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Full Length Research Paper

Interacting fading memory modified input estimation for maneuvering target tracking

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The modified input estimation (MIE) has been introduced recently and it provides fast initial convergence rate as well as satisfactory tracking performance in low and medium maneuvering target cases. Unfortunately, it fails to track a high maneuvering target accurately due to modeling errors relating to the target acceleration dynamics. In this paper, an improvement on the MIE is proposed for maneuvering target tracking. With the advantage of reduced sensitivity to modeling errors, a set of fading memory is selected to indicate different maneuver levels. The proposed method jumps between these different fading memories according to a Markov chain. Therefore, it can assign different fading memories different weights in different stages of the target motion to compensate for the influence of model errors. Experimental results show that the proposed method has more efficiency in tracking a maneuvering target than the MIE with conventional fading memory and the simple MIE.

Key words: Modified input estimation, fading memory, interacting multiple model, maneuvering target tracking.

INTRODUCTION

Target maneuvers, referring to unpredictable changes in target motion, may cause serious inaccuracies in modeling the system. A Kalman filter using a single state space model is restricted in accuracy of the estimate. To solve this problem, the multiple model (MM) algorithm was introduced. The MM adaptive estimation approach is based on the fact that the behavior of a target cannot be characterized at all times by a single model, but a finite number of models can adequately describe its behavior in different regimes (Mazor et al., 1998). In this algorithm, each model characterizes a specific motion of a target, which makes it possible to describe the whole motion. Blom and Bar-Shalom (1988) proposed a safe adaptation or "soft switching" approach, interacting multiple model (IMM). Using this technique, problems relating to identification - based adaptation are substantially mitigated. The basic idea of the IMM algorithm is to weigh each mode by probability and combine these estimates without hard decision (Bar-Shalom et al., 1989). Although, the IMM filter is efficient in tracking maneuvering targets, it requires a priori, the suitable choice for modeling transition probability. Moreover, the filter performance may not be satisfactory under the presence of external inputs that comply with none of the models (Lee and Tahk, 1999).

Input estimation (IE) (Chan et al., 1979; Lee and Tahk, 1999; Whang et al., 1994) is a totally different approach which detects the existence of target maneuvers and directly estimates the magnitude of the unknown maneuvers from the residuals and uses the estimates to update the Kalman filter. Unfortunately, basic IE schemes need additional effort for the estimation and detection of acceleration, and the maneuver detection delay is inevitable. Among the input estimation, modified input estimation (MIE) has been recently proposed (Khaloozadeh and Karsaz, 2009). In their approach, the acceleration is treated as an additive input term in the corresponding state equation. This modeling method has provided a special augmentation in the state space model which considers both the state vector and an unknown acceleration vector as a new augmented state. In this

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scheme, the original state and acceleration vectors are estimated simultaneously with a standard Kalman filter. MIE provides fast initial convergence rate as well as satisfactory tracking performance in low and medium maneuvering target cases. It does not need the maneuver detection stage and also, it does not consume any time for maneuver detection. Although, the MIE is theoretically optimal, it fails to track a high maneuvering target accurately due to modeling errors relating to the target acceleration dynamics.

To overcome different modeling errors, fading memory (Sorensen and Sacks, 1971; Statman, 1987) has been introduced. It can reduce sensitivity to modeling errors and help to reach more accuracy in tracking maneuvering targets. In conventional methods, the factor of the fading memory is determined off-line by the designers and remains constant in the process of filter. However, in non-maneuvering mode, larger factor leads to larger filter gain which overcompensate the state of filter; in high maneuvering mode, smaller factor leads to smaller filter gain which incompletely compensate the state. To overcome the drawback of the conventional fading memory, the fuzzy fading memory was proposed (Bahari et al., 2009) recently. In their method, the factor of fading memory is determined using fuzzy logic based on the values of target acceleration. Although, it can intelligently adjust the factor and improve the efficiency of MIE, the fuzzy fading memory has to detect the target maneuver and a fuzzy set must be selected in advance. When fuzzy membership functions are employed for fuzzy sets, a threshold selected by using the prior knowledge is necessary. Similar improvements on MIE have been proposed recently (Bahari and Pariz, 2009; Beheshtipour and Khaloozadeh, 2009), similar to the algorithm of Bahari et al. (2009), but their methods have poor real-time performances and the tracking accuracy depends on the fuzzy reasoning rules which have been designed off-line.

