Scientific Research and Essay Vol.4 (10), pp. 936-945, October, 2009
Available online at http://www.academicjournals.org/sre
ISSN 1992-2248 © 2009 Academic Journals

Review

High maneuvering target tracking using an input estimation technique associated with fuzzy forgetting factor

Mohamad Hasan Bahari* and Naser Pariz

Ferdowsi University of Mashhad, No. 11, Touraj 14 Aly, Kolahdouz 27, Mashhad, Iran.

Accepted 2 June, 2009

In this paper, a new fuzzy forgetting factor (FFF) is developed in order to aid a modified input estimation (MIE) technique and enhance its performance in tracking high maneuvering targets. The MIE has been introduced recently and succeeds in presenting reasonably accurate target trajectory, velocity and acceleration estimation in low and mild maneuvering situations. However, after some iteration its steps become small. Due to small steps, the accuracy of target tracking may be seriously degraded in the presence of high maneuvers. In this study we present an intelligent self-tuning approach based on a fuzzy forgetting factor in order to enjoy satisfactory tracking performance in low, Medium and high maneuvering target cases. Simulations visualize the efficiency of the proposed method and emphasize on its accuracy in tracking high maneuvering targets. Furthermore, simulation results illustrate that proposed method is not sensitive to the sampling time.

Key words: High maneuver target tracking, modified input estimation (MIE), fuzzy logic, self- tuning, forgetting factor.

INTRODUCTION

Although the linear Kalman filter (KF) has been broadly used for the tracking problem, its performance may be seriously shrunk if the target maneuvers (Lee et al., 2004). To deal with unknown and fast target accelerations, many techniques and methods have been suggested during last years (Duh et al., 2004; Cardillo et al., 1999). The methods used for Maneuvering Target Tracking (MTT) problem are roughly categorized into two main approaches: Input estimation (IE) techniques (Lee and Tahk, 1999; Whang et al., 1994) and Multiple Model (MM) methods (Kirubarajan et al., 2000; Li and Zhang, 2000; Lee et al., 2004). Unfortunately, each category deals with different problems. Basic IE schemes need to additional effort for the estimation and detection of acceleration, and the compenation of estimated state. MM methods usually suffer from large computational load imposed by using multiple sub-filters (Lee et al., 2004).

Furthermore, many suggested schemes were developed based on different assumptions about the target dynamics and available facilities. For example, some researchers developed their algorithms with constant velocity or constant acceleration assumption (Wang and Varshney, 1993; Munu et al., 1992; Blair, 1993; Mook and Shyu, 1992). Some other methods need to use small sampling times (duration between two scans) to operate accurately (Munu et al., 1992; Blair et al., 1991; Mook and Shyu, 1992; Rokhsaz and Steck, 1991).

Among IE techniques, the MIE approach yields reasonable performance without constant acceleration or small sampling time assumptions. Furthermore, it not only provides fast initial convergence rate, but it can also track a maneuvering target with fairly good accuracy. In this 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 (Khaloozadeh and Karsaz, 2009). Although the MIE yields fairly good accuracy in tracking non-maneuvering or mild maneuvering targets, its steps get smaller after some iterations. Small steps lead to a delay in tracking when the target stars to maneuver, especially, when the magnitude of maneuver is high.

*Corresponding author. E-mail: m.h.bahari@ieee.org. Tel: +98-511-7281586. Postal Code: 9184837898.

To overcome the above-mentioned problem, self-tuning approaches with variable forgetting factor can be employed. A well-known self-tuning method has been proposed by Fortescue et al. (1981). This method was applied to many applications and the results were very encouraging (Osorio Cordero and Mayne, 1981). In this scheme, the value of the forgetting factor in each iteration is very important. Obviously, this parameter should be determined based on the magnitude of acceleration. The main drawback of applying method of Fortescue et al. (1981) to target tracking problem is that the target acceleration plays no role in self-tuning mechanism of this method. To cope with this trouble, Bahari et al. (2007, 2008) proposed a soft computing approach to determine this parameter adaptively.

