UAV Sensing Data Optimisation: Comparison and Application of Key Filtering Algorithms

Junhao Cai

SWJTU-Leeds Joint School, Southwest Jiaotong University, Chengdu, 610000, China
el22j2c@leeds.ac.uk

Abstract. With the wide application of UAV technology in several fields, the accuracy and reliability of the sensed data become critical. Therefore, this paper aims to explore the current status of the application of key filtering algorithms in the field of UAVs. This paper firstly introduces the development history of filtering algorithms, and then analyses in detail the basic principles, and mathematical models, as well as the advantages and disadvantages of various filtering algorithms. It is found that despite the theoretical advantages of Kalman filtering and its derivative algorithms, they still face many challenges in practical applications, such as nonlinear processing and computational complexity problems. Although particle filtering is able to deal with a wider range of nonlinear and non-Gaussian problems, its particle degradation and resampling problems are still difficult to study. The significance of this paper is to sort out these algorithms, as well as their advantages and disadvantages, and determine their applicability in application scenarios such as UAV navigation, localisation and target tracking, in order to enhance the performance and robustness of UAVs, reduce the impact of sensor noise and external interference, promote technological innovation, and facilitate the advancement of UAV technology.

Keywords: UAVs, Filtering Algorithms, Kalman Filtering, Nonlinear Systems, Data Fusion

1 Introduction

With the wide application of UAV technology in military reconnaissance, aerial photography, logistics and distribution, the accuracy and reliability of UAV sensing data has become particularly important. When a UAV performs a mission, the sensors it carries (e.g., accelerometers, gyroscopes, magnetometers, etc.) are affected by a variety of factors, including environmental noise, the drift and error of the sensors themselves, etc., which lead to errors in the sensor data, which in turn affects the positioning accuracy and flight control performance of the UAV. In order to improve the accuracy of UAV sensing data, researchers have proposed a variety of data filtering algorithms, to reduce noise interference and correct sensor errors, thereby enhancing the stability and mission execution capability of UAVs.

Among the many filtering algorithms, Kalman filtering (KF) and its derivatives have received much attention for their efficiency and accuracy in estimating the state of

J. Iqbal (ed.), *Proceedings of the 2025 2nd International Conference on Mechanics, Electronics Engineering and Automation (ICMEEA 2025)*, Advances in Engineering Research 272,
https://doi.org/10.2991/978-94-6463-821-9_19

dynamic systems. KF is a recursive filter capable of estimating the state of a dynamic system from a series of noise-laden measurements, and its core advantage lies in its ability to update the estimation of the system state in real time and minimise the estimation error [1-3]. As the technology has evolved, variants of KF, such as Extended Kalman Filtering (EKF), Untraceable Kalman Filtering (UKF), and Particle Filtering (PF), have also been proposed to cope with more complex nonlinear and non-Gaussian systems. These algorithms show great potential and value in UAV sensing data processing.

However, despite their theoretical advantages, these algorithms still face many challenges in practical applications. For example, EKF suffers from a large truncation error when dealing with strongly nonlinear systems [4,5], and although UKF reduces the linearisation error, it is computationally intensive and requires high processor performance [6,7]. Particle filtering, as a sequential Monte Carlo method based on Monte Carlo methods, is able to deal with a wider range of nonlinear and non-Gaussian problems, but its particle degradation and resampling problems are still difficult to study [8,9]. Therefore, how to design and optimise the filtering algorithms suitable for UAV sensing data and improve their performance and reliability in practical applications has become a hot research issue in the field of UAVs.

This thesis aims to explore the development of key filtering algorithms in the field of UAVs, including first-order hysteresis filtering, Kalman filtering, extended Kalman filtering, traceless Kalman filtering, and particle filtering, and to evaluate their performance in the processing of UAV sensing data. The aim of the research is to sort out these algorithms and compare their strengths and weaknesses, and to determine their applicability in application scenarios such as UAV navigation, localization and target tracking. The significance of this research is to enhance the performance and robustness of UAVs, to reduce the impact of sensor noise and external interference by selecting and optimising suitable filtering algorithms, as well as to promote technological innovations to advance UAV technology.

