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Intelligent fading memory for high maneuvering target tracking

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In this paper, a new fuzzy fading memory (FFM) is developed in order to aid a modified input estimation (MIE) technique and to enhance its performance in tracking high maneuvering targets. The MIE has been introduced recently and performs well in tracking low and medium maneuvering targets. However, this method does not represent desirable accuracy in tracking high maneuvering or jerking targets. In fact, this trouble is originated in mismodeling the target acceleration dynamics. An effective approach to cope with different modeling uncertainties is fading memory. However, conventional fading memory method suffers from some deficiencies leading to surplus fading information in non-maneuvering mode or incomplete compensation in high maneuvering situations. To overcome these difficulties, an intelligent fading memory is presented in this paper. Simulation results prove the efficiency of proposed method in tracking high maneuvering targets.

Key words: High maneuver target tracking, Modified Input Estimation (MIE), fuzzy logic, fading memory, modeling uncertainties.

INTRODUCTION

Many Kalman filter-based (KF) methods have been applied to the target tracking problem during last decades (Lee et al., 2004; Bahari et al., 2008; Lee and Tahk, 1999; Hsieh and Chen, 2000). A major number of these methods include input estimation (IE) approaches (Chan et al., 1979; Bahari and Pariz, 2009; Whang, 1994). These methods use different techniques to estimate the target acceleration. One of the most successful IE techniques has been recently proposed by Khaloozadeh and Karsaz (2009). This modified input estimation (MIE) technique provides fast initial convergence rate as well as satisfactory tracking performance in low and medium maneuvering target cases. In this approach, the acceleration is treated as an additive input term in the corresponding state equation. This kind of modeling has provided a special augmentation in the state space model, which considers both the states vector and unknown acceleration vector as two new augmented states (Khaloozadeh and Karsaz, 2009). Although the MIE is theoretically optimal, it fails to track a high maneuvering target accurately due to modeling errors related to the target acceleration dynamics.

Several techniques have been introduced during last years to overcome different modeling errors (Simon, 2006). Among those, using fading memory and fictitious process noise are more popular due to some practical concerns including easy implementation and effectiveness. In this research, we focus on fading memory. In fact, using the fading memory is a way of putting more emphasis on the recent measurements and discounting the information from distant past. Therefore, applying this method can help to cope with mismodeling of target acceleration and consequently reach more accuracy in

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Abbreviations: FFM, Fuzzy fading memory; **MIE,** modified input estimation; **IE,** input estimation; **KF,** Kalman filter.

tracking accelerating (maneuvering) targets. Obviously, using fading memory provides a suboptimal filter. However, a suboptimal filter which yields higher tracking accuracy and restores stability is preferred to an optimal filter which isunable to provide required results and may diverge.

Although the conventional fading memory is attractive from several aspects, it still suffers from some deficiencies. To be more precise, conventional fading memory scheme employs a very important factor. Any changes in this factor, significantly, influence the tracking performance. However, this factor is determined off-line and remains constant during the operation. This problem leads to undesired fading information in non-maneuvering mode or imperfect compensation in high maneuvering situations.

On the other hand, different capabilities of intelligent systems such as intelligent information fusion and intelligent adaptation make them popular in various applications including target tracking (Duh and Lin, 2004; Chan et al., 1997; Chin, 1994; Bahari et al., 2009). Therefore, to overcome the aforementioned deficiency of conventional fading memory, we employed fuzzy logic. To clarify, in this research, we introduce a new method to determine the values of fading memory factor adaptively and intelligently in each iteration.

Statement of the problem

It is assumed that the target moves in a two-dimensional plane. The state equation for the non-maneuvering model is given by equation 1.

$$\begin{aligned} X(n+1) &= F(n)X(n) + C(n)u(n) + G(n)w(n) \\ z(n) &= H(n)X(n) + v(n) \end{aligned} \tag{1}$$

Where

$X(.)$: State vector

$u(n)$: is the target acceleration which is modeled as an unknown variable.

