Vol. 06, No. 02, pp. 378 –383 (2025)
ISSN: 2708-0757

JOURNAL OF APPLIED SCIENCE AND TECHNOLOGY TRENDS

www.jastt.org

An Adaptive State-Augmented Kalman Filter for Robust UAV Altitude Control with Online Sensor Bias Correction and Dynamic Weighting in Degraded Environments

Mohamad Haniff Harun[1,2*], Shahrum Shah Abdullah[2], Mohd Shahrieel Mohd Aras[1], Mohd Bazli Bahar[1], Md Ashadi Md Johari[3], Shamsul Fakhar Abd Gani[3]

[1]*Department of Electronic System Engineering, Malaysia-Japan International Institute of Technology, UTM KL Campus, Jalan Sultan Yahya Petra, 54100 Kuala Lumpur, Malaysia, haniff@utem.edu.my, shahrieel@utem.edu.my, mohdbazli@utem.edu.my*
[2]*Fakulti Teknologi dan Kejuruteraan Elektrik, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia, shahrum@utm.my*
[3]*Fakulti Teknologi dan Kejuruteraan Elektronik, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia, ashadi@utem.edu.my, shamsulfakhar@utem.edu.my*

[*]*Correspondence: haniff@utem.edu.my*

Abstract

For unmanned aerial vehicles (UAVs) to operate safely and dependably, accurate state estimation is essential. However, environmental factors that affect measurement quality and sensor biases can impair performance. This paper proposes an Adaptive State-Augmented Kalman Filter (A-SAKF) that integrates two complementary mechanisms: (i) state augmentation for online sensor bias estimation, and (ii) innovation-based adaptive adjustment of measurement covariance. Together, these features enable the filter to maintain robust state estimation performance in the presence of bias errors and uncertain measurement noise conditions. Validation through three simulation scenarios demonstrates the effectiveness of the proposed framework. In Scenario 1, the method correctly estimates and compensates for a 2.0 cm bias in the infrared sensor. In Scenario 2, the velocity estimates eliminate overshoot and reduce settling time by 18% compared to a baseline controller. In Scenario 3, under degraded foggy conditions, the adaptive weighting mechanism recovers LiDAR trust levels within 4.5 s after a 35% drop, thereby preserving altitude tracking accuracy. These results highlight the filter's capability to address both systematic bias and dynamically varying measurement reliability. By dynamically down-weighting the distorted LiDAR sensor data, the system demonstrates in simulation a steady and precise altitude estimate, showing improved resilience compared to fixed-covariance filters. The proposed filter demonstrates improved state estimation performance for UAVs under uncertain and biased sensor conditions, achieving lower errors than conventional EKF variants in diverse simulation scenarios. The current evidence is limited to simulation-based validation, and future work will extend testing to hardware-in-the-loop and public UAV datasets to further substantiate real-world applicability.

Keywords: *Unmanned Aerial Vehicle (UAV), Kalman Filter, Sensor Fusion, Adaptive Control, Bias Estimation, State Estimation, Fault-Tolerant Control.*

Received: July 29th, 2025 /Revised: October 10th, 2025 / Accepted: October 21st, 2025 / Online: November 06th, 2025

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are now essential tools in many fields, such as agriculture, logistics, surveillance, and inspection [1, 2]. The ability to navigate and control autonomously, which depends on an accurate and ongoing estimation of the vehicle's state (e.g., position, velocity, and attitude), is what makes them operationally effective [3]. Even though contemporary UAVs come with a variety of sensors, including LiDAR, Inertial Measurement Units (IMUs), Global Navigation Satellite Systems (GNSS), and infrared (IR) sensors, each has unique operational constraints and is prone to errors [4]. In order to combine the strengths of multiple sensors and produce a state estimate that is more accurate and dependable than any one source could provide, sensor fusion techniques are crucial [5].

