Sensor Data Adaptive Treatment in Time-Varying UAV Medium: Approaches and Methods

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ABSTRACT

Unmanned Aerial Vehicles (UAVs) that can navigate independently in a variety of situations are in high demand. Thus, distinct UAV configurations that incorporate a range of components, including communication devices, navigation sensors, and additional payloads, are needed, necessitating the development of action models which take into account the dynamic environment and operational goals while limiting the use of resources. The current study presents an integrative review of approaches, methods, concerns, and prospects in the field of adaptive sensor data treatment in a time-varying UAV environment. It provides a comprehensive overview of UAV route planning approaches, such as integrated algorithmic frameworks, biologically inspired approaches, stochastic sampling techniques, and deterministic models. The literature review revealed that sensing accuracy directly affects performance, while substantial research has been conducted to provide trustworthy sensing data to guarantee normal flying. Moreover, it is believed that the prediction accuracy of current filter-based statistical models is independent of the flying conditions. This research highlights the effectiveness of recent data-driven adaptive fusion state-space models in measuring the prediction uncertainty of the system model to prevent degradation in the performance estimation. The study also reviews techniques for adjusting the noise parameter of the statistical model based on the estimated variance, depending on the multi-output Gaussian Process Regression (GPR). The sparse GPR model is proposed for incorporating available characteristics and achieving high estimation accuracy under dynamic operating situations.

Keywords-UAV control system; unscented Kalman filter; autonomous navigation; Gaussian process regression

I. INTRODUCTION

Advances in digital technologies, robotics, electronics, and computing have led to the rethinking of UAV concepts, their further development, the improvement of information systems and interfaces, and their multi-purpose nature. UAVs occupy a prominent place in the production programs of the world's leading aircraft manufacturers.

UAVs are being actively implemented in many fields and used to solve practical problems such as forest fire detection, aerial photography, monitoring of pipelines, agricultural land, settlements, etc. The diversity of tasks they solve has led to the development of various UAV designs, including tricopters, conventionally configured aircraft, quadcopters, and gliders. Military UAV technologies undergo rapid development.

To improve navigation and control accuracy, methods for integrating data from various sources are often used. Ensuring the required level of estimation of object orientation parameters requires reducing the degree of uncertainty during UAV operation, particularly in the absence of satellite signals. Navigation sensors play a key role in UAV autonomous navigation. Several navigation systems, including mapping, obstacle avoidance, and status assessment, determine the degree of autonomy of the UAV. One of the most important aspects of the design process is choosing the right components. However, as there are numerous technologies and components on the market, each with unique benefits and drawbacks, this can be an exceptionally challenging process, especially for beginners.

Computer vision technology combined with UAVs offers state-of-the-art visual navigation, localization, and obstacle avoidance capabilities, enabling autonomous operations.

However, they are not appropriate for areas where the Global Positioning System (GPS) is not available due to their limited ability to navigate autonomously. Vision-based methods that employ economic and more flexible visual sensors have demonstrated significant advantages in UAV navigation. Essential elements of visual navigation are path planning, obstacle avoidance, and visual localization and mapping [1].

There are a number of challenges in the UAV flight environment, including obstacle avoidance, dynamic course planning, and environmental recognition. Moreover, UAVs must successfully combine several sensors to travel and complete tasks. Despite rapid advancement in autonomous flight technology, several drawbacks remain, especially in data processing and environmental adaptation. In addition, different types of sensors are required to gather additional environmental data, as traditional single sensors might not be able to do so accurately and completely.

Reliable control of UAVs depends on accurate sensing. The Unscented Kalman Filter (UKF) has demonstrated exceptional performance in terms of computation efficiency and estimation accuracy, making it appropriate for onboard sensor augmentation. However, the prediction accuracy of current filter-based statistical models is independent of the flying conditions. Innovative data-driven adaptive fusion state-space models are required to predict uncertainty to prevent deterioration in estimation performance. To address these challenges, the present study provides the latest developments in UAV flight control sensing augmentation using a data-driven adaptive fusion model and offers further perspectives in this area.

II. LITERATURE REVIEW

A. Background

1) Adaptive Fusion

Adaptive fusion is a system or algorithm that dynamically modifies the combination of data from several sensors or information sources according to the data's real-time quality, dependability, and environmental context. Adaptive fusion estimates of the UAV's state (e.g., location, orientation, or surrounding environment) that are more reliable, accurate, and robust than any one sensor or static fusion technique could produce on its own.

2) Probabilistic Modeling

Probabilistic modeling is a mathematical and statistical framework for representing and quantifying uncertainty in the system's operations and surroundings, allowing the UAV to make sound, risk-based decisions.

3) Sensor Uncertainty

Sensor uncertainty is the quantifiable uncertainty or range of error in data from onboard sensors (such as GPS, LiDAR, and cameras) caused by physical limitations, environmental factors (wind, rain, lighting), or internal issues that affect the UAV's perception, localization, and decision-making. This uncertainty is managed using techniques, such as sensor fusion and adaptive filtering, to ensure safe, reliable operation.