2 UAV Filtering Algorithm Development

The traditional first-order filter originated in the early 20th century, which is widely used in signal acquisition and processing systems for signal smoothing by simple weighted averaging of historical and current data. With the development of technology, more sophisticated filtering methods emerged. in 1960, Kalman proposed the Kalman filter, which is based on state-space and time-domain design with a recursive algorithm that significantly reduces the computational complexity and is widely used for signal estimation. However, the original Kalman filter was only applicable to linear systems, so researchers developed the EKF to deal with nonlinear problems, albeit with a higher computational pressure.The UKF is another method to deal with nonlinear problems, which does not require the computation of Jacobi matrices but rather captures the nature of the nonlinearities through a sampling technique, with higher estimation accuracy and robustness. The PF algorithm was introduced by Isard et al. and is applicable to strongly nonlinear non-Gaussian systems, but suffers from particle degradation and high computational effort when dealing with high manoeuvrability targets, leading to poor tracking results.

The evolution of filtering algorithms for UAV sensing data has progressed along with the development of filtering techniques. Initially, first-order lag filtering was applied to UAV data processing due to its simple and effective characteristics, providing basic support for UAVs in early navigation and positioning tasks. However, with the complexity of UAV application scenarios and the increase in accuracy requirements, the limitations of first-order lag filtering have gradually emerged. The emergence of Kalman filtering has revolutionised UAV sensing data processing. Through state space modeling and recursive algorithms, it can effectively deal with the noise problem of linear systems and significantly improve the navigation accuracy and stability of UAVs in complex environments. The introduction of this algorithm enables UAVs to better estimate their states when performing precision flight missions, providing reliable data support for subsequent flight control and decision-making.

With the advancement of UAV technology, the applications of filtering algorithms are also evolving, especially in the fields of visual target tracking, formation flying and attitude solving in complex environments. For example, in visual target tracking and localisation and navigation, the UKF and PF algorithms can estimate the target state more accurately and improve the tracking accuracy and robustness [6,9,10]; in formation flying, these algorithms can effectively deal with the cooperative control problem among multiple UAVs to ensure the stability and consistency of the flight formation; in UAV attitude solving, the KF and EKF algorithms can provide a more accurate estimate of the target state based on the provided In UAV attitude solving, the KF and EKF algorithms can effectively fuse and filter the data from the inertial navigation unit (IMU) according to the provided mathematical model of the system, providing relatively accurate attitude data for UAV attitude control; in UAV motor driving, the first-order hysteresis filtering algorithm can filter the signals such as the motor angle, rotational speed, and current based on the frequency-domain characteristics of the return signals from the motor encoder, so as to enhance the robustness of UAV motor control. With the continuous development of technology, the research on UAV filtering algorithms is also deepening, aiming to further improve the performance and robustness of UAVs in various environments and to meet the growing application needs.

3 Comparative Analysis of Agorithms

3.1 First-order hysteresis filter

When dealing with motor encoder data, the motor mathematical model is complex, with temperature, load and other nonlinear and dynamic factors, KF and its variants are difficult to meet the real-time requirements due to the need for an accurate model and noise characteristics to deal with highly nonlinear systems and the complexity of the calculations, which makes it difficult to be applied directly. First-order hysteresis filtering algorithm is simple and easy to implement, can eliminate the rapid noise and fluctuations of the motor encoder data, low latency, in line with the needs of the field, is widely used to provide accurate data support for motor control and analysis.

However, the first-order hysteresis filter is not perfect. Its filtering parameters cannot be adjusted adaptively after they are determined, and when the motor's operating state changes drastically, such as rapid acceleration and deceleration or abnormal load impacts, the filtering effect deteriorates due to the fixed parameters. It is a low-pass filter, suppressing high-frequency noise will attenuate the high-frequency component, and when dealing with encoder data containing important high-frequency information, it will weaken the key details, affecting the accurate judgment of the motor's operating state. Moreover, in the face of fast-changing and complex noise signals, its response speed is limited, and the error is large when the signal changes suddenly, which reduces the timeliness and accuracy of data processing and limits the application in complex motor control scenarios.