This method used a fuzzy target maneuver detector in order to decide about resetting the covariance matrix. Although this method was attractive from several aspects, it did not succeed in increasing the tracking accuracy considerably. This deficiency was due to the weakness of its maneuver detector system. Beheshtipour and Khaloozadeh (2008) have tried to solve this problem by utilizing the MIE method instead of the standard Kalman filter. Therefore, in this method the need for a separated maneuver detector system was overcome (Khaloozadeh and Karsaz, 2009). They also used a fuzzy system to reset the covariance matrix intelligently. However, the designed fuzzy system was not properly setup.

Furthermore, the criterion of resetting the covariance matrix was erroneous. Moreover, they did not follow the instruction of self-tuning methods correctly. In this paper, we introduce a new fuzzy self-tuning method for the MIE in order to track maneuvering targets with high accuracy. The proposed method can determine the optimal values of forgetting factor in each iteration effectively with the use of fuzzy logic.

The rest of the paper is organized as follows. The problem formulation is derived in Section 2. In the following section, the MIE method is presented. The proposed method is introduced in Section 4. Section 5 includes three examples of targets moving with high maneuver in a two-dimensional plane in order to visualize the efficiency of the proposed method in comparison with those of the MIE. The paper ends with Section 6 on conclusions.

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 (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;

n : Discrete time index.

$x(.)$: 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 expression 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 input term in the corresponding state equation. The formulation of this method is as follows.

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

$$z(n+1) = \begin{bmatrix} HF & HC \end{bmatrix} \begin{bmatrix} x(n) \\ u(n) \end{bmatrix} + HGw(n) + v(n+1) \quad (2)$$

Therefore, the augmented state equations can be derived as relation 3.

$$x_{Aug}(n+1) = F_{Aug} X(n) + G_{Aug} W_{Aug}(n)$$

$$Z_{Aug}(n) = z(n+1) = H_{Aug}(n) x_{Aug}(n) + V_{Aug}(n). \quad (3)$$

Where; $x_{Aug}(n)$, F_{Aug} , G_{Aug} , W_{Aug} , H_{Aug} , $V_{Aug}(n)$ are as follows.

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

$$W_{Aug} = w, H_{Aug} = \begin{bmatrix} HF & HC \end{bmatrix} \text{ and } V_{Aug}(n) = HGw(n) + v(n+1) \quad (4)$$

The optimal target maneuver estimator for the augmented system is:

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

In this method Kalman gain is:

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

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

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

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

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 as follows:

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

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

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

$$T_{Aug}(n) = E\{W_{Aug}(n)V_{Aug}^T\} = QG^T(n)H^T(n) \quad (7)$$

FUZZY SELF-TUNING

In the MIE, the error covariance matrix ($P_{Aug}(n|n)$) becomes small after a few iterations. Hence, their steps become small (Beheshtipour and Khaloozadeh, 2008). Consequently, when the target begins to maneuver with high acceleration, the MIE tracker would not be functionally accurate. This motivates a related scheme in which we reset $P_{Aug}(n|n)$ at various times. In other words, old data is discarded to keep the algorithm alive.

CONVENTIONAL FORGETTING FACTOR

One of the most successful self-tuning methods was proposed by Fortescue et al. (1981). In this method, the trace norm was used as a matrix measure. Fortescue and his colleagues explained that, after some iterations the error covariance matrix norm ($Trace\ [P_{Aug}(n+1|n+1)]$) becomes smaller than a specified value (*TL*). In this situation, in order to tune the regulator the following resetting action should be performed.

$$If \quad \frac{1}{\lambda(n+1)} \times Trace\ [P_{Aug}(n+1|n+1)] < TL \quad \Rightarrow$$

$$P_{Aug}^{New}(n+1|n+1) = \frac{1}{\lambda(n+1)} \times P_{Aug}(n+1|n+1) \quad (8)$$