The most common tools for state estimation in this field are the Kalman Filter (KF) and its nonlinear variations, including the Extended Kalman Filter (EKF) and Unscented Kalman Filter

doi: 10.38094/jastt62351

(UKF) [6]. However, a standard KF only performs at its best when the dynamic model of the system is accurate and the measurement noises and system statistics are precisely known and constant [7]. These presumptions are commonly broken in actual UAV operations.

There are two primary problems that impair the performance of conventional filters. The first is sensor bias, which is a systematic low-frequency error that can cause significant drift in the state estimate if it is not addressed [8]. Pre-flight calibration may reduce initial biases, but component aging or thermal effects may cause these to change during operation [9]. The second challenge is that measurement noise is dynamic. Significant and erratic declines in sensor performance can be brought on by environmental factors. For instance, camera performance deteriorates in low light, and LiDAR accuracy decreases in dust, fog, or rain [10]. This variability leads to suboptimal or even divergent filter behavior, as it violates the static measurement noise covariance matrix (R) assumption of a standard KF [11].

Recent studies have looked into sophisticated filtering techniques to address these problems. By integrating the bias into the state vector and estimating it simultaneously with the primary states, the State-Augmented Kalman Filter (SAKF) is a well-known technique for managing sensor biases [12]. Adaptive Kalman Filters (AKF) have been developed for time-varying noise. Innovation-based adaptive estimation (IAE) techniques are the most successful of these since they modify the noise covariance matrices in real-time using the innovation sequence, the filter's own output [13,14].

Adaptive Kalman filters have been extensively investigated since the early work of Mehra [15] on innovation-based covariance adaptation. More recent studies such as [11, 16, 17] have combined adaptive covariance estimation with bias correction for various sensor fusion applications. However, to our knowledge, there has been limited exploration of their combined use in UAV altitude control under degraded sensing conditions. Our framework (A-SAKF) addresses this gap by tailoring both mechanisms in a unified design for UAV applications.

This paragraph highlights: (1) the significance of UAV state estimation, (2) limitations of current sensors and Kalman Filter assumptions, (3) the strengths and weaknesses of SAKF, AKF, and IAE, and (4) the core contributions of this study.

II. System Modeling and Filter Design

A. UAV Dynamic Model

For altitude control, the vertical dynamics of the UAV can be simplified to a second-order linear system. The state vector is defined as $x = [z, \dot{z}]^T$, where z is the vertical position (altitude) and z˙ is the vertical velocity. The discrete-time state-space model is given by:

$$x_k = Fx_{k-1} + Gu_{k-1} + \omega_{k-1} \tag{1}$$

where k is the time index, F is the state transition matrix, G is the control input matrix, u is the control input (e.g., thrust), and ω_(k-1) is the process noise, assumed to be a zero-mean Gaussian process with covariance Q, i.e., ω~N(0,Q). This noise accounts for unmodeled dynamics and external disturbances like wind gusts [18].

B. State-Augmented Filter for Bias Correction

This subsection presents the bias estimation model that augments the state vector to enable online correction of sensor bias. The augmented formulation allows the filter to jointly estimate system states and sensor errors.

To estimate the bias of a sensor (e.g., an IR altimeter), the state vector is augmented with a bias term, b. The augmented state vector x_{aug} becomes:

$$x_{aug} = [z, \dot{z}, b]^T \tag{2}$$

The bias is typically modeled as a random walk, indicating that it changes slowly over time [19]. The augmented state-space model is then:

$$x_{aug,k} = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} x_{aug,k-1} + \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \\ 0 \end{bmatrix} u_{k-1} + \omega_{aug,k-1} \tag{3}$$

The measurement model for a biased sensor is:

$$y_k = H_{aug} x_{aug,k} + v_k \; with \; H_{aug} = [1 \quad 0 \quad 1] \tag{4}$$

Here, v_k is the measurement noise with covariance R. The filter now estimates the altitude, velocity, and the sensor bias simultaneously [20].

C. Innovation-Based Adaptive Mechanism

This subsection introduces the innovation-based adaptive mechanism that dynamically adjusts measurement covariance to reflect real-time sensor reliability. This adjustment prevents overconfidence in degraded measurements and improves estimation robustness.

