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Full Length Research Paper

High maneuvering target-tracking based on strong tracking modified input estimation

Jin-Long Yang* and Hong-Bing Ji

School of Electronic Engineering, Xidian University, Xi'an 710071, P. R. China.

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When tracking a high maneuvering target, the sudden changes of target states may cause a serious decline or even divergence in the performance of the conventional modified input estimation (MIE) technique. Taking this into account, in this paper, strong tracking filter multiple fading factors are introduced in order to enhance the tracking performance of MIE for high maneuvering targets. As 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, this algorithm keeps a good tracking performance in low, medium and high maneuvering target cases. Simulations show the effectiveness of the proposed method. Compared with the Fuzzy adaptive MIE algorithm, this algorithm has a higher tracking accuracy and a better real-time performance.

Key words: High maneuvering target, modified input estimation (MIE), strong tracking filter (STF), multiple fading factors.

INTRODUCTION

With the rapid development of modern aviation technology, the maneuverability of fighter planes and other aircrafts is growing stronger and stronger. The uncertainty of changes in the maneuvering target acceleration makes the maneuvering target tracking increasingly difficult, which arouses wide attention. Singer (1970) suggested a zero-mean and 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 (Helferty, 1996; Zhou and Kumar, 1984). The "current" statistical model (Zhou and Kumar, 1984) is more realistic than Singer's model on the target mobile pre-assumptions, which is recognized as an effective method for tracking maneuvering targets. However, the target tracking accuracy of these models 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 the inappropriate value of the *a priori* parameters (Chen and Chang, 2009). Interacting multiple mode (IMM) algorithm, proposed by Blom (1988), is considered as a good compromise between the tracking performance and the computational complexity (Boers and Driessen, 2003), but the tracking accuracy still depends on the match degree of pre-designed models with the actual situation of a maneuvering target (Li and Bar-Shalom, 1996). In addition, with the increase in the number of models, the calculational cost will also increase significantly, which seriously affects the real-time performance for tracking a maneuvering target.

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, after some iterations, its steps become small, leading to a serious degradation of the tracking accuracy in the presence of high maneuvers (Bahari and Pariz, 2009). To overcome the aforementioned problem, a new MIE algorithm was proposed with the introduction of a Fuzzy forgetting factor or a Fuzzy fading memory (Bahari

*Corresponding author. E-mail: yjlgedeng@163.com.

and Pariz, 2009; Bahari et al., 2009; Beheshtipour and Khaloozadeh, 2009), making an effective improvement of the tracking accuracy for high maneuvering targets. However, the Fuzzy reasoning rules depend on some priori knowledge of the maneuvering targets and need a high computational cost. So, the method of Bahari (2009) has a poor real-time performance and the tracking accuracy depends on the Fuzzy reasoning rules that are designed.

To solve the problems mentioned above, this paper presents a new strong tracking MIE algorithm (STMIE), using the idea of strong tracking filter (Zhou and Frank, 1996), and the formula of multiple fading factor matrices is derived based on the residuals. Different data channels are faded at different rates by the multiple time-varying fading factors. Thus, the gain of the filter will be adjusted in real time to enhance the tracking capacity of the proposed algorithm for maneuvering targets. This algorithm also keeps a high tracking accuracy for uniform and/or low maneuvering targets and has a good real-time performance.

The remainder of this paper is organized as follows: The MIE algorithm is reviewed; the STMIE algorithm is introduced; two examples of a target moving with high maneuver in order to show the effectiveness of the proposed method and some conclusions are drawn.

THE MIE ALGORITHM

The state equation and the measurement equation of a maneuvering target in two-dimensional cases are described as follows, respectively:

$$\boldsymbol{X}(k+1)=\boldsymbol{F}\boldsymbol{X}(k)+\boldsymbol{C}\boldsymbol{U}(k)+\boldsymbol{G}\boldsymbol{W}(k) \tag{1}$$

$$\boldsymbol{Z}(k)=\boldsymbol{H}\boldsymbol{X}(k)+\boldsymbol{V}(k) \tag{2}$$

where

$\boldsymbol{X}(k)$: The state vector at time k.

$\boldsymbol{Z}(k)$: The measurement vector at time k.

$\boldsymbol{U}(k)$: The unknown acceleration vector.

$\boldsymbol{W}(k)$: The state noise.

$\boldsymbol{V}(k)$: The measurement noise.

$\boldsymbol{Q}(k)$: The process covariance matrix.

