To assess the reliability of the system, GPS signals were intentionally blocked during the time intervals k 205 to 245 s and k 645 to 685 s. The trajectory outcomes are depicted in Fig. 5, where two black rectangles emphasize the durations of GPS signal lost. As illustrated in Fig. 5, the GPS-measured positions are absent during these intervals, yet the fusion outcomes, represented by the red line, remain in close approximation to the actual trajectory (black line). This demonstrates the algorithm's capability to accurately estimate UAV's position and effectively reconstruct UAV's trajectory amidst GPS signal interruptions.

The actual environmental influences, such as the wind, altered the trajectory of the UAV, as shown in Fig. 5. The blue line shows raw GPS data collected during the trial. The results show that the UAV successfully navigated through the three waypoints in sequence and arrived at the target point despite encountering two obstacles as planned.

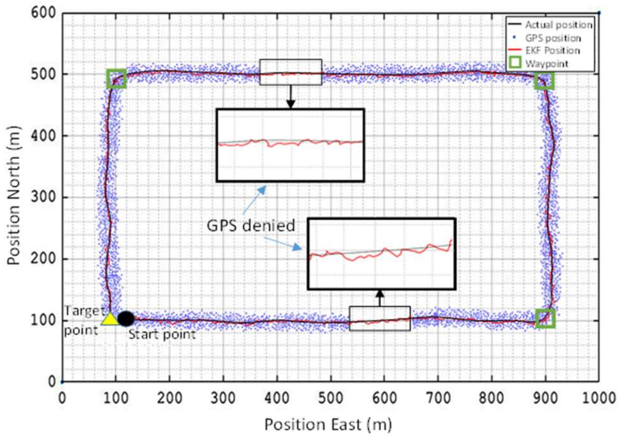
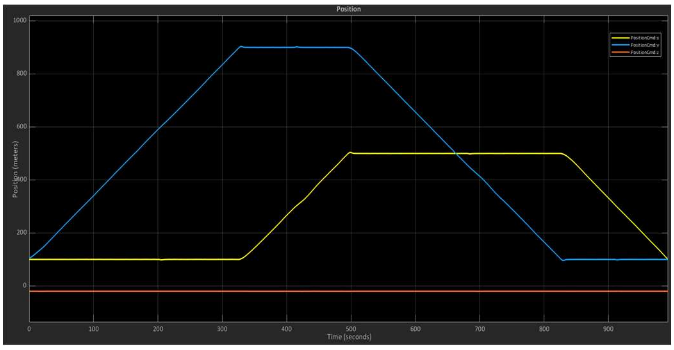
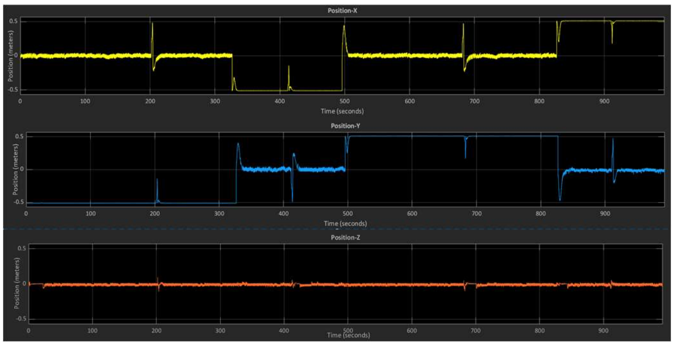


Figure 5. Simulation results of the recovered trajectory of UAV navigation with two short-term GPS blockages.

The positions of the UAV on the X-Y-Z axes are shown in Fig. 6. The position information at which the UAV reached the predetermined waypoints is shown in Fig. 6 (a). The difference between the desired and actual positions is shown in Fig. 6 (b). The yaw angle is shown in Fig. 7.



(a) Real positions



(b) Difference between real and desired positions

Figure 6. (a) UAV's position information (b) UAV's desired and real positions differences.

