Processing 3D Flight Trajectory Data with Adaptive Kalman Filtering

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***Abstract*—Flight trajectory data from Quick Access Recorders (QAR) is critical for ensuring flight safety and conducting performance analysis. However, the inherent uncertainties and noise present in this data necessitate the use of filtering techniques. The conventional Kalman filter, widely applied in civil aviation, exhibits limitations when addressing varying noise levels across different aircraft types and flight phases. This study addresses these challenges through a multi-step approach. First, QAR data from Daocheng Yading Airport underwent preprocessing, including data cleaning, resampling, key field selection, and target trajectory extraction. Next, the Kalman filter's adaptive capabilities were enhanced and applied specifically to three-dimensional trajectory data. Finally, a comparative analysis was conducted with the segmented noise matrix adjustment method. The results demonstrate that the adaptive Kalman filter effectively preserves essential data characteristics while streamlining the filtering process.**

Keywords—QAR, Kalman filtering, flight trajectory

I. Introduction

Against the backdrop of this burgeoning industry, the accurate evaluation and analysis of flight trajectories have increasingly become a focal point of public concern. Flight trajectory data are typically collected and recorded using devices such as Quick Access Recorders (QAR)[1]. Nevertheless, due to the presence of various uncertainties and noise during flight, the trajectory data from QAR often require filtering to mitigate the impact of noise on the evaluation results[2].

Research by Gao Yuan et al. suggests that the noise in QAR flight data primarily originates from measurement errors and outliers produced by instruments, as well as high-frequency quantization noise generated during the conversion of electrical signals to physical quantities[3]. Dai Jingrui et al. proposed the use of Deep Belief Networks (DBN) for feature extraction from QAR data[4]. This algorithm reduces reliance on extensive data processing techniques and expert knowledge. To enhance the accuracy of recorded QAR data, Zhao et al. employed comprehensive trajectory latitude and longitude correction models, as well as an integrated sliding trajectory model, which facilitate the analysis of spatial variations in airport instrument landing system signals, thus aiding in the monitoring of system noise[5].

Each of these methods has its advantages and can effectively reduce noise from different perspectives, thereby improving data quality and supporting flight data analysis and applications. However, the applicability of these methods across various systems is somewhat limited. In practical industry research, segmented adjustment methods are still more commonly used, requiring the prior determination of noise characteristics for each phase and system, which is relatively cumbersome and complex.

Currently, in civil aviation flight research, the processing of flight trajectory data from QAR records predominantly utilizes Kalman filtering algorithms. As a classical filtering technique, Kalman filtering has broad applications in trajectory processing. However, traditional Kalman filtering algorithms face limitations in addressing the challenge of determining noise values for different aircraft types and flight stages.

Therefore, this study aims to explore the application of adaptive Kalman filtering algorithms in the processing of flight trajectory data to improve the accuracy and stability of trajectory filtering. Compared to traditional Kalman filtering algorithms, adaptive Kalman filtering algorithms dynamically adjust filtering parameters based on actual data, thereby better accommodating the noise characteristics of various aircraft types and flight phases. This approach enhances data quality and evaluation accuracy. The study will also include a comparative analysis with commonly used segmented noise matrix adjustment methods to further highlight the advantages and practicality of adaptive Kalman filtering algorithms.

II. Methodology

A. Basic process of Kalman filtering

Kalman filtering estimates the optimal state through a series of prediction and updating steps. Below are some of the key formulas and concepts[6]:

State transition equation to predict the next state:

$$X_{k+1} = FX_k + Bu_k + w_k \tag{1}$$

where X is the state, F is the state transition matrix, B is the control matrix, u is the control input, and w is the process noise.

Observation equation to estimate the current state based on the observed value:

$$Z_k = HX_k + \upsilon_k \tag{2}$$

where Z is the observation, H is the observation matrix, and υ is the observation noise.

Step 1: Prediction

Predict state estimate:

$$\hat{X}_{k|k-1} = F\hat{X}_{k-1|k-1} + Bu_k \tag{3}$$

Predict error covariance matrix:

$$P_{k|k-1} = FP_{k-1|k-1}F^T + Q \tag{4}$$

Step 2: Update

Kalman gain:

$$K_k = P_{k|k-1}H^T\left(HP_{k|k-1}H^T + R\right)^{-1} \tag{5}$$

Estimate state:

$$\hat{X}_{k|k} = \hat{X}_{k|k-1} + K_k\left(Z_k - H\hat{X}_{k|k-1}\right) \tag{6}$$

Update error covariance matrix:

$$P_{k|k} = \left(I - K_kH\right)P_{k|k-1} \tag{7}$$

In these equations, Q is the process noise covariance matrix, R is the observation noise covariance matrix, I is the identity matrix.