$w(.)$: White system driving uncertainty

$X(0)$: Initial condition which may be uncertain

$z(.)$: Observation vector

$v(.)$: White observation uncertainty.

$$E\{v(n_1)v^T(n_2)\} = \begin{cases} R(n_1) & n_1 = n_2 \\ 0 & n_1 \neq n_2 \end{cases}$$

$$E\{w(n_1)w^T(n_2)\} = \begin{cases} Q(n_1) & n_1 = n_2 \\ 0 & n_1 \neq n_2 \end{cases}$$

$$E\{x(0)x^T(0)\} = \psi, E\{\mathrm{x}(0)\} = 0$$

$$E\{\mathrm{w}(0)\} = 0, E\{\mathrm{v}(0)\} = 0$$

$$E\{v(.)w(.)^T\} = 0$$

$$X(n) = \begin{bmatrix} x(n) & v_x(n) & y(n) & v_y(n) \end{bmatrix}^T, \; u(n) = \begin{bmatrix} u_x(n) & u_y(n) \end{bmatrix}^T$$

Where $R(.)$, $Q(.)$ and ψ denote the measurement, process and initial state covariance matrices, respectively. The expressions for $G(n)$, $F(n)$, $C(n)$ and $H(n)$ as functions of the update time T (T is the time interval between two consecutive measurements) are:

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

The MIE

Modified input estimation (MIE) technique was proposed by Khaloozadeh and Karsaz recently (2009). In this method the acceleration is treated as an additive state term in the corresponding state equation. The formulation of this method is as follows.

$$\begin{aligned} \begin{bmatrix} X(n+1) \\ u(n+1) \end{bmatrix} &= \begin{bmatrix} F & C \\ 0 & I \end{bmatrix} \begin{bmatrix} X(n) \\ u(n) \end{bmatrix} + \begin{bmatrix} G \\ 0 \end{bmatrix} w(n) \\ z(n+1) &= \begin{bmatrix} HF & HC \end{bmatrix} \begin{bmatrix} X(n) \\ u(n) \end{bmatrix} + HGw(n) + v(n+1) \end{aligned} \tag{2}$$

Therefore, the augmented state equations can be derived as:

$$\begin{aligned} X_{Aug}(n+1) &= F_{Aug}X(n) + G_{Aug}W_{Aug}(n) \\ Z_{Aug}(n) &= z(n+1) = H_{Aug}(n)X_{Aug}(n) + V_{Aug}(n). \end{aligned} \tag{3}$$

Where, $X_{Aug}(n)$, F_{Aug}, G_{Aug}, W_{Aug}, H_{Aug}, $\mathrm{V}_{Aug}(n)$ are as follows:

$$\begin{aligned} & X_{Aug}(n) = \begin{bmatrix} X(n) \\ u(n) \end{bmatrix}, F_{Aug} = \begin{bmatrix} F & C \\ 0 & I \end{bmatrix}, G_{Aug} = \begin{bmatrix} G \\ 0 \end{bmatrix} \\ & W_{Aug} = w, H_{Aug} = \begin{bmatrix} HF & HC \end{bmatrix} \text{ and } \mathrm{V}_{Aug}(n) = HGw(n) + v(n+1) \end{aligned} \tag{4}$$

The optimal target maneuver estimator for the augmented system is:

$$\hat{X}_{Aug}(n+1|n+1) = F_{Aug}(n)\hat{X}_{Aug}(n|n) + K_{Aug}(n+1)[Z_{Aug}(n+1) - H_{Aug}(n+1)F_{Aug}(n)\hat{X}_{Aug}(n|n)] \tag{5}$$

In this method Kalman gain is:

$$K_{Aug}(n+1)=[P_{Aug}(n+1\mid n)H_{Aug}^{T}(n+1)+G_{Aug}(n)T_{Aug}(n)]R_{Aug}^{-1}(n+1)$$

$$P_{Aug}(n+1\mid n+1)=P_{Aug}(n+1\mid n)-P_{Aug}(n+1\mid n)H_{Aug}^{T}(n+1)\times$$

$$[R_{Aug}(n+1)+H_{Aug}(n+1)P_{Aug}(n+1\mid n)H_{Aug}^{T}(n+1)]^{-1}H_{Aug}(n+1)P_{Aug}(n+1\mid n)$$

$$P_{Aug}(n+1\mid n)=F_{Aug}(n)P_{Aug}(n\mid n)F^{T}{}_{Aug}(n)+G_{Aug}(n)Q_{Aug}(n)G^{T}{}_{Aug}(n) \quad (6)$$