B. UAV Design Concerns about Sensory Data Precision

The reliability and safety of UAVs became a significant issue due to their rapid development in both military and civilian domains [2-4]. Real-time object detection involves the use of sophisticated sensors, such as LiDAR and ultrasonic, and the integration of sensor data with path planning algorithms. These algorithms use available data to determine possible waypoints to be included in their path generation. Meanwhile, the calculated trajectories are rather unclear due to sensor measurement noise and the drone's ability to follow waypoints. This is the most critical source of uncertainty caused by gusts of wind. Thus, it is important to create a closed-loop control system that can improve the UAV's agility and follow the planner's trajectories in real time [5].

The flight control system manages the UAV to complete different flight tasks in real time. Deviation in the flight control system leads to UAV malfunction, making trajectory guarantees impossible, and thus substantially affecting the UAV's operational safety [6]. The precision of sensing has a direct impact on the control effect since it is the system's input. To ensure normal flying, researchers have been investigating accurate sensor data collection.

Several strategies supported by vision-based systems have been developed for UAV navigation. A successful UAV flight involves the shortest path and obstacle avoidance. Path planning, mapping, and localization are the three primary steps in navigation [7]. First, localization is established. In addition to assigning appropriate landing spots, a map is then graphically created to help hone the search and steer clear of obstructions. The ultimate goal of planning is to use an appropriate optimization method to find the shortest path. Inertial, satellite, and vision-based navigation are the three primary types of navigation techniques. Due to their exceptional anti-inference ability and high perception application, vision-based navigation employing visual sensors offers real-time information in a dynamic environment [8].

For navigation, exteroceptive and proprioceptive sensors are used. After internal preprocessing of the dataset for mapping and localization, obstacle avoidance, and path planning, outputs are eventually supplied to direct the UAVs to the desired location. Navigation uses several conventional sensors, including Internal Navigation Systems (INS), gyroscopes, axis acceleration, and GPS [9]. The performance accuracy of these sensors is higher than that of their counterparts. However, the propagation of bias errors caused by integral drift leads to a loss of accuracy in INSs. Also, GPS's position accuracy depends on the number of available satellites, and this dependability is a major drawback of GPS [10].

C. Environment Uncertainty: Challenges and Implications

Autonomous drone navigation is very effective when the environment is unknown, GPS or radio signals are not available, and there are no 3D models available to plot a course in advance. LiDAR, sonar, Inertial Measurement Units (IMUs), and cameras are some of the sensors used in traditional navigation techniques. These sensors make drones heavier and more expensive. Using visual data from a monocular camera in a simulator, authors in [11] investigated autonomous drone navigation from point A to point B. An occupancy grid map of the surrounding region was prepared using a depth image estimate model. The best routes to end goals were also identified while avoiding obstacles using a path-planning algorithm. The simulations were run using AirSim in Unreal Engine. To evaluate and compare vision-based autonomous UAV navigation techniques, the present study reviewed an open-source framework for three distinct scenarios with ranging complexity. Authors in [11] used fine-tuned models based on synthetic RGB and depth image data for each environment, resulting in a significant improvement in depth estimation accuracy, with Mean Absolute Percentage Error (MAPE) reductions from 120.45% to 33.41% in AirSimNH, from 70.09% to 8.04% in Blocks, and from 121.94% to 32.86% in MSBuild 2018. The autonomous UAV navigation framework used depth images directly from AirSim to achieve 38.89%, 87.78%, and 13.33% success rates in the AirSimNH, Blocks, and MSBuild2018 environments, respectively. The method with pre-trained depth estimation models fails to reach any of the scenarios' endpoints. The fine-tuned depth estimation models improved performance, boosting the number of goals completed by 3.33% for AirSimNH and 72.22% for Blocks. These findings show the advantages of tailoring vision-based models to specific surroundings, increasing UAV autonomy in visually assisted navigation tasks.

According to [12], state estimation is an effective strategy for increasing the UAV's sensing accuracy. It enables a real-time estimation of the flight control system's operational state and helps identify any anomalies or malfunctions. This allows proper actions to be taken to lessen their impact and prevent major flight failures. Two types of approaches are used for state evaluation: deterministic observer-based approaches and stochastic filter-based approaches, both of which use a similar framework to develop state estimation models [13]. In contrast to the former, stochastic filter-based techniques consider the uncertainties inherent in the system model and measurement data, making them more effective for data-based applications.

Kalman filter methods are stochastic filter-based estimation techniques, capable of using both the physical mechanism and the flight control system's measurement data [14]. The information obtained from the two different features is merged to produce precise estimation of the states, thus making the estimation more reliable. UKF is extensively explored due to its excellent computing efficiency and capacity to handle nonlinear characteristics [15]. It retains accuracy with minimal computing cost by estimating the states by unscented transformation, which eliminates the need for linearization of the nonlinear system. However, when used with UAVs, UKF still has some drawbacks, which are typical of most filter-based methods. These drawbacks include the cost, difficulty in obtaining a precise physical model for UAV, and difficulty in updating the noise parameter for the system statistical model in dynamic situations.