Where, $\lambda(n+1)$ is the forgetting factor. It is roughly

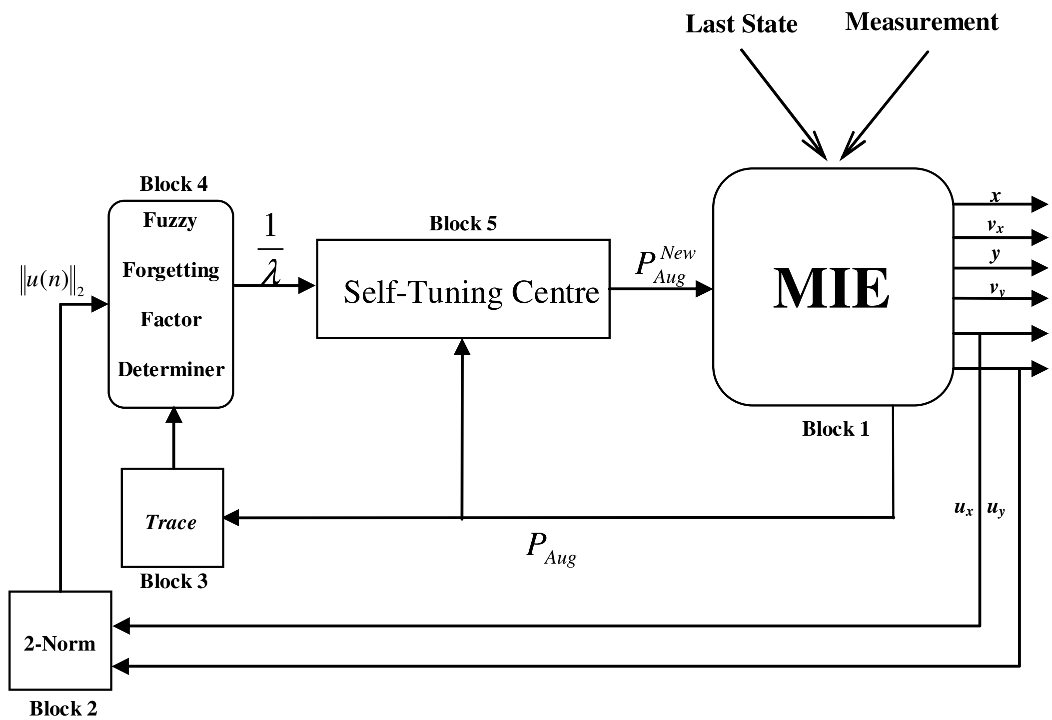

Figure 1. Block diagram of the proposed method.

equal to 1 under steady state condition and suddenly decreases when quick changes to the process arise. However, in computing $\lambda(n+1)$, there is a parameter called δ which should be determined off-line.

The main drawbacks of the conventional self-tuning methodology are:

1. The *TL* is determined off-line and remains constant during the simulation. This drawback may lead to a delay in tuning the filter when the target maneuvers. Further- more, it can result in surplus resetting when the target does not maneuver.
2. The δ is determined off-line and remains constant during the simulation. This drawback may result in a small Kalman gain when the target maneuvers (incomplete compensation) or a large Kalman gain when the target does not maneuver.

FUZZY FORGETTING FACTOR

To overcome the drawbacks of the self-tuning approach proposed by Fortescue et al. (1981) a fuzzy self-tuning algorithm is suggested in this paper. In this method $\frac{1}{\lambda(n+1)}$ is determined intelligently based on the target acceleration.

A block diagram of the proposed intelligent method is illustrated in Figure 1.

In this Figure, Block 1 is the MIE. Inputs of this block are last state, measurement and the updated error covariance matrix obtained using fuzzy logic, ($P_{Aug}^{New}(n+1|n+1)$). The procedure for calculating $P_{Aug}^{New}(n+1|n+1)$ will be elaborated. This block has two outputs. One of them is the new state and the other is the error covariance matrix before updating procedure ($P_{Aug}(n+1|n+1)$).

Block 2 computes the 2-norm of vector $u(n)=[u_x(n) \quad u_y(n)]^T$. The output of this block is $\|u(n)\|_2=\sqrt{u_x(n)^2+u_y(n)^2}$.

Block 3 computes the *Trace* norm of $P_{Aug}(n+1|n+1)$.