The new covariance matrix of the augmented process noise $W_{Aug}(n)$, measurement noise $V_{Aug}(n)$ and cross-covariance between them $T_{Aug}(n)$ are:

$$E\begin{bmatrix} W_{Aug}(n_1) \\ V_{Aug}(n_1) \end{bmatrix}\begin{bmatrix} W_{Aug}^{T}(n_2) & V_{Aug}^{T}(n_2) \end{bmatrix}=\begin{cases} \begin{bmatrix} Q_{Aug}(n_1) & T_{Aug}(n_1) \\ T^{T}{}_{Aug}(n_1) & R_{Aug}(n_1) \end{bmatrix}, & n_1=n_2 \\ 0, & n_1\neq n_2 \end{cases}$$

$$E\left\{\begin{bmatrix} W_{Aug}(n_1) \\ V_{Aug}(n_1) \end{bmatrix}\begin{bmatrix} W_{Aug}^{T}(n_1) & V_{Aug}^{T}(n_1) \end{bmatrix}\right\}=E\{w(n)w^{T}(n)\}=Q \quad (7)$$

$$R_{Aug}(n)=E\{V_{Aug}(n)V_{Aug}^{T}(n)\}=H(n)G(n)Q(n)G(n)^{T}H(n)^{T}+R(\mathrm{n})$$

$$T_{Aug}(n)=E\{W_{Aug}(n)V_{Aug}^{T}\}=QG^{T}(n)H^{T}(n).$$

PROPOSED METHOD

In this section the proposed intelligent approach is introduced.

Conventional fading memory

As mentioned, if the process model does not match the reality, Kalman filter may diverge. Evidently, different target acceleration dynamics including fast changes in target speed and direction were not modeled correctly and completely in afore-mentioned relations. One method to overcome this problem is to use the fading memory (Simon, 2006). In this method, equation 8 is used to calculate $P_{Aug}(n+1\mid n)$ instead of 6.

$$P_{Aug}(n+1\mid n)=\alpha^{2}F_{Aug}(n)P_{Aug}(n\mid n)F^{T}{}_{Aug}(n)+G_{Aug}(n)Q_{Aug}(n)G^{T}{}_{Aug}(n) \quad (8)$$

Where α is the factor of fading memory. $\alpha\geq 1$ is chosen based on how much designers want the filter to forget past measurements. The main drawback of the conventional method is that the factor of fading memory is determined off-line and remains constant. This leads to surplus fading information in non-maneuvering mode or incomplete compensation in high maneuvering situation.

Fuzzy fading memory

To overcome the drawbacks of the conventional fading memory the FFM is proposed in this paper. In this method α is determined intelligently based on the values of target acceleration.

Block diagram of the proposed intelligent method is given in figure

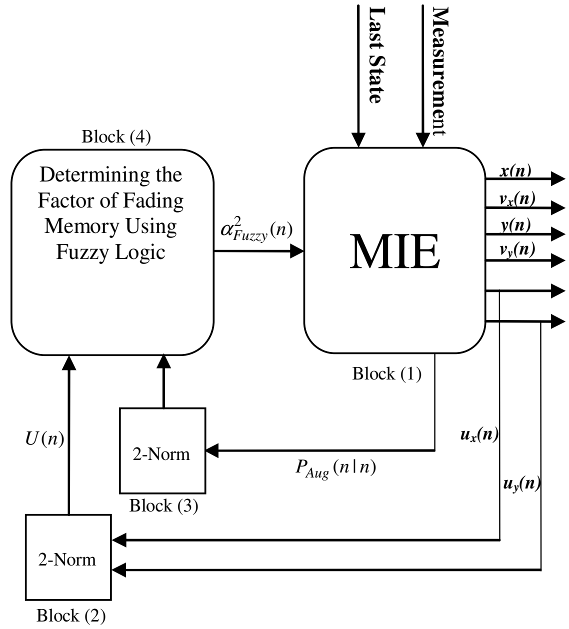

Figure 1. Block diagram of the proposed method.