3.2 Kalman Filter

KF is commonly used for IMU data processing and UAV attitude solving [2,3,11]. Taking the electronic IMU as an example, when the operating temperature of the IMU is constant, the bias of its angular velocity is about a fixed value, and according to this fixed bias and the angular velocity data returned from the gyroscope, the linear system equation of the UAV Euler angle about the angular velocity and bias can be constructed, so as to provide more accurate data for the UAV attitude solving.

However, when the working environment of the IMU changes, especially when the temperature fluctuates greatly, the situation becomes complicated. The change of temperature will cause the parameters of IMU to drift, and the angular velocity bias is no longer a fixed value. At this time, the linear system equations originally constructed based on the constant bias are no longer applicable, and the UAV's attitude solving faces a large error. Moreover, the computation process involves matrix operations, which puts high demands on the limited computational resources of the UAV, and the real-time performance is difficult to guarantee, and the processor's arithmetic power is required to be high.

Compared with first-order hysteresis filtering, Kalman filtering demonstrates greater adaptability and accuracy when dealing with complex and changing system environments. It not only effectively suppresses noise, but also maintains high attitude resolution accuracy despite dynamic changes in the system model. This makes Kalman filtering an indispensable key technology in scenarios with demanding requirements for UAV attitude control accuracy, such as precision flight performance of UAVs, complex terrain mapping and other tasks. However, it cannot be ignored that Kalman filtering has a high demand for computational resources, which requires the UAV to be equipped with a processor with sufficiently strong performance to guarantee the efficient operation of the Kalman filtering algorithm, or else the real-time performance of the UAV's attitude solving may be affected due to the failure of the computational speed to keep up with the algorithm.

3.3 Extended Kalman Filter

EKF is widely used in UAV coordinate solving. In communication and navigation systems, the relative coordinates sent from base stations to UAVs are mostly spherical coordinates containing radial distance, elevation and azimuth. It is crucial to convert the spherical coordinates to spatial rectangular coordinates, but this conversion is nonlinear and involves trigonometric operations. In practice, the spherical coordinate data are interfered with by noise, assuming that the noise is Gaussian distribution in spherical coordinates, which will become non-Gaussian distribution after the nonlinear conversion, which makes the processing difficult, and it is difficult to cope with the traditional linear filtering, whereas the EKF has a unique advantage [5,11].

However, EKF also has disadvantages. It relies on an accurate system model, which makes accurate modelling difficult when the flight environment is complex, and small errors will be amplified by iteration, affecting the accuracy of the solution. Its computational complexity is high, involving matrix operations (e.g., Jacobi matrix, multiplication, inverse), which consumes a large amount of on-board processor resources during high-frequency updates or complex tasks, resulting in processing delays, affecting real-time performance, and is detrimental to obstacle avoidance for high-speed flying UAVs. It is sensitive to the initial state estimation and the initial value of the noise covariance matrix, inaccuracy will lead to convergence problems or estimation bias, flight state change or dynamic environment to set the initial value is difficult, will limit its performance and application range, the use of trade-offs need to be optimised.

Compared to other filtering algorithms, EKF is superior when both nonlinear data processing capability and processor performance requirements need to be taken into account. Mean value filtering simply averages the data only, cannot handle dynamic and nonlinear problems, and is not suitable for UAS. First-order lag filtering smoothes the data but has limited ability to handle highly nonlinear systems. Compared to UKF, EKF approximates the nonlinear problem with linearisation, and UKF uses the traceless transform and Sigma points. UKF performance may be better in highly nonlinear systems because EKF linearisation introduces errors, however, UKF is more computationally resource-intensive, especially in high-dimensional systems. Therefore, it is important to choose the appropriate algorithm according to the system characteristics, performance requirements and resource constraints. EKF is better when the system model is easy to build and the resources are limited, while UKF can be considered when the system is highly nonlinear and the resources are sufficient.