Block 4 is the fuzzy forgetting factor determiner. As can be interpreted from Figure 1, Block 4 has two inputs and one output. Inputs are the target acceleration magnitude (output of Block 2) and $Trace\ [P_{Aug}(n+1|n+1)]$ (output of Block 3). The output of this fuzzy controller is the optimum value of $\frac{1}{\lambda(n+1)}$ in each iteration. Obviously, error covariance matrix should be reset when the target starts to maneuver and tracker steps are not large enough($Trace\ [P_{Aug}(n+1|n+1)]$ is small) to track the target. In such a situation, the fuzzy system in Block 4 determines a proper value for $\frac{1}{\lambda(n+1)}$, which is proportional to the target acceleration. While the target does not maneuver or $\frac{1}{\lambda(n+1)}$ is large enough to track the target accurately, the output of Block 4 approaches 1. Therefore, the rules of designed fuzzy system are as follows:

Rule 1: If $Trace\ \left[P_{Aug}(n+1 \mid n+1)\right]$ is high or $\|u(n)\|_2$ is low then $\frac{1}{\lambda(n+1)}$ is low

Rule 2: If $Trace\ \left[P_{Aug}(n+1 \mid n+1)\right]$ is low and $\|u(n)\|_2$ is high then $\frac{1}{\lambda(n+1)}$ is high

Inputs and output fuzzy sets all have two Gaussian membership functions with the following membership grade $g_i^j(x_i)$.

$$g_i^j(x_i) = \exp\left[-\frac{1}{2}\left(\frac{x_i - c_i^j}{\sigma_i^l}\right)^2\right] \tag{9}$$

Where; c_i^j and σ_i are the mean and the standard deviation of Gaussian membership function for the i^{th} input variable of the j^{th} fuzzy rule, respectively. The fuzzy inference rules support afore-mentioned information.

Block 5 is the self-tuning centre. Inputs of this block are $\frac{1}{\lambda(n+1)}$ and $P_{Aug}(n+1|n+1)$. The system tunes itself in this block using the following relation.

$$P_{Aug}^{New}(n+1|n+1) = \frac{1}{\lambda(n+1)} \times P_{Aug}(n+1 \mid n+1) \tag{10}$$

The output of this block is the updated error covariance matrix obtained using fuzzy logic ($P_{Aug}^{New}(n+1|n+1)$).

As can be interpreted from the procedure of applying the FFF to the MIE, FFF increases the steps of MIE in maneuvering mode effectively and do not change the steps of MIE in non-maneuvering mode. Consequently, the esti- mation accuracy of MIE associated with FFF is significantly higher than a simple MIE.

SIMULATION RESULTS

This section demonstrates the improvement of state estimation achieved by the proposed method. To evaluate the new tracking scheme and compare it with the MIE (Khaloozadeh and Karsaz, 2009) three examples are considered.

In all simulations of this section the elements of the covariance matrices of system noise and measurement noise are selected as $Q_k^x = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}$ 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 the target are unknown for the trackers.

Example 1: In this case study, our intention is to evaluate the proposed method in high maneuvering target situation.

In this simulation the sampling time is $T = 1(s)$. The initial position of the 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 $[u_x(0), u_y(0)] = [\text{-}0.5(\text{ms}^{-2}), -0.5\,(\text{ms}^{-2})]$ until $t = 100(s)$. Then, it starts to maneuver with acceleration of $[u_x(101), u_y(101)] = [2(\text{ms}^{-2}), 10(\text{ms}^{-2})]$. This acceleration continues to $t = 400(s)$. Then, the target starts another maneuver with acceleration of $[u_x(401), u_y(401)] = [-10\,(\text{ms}^{-2}), -30\,(\text{ms}^{-2})]$. The target moves with this acceleration up to the end of this simulation at $t = 500(s)$.

Figures 2 and 3 show the actual values and estimations of target range and azimuth, and also their corresponding errors by the proposed method and the MIE, respectively. Figure 4 illustrates the target velocity estimation by two methods. Figure 5 indicates the errors of velocity estimation in X and Y directions. The accuracy of the proposed

