International Journal of Control and Automation
Vol.8, No.10 (2015), pp.295-308
http://dx.doi.org/10.14257/ijca.2015.8.10.28

Curve Model of Adaptive Interaction Model Algorithm Tracking Method

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Abstract

Firstly, through the principle analysis and simulation experiment, the maneuvering target tracking algorithm of curve model interacting multiple model tracking algorithm was given. Because the algorithm is simple structure and high cost efficiency, it becomes generally applicable algorithm for the curve tracking model. But, the target mobility is very high in practice, Single target tracking model is no longer applicable curve tracking model. To improve the accuracy of tracking, the adaptive grid interacting multiple model (AGIMM) algorithm was given. The algorithm has two fatal weaknesses in the practical application. First, in maneuvering target tracking process, when the model changes and gradual change, the tracking precision is not high; Second, because the changing model structure is very large model sets, the algorithm is complexity and system processing speed is very slow, which cannot be widely used. To improve the accuracy and its scope of application of the algorithm, The paper proposed the adaptive Kalman filter adaptive interacting multiple model algorithm (AKFAIMM).The algorithm introduced the parameter in the adaptive Kalman filter, and adjusted parameter in maneuvering target tracking, the parameter was adjusted continuously in the curve motion model, it could greatly improve the tracking precision and the application of the model. Second, to improve the algorithm complexity. The paper improved that the angular velocity estimation method replaced centripetal acceleration estimation method on turning curve. The estimation method reduced the number of model set and reduced greatly of computation. At the same time, according to the algorithm in the model changes, the centripetal acceleration could be continuously adjusted and improved the adaptability of the model. The algorithm improved maneuvering target tracking algorithm accuracy. The effectiveness of algorithm was proved the validity by simulation.

Keywords: *Curve Model, Adaptive Model, Parameter Adaptive Algorithm, Adaptive Kalman Filter*

1. Introduction

In maneuvering target tracking, the selection of the tracking model directly affects the accuracy of target tracking， Therefore, it is important to select a targeting model. but it is a difficulty .Target tracking model can be divided into single model target tracking and multiple model target tracking, Single model target tracking is used a single model filter to work, It is very key to choice and fit the model of tracking maneuvering . According to different target model is very important.Multiple model target tracking refers to choose different models according to the movement characteristics of target. Its main purpose is to improve the precision of target tracking. Now, the commonly is used adaptive time-varying model interacting multiple model tracking model (IMM) [1-2], it is a powerful tool in the design of tracking model [3]. Because the algorithm is simple structure and

ISSN: 2005-4297 IJCA

high cost efficiency, it becomes generally applicable of algorithm for curve tracking model. But if it describes the curve motion model, it is not accurate or not covering the motor model, the tracking of maneuvering model accuracy will greatly reduce. Recently, many curve model tracking algorithms have been proposed, such as the adaptive switching grid interacting mesh model (SGIMM), the adaptive grid interacting multiple model (AGIMM) [4], the fixed grid interacting multiple model (FGIMM) and so on. In these models, the adaptive grid interacting multiple model (AGIMM) is widely used. But these algorithms have two fatal weaknesses in the practical application. First, in maneuvering target tracking process, when the model changes and gradual change, the tracking precision is not high; second, because the changing model structure is very large model set, the algorithm is complexity and system processing speed is very slow, which cannot be widely used. In order to better describe the maneuvering target and improve the tracking accuracy, the paper increases the model set and adjusts some parameters of the interacting multiple tracking model (IMM). An improved algorithm is the adaptive Kalman filter adaptive interacting multiple model algorithm (AKFAIMM). The algorithm improves the disadvantages of these models.

2. Related Work

2.1. Maneuvering Target Modeling

Assuming the target motion trajectory in the two-dimensional plane, the equations of motion can be described as [5-6]:

$$X(k+1) = F(\omega)X(k) + GW(k) \tag{1.1}$$

$$Z(k+1) = H(k)X(k) + V(k) \tag{1.2}$$

Where the W (k) and the V (k) represent an independent process noise and observation noise.