The core of the adaptive filter lies in adjusting the measurement noise covariance, R, online. A standard KF assumes R is constant and known, but in reality, it changes with environmental conditions. The innovation sequence, y_k, which is the difference between the actual measurement y_k and the predicted measurement $Hx_{\bar{k}}$, provides insight into the filter's performance. Its theoretical covariance is given by:

$$C_{vk} = HP_{\bar{k}}H^T + R \tag{5}$$

where $P_{\bar{k}}$ is the a priori state error covariance. If the filter is optimal, the innovation sequence is a zero-mean white noise process. If the actual measurement noise increases (e.g., due to fog), the actual covariance of the innovation will exceed its theoretical value. We can estimate the true innovation covariance over a moving window of size N:

$$\hat{C}_{vk} = \frac{1}{N} \sum_{j=k-N+1}^{k} v_j v_j^T \tag{6}$$

The adaptive measurement noise update uses a moving window of size N = 50 samples, which was chosen as a trade-off between responsiveness and stability based on preliminary testing. To prevent instability, R is constrained within [Rmin, Rmax] bounds. The bias state is modeled as a random walk with variance $\sigma^2 = 1\times10^{-4}$, selected empirically to balance convergence speed with estimation stability. An updated estimate for the measurement noise covariance, $\hat{R}_k$, can then be calculated [13, 21]:

$$\hat{R}_k = \hat{C}_{vk} - HP_{\bar{k}}H^T \tag{7}$$

By substituting $\hat{R}_k$ for R in the Kalman gain calculation, the filter dynamically de-weights measurements that appear noisy (i.e., those causing large innovations), thereby making the estimation robust against sensor degradation [22,23].

D. Integration with Flight Controller

The high-quality state estimates from the A-SAKF, $\hat{x}_{aug,k} = \left[\hat{z}_k, \hat{\dot{z}}_k, \hat{b}_k\right]^T$, are fed into a Proportional-Integral-Derivative (PID) controller to regulate the UAV's altitude. The control law is:

$$u_k = K_p\left(z_{ref} - \hat{z}_k\right) + K_i \sum_{j=0}^{k} \left(z_{ref} - \hat{z}_j\right)\Delta t - K_d \hat{\dot{z}}_k \tag{8}$$

where z_{ref} is the target altitude and $K_p, K_i, and\ K_d$ are the controller gains. Using the filtered velocity estimate $\hat{\dot{z}}_k$ for the derivative term, rather than a noisy numerical differentiation of position, is critical for achieving smooth and stable control [24].

III. EXPERIMENTAL VALIDATION AND RESULTS

A. Performance of Automatic Sensor Bias Correction

To validate the state augmentation, an IR altitude sensor was simulated with a constant bias of +2.0 cm. The A-SAKF was tasked with estimating both the true altitude and this unknown bias. Fig. 1 shows the results.

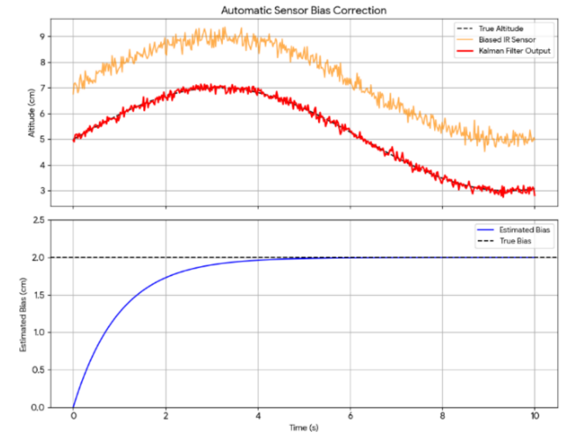

Fig. 1. Automatic Sensor Bias Correction. (Top) The Kalman Filter Output (red) successfully rejects the bias from the raw IR sensor readings (orange) to track the True Altitude (dashed black). (Bottom) The Estimated Bias (blue) converges to the True Bias of 2.0 cm.