1. In this figure, block (1) is the MIE. Inputs of this block are the last state, the measurement and the determined factor of fading memory ($\alpha^{2}_{Fuzzy}(n)$) using fuzzy logic. Outputs of this block are the new state and $P_{Aug}(n|n)$. $P_{Aug}(n+1\mid n)$ in the MIE of this block is determined using the following relation:

$$P_{Aug}(n+1\mid n)=\alpha^{2}_{Fuzzy}(n)F_{Aug}(n)P_{Aug}(n\mid n)F^{T}{}_{Aug}(n)+G_{Aug}(n)Q_{Aug}(n)G^{T}{}_{Aug}(n) \quad (9)$$

Calculating procedure of $\alpha^{2}_{Fuzzy}(n)$ will be elaborated later in this paper.

Block (2) computes the 2-norm of vector $u(n)=[u_x(n) \quad u_y(n)]^{T}$. The output of this block is $U(n)=\sqrt{u_x(n)^2+u_y(n)^2}$. Block (3) computes the 2-norm of $P_{Aug}(n|n)$. In fact, 2-norm is used to have a criteria about the size of $P_{Aug}(n|n)$. Any other norms can be applied too.

Block (4) is where the $\alpha^{2}_{Fuzzy}(n)$ is determined. As can be seen from figure 1, block (4) has two inputs and one output. Inputs are the target acceleration magnitude (output of Block (2)) and *2*-norm of $P_{Aug}(n|n)$ (output of Block (3)). Output of this fuzzy system is the value of $\alpha^{2}_{Fuzzy}(n)$ determined intelligently based on the magnitude of maneuver (amount of model uncertainties) in each iteration. Obviously, the factor of fading memory should increase suddenly when the target starts to maneuver and tracker steps are not large enough (*2*-norm of $P_{Aug}(n|n)$ is small) to track the target. While the target does not maneuver or tracker steps are large enough (2-norm of $P_{Aug}(n|n)$ is large enough) to track the target accurately, output of block (4) approaches to 1. The designed fuzzy system in block (4) supports the above-mentioned rules. To clarify, fuzzy logic is used in order to decide about the values of $\alpha^2_{Fuzzy}(n)$ so that the overall tracker remains optimal in non-maneuvering situations (when the mismodeling of target acceleration is low) by choosing $\alpha^2_{Fuzzy}(n)=1$ and it increases its own steps in maneuvering situations (when the mismodeling of target acceleration is high) to provide more accurate tracking result by choosing $\alpha^2_{Fuzzy}(n)>1$. In other words, the proposed architecture detects the target accelerations and determines the values of $\alpha^2_{Fuzzy}(n)$ based on the magnitude of target acceleration. Inputs and output fuzzy sets all have two Gaussian membership functions. It should be noted that we employed Gaussian membership functions because this type of membership functions can provide smooth output and represents the uncertainties adequately (Kreinovich et al., 1992).

SIMULATION RESULTS

This section provides two examples to visualize the effectiveness of proposed method in tracking low, medium and high maneuvering targets. The new scheme is compared with two conventional approaches, the simple MIE (Khaloozadeh and Karsaz, 2009) and MIE with conventional fading memory (MIECFM).

In all simulations of this section, the elements of covariance matrices of system noise and measurement noise are selected as $Q^x_k=\begin{bmatrix}0.5 & 0\\ 0 & 0.5\end{bmatrix}$ and $R_k=\begin{bmatrix}(100)^2\,m^2 & 0\\ 0 & (100)^2\,m^2\end{bmatrix}$ respectively. Furthermore, the initial position and speed of targets are unknown for the trackers.

