

A Maneuvering Target Tracking Algorithm Based on the Interacting Multiple Models

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Abstract

In view of the limitation of the traditional Kalman filter with which the tracking has big calculation amount and low tracking precision base on the model of CV or CA movement, a algorithm is suggested in the present article which is the Interacting Multiple Models Kalman filter (IMM-KF) with the CV and CA model under keeping invariant of the tracking precision of linear motion. This method can make the tracking precision of curve motion approach the linear motions. The system simulation results show that this algorithm improved the tracking precision of system with the IMM-KF.

Keywords: Kalman filter, target tracking, maneuver, IMM (Interacting Multiple Models), system simulation

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1. Introduction

Maneuvering target tracking uses a variety of detection methods (such as radar, sonar, infrared, etc.) on moving targets such as aircraft missiles, such as the state of motion (such as position, velocity, acceleration, height) method to estimate and track. Maneuvering target tracking contains a simpler single sensor single target tracking, multi-sensor single target tracking and complex multi-sensor multi-target tracking. Maneuvering Target Tracking solve several important problems [13] [14]:

- (1) Maneuvering target model.
- (2) Maneuvering target tracking and maintenance. Including tracking gate formation, maneuver detection and adaptive filtering.
- (3) Maneuvering target tracking data association (Data Association). Cluttered multi-objective and multi-sensor data association.
- (4) Start and end of maneuvering target tracking (Initiation and Termination).
- (5) Tracking performance analysis.

One of the basic elements of maneuvering target tracking target motion model. The general principles of the establishment of the target model is that the model is necessary to meet the actual target, but also to facilitate real-time processing of the data. The target model is divided into two categories according to whether the target mobile: mobile target model, mainly first-order time-dependent model (Singer model) [1] [3] and the current statistical model [1] [3]; another type of non-maneuvering target model, the main CV and CA model.

CV and CA models are two models. Not only the basic target motion model is the most widely used of the two models, but also the basis for export to other models. Small amount of calculation, and the need for timely tracking. For uniform and uniformly accelerated linear motion or nearly uniform and uniformly accelerated linear motion, the model can achieve high tracking accuracy. But when the target is a strong motor, using the CV model will cause large errors, and the need to take full account of the goal of the motor state. Therefore, in order to further improve the tracking accuracy Kalman tracking filter as a target motion model with uniform velocity (CV) or constant acceleration (CA) movement, this paper presents an interactive CV and CA movement model maneuvering target tracking algorithm [1] [2] [15].

In the maneuvering target tracking, target movement cannot rely on a model to describe only the use of multiple models. Different models can be well described by the movement of the target in the different segments of the movement. Passive positioning itself with silence, the radiation source target in the navigation or flight is unlikely to often in violent maneuver to avoid

the enemy, so the choice of the model to the model-based target uniform state, together with the longitudinal acceleration or cornering maneuver model.

Interacting Multiple Model (Interacting Multiple Model, IMM) algorithm [9] [10] is based on the ideology of Studies have shown that interacting multiple model algorithm can well realize the maneuvering target tracking. The method uses the parallel plurality of model filter to achieve the target tracking. Between the various models to achieve adaptive soft switch, its various timing estimation result of the estimation result of the different models resulting weighted mixed. Interacting multiple model algorithm is a recursive cycle which consists the input interaction model filtering model probability updates and interactive output of four steps [4] [5].

The IMM algorithm also has adaptive characteristics. It can effectively adjust the probability of each model [6] [7], especially suitable for positioning maneuvering target tracking. Interacting multiple model algorithm contains multiple filters (each corresponding mold keiki, an interactive role and an estimate of the mixer), motor sport multi-model interaction tracking a target. Each model transfer matrix is determined by the Markov probability, where in the element represents a transfer target by the i-th motion model to the probability of the j-th motion model. In this paper, based on an interactive multi-model Kalman filter derived the expression of the likelihood function, thus giving a complete cycle.

2. Basic Motion Model of a System

When the target maneuvers do uniform or uniformly accelerated linear motion, second order constant velocity CV model or third-order ordinary accelerate the CA model were used.

CV model:

$$\begin{bmatrix} x' \\ x'' \end{bmatrix} = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \begin{bmatrix} x \\ x' \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \omega(t) \quad (1)$$

In the above formula, x , x' and x'' are respectively, the position of the moving target, velocity and acceleration of the components; $\omega(t)$ is zero mean and variance of the white Gaussian noise.