To solve the problems mentioned previously, this paper presents a novel interacting fading memory modified input estimation algorithm for maneuvering target tracking. With the advantage of reduced sensitivity to modeling errors, a set of fading memory is selected to indicate different maneuver level. The proposed method jumps between these different fading memories according to Markov chain. Therefore, it does not include any hard decision and the compensation to the state of filter is more accurate.

MODIFIED INPUT ESTIMATION

Modified input estimation (MIE) technique was proposed by Khaloozadeh and Karsaz (2009) in their work. In this method, the acceleration is treated as an additive state term in the corresponding state equation. It is assumed that a target moving in a two-dimensional plane and the acceleration is treated as an additive term. The kinematic and measurement equations with maneuvering model are given by:

$$X(n+1) = FX(n) + Cu(n) + Gw(n) \tag{1}$$

and

$$z(n+1) = HX(n+1) + v(n+1) \tag{2}$$

where the state vector at time *n* is $X(n) = [x(n), v_x(n), y(n), v_y(n)]^T$; representing the positions and velocities in *x* and *y* directions, $z(n)$ is the measurement vector, $u(n) = [a_x(n), a_y(n)]^T$ is the acceleration input vector. It is assumed that the acceleration *u* is a completely unknown input which models the target maneuvers. When there is no maneuver, *u* is 0.

Let *T* denotes the time interval between two consecutive measurements; *G*, *F*, *C* and *H* are all functions of *T*, as follows:

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

Furthermore, $w(n)$ and $v(n)$ are assumed to be mutually independent and zero-mean white noise with covariance $Q(n)$ and $R(n)$, respectively.

The additive maneuver term $u(n)$ is treated as a new state and the maneuvering model (Equation 1) can be revised to a nonmaneuvering model with an augmented kinematic equation as:

$$\begin{bmatrix} X(n+1) \\ u(n+1) \end{bmatrix} = \begin{bmatrix} F & C \\ 0 & I \end{bmatrix} \begin{bmatrix} X(n) \\ u(n) \end{bmatrix} + \begin{bmatrix} G \\ 0 \end{bmatrix} w(n) \tag{3}$$

or

$$X_{Aug}(n+1) = F_{Aug} X_{Aug}(n) + G_{Aug} W_{Aug} \tag{4}$$

The augmented measurement equation can be expressed as:

$$z(n+1) = [HF \quad HC] \begin{bmatrix} X(n) \\ u(n) \end{bmatrix} + HGw(n) + v(n+1) \tag{5}$$

or

$$Z_{Aug}(n) = H_{Aug}(n) X_{Aug}(n) + V_{Aug}(n) \tag{6}$$

where $X_{Aug}(n) = \begin{bmatrix} X(n) \\ u(n) \end{bmatrix}$, $F_{Aug} = \begin{bmatrix} F & C \\ 0 & I \end{bmatrix}$, $G_{Aug} = \begin{bmatrix} G \\ 0 \end{bmatrix}$,

$W_{Aug} = w$, $H_{Aug} = [HF \quad HC]$ and $V_{Aug} = HGw(n) + v(n+1)$.