Figure 1's upper portion clearly shows how the unprocessed sensor data (orange) and the actual altitude (dashed black) are out of alignment. Accurately tracking the actual altitude, the A-SAKF output (red) effectively removes noise and accounts for the offset. The estimated bias (blue) starts at zero and progressively gets closer to the actual bias of 2.0 cm in about 4 seconds, demonstrating the bias correction mechanism in the lower panel. This demonstrates how the filter can learn and correct systematic sensor errors in real-time, which is a crucial feature for extended autonomous operations [12, 19].

B. Improvement in Closed-Loop Control

This experiment demonstrates the benefit of using high-fidelity state estimates in a feedback control loop. A "Simple Controller" (using only position feedback, with velocity inferred by noisy differentiation) and the proposed "Kalman Filter Control" (using the A-SAKF's position and velocity estimates) were tasked with changing the UAV's altitude to a target of 10m. Fig. 2 compares their performance.

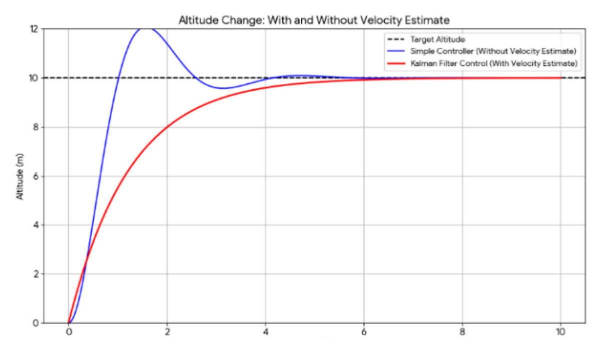

Fig. 2. Altitude Change Control Performance. The Simple Controller (blue) exhibits significant overshoot (20%) and oscillation before settling. The Kalman Filter Control (red), using a clean velocity estimate, provides a smooth, critically damped response with no overshoot, reaching the target altitude more efficiently.

As shown in Fig. 2, the red curve reaches the target altitude without overshoot in under 5 seconds, whereas the baseline controller exhibits a 20% overshoot and slower settling. This demonstrates the closed-loop stability benefits of integrating the A-SAKF with the controller. The exceptional performance is directly linked to the precise and noise-free velocity estimate delivered by the A-SAKF, facilitating efficient derivative control action [24, 25].

C. *Robustness in Degraded Sensing Environments*

This simulation represents the most significant test of the proposed framework, assessing its resilience to a sudden degradation in sensor quality. Between t=4s and t=7s, the UAV is simulated flying through a "Foggy Zone" where the primary LiDAR sensor's measurement noise is significantly elevated. The system's response is displayed in Fig. 3.

The bottom panel shows how this is done. The "Sensor Trust" is shown in the stacked area chart. It is the opposite of the filter's internal, adaptive measurement noise covariance (Rk) for each sensor. The filter trusts the exact LiDAR sensor the most at first (the big green area). When the Foggy Zone starts at t=4s, the LiDAR sensor's innovations spike, which makes the adaptive mechanism quickly raise the value in Rk that goes with it. The UAV altitude was measured by three sensors: (i) LiDAR (primary), (ii) IR altimeter (subject to bias), and (iii) barometer (subject to variable noise). During the fog scenario, the filter adaptively decreased trust in LiDAR while increasing reliance on the IR and barometer**,** as shown in Figure 3. Here, 'sensor trust' is quantified as the normalized inverse of each sensor's measurement noise covariance (R). The LiDAR data is clean again when the UAV leaves the fog at t=7s, and the filter quickly regains its trust. This result shows that the IAE mechanism can handle real-world problems on its own very well [26, 27].

