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Study of Trajectory Filtering Methods for ADS-B Based on VSIMM-RSRCKF

Ruixin Li, Hongping Pu *

Sichuan University of Science & Engineering, Zigong, Sichuan, 10622, China
* **Corresponding author**: Hongping Pu (Email: 348108700@qq.com)

Abstract: In this paper, an advanced ADS-B trajectory filtering method combining Variable Structure Interactive Multi-Modeling (VSIMM) and Reduced Square Root Volume Kalman Filter (RSRCKF) is proposed. After deeply analyzing the operational characteristics of ADS-B system and the application requirements in the field of aviation, this paper aims to improve the accuracy of ADS-B trajectory tracking by this novel filtering method. In order to cope with the tracking performance problems that may be caused by the model set selection in the traditional interacting multi-model algorithm, the Variable Structure Interacting Multi-Model (VSIMM-RSRCKF) algorithm based on the Simplified Square Root Volume Kalman Filtering is adopted in this study for trajectory filtering. By constructing a comprehensive VSIMM model set to describe the dynamic system of maneuvering targets, the filtering method in this paper simplifies the computational process and reduces the computational complexity by squaring the covariance matrix in the iteration, and at the same time ensures the non-negative qualitative nature of the covariance matrix, which effectively avoids the divergence problem that may occur in the filtering process. The goal of this research is to significantly improve the positioning accuracy and reliability of aircraft using the ADS-B system.

Keywords: ADS-B; Trajectory Filtering; Variable Structure Interaction Multi-Model; Simplified Square Root Volume Kalman Filter.

1. Introduction

Automatic Dependent Surveillance-Broadcast (ADS-B), as a key technology to enhance the efficiency and safety of air traffic management, has become a development trend in the global aviation industry. ADS-B technology is able to provide accurate aircraft position information and realize real-time monitoring of flights[1]. However, due to signal interference, multipath effect, receiving equipment performance and other factors, the data received by ADS-B system has a certain degree of error and instability. In order to ensure the safety of flights and improve the navigation accuracy, effective filtering of ADS-B signals is particularly important. At present, the filtering research for ADS-B data mainly focuses on the traditional Kalman filter and its improved algorithms. Although these methods improve the accuracy of filtering to some extent, they still have problems such as model switching lag and poor adaptability to dynamic environment[2]. To overcome these challenges, researchers have begun to explore filtering techniques that combine multi-model and simplified square-root volumetric Kalman filters. Considering the characteristics of the ADS-B system and the limitations of the existing methods, this study aims to propose a new filtering method based on Variable Structure Interactive Multi-Model (VSIMM) and Simplified Square Root Volume Kalman Filter (RSRCKF). The method intends to achieve a more accurate and stable filtering effect on ADS-B data by dynamically adjusting the filtering model structure, combined with the integration of regional information, in order to enhance the positioning accuracy and reliability of aircraft when using the ADS-B system.

2. Related Research

Automatic Dependent Surveillance-Broadcast (ADS-B) is an air traffic surveillance technology based on aeronautical data link. Compared with primary and secondary radar surveillance, ADS-B has lower construction cost, wider coverage, higher accuracy, and faster data update, and is therefore widely used in air traffic surveillance and field surveillance. However, when an airplane broadcasts ADS-B messages, it may be affected by external environmental factors such as temperature, atmosphere, wind direction, etc., which requires a filtering method to predict and correct the data to improve the accuracy of the trajectory. Traceless Kalman filter has poor convergence when dealing with high-dimensional nonlinear models; volumetric Kalman filter is computationally intensive and numerically unstable during the recursive process; and simplified square root volumetric Kalman filter has a concise design with fewer parameters to be adjusted, a rigorous mathematical reasoning process and better convergence, and is an optimal estimation based on Gaussian process, with a more accurate estimation accuracy than traceless and volumetric Kalman filters. Kalman filter is more accurate than the traceless Kalman filter and volumetric Kalman filter[3]. The interactive multi-model filtering algorithm is a soft-switching algorithm, which uses multiple models to represent the states in the filtering process, and then estimates the state of the system through a weighted fusion method, thus solving the problem of large estimation error of single model. However, the tracking performance of the interactive multi-model filtering algorithm depends heavily on the selected set of models, and more models need to be added in order to improve the tracking performance, which not only increases the amount of computation, but also may degrade the tracking performance in some cases. In contrast, the variable-structure interactive multi-model algorithm is able to dynamically update the model set, which reduces the computational effort and improves the adaptivity relative to the fixed-structure interactive multi-model algorithm[4]. In summary this paper uses a variable structure interactive multi-model algorithm combined with a simplified square root volume Kalman filter to filter the trajectory in the context of ADS-B message data trajectory filtering applications.