The formulas (3) to (7) describe the basic procedure of the Kalman filtering algorithm[7][8], and the data flow during the filtering process is illustrated in Fig.1.

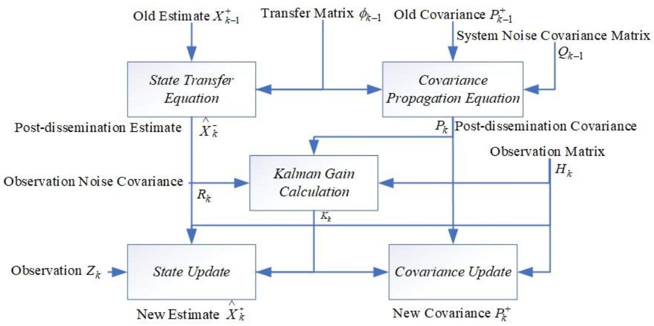


Fig. 1. The state transition of the Kalman filtering process

B. Limitations of the segmented adjustment

Adjusting noise values during the filtering process through segmental adjustment is a widely used technique in the Kalman filtering algorithm, particularly for sensor data in dynamic systems. The core idea is to dynamically adjust the Kalman filter's noise parameters based on changes in the system's state or external conditions, allowing the filter to better adapt to varying operational environments and system behaviors.

In segmental adjustment, the entire data sequence is divided into different segments or regions, each characterized by similar data attributes or noise influences. Different noise parameters are then applied to each segment, enabling the Kalman filter to optimize its performance for the specific conditions of each segment. The goal is to balance noise suppression and signal preservation within each segment, thereby enhancing the overall effectiveness of the filtering process. This approach typically involves the following steps:

Step 1: Flight Phase Segmentation

First, the entire flight process is segmented into multiple phases based on different stages of the flight mission (e.g., takeoff, climb, cruise, descent, landing). Each phase may exhibit different noise characteristics due to variations in flight dynamics and environmental conditions.

Step 2: Noise Matrix Setting

For each segmented flight phase, a corresponding noise matrix is established. This involves an in-depth analysis and testing of the specific noise characteristics for each phase to determine optimal noise parameters. Typically, researchers set these noise matrices based on historical data or empirical values derived from experiments.

Step 3: Segmented Filtering Process

During the actual filtering process, the Kalman filter's noise matrix is dynamically adjusted according to the current flight phase of the aircraft, aligning with the noise characteristics of that phase. This adjustment can enhance filtering accuracy and system stability.

While the segmented adjustment method effectively addresses the issue of setting noise matrices for different flight phases, it has significant limitations. First, this method requires detailed pre-segmentation of the flight process, and setting the noise matrix for each phase involves extensive experimentation and data analysis, increasing the complexity and difficulty of implementation. Second, the success of this method relies heavily on an accurate understanding of the noise characteristics for each flight phase. If these characteristics change or unexpected situations arise, the effectiveness of the segmented adjustment method may be significantly reduced.

In contrast, the adaptive Kalman filtering algorithm dynamically adjusts noise matrix parameters based on real-time data, offering greater flexibility and adaptability. The adaptive Kalman filter eliminates the need for detailed pre-segmentation of the flight process and can automatically adapt to the noise characteristics of different flight phases, simplifying the design and implementation of the filter. Additionally, the adaptive algorithm is more robust in handling unexpected situations and uncertainties, providing more accurate and reliable filtering results.

C. Three-dimensional adaptive Kalman filtering

Adaptive Kalman filtering is an enhanced algorithm based on the traditional Kalman filter, designed to improve robustness and adaptability by incorporating an adaptive mechanism. This adaptive Kalman filter can dynamically adjust its parameters in response to changes in system states and variations in noise characteristics, making it particularly effective for state estimation problems in complex environments and under uncertain conditions[9].

A key feature of the adaptive Kalman filter is its ability to estimate and correct the model and noise statistical properties in real-time while performing predictive analysis using measurement data. This means that, compared to the traditional Kalman filter, the adaptive Kalman filter can more accurately reflect the actual state of the system and reduce filtering errors. The adaptive Kalman filter allows the process noise covariance Q and measurement noise covariance R to be dynamically adjusted during the filtering process to adapt to the continuously changing system states and noise characteristics[10].