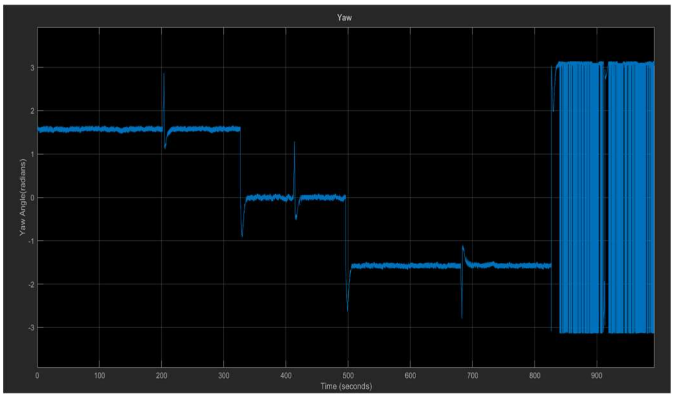


Figure 7. UAV's yaw angle.

The desired course, as shown in Fig. 8, indicates the intended direction of UAV movement, which aligns with its velocity vector. Expressed as an angle measured clockwise from north, the desired course ranged from -π to π rad. It is important to note that the desired course differs from the desired yaw, which refers to the UAV's intended orientation along the vertical axis.

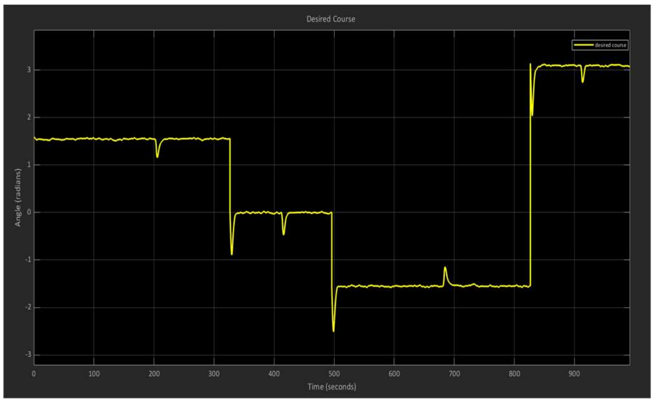


Figure 8. UAV's desired course.

The cross-tracking error (CTE) from the UAV's location to the road measures the deviation of the UAV from the specified route. This error is the perpendicular distance from the current position of the UAV to its' closest point on its designated route. If the error returns to a positive numerical value, the UAV deviates from its course to the right. The measured distance is expressed in meters. It is important for a UAV to follow its route accurately, and the cross-tracking error is used to determine the deviation from the route, and correct the route, if necessary. In this manner, it is ensured that the UAV performs its mission effectively and accurately to explore the desired area. A cross-track error appeared, as shown in Fig. 9. Deviations appear after waypoints. During the waypoint transitions, deviations were observed because the UAV adjusted its position and orientation.

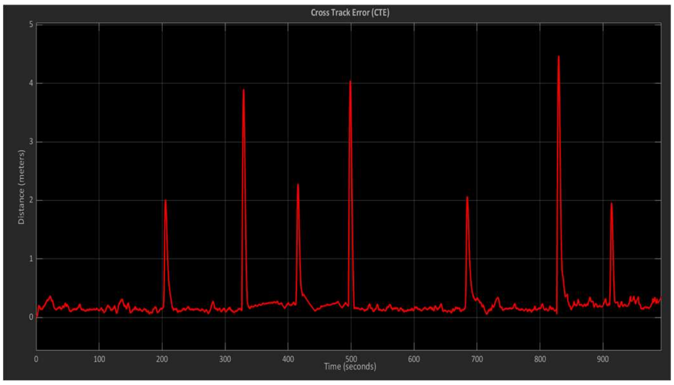


Figure 9. UAV's Cross track error.

The yaw pitch roll and thrust values required for the movement of UAV engines during flight are shown in Fig. 10.