(1) Constant linear velocity model (CV)

When ω tends to 0, the motion approximates uniform linear motion model in small region. The acceleration of the model is regarded as the state noise. The target state is $X(K) = [x(k), \dot{x}(k), y(k), \dot{y}(k)]^T$, The following are state transition matrix, the interference matrix and the observation matrix:

$$F = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}, G = \begin{bmatrix} T^2/2 & 0 \\ 0 & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix}, H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

(2) Constant turn model (CT)

When $\omega > 0$, the motion turns left in small region. When $\omega < 0$, the motion turns right in small region. According to the actual situation of moving target, the ω can be limited $[\omega_{-\max}\ \omega_{\max}]$. The following are state transition matrix, the interference matrix and the observation matrix:

$$F = \begin{bmatrix} 1 & \frac{\sin\omega T}{\omega} & 0 & -\frac{1-\cos\omega T}{\omega} \\ 0 & \cos\omega T & 0 & -\sin\omega T \\ 0 & \frac{-\cos\omega T}{\omega} & 1 & \frac{\sin\omega T}{\omega} \\ 0 & \sin\omega T & 0 & \cos\omega T \end{bmatrix}, \quad G = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

Where X (k) represents maneuvering target horizontal speed; $\dot{x}(k)$ represents maneuvering target transverse coordinate acceleration; Y (k) represents maneuvering target ordinate speed; $\dot{y}(k)$ represents maneuvering target longitudinal coordinate acceleration, T represents the sampling time.

2.2. The Principle of the Algorithm IMM

Suppose that there are r models:

$$X(k+1) = F_j X(k) + G_j W(k), j = 1,2,k,r$$

Where, $W_j(k)$ is White noise series, and it is a zero mean and its variance is Q_j . Assuming the metastasis model of the maneuvering target is Markov process. The transfer matrix is P， following is the transfer matrix P :

$$P = \begin{bmatrix} p_{11} & L & P_{1r} \\ M & O & M \\ P_{1r} & L & P_{rr} \end{bmatrix}$$

$$Z(k) = H_j(k) X_j(k) + V_j(k)$$

Figure 1 shows flow chart of IMM, The algorithm of IMM includes interaction device, linear Kalman filter, model probability estimator and mixed estimator. The calculation method is: first, initial value is inputted interaction, initial value of filter J of K+1 time is calculated ,these are the state estimation $\hat{X}^j(k+1)/(k+1)$,the covariance $P^j(k+1)/(k+1)$, the residuals $V^j(k+1)/(k+1)$, the covariance $S^j(k+1)/(k+1)$. Second,

The models are updated, estimation of the interaction matrix of $\hat{X}(k+1)/(k+1)$ and $P(k+1)/(k+1)$ are calculated。

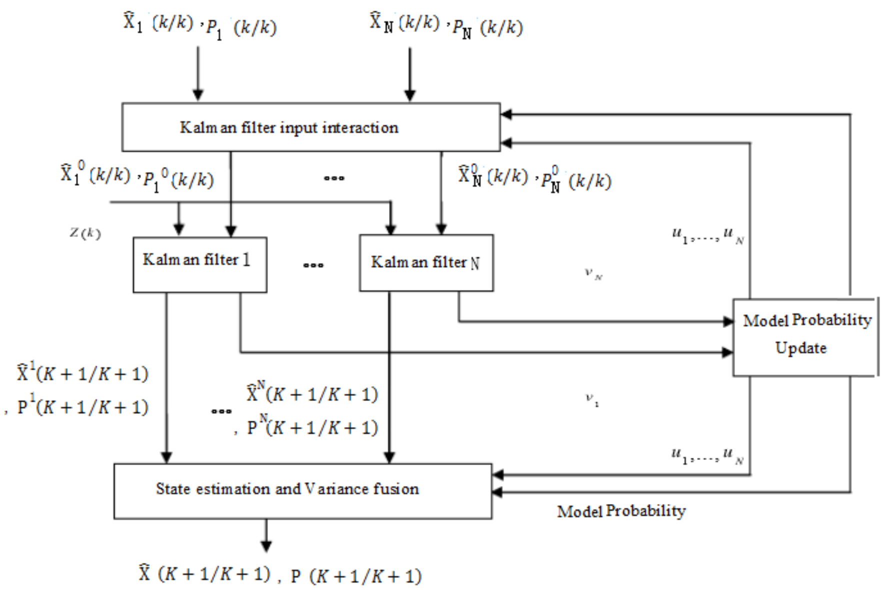

Figure 1. Flow Chart IMM

3. An Improved Kalman Algorithm

When the interacting multiple model (IMM) is use for target tracking, the algorithm itself is adaptive. But the algorithm exists problem of model selection. According to the different selection model, the variable structure interacting multiple model (VIMM) algorithm and adaptive interaction multiple model (AIMM) and so on. Because these algorithm increase the model set [7], when motion state changes, algorithm parameters must also be adjusted. The tracking effect of these algorithms is good in short distance. But it is more difficult to determine origin or goal of the maneuvering target, and it is bad for the tracking of long distance. Because of the shortcoming, this paper presents a parameter adaptive model structure.