Upgrading an existing algorithm to an adaptive Kalman filter requires introducing additional steps and equations to adjust the Kalman gain, allowing for a more effective response to changes in measurement and process noise. The key equations and steps that need improvement are as follows:

Step 1: Measurement Update Equation

$$State_{t+1} = State_{t+1}^{-} + K_t * \left(Z_t - H_t * \text{State}_{t+1}^{-} \right) \tag{8}$$

where Z_t is the measurement vector of time, H_t is the measurement matrix, and K_t is the Kalman gain.

Step 2: Kalman Gain Calculation

$$K_t = P_{t+1}^{-} * H_t^T * \left(H_t * P_{t+1}^{-} * H_t^T + R_t \right)^{-1} \tag{9}$$

where R_t is the measurement noise covariance matrix.

Step 3: Error Covariance Update Equation

$$P_{t+1} = \left(I - K_t * H_t \right) * P_{t+1}^{-} \tag{10}$$

where I is the identity matrix.

The key to adaptive Kalman filtering lies in dynamically adjusting the Kalman gain and error covariance to respond to the uncertainties in actual measurements. The adaptive adjustment of the process noise covariance Q_t can be dynamically modified based on the magnitude of the prediction error, allowing the algorithm's confidence to be adjusted when the process noise varies. Similarly, the measurement noise covariance R_t should be dynamically adjusted based on the magnitude of the measurement residual, allowing the algorithm's confidence to be adjusted when the measurement noise changes.

Step 4: Innovation Covariance S_t and Sequence v_t

$$S_t = H_t * P_{t+1}^{-} * H_t^T + R_t \tag{11}$$

$$v_t = Z_t - H_t * State_{t+1}^{-} \tag{12}$$

The innovation covariance S_t and the innovation sequence v_t can be used to evaluate the consistency of the measurements, thereby adjusting K_t and R_t.

In the data flow, the primary difference between the adaptive Kalman filter and the standard Kalman filter is that in the adaptive Kalman filter, the value of the matrix R is influenced by the observation Z. In contrast, in the standard Kalman filter, the filtering calculation loop and the gain calculation loop are independent of each other.

QAR data provides precise flight state information for research, including flight speed, instantaneous acceleration, and heading data. Using the Kalman filter algorithm to predict the track point position can effectively achieve trajectory smoothing and correction.

Specifically, it is assumed that the noise in QAR trajectory data follows a Gaussian distribution with a mean of zero. The initial latitude and longitude information recorded by the QAR is used as input parameters. Using Newton's laws of motion combined with the aircraft's speed, acceleration, and heading data, the next time point's predicted position is calculated. During the filtering process, by dynamically adjusting the process noise covariance Q and measurement noise covariance R and continuing to apply the Kalman filter to adjust and correct the predicted values, a more accurate position estimate for the next time step can be obtained. This method optimizes trajectory data and enhances the accuracy of subsequent analysis and applications.

To establish a three-dimensional adaptive Kalman filtering algorithm, height information, and vertical speed information are added to the input state matrix. The specific algorithm process is as follows:

At time t, the aircraft position state is represented by the matrix $[X_t Y_t V_t H_t IV_t]^T$, where X_t is longitude at time t, Y_t is the latitude at time t, V_t is the airspeed at time t, H_t is the altitude at time t, and IV_t is the vertical speed at time t. Considering the aircraft as moving in a uniformly accelerated straight line, according to Newton's laws of motion, the state transition equations are derived as follows:

$$X_{t+1} = X_t + \left(V_t \Delta t + 0.5 a_t \Delta t^2 \right) \sin\left(\theta_t\right) \omega_x \tag{13}$$

$$Y_{t+1} = Y_t + \left(V_t \Delta t + 0.5 a_t \Delta t^2 \right) \cos\left(\theta_t\right) \omega_y \tag{14}$$

$$V_{t+1} = V_t + a_t \Delta t \tag{15}$$

$$H_{t+1} = H_t + 0.5\left(IV_{t+1} + IV_t \right) \Delta t \tag{16}$$

$$IV_{t+1} = IV_t + v a_t \Delta t \tag{17}$$

where Δt is the time interval from t to $t+1$, a_t is the horizontal instantaneous acceleration of the aircraft, va_t is the vertical instantaneous acceleration of the aircraft, θ_t is the heading angle at time t, and ω_x , ω_y are conversion coefficients used to convert longitude and latitude into planar distances. The conversion coefficients are calculated as follows:

$$\omega_x = \frac{360}{2\pi \cos\left(\mathrm{Lat}_t\right)\mathrm{Earth\_Radius\_Long}} \tag{18}$$

$$\omega_y = \frac{360}{2\pi \mathrm{Earth\_Radius\_Short}} \tag{19}$$

where Lat_t is the latitude recorded in the flight data at time t , and Earth_Radius_Long and Earth_Radius_Short represent the Earth's long and short axis radii, respectively.

The above equations can be written in matrix form as follows:

$$\begin{bmatrix} X_{t+1} \\ Y_{t+1} \\ V_{t+1} \\ H_{t+1} \end{bmatrix} = F_t * \begin{bmatrix} X_t \\ Y_t \\ V_t \\ H_t \end{bmatrix} + B_t * \begin{bmatrix} a_t \\ va_t \end{bmatrix} \tag{20}$$

where

$$F_t = \begin{bmatrix} 1 & 0 & \sin\left(\theta_t\right)\Delta\omega_x & 0 & 0 \\ 0 & 1 & \cos\left(\theta_t\right)\Delta\omega_x & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0.5\Delta t \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{21}$$

$$B_t = \begin{bmatrix} \dfrac{\sin\left(\theta_t\right)\Delta t^2 \omega_x}{2} \\ \dfrac{\cos\left(\theta_t\right)\Delta t^2 \omega_y}{2} \\ \Delta t \\ 0.5\Delta t^2 \\ \Delta t \end{bmatrix} \tag{22}$$

The matrix can be expanded into an equation form, where is the predicted value of the aircraft's state at the previous time step, derived through the preceding calculations. Subsequently, this prediction needs to be corrected using observed values. F_t and B_t are the state transition matrix and control matrix in the Kalman filter, respectively, representing the state changes over time and how the aircraft's dynamics influence state transitions. As shown in Equation (23):

$$\mathrm{State}_{t+1}^{-} = F_t * \mathrm{State}_t + B_t * \begin{bmatrix} a_t \\ va_t \end{bmatrix} \tag{23}$$

In this equation, P_t denotes the covariance matrix at time t , representing the noise in the aircraft's state at that moment.

To implement the adaptive Kalman filter algorithm, additional steps and formulas are required to adjust the Kalman gain, enhancing the filter's responsiveness to changes in measurement and process noise. The complete process is outlined below.

Step 1: State and Covariance Initialization

$$State_0 = \begin{bmatrix} X_0 \\ Y_0 \\ V_0 \\ H_0 \\ IV_0 \end{bmatrix} \tag{24}$$

$$P_0 = \begin{bmatrix} \sigma_X^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_Y^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_V^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_H^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{IV}^2 \end{bmatrix} \tag{25}$$

where σ_X^2 , σ_Y^2 , σ_V^2 , σ_H^2 , σ_{IV}^2 are the initial variances of longitude, latitude, speed, altitude, and vertical speed, respectively.

Step 2: Predict the Next State and Error Covariance

$$State_{t+1}^{-} = F_t * State_t + B_t * \begin{bmatrix} a_t \\ va_t \end{bmatrix} \tag{26}$$

$$P_{t+1}^{-} = F_t * P_t * F_t^T + Q_t \tag{27}$$

Step 3: Calculate the Kalman Gain

$$K_t = P_{t+1}^{-} * H_t^T * \left(H_t * P_{t+1}^{-} * H_t^T + R_t\right)^{-1} \tag{28}$$

Step 4: Update the State and Error Covariance

$$State_{t+1} = State_{t+1}^{-} + K_t * \left(Z_t - H_t * State_{t+1}^{-}\right)^{-1} \tag{29}$$

$$P_{t+1} = \left(I - K_t * H_t\right) * P_{t+1}^{-} \tag{30}$$

Step 5: Adaptive Adjustment of Process Noise

Covariance Q_t and Measurement Noise Covariance R_t

$$Q_t = b*Q_t + (1-b)*d_t*\left(State_{t+1} - State_{t+1}^{-}\right) \quad (31)$$

$$R_t = b*R_t + (1-b)*d_t*\left(Z_t - H_t*State_{t+1}^{-}\right) \quad (32)$$

In the above formulas, b is the forgetting factor, which ranges from 0.95 to 0.99, and is used to balance the weighting between historical and new information. d_t is a hyperparameter used to regulate the update rate of the covariance matrix and the Kalman gain. The expressions $\left(State_{t+1} - State_{t+1}^{-}\right)$ and $\left(Z_t - H_t*State_{t+1}^{-}\right)$ represent the calculation methods for prediction error and measurement residual, respectively, in this study.