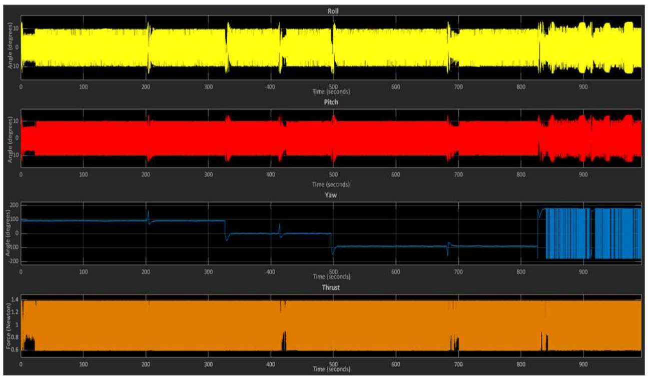
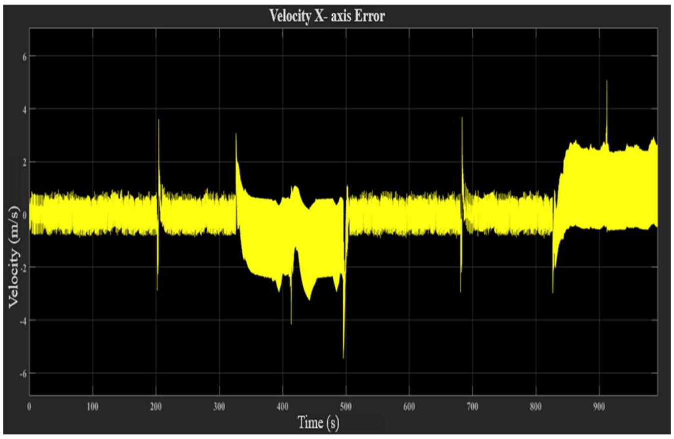
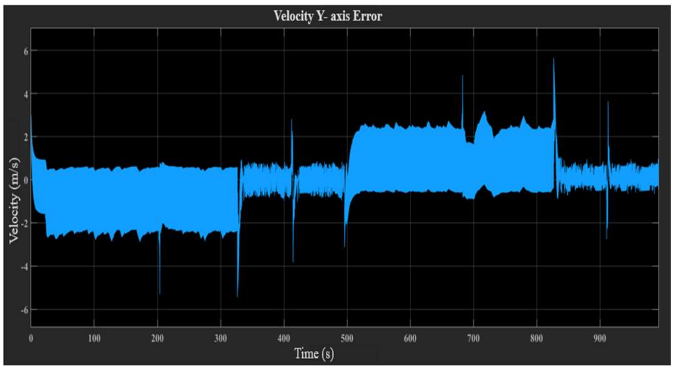


Figure 10. Yaw, pitch, roll and thrust values during the flight of UAV.

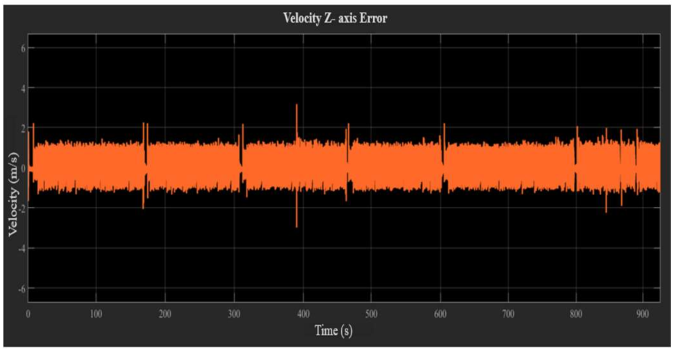
The velocity error values along the X-Y- Z axes of the UAV are shown in Fig. 11.



(a) UAV's Velocity X – axis error



(b) UAV's Velocity Y – axis error



(c) UAV's Velocity Z – axis error

Figure 11. UAV's X-Y-Z Axes Velocity error values.

SCENARIO 2: SIMULATION STUDIES WITH REAL-WORLD DATA

This section addresses simulation studies carried out using real-world data for a more realistic approach. This allows for a more detailed analysis of how well the system adapts to real-world conditions and how it responds to unexpected situations. Simulations conducted with real data provide the opportunity to evaluate the system's performance more realistically and identify potential problems in advance. These studies, in particular, have played a significant role in evaluating parameters such as immunity to signal interference and overall maneuverability.

To form the basis of these studies, data collected from previous flights (GPS coordinates, Inertial Measurement Unit data, weather information, etc.) were recorded from the UAV flying along a specific route. Subsequently, MATLAB objects that behave like GPS and IMU sensors were developed using these data. For a realistic offline simulation, a mission scenario incorporating 24 waypoint points over a 6000 m long route was designed. This route consists of eight fixed and four randomly placed moving obstacles. This environment provides an ideal ground for testing the UAV's navigation and obstacle recognition capabilities.