Example 1

In this case study, our purpose is to evaluate the proposed method in high maneuvering target situation. In this simulation the sampling time is $T=10(s)$. The initial position of target is given by $[x(0),\, y(0)]=[200(m),0(m)]$ with an initial speed of $[v_x(0),v_y(0)]=[18(ms^{-1}),0(ms^{-1})]$. The target moves with constant acceleration of $[u_x(0),u_y(0)]=[0.9(\mathrm{ms}^{-2}),0.9\,(\mathrm{ms}^{-2})]$ until $t=130(s)$. Then, it starts to maneuver with acceleration of $[u_x(13),u_y(13)]=[-2(\mathrm{ms}^{-2}),-2(\mathrm{ms}^{-2})]$. This acceleration continues to $t=260(s)$. Then, the target starts another maneuver with acceleration of $[u_x(26),u_y(26)]=[10\,(\mathrm{ms}^{-2}),10\,(\mathrm{ms}^{-2})]$. The target

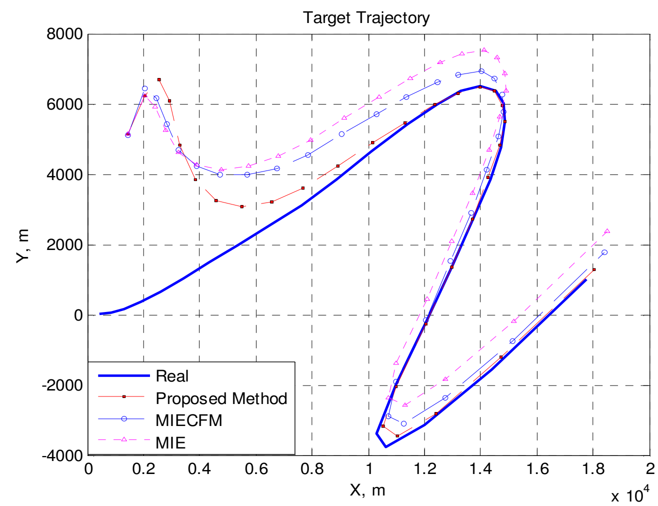

Figure 2. Target trajectory in Cartesian coordinates and the tracking result of proposed method, MIE and MIECFM in Example 1.

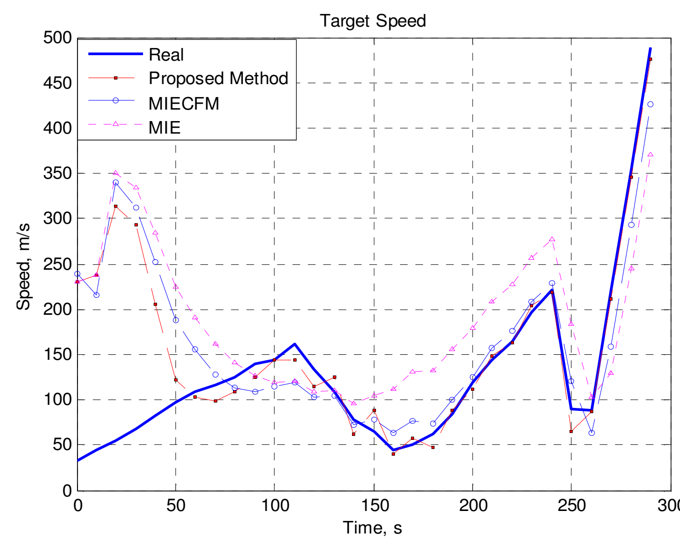

Figure 3. Target velocity and the estimation result of proposed method, MIE and MIECFM in Example 1.

moves with this acceleration up to end of this simulation at $t=500(s)$.

Figure 2 shows the target trajectory estimation by all aforementioned methods in this case study. Figure (3) indicates the target velocity estimation. Figure (4) illustrates the high performance of proposed method for tracking the target course in comparison with two other methods. Figures (5) and (6) emphasize on the ability of fuzzy tracker in the target azimuth and range estimation. High accurate estimation and fast initial convergence rate of new scheme can be interpreted from these figures.