Obviously, the augmented measurement noise V_{Aug} is time correlated with the process noise W_{Aug}, while it is still a white process. By defining the cross-covariance T_{Aug}, one can obtain:

$$E\begin{bmatrix} W_{Aug}(n_1) \\ V_{Aug}(n_1) \end{bmatrix}\begin{bmatrix} W_{Aug}^T(n_2) & V_{Aug}^T(n_2) \end{bmatrix}$$

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

$$Q_{Aug}(n) = E\left[W_{Aug}(n)W_{Aug}^T(n)\right] = E\left[w(n)w^T(n)\right] = Q$$

$$R_{Aug}(n) = E\left[V_{Aug}(n)V_{Aug}^T(n)\right] =$$

$$= H(n)G(n)Q(n)G^T(n)H^T(n) + R(n)$$

$$T_{Aug}(n) = E\left[W_{Aug}(n)V_{Aug}^T(n)\right] = QG^T(n)H^T(n)$$

The optimal target maneuver estimator for the augmented system is:

$$\hat{X}_{Aug}(n+1|n+1) = F_{Aug}(n)\hat{X}_{Aug}(n|n) + K_{Aug}(n+1)[Z_{Aug}(n+1) - H_{Aug}(n+1)F_{Aug}(n)\hat{X}_{Aug}(n|n)] \quad (7)$$

The new Kalman gain is modified on the basis of $T_{Aug}(n)$ as:

$$K_{Aug}(n+1) = [P_{Aug}(n+1|n)H_{Aug}^T(n+1) + G_{Aug}(n)T_{Aug}(n)]R_{Aug}^{-1}(n+1) \quad (8)$$

$$P_{Aug}(n+1|n+1) = P_{Aug}(n+1|n) - P_{Aug}(n+1|n)H_{Aug}^T(n+1)[R_{Aug}(n+1) + H_{Aug}(n+1)P_{Aug}(n+1|n)H_{Aug}^T(n+1)]^{-1}H_{Aug}(n+1)P_{Aug}(n+1|n) \quad (9)$$

$$P_{Aug}(n+1|n) = F_{Aug}(n)P_{Aug}(n|n)F_{Aug}^T(n) + G_{Aug}(n)Q_{Aug}(n)G_{Aug}^T(n) \quad (10)$$

INTERACTING FADING MEMORY MODIFIED INPUT ESTIMATION

The MIE has ability to tracking a maneuvering target, because the acceleration as an unknown input is treated as a part of the state of the target and the original state and acceleration vectors are estimated simultaneously. But it would not be functionally accurate when the target begins to maneuver with high acceleration. In this situation, different target acceleration dynamics, including abrupt changes in target speed and direction were not modeled correctly and completely in process model of MIE.

One successful approach to overcome this mismodeling is fading memory that applies an exponentially decaying weight to past measurements. Based on fading memory, the augmented predicted covariance instead of Equation 10 is:

$$P_{Aug}(n+1|n) = \alpha^2 F_{Aug}(n)P_{Aug}(n|n)F_{Aug}^T(n) + G_{Aug}(n)Q_{Aug}(n)G_{Aug}^T(n) \quad (11)$$

where α is a factor of fading memory. By choosing $\alpha \geq 1$, one can determine how much the filter forgets the past measurements. When $\alpha = 1$, there is no "fading in the memory" and the gain is equal to the Kalman gain.

From the view of model, a maneuver target motion can be described by different models. However, in MIE, the maneuver term is treated as a new state and any maneuvering model can be revised to a nonmaneuvering model; therefore, a maneuver target motion can be characterized as different maneuver levels. Maneuver level is defined as a nominal acceleration level. A low maneuver level represents a slow and varying acceleration and a high maneuver level represents an abrupt change in acceleration. In fact, different factor of fading memory (to simplify, call it fading memory directly) implies different maneuver level of the target.

Similar to IMM, a set of fading memory is selected in advance to indicate different maneuver level. The proposed method jumps between these different fading memories according to a Markov chain. In this algorithm, each fading memory characterizes a specific maneuver level of a target, which makes it possible to describe the whole motion. The resulting algorithm is "decision free" in the sense that at each time the probabilities of each fading memory being the prevailing one are evaluated.