In the offline simulation studies, data from a point located in the Gölbaşı district of Ankara/Türkiye province were taken as the initial position. The initial position is expressed in terms of latitude, longitude, and altitude. The coordinates of the initial position used in the simulation are 39° 42.705' North - 32° 41.483' East, and the altitude is 59.33350583 m.

Since the GPS sensor requires a reference position to obtain accurate location information, the latitude, longitude, and altitude data specifying the initial position were used in degrees, degrees, and meters, respectively. This reference location is a reference point used in processing sensor data. Therefore, changing the reference point will alter the predicted position and orientation information in the simulation. The GPS data utilize the difference between the reference location and the sensor's current location when making location predictions. Thus, changing the initial location affects this difference and, consequently, the location prediction. Fig. 12 shows the orientation data related to the flight information of the UAV in a three-dimensional offline simulation environment.

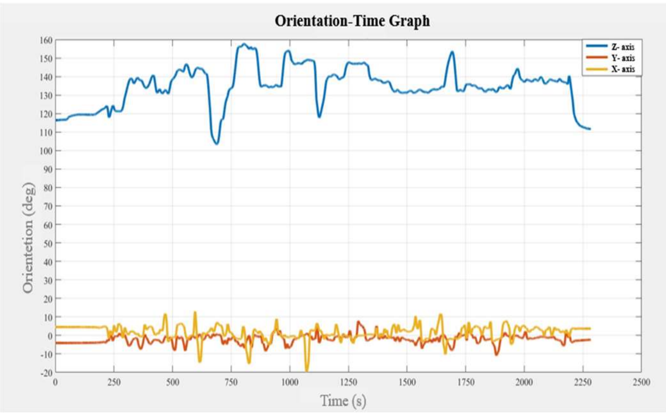


Figure 12. Orientation values in XYZ Axis.

Fig.13 and Fig.14 show the position and speed data of the UAV in a 3D offline simulation environment, respectively. Fig.15 shows the position error and the orientation difference value, which is the quaternion distance, in the XYZ axes of the UAV in a 3D offline simulation environment.

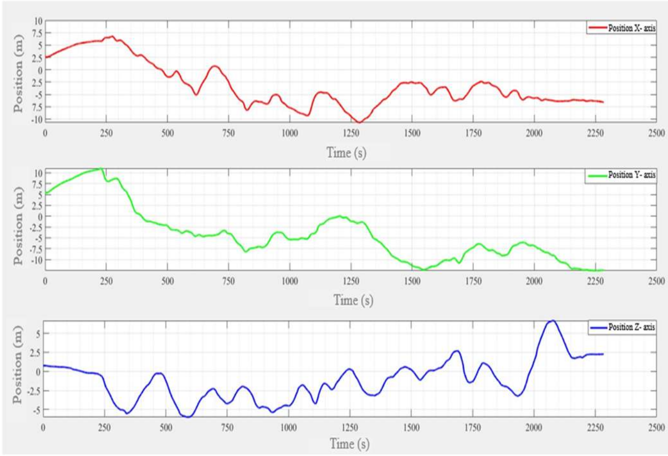


Figure 13. Position values on the XYZ axes regarding the flight data in the offline simulation environment.

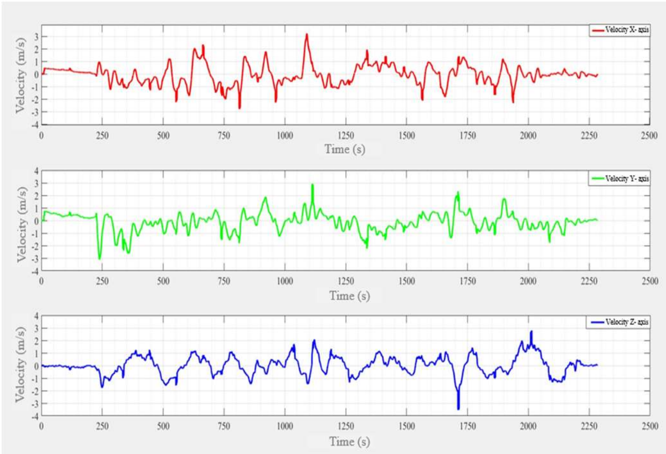


Figure 14. Speed values on the XYZ axes related to the flight data in the offline simulation environment.