Example 2

In this example, our purpose is to evaluate the proposed

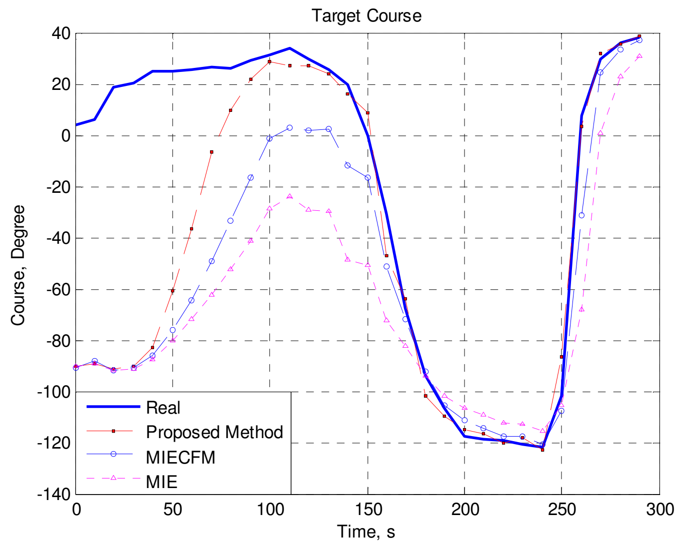

Figure 4. Target course and the estimation result of proposed method, MIE and MIECFM in Example 1.

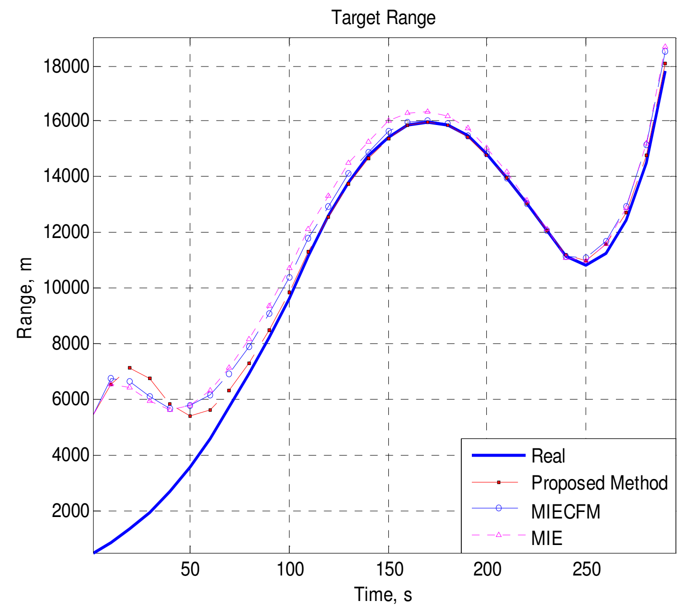

Figure 6. Target range and the estimation result of proposed method, MIE and MIECFM in Example 1.

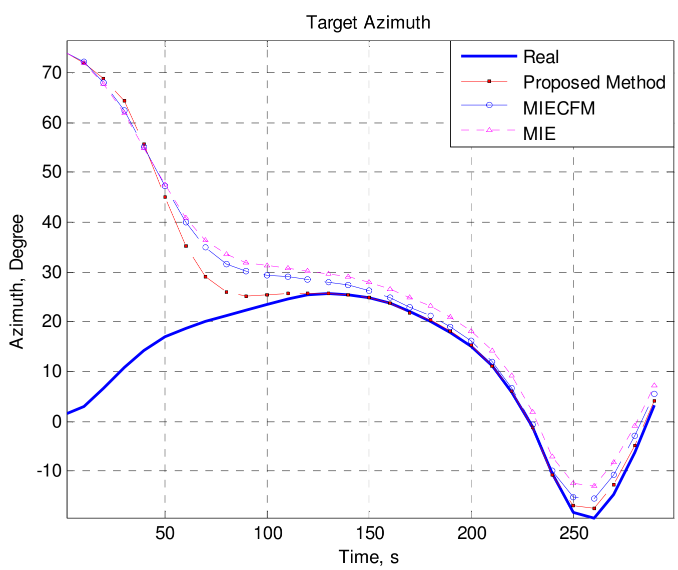

Figure 5. Target azimuth and the estimation result of proposed method, MIE and MIECFM in Example 1.