Various data-driven and adaptive estimating techniques have been proposed to address the aforementioned drawbacks to create a more precise system model and produce better filtering results [15]. Although these methods enabled enhancing estimation accuracy, the filtering framework does not adequately take into account and use the prediction probability of the data-based model to produce adaptive state space estimation results. Since it is typically challenging to quantify the prediction probability for system models, methods like GPR, which have an intrinsic probabilistic prediction property, have gained popularity. Furthermore, in order to improve fusion results, the strategy of using these probability values within a filtering framework must be considered, while the prediction model can estimate the probabilities of the system model. To create the adaptive fusion state-space estimation model, a particular mapping rule must be designed because the probability values are not linear to the prediction errors.

Authors in [16] demonstrated the effectiveness of the adaptive Unscented Kalman Filter (AUKF) method, which accounts for pointwise prediction accuracy of the system model. It was emphasized that AUKF simultaneously addresses the problems of state transition modeling and noise parameter adjustment. Multi-output GPR was initially used to obtain a model of a Multi-Input Multi-Output (MIMO) system. The Multi-output GPR, which is more appropriate for the UAV flight control system since the variables are primarily correlated, has a more satisfactory correlation extraction capability due to the inclusion of hidden layers in the traditional GPR technique. Since the UAV's flight modes are complex and its flight data contain a variety of features, the regression model is made sparse to meet the requirement of handling a vast amount of flight data. In contrast to earlier research, AUKF offers a unique method for improving flight control sensing, resulting in precise point-by-point estimation of the system model's prediction uncertainty.

The quick development of UAV technology has created new possibilities for a range of uses, such as environmental monitoring, communication, and surveillance. However, communication is a major problem for UAV systems, especially when they operate in dynamic and complicated situations.

D. Computer Vision: Solutions and Developments

Authors in [17] investigated vision-based UAV navigation techniques. Existing techniques have been categorized and thoroughly analyzed in terms of their capabilities and characteristics. Then, they are qualitatively compared in terms of several characteristics. Unresolved issues and research challenges in the design and implementation of vision-based navigation systems for UAVs were also explored.

When paired with other navigation techniques, like GPS/INS, visual navigation offers better guidance and location accuracy [18]. Authors in [18], based on the type of landing destination, categorized their research findings in the area of vision-based autonomous landing for UAVs into static, dynamic, and complicated scenarios. The dynamic scenario is separated into two categories: ship-based autonomous landing and vehicle-based autonomous landing; the static scenario has two categories: cooperating targets and natural landmarks. Development trends were highlighted, together with a summary, comparison, and analysis of the important technologies, which might serve as a guide for future research on vision-based autonomous UAV landing.

Cameras are mounted on UAVs for surveillance and offer a number of advantages over GNSS, including increased data rate and excellent accuracy [19]. Additionally, they can be used in urban areas, especially in areas where GNSS is prohibited. When used in conjunction with a video processing system, a camera can provide position and attitude (up to a scale factor); however, its data processing speed is slower than that of inertial sensors, and its measurements have latencies that can affect the flight control system's performance and efficacy. By combining inertial sensors and a camera, it is possible to take advantage of the superior qualities of both systems, leading to improved position and attitude estimate results.

Electronic interference presents a significant obstacle to UAV tracking systems, jeopardizing operational safety and navigation accuracy in important applications including infrastructure inspection, disaster response, and surveillance [20]. With an emphasis on fixed-reference settings, authors in [20] presented a novel use of the Auxiliary Particle Filter (APF) for reliable UAV tracking in interference-prone environments. To successfully reduce interference-induced measurement errors, the APF uses resilient weight updates and adaptive proposal distributions. With a mean Root Mean Square Error (RMSE) of 4.82 m and low variability ($\sigma = 0.30$ m), the APF exhibits exceptional accuracy through extensive simulation that assesses performance under various interference and sensor degradation scenarios. This performs noticeably better than conventional filters, such as the UKF and Extended Kalman Filter (EKF). APF continues to function steadily even in the case of extreme interference, whereas other methods exhibit significantly deteriorated performance. These gains are supported by statistical validation in every test scenario ($p < 0.001$). Adoption in a variety of operational scenarios is made possible by implementing the recommendations of [20]. Future research should concentrate on resolving the observed constraints and extending the framework to more intricate operational settings [20]. In [20], it is implied that APF might be used as a starting point for creating increasingly complex tracking systems for autonomous UAV operations in difficult conditions.

E. Adaptive Control

Authors in [21] employed the adaptive weighted average method in conjunction with data from three-Dimensional (3D) optical detection and ranging, IMUs, and a GPS. The merged velocity data were then smoothed using linear Kalman filtering. It was shown that the dynamics of UAVs are better adapted by using flight constraint formulas and high-order B-spline curves for route planning. With the greatest accuracy, real-time performance, robustness, and consistency of 94.2%, 100%, 93.7%, and 95.6%, respectively, the enhanced adaptive weighting algorithm demonstrated outstanding performance for multi-sensor data fusion. It was claimed that autonomous flight routes designed with high-order B-spline curves can also satisfy the requirements of UAV flying in complicated flight environments, and the fusion of multi-sensor data can be eased by the use of adaptive weighted fusion and linear Kalman filtering.