3.1. Improved Motion Equation

In 3.1, $W(K)$ represents the process noise movement, the noise is mainly caused by the velocity error. And in this state equation is average ($\overline{\alpha}$) for colored noise. Because the noise is nonlinear, it is not easy to estimate. For easy analysis maneuvering target motion state, $W(K)$ equations for:

$$W(K) = \bar{a} + \tilde{w}(t) \tag{3.1}$$

Where, $\tilde{\omega}(t)$ represents mean zero and Gauss noise the variance of $\delta^2 Q$, $\bar{a}$ represents the mean of colored noise , the range of $\bar{a} = [\bar{a}_x \quad \bar{a}_y]^T$, The equation of 2.2 to 1.1 can be the following equation:

$$X(k+1) = F(\omega)X(k) + B(\omega)\bar{a} + G\tilde{W}(k) \tag{3.2}$$

The matrix of the $B(\omega)$ is:

$$B(\omega) = \begin{bmatrix} T - \frac{\sin \omega T}{\omega} & \frac{1-\cos\omega T}{\omega} \\ T - \cos \omega T & \sin \omega T \\ -\frac{1-\cos\omega T}{\omega} & T - \frac{\sin\omega T}{\omega} \\ -\sin \omega T & T - \cos \omega T \end{bmatrix};$$

The model of noise variance: $Q(k) \cong \begin{bmatrix} \frac{T^4}{3} & \frac{T^3}{2} \\ \frac{T^3}{2} & T^2 \end{bmatrix}$, $\delta_\omega^2 = \beta \ (\overline{\alpha}_{max} - \overline{\alpha})$

Where, β is a constant coefficient; $\overline{\alpha}_{max}$ is the velocity limit of two-dimensional plane, $\overline{\alpha}_{max} = [\overline{\alpha}_{xmax}\, \overline{\alpha}_{ymax}]^T$.

In maneuvering target tracking , the Kalman filter algorithm is commonly used mathematical model to describe and estimate the maneuvering target parameters [8]. But the recursive algorithm is applied for the noisy linear dynamic system state. The recursive algorithm is the process of continuous prediction and correction. When the system model, observation model and noise are linear and the Gaussian distribution, the model is optimal. In order to improve these disadvantages, If the $\bar{a}$ is a previous cycles filtering speed, the model is equivalent to the adaptive Kalman filter algorithm, and assuming the metastasis model of the maneuvering target is Markov process. The transfer matrix is $[P_{ij}]$, following procedures is from K to K+1 of calculation steps:

(1) according to the probability model u^j and the transfer matrix of the value, the initial state of the input $\hat{X}^{0j}(k/k)$ and $P^{0j}(k/k)$ are determined;

(2) The following adaptive Kalman filter algorithm:

(3) State prediction:

$$\hat{X}^j\left(k+1/_k\right) = F(\omega_j)\hat{X}^{0j}(k/k) + B(\omega_j)\bar{a} \tag{3.3}$$

(4) State prediction error covariance:

$$P^j\left(k+1/_k\right) = F(\omega_j)P^{0j}\left(^k/_k\right)F(\omega_j)^T + Q^j(k) \tag{3.4}$$

(5) Measurement predictor:

$$\hat{Z}^j\left(k+1/_k\right) = H^j(k+1)\hat{X}^j\left(k+1/_k\right) \quad (3.5)$$

（6） Residual covariance matrix:

$$S^j(k+1) = H^j(k+1)P^j\left(k+1/_k\right)H^j(k+1)^T + R^j(k+1) \quad (3.6)$$

（7） Matrix gain adaptive Kalman filter:

$$K^j(k+1) = P^j\left(k+1/_k\right)H^j(k+1)^T S^j(k+1)^{-1} \quad (3.7)$$

（8） Status update：

$$\hat{X}^j\left(K+1/_{K+1}\right) = \hat{X}^j\left(k+1/_k\right)K^j(k+1)\left[Z^j(k+1) - \hat{Z}^j\left(k+1/_k\right)\right] \quad (3.8)$$

（9） Filtering covariance matrix：

$$P^j\left(K+1/_{K+1}\right) = P^j\left(k+1/_k\right) + K^j(k+1)S^j(k+1)K^j(k+1)^T \quad (3.9)$$

（10） Calculate the corrected probability and the mixed output:

$$\hat{X}^j\left(K+1/_{K+1}\right) \text{ and } P^j\left(K+1/_{K+1}\right)$$

3.2. Simulation Comparison for the Improved Filter Model

In order to test the validity of the algorithm, tracking simulation waveform of the kalman filter (KF) and adaptive kalman filter (AKF) are given under the condition of same and the same target tracking state. Its state of motion shows in Table 1:

Table 1. Motion State

Serial	time（s）	ω	State	sampling period（s）	experiments number
1	0—35	0	Linear motion	one	fifty
2	36—101	-5.6	Turn right		
3	102—136	0	Linear motion		
4	137—182	5.6	Turn left		
5	183—200	0	Linear motion		

According to the adaptive Kalman filter algorithm steps，the transfer matrix $F(\omega)$ and the control matrix $B(\omega)$are function of $\omega$the function in the equation of state（type2.2） of maneuvering target.. Suppose $\omega \in [\omega_{-max} \quad \omega_{max}]$，and $\omega \approx 0$ is uniform linear motion model of maneuvering target, therefore according to the maneuvering target in the two-dimensional plane motion, the moment of K three target models (2.11), the model probability matrix(2.12) and the transfer matrix(2.13) respectively show :

$$M(k) = [\omega_L(k) \quad \omega_C(k) \quad \omega_R(k)] \quad (3.10)$$

$$u(k) = [u_L(k) \quad u_C(k) \quad u_R(k)] \quad (3.11)$$

$$P_{LCR} = \begin{bmatrix} P_{LL} & P_{LC} & P_{LR} \\ P_{LC} & P_{CC} & P_{CR} \\ P_{LR} & P_{RC} & P_{RR} \end{bmatrix} \quad (3.12)$$

Where $F(-5.6)$、$F(0)$和$F(5.6)$,probability model $u = [0.3 \quad 0.4 \quad 0.3]$, the transfer matrix $P_{LCR} = \begin{bmatrix} 0.8 & 0.1 & 0.1 \\ 0.1 & 0.8 & 0.1 \\ 0.1 & 0.1 & 0.8 \end{bmatrix}$, $\beta = 0.2$, The motion trajectory shows in Figure1, the simulation results show in Figure 3-Figure 5.

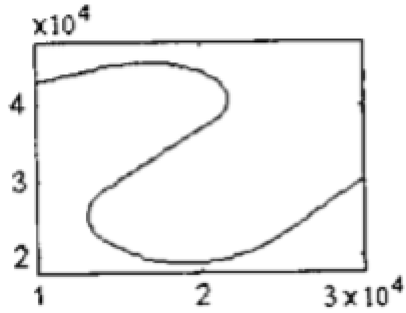

Figure 2. Target Trajectory

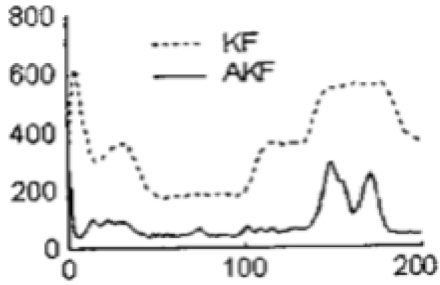

Figure 3. $F(-5.6)$ Variance Curve

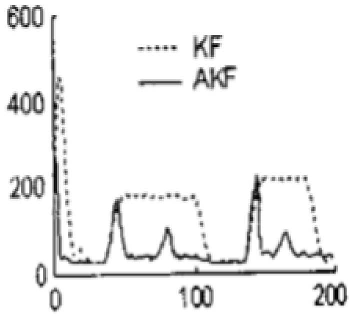

Figure 4. $F(0)$ Variance Curve

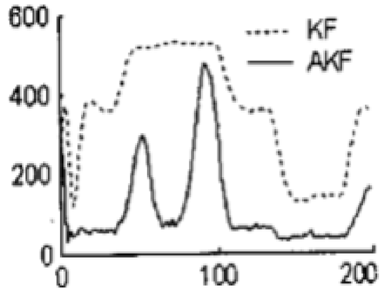

Figure 5. $F(5.6)$ Variance Curve

From the simulation results can be shown, the adaptive Kalman filter is obviously superior than the Kalman filter.

4. Adaptive Kalman Filtering with Adaptive Interactive Multiple Model Tracking Algorithm

Because Kalman filtering with adaptive interactive multiple model tracking algorithm is not high in the target tracking accuracy. In order to improve the algorithm, an adaptive Kalman filtering with adaptive interactive multiple model tracking algorithm is proposed in this paper. The algorithm is confirmed that the target tracking accuracy is improve and forecasted well the start position and end position of maneuvering target by simulation.