$\boldsymbol{R}(k)$: The measurement covariance matrix.

$\boldsymbol{X}(k)=[x(k)\ \ v_x(k)\ \ y(k)\ \ v_y(k)]^{\mathrm{T}}$

$\boldsymbol{U}(k)=[a_x(k)\ \ a_y(k)]^{\mathrm{T}}$

$$\boldsymbol{F}=\begin{bmatrix}1 & T & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & T\\ 0 & 0 & 0 & 1\end{bmatrix}\quad \boldsymbol{H}=\begin{bmatrix}1 & 0\\ 0 & 0\\ 0 & 1\\ 0 & 0\end{bmatrix}^{\mathrm{T}}\quad \boldsymbol{C}=\begin{bmatrix}\frac{T^2}{2} & 0\\ T & 0\\ 0 & \frac{T^2}{2}\\ 0 & T\end{bmatrix}\quad \boldsymbol{G}=\begin{bmatrix}\frac{T^2}{2} & 0\\ T & 0\\ 0 & \frac{T^2}{2}\\ 0 & T\end{bmatrix}$$

The uncertainty of the acceleration vector in Equation (1) makes the maneuvering target tracking difficult. In many researches, it has been attempted to detect the target's maneuver as quickly as possible. To solve this problem, a new MIE approach was proposed, which does not need any maneuver detection procedure and can operate in both the non-maneuvering and maneuvering modes (Khaloozadeh et al., 2009). In the MIE method, the unknown acceleration vector is considered as a new augmented component of the target states and the maneuvering target state model is converted into a non-maneuvering target state model. The augmented state equation is given as:

$$\begin{bmatrix}\boldsymbol{X}(k+1)\\ \boldsymbol{U}(k+1)\end{bmatrix}=\begin{bmatrix}\boldsymbol{F} & \boldsymbol{C}\\ \boldsymbol{0} & \boldsymbol{I}\end{bmatrix}\begin{bmatrix}\boldsymbol{X}(k)\\ \boldsymbol{U}(k)\end{bmatrix}+\begin{bmatrix}\boldsymbol{G}\\ \boldsymbol{0}\end{bmatrix}\boldsymbol{W}(k) \tag{3}$$

Then, the measurement information at time $k+1$ is:

$$\begin{aligned}\boldsymbol{Z}(k+1)&=\boldsymbol{H}\boldsymbol{X}(k+1)+\boldsymbol{V}(k+1)\\ &=\boldsymbol{H}\{\boldsymbol{F}\boldsymbol{X}(k)+\boldsymbol{C}\boldsymbol{U}(k)+\boldsymbol{G}\boldsymbol{W}(k)\}+\boldsymbol{V}(k+1)\\ &=[\boldsymbol{HF}\ \ \boldsymbol{HC}]\begin{bmatrix}\boldsymbol{X}(k)\\ \boldsymbol{U}(k)\end{bmatrix}+\boldsymbol{HG}\boldsymbol{W}(k)+\boldsymbol{V}(k+1)\end{aligned} \tag{4}$$

According to Equations (3) and (4), a standard non-maneuvering augmented state model can be derived as:

$$\boldsymbol{X}_{\mathrm{aug}}(k+1)=\boldsymbol{F}_{\mathrm{aug}}(k)\boldsymbol{X}_{\mathrm{aug}}(k)+\boldsymbol{G}_{\mathrm{aug}}(k)\boldsymbol{W}_{\mathrm{aug}}(k) \tag{5}$$

$$\boldsymbol{Z}_{\mathrm{aug}}(k)=\boldsymbol{H}_{\mathrm{aug}}(k)\boldsymbol{X}_{\mathrm{aug}}(k)+\boldsymbol{V}_{\mathrm{aug}}(k) \tag{6}$$

where

$$\boldsymbol{X}_{\mathrm{aug}}(k+1)=\begin{bmatrix}\boldsymbol{X}(k+1)\\ \boldsymbol{U}(k+1)\end{bmatrix},\boldsymbol{F}_{\mathrm{aug}}(k)=\begin{bmatrix}\boldsymbol{F} & \boldsymbol{C}\\ \boldsymbol{0} & \boldsymbol{I}\end{bmatrix}$$

$$\boldsymbol{G}_{\mathrm{aug}}(k)=\begin{bmatrix}\boldsymbol{G}\\ \boldsymbol{0}\end{bmatrix},\boldsymbol{W}_{\mathrm{aug}}(k)=\boldsymbol{W}(k)$$

$$\boldsymbol{Z}_{\mathrm{aug}}(k)=\boldsymbol{Z}(k+1),\boldsymbol{H}_{\mathrm{aug}}(k)=[\boldsymbol{HF}\ \ \ \boldsymbol{HC}]$$

$$\boldsymbol{V}_{\mathrm{aug}}(k)=\boldsymbol{HG}\boldsymbol{W}(k)+\boldsymbol{V}(k+1)$$