Assuming that there is a set of fading memories, including *N* different ones used for interaction. M_f denotes the fading memory set. The transition between these fading memories is governed by a Markov chain, characterized by the transition probability p_{ij}, which is selected at the beginning of the algorithm. The algorithm can be divided into four parts, namely, interacting, filtering, fading memory probability calculation and estimate combination.

Interaction of the estimates

$$\forall i, j \in M_f \quad , \quad \mu_{i|j}(n-1|n-1) = \frac{1}{\bar{c}_j} p_{ij}\mu_i(n-1) \quad \text{(mixed probability)},$$

where $\bar{c}_j$ is a normalization factor.

$$\bar{c}_j = \sum_i p_{ij}\mu_i(n-1) \quad (12)$$

$$\hat{X}_{Aug}^{j0}(n-1|n-1) = \sum_i \hat{X}_{Aug}^i(n-1|n-1)\mu_{i|j}(n-1|n-1) \quad (13)$$

$$P_{Aug}^{j0}(n-1|n-1)=\sum_{i}\{P_{Aug}^{i}(n-1|n-1)+[\hat{X}_{Aug}^{i}(n-1|n-1)-\hat{X}_{Aug}^{j0}(n-1|n-1)]$$
$$[\hat{X}_{Aug}^{i}(n-1|n-1)-\hat{X}_{Aug}^{j0}(n-1|n-1)]^{T}\}\mu_{i|j}(n-1|n-1) \quad (14)$$

Filtering

The *j*th filter is updated by MIE from Equations 8, 9, 11 and 7 using α_j as the *j*th fading memory.

Fading memory probability

The augmented residual (innovation) is:

$$v_{Aug}^{j}(n+1)=Z_{Aug}^{j}(n+1)-H_{Aug}^{j}(n+1)F_{Aug}^{j}(n)\hat{X}_{Aug}^{j}(n|n) \quad (15)$$

The covariance of the innovation is:

$$B_{Aug}^{j}(n)=H_{Aug}^{j}(n)P_{Aug}^{j}(n+1|n)^{T}H_{Aug}^{j}(n)^{T}+R_{Aug}^{j}(n) \quad (16)$$

Likelihood of the fading memory *j* is:

$$\Lambda_{j}(n)\sim N[v_{Aug}^{j}(n);0,B_{Aug}^{j}(n)] \quad (17)$$

Fading memory probability is:

$$\mu_{j}(n)=\frac{1}{c}\Lambda_{j}(n)\overline{c}_{j} \quad (18)$$

where $c=\sum_{j}\Lambda_{j}(n)\overline{c}_{j}$ is a normalizing factor.

Combination

$$\forall j\in M_{f}\ \ \hat{X}_{Aug}(n|n)=\sum_{j}\hat{X}_{Aug}^{j}(n|n)\mu_{j}(n) \quad (19)$$

$$P_{Aug}(n|n)=\sum_{j}\{P_{Aug}^{j}(n|n)+[\hat{X}_{Aug}^{j}(n|n)-\hat{X}_{Aug}(n|n)][\hat{X}_{Aug}^{j}(n|n)-\hat{X}_{Aug}(n|n)]^{T}\}\mu_{j}(n) \quad (20)$$

As implied by the aforementioned flow of the proposed algorithm, in maneuvering stage, the larger factor of fading memory will acquire a larger probability (can be seen as a weight in fact) to compensate for the influence of model errors relating to the target acceleration dynamics; whereas, in nonmaneuvering stage, the smaller fading memory will acquire a larger probability to avoid overcompensating the state of filter. In summation, the proposed algorithm assigns different fading memory, different weight in different stage of the target motion to compensate for the influence of model errors more accurately.