method in countering a target with low, medium and high maneuvers. Therefore, three simulations were performed as follows. In these simulations, the sampling time is $T = 10(s)$ and the initial position, velocity and aceleration of the target are given by

$[x(0), y(0)] = [200(m), 0(m)]$, $[v_x(0), v_y(0)] = [18(ms^{-1}), 0(ms^{-1})]$ and $[u_x(0), u_y(0)] = [0(\mathrm{ms}^{-2}), 0\,(\mathrm{ms}^{-2})]$, respectively.

Simulation of low maneuvering target case

The target moves with its initial acceleration until $t = 150(s)$. Then, it maneuvers with acceleration of $[u_x(151), u_y(151)] = [0.2(\mathrm{ms}^{-2}), 0.2\,(\mathrm{ms}^{-2})]$ up to the end of this simulation at $t = 300(s)$.

Simulation of medium maneuvering target case

The target moves with its initial acceleration until $t = 150(s)$. Then, it maneuvers with acceleration of $[u_x(151), u_y(151)] = [2(\mathrm{ms}^{-2}), 2\,(\mathrm{ms}^{-2})]$ up to the end of this simulation at $t = 300(s)$.

Simulation of high maneuvering target case

The target moves with its initial acceleration until $t = 150(s)$. Then, it maneuvers with acceleration of $[u_x(151), u_y(151)] = [20(\mathrm{ms}^{-2}), 20\,(\mathrm{ms}^{-2})]$ up to the end of this simulation at $t = 300(s)$.

Each of three simulations was repeated 100 times and root mean square errors (RMSE) of estimation were computed based on the Monte-Carlo method (Doucet et al., 2001; Chen and Liu, 2000). Table 1 provides the estimation result of three methods in estimating different target parameters.

Table 1. Estimation error in simulations of low, medium and high maneuvering target cases (RMSE).

Simulation	Parameter	RMSE			Improvement Percentage to MIE (%)	Improvement Percentage to MIECFM (%)
		MIE	MIECFM	Proposed Method		
Low maneuvering target Case	X-position (m)	1432	1412	1398	2.37	0.99
	Y-position (m)	1306	1286	1270	2.75	1.24
	X-velocity (m/s)	103	93	69	33	25.80
	Y-velocity (m/s)	94	83	66	29.78	20.48
	Acceleration (m/ s^2)	31	28.8	25	19.35	13.19
	Range	1816	1815	1840	- 1.32	- 1.37
	Azimuth	45	44	39	13.33	11.36
Medium maneuvering target case	X-position (m)	1447	1427	1417	2.07	0.7
	Y-position (m)	1595	1575	1565	1.88	0.63
	X-velocity (m/s)	105	95	75	28.57	21.05
	Y-velocity (m/s)	115	105	65	43.47	38.09
	Acceleration (m/ s^2)	33	31	26	21.21	16.13
	Range	2000	1990	2000	0	- 0.5
	Azimuth	40	39	35	12.5	10.25
High maneuvering target Case	X-position (m)	1811	1780	1650	8.89	7.3
	Y-position (m)	1548	1500	1371	11.43	8.6
	X-velocity (m/s)	139	123	89	35.97	27.64
	Y-velocity (m/s)	120	101	71	40.83	29.70
	Acceleration (m/ s^2)	35	33	29	17.14	12.12
	Range	2177	2136	2040	6.29	4.49
	Azimuth	42	41	38	9.52	7.3

Conclusion

In this paper, a fuzzy fading memory has been applied to the MIE in order to increase its effectiveness in tracking high maneuvering targets. Although the simple MIE represents a well performance in tracking non-maneuvering or low maneuvering targets, its accuracy fatally diminishes in high maneuvering target cases due to the mismodeling of target acceleration dynamics. To associate the MIE in coping with this deficiency, a new intelligent approach based on fading memory has been suggested in this paper. Simulation results in different case studies highlight on the effectiveness of new intelligent scheme in tracking high maneuvering targets.

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