3. Methodologies

3.1. VSIMM

The Variable Structure Interactive Multi-Modeling is an advanced multi-model based filtering strategy. This strategy improves the accuracy and robustness of filtering by dynamically adapting the model structure to various states of the system. The model structure of VSIMM consists of two main parts: the model collection and the model switching mechanism. The model collection covers all possible states of the system, and each state corresponds to a model[5]. The model switching mechanism dynamically selects the most suitable model for the current state based on the actual observation data of the system. The working principle of VSIMM mainly includes two steps: prediction and update. In the prediction step, VSIMM predicts the next state of the system based on the currently selected model. In the updating step, VSIMM updates the state and weights of the model based on the actual observation data and selects a new model based on the weights.

3.2. RSRCKF

The Reduced-Order Square-Root Cubature Kalman Filter (RSRCKF) represents an innovative improvement over traditional Kalman filtering techniques. The filter effectively reduces the computational complexity by optimizing the computational process, while ensuring highly accurate filtering results. The core of the RSRCKF algorithm consists of two key steps: prediction and update. In the prediction phase, RSRCKF predicts the state and its covariance at the next moment based on existing state estimates and system models. And in the updating phase, the filter utilizes the newly acquired observations to correct the state estimates and covariances to improve the filtering performance.

3.3. VSIMM-RSRCKF

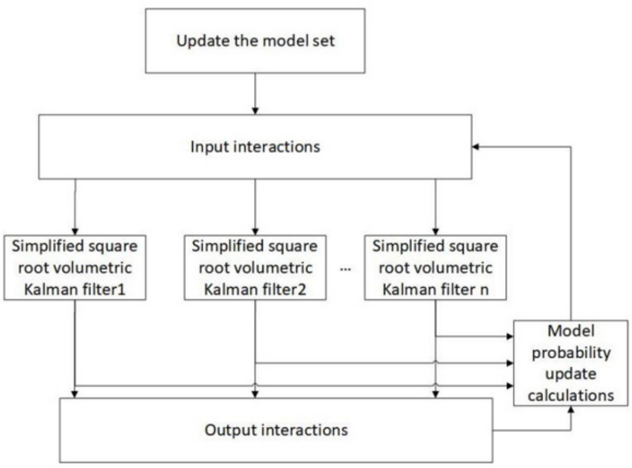

Fig 1. VSIMM-RSRCKF algorithm flow chart

The tracking research of moving targets mainly depends on two aspects: firstly. Firstly, the correct establishment of the model set can accurately reflect the running state of the moving target; secondly, the appropriate filtering algorithm can effectively filter out the errors and improve the accuracy of ADS-B track filtering[6]. VSIMM algorithm model set and probabilistic transfer matrix can be variable according to the target's movement, terrain and other factors, etc., and different model sets are used under different conditions, which not only improves the system's computational efficiency but also ensures that the selected model matches the system's movement. VSIMM-RSRCKF algorithm uses the VSIIMIMI algorithm to optimize the model set [7]. The VSIMM-RSRCKF algorithm uses the VSIMM algorithm to optimize the model set, and the RSRCKF algorithm, which is a more rigorous filtering algorithm, is used.