At this point, although the augmented measurement noise and the state noise are time-related, they are still Gaussian white noises. Therefore, the optimal estimation of the target states can be obtained by the standard Kalman filter in the augmented system. The augmented measurement noise and the state noise covariance are:

$$\mathrm{E}\begin{bmatrix}\boldsymbol{W}_{\mathrm{aug}}(k_1)\\ \boldsymbol{V}_{\mathrm{aug}}(k_1)\end{bmatrix}\begin{bmatrix}\boldsymbol{W}^{\mathrm{T}}_{\mathrm{aug}}(k_2)\boldsymbol{V}^{\mathrm{T}}_{\mathrm{aug}}(k_2)\end{bmatrix}=\begin{cases}\begin{bmatrix}\boldsymbol{Q}_{\mathrm{aug}}(k_1) & \boldsymbol{T}_{\mathrm{aug}}(k_1)\\ \boldsymbol{T}^{\mathrm{T}}_{\mathrm{aug}}(k_1) & \boldsymbol{R}_{\mathrm{aug}}(k_1)\end{bmatrix}, & k_1=k_2\\ \boldsymbol{0}, & k_1\neq k_2\end{cases}$$

where

$$Q_{\text{aug}}(k)=\mathrm{E}\left[W_{\text{aug}}(k)W_{\text{aug}}^{\mathrm{T}}(k)\right]=E\left[W(k)W^{\mathrm{T}}(k)\right]=Q(k)$$
$$R_{\text{aug}}(k)=\mathrm{E}\left[V_{\text{aug}}(k)V_{\text{aug}}^{\mathrm{T}}(k)\right]=HGQ(k)G^{\mathrm{T}}H^{\mathrm{T}}+R(k)$$
$$T_{\text{aug}}(k)=\mathrm{E}\left[W_{\text{aug}}(k)V_{\text{aug}}^{\mathrm{T}}(k)\right]=Q(k)G^{\mathrm{T}}H^{\mathrm{T}}.$$

The standard Kalman filter in the augmented system is derived under the following procedure:

Step 1: Predicting

$$\hat{X}_{\text{aug}}(k+1|k)=F_{\text{aug}}(k)\hat{X}_{\text{aug}}(k|k) \quad (7)$$

$$P_{\text{aug}}(k+1|k)=F_{\text{aug}}(k)P_{\text{aug}}(k|k)F_{\text{aug}}^{\mathrm{T}}(k)+G_{\text{aug}}(k)Q_{\text{aug}}(k)G_{\text{aug}}^{\mathrm{T}}(k) \quad (8)$$

Step 2: Updating

$$\hat{X}_{\text{aug}}(k+1|k+1)=\hat{X}_{\text{aug}}(k+1|k)+K_{\text{aug}}(k+1)(Z_{\text{aug}}(k+1)-H_{\text{aug}}(k+1)\hat{X}_{\text{aug}}(k+1|k)) \quad (9)$$

$$P_{\text{aug}}(k+1|k+1)=P_{\text{aug}}(k+1|k)-P_{\text{aug}}(k+1|k)H_{\text{aug}}^{\mathrm{T}}(k+1)[R_{\text{aug}}(k+1)+H_{\text{aug}}(k+1)P_{\text{aug}}(k+1|k)H_{\text{aug}}^{\mathrm{T}}(k+1)]^{-1}H_{\text{aug}}(k+1)P_{\text{aug}}(k+1|k) \quad (10)$$

where the gain of this filter is:

$$K_{\text{aug}}(k+1)=[P_{\text{aug}}(k+1|k)H_{\text{aug}}^{\mathrm{T}}(k+1)+G_{\text{aug}}(k)T_{\text{aug}}(k)]R_{\text{aug}}^{-1}(k) \quad (11)$$

In Equation (7), although $F_{\text{aug}}(k)$ does not cause any transition in the acceleration vector, that is, $U(k+1|k)=U(k|k)$, the estimations of the acceleration states are modified through the new filter gain $K_{\text{aug}}(k+1)$. In addition, as can be seen from Equation (11), $K_{\text{aug}}(k+1)$ is determined by the prediction covariance $P_{\text{aug}}(k+1|k)$ and the cross-covariance $T_{\text{aug}}(k)$. Usually, when the system reaches a stable state, the prediction covariance will tend to be minimum. Thus, when a low and/or medium maneuver occurs, $T_{\text{aug}}(k)$ will play a decisive role in the filter gain adjustment, which guarantees the filter's convergence; but when a high maneuver occurs suddenly, the residuals increase 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 to track a high maneuvering target.

