International Journal of the Physical Sciences Vol. 6(14), pp. 3347-3353, 18 July, 2011
Available online at http://www.academicjournals.org/IJPS
DOI: 10.5897/IJPS11.095
ISSN 1992 - 1950 ©2011 Academic Journals

Full Length Research Paper

A novel algorithm for multiple maneuvering target tracking

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Accepted 11 April, 2011

It is difficult to track multiple maneuvering targets in clutter due to the uncertain acceleration and the disturbance of the clutter. Taking these into account, a strong tracking modified input estimation (STMIE) is presented in this paper, which is combined with maximum entropy fuzzy joint probabilistic data association for multiple maneuvering target tracking. Strong tracking multiple fading factors are introduced in order to enhance the tracking performance of MIE for high maneuvering targets. The prediction covariance can be adjusted in real time by the multiple time-varying fading factors and the different data channels are faded at different rates. Simulations show the effectiveness of the proposed method for the cross and high maneuvering target tracking. Compared with the conventional current statistical model (CS) combined with maximum entropy fuzzy joint probabilistic data association, the proposed algorithm has higher tracking accuracy and good engineering application prospect.

Key words: Multiple maneuvering target tracking, data association, strong tracking filter, modified input estimation, multiple fading factor.

INTRODUCTION

With the increasingly complexity of war environments, the requirement of target tracking technologies has been on the increase. Recently, multi-target tracking has gain wide attention. Particularly, with the rapid development of modern aviation technology, the maneuverability of fighter planes and other aircrafts is growing stronger and stronger, which makes multiple maneuvering targets tracking an extremely difficult problem in target tracking filed.

In early multi-target tracking algorithm, data associated technologies, such as Joint Probabilistic Data Association (JPDA) (Fortmann et al., 1983), Joint Integrated Probabilistic Data Association (JIPDA) (Musicki and Evans, 2004) and Multiple Hypothesis Tracking (MHT) (Blackman, 2004), were widely used for multi-target state estimation. However, these algorithms have high computational complexity. In addition, as the target number increases, the computational cost increases exponentially, seriously affecting the real-time performance. Some improved algorithms were proposed (Roecker and Pillis, 1993; Roecker, 1994; Purank and Tugnait, 2007), but most of which decrease the computational burden at the cost of tracking accuracy. Taking the uncertainty of the target motion models into account, maximum entropy fuzzy (MEF) joint probabilistic data association filter was proposed (Li et al., 2006), clustering the validate measurements by a multi-parallel fuzzy clustering structure, and reconstructing the association probability matrix according to the values of membership. This association technology can track cross multiple targets well, and has a better real-time performance than the JPDA technology.

For a maneuvering target tracking, Singer (1970) suggested a zero-mean, time-correlated maneuvering acceleration model, which has been one of the foundations in the problem of state estimation for maneuvering targets, and varieties of adaptive algorithms have been developed in recent years. The "current" statistical (CS) model is more realistic than Singer's model on the target mobile pre-assumptions, which is recognized as an effective method for maneuvering targets tracking (Zhou and Kumar, 1984). However, the target tracking accuracy of this method often depends on the priori parameters of maneuvering targets, such as the maneuvering frequency and maximum acceleration, etc. The tracking performance will be seriously affected by

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inappropriate value of the priori parameters. Interacting Multiple Mode (IMM) algorithm, proposed by Blom (1988), is considered as a good compromise between the tracking accuracy and computational complexity, but the tracking accuracy depends on the match degree of pre-designed models with the actual situation of the maneuvering target. In addition, with the increase in the number of models, the calculational cost will also increase significantly, thus seriously affecting the real-time performance for maneuvering target tracking. Khaloozadeh and Karsaz (2009) introduced a new algorithm of state estimation called modified input estimation (MIE). The MIE method has provided a special augmentation in the state model by considering the unknown acceleration vector as a new augmented component of the target state, which succeeds in estimating the target trajectory, velocity and acceleration in low and mild maneuvering situations. However, the performance of MIE will be serious degradation for high maneuvering target tracking. Fuzzy MIE algorithm was proposed with the introduction of a fuzzy forgetting factor or a fuzzy fading memory, making an effective improvement of the tracking accuracy for high maneuvering target tracking (Bahari et al., 2009; Bahari and Pariz, 2009, 2010). However, the fuzzy reasoning rules depend on some priori knowledge of the maneuvering targets and need high computational cost, so this method has a poor real-time performance, and the tracking accuracy depends on the fuzzy reasoning rules designed.