The main advantages of the proposed algorithm are concluded as follows:

1. Since the target maneuver was described by the maneuver level, the proposed method does not need any maneuver model which has to be determined in advance in the traditional methods, such as IMM.
2. Since the proposed algorithm mixes the estimates from different fading memories instead of choosing which fading memory is true in each time step, it is in fact a soft switching algorithm, which does not include any hard decision. Therefore, it does not consume any time for maneuver detection.3.

As a maneuver target motion can be characterized as different maneuver levels and each fading memory implies a specific maneuver level of a target, the proposed method jumps between these different fading memories according to a Markov chain. It also has the advantage of being implementable without a priori knowledge of the maneuvering characteristics of the target.

SIMULATION RESULTS AND ANALYSIS

Here, simulations were done to verify the efficiency of the novel modified input estimation with interacting fading memory. The proposed scheme was compared with the MIE and the MIE with conventional fading memory (MIECFM) in tracking maneuvering targets.

Example 1

It is assumed that a target moves in a two-dimensional space. The sampling time is *T=1s* and the elements of the covariance matrices of the system and measurement noises are chosen as $Q_{ii}=1$ and $R_{ii}=(20)^2m^2$, respectively.

The initial state of a target is given by $X(0)=[2000m \quad 180m/s \quad 0m \quad 0m/s]^T$, and the target moves with constant acceleration of $u(t)=[9m/s^2 \quad 9m/s^2]^T$ for $0\le t\le 13s$. Then, it starts another higher maneuver with acceleration of $u(t)=[-20m/s^2 \quad -20m/s^2]^T$ up to the end of this simulation at $t=40s$. The set M_f is constructed by two fading memories, one is $\alpha_1=1$ and the other is $\alpha_2=1.08$. The initial probability of fading memory α_1 and α_2 is 0.7 and 0.3, respectively. The transition probabilities between these two fading memories are taken as:

$$\begin{bmatrix}0.7 & 0.3\\ 0.3 & 0.7\end{bmatrix}.$$

Figure 1 illustrates the actual target trajectory and that estimated by the MIE algorithm, the MIE with conventional fading memory (MIECFM) and the proposed

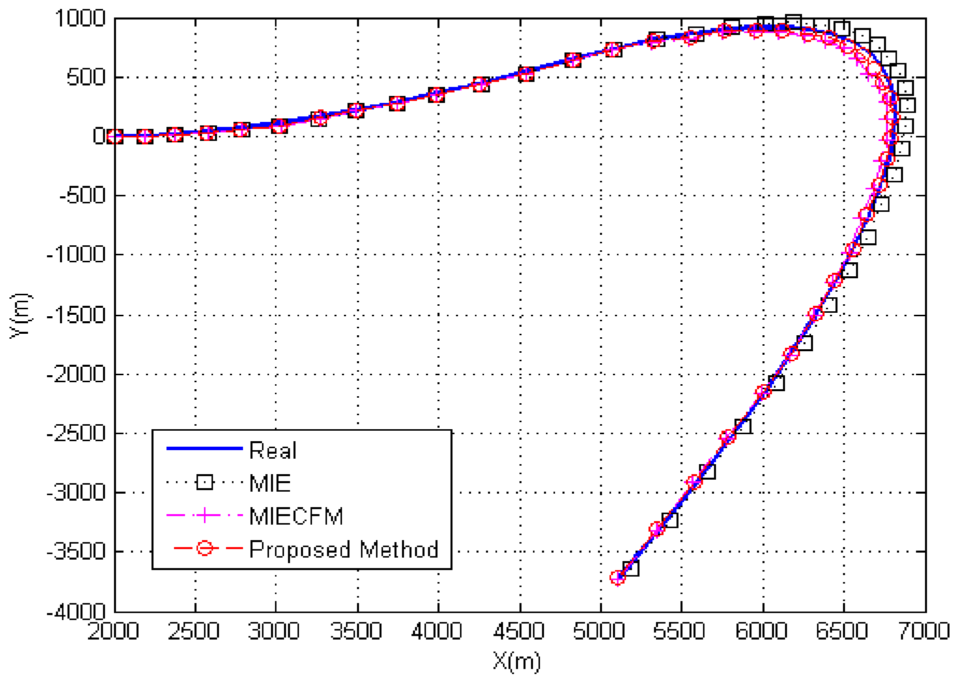

Figure 1. Target trajectory in Cartesian coordinates and the tracking results of the proposed method, MIE and MIECFM in Example 1.