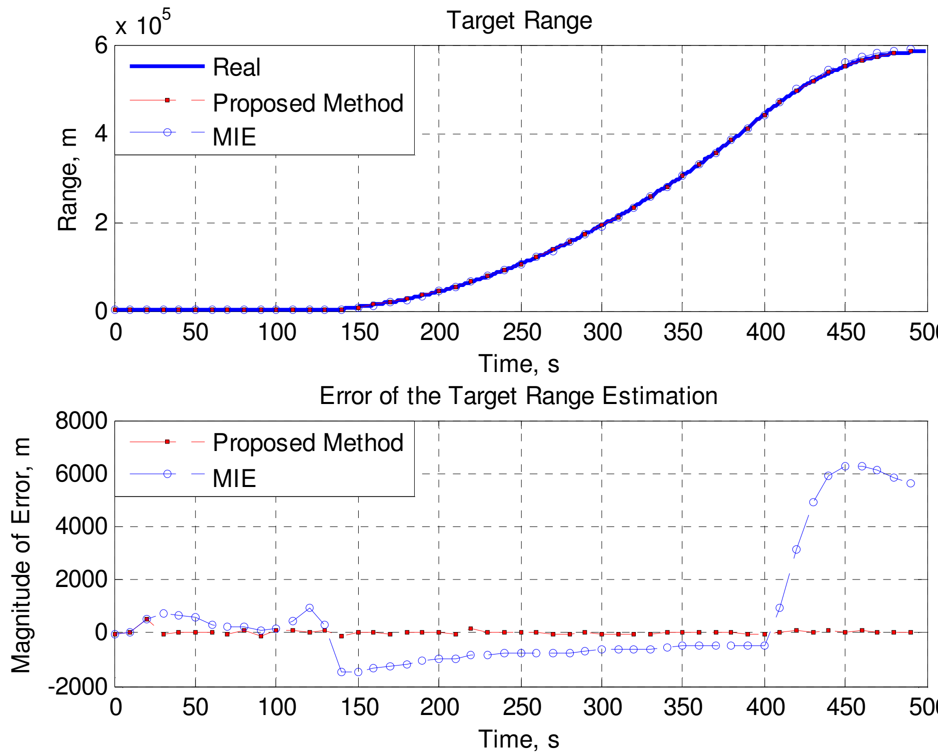

Figure 2. The actual value and estimation of the target range and the corresponding errors by the proposed method and MIE in Example 1.

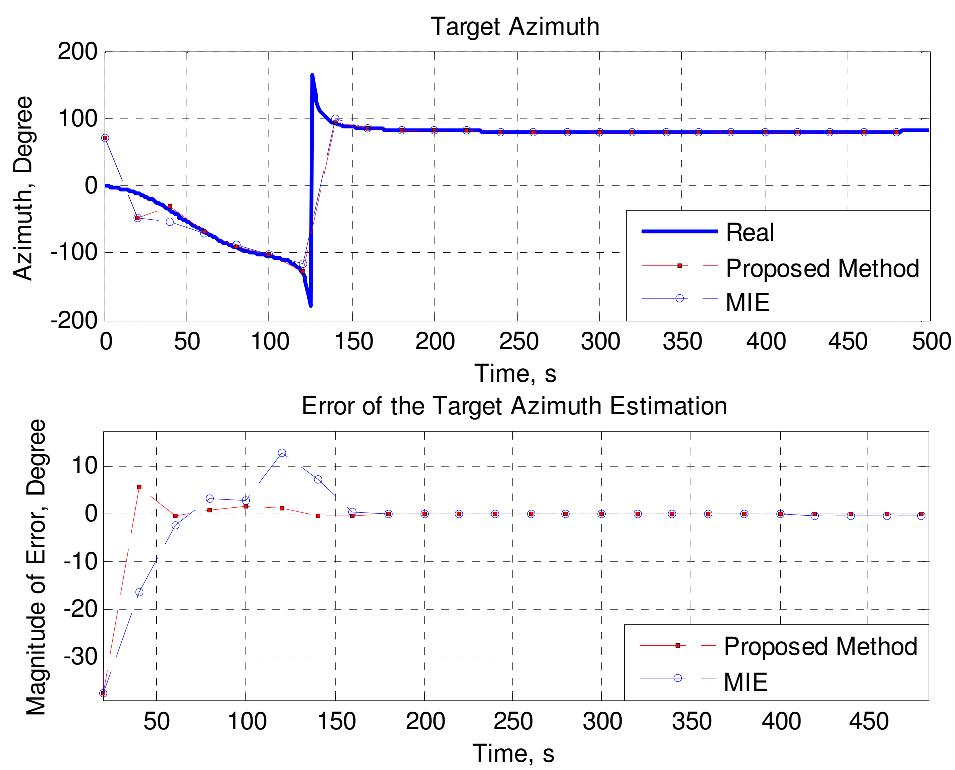

Figure 3. The actual value and estimation of the target azimuth and the corresponding errors by the proposed method and conventional MIE in Example 1.