Authors in [5] studied adaptive control of UAVs with variable payload and complete parametric uncertainty. It was argued that a static control method becomes ineffective when payload changes because it brings time-varying parametric uncertainty into the dynamical model. Two adaptive techniques were created to address this problem and preserve the uncertainty in the rotational and translational dynamics. To stabilize the horizontal position, a virtual Proportional Derivative (PD) was created. However, an adaptive controller was proposed to produce the UAV's complete thrust because of an uncertain and time-varying mass. To manage parametric uncertainties, such as inertia and external disturbance factors, an adaptive controller was also created for the rotational dynamics. The assurance equivalency principle was used to expand and construct a standard adaptive scheme in both schemes. The performance of the proposed controllers was demonstrated through a stability analysis with rigorous analytical proofs, and simulations were used to evaluate the performance in comparison to other current techniques. Tracking fitness and total control efforts were computed and contrasted with Adaptive Sliding Mode Control (ASMC) and Closed-Loop Adaptive Tracking Control (CLATC). According to the findings, the proposed design improved UAV stability.

Authors in [22] stressed the importance of multi-sensor data fusion technology. Integrating data from several sensors increases not only the accuracy of environmental perception but also the system's overall robustness. Multi-sensor data fusion can provide more detailed, accurate, and reliable information for UAV autonomous flight control. Data fusion from numerous sensors can increase data accuracy and robustness while also increasing environmental awareness.

Authors in [23] presented multi-sensor fusion based on the UKF with Sequential Measurement Updates (SMU-UKF) for autonomous UAV navigation. A novel multi-sensor fusion filtering framework was presented and implemented in a low-cost strapdown inertial navigation system for UAVs. In the new framework of SMU-UKF, the navigation system integrates multiple sensor information sources from inexpensive sensor suites, including an IMU, a GPS, and a three-axis magnetometer. Specifically, sensor readings are simply fused, independent of sensor data size, update rates, and sensor counts.

By adding an update mechanism to the chosen filtering model, most current estimate techniques under the Kalman filtering framework adaptively adjust the system model's noise value. Two distinct adaptive state estimation techniques were proposed in [24]. By employing the MIT rule and a parallel filter, respectively, the proposed methods can recursively estimate the filter's noise parameters. Similarly, authors in [25] presented a master-slave UKF to solve the adaptive estimation problem. The master filter is a powerful tracking filter, and the slave filter uses the master filter's innovation to estimate its uncertainties. The Master-Slave Filter (MS-UKF) is an adaptive state estimation technique. The performance of the MS-UKF methods is constrained by the requirement of a recursive convergence procedure to attain the expected values for the noise parameters, and MS-UKF methods do not make use of the system model's inherent prediction probability.

Even though sensor data adaptive treatment for UAV path planning in time-varying media has advanced significantly, there are still several technical obstacles in real-world implementations. For example, current path planning techniques frequently exhibit inadequate adaptability to highly variable settings in real-time application scenarios, and the computing complexity of algorithms remains a significant barrier in large-scale or high-dimensional environments.

III. METHODOLOGY

The proposed methodology is based on an integrative review technique, because the integrative review focuses on a phenomenon of interest and gives the freedom for diverse research. It aims towards the analysis of both experimental and non-experimental research simultaneously to determine and reveal new concepts [26]. A systematic review typically focuses on a single issue in a specific context and uses a pre-established process to synthesize data from related studies, whereas an integrative review may incorporate a broad array of studies and provide an overall picture along with both interpretation and critique.

The Consensus platform, which simultaneously searches many databases via a single interface, was utilized to generate the sample of literature entries. Based on the study themes, general scientometric libraries' profiles, and appropriate resources, the following databases were selected: IEEE, MDPI, Springer, ScienceDirect, and ResearchGate. In this interface, the additional limitation "English language" was also set. Also, the following inquiries were set: 'time-varying UAV medium–sensor data'; 'adaptive fusion–UAV in time-varying environments'; 'UAV–Kalman filter–unstable environment'; and 'modelling–UAV sensor data adaptive treatment–time-varying medium'. Inclusion criteria also include a period from 2014 to 2025, a thorough review paper or empirical research, clearly formulated contribution of the paper.

A total of 113 resources were found as a result of the conducted search. After removing duplicate items, 74 entries were selected. The publication year, scope, scientific quality, and relevance to the subject were all evaluated during the screening process. This further selection procedure led to the selection of 31 literature sources for review. During the review, a secondary analysis was also conducted, based on sources mentioned in some of the publications. This allows for determining an additional 14 entries for review. Thus, the final sample included 45 studies.