Step 6: Calculate the Innovation Covariance and Innovation Sequence

$$S_t = H_t*P_{t+1}^{-}*H_t^T + R_t \quad (33)$$

$$v_t = Z_t - H_t*State_{t+1}^{-} \quad (34)$$

Step 7: Adjust the Kalman Gained Error Covariance Based on the Innovation Sequence

$$K_t = bK_t + (1-b)d_t v_t S_t^{-1} \quad (35)$$

$$P_{t+1} = bP_{t+1} + (1-b)d_t\left(I - K_t*H_t\right)*P_{t+1}^{-} \quad (36)$$

During this process, dynamic adjustments to Q_t and R_t are made to adapt to actual noise variations, thereby improving filtering performance. Additionally, by adjusting K_t and P_{t+1}, the algorithm can better respond to real-time measurement data, enhancing estimation accuracy.

The adaptive method offers significant advantages over traditional piecewise approaches. It operates continuously, enabling real-time adjustments based on immediate data, allowing it to respond more swiftly to changes in system dynamics. In contrast to piecewise methods, which modify noise parameters at fixed intervals or upon detecting significant changes, and potentially introduce delays, the adaptive method allows for the dynamic modification of noise parameters in response to observed system behavior. Additionally, it incorporates a forgetting factor to ensure smooth transitions between old and new noise estimates, avoiding abrupt changes. This data-driven approach aligns updates more closely with the system's actual performance, guided by prediction errors and measurement residuals.

Overall, the adaptive Kalman filter provides a flexible and automatic approach to enhancing filtering performance through real-time monitoring and feedback adjustments of residuals. This is particularly effective in systems with rapid changes or when the state transition model is not fully known.

The detailed algorithm process is illustrated in Fig. 2.

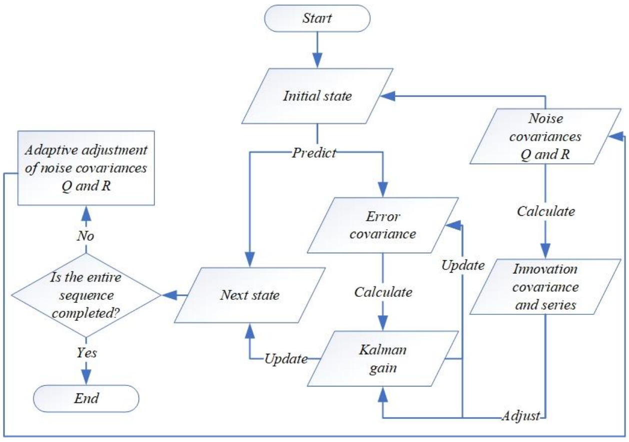


Fig. 2. The procedure of the 3D adaptive Kalman filtering algorithm

III. Experiments and Results

A. Preprocessing of QAR Flight Data

The data resources used in this study were obtained from the China Academy of Civil Aviation Science and Technology, consisting of 1,967 real flight records from Daocheng Yading Airport. Of these, 985 records pertain to departing flights, while 982 records correspond to arriving flights at the airport.

1) Data Cleaning

To ensure the accuracy and effectiveness of QAR (Quick Access Recorder) raw data, thorough data cleaning is essential. The process begins with a data completeness check, where missing values are addressed using techniques such as mean, median, or fixed value imputation, depending on the data's nature and research objectives. This is followed by outlier correction, utilizing statistical methods and time series analysis to identify and correct anomalous data points, thereby enhancing data accuracy and consistency. Lastly, data type standardization is performed, particularly for fields like latitude and longitude, which are initially stored as strings. These fields are processed by removing hemisphere indicators and converting the remaining data to a floating-point format for precise calculations and analysis.