3.4 Untraceable Kalman Filter

UKF is important in visual target tracking and navigation and localisation of UAVs. In visual target tracking, the UAV acquires the target image information through the onboard camera and extracts its position, size and velocity, etc. However, the relationship between this information and the actual states of the UAV and the target is nonlinear and involves complex transformations such as perspective projection.UKF adopts the traceless transformation to generate Sigma points based on the state mean and covariance, which are propagated through the nonlinear state equations. The initial state vectors contain the position, velocity, attitude and other information of the target and the UAV, and the Sigma points are updated according to the equations of motion of the UAV and the target and the perspective projection relationship. During the update, the target position extracted from the image is compared with the position predicted by the Sigma points, and the state estimate is updated using Kalman gain [6,7,11].

Under normal circumstances, when the target is moving steadily and the UAV is flying smoothly, the UKF can track the target better and continuously, providing accurate data for the tracking system. However, there are challenges when the environment is complex, such as poor lighting with high image noise or even loss of the target, rapid target manoeuvring or partial occlusion will enhance the non-linearity of the trajectory, and the rapid manoeuvring of the UAV itself will make the state equation more complex, affecting the estimation of the state of the UKF.

In navigation and positioning, UKF can fuse different data sources when combining GPS, IMU and visual odometry data; GPS is accurate but slow to update and susceptible to interference, IMU is high-frequency but subject to drift, and visual odometry is affected by ambient texture and lighting; Sigma points propagate according to their respective nonlinear dynamical equations, and the position estimation can be corrected in the presence of GPS signals, while in the absence of signals, it relies on IMU and visual odometry data. Positioning [7,8].

However, UKF calculation involves a large number of operations, and when the state vector dimension is high, there are many Sigma points and a large amount of computation, and when updating the position and tracking the target at a high frequency, the performance of the onboard processor is highly required, which will cause processing delay and affect the real-time performance. Moreover, the selection of Sigma points and weight calculation need to be carefully adjusted, otherwise the performance will be affected.

Compared with other algorithms, UKF is more suitable for dealing with complex nonlinear systems. While first-order hysteresis filtering is only used for simple noise suppression, UKF can synthesise data from multiple sources, which has obvious advantages in high-precision target tracking and navigation and positioning in complex environments and provides support for UAV flight safety and mission completion. However, it has a high demand for computational resources and requires a powerful processor to guarantee real-time performance and mission completion, otherwise the performance will be affected.

3.5 Particle Filter

In UAV GPS positioning processing, the GPS signal is susceptible to building obstruction and ionospheric interference, and the positioning data will jump and have large errors.KF and its improved algorithms need to accurately know the GPS error characteristics and the UAV motion model, which is ineffective in complex environments such as urban canyons, due to the difficulty of constructing the motion model and the complexity of the noise.PF uses a large number of particles to simulate the probability distribution of the state, which has little dependence on the model, and can provide more accurate positioning when the signal is poor, so it is widely used to provide data support for path planning and navigation[8]. PF uses a large number of particles to simulate the state probability distribution, with little dependence on the model, and can locate more accurately without relying on the accurate model, and still have accuracy when the signal is poor, so it is widely used in UAV positioning to provide data support for path planning and navigation [8-11].

However, PF has disadvantages. First, the computational complexity is high, and the number of particles grows exponentially when the system dimension increases, which affects the real-time performance of the onboard processor and is unfavorable for high-speed flight or high-precision real-time path planning. Secondly, the performance depends on the number and distribution of particles, the estimation of fewer particles is inaccurate, while more particles are a large computational burden, and improper initialisation and resampling will cause particle degradation, affecting the performance and accuracy. Thirdly, it is difficult to ensure the uniform coverage of particles when dealing with continuous state space, and the estimation bias is easy to occur in high-dimensional space.

Compared to other algorithms, PF is less dependent on the system model. However, Kalman filtering is computationally efficient when dealing with linear or nearly linear systems, and particle filtering can be redundant and have additional performance overheads. Compared with UKF, UKF handles nonlinear systems and avoids linearisation errors, has more reasonable computational resource requirements, and performs well in moderately nonlinear systems, whereas particle filtering, although it has advantages in dealing with complex nonlinear systems, its high cost and particle degradation limit its application in real-time and resource-demanding scenarios. Compared with mean filtering, PF can handle nonlinear and non-Gaussian noise with more accurate estimation, but the computational resources and complex structure make it difficult to implement maintenance in resource-limited platforms.