STRONG TRACKING MIE (STMIE)

Since the prediction covariance and the gains of KF and EKF cannot be changed with the variation of the residuals, a strong tracking filter was proposed by Zhou (1996), which can deal very well with this problem. The filter makes the output residuals approximate to Gaussian white noise by selecting appropriate time-varying gains online. Compared with some conventional filters, this filter has a stronger robustness for mismatching model para-meters, a stronger capability for estimating target states with sudden changes and a moderate computational complexity and so on (Zhou et al., 1996, 1999). In this paper, multiple time-varying fading factors are introduced based on the idea of the strong tracking filter in order to adjust the tracking performance towards the maneuvering target in real time.

In the light of the design of the strong tracking filter (Zhou et al., 1996, 1999), in order to ensure that the MIE filter has a strong tracking filter performance, the filter gains must satisfy the orthogonal principle:

$$E\left\{[X_{\text{aug}}(k+1)-\hat{X}_{\text{aug}}(k+1|k+1)][X_{\text{aug}}(k+1)-\hat{X}_{\text{aug}}(k+1|k+1)]^{\mathrm{T}}\right\}=\min \quad (12)$$

$$E[d_{\text{aug}}^{\mathrm{T}}(k+1)d_{\text{aug}}(k+1+j)]=0, k=0,1,\cdots, j=1,2,\cdots. \quad (13)$$

where $d_{\text{aug}}(k+1)$ denotes the residual,

$$d_{\text{aug}}(k+1)=Z_{\text{aug}}(k+1)-H_{\text{aug}}(k+1)\hat{X}_{\text{aug}}(k+1|k) \quad (14)$$

As can be seen from Equation (11), to obtain the appropriate time-varying gain, $P_{\text{aug}}(k+1|k)$ needs to be adjusted in real time in the filtering process. In order to obtain the optimal $K_{\text{aug}}(k+1)$, Equation (8) can be written as:

$$P_{\text{aug}}(k+1|k)=\Lambda(k+1)F_{\text{aug}}(k)P_{\text{aug}}(k|k)F_{\text{aug}}^{\mathrm{T}}(k)+G_{\text{aug}}(k)Q_{\text{aug}}(k)G_{\text{aug}}^{\mathrm{T}}(k) \quad (15)$$

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

Through some derivations, $\Lambda(k+1)$ can be obtained:

$$\Lambda(k+1)=\mathrm{diag}[\lambda_1(k+1),\lambda_2(k+1),\cdots,\lambda_n(k+1)] \quad (16)$$

where $\lambda_i(k+1), i=1,2,\cdots,n$ denote the fading factors,

$$\lambda_i(k+1)=\begin{cases}a_i c(k+1), & a_i c(k+1)>1\\ 1, & a_i c(k+1)\le 1\end{cases} \quad (17)$$

$$c(k+1)=tr[N(k+1)]\Big/\sum_{i=1}^{n}a_i M_{ii}(k+1) \quad (18)$$

$$N(k+1)=S_0(k+1)-\beta R_{\text{aug}}(k+1)-H_{\text{aug}}(k+1)G_{\text{aug}}(k)Q_{\text{aug}}(k)G_{\text{aug}}^{\mathrm{T}}(k)H_{\text{aug}}^{\mathrm{T}}(k+1) \quad (19)$$

$$M(k+1)=F_{\text{aug}}(k)P_{\text{aug}}(k|k)F_{\text{aug}}^{\mathrm{T}}(k)H_{\text{aug}}^{\mathrm{T}}(k+1)H_{\text{aug}}(k+1) \quad (20)$$

where $N(k+1)$ and $M(k+1)$ are derived to ensure that the residuals at different points in time can remain approximate to orthogonality, without specific meaning.