To solve the aforementioned problems, we have proposed a strong tracking MIE (STMIE) algorithm (Yang and Ji, 2010), which can properly track a high maneuvering target by introducing multiple fading factors to adjust the predicted covariance and the corresponding filter gain in real time. In this paper, the STMIE algorithm will be extended to track multiple maneuvering targets in clutter. The crucial idea is that the maximum entropy fuzzy joint probabilistic data association filter is introduced and combined with the STMIE method for multiple maneuvering target tracking. Simulation results show that the proposed method has better tracking performance than the conventional method, and has a good application prospect in engineering.

MIE METHOD

Suppose that the state equation and the measurement equation of a single maneuvering target in two-dimensional case are described as follows, respectively:

$$X(k+1) = FX(k) + CU(k) + GW(k) \tag{1}$$

$$Z(k) = HX(k) + V(k) \tag{2}$$

Where $X(k) = [x(k) \;\; v_x(k) \;\; y(k) \;\; v_y(k)]^{\mathrm{T}}$ is a state vector at time k, including the information of position and velocity, $Z(k)$ is a measurement vector, $U(k) = [a_x(k) \;\; a_y(k)]^{\mathrm{T}}$ is an unknown acceleration vector. $W(k)$ and $V(k)$ are the state noise and the measurement noise, respectively, and are uncorrelated Gaussian white noise vectors. The covariance matrixes of $W(k)$ and $V(k)$ are $Q(k)$ and $R(k)$, respectively.

The uncertainty of the acceleration vector in Equation (1) makes tracking maneuvering target difficult. Khaloozadeh et al. (2009) suggested expanding the acceleration vector of the uncertain state into a new augmented component of a target state, and converting the maneuvering target state model into a non-maneuvering state model in augmented state. Augmented state equation is as follows:

$$X_{\mathrm{aug}}(k+1) = F_{\mathrm{aug}}(k)X_{\mathrm{aug}}(k) + G_{\mathrm{aug}}(k)W_{\mathrm{aug}}(k) \tag{3}$$

$$Z_{\mathrm{aug}}(k) = H_{\mathrm{aug}}(k)X_{\mathrm{aug}}(k) + V_{\mathrm{aug}}(k) \tag{4}$$

The filter gain is defined as:

$$K_{\mathrm{aug}}(k+1) = [P_{\mathrm{aug}}(k+1\,|\,k)H_{\mathrm{aug}}^{\mathrm{T}}(k+1) + G_{\mathrm{aug}}(k)T_{\mathrm{aug}}(k)]R_{\mathrm{aug}}^{-1}(k) \tag{5}$$

As can be seen from Equation (5), $K_{\mathrm{aug}}(k+1)$ is determined by the prediction covariance, $P_{\mathrm{aug}}(k+1\,|\,k)$ and $T_{\mathrm{aug}}(k)$, $T_{\mathrm{aug}}(k)$ denotes the cross-covariance and is discussed (Khaloozadeh and Karsaz, 2009). Usually, when the system reaches a stable state, the prediction covariance will tend to the minimum. Thus, when a low and/or medium maneuver occurs, $T_{\mathrm{aug}}(k)$ will play a decisive role in the filter gain adjustment, which guarantees the filter's convergence. But, when a high maneuver occurs suddenly, the residues increases rapidly, while the prediction covariance cannot be promptly adjusted, thus causing the filter gain to fail reasonable adjustment, eventually leading to the loss in the capability of the MIE algorithm for high maneuvering target tracking.

STMIE ALGORITHM

In order to ensure the MIE filter a strong tracking filter performance, multiple fading factors were introduced to adjust the predicted covariance (Yang and Ji, 2010). In the light of the design of the strong tracking filter, the filter gains must satisfy the following equations:

$$E\left\{[x_{\mathrm{aug}}(k+1) - \hat{x}_{\mathrm{aug}}(k+1\,|\,k+1)]\cdot[x_{\mathrm{aug}}(k+1) - \hat{x}_{\mathrm{aug}}(k+1\,|\,k+1)]^{\mathrm{T}}\right\} = \min \tag{6}$$

$$E[d_{\mathrm{aug}}^{\mathrm{T}}(k+1)\cdot d_{\mathrm{aug}}(k+1+j)] = 0, k = 0,1,\cdots, j = 1,2,\cdots. \tag{7}$$

where $d_{\mathrm{aug}}(k+1)$ is the residue ,

$$d_{\mathrm{aug}}(k+1) = Z(k+1) - H_{\mathrm{aug}}(k+1)\hat{x}_{\mathrm{aug}}(k+1\,|\,k) \tag{8}$$