Model set updating definition $M=\{m_1,m_2,\cdots,m_N\}$is the total model set describing the system, based on the target state estimation at the (k-1) moment and the information of the model set M'_{k-1} at the (k-1) moment to delete invalid models and update the model set M'_k, where $M'_{k-1}\in M, M'_k\in M$. m_k denotes the model that matches the target movement during this time, $m_k^s(s\in M'_k)$ denotes the model that matches model s during this time, μ_k^s denotes the transfer probability of model s, and μ_k^s denotes the transfer probability of model s during the k moment. motion, $m_k^s(s\in M'_k)$ denotes that the matching model is s at moment k, and μ_k^s denotes the transfer probability for model s.

Input Interaction Assuming that the matching models are r and s at moments (k -1) and k, $r\in M'_{k-1}$and $s\in M'_k$, the transfer probability of switching from the matching model r at the moment of (k-1) to the matching model s at the moment of k is related to M'_{k-1} and M'_k, which is shown in Eq. (1) as follows.

$$P_{rs}[M'_{k-1},M'_k]= P\{m_k^s\in M'_k \mid m_{k-1}^r\in M'_{k-1}\} \tag{1}$$

The predicted probability of model s is expressed as

$$c^s=\sum_{r\in M'k-1} P_{rs}[M'_{k-1},M'_k]u_{k-1}^r \tag{2}$$

The mixing probability of the model is

$$\mu_{k-1|k-1}^{rs}=P\{m_{k-1}^r \mid m_k^s,\boldsymbol{Z}_{k-1}\}= \frac{P_{rs}[M'_{k-1},M'_k]\mu_{k-1}^r}{c^s}, \tag{3}$$

$$\boldsymbol{x}_{k-1|k-1}^{0s}=\sum_{r\in M'k-1}\boldsymbol{X}_{k-1|k-1}^r\mu_{k-1|k-1}^{rs} \tag{4}$$

$$\boldsymbol{P}_{k-1|k-1}^{0s}=\sum_{r\in M'k-1}\mu_{k+1|k+1}^{rs} [\boldsymbol{P}_{k-1|k-1}^r+\{\boldsymbol{x}_{k-1|k-1}^r-\boldsymbol{x}_{k-1|k-1}^{0s}\}\cdot \{\boldsymbol{x}_{k-1|k-1}^r-\boldsymbol{x}_{k-1|k-1}^{0s}\}^{\mathrm{T}}]_0 \tag{5}$$

Model probability update the model probability update is the computation of s model probability in$\in M'_k$, i.e.

$$\mu_k^s=\frac{\Lambda_k^s\sum_{r\in M'k-1}P_{rs}[M'_{k-1},M'_k]\mu_{k-1}^r}{\sum_{l\in M'k}\Lambda_k^l\sum_{l\in M'k_{k-1}}P_{rl}[M'_{k-1},M'_k]\mu_{k-1}^r}= \frac{1}{c}\Lambda_k^s c^s, \tag{6}$$

where $c=\sum_{l\in M'k}\Lambda_k^l c^l$.

Estimation fusion is to give the overall estimate and the overall estimation error covariance at moment k, respectively

$$\boldsymbol{x}_{k|k}=\sum_{s\in M'k}\mu_k^s\boldsymbol{x}_{k|k}^s \tag{7}$$

$$\boldsymbol{P}_{k|k}=\sum_{s\in M'k}\mu_k^s\{\boldsymbol{P}_{k|k}^s+ [\boldsymbol{x}_{k|k}^s-\boldsymbol{x}_{k|k}][\boldsymbol{x}_{k|k}^s-\boldsymbol{x}_{k|k}]^{\mathrm{T}}\} \tag{8}$$

3.4. Simulation Results and Analysis

The initial condition of the target is set as X= [0 15 0 2000 0 0], and the target makes a uniform motion along the x-axis at t=0~400s, a slow turn to the y-axis at t=400~600s, a uniform motion along the y-axis at t=600~610s, a fast turn to the x-axis at t=610 ~ 660s, and a uniform motion along the x-axis at t=660 ~ 900s, and the trajectory of the motion is shown in Fig. 2. The sampling period T=2s, the transfer probability matrix of Markov chain of the control model conversion is

$$\boldsymbol{P}=\begin{bmatrix}0.950 & 0.025 & 0.025\\ 0.025 & 0.950 & 0.025\\ 0.025 & 0.025 & 0.950\end{bmatrix} \tag{9}$$