$$S_0(k+1) = E[d_{aug}(k+1)d_{aug}^T(k+1)] = \begin{cases} d_{aug}(1)d_{aug}^T(1), & k=0 \\ [\rho S_0(k) + d_{aug}(k+1)d_{aug}^T(k+1)]/(1+\rho), & k \geq 1 \end{cases} \quad (21)$$

In Equations (17) - (21), $0 < \rho \leq 1$ is a forgetting factor, generally taking 0.95. $\beta \geq 1$ is a softening factor, which can make the state estimated value more smooth; $S_0(k)$ is a residual second-order moment and $a_i \geq 1, i = 1, 2, \cdots, n$ are pre-determined coefficients. If a component of the state changes rapidly, a larger a_i will be selected to further improve the tracking performance of the filter. If $a_i = 1, i = 1, 2, \cdots, n$, then, the multiple fading factors will degenerate into a single fading factor. The selection of some parameter values can refer to the literatures of Zhou (1996, 1999). When the system is in a stable state, $\Lambda(k+1)$ will approximate to the unit matrix, then, the STMIE filtering algorithm will degenerate into the MIE algorithm, and at this time, it is still able to maintain the tracking capability for a general uniform or low maneuvering target. Suppose $\hat{X}_{aug}(k \mid k)$ is an optimal estimation at time k in the fusion center, $P_{aug}(k \mid k)$ is the corresponding state covariance matrix. Then, the recursive steps of the STMIE algorithm for the optimal state estimation at time $k+1$ are as follows:

Step 1: According to Equation (7), one step prediction value $\hat{X}_{aug}(k+1 \mid k)$ can be worked out;

Step 2: According to Equation (14), the residual $d_{aug}(k+1)$ can be worked out;

Step 3: According to Equation (16), a multiple fading factor matrix $\Lambda(k+1)$ can be worked out;

Step 4: According to Equation (15), the prediction covariance $P_{aug}(k+1 \mid k)$ can be worked out;

Step 5: According to Equation (9), $\hat{X}_{aug}(k+1 \mid k+1)$ can be worked out;

Step 6: According to Equation (10), $P_{aug}(k+1 \mid k+1)$ can be worked out.

SIMULATION RESULTS AND ANALYSIS

The effectiveness and real-time performance of the STMIE algorithm will be illustrated through two examples of a maneuvering target tracking. Taking the root mean square error (RMSE) and computational time as the performance indicators, the study compared the STMIE algorithm with the MIE algorithm and the algorithm proposed by Bahari (2009). A two-dimensional plane is taken into consideration in this section and the covariance matrices of system noise and measurement noise in all simulations are selected as $Q(k) = \mathrm{diag}[0.5,\ 0.5]$ and $R(k) = \mathrm{diag}[(50)^2\mathrm{m}^2,\ (50)^2\mathrm{m}^2]$, respectively. Furthermore, the initial position and speed of the target are unknown for the trackers.

Example 1

Assuming the initial location of a target is $(x, y) = (100\mathrm{m}, 400\mathrm{m})$, and the initial velocity is $(v_x, v_y) = (-80\mathrm{m/s}, 100\mathrm{m/s})$, the target makes a uniform motion during the first 100 seconds and then starts to take a high maneuver from the 101st second, with an acceleration $(a_x, a_y) = (20\mathrm{m/s}^2, 30\mathrm{m/s}^2)$, lasting 200 seconds.

In this simulation, the sampling time is $T = 1s$, and sampling 300 times in all, 21 Fuzzy reasoning rules are selected in the algorithm of Bahari and Pariz (2009). The Monte Carlo simulations are carried out for 100 times. The RMSE of the target position at time k and the average error of estimated position at all sampling times are defined as in Equations (22) and (23), respectively:

$$RMSE(k) = [\frac{1}{M}\sum_{i=1}^{M}((\hat{x}^i(k) - x^i(k))^2 + (\hat{y}^i(k) - y^i(k))^2]^{1/2} \quad (22)$$

$$Error = \frac{1}{N}\sum_{k=1}^{N} RMSE(k) \quad (23)$$

where $M = 100$ is the number of times of Monte Carlo simulation, $N = 300$ is the total number of samples, $(\hat{x}^i(k), \hat{y}^i(k))$ and $(x^i(k), y^i(k))$ are the estimated and actual value of the target position at time k , respectively. The RMSE and the average estimation error of the speed and acceleration can be defined in the same way as Equations (22) and (23).