To obtain the appropriate time-varying gain $K_{\text{aug}}(k+1)$ $P_{\text{aug}}(k+1|k)$ needs to be adjusted in real time, that is:

$$P_{\text{aug}}(k+1|k) = \Lambda(k+1)F_{\text{aug}}(k)P_{\text{aug}}(k|k)F_{\text{aug}}^{\mathrm{T}}(k) + G_{\text{aug}}(k)Q_{\text{aug}}(k)G_{\text{aug}}^{\mathrm{T}}(k) \quad (9)$$

where $\Lambda(k+1)$ denotes the multiple fading factor matrix, which can adjust the prediction covariance in real time by the changes of the residues, and thereby adjusting the corresponding filter gain $K_{\text{aug}}(k+1)$.

Multiple fading factor matrix is defined as:

$$\Lambda(k+1) = \mathrm{diag}[\lambda_1(k+1), \lambda_2(k+1), \cdots, \lambda_n(k+1)] \quad (10)$$

where $\lambda_i(k+1) = \max\{a_i c(k+1), 1\}, i = 1, 2, \cdots, n$, the derivation of fading factor $\lambda_i(k+1)$ refer to (Zhou and Frank, 1999).

Remark

When a high maneuver occurs suddenly, the residue increases rapidly, and the prediction covariance will be promptly adjusted by $\Lambda(k+1)$, thus causing the filter gain to be reasonably adjusted, and the $\Lambda(k+1)$ fading the different data channels at different rates so that the tracking system can achieve a stable state in a short time, so that the STMIE method can properly track high maneuvering targets. When tracking system in a stable state, $\Lambda(k+1)$ will turn into an approximate unit matrix, and then the STMIE method will degenerate into the MIE method. $T_{\text{aug}}(k)$ will play a decisive role in the filter gain adjustment, which can better maintain the system stability and achieve the optimal estimation of the target state and guarantee the filter's convergence.

MAXIMUM ENTROPY FUZZY JOINT PROBABILISTIC DATA ASSOCIATION

Suppose a measure set $\{z_j, j = 1, 2, \cdots M_k\}$ is related to the target set $\{c_i, i = 1, 2, \cdots c\}$. The clustering process can be formulated as an optimization problem and the corresponding cost function is defined as:

$$E = \sum_{j=1}^{M_k}\sum_{i=1}^{c}(\mu_{ji} \cdot d(z_j, c_i)) \quad (11)$$

where $d(z_j, c_i)$ and μ_{ji} are the squared Euclidean distance and the degree of membership between the given data point z_j and the cluster center c_i, respectively. μ_{ji} subjects to the following constraints:

$$\sum_{i=1}^{c}\mu_{ji} = 1, \quad \forall \mu_{ji} \in [0,1] \quad (12)$$

According to the information theory, in order to minimize unbiased membership between the data points and the cluster center, the objective function is defined according to the maximum entropy principle as follows (Li et al., 2006):

$$J(U,C) = -\sum_{j=1}^{M_k}\sum_{i=1}^{c}(\mu_{ji}\ln\mu_{ji}) - \sum_{j=1}^{M_k}\alpha_j\sum_{i=1}^{c}(\mu_{ji} \cdot d(z_j,c_i)) + \sum_{j=1}^{M_k}\lambda_j(\sum_{i=1}^{c}\mu_{ji} - 1) \quad (13)$$

where α_j and λ_j are the Lagrange multipliers. By maximizing Equation (13), the membership function of the data z_j belonging to a cluster center c_i is derived as:

$$\mu_{ji} = \frac{\exp(-\alpha_j \cdot d(z_j, c_i))}{\sum_{k=1}^{c}\exp(-\alpha_j \cdot d(z_j, c_i))} \quad (14)$$

By varying α_j, it adjusts the value of membership of data point z_j with its nearest cluster center c_i. α_j is known as the "discriminating factor" (Li et al., 2006), where the proposed optimal value is given as:

$$\alpha_{opt} = -\frac{\ln(\varepsilon)}{d_{\min}(z_j, c_i)} \quad (15)$$

where ε is a small positive constant.