4.1. The Principle of the Improved Algorithm and Steps

Through type 3.10. 3.11and 3.12, K time model is built. That is K+1 moment's adaptive filtering algorithm with adaptive interacting multiple model algorithm in a cycle. Following steps:

Step 1: Center Model:$\omega_C(k)$

$$\omega_C(k) = u_L(k)\omega_L(k) + u_C(k)\omega_C(k) + u_R(k)\omega_R(k) \tag{4.1}$$

Step 2: Turn left model and right turn model:

$u_C(k) = \max[u_L(k) \quad u_C(k) \quad u_R(k)]$,

$$\begin{cases}\omega_L(k) = \max[\omega_{-max}, \omega_C(k) - \alpha\lambda_L] \\ \omega_R(k) = \min[\omega_{max}, \omega_C(k) - \alpha\lambda_R]\end{cases} \tag{4.2}$$

$u_L(k) = \max[u_L(k) \quad u_C(k) \quad u_R(k)]$,

$$\begin{cases}\omega_L(k) = \max[\omega_{-max}, \omega_C(k) - 2\lambda_L] \\ \omega_R(k) = \min[\omega_{max}, \omega_C(k) + \lambda_R]\end{cases} \tag{4.3}$$

$u_R(k) = \max[u_L(k) \quad u_C(k) \quad u_R(k)]$,

$$\begin{cases}\omega_L(k) = \max[\omega_{-max}, \omega_C(k) - \lambda_L] \\ \omega_R(k) = \min[\omega_{max}, \omega_C(k) + 2\lambda_R]\end{cases} \tag{4.4}$$

Type in:

$$\lambda_L = \max[\overline{\omega}, \omega_C(k-1) - \omega_L(k-1)] \tag{4.5}$$

$$\lambda_R = \max[\overline{\omega}, \omega_R(k-1) - \omega_C(k-1)] \tag{4.6}$$

Type in: $\overline{\omega}$ is a given constant; $0 < \alpha < 1$.

Step 3: The current model is filtered with the adaptive Kalman computing, and calculated the mixed output model.

The algorithm has shown some improvement, but model set and the load calculation system is greatly increased. It is the key problem that the motion model and control model are as small as possible in the case of contains effective movement patterns. The reason is mainly the model set increase in turn maneuvering target tracking, if the turning model is as small as possible, then curve model becomes small.

4.2. The Theoretical Analysis of Turn Model

In the critical study of maneuvering target tracking is turn model [9].Assuming that a goal of turn model is shown in Figure 6, the tangential acceleration of the goal is α_t,the normal acceleration of the goal is α_n , the turning angle of a cycle is $\Delta\theta$, The direction angle is $\Delta\emptyset$, in a circle linear momentum and angular momentum of the particles is described as :

$$v(t) = r\omega(t) \tag{4.7}$$

$$\alpha_t = \frac{dv(t)}{dt} = r\beta \tag{4.8}$$

Where r is radius of turning circle; $\beta$is angular acceleration.

$$\alpha_n = r\omega(t)^2 = v(t)\omega(t) \tag{4.9}$$

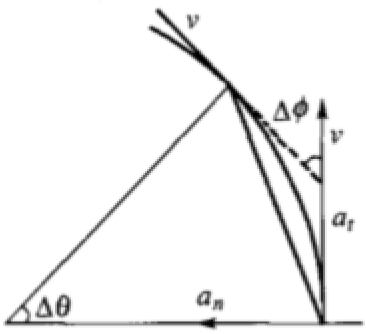

Figure 6. Maneuvering Target Turn Model

According to Figure 6, two-dimensional plane of each velocity component are :

$$\dot{x}(t) = v(t)\sin(\emptyset(t)) \tag{4.10}$$

$$\dot{y}(t) = v(t)\cos(\emptyset(t)) \tag{4.11}$$

By (4.7) - (4.11)， the two-dimensional plane continuous state equation of the maneuvering target can be described as：

$$\begin{bmatrix} \dot{x}(t) \\ \ddot{x}(t) \\ \dot{y}(t) \\ \ddot{y}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x(t) \\ \dot{x}(t) \\ y(t) \\ \dot{y}(t) \end{bmatrix} + \begin{bmatrix} 0 & 1 \\ \sin\emptyset(t) & \cos\emptyset(t) \\ 0 & 0 \\ \cos\emptyset(t) & -\sin\emptyset(t) \end{bmatrix} \begin{bmatrix} \alpha_t \\ \alpha_n \end{bmatrix} + \tilde{w}(t) \tag{4.12}$$

Assuming that each sampling period of maneuvering target is $kT \le t \le (k+1)$ in α_t and α_n piecewise constant， the state equation of curve of its discrete form is [10-12]:

$$\left|\frac{\dot{\alpha}_n}{\alpha_n}\right| \ll \frac{\alpha_t(t)}{v(t)} \tag{4.13}$$