IV. RESULTS AND DISCUSSION

Support systems carry out pertinent duties, such as obstacle avoidance, tracking, and detection (static or dynamic). A strong and effective navigation system is necessary for higher degrees of autonomy and flight stability [27]. Computer vision techniques can be applied to monocular cameras to improve navigation. Table I illustrates how navigation systems can be divided into primary subsystems: Pose estimation, which estimates the UAV's position and attitude using two-Dimensional (2D) and 3D representations; obstacle detection and avoidance, which identifies and relays the location of any obstacles it encounters; visual servoing, which controls and transmits maneuver commands to maintain the UAV's stability and trajectory during flight; and the position estimation subsystem.

TABLE I. SUBSYSTEMS OF UAV NAVIGATION SYSTEM

Subsystem	Explanation	Approach
Estimating the pose (localization)	Orientation and location estimation of the UAV in 2D and 3D	Simultaneous Localization And Mapping (SLAM) and visual odometry-based
Identifying and avoiding obstacles	Making the right choices to stay clear of collision zones and barriers	Monocular and stereo camera-based
Visual servoing	Maintaining stability and flying maneuvers by utilizing visual data	Visual image-based

Most autonomous UAV operations require proper flight circumstances with adequate vision (no rain, fog, or smoke), and autonomous UAVs usually rely on the use of GPS. However, the drone's capacity to localize itself is limited in some challenging locations due to partial or nonexistent GPS signals. Additionally, by reducing the UAV's visibility, optical obscurants impair its performance and behavior and complicate certain subsystems, like target identification. A framework for autonomous drone navigation and exploration in GPS-denied situations affected by visual obscurants has been developed and presented in many studies. The navigation and target detection problem is formulated as an autonomous Sequential Decision Problem (SDP) with uncertainty brought on by poor sight and the absence of GPS [29]. The Adaptive Belief Tree (ABT) algorithm is used to test the SDP, which is modeled as a Partially Observable Markov Decision Process (POMDP). A standard SAR operation in a congested interior environment with optical obscurants served as the model for the navigation. A vision-based camera's target detection under uncertainty was part of the framework. The formulated SDP was evaluated in a simulated environment with partial observability and smoke [29]. The framework used Gazebo, Robot Operating System (ROS), Software In The Loop (SITL), and PX4 firmware to simulate a SAR scenario. Trials in the simulated SAR situation examined the target, finding problems at various levels of sight, with the target position unknown and pose uncertainty modeled using real-world flying trials. The experiments in normal visibility were successful; however, the established framework was limited in the presence of visual obscurants, resulting in a lower detection rate. Allowing a UAV to navigate autonomously in an adverse environment with low visibility conditions intends to broaden the UAV's use in important applications, such as SAR and mining, where human participation is often risky and impractical.

There is a need to improve the GNSS positioning capability of low-cost FCS even in the densely populated Hong Kong central business district locations [28]. As a result, the reason for GNSS localization inaccuracy must be identified. GNSS satellites emit signals providing information about the satellite clock/orbit and transmit time. The signal travels through the atmosphere and is detected by the receiver on Earth. Finally, the position of the receiver can be inferred using the triangulation theory. In general, the triangulation is linearized by taking the first-order Taylor series and then using least squares to estimate the receiver position [28]. Several mistakes occur during the process, including ionosphere delay, troposphere delay, satellite orbit/clock error, receiver thermal noise, and multipath effects. The Differential GNSS (DGNSS) and Real-Time Kinematics (RTK) techniques work on the assumption that the majority of error causes can be distinguished between the GNSS reference station and the aircraft, enabling submeter or centimeter-level GNSS positioning accuracy. However, the GNSS signal experiences several localization errors in urban canyons due to signal obstructions, diffraction, and reflection by skyscrapers and other structures. Since the base station and the aerial rover do not share the same signal reflection, differential methods are unable to remove these effects. Currently, there is no uniform model or method to address the multipath effect and Non-Line-Of-Sight (NLOS) reception. Thus, GNSS localization remains a challenge in urban environments. The multipath and NLOS are the major sources of errors in GNSS positioning in megacities such as Hong Kong, Tokyo, and New York [28]. These sources can lead to 70 m error in GNSS positioning, as shown in Figure 1(a). Compared with the distances between buildings in an urban area, this level of positioning performance is hazardous for UAVs, as depicted in Figure 1(b). In Figure 1, the actual trajectory and position solution of a GNSS receiver integrated into a commercial FCS are shown by the yellow and blue lines, respectively [28].

Hardware redundancy for sensors is frequently used to improve the estimation accuracy of actual flying states. Meanwhile, intelligent state estimation techniques based on mathematical models appeared more effective, especially for small UAVs, because of the limitations of internal space and weight requirements for UAVs. Authors in [16] modeled a discrete-time flight control system for extremely nonlinear interaction between various flight variables, as defined in:

$$\{x_k = f(x_{k-1}, u_{k-1})\ y_k = h(x_k)\ \} \qquad (1)$$

where $F(\cdot)$ and $h(\cdot)$ denote the system and measurement function, respectively, u_{k-1} represents the actuators' control input vector, while x_k and y_k represent the flight state and measurement vectors, respectively. Kalman filter-based state estimation techniques are based on (1).