In case of multiple target tracking, we need reconstruct the association probability matrix:

$$\boldsymbol{\beta} = \{\beta_{ji}\} = \begin{pmatrix} \beta_{11} & \cdots & \beta_{1c} \\ \vdots & \ddots & \vdots \\ \beta_{M_k 1} & \cdots & a_{M_k c} \end{pmatrix} \quad (16)$$

]where β_{ji} is the association probability between the measurement z_j and the target i,

$$\beta_{ji} = \begin{cases} \mu_{ji}, & \text{if measurement } z_j \text{ is a validation measurement of target } i \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

Because of the complexity of environment and the inaccuracy of sensors, there are some conflict and ambiguity in data association. For example, one measurement may be associated with multiple targets, or multiple measurements originate from one target. In order to deal with these problems, the association probability matrix should be reconstructed according to the following rule: (i) If the measurement $Z_j(k)$ is only associated with a target, the association probability remains the same; (ii) If the measurement $Z_j(k)$ is associated with multiple targets, we reconstruct the

Table 1. Simulation parameters of two high maneuvering targets.

Simulation	Initial Position (m)	Initial velocity (m/s)	Acceleration (m/s^2)		
			0 - 20s	21- 40s	41 - 90s
Target 1	(100,400)	(80,100)	(0,0)	(5,10)	(0,-20)
Target 2	(100,10000)	(80,-100)	(0,0)	(5,-10)	(0,20)

association probability matrix $\boldsymbol{\beta}$ and process the uncertainty according to Equation (18):

$$\beta_{ji} = \begin{cases} \beta_{ji}, & \text{if } \beta_{ji} = \max_{m=1:M_k} \beta_{mi} \\ \min_{i\in\Omega}\{\beta_{ji}\}, & \text{otherwise} \end{cases} \tag{18}$$

where Ω is the set of all tracks associated with measurement $Z_j(k)$.

STEPS OF THE PROPOSED METHOD FOR MULTIPLE MANEUVERING TARGET TRACKING

Assuming that $\{\hat{X}^i_{\text{aug}}(k\mid k), i=1,2,\cdots n\}$ are the optimal estimations of n targets at time k in the fusion center, $\{P^i_{\text{aug}}(k\mid k), i=1,2,\cdots n\}$ are the corresponding state covariance matrices. Then, the iterative steps of the STMIE algorithm for the optimal multiple maneuvering targets estimation at time $k+1$ are thus explained in steps:

Step 1: The prediction of augmented states and measurements can be calculated by Equations (19) and (20):

$$\hat{X}^i_{\text{aug}}(k+1\mid k) = F_{\text{aug}}\hat{X}^i_{\text{aug}}(k\mid k) \tag{19}$$

$$Z^i_{\text{aug}}(k+1\mid k) = H_{\text{aug}}(k+1)\hat{X}^i_{\text{aug}}(k+1\mid k) \tag{20}$$

Step 2: Confirmation of effective measurements corresponding to the targets according to the equation:

$$\{Z_j(k) : g^2_{\text{aug}} \le \gamma, j=1,2,\cdots,M_k\}$$

where γ is a threshold:

$$S(k+1) = E[(Z_j(k+1)-Z^i_{\text{aug}}(k+1\mid k))(Z_j(k+1)-Z^i_{\text{aug}}(k+1\mid k))^{\mathrm{T}}],$$
$$g^2_{\text{aug}} = (Z_j(k+1)-Z^i_{\text{aug}}(k+1\mid k))^{\mathrm{T}} S^{-1}(k+1)(Z_j(k+1)-Z^i_{\text{aug}}(k+1\mid k)).$$

Step 3: Calculation of multiple fading factor matrix $\Lambda(k+1)$ according to Eq. (10).

Step 4: Prediction of covariance.

$$P^i_{\text{aug}}(k+1\mid k) = \Lambda(k+1)F_{\text{aug}}(k)P^i_{\text{aug}}(k\mid k)F^{\mathrm{T}}_{\text{aug}}(k) + G_{\text{aug}}(k)Q^i_{\text{aug}}(k)G^{\mathrm{T}}_{\text{aug}}(k) \tag{21}$$

Step 5: Reconstruction of the association probability matrix $\boldsymbol{\beta}$ by Equation (16) and processing the uncertainty by Equation (18).