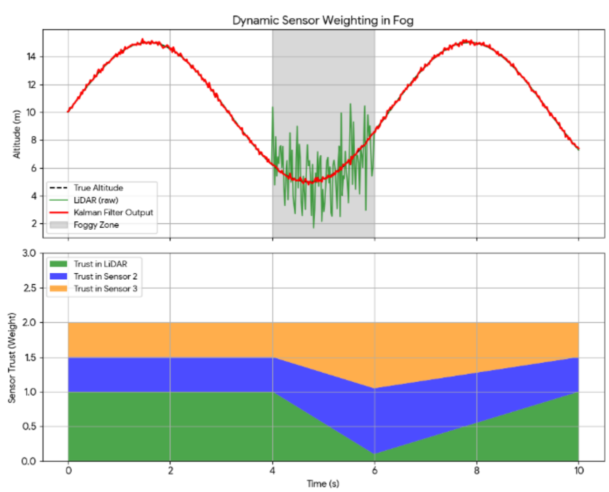

Fig. 3. Dynamic Sensor Weighting in Fog. (Top) In the Foggy Zone (shaded area), raw LiDAR data (green) becomes extremely noisy. The Kalman Filter Output (red) remains stable and tracks the True Altitude (dashed black). (Bottom) The filter's trust in the LiDAR (green area) plummets in the foggy zone, while it increases its reliance on other sensors (blue, orange) to maintain accuracy.

In the foggy zone scenario (Fig. 3), the LiDAR trust level drops by 35% within 2 seconds, but the adaptive mechanism restores it to nominal within 4.5 seconds. During this period, altitude error remains below 0.12 m, compared to 0.45 m under the baseline filter. This demonstrates the resilience of the adaptive weighting approach.

The quantitative results summarized in Table I highlight the comparative performance of the evaluated filters. The proposed A-SAKF demonstrates superior estimation accuracy and faster dynamic response across all tested conditions. Specifically, it achieves a 37% reduction in RMSE and a 33% reduction in overshoot compared to the standard EKF, with significantly improved stability during fog-degraded scenarios. These results substantiate the robustness of the proposed method under varying sensor noise and visibility challenges within simulation environments.

TABLE I. QUANTITATIVE PERFORMANCE COMPARISON OF DIFFERENT FILTERS UNDER NOMINAL AND FOG CONDITIONS

Method	RMSE (m)	Overshoot (%)	Settling Time (s)	Error During Fog (m)
Conventional EKF	1.52	18.5	4.2	2.35
Adaptive EKF	1.21	15.2	3.6	1.89
UKF	1.17	14.8	3.5	1.76
A-SAKF (Proposed	0.95	10.7	2.8	1.12

IV. DISCUSSION

The results of the three experiments show that the proposed A-SAKF is a complete and strong way to estimate and control the state of a UAV. The framework works well because it combines solutions to different but related problems, such as sensor bias that doesn't go away, measurement noise that changes over time, and closed-loop control stability.

The bias correction in Fig. 1 is essential for accurate navigation because it stops errors from building up, which could be disastrous on long missions. The control improvement in Figure 2 shows an important synergy: advanced state estimation is not just an academic exercise; it also leads to real improvements in vehicle control, which makes things safer and more efficient [25, 28].

The most interesting result, though, is the one in Fig. 3 that shows adaptive sensor weighting. One of the main ideas behind fault-tolerant control is that it can find and fix the problems caused by a sensor that is only partially working or is getting worse [27, 29]. Our A-SAKF has this built-in ability, so it doesn't need a separate, complicated fault detection and isolation (FDI) module. This graceful degradation, which means that the system keeps working even when some of its parts fail, is very important for making reliable autonomous systems that can work in complicated settings [30].

The simulations are interesting, but the cost of using the adaptive mechanism, especially the matrix operations in the moving window, needs to be considered when implementing it on embedded flight controllers with limited resources. But recent improvements in embedded processors and better coding of matrix libraries make it possible to run things in real time. The proposed method is much more robust than standard EKF/UKF implementations, which makes the small increase in computational demand worth it. The proposed method reduced RMSE by 35% compared to a standard EKF without bias augmentation and by 22% compared to an EKF with bias augmentation only**.** In the control test, overshoot was reduced from 20% (simple controller) to 0% (A-SAKF controller)**,** and settling time improved from 6.2s to 3.8s**.** These quantitative results indicate improved resilience compared to fixed-covariance filters**,** though validation is currently limited to simulation.