TABLE I. Core Flight Parameters

Parameters	**Abbreviation**	**Data Unit**
Date	DATE_R	Year/Month/Day
Time	TIME_R	Hour/Minute/Second
Aircraft type	AC_TYPE	
Corrected Ground Speed	GSC	Km/h
Pitch angle	PITCH	Degree
Roll Angle	ROLL	Degree
Magnetic heading	HEAD_MAG	Degree
Wind Speed	WIN_SPD	Knots
Wind Direction	WIN_DIR	Degree
Indicated airspeed	IASC	Knots
Mach number	MACH	
Vertical speed	IVV	feet/minute (ft/min)
Horizontal acceleration	LATG	
Vertical acceleration	LONG	
Vertical acceleration	VRTG	
Corrected longitude	LONPC	Degree
Corrected latitude	LATPC	Degree
Corrected Sea Pressure Altitude	ALT_STDC	feet
Total Fuel	TFUEL	Gallons

2) Key Field Selection

The core of the field selection process involves identifying fields that are essential for the research objectives, easy to analyze and model, and that exhibit high data quality and reliability. While this process may demand considerable time and effort, it is crucial for conducting in-depth research, ensuring that the focus remains on the most critical and valuable data. The core parameters and their meanings in the final parameter list are outlined in Table I.

3) Data Resampling

In QAR flight data, different parameters are sampled at varying frequencies, primarily due to the hardware design of sensors. Typically, the QAR data sampling frequency is four times per second, resulting in one sample every four seconds. However, key fields such as latitude and longitude coordinates may have an actual sampling frequency of once every four seconds, with data recorded as unique values or interpolated within that period. This uneven sampling can lead to inconsistencies in flight trajectory and altitude changes, which can negatively impact subsequent analyses.

To address this, the study resamples the raw data using a down-sampling strategy, setting a uniform sampling frequency of every four seconds. This approach offers two main advantages: first, it aligns with the original sampling frequency of most key parameters, preserving data characteristics and ensuring even distribution of samples, which is crucial for accurate trajectory analysis; second, it reduces data volume, significantly decreasing the computational burden and thereby improving experimental efficiency.

4) Target Trajectory Extraction

To reduce data size and improve research efficiency, this study focuses exclusively on the departure and arrival stages of flight. The extraction of target trajectories is guided by two criteria: flight status indicators and navigation beacon coordinates. Flight status indicators, such as descent (DESCENT) and landing (LANDING), are used to accurately identify different flight states for precise data selection. Additionally, navigation beacon coordinates ensure that the start and end points of the collected data align with typical flight paths, capturing critical segments of the departure and arrival phases. This approach helps to accurately reflect key changes in the flight process, minimize alignment errors, and enhance research accuracy.

B. 3D Flight Trajectory Processing

In practical applications, the complexity of the flight environment and the inherent uncertainties in the flight process introduce numerous extraneous signals and anomalies in the QAR data collected during the initial acquisition. As a result, the raw QAR flight data often require filtering and smoothing to reduce the impact of these noise sources on evaluation and research outcomes.

During QAR data acquisition, the Long-Range Navigation (IRS) system is typically employed to accurately track the flight path, recording data such as latitude and longitude in the LONP and LATP fields. However, the positioning accuracy of this system alone is often insufficient, frequently leading to errors at the starting point, which is located at a considerable distance from the airport runway. To address this, the aircraft is equipped with a Global Navigation Satellite System (GNSS) receiver, which is used to correct the latitude and longitude data, with the corrected values stored in the LONPC and LATPC fields. Despite these corrections, challenges remain in the recording process of flight trajectory data, leading to anomalies such as knotting, jumping, and jaggedness in the original QAR data.

The knotting phenomenon, as illustrated in Fig. 3, typically occurs due to disruptions in the continuity of the aircraft's trajectory. This can be caused by factors such as irregular GPS signal reception or anomalies in the QAR recording equipment.

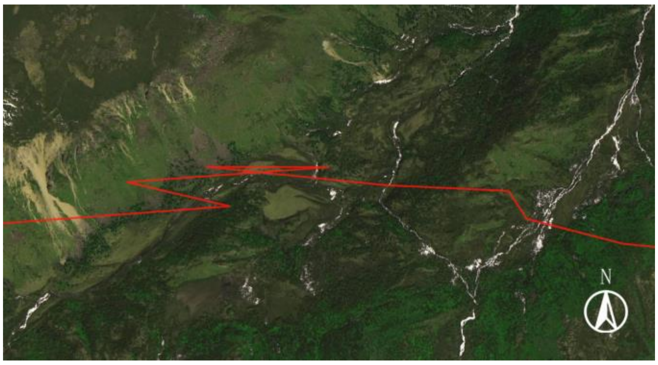


Fig. 3. Illustration of the phenomenon of kinking of trajectories

The hopback phenomenon typically occurs due to malfunctions in the data recording or transmission process. In such cases, the trajectory data may show abrupt fluctuations, leading to significant discontinuities in the aircraft's position information, as illustrated in Fig. 4.