Step 6: Update of State:

$$\hat{X}^i_{\text{aug}}(k+1\mid k+1) = \hat{X}^i_{\text{aug}}(k+1\mid k) + K^i_{\text{aug}}(k+1)\sum_{j=1}^{M_k}\beta_{ji}(k+1)v_{ji}(k+1) \tag{22}$$

$$v_{ji}(k+1) = Z_j(k+1) - Z^i_{\text{aug}}(k+1\mid k) \tag{23}$$

Step 7: Update of covariance:

$$P^i_{\text{aug}}(k+1\mid k+1) = P^0_{\text{aug}}(k+1\mid k+1) + K^i_{\text{aug}}(k+1)\cdot [\sum_{j=1}^{M_k}\beta_{ji}(k+1)v_{ji}(k+1)v^{\mathrm{T}}_{ji}(k+1) - v_{ji}(k+1)v^{\mathrm{T}}_{ji}(k+1)](K^i_{\text{aug}}(k+1))^{\mathrm{T}} \tag{24}$$

where

$$P^0_{\text{aug}}(k+1\mid k+1) = P^i_{\text{aug}}(k+1\mid k) - K^i_{\text{aug}}(k+1)S(k+1)(K^i_{\text{aug}}(k+1))^{\mathrm{T}} \tag{25}$$

SIMULATION RESULTS AND ANALYSIS

The purpose of this example is to compare multiple maneuvering targets tracking between the proposed algorithm (STMIE-MEF) and the traditional "Current" Statistical (CS) (Zhou and Kumar, 1984) method combined with MEF (CS-MEF). Assuming that there are two maneuvering targets, first, they take uniform motion, then, high maneuvering turns occur at the 21st second and 41st second, respectively. The two targets cross two times one after another in the motion. Simulation parameters are shown in Table 1. The covariance matrices of system noise and measurement noise are selected as $\boldsymbol{Q}(k)=\text{diag}[1, 1]$ and $\boldsymbol{R}(k)=\text{diag}[(60)^2\text{m}^2, (60)^2\text{m}^2]$, respectively. Assuming that the clutter density is 1 clutter point/km^2, the maximum acceleration in CS method is 100 m/s^2 and the jerk frequency is 0.1. $\varepsilon = 0.51$ in Equation (15). The real tracks and the estimated tracks by the proposed method and the CS-MEF method are

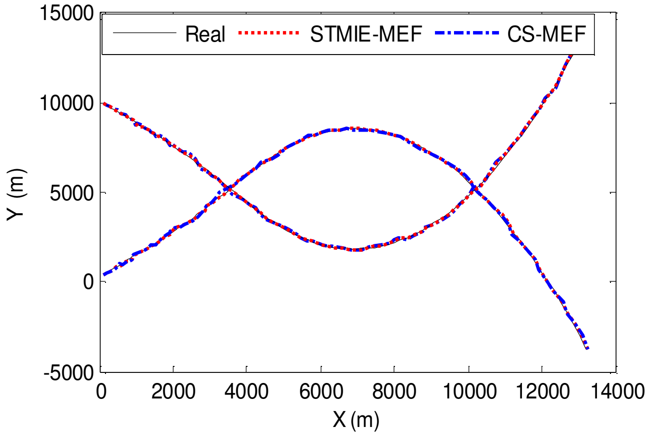

Figure 1. Real tracks and estimated tracks.

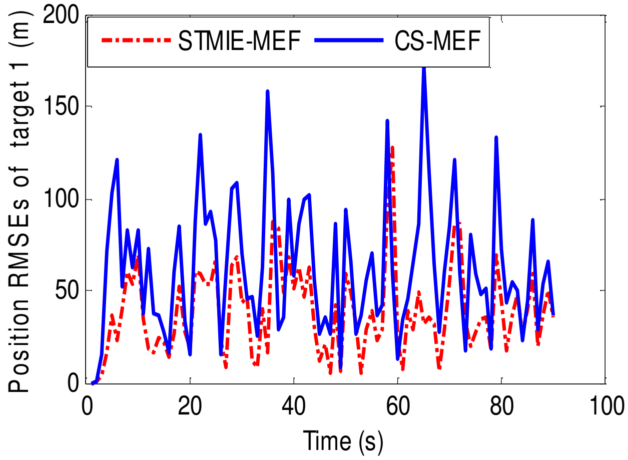

Figure 2. Position RMSEs of target 1.