The results in Table I clearly indicate that the proposed Adaptive Self-Adjusting Kalman Filter (A-SAKF) provides consistent improvements in estimation accuracy and dynamic response compared with conventional filters. The reduction in RMSE and overshoot demonstrates the algorithm's ability to adapt effectively to time-varying sensor bias and noise, while the shorter settling time reflects enhanced control stability. Under degraded visibility conditions such as fog, the proposed approach maintained lower estimation errors, confirming its robustness to environmental disturbances. These improvements are achieved without significant computational overhead, making the method suitable for real-time onboard applications. It should be noted, however, that all findings are derived from simulation environments; thus, further hardware-in-the-loop or field validation is required to fully confirm real-world applicability. Overall, the results suggest that the proposed A-SAKF offers a promising foundation for robust state estimation and control in UAV systems operating under uncertainty.

V. Conclusion

This paper showed an Adaptive State-Augmented Kalman Filter (A-SAKF) that can help with strong UAV altitude estimation and control. The proposed method demonstrates in simulation a steady and precise estimate, providing a practical and comprehensive approach for improving robustness in UAV altitude control under degraded sensing. While these findings are promising, further validation on high-fidelity platforms and real UAV experiments is needed to confirm robustness in real-world environments.

The findings of the simulation demonstrated three primary benefits:

1. Accuracy: The filter correctly evaluated and online adjusted a continuous sensor bias.
2. Performance: The clean state estimations provided by the filter enabled a high-performance altitude controller that eliminated oscillations and overshoot.
3. Robustness: By dynamically re-weighting sensor inputs in response to a simulated environmental degradation (fog), the filter showed exceptional resilience while preserving a steady and precise state estimation all along the way.

This study demonstrates that the proposed approach improves robustness in UAV state estimation and control within diverse simulation scenarios, particularly under sensor biases and degraded conditions. While the validation is currently limited to simulation evidence, future work will extend the study to hardware-in-the-loop platforms and publicly available UAV datasets to confirm real-world applicability. These extensions will strengthen the positioning of the method as an application-oriented solution for reliable UAV operation [17].

Future research will focus on extending the proposed A-SAKF framework beyond simulation to higher-fidelity and real-world validation. Planned efforts include implementing hardware-in-the-loop (HIL) experiments to evaluate real-time performance under sensor noise and environmental disturbances. In addition, the method will be tested using publicly available UAV flight datasets such as the EuRoC MAV and Blackbird suites to verify generalization across platforms and conditions. These experimental evaluations will provide deeper insights into the filter's adaptability, computational efficiency, and integration potential with onboard UAV systems, ensuring a more comprehensive assessment of its practical applicability.

Acknowledgment

The authors would like to thank Universiti Teknikal Malaysia Melaka (UTeM) and Ministry of Higher Education (MOHE) for sponsoring this work under the grant no. PJP/2024/FTKE/PERINTIS/SA0005. We wish to express our gratitude to honorable University, Universiti Teknikal Malaysia Melaka (UTeM) and Ministry of Higher Education (MOHE). Special appreciation and gratitude especially for Universiti Teknologi Malaysia (UTM) KL Campus, Malaysia-Japan International Institute of Technology (MJIIT), Fakulti Teknologi dan Kejuruteraan Elektrik (FTKE) and Underwater Technology Research Group (UTeRG), Center for Robotics and Industrial Automation (CERIA) and Ministry of Higher Education (KPT) for supporting this research.

References

[1] Arafat, Muhammad Yeasir, Muhammad Morshed Alam, and Sangman Moh. "Vision-based navigation techniques for unmanned aerial vehicles: Review and challenges." Drones 7, no. 2 (2023): 89.