The discrete-time system expression:

$$\begin{bmatrix} x(k+1) \\ x'(k+1) \end{bmatrix} = \begin{pmatrix} 1 & T \\ 0 & 1 \end{pmatrix} \begin{bmatrix} x(k) \\ x'(k) \end{bmatrix} + \begin{bmatrix} T^2/2 \\ T \end{bmatrix} \omega(k) \quad (2)$$

Which is zero mean Gaussian white noise variance.

CV model:

$$\begin{bmatrix} x' \\ x'' \\ x''' \end{bmatrix} = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix} \begin{bmatrix} x \\ x' \\ x'' \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \omega(t) \quad (3)$$

The discrete-time system expression:

$$\begin{bmatrix} x(k+1) \\ x'(k+1) \\ x''(k+1) \end{bmatrix} = \begin{pmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{pmatrix} \begin{bmatrix} x(k) \\ x'(k) \\ x''(k) \end{bmatrix} + \begin{bmatrix} T^2/2 \\ T \\ 1 \end{bmatrix} \omega(k) \quad (4)$$

3. The Basic Principles of the KALMAN Filter

The random signal value of the estimated observational data with noise (additive background noise) is called a waveform estimate. The basic waveform evaluation method is linear minimum mean square estimation to achieve the estimated typical filter is the Kalman filter [13].

3.1. The Equation of State

The assumed target state equation:

$$X(k+1) = F(k)X(k) + U(k)\bar{a}(k) \quad (5)$$

Measurement equation:

$$Z(k) = H(k)X(k) + V(k) \quad (6)$$

In the above formula, $X(k) = [x(k), x'(k), x''(k)]^T$, the state of the input matrix for U(k), the "current" motor acceleration mean for $\bar{a}(k)$. Basic Kalman filter equations:

Step predictive value

$$\hat{X}(k/k-1) = F(k/k-1)\hat{X}(k-1/k-1) \quad (7)$$

Step prediction mean square error

$$P(k/k-1) = F(k)P(k-1/k-1)F^T(k) + Q(k-1) \quad (8)$$

Filter gain matrix

$$K(k) = P(k/k-1)H^T(k)[H(k)P(k/k-1)H^T(k) + R(k)]^{-1} \quad (9)$$

The filtering mean square error array

$$P(k/k) = [I - K(k)]P(k/k-1) \quad (10)$$

State filtering value

$$\hat{X}(k/k) = \hat{X}(k/k-1) + K(k)[Z(k) - H(k)\hat{X}(k/k-1)] \quad (11)$$

3.2. The Basic Steps of the Kalman Filter

(1) According to the previous first filtered value $\hat{X}(k-1/k-1)$ (or the initial value for $\hat{X}(0/0)$) by calculating the predicted value

$$\hat{X}(k/k-1) = \Phi(k, k-1)\hat{X}(k-1/k-1) \quad (12)$$

(2) According to the the last filtering error covariance matrix $P_x(k-1/k-1)$ (or the initial value $P_x(0/0)$) prediction error covariance matrix

$$P_x(k/k-1) = \Phi(k, k-1)P_x(k-1/k-1)\Phi^T(k, k-1) + \Gamma(k-1)Q(k-1)\Gamma^T(k-1) \quad (13)$$

(3) Calculate the Kalman gain

$$K(k) = P_x(k/k-1)C^T(k) \left[C(k)P_x(k/k-1)C^T(k) + R(k) \right]^{-1} \quad (14)$$

(4) Calculate the filter estimated

$$\hat{\mathbf{X}}(k/k) = \hat{\mathbf{X}}(k/k-1) + \mathbf{K}(k) [\mathbf{Z}(k) - \mathbf{C}(k) \hat{\mathbf{X}}(k/k-1)] \quad (15)$$

(5) Filtering error covariance matrix

$$\mathbf{P}_x(k/k) = [\mathbf{I} - \mathbf{K}(k) \mathbf{C}(k)] \mathbf{P}_x(k/k-1) \quad (16)$$

Kalman filter algorithm successfully introduced into the state variable method filter theory to describe the state space suitable for the computer to operate directly linked discrete-time updates. Kalman filter algorithm is no longer required to save the last measurement data, the state transition equation, by means of the system itself, according to new data and the previous estimate of the time when the new data measured in accordance with a set of delivery push the formula, you can calculate the new estimate, thus greatly reducing the storage overhead required for filtering and computational overhead, and break through the restrictions of a stationary random process. Kalman filter algorithm has better prospects in the application.