When $\frac{\alpha_t(k)}{v_k} \ll \frac{2}{T}$,K is sampling time, T is sampling period :

$$\begin{bmatrix} x(k+1) \\ \dot{x}(k+1) \\ y(k+1) \\ \dot{y}(k+1) \end{bmatrix} =$$

$$\begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \end{bmatrix} + \begin{bmatrix} \frac{\cos\emptyset_k}{\omega_k^2} - \frac{T\sin\emptyset_K}{\omega_k} - \frac{\cos(\emptyset_k+T\omega_k)}{\omega_k^2} \\ \frac{\sin(\emptyset_k+T\omega_k)}{\omega_k} - \frac{\sin\emptyset_K}{\omega_k} \\ \frac{\sin(\emptyset_k+T\omega_k)}{\omega_k^2} - \frac{\sin\emptyset_K}{\omega_k^2} - \frac{T\cos\emptyset_k}{\omega_k} \\ \frac{\cos(\emptyset_k+T\omega_k)}{\omega_k} - \frac{\cos\emptyset_k}{\omega_k} \end{bmatrix} \alpha_n(k) +$$

$$\begin{bmatrix} \frac{T\cos\emptyset_k}{\omega_k} + \frac{\sin\emptyset_K}{\omega_k^2} - \frac{\sin(\emptyset_k+T\omega_k)}{\omega_k^2} \\ \frac{\cos\emptyset_k}{\omega_k} - \frac{\cos(\emptyset_k+T\omega_k)}{\omega_k} \\ \frac{\cos\emptyset_k}{\omega_k^2} - \frac{T\sin\emptyset_K}{\omega_k} - \frac{\cos(\emptyset_k+T\omega_k)}{\omega_k^2} \\ \frac{\sin(\emptyset_k+T\omega_k)}{\omega_k} - \frac{\sin\emptyset_K}{\omega_k} \end{bmatrix} \alpha_t(k) + \Gamma W(k) \tag{4.14}$$

When Γ is proper values, the equation of state curves model is:

(1) When $\alpha_n(k) = 0$, $\alpha_t(k) = 0$, the maneuvering targets becomes uniform rectilinear motion model.

(2) When $\alpha_n(k) = 0$, $\alpha_t(k) \neq 0$, (4.14) type third coefficient is $[0.5T^2 \sin\emptyset_k \quad T\sin\emptyset_k \quad 0.5T^2\cos\emptyset_k \quad T\cos\emptyset_k]$, maneuvering target becomes uniform speed linear motion model.

(3) When $\alpha_n(k) \neq 0$, $\alpha_t(k) = 0$, maneuvering targets becomes uniform circular motion model[13-14].

(4) Combined with (4.9) - (4.11) , when the first and the second of (4.14) merge that the curve of the maneuvering target model is :

$$\begin{bmatrix} x(k+1) \\ \dot{x}(k+1) \\ y(k+1) \\ \dot{y}(k+1) \end{bmatrix} =$$

$$\begin{bmatrix} 1 & \frac{\sin T\omega\emptyset_K}{\omega_k} & 0 & \frac{1-\cos(T\omega_k)}{\omega_k} \\ 0 & \cos(T\omega_k) & 0 & \sin T\omega_k \\ 0 & \frac{\cos(T\omega_k)-1}{\omega_k} & 1 & \frac{\sin T\omega_k}{\omega_k} \\ 0 & -\sin(T\omega_k) & 0 & \cos(T\omega_k) \end{bmatrix} \begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \end{bmatrix} + \begin{bmatrix} \frac{T\cos\emptyset_k}{\omega_k} + \frac{\sin\emptyset_K}{\omega_k^2} - \frac{\sin(\emptyset_k+T\omega_k)}{\omega_k^2} \\ \frac{\cos\emptyset_k}{\omega_k} - \frac{\cos(\emptyset_k+T\omega_k)}{\omega_k} \\ \frac{\cos\emptyset_k}{\omega_k^2} - \frac{T\sin\emptyset_K}{\omega_k} - \frac{\cos(\emptyset_k+T\omega_k)}{\omega_k^2} \\ \frac{\sin(\emptyset_k+T\omega_k)}{\omega_k} - \frac{\sin\emptyset_K}{\omega_k} \end{bmatrix} \alpha_t(k) +$$

$$\Gamma W(k) \tag{4.15}$$

4.3. Adaptive Interacting Multiple Model Tracking Model (AIMM)

If the model set $\left\{\{(\alpha_n^i, \alpha_t^j) | i = 1,2,\cdots,M, j = 1,2,\cdots,M\}\right\}$ corresponding to the standard AIMM state estimation is [15]:

$$\hat{x}(k+1/k+1) = \sum_{i=1}^{M}\sum_{j=1}^{M} \hat{x}^{ji}(k+1/k+1) Pr\{(\alpha_n, \alpha_t) = (\alpha_n^i, \alpha_t^j)/Z^{k+1}\} \tag{4.16}$$

The algorithm requires M×M estimator from the (4.16) type. The algorithm improves the performance of tracking maneuvering target at the same time, the calculation of system also increased greatly, to reduce computational complexity of maneuvering targets, the following an improved algorithm.