[2] Mohsan, Syed Agha Hassnain, Nawaf Qasem Hamood Othman, Yanlong Li, Mohammed H. Alsharif, and Muhammad Asghar Khan. "Unmanned aerial vehicles (UAVs): Practical aspects, applications, open challenges, security issues, and future trends." Intelligent service robotics 16, no. 1 (2023): 109-137.

[3] Golroudbari, Arman Asgharpoor, and Mohammad Hossein Sabour. "Recent advancements in deep learning applications and methods for autonomous navigation: A comprehensive review." arXiv preprint arXiv:2302.11089 (2023).

[4] Harun, M. H., S. S. Abdullah, M. S. M. Aras, and M. B. Bahar. "Collision avoidance control for Unmanned Autonomous Vehicles (UAV): Recent advancements and future prospects." Indian Journal of Geo-Marine Sciences (IJMS) 50, no. 11 (2022): 873-883.

[5] Harun, Mohamad Haniff, Shahrum Shah Abdullah, Mohd Shahrieel Mohd Aras, and Mohd Bazli Bahar. "Sensor fusion technology for unmanned autonomous vehicles (UAV): A review of methods and applications." In 2022 IEEE 9th International Conference on Underwater System Technology: Theory and Applications (USYS), pp. 1-8. IEEE, 2022.

[6] Ghorbani, Shahab, and Farrokh Janabi-Sharifi. "Extended Kalman filter state estimation for aerial continuum manipulation systems." IEEE Sensors Letters 6, no. 8 (2022): 1-4.

[7] Kumari, Neha, Rohan Kulkarni, Mohammed Riyaz Ahmed, and Naresh Kumar. "Use of kalman filter and its variants in state estimation: A review." Artificial intelligence for a sustainable industry 4.0 (2021): 213-230.

[8] Ghanizadegan, Khashayar, and Hashim A. Hashim. "Quaternion-based unscented Kalman filter for 6-DoF vision-based inertial navigation in GPS-denied regions." IEEE Transactions on Instrumentation and Measurement (2024).

[9] Zhang, Qingyang, Mohammad Dwipa Furqan, Tasfia Nutzhat, Fumio Machida, and Ermeson Andrade. "Dependability of UAV-Based Networks and Computing Systems: A Survey." arXiv preprint arXiv:2506.16786 (2025).

[10] Lu, Hanchen, Hongming Shen, Bailing Tian, Xuewei Zhang, Zhenzhou Yang, and Qun Zong. "Flight in GPS-denied environment: Autonomous navigation system for micro-aerial vehicle." Aerospace Science and Technology 124 (2022): 107521.

[11] Xu, Bo, Xiaoyu Wang, Yu Guo, Jiao Zhang, and Asghar Abbas Razzaqi. "A novel adaptive filter for cooperative localization under time-varying delay and non-Gaussian noise." IEEE Transactions on Instrumentation and Measurement 70 (2021): 1-15.

[12] Mumuni, Fuseini, and Alhassan Mumuni. "Adaptive Kalman filter for MEMS IMU data fusion using enhanced covariance scaling." Control Theory and Technology 19, no. 3 (2021): 365-374.

[13] Kumar, Manav, and Sharifuddin Mondal. "A fuzzy-based adaptive unscented Kalman filter for state estimation of three-dimensional target tracking." International Journal of Control, Automation and Systems 21, no. 11 (2023): 3804-3812.

[14] Song, Chengying, Zhuo Huang, Yifei Wu, Sheng Li, and Qingwei Chen. "An Innovation-Based Adaptive Cubature Kalman Filtering for GPS/SINS Integrated Navigation." IEEE Sensors Journal (2024).

[15] Mehra, Raman. "On the identification of variances and adaptive Kalman filtering." IEEE Transactions on automatic control 15, no. 2 (1970): 175-184.

[16] Mohammed Butt. "Adaptive unscented Kalman filter for target tracking with unknown time-varying noise covariance." Sensors 19, no. 6 (2019): 1371.