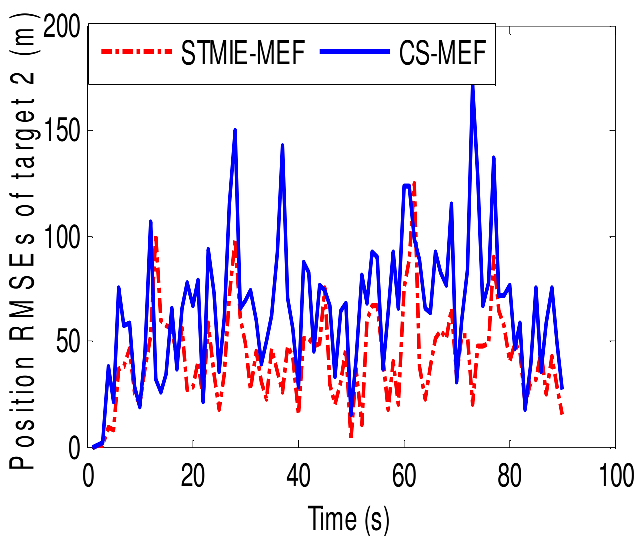

Figure 3. Position RMSEs of target 2.

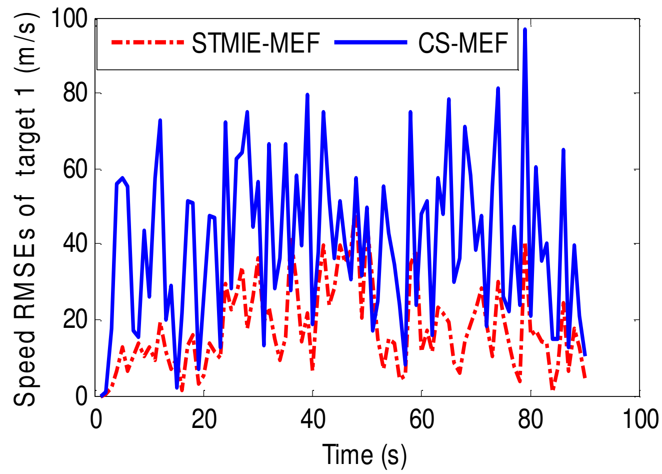

Figure 4. Speed RMSEs of target 1.

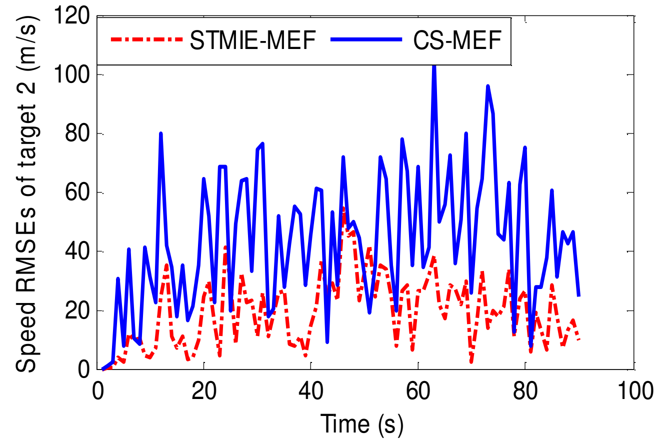

Figure 5. Speed RMSEs of target 2.

shown in Figure 1.

Figures 2 to 7 illustrate the RMSEs of position, speed and acceleration, respectively. As can be seen from these figures, it can be concluded that the STMIE-MEF can perform better than the CS-MEF method. At the 21st second and the 41st second, two high maneuvers happen to the targets one after another, the STMIE-MEF algorithm has the fastest speed of convergence, which, especially, can be seen in Figures 6 and 7. As the multiple fading factors take full advantages of the useful information about the residues, they are able to adjust the prediction covariance and the corresponding filter gain in real time, which makes the filter converge rapidly in a short time. While the CS-MEF algorithm needs the prior information of the maneuvering targets, uncertain maneuvering information causes the estimation of target states to be inaccurate, making the tracking accuracy inferior to the proposed method. From Table 2, the same