4 Conclusion

This paper comprehensively analyses five filtering algorithms commonly used in the UAV field: first-order lag filtering, KF, EKF, UKF, and PF. These algorithms play a key role in the accuracy and reliability of UAV sensing data. First-order lag filtering is favoured for its simplicity and efficiency but suffers from phase delays and limited ability to handle nonlinear systems.KF is widely praised for its efficiency and accuracy in state estimation of dynamic systems but is very sensitive to the accuracy of the system model and initial conditions.EKF extends the application of the Kalman filter by linearising the nonlinear function but introduces truncation errors.UKF captures the nature of the nonlinearity through sampling techniques and provides more accurate results than the EKF, but has a higher computational complexity. Particle filtering is capable of handling a wider range of nonlinear and non-Gaussian problems, but its particle degeneration and resampling problems remain difficult to study.

The performance and robustness of UAVs, and to reduce the impact of sensor noise and external interference by selecting and optimising suitable filtering algorithms. Future research can further explore how to design and optimise filtering algorithms suitable for UAV sensing data, such as reducing computational complexity, developing adaptive filtering algorithms, combining filtering algorithms with deep learning techniques, researching more advanced data fusion techniques, improving the robustness of the filtering algorithms to outliers and model errors, and improving their performance and reliability in practical applications, so as to promote the UAV technology's Progress.

References

1. R. E. Kalman, "A New Approach to Linear Filtering and Prediction Problems," Journal of Basic Engineering, vol. 82, no. 1, p. 35, 1960.
2. K. Ansari and Punyawi Jamjareegulgarn, "Effect of Weighted PDOP on Performance of Linear Kalman Filter for RTK Drone Data," IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1–4, Jan. 2022
3. H.-M. Deng, H. Yong, X.-J. Yu, and W. Cheng-Tong, "Research and Application Based on Kalman in Small UAV Attitude," Nov. 2019.
4. M. Mammarella, G. Campa, M. R. Napolitano, Mario Luca Fravolini, Y. Gu, and M. G. Perhinschi, "Machine Vision/GPS Integration Using EKF for the UAV Aerial Refueling Problem," IEEE transactions on systems, man and cybernetics, vol. 38, no. 6, pp. 791–801, Nov. 2008.
5. Y. Liu, X. Liao, Z. Wang, X. Chen, X. Liu, and Z. Li, "Event-Triggered Extended Kalman Filter for UAV Monitoring System," 2022 IEEE International Symposium on Circuits and Systems (ISCAS), pp. 1–5, Sep. 2020.
6. None Xu Wanli, None Bao Shuo, and None Liu Zhun, "The state estimation of UAV based on UKF," 2014 IEEE Workshop on Advanced Research and Technology in Industry Applications (WARTIA), vol. 3, pp. 402–405, Sep. 2014.
7. C. Gao, G. Zhao, and J. Lu, "In-flight misalignment attitude estimation for UAV based on GPS and UKF/MPF filter," Proceedings of 2014 IEEE Chinese Guidance, Navigation and Control Conference, vol. 15, pp. 452–457, Aug. 2014.
8. Q. Xin and S. Wang, "GPS Positioning Method of UAV Based on Improved Particle Filter," 2020 International Conference on Communications, Information System and Computer Engineering (CISCE), Jul. 2020.
9. Y. Bo, Guo Shuxia, L. Ning, and H. Jun, "Estimation with particle filter under model uncertainty," 2022 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC), pp. 1–5, Sep. 2011.
10. W. Xie, L. Wang, B. Bai, B. Peng, and Z. Feng, "An Improved Algorithm Based on Particle Filter for 3D UAV Target Tracking," ICC 2019 - 2019 IEEE International Conference on Communications (ICC), pp. 1–6, May 2019.
11. P. Ma, S. Bian, S. Chen, Y. Qi, Q. Xiao, and X. Yang, From ROS1 to ROS2: A practical Guide to drone programming. Chemical Industry Press, 2023, pp. 473–501.