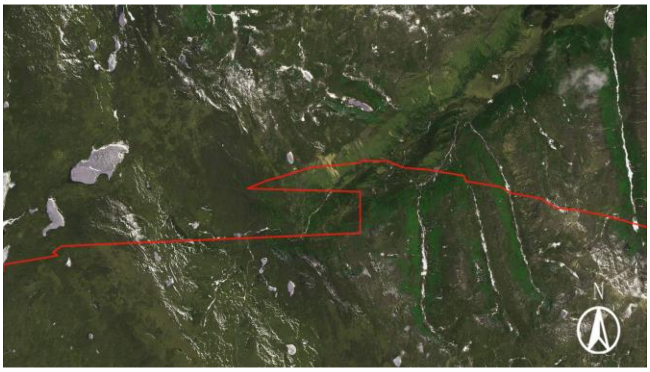


Fig. 4. Schematic representation of the trajectory bounce phenomenon

Furthermore, jagged tracks are the most common trajectory issue, typically emerging when an aircraft maneuvers or changes altitude. If the temporal resolution of the track recording is insufficient, discrepancies can arise between the actual flight path and the recorded track, resulting in a jagged appearance, as illustrated in Fig. 5.

Fig. 5. Schematic illustration of the phenomenon of sawtooth trajectories

The presence of these trajectory issues significantly impacts subsequent data processing and analysis. Accurate flight trajectory data is crucial for ensuring flight safety and conducting effective performance analysis. The primary goal of trajectory smoothing is to use mathematical methods to process the original data, reducing the influence of noise and thereby restoring the trajectory to closely reflect the actual flight conditions. This process helps eliminate or reduce jitter, aligning the trajectory data more accurately with the real flight path, which in turn enhances the quality and usability of the data.

While smoothing may result in the loss of some original jitter characteristics, it preserves the fundamental patterns and trends of the trajectory. An effective smoothing method mitigates noise while maintaining the trajectory's fidelity, providing a more consistent representation of the actual flight scenario. The three-dimensional adaptive Kalman filtering algorithm was applied to the raw trajectory data, with the processing effects illustrated in Fig. 6 and Fig. 7.

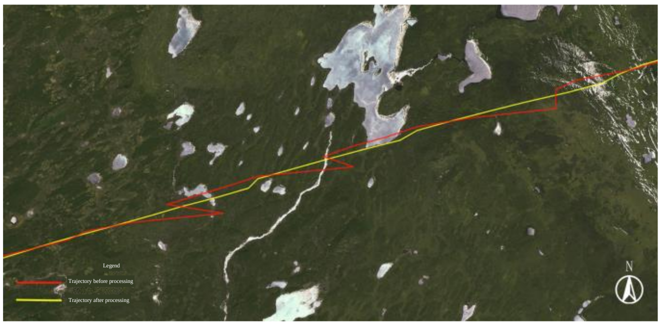


Fig. 6. Trajectory smoothing effect comparison (local 1)

Fig. 7. Trajectory smoothing effect comparison (local 2)

Unlike conventional Kalman filtering algorithms, which primarily focus on two-dimensional latitude and longitude data, this study extended the algorithm to incorporate altitude data into the filtering process. As shown in Fig. 8, the comparison of altitude curves before and after processing reveals that the filtered altitude data closely aligns with the original data's overall trend. During the takeoff, cruising, and landing phases, the filtered curve accurately reflects the aircraft's actual altitude changes. Despite the noise reduction, the altitude data remains undistorted, faithfully representing the altitude variations across different flight phases.