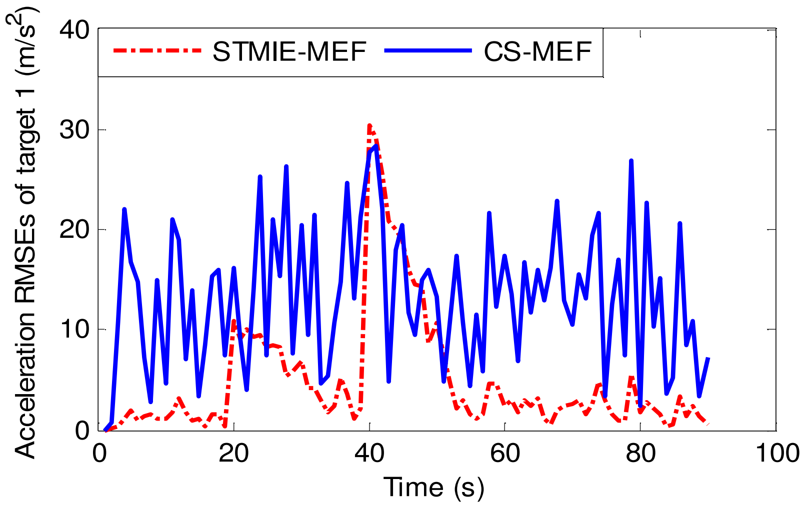

Figure 6. Acceleration RMSEs of target 1.

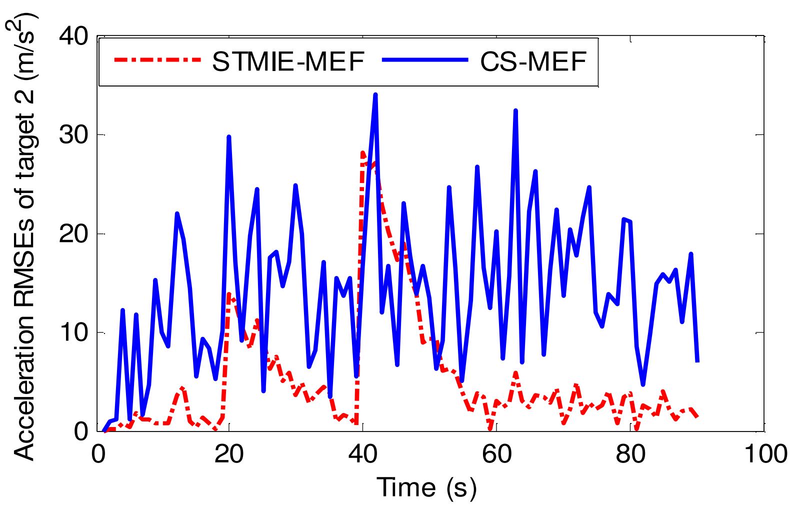

Figure 7. Acceleration RMSEs of target 2.

Table 2. Comparison of the two algorithms for two high maneuvering targets tracking.

Simulation	Algorithm	RMSE		
		Position (m)	**Velocity (m/s)**	**Acceleration (m/s^2)**
Target 1	STMIE-MEF	36.63	17.41	4.96
	CS-MEF	56.65	39.05	13.12
Target 2	STMIE-MEF	38.50	16.47	4.88
	CS-MEF	58.58	36.35	12.03

conclusion can be obtained. In addition, we can calculate the tracking accuracy in position and velocity of the STMIE-MEF method to be about 30 and 50% higher than that of the CS-MEF algorithm, respectively.

CONCLUSIONS

In this paper, a new filtering algorithm STMIE-MEF is proposed on the basis of strong tracking filter idea and maximum entropy fuzzy joint probabilistic data association for tracking multiple maneuvering targets. The multiple fading factors are introduced in order to adjust the prediction covariance and the corresponding filter gain in real time, making the filter converge rapidly in a short time. Particularly, the proposed method has a high tracking accuracy for high maneuvering targets tracking. Simulation results are compared with the CS-MEF method, showing the effectiveness of the proposed method in tracking high maneuvering targets.

ACKNOWLEDGEMENTS

This paper is supported by the National Natural Science Foundation of China (NSFC) under Grant Number 60871074. The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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