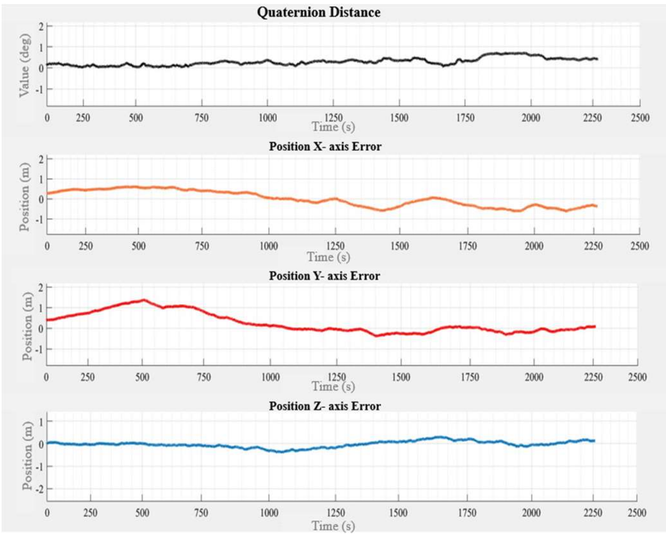


Figure 15. Error and quaternion distance values in XYZ axes.

A total of 15 offline simulation studies were conducted to test the performance of the developed UAV. In all simulations, it completed its movement on a route containing 3D location data of approximately 6000 meters in 3 axes. The comparison of the test results obtained in the offline simulations on the performance of EKF and UAV is given in Table 1.

Table 1. Offline simulation results of EKF and UAV location estimation

Sim. No	$E(\hat{x}-x)$	$\sigma(\hat{x}-x)$	$E(\hat{y}-y)$	$\sigma(\hat{y}-y)$	$E(\tilde{d})$	$\sigma(\tilde{d})$
1	8,46688	40,28857	-9,93420	35,53813	34,85081	45,54685
2	7,01288	39,70097	-10,68822	34,64707	33,39099	45,28227
3	8,73760	41,42601	-10,79378	35,93120	35,21182	47,01834
4	8,14672	54,11383	-11,23677	37,35274	35,01597	61,30886
5	6,99696	43,60014	-11,04640	36,58327	35,39591	49,30191
6	7,42344	39,55290	-9,90417	35,34048	34,92325	44,28903
7	7,87600	48,23384	-11,00681	36,84619	36,06344	54,00581
8	5,82736	40,61038	-11,12693	33,73748	34,48783	44,48786
9	7,39352	39,99494	-11,21311	35,21293	35,27438	44,67197
10	6,91040	45,73955	-11,25643	37,16775	36,00672	51,53078
11	6,87262	36,44549	-10,88061	35,61719	33,73425	43,51753
12	6,85702	40,02493	-11,24523	37,60760	35,75978	47,38051
13	7,71848	44,27867	-11,20494	37,87788	36,43418	51,90109
14	5,71081	37,28033	-11,32722	34,68213	34,84237	42,75408
15	7,24565	36,71536	-11,41495	36,19890	35,63700	42,93101
Ave-rage	**7,27976**	**41,86706**	**-10,95198**	**36,02273**	**35,13525**	**47,72853**

The offline simulation results are evaluated by considering the mean error of the state estimates, $E(\hat{x}-x)$ and $E(\hat{y}-y)$, the standard deviations of the errors (σ), and the mean difference between the estimated position and the actual GPS position. Two important measures of the location estimation accuracy are the mean value of the distance between the estimated position and the actual position, $E(\tilde{d})$, and the standard deviation of this distance, $\sigma(\tilde{d})$. Here $\tilde{d}$ is calculated by the equation in Equation (8).

$$\tilde{d} = \sqrt{(\hat{x}-x)^2 + (\hat{y}-y)^2} \tag{8}$$

These values are used to evaluate the accuracy of the location estimation algorithms; a lower value indicates higher accuracy.