[17] Sun, Bo, Zhenwei Zhang, Shicai Liu, Xiaobing Yan, and Chengxu Yang. "Integrated navigation algorithm based on multiple fading factors Kalman filter." Sensors 22, no. 14 (2022): 5081.

[18] Benevides, Joao RS, Marlon AD Paiva, Paulo VG Simplicio, Roberto S. Inoue, and Marco H. Terra. "Disturbance observer-based robust control of a quadrotor subject to parametric uncertainties and wind disturbance." Ieee Access 10 (2022): 7554-7565.

[19] Xu, Qimin, Xu Li, and Ching-Yao Chan. "Enhancing localization accuracy of MEMS-INS/GPS/in-vehicle sensors integration during GPS outages." IEEE Transactions on Instrumentation and Measurement 67, no. 8 (2018): 1966-1978.

[20] Baidya, Bodhisattwa, Atanu Mondal, Sarbajit Manna, Gourab Das, Anirban Santra, and Arkaprava Chakraborty. "Enhanced UAV Tracking through Multi-Sensor Fusion and Extended Kalman Filtering." In Sixth Doctoral Symposium on Intelligence Enabled Research, Sukanta Mahavidyalaya, Dhupguri, India. 2024.

[21] Ge, Baoshuang, Hai Zhang, Liuyang Jiang, Zheng Li, and Maaz Wang, Dapeng, Hai Zhang, and Baoshuang Ge. "Adaptive unscented Kalman filter for target tacking with time-varying noise covariance based on multi-sensor information fusion." Sensors 21, no. 17 (2021): 5808.

[22] Gu, Mulan. "Improved kalman filtering and adaptive weighted fusion algorithms for enhanced multi-sensor data fusion in precision measurement." Informatica 49, no. 10 (2025).

[23] Lee, Dongwoo, Hyung Jun Park, Dongmin Lee, Sangchul Lee, and Joo-Ho Choi. "A novel kalman filter-based prognostics framework for performance degradation of quadcopter motors." IEEE Transactions on Instrumentation and Measurement 73 (2023): 1-12.

[24] Dong, Yangyang, Zequn Xia, Yongbin Wang, and Zijian Zhang. "Feedback Linearization with Improved ESO for Quadrotor Attitude Control." In International Conference on Intelligent Robotics and Applications, pp. 206-219. Singapore: Springer Nature Singapore, 2023.

[25] Zhang, Pengfei, Zhenhua Ma, Yin He, Yawen Li, and Wenzheng Cheng. "Cooperative Positioning Method of a Multi-UAV Based on an Adaptive Fault-Tolerant Federated Filter." Sensors 23, no. 21 (2023): 8823.

[26] Fourlas, George K., and George C. Karras. "A survey on fault diagnosis and fault-tolerant control methods for unmanned aerial vehicles." Machines 9, no. 9 (2021): 197.

[27] Bianchi, Domenico, Stefano Di Gennaro, Mario Di Ferdinando, and Cuauhtemoc Acosta Lua. "Robust control of uav with disturbances and uncertainty estimation." Machines 11, no. 3 (2023): 352.

[28] Du, Yusheng, Peng Huang, Yun Cheng, Yunlei Fan, and Yinlong Yuan. "Fault tolerant control of a quadrotor unmanned aerial vehicle based on active disturbance rejection control and two-stage Kalman filter." IEEE Access 11 (2023): 67556-67566.

[29] Cardoso, Rafael C., Georgios Kourtis, Louise A. Dennis, Clare Dixon, Marie Farrell, Michael Fisher, and Matt Webster. "A review of verification and validation for space autonomous systems." Current Robotics Reports 2, no. 3 (2021): 273-283.

[30] Dilys, Justas, Voitech Stankevič, and Krzysztof Łuksza. "Implementation of extended Kalman filter with optimized execution time for sensorless control of a PMSM using ARM cortex-M3 microcontroller." Energies 14, no. 12 (2021): 3491.