In maneuvering target tracking, curve motion model is the main reason that it causes the model set to increase and track poor accuracy. In fact, it can be gained from the formula (4.15) , estimation of centripetal acceleration only need to estimate real time angular velocity. The angular velocity estimation method is as follows:

Determining a time-varying model set:

$$\omega(k+1) = \omega(k) + T\beta \tag{4.17}$$

If the maneuvering target is uniform circular motion, $\beta = 0$, according to the formula

(4.7) - (4.9) :

$$\omega(k+1) = \omega(k) + \frac{T\omega(k)}{v(k)}\alpha_t(k) \cong \frac{\Delta\theta}{v(k)}\alpha_t(k) \tag{4.18}$$

According to Figure 6 :

$$\begin{cases} \Delta\theta(k) = \Delta\emptyset(k) \\ \emptyset(k) = \mathrm{arctg}(\dot{x}(k)/\dot{y}(k)) \end{cases} \tag{4.19}$$

(4.19) into (4.18) :

$$\omega(k+1) = \omega(k) + \frac{\Delta\theta}{v(k)}\alpha_t(k) = \frac{\mathrm{arctg}(x(k)/y(k)) - \mathrm{arctg}(x(k-1)/y(k-1))}{\sqrt{x(k)^2 + y(k)^2}}\alpha_k(k) \tag{4.20}$$

$$\begin{bmatrix} x(k+1) \\ \dot{x}(k+1) \\ y(k+1) \\ \dot{y}(k+1) \\ \omega(k+1) \end{bmatrix} = \begin{bmatrix} 1 & \frac{\sin T\omega\emptyset_K}{\omega_k} & 0 & \frac{1-\cos(T\omega_k)}{\omega_k} & 0 \\ 0 & \cos(T\omega_k) & 0 & \sin T\omega_k & 0 \\ 0 & \frac{\cos(T\omega_k)-1}{\omega_k} & 1 & \frac{\sin T\omega_k}{\omega_k} & 0 \\ 0 & -\sin(T\omega_k) & 0 & \cos(T\omega_k) & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \\ \omega(k) \end{bmatrix} + \begin{bmatrix} \frac{T\cos\emptyset_k}{\omega_k} + \frac{\sin\emptyset_K}{\omega_k^2} - \frac{\sin(\emptyset_k + T\omega_k)}{\omega_k^2} \\ \frac{\cos\emptyset_k}{\omega_k} - \frac{\cos(\emptyset_k + T\omega_k)}{\omega_k} \\ \frac{\cos\emptyset_k}{\omega_k^2} - \frac{T\sin\emptyset_K}{\omega_k} - \frac{\cos(\emptyset_k + T\omega_k)}{\omega_k^2} \\ \frac{\sin(\emptyset_k + T\omega_k)}{\omega_k} - \frac{\sin\emptyset_K}{\omega_k} \end{bmatrix} \alpha_t(k) + \Gamma W(k) \tag{4.21}$$

If the type (4.21) is used to estimate, only need M models for interaction in $\{\alpha_t^j | j = 1,2,\cdots,M\}$, While the centripetal acceleration is adjusted appropriately , The problem of large model set of IMM is effectively solved and determined. The calculation greatly reduces in tracking system, because it effectively reduces the amount of calculation turn model. It is shown in Table 2.

4.4. The Improved Algorithm Simulation

The same model of maneuvering target tracking is simulated in two-dimensional. Where $\omega \in [-5.6 \;\; 5.6]$, when $\overline{\omega} = 1.5$, the model adds noise. The adaptive interacting multiple model algorithm (AIMM) and the adaptive grid interacting multiple model (AGIMM) are compared. Through simulation 50 times, Figure 7 shows the position variance curve, and Figure8 shows speed variance curve. Figure 7 and Figure 8 show that the adaptive grid interacting multiple model (AGIMM) is better than the adaptive interacting multiple model algorithm (AIMM). Using the same method comparing the adaptive variable structure interacting multiple model algorithm (AGIMM) the adaptive Kalman filter adaptive interacting multiple model algorithm (AKFAIMM). Figure 9 and Figure 10 show that the adaptive filter structure adaptive interacting multiple model algorithm (AGAIMM) is better than the adaptive variable structure interacting multiple model (AGIMM).