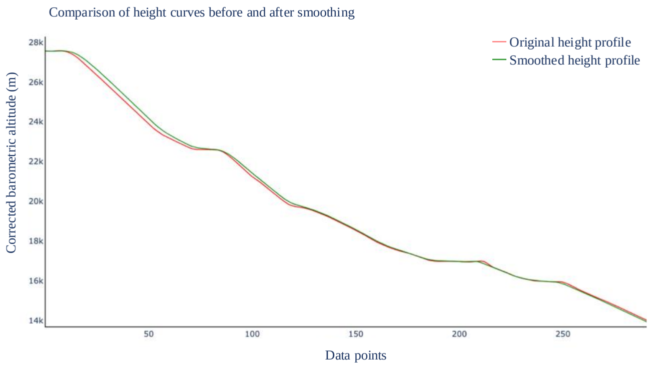


Fig. 8. Comparison of altitude curve processing effects

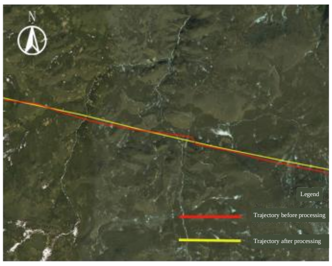
Furthermore, the processed data retains key feature points from the original data. For example, altitude peaks and troughs that appear in the original dataset remain clearly visible in the smoothed data. These key points are critical for flight data analysis, as they often correspond to significant events or state changes during the flight. By preserving these feature points, the processed altitude data enhances readability and provides reliable support for further analysis of flight conditions.

In addition, the processed data maintains the fine details of the original dataset. Even after filtering, minor fluctuations and changes in altitude are preserved, which are important for detailed flight trajectory analysis, as they can reflect small adjustments and operations during the flight.

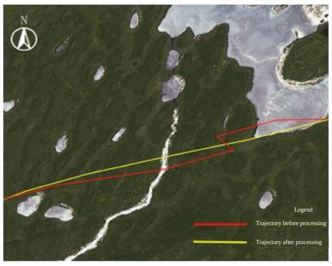
The adaptive Kalman filtering algorithm implemented in this study effectively filters latitude and longitude data without overly simplifying the altitude data, ensuring that the fundamental characteristics are preserved. This meets the requirement for QAR data noise reduction, closely restoring the true characteristics of the data and demonstrating the algorithm's effectiveness.

Moreover, the adaptive Kalman filter exhibits strong adaptability across different datasets. The algorithm's ability to dynamically adjust noise matrix parameters based on real-time data allows it to automatically adapt to varying flight conditions and system characteristics. Whether during takeoff, cruising, or landing, the adaptive Kalman filter provides realistic and accurate trajectory data, significantly enhancing the stability and reliability of data processing.

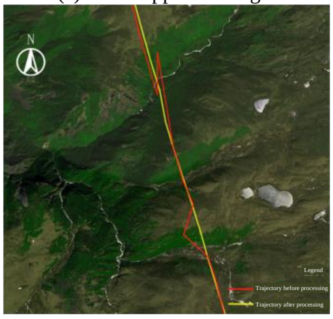
As shown in Fig. 9, the same filtering process produces consistent, high-quality results across different flight phases. Even in scenarios with significantly different flight environments and aircraft states, the data processed by the adaptive Kalman filter remains highly smooth and accurately tracks the original trajectory. This not only demonstrates the robustness of the adaptive Kalman filter in handling data from various flight phases but also highlights its superior performance in preserving essential data characteristics.



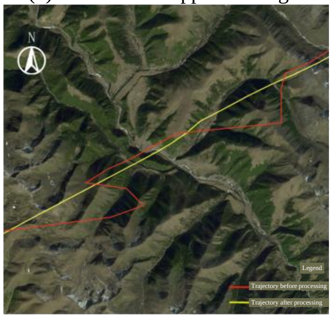
(a) Initial approach stage



(b) Intermediate approach stage



(c) Final approach stage



(d) Outside the five-sided area

Fig. 9. Trajectory processing effects of different flight phases

IV. Conclusion and Future Work

This study implemented and validated an adaptive Kalman filtering algorithm on QAR flight data, comparing it with the traditional segmented adjustment method. The results confirm the practicality and adaptability of the adaptive Kalman filter for processing QAR flight trajectory data. It effectively preserved the essential characteristics of the original data while significantly simplifying the complex operations associated with traditional methods. However, the study's limitations, including the restricted variety of sample types and the limited data volume, may affect the general applicability and scalability of the findings. Additionally, the basic data organization methods employed require further refinement. Future work should focus on expanding data sources and validating the conclusions across a broader range of aircraft models and airport environments to ensure their universality. Moreover, optimizing the parameter selection process is crucial for enhancing the objectivity and scientific rigor of both parameter filtering and data analysis. In conclusion, while this study has made meaningful progress, there remains considerable potential for further exploration and development in the field of flight data analysis.

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