Figures 1 - 6 illustrate the actual values and the estimations of position, velocity and acceleration of the STMIE algorithm, the MIE algorithm and the algorithm of Bahari and Pariz (2009) in x and y-axis directions. Figures 7 - 9 show the comparison of the estimated RMSE among the three algorithms in terms of the position, velocity and acceleration.

From Figures 1 - 9, it is clear that, when the target is making a uniform motion within the first 100 s, the three algorithms have a similar performance. At the 100th second, a high maneuver happens to the target, thereby making the STMIE algorithm to have the fastest speed of convergence. As the multiple fading factors take full advantages of the useful information about the residuals, they have the ability to adjust the prediction covariance and the corresponding filter gain in real time, which makes the filter converge rapidly in a short period of time. The algorithm of Bahari is the second in convergence speed. Of course, the tracking performance of Bahari's

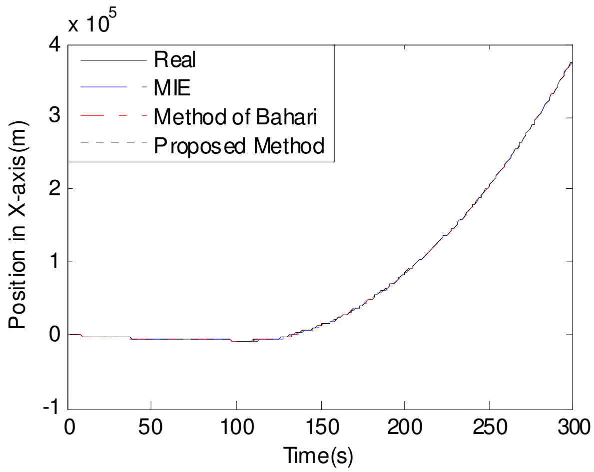

Figure 1. Estimated position in x-axis direction.

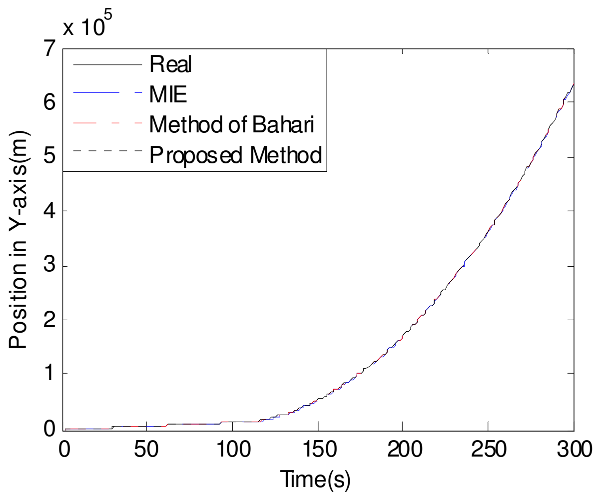

Figure 2. Estimated position in y-axis direction.

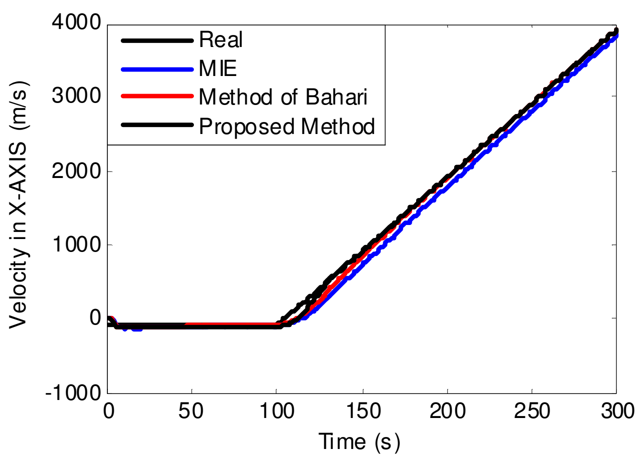

Figure 3. Estimated velocity in x-axis direction.

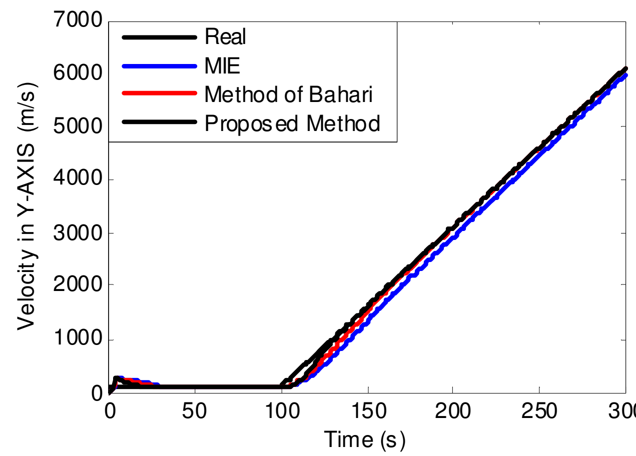

Figure 4. Estimated velocity in y-axis direction.