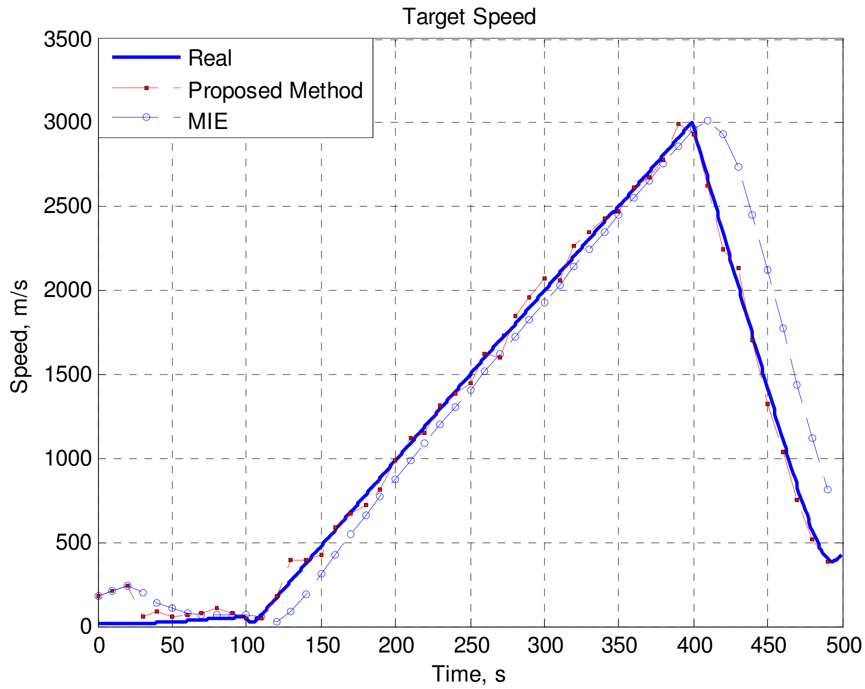

Figure 4. Target speed and the estimation result of the proposed method and MIE technique in Example 1.

algorithm in comparison with the MIE can be interpreted from these figures.

Example 2: In this example, our intention is to evaluate the proposed method in countering a target with low, medium and high maneuvers. Therefore, three simulations are performed as follows. In these simulations, the sampling time is $T = 10(s)$ and the initial position, velocity and acceleration 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.

Case 1: Simulation of low maneuvering target. 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 $t = 300(s)$.

Case 2: Simulation of medium maneuvering target. 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 =30 s.

Case 3: Simulation of high maneuvering target. 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 = 130 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 (Chen and Liu, 2000; Doucet et al., 2001).

Table 1 provides the estimation results of the two methods in estimating different target parameters.

Example 3: Many tracking algorithms are very sensitive to the sampling times or T (Munu et al., 1992; Blair et al., 1991; Mook and Shyu, 1992; Rokhsaz and Steck, 1991). In this example, our intention is to assess the proposed method in the case of sensors with a wide range of sampling times. The following stimulation was repeated