SCENARIO 3: REAL-WORLD TESTS

In Scenario 3, the performance of the UAV in tracking waypoints and its maneuverability in the absence of GPS signals in the two regions were evaluated in a real-world setting.

After the simulation results were successfully validated, the UAV system was subjected to comprehensive real-world testing to evaluate its practical capabilities under actual scenarios. These tests cover the full spectrum of basic navigation in uncluttered areas for more intricate maneuvers. The tests involved navigating the UAV through pre-designed routes, with the multiple-sensor data fusion system combining information from the IMU and other sensors to determine the UAV's position and orientation. Real-world tests are crucial for proving the system's capacity in GPS-disabled environments, where traditional navigators would have difficulty.

The experimental data stored in the UAV trial were used to evaluate system capabilities. By applying the scenario, the UAV was assigned a mission to track three waypoints. During the operation, the GPS raw measurements were set to be blocked for two short time periods, and the updated trajectory result is shown in Fig. 16, where the two periods when the GPS signal was lost are highlighted by black rectangles. The results indicate that the system recovers trajectories when a GPS signal is unavailable and provides a continuous estimation of the position.

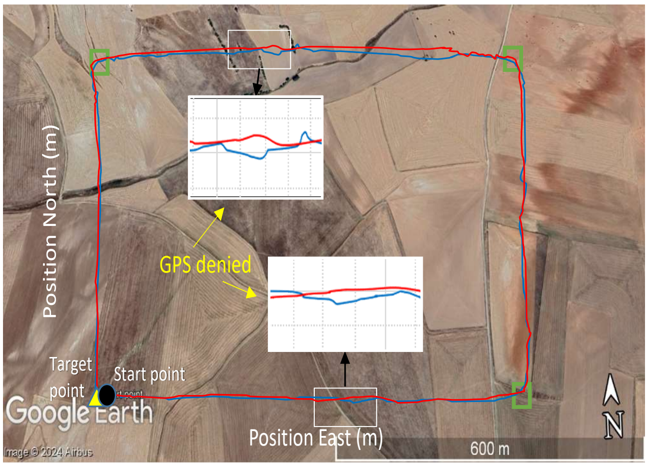


Figure 16. Trajectory fusion results with two blockages of GPS signal.

The findings from both the simulation and experimental validation underscore the potential of MSDF techniques to overcome the limitations of GPS-dependent navigation for UAVs. By leveraging the complementary strengths of different sensors, UAVs can achieve improved operational robustness and versatility, paving the way for deployment in a wide range of applications.

V. CONCLUSION

In this study, a system has been developed to enable an AUAV to fly along a predetermined route while reliably detecting both fixed and moving obstacles in challenging environments where GPS signals are weak or unavailable, and to perform effective avoidance maneuvers to prevent potential collisions, thereby enhancing situational awareness and operational efficiency. To evaluate the proposed systems, the functionality of the UAV was studied in a real environment The investigation included a series of tests designed to assess the capabilities of UAV for a variety of key parameters, including waypoint tracking, obstacle avoidance, immunity to signal interference, and general maneuverability. Tests were conducted based on three different scenarios, each carefully designed to reflect the complexity of the real-world environment depicted on the corresponding map. This comprehensive testing approach helps to verify UAV's operational effectiveness and adaptability of UAVs to unforeseen challenges, highlighting their potential applicability in diverse and complex operational environments. The findings from both the simulation and experimental validation underscore the potential of MSDF techniques to overcome the limitations of GPS-dependent navigation for UAVs. The results also indicate that by leveraging the complementary strengths of different sensors, UAVs can achieve improved operational robustness and versatility, thereby paving the way for deployment in a wide range of applications.

The increasing use of UAVs presents significant ethical and legal challenges. Autonomous operation raises privacy concerns due to the potential for unauthorized surveillance. Determining accountability in accidents or misuse becomes complicated without GPS data, relying instead on less established sensor fusion. Proactive engagement with these issues is crucial for responsible technological development.

Further research should explore the integration of artificial intelligence for intelligent decision-making and predictive navigation, which presents promising avenues for improvement. Additionally, investigating novel sensor modalities, such as bio-inspired sensors or advanced vision systems, could further enhance UAV autonomy and resilience in GPS-denied environments.

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