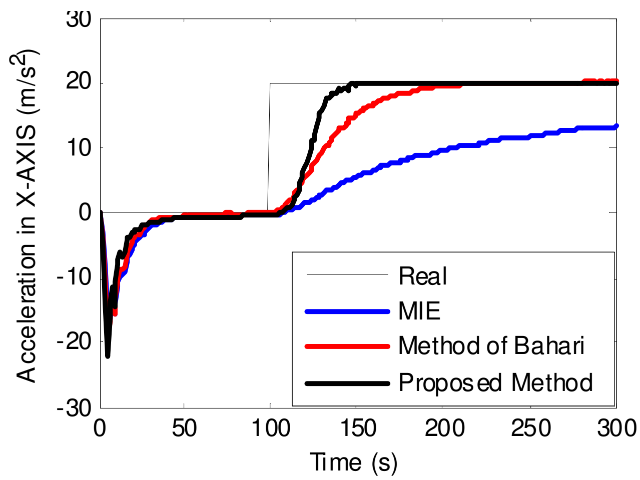

Figure 5. Estimated acceleration in x-axis direction.

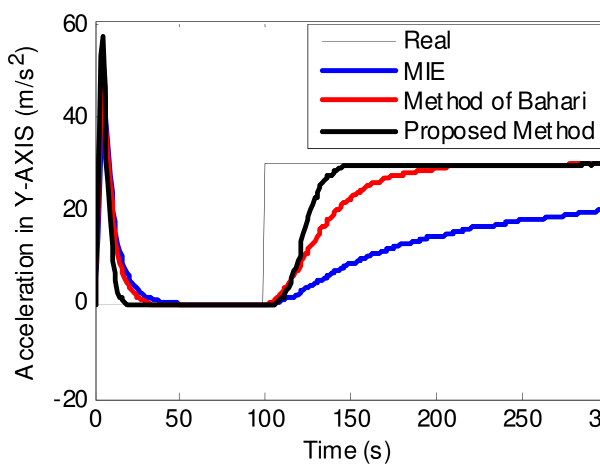

Figure 6. Estimated acceleration in y-axis direction.

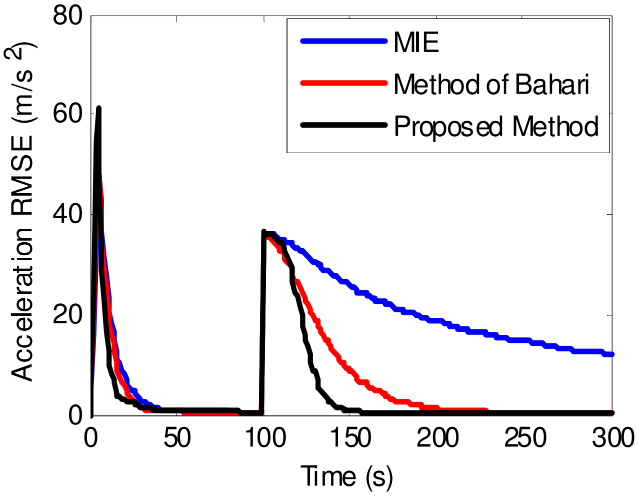

Figure 7. RMSE of the estimated acceleration.

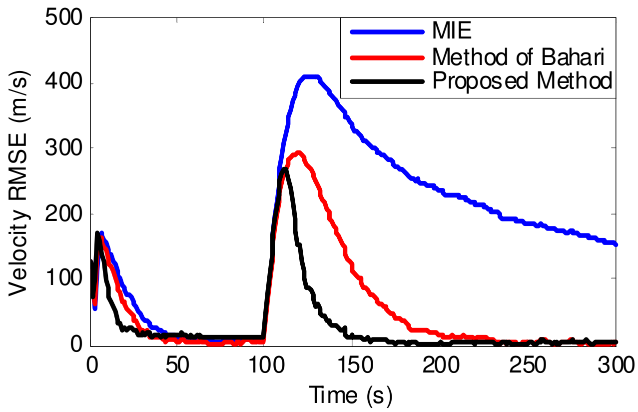

Figure 8. RMSE of the estimated velocity.

tracking performance of Bahari's algorithm can be further improved by increasing the Fuzzy reasoning rules, however, along with an increase of the computational burden. The MIE algorithm has the worst speed of convergence, which is due to the fact that the prediction covariance cannot be adjusted timely in case of high maneuvering target tracking, resulting in the decline or even divergence of the tracking performance.