4. Interactive Model Maneuvering Target Tracking Algorithm

Studies have shown that, when the relative acceleration is zero between the target and the sensor, the distance of the target state is not observed. In order to solve this problem, a single platform passive tracking platform has higher mobility than the target. Because of the passive tracking system cannot measure the distance to the target is a weak incomplete observation strongly nonlinear systems that can be observed. This will lead to instability of the tracking filter and the diverging phenomena. But if the platform has a higher mobility than the target, the movement of the carrier aircraft requirements are very exact, and its performance is not satisfied. While the use of multiple platforms on the target fusion tracking can effectively compensate for the deficiencies of the measurement information, the azimuth information obtained by the different platforms fusion processing. To achieve accurate track, the target is stable, while avoiding strong maneuverability of the platform.

Estimated that the state has a coefficient of linear Markov switching system but a major issue in this problem, the dynamic characteristics of the system assumes that the correct model described. IMM algorithm is a modern method of merging different model assumptions. The Markov switching coefficient of linear system can be described as follows:

$$\mathbf{X}_{k+1} = \mathbf{F}_k(\theta_{k+1}) \mathbf{X}_k + \mathbf{G}(\theta_{k+1}) \mathbf{w}_k \quad (17)$$

$$\mathbf{Z}_k = \mathbf{H}_k(\theta_k) \mathbf{X}_k + \mathbf{v}_k \quad (18)$$

Here θ_i is a finite state Markov chain, the probability P_{ij} of transfer from the model i to model j values in the range of $\{1, 2, 3, N\}$.

IMM algorithm for tracking maneuvering target model by mixing interaction. Assumed model switched from an initial Markov chain control input of the estimated mixer model probability model switching probability to calculate the estimates of each filter mixed. Each filter after mixing of the estimates and measurements, calculating a new set of estimates and the likelihood of. The likelihood that a priori probability model, and the model switching probability is used to calculate a new probability model. With the new state estimation model and their probability, all of the state estimation can be calculated. The IMM Algorithm N model several steps as follows:

(1) Mixed state estimation

The filtering process starting in the state estimated state error covariance and correlation model probability. The initial state estimate at time k of model j , the calculation process is as follows:

$$X_{k-1/k-1}^{0j} = \sum_{i=1}^N \mu_{k-1/k-1}^{i/j} X_{k-1/k-1}^i \quad (19)$$

Here

$$\mu_{k-1/k-1}^{i/j} = \frac{\mu_{k-1}^i P_{ij}}{\bar{C}_j}, \quad \bar{C}_j = \sum_{i=1}^N \mu_{k-1}^i P_{ij} \quad (20)$$

Mixing after covariance calculation:

$$P_{k-1/k-1}^{0j} = \sum_{i=1}^N \mu_{k-1/k-1}^{i/j} [P_{k-1/k-1}^i + (X_{k-1/k-1}^i - X_{k-1/k-1}^{0i}) \times (X_{k-1/k-1}^i - X_{k-1/k-1}^{0i})^T] \quad (21)$$

(2) Calibration of the model constraints

Kalman filter equations provide the calibration of the model constraints.

(3) Model likelihood calculation

Likelihoods calculated as follows:

$$\Lambda_k^j = \frac{1}{\sqrt{|2\pi T_k^j|}} \exp[-0.5(\bar{Z}_k^j)^T (T_k^j)^{-1} \bar{Z}_k^j] \quad (22)$$

(4) Model probability of correction

Model the probability of correction as follows:

$$\mu_k^j = \frac{1}{C} \Lambda_k^j \bar{C} \quad \text{and} \quad C = \sum_{i=1}^N \Lambda_k^i \bar{C}_i \quad (23)$$

(5) Combination of the output state estimation

The state estimates and error covariance of the output can be obtained by the following formula:

$$X_{k/k} = \sum_{i=1}^N \mu_k^j X_{k/k}^i \quad (24)$$

$$P_{k/k} = \sum_{i=1}^N \mu_k^i [P_{k/k}^i + (X_{k/k}^i - X_{k/k})(X_{k/k}^i - X_{k/k})^T] \quad (25)$$

5. Simulation Results and Analysis

In order to test the tracking performance of the new algorithm, the IMM-KF algorithm 200 times Monte Carlo simulation, compared with CA-CV algorithm. The simulation results shown in Figure 1, as shown in Figure 2.