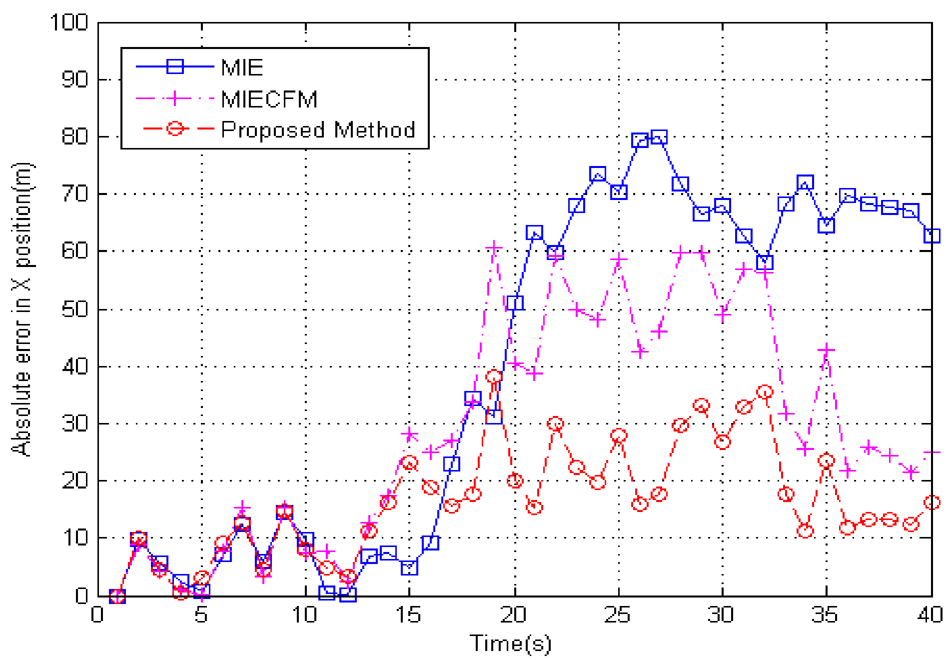

Figure 2. Absolute position error in X-direction.

algorithm in x-y plane. The absolute tracking errors of position, velocity and acceleration in *x* direction depicted in Figures 2 to 4, respectively are similar to those in *y* direction. Obviously, the proposed scheme has more efficiency in tracking a maneuvering target than the other two algorithms.