Because of their low correlation, the UAV flight control system is often separated into lateral and longitudinal subsystems for study. For simplification, the present study focuses on the longitudinal system's states, with observable state parameters presented in Table II [16].

TABLE II. STATUS OF LONGITUDINAL SUBSYSTEM: KEY PARAMETERS

Parameter	Symbol	Unit
Velocity, X-axis	u	m/s
Velocity, Z-axis	w	m/s
Pitch rate	q	rad/s
Pitch angle	θ	rad

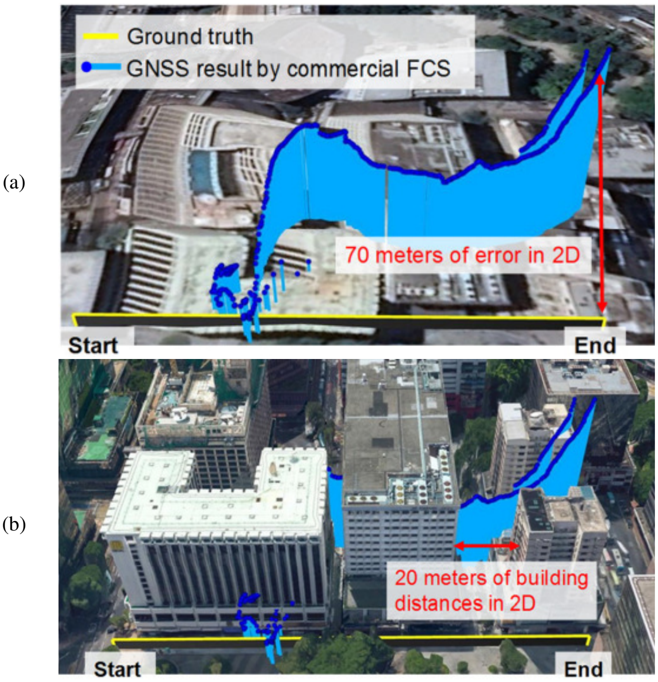

Fig. 1. (a) GNSS location errors in urban environments, and (b) error with and without the inclusion of a 3D building model.

UKF is suitable for filter-based approaches for performing flight state estimation of the UAV, as it is capable of handling the nonlinearity in flight data and is computationally inexpensive. This is important given the limited computation resources of the onboard computer for the UAV and the nonlinear model for the control system [30]. The UKF framework is used for the modeling and adaptive parameter adjustment to enhance performance. Both online measurement and historical data related to flight are used to create an accurate estimation model that can dynamically handle the uncertainties in the data to estimate the states of the adaptive flight control system under different operating conditions [30]. An adaptive fusion approach is applied for integrating online sensor data with prediction outputs from the sparse multi-output GPR model.

UKF solves a posterior distribution task without linearization by building $2n + 1$ distributed sigma points and projecting them via the system function, where n represents the dimension of the states [30]. State distribution information is used to construct the sigma points, further updated recursively depending on the measurement, the system function, and the uncertainties. Let us assume that the flight control system's state space model in stochastic form is:

$$\{x_k = f(x_{k-1}, u_{k-1}) + w_{k-1}\ y_k = h(x_k) + v_k\ \} \quad (2)$$

The sparse multi-output GPR approach can be employed to create a precise state space model intended for the flight control system. This method can handle the flight control system's complex flight data and simultaneously provide variance estimates in addition to the prediction results [31]. For simplicity, authors in [31] considered u_{k-1} as part of the input state variables in x_{k-1} in (2). It is further assumed that t_{k-1}^{p} is the training vector for the p^{th} state variable at the $(k-1)^{th}$ sample point, and x_k^p is the p^{th} output of the state transition function. x_k^p is presented as the convolution of a smoothing kernel $kp(t_{k-1}^p)$ with a set of latent functions $\{u_r(z^p)\}_{r=1}^R$, experiencing the impact of an independent process $wp(t_{k-1}^p)$ as:

$$x_k^p = \sum_{r=1}^R \int_{-\infty}^{\infty} k_{pr}\left(t_{k-1}^p - z^p\right) u_r(z^p) dz^p + w_p\left(t_{k-1}^p\right) \quad (3)$$

It is possible to obtain the complete Gaussian process model over all outputs by suggesting independence of the latent functions from Gaussian noise processes:

$$p(X|T,\phi) = N(0, K_f + \Sigma) \quad (4)$$

where $X = [x_1^T, \dots, x_p^T]^T$ represents the set of outputs with $x_p = [x_1^P, \dots, x_N^P]^T$, $1 \le p \le P$; P is the number of output variables, N is the number of output samples; $K_{f,f} \in \Re\text{PN} \times \text{PN}$ represents the covariance matrix for all sample points of all outputs, and Σ is a diagonal matrix representing the power of the noises. Let us assume that ϕ denotes the set of parameters for the covariance matrix, and $T = \{t_1 \dots\dots t_p\}$ is the set of input samples with $t_p = \left[t_0^p, \dots, t_{N-1}^p\right]$,$1 \le p \le P$. Thus, it is possible to calculate the probability distribution for new inputs T* as:

$$(X^*|X,T,T^*,\phi) = N\left((K_{f,f} + \Sigma)^{-1} X, K_{f^*,f^*} - K_{f^*,f}(K_{f,f} + \Sigma)^{-1} K_{f,f} + \Sigma\right. \quad (5)$$