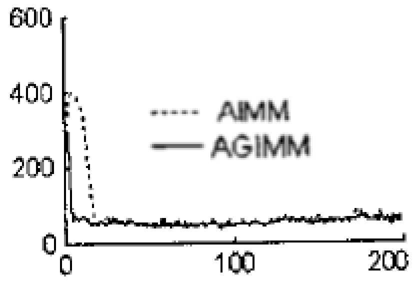

Figure 7. Position Variance Curve

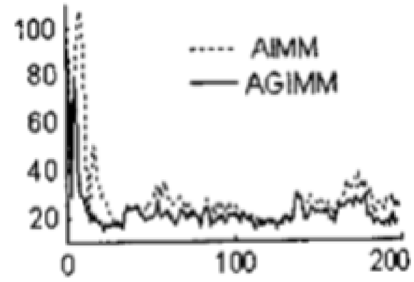

Figure 8.Speed Variance Curve

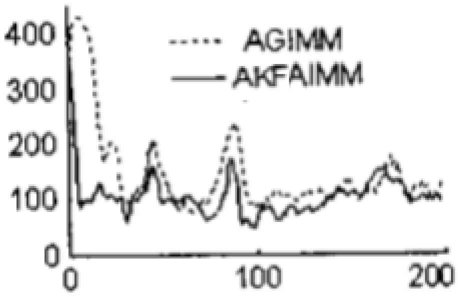

Figure 9. Position Variance Curve

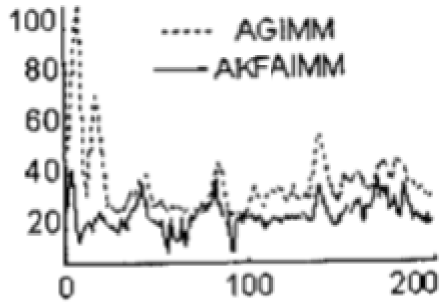

Figure 10. Speed Variance Curve

The simulation experiment shows that the proposed algorithm can cover well the maneuvering model in the paper, the algorithm obtained the very good tracking performance in position and speed, it is showed in Figure 8, 9 and 10. In calculation of load, the algorithm is better in the paper, Because secondary information, information covariance matrix and model probability need not calculate in the estimation of tangential acceleration, it reduces greatly operating time of the system .Table 2 shows three methods of using CPU in the same environment of single step operation time.

Table 2. Three Methods for Performance Comparison

algorithm	CPU time (ms)	position of the peak error (m2)	Peak velocity error ((m/s) 2)
AIMM	4.8	70.1	52.7
AGIMM	6.1	78.6	74.9
AKFAIMM	5.0	60.9	30.2

5. Conclusion and Future Work

The paper studies the adaptive Kalman filter adaptive interacting multiple model algorithm (AKFAIMM). The algorithm based on adaptive interacting multiple model algorithm (AIMM), So it improves two aspects: First, the parameter adaptive algorithm improves the tracking accuracy and determine the starting point and end point accuracy of maneuvering target in maneuvering target tracking; Second, the parameter adaptive algorithm reduces the number of maneuvering target motion curve turn model, and improves the system of execution speed. By comparison of simulation results the adaptive grid interacting multiple model algorithm (AGIMM) is better than adaptive interacting multiple model algorithm (AIMM), because adaptive interacting multiple model algorithm (AIMM) uses a fixed model set, when the algorithm model doesn't match for the actual mode, error greatly increases. The adaptive grid interacting multiple model algorithm (AGIMM) is compared with the improved algorithm in the paper. The accuracy and range of use of the adaptive Kalman filter adaptive interacting multiple model algorithm (AKFAIMM) is obviously better than the adaptive grid interacting multiple model algorithm (AGIMM) in maneuvering target tracking, because The adaptive grid interacting multiple model algorithm (AGIMM) doesn't use adaptive algorithm in the parameter selection. Table 3, Although the adaptive Kalman filter adaptive interacting multiple model algorithm (AKFAIMM) and adaptive interacting multiple model algorithm (AIMM) compared to increase the computational load but the peak error is smaller. When the use of the adaptive Kalman filter adaptive interacting multiple model algorithm (AKFAIMM), Because of fixed model using constant centripetal acceleration, Constant selection must be based on the motor model of concrete, or directly affects the accuracy of the maneuvering target tracking.

Acknowledgements

The authors are grateful to construction project of the Principle of Communication excellent course (Projects for creation teams) (No. 2014).

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