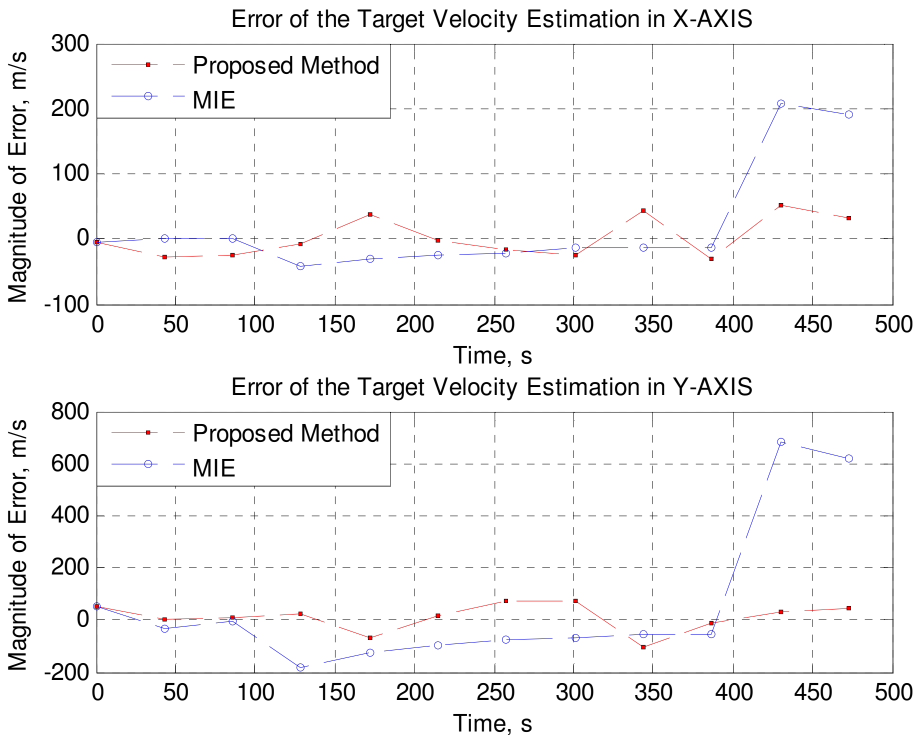

Figure 5. Errors of target velocity estimation in X and Y directions by the proposed method and MIE in Example 1.

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

Simulation	Parameter	RMSE		Improvement percentage (%)
		MIE	Propose method	
Low maneuvering target case	X-position (m)	1432	1420	0.83
	Y-position (m)	1306	1296	0.76
	X-velocity (m/s)	103	81	21
	Y-velocity (m/s)	94	74	21
	Acceleration (m/ s^2)	31	14	55
	Range	1816	1827	-0.6
	Azimuth	45	41	9
Medium maneuvering target case	X-position (m)	1447	1431	1
	Y-position (m)	1595	1582	0.8
	X-velocity (m/s)	105	82	21
	Y-velocity (m/s)	115	90.5	21
	Acceleration (m/ s^2)	33	16	51
	Range	2000	2000	0
	Azimuth	40	37	7.5
High maneuvering target case	X-position (m)	1811	1670	7.7
	Y-position (m)	1548	1399	9.62
	X-velocity (m/s)	139	94	32
	Y-velocity (m/s)	120	79	34
	Acceleration (m/ s^2)	35	16	54
	Range	2177	2029	6.79
	Azimuth	42	39	7

Table 2. Tracking result in example 3 (RMSE).

Parameter	RMSE		Improvement percentage (%)
	MIE	Proposed method	
X-position (m)	814	360	55.77
Y-position (m)	815	346	57.54
velocity (m/s)	96	50	47.91
Range	1039	396	61.88
Azimuth	7.77	7.22	7
Course	18	14	22.22

with different sampling times. To be more precise, we increased the sampling time from T = 0.1 to 10 s to with step 0.1 s in the following simulation. Therefore this simulation was repeated 150 times.

In this simulation, the initial position of the 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 $[u_x(0), u_y(0)] = [2(\mathrm{ms}^{-2}), 2\,(\mathrm{ms}^{-2})]$ until time step 250. Then, it starts to maneuver with acceleration of $[u_x(251), u_y(251)] = [-10(\mathrm{ms}^{-2}), -10\,(\mathrm{ms}^{-2})]$. The target moves with this acceleration up to the end of this simulation at time step 500.

Table 2 shows the mean values of RMSE in estimation over the 150 runs.

CONCLUSIONS

In this paper, a fuzzy forgetting factor has been applied to the MIE technique in order to increase its accuracy in tracking high maneuvering targets. Although the simple MIE technique –without forgetting factor– works well in non-maneuvering or low maneuvering target cases, its steps get small after a few iterations. Small steps result in low performance when the target moves with a high acceleration. To over this problem, fuzzy forgetting factor has been suggested in this paper.

The proposed intelligent self-tuning approach provides an algorithm for determining optimal values of the forgetting factor based on the target acceleration in each iteration. For further researches, one can try to find the optimal parameters of fuzzy systems used in this research utilizing different optimization techniques such as Genetic Algorithm (GA). Simulation results in different case studies emphasize the accuracy of new intelligent scheme in tracking a high maneuvering target in comparison with the MIE technique.