Authors in [31] also emphasized that to describe enormous amounts of UAV data in dynamic situations, the multi-output GRP technique must be sparse in order to prevent dimensional disaster due to the UAV's high sampling rate. The input samples subset is chosen to reduce the dimension of the covariance matrix, and the latent functions become $u = [u_1^T, \dots, u_R^T]T$ with $ur = [ur(\mathbb{Z}_1), \dots\dots, ur(\mathbb{Z}_M)]T$, where M is the number of samples chosen from the original inputs; $K_{u,u}$ and $K_{f,u}$ share a similar definition as $K_{f*,f*}$; $\mathbb{Z} = \{\mathbb{Z}_1, \dots, \mathbb{Z}_M\}$ is the sparse set of input vectors used to calculate the covariance $K_{u,u}$. When the samples from the latent functions are assumed to be conditionally independent, their probability distribution is written as:

$$p(X|u,Z,T,\theta) = N(K_{f,u} K_{u,u}^{-1} u, C + \Sigma) \quad (6)$$

Sensor augmentation for the UAV's flight control system can be achieved by a data-driven adaptive fusion state space model. The estimating procedure can be realized with this method without the need for an online convergence process. To adjust the model adaptively to dynamic operating conditions, a piecewise function is predetermined.

The relevance of this study to the scope of lies in its focus on advancing adaptive sensing and data fusion methods that enhance the autonomy and precision of UAV operations in dynamic environments [32]. The proposed data-driven adaptive fusion state space model, based on GPR, addresses this critical challenge by improving prediction reliability and resource optimization. Similar to recent research in the journal, such as [33], which developed an efficient geometric transformation-based approach for multi-UAV image stitching. The present study contributes to the broader field of UAV technologies by providing innovative computational methods for enhancing autonomous performance and sensor data integrity in time-varying operational conditions.

Developments have made it possible to use reinforcement learning in uncertain conditions in the presence of noise, interference, drift, sensor zero offset, adverse environmental factors (wind, temperature fluctuations, magnetic disturbances), time delays, integration errors, etc. [34]. UAVs operate precisely in such uncertain conditions; therefore, accurate determination of their orientation angles is crucial for autonomous navigation to ensure reliable control of their movement. For this purpose, the Kalman filter is the most often used.

It should be noted that FC still needs improvement, as measurement sensor errors affect parameter evaluation results. In addition, UAV flight can be stable or accompanied by maneuvering; therefore, accelerometers record different apparent acceleration (total linear acceleration minus gravitational acceleration). When a UAV performs sharp maneuvers, the accelerometer not only measures linear acceleration, but also experiences the effects of other forces, such as centrifugal or Coriolis forces. If these data are used in a Kalman filter with a constant R matrix (measurement noise covariance matrix), the probability of incorrect orientation angle estimation increases. A constant R matrix does not take into account changes in measurement noise caused by the influence of additional factors, which leads to inaccuracy in determining the orientation angles of the UAV. To avoid this, the R matrix needs to be adapted, which is achieved using OP. To estimate the orientation angles of the UAV, input data from gyroscopes, accelerometers, and magnetometers are required, which are then processed in the Kalman filter to obtain orientation parameters in the form of Euler angles or quaternions.

When using a system model, the Kalman filtering procedure consists of two stages: the first stage involves a priori prediction (or state vector prediction), and the second stage involves its correction (update) using the measurement model. The Generalized Kalman Filter (GKF) takes into account the linearized system model and the measurement model relative to the estimated state vector. The measurement noise covariance matrix (denoted as R and subject to adaptation) and the state matrix or process noise covariance matrix (denoted as Q_f) are used in both stages of GKF [35]. As a rule, when calculating orientation angles using the Kalman filter method, the R and Q_f matrices are assumed to be constant, which is only true in steady flight mode, which cannot be guaranteed in real-time due to the presence of noise, interference, measurement errors, etc. The covariance of measurement noise is influenced by time period, location, and maneuvering. Thus, even if the true covariance matrix is known, sometimes (for example, during maneuvering) it is useful not to include measurements in Kalman calculations, since in these cases the measurement model is invalid. The proposed methods for adapting sensor noise covariance matrices at the measurement stage involve the use of reinforcement learning based on Q-learning. This allows the value of the *R* matrix, which changes dynamically during flight, to be found at any given moment in time.

Authors in [36] proposed a method based on Q-learning for the automatic tuning of the covariance matrix of measurement noise and disturbances. A reinforcement learning mechanism was formed that controls a predefined set of possible noise covariance matrices in such a way that it can include a pair of matrices with the smallest difference between the output and predicted measurement values. The effectiveness of Q-training is confirmed by real flight data obtained from UAVs and processed employing the Monte Carlo method, which is used to estimate orientation angles using GKF.