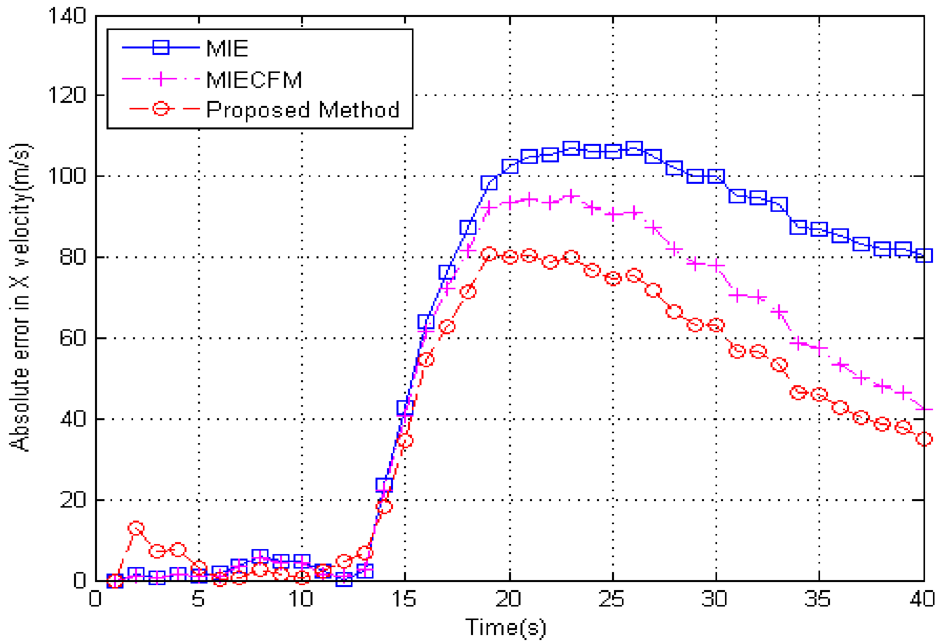

Figure 3. Absolute velocity error in X-direction.

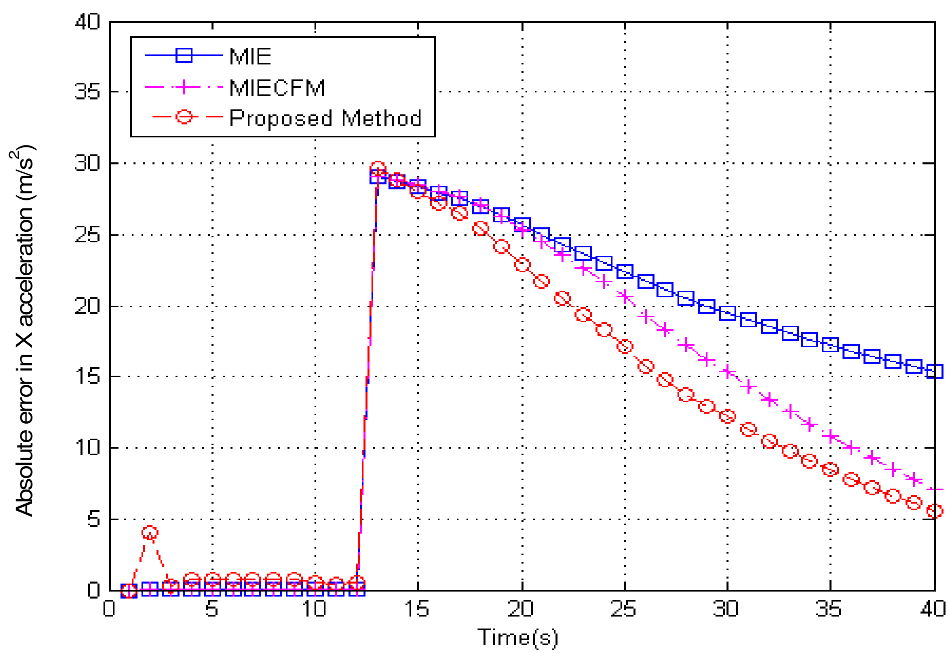

Figure 4. Absolute acceleration error in X-direction.

The probabilities of two different fading memories versus time are illustrated in Figure 5. It is seen that the probabilities of two different fading memories vary with sampling time; actually, target motion. In the beginning of high maneuvering stage, the fading memory 2 which is suitable for high maneuver level is growing to a prevailing one rapidly. In the following stage, since the maneuver level is decreasing due to the acceleration remaining