REFERENCES

Bahari MH, Karsaz A, Naghibi-S MB (2008). Intelligent Error Covariance Matrix Resetting for Maneuver Target Tracking. J. Appl. Sci. 8(20): 3630-3637.

Bahari MH, Moharrami FN, Ebrahimi Ganjeh M, Karsaz A (2007). Tracking a High Maneuver Target Based on Intelligent Matrix Covariance Resetting, Proc. Int. IEEE Symp. Image and Signal Processing and Analysis. Istanbul, Turkey pp. 35-40.

Beheshtipour Z, Khaloozadeh H (2008). High Maneuvering Target Tracking using Fuzzy Covariance Presetting. J. Appl. Sci. 8(12): 2279-2285.

Blair WD (1993). Fixed-Gain Two-Stage Estimators for Tracking Maneuvering Targets. IEEE Trans. Aerosp. Electron. Syst. 29: 1004-1014.

Blair WD, Gray JE, Boyd MD (1991). Design Analysis for the Two-Stage α, β, γ Estimator. IEEE Proc. 2: 1050-1054.

Cardillo GP, Mrstik AV, Plambeck T (1999). A Track Filter for Reentry Objects with Uncertain Drag. IEEE Trans. Aerosp. Electron. Syst. 35(2): 395-409.

Chen R, Liu N (2000). Mixture Kalman Filter. J. R. Stat. Soc. 62 (3): 493-508.

Doucet A, De Freitas N, Gordon N (2001). An Introduction to Sequential Monte Carlo Methods. New York, Springer-Verlag.

Duh FB, Lin CT (2004). Tracking a maneuvering target using neural fuzzy network. IEEE Trans. Syst. Man Cybernet. Part B. 34 (1): 16-33.

Fortescue TR, Kershenbaum LS, Ydstie BE (1981). Implementation of Self-Tuning Regulators with Variable Forgetting Factors. Automatica, 17(6): 831-835.

Khaloozadeh H, Karsaz A (2009). A Modified Input Estimation Technique for Tracking Maneuvering Targets. IET Proc. Radar Sonar Navig. 3(1): 30-41.

Kirubarajan T, Bar-Shalom Y, Pattipati K, Kadar I (2000). Ground target tracking with variable structure IMM estimator. IEEE Trans. Aerosp. Electron. Syst. 36(1): 26-46.

Lee BJ, Park JB, Joo YH, Jin SH (2004). Intelligent Kalman filter for tracking a manoeuvring target. IEE Proc. Radar Sonar Navig. 151: 244-350.

Lee H, Tahk MJ (1999). Generalized input-estimation technique for tracking maneuvering targets. IEEE Trans. Aerosp. Electron. Syst. 35(4): 1388-1402.

Li X, Zhang Y (2000). Multiple-model estimation with variable structure - part V: likely-model set algorithm. IEEE Trans. Aerosp. Electron. Syst., 36(2): 448-465.

Mook DJ, Shyu IM (1992). Nonlinear Aircraft Tracking Filter Utilizing Control Variable Estimation. Am. Inst. Aeronaut. Astronaut. 15: 228-237.

Munu M, Harrison I, Wilkin D, Woolfson MS (1992). Comparison of Adaptive Target-Tracking Algorithms for Phased-Array Radar. Inst. Elec. Eng. Proc. Pt. F. 139(5): 336-342.

Munu M, Harrison I, Woolfson MS (1992). Comparison of the Kalman and α, β Filters for the Tracking of Targets Using Phased Array Radar (1992). Proc. IEE Conf. Radar '92, Brighton, U.K., pp. 196-199.

Osorio Cordero A, Mayne DQ (1981). Deterministic Convergence of a Self-Tuning Regulator with Variable Forgetting Factor. IEE Proc. Control Theory Appl. 128(1): 19-23.

Rokhsaz K, Steck JE (1991). Use of Neural Networks in Control of High-Alpha Maneuvers. J. Guid. Contr. Dyn. 16 (5): 934- 939.

Wang TC, Varshney PK (1993). A tracking algorithm for maneuvering targets. IEEE Trans. Aerosp. Electron. Syst. 29(3): 910-924.
Whang HI, Lee JG, Sung TK (1994). Modified input estimation technique using pseudoresiduals. IEEE Trans. Aerosp. Electron. Syst. 30(1): 220-228