In [37], the orientation angles were calculated using an integrated algorithm, Left-Invariant EKF (LI-EKF) combined with an adaptive noise covariance estimation algorithm. The latter is an iterative expectation maximization algorithm for adapting time-varying noise parameters. In [38], a fuzzy inference system was considered to adapt the noise covariance matrix of measurements in a Kalman filter using accelerometers and gyroscopes. The developed method proved to be better than conventional FC. For the same purpose, a fuzzy inference system was also applied in [39], with measurements from gyroscopes, accelerometers, and magnetometers serving as input data. The orientation angles of the picosatellite were calculated using a UKF, which leads to a reduction in accuracy and divergence over time in the case of systemic uncertainty or incorrect measurements. In this regard, authors in [40] developed a fault-tolerant algorithm to estimate orientation angles based on a robust adaptive UKF capable of correcting the covariance of the generating noise (Q-adaptation) or measurement noise (R-adaptation), depending on the type of malfunction. The new adaptation scheme developed for traditional UKF allows the fault to be detected and isolated, after which mandatory adaptation is performed according to the type of defect.

An approach combining Q-learning and GKF has been proposed for more accurate determination of UAV orientation angles using IMU data in the absence of GPS signals. GKF alone is sufficient to solve this problem, but Q-learning reduces the error in angle estimation and provides dynamic adaptation of the measurement covariance matrix *R* to external conditions. It is assumed that the new method can significantly improve the accuracy of orientation parameter determination compared to traditional GKF-based approaches, the effectiveness of which is evaluated by standard indicators, such as the mean error or RMSE [41].

In addition, autonomous navigation algorithms that enable the analysis of the external environment and rapid adjustment of flight trajectories, taking into account potential threats, have been examined [42]. The possibilities of applying machine vision, neural network algorithms, data preprocessing methods, object detection, semantic segmentation, trajectory planning algorithms, predictive control, and adaptive route optimization for identifying obstacles, moving objects, and flight restriction zones have been evaluated. The role of intelligent control systems in UAV architecture and their impact on improving autonomy, stability, and task performance in dynamically changing conditions have been analyzed [43]. The proposed solutions are aimed at reducing the risks associated with abnormal situations through the implementation of adaptive flight management strategies.

Multi-agent control and swarm intelligence enable decentralized coordination that adapts to user density, obstructions, and mission priorities, thereby improving resilience and scalability during dynamic incidents [44]. Reported methods optimize topology, routing, and resource allocation in real time. To reach operational maturity, these approaches should expose stability margins, convergence behavior, compute energy budgets on representative avionics, and include fallback policies when sensing is degraded.

Ongoing technological deficiencies as well as a number of interesting options that could significantly improve sensor data adaptive treatment in a time-varying UAV medium have been revealed. Despite evident advances, current literature actually lacks comprehensive analyses integrating network architectures. Consequently, there is a lack of rigorous, methodologically structured reviews addressing tested practical solutions in this field. Furthermore, cross-sectional investigations connecting optimization parameters to performance measures are lacking.

Additionally, there are still research gaps in the areas of application-layer protocol representation, performance parameter standardization, heterogeneous communication technology integration, and the creation of experimental testbeds to verify practical applicability.

V. CONCLUSION

Obstacle avoidance, dynamic course planning, and environmental recognition are major challenges for Unmanned Aerial Vehicles (UAVs) during complicated situations. Although autonomous flight technology is now advancing rapidly, there are still several drawbacks, especially in data processing and environmental adaptation. Multiple sensors are required to collect additional environmental data, as traditional single sensors are inadequate for effective flight control. The multi-sensor data fusion technology is important in this situation. To simultaneously address the challenge of state transition modeling and noise parameter tuning, this study confirms the effectiveness of the adaptive unscented Kalman Filter (UKF) approach, which considers the pointwise prediction accuracy of the system model.

Further studies, aimed at finding more effective ways to estimate real-time channel parameters, such as employing machine-learning-based strategies, are one of the potential vectors for development. By lowering the computational load associated with continuously monitoring the channel state, these methods can increase the system's scalability and adaptability to various operating environments. With the addition of more sophisticated models that capture interactions between these components, it becomes possible to relax the assumption of separate Line-of-Sight (LoS) and Non-Line-Of-Sight (NLOS) components. This would provide a more accurate picture of the communication medium, particularly in places with high multipath interference, like urban canyons. Future studies should focus on creating algorithms that are both lightweight and operate effectively with the constrained processing capabilities of UAVs. To further improve the parameters of the system's resilience in noisy or dynamic situations, hybrid systems that incorporate several estimating techniques, such as Kalman filtering or deep learning methods, could be studied. Finally, to evaluate the practical efficacy of the proposed method, experimental validation under various UAV operating situations will be essential. In-depth field testing should be part of future research to assess performance in a range of environmental conditions, such as indoor or urban settings with difficult multipath propagation and interference.

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