Table 1 shows the comparison of the tracking accuracy and computational time of the three algorithms. As can be seen from Table 1, the STMIE algorithm has the highest tracking accuracy for the estimation of position, velocity and acceleration. As the different data channels are faded at different rates by the multiple time-varying fading factors, the tracking system can achieve a stable state quickly in a short time. At this time, the multiple fading factor matrix turns into an approximate unit matrix, and then the STMIE method will degenerate into the MIE method, which can better maintain the system stability

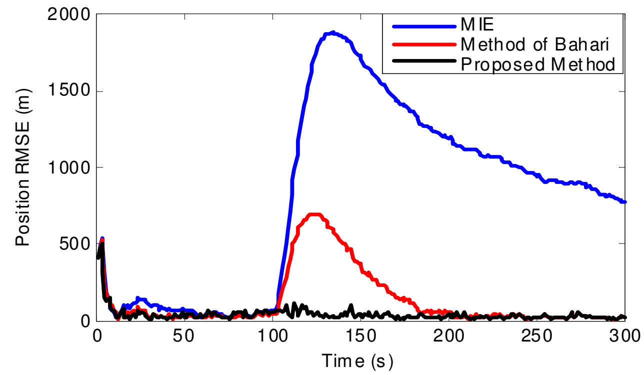

Figure 9. RMSE of the estimated position.

and achieve the optimal estimation of the target state, while the other two algorithms cannot.

The study can also conclude that the STMIE algorithm has a better real-time performance, with the computing time being 0.1410s, next to the MIE algorithm in computing speed and being only 1.59% of the computational time used by Bahari's algorithm.

Example 2

In this example, the study's intention is to evaluate the proposed method in tracking a target with low and medium maneuvers, and two simulations are performed as follows: The initial position, velocity and acceleration of the target are the same as those in Example 1 and lasting 100 s, whereas, the accelerations are different in the later 200 s. Case 1: Simulation of a low maneuvering target, $(a_x(101), a_y(101)) = (1\text{m/s}^2, 1\text{m/s}^2)$. Case 2: Simulation of a medium maneuvering target, $(a_x(101), a_y(101)) = (5\text{m/s}^2, 5\text{m/s}^2)$. Each of the simulations was repeated 100 times and the RMSE of estimation was computed based on the Monte Carlo method.

Table 2 lists the estimation error of three methods in estimating different target parameters. As can be seen from Table 2, the STMIE method also has a good tracking performance for a low or medium maneuvering target. Its tracking accuracy is next to the Bahari's algorithm in Case 1, but higher in Case 2. Moreover, the computing time of the STMIE method is far less than the Bahari's method known from Table 1.

Conclusions

In this paper, a new filtering algorithm STMIE is proposed on the basis of strong tracking filter idea. The multiple fading factors are introduced in order to adjust the prediction covariance and the corresponding filter gain in

Table 1. The comparison of the three algorithms in the tracking accuracy and computing time.

Algorithm	Error			Computational time (s)
	Position (m)	Velocity (m/s)	Acceleration(m/s^2)	
MIE	814.45	178.71	15.76	0.0620
Method of Bahari	132.10	55.78	6.25	8.8590
STMIE	37.30	29.36	4.48	0.1410

Table 2. Estimation error in simulations of low and medium maneuvering target cases.

Simulation	Algorithm	Error		
		Position (m)	Velocity (m/s)	Acceleration (m/s^2)
Case 1	MIE	68.42	21.71	2.49
	Method of Bahari	38.15	15.43	1.61
	STMIE	45.03	18.74	1.95
Case 2	MIE	178.97	46.30	4.54
	Method of Bahari	47.99	21.27	2.56
	STMIE	42.63	23.01	2.51

real time, thereby making the filter converge rapidly in a relatively short time. Particularly, this method has a high tracking accuracy and real-time performance for tracking high maneuvering targets. Simulation results are compared with that of Bahari, showing the effectiveness of this method in tracking high maneuvering targets.

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