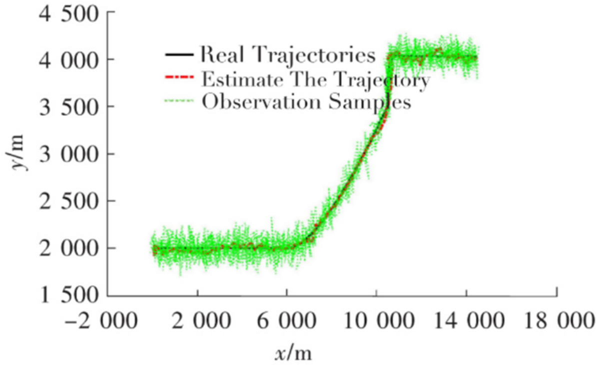

Fig 2. Target motion track

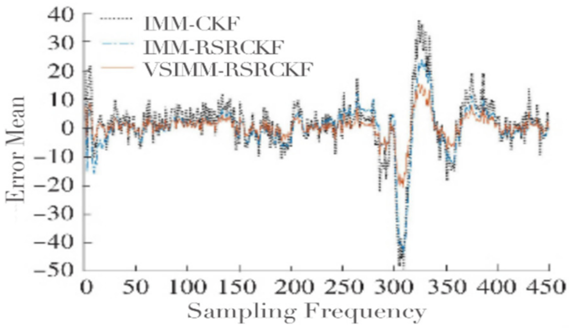

Fig 3. Mean estimation error in x direction

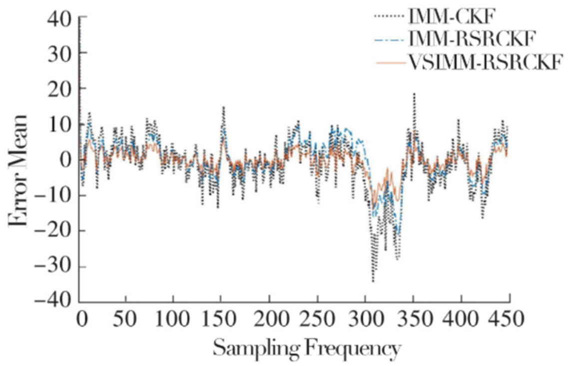

Fig 4. Mean estimation error in y direction

Fig. 3 and Fig. 4 show the mean estimation error (MAE) of the three algorithms IMM-CKF, IMM-RSRCKF, VSIMM-RSRCKF in the x-direction and y-direction, respectively, and it can be seen that the MAE of VSIMM-RSRCKF algorithm is smaller than that of IMM-CKF and IMM-RSRCKF algorithms.

IMM-RSRCKF algorithms, and the mean error values of the three algorithms fluctuate greatly around 310s, which is caused by the fast turning motion of the target in 305~330s, but the mean error value of the VSIMM-RSRCKF algorithm still remains within -20~20, which indicates that the VSIMM-RSRCKF algorithm has better tracking accuracy.

4. Conclusion

In In this study, a variable structure interactive multi-model algorithm based on simplified square root volume Kalman is proposed for filtering aircraft trajectories. The algorithm has the ability to dynamically update the model set, which can improve the computational efficiency and show excellent adaptivity. We compare the simulation results of the VSIMM-RSRCKF algorithm with the IMM-CKF algorithm and the IMM-RSRCKF algorithm in terms of mean absolute error (MAE). Also, we quantitatively measure the errors of these algorithms from the perspective of the average value of the MAE metric. The results show that the VSIMM-RSRCKF algorithm outperforms the IMM-CKF algorithm and the IMM-RSRCKF algorithm in terms of filtering accuracy and has a higher computational efficiency. Applying the VSIMM-RSRCKF algorithm to ADS-B trajectory filtering can realize accurate and real-time tracking of aircraft, which is an important reference value for future ADS-B trajectory filtering. However, the data in this study is derived from simulation, and it needs to be verified in the real environment in the future.

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