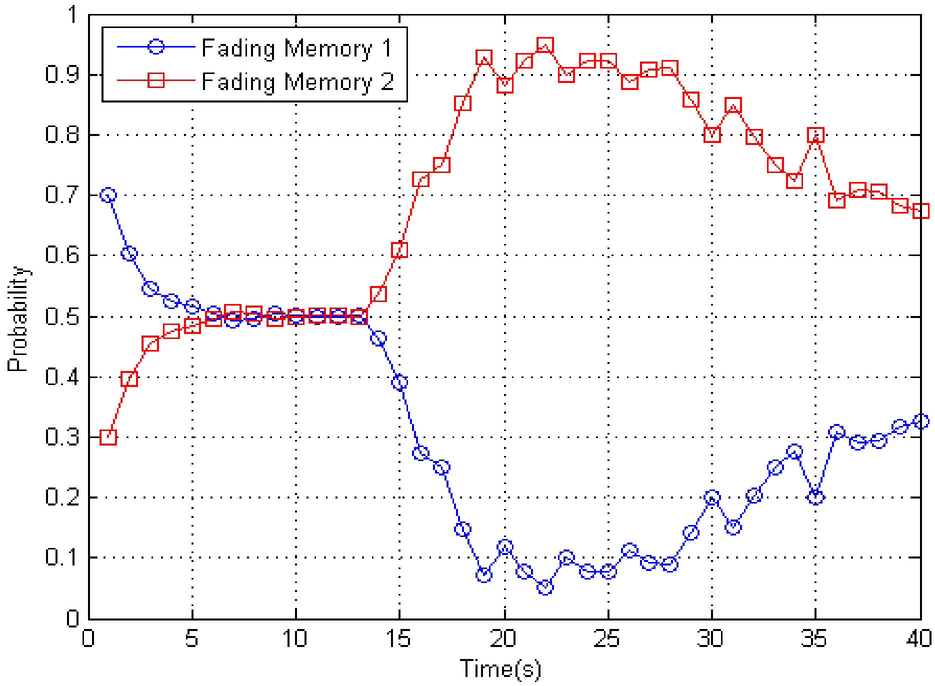

Figure 5. Probabilities of two different fading memories versus time.

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

Maneuver level	Parameter (m)	RMSE			Improvement Percentage to MIE (%)	Improvement Percentage to MIECFM (%)
		MIE	MIECFM	Proposed method		
Low	*X*-position	22.14	17.43	12.89	41	26
	Y-position	22.15	17.33	12.86	41	25
Medium	X-position	52.97	34.98	20.49	61	41
	Y-position	53.22	35.15	20.80	60	40
High	X-position	88.37	57.26	32.17	63	43
	Y-position	88.70	56.93	31.84	64	44

constant, the probability (can be viewed as weight) of the fading memory 2 decreased gradually. The presented method has higher efficiency in tracking a maneuvering target than the MIE with conventional fading memory and the simple MIE, because of the interaction of different fading memories

Example 2

To evaluate the performance of tracking low, medium and high maneuvering target, similar simulations were pre-formed as follows. In simulation of tracking medium maneuvering target, the parameters are the same as in Example 1.

In tracking low and high maneuvering target, it starts another maneuver with same acceleration in *x* and *y* direction of $-2m/s^2$ and $-40m/s^2$ up to the end, respectively. Each of the simulations was repeated 100 times and root mean square errors (RMSE) of estimation were computed based on the Monte Carlo method. Estimation results are listed in Table 1.

As seen in Table 1, obviously, in comparison to the method of intelligent fading memory based MIE (Bahari et al., 2009), the improvement percentages to MIE and MIECFM are much higher in the stage of maneuver.

Conclusion

An improvement on modified input estimation is presented in this paper. A set of fading memories which characterize the specific maneuver levels of a target make it possible to describe the whole target motion. The proposed method jumps between these different fading memories according to a Markov chain. Therefore, it has ability to assign different fading memory different weight in different stage of the target motion to compensate for the influence of model errors more accurately. As a soft switching algorithm, it does not consume any time for maneuver detection. Numerical examples show that the proposed scheme has more efficiency in tracking a maneuvering target than the conventional fading memory based MIE and the simple MIE.

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