IMM-KF algorithm target original trajectory curve given above, to measure the data curve, curve and the position of the filter data estimation error standard deviation curve. It can be seen from these figures, at the beginning of the filtering error, but as time goes on, the filtering error quickly lower the estimated value gradually approaching real trajectory will bring large errors when the model conversion between. Use the IMM-KF motor algorithm for target tracking, filtering effect by the transition probability matrix of the Markov chain control model conversion and Initial setting certain.

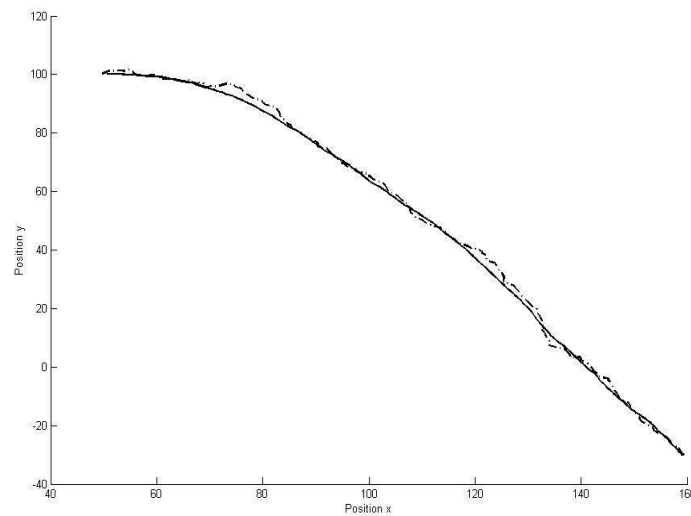


Figure 1. Sports model curve

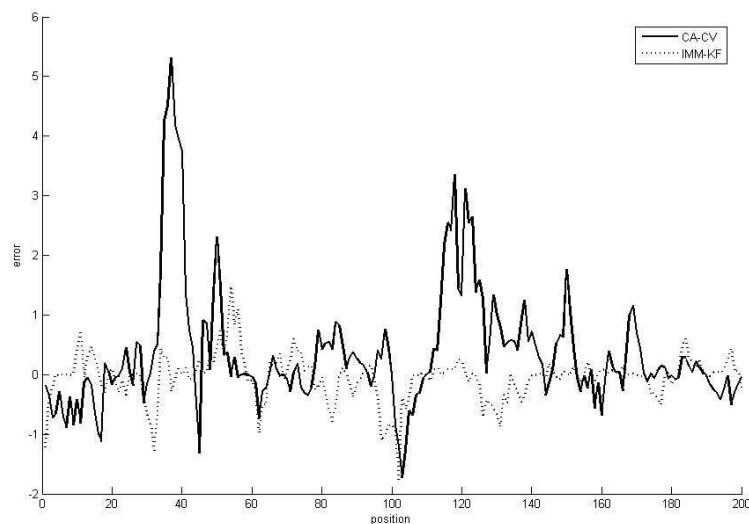


Figure 2. Position estimated standard deviation of the curve

6. Conclusion

In this paper, the single-platform target passive tracking problems of low inherent tracking accuracy and weak observability proposed target tracking algorithm are based on an interactive multi-platform. Derivation of the interactive process of the Kalman filter (IMM-KF) algorithm, in combination with CA and CV model, are succeed in passive tracking of maneuvering targets. The theoretical study and experiments show that:

- (1) The combination of CA and CV interactive motion model Kalman filter (IMM-KF) has better tracking accuracy and stability than CA and CV, and compared the accuracy and stability, a more real-time;
- (2) Multi-platform integration of passive target tracking, interactive filters than distributed filter better performance compared to other centralized improved filter, IMM-KF with better performance;

- (3) Using target mobile interactive multiple model filtering algorithm is better than a single model filtering algorithm performance and IMM-KF better tracking accuracy and stability, and strong real-time. Through experimental analysis shows that, IMM-KF with high filtering accuracy, stable performance and strong real-time, has a good practical application value.

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