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HIGH MANEUVERING TARGET TRACKING USING A NOVEL HYBRID KALMAN FILTER-FUZZY LOGIC ARCHITECTURE

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Abstract. *In this paper, a fast target maneuver detection technique and high accurate tracking scheme is proposed with the use of a new hybrid Kalman filter-fuzzy logic architecture. Due to the stressful environment of target tracking problem such as inaccurate detection and target maneuver, most of existing trackers do not represent desired performance in different situations. In practice, while the conventional Kalman filters (KF) perform well in tracking a target with constant velocity, their performance may be seriously degraded in the presence of maneuver. To reach an accurate target tracking system in such a stressful environment, fuzzy logic-based algorithms with intelligent adaptation capabilities have recently been issued. Although these methods yield reasonable performance in tracking maneuvering targets, their accuracy in non-maneuvering mode was not satisfactory. In this research, based on information about the target maneuver dynamics, a new hybrid tracker (HT) is introduced. The proposed algorithm combines two methodologies into one architecture synergistically. In other words, the KF is used when the target velocity is approximately constant, whereas fuzzy estimator is used when the target maneuvers. Simulation results show that the proposed method is superior to some conventional approaches in tracking accuracy.*

Keywords: High maneuver target tracking, Kalman filter, Fuzzy logic, Hybrid tracker

1. Introduction.

Tracking maneuvering targets is required in a wide range of civilian applications such as intelligent transportation system, air traffic control and surveillance. Therefore, researchers have concerned about this issue during the past several decades and introduced many different tracking filters. However, there are still many challenges that make this issue difficult.

The linear Kalman filter (KF) has been widely used in tracking problem but its performance may fatally degrade in the presence of maneuver [1,2]. To be more precise, a short-term maneuver may lead to a bias in the estimation sequence. To cope with unknown target maneuvers, Input Estimation (IE) techniques have been introduced. The first IE approach was proposed by Chan, et al. [3]. IE techniques consist of three steps; input estimation, maneuver detection and state estimate correction. To clarify, in this approach, the standard KF is used merely during periods of no maneuver movement. When a maneuver is detected, least-square estimation on the measurement residues is applied to determine the magnitude of acceleration. The estimated acceleration is then used in conjunction with the standard KF to compensate the estimation sequence. Although this algorithm was attractive from several aspects, it suffers from a major deficiency originated in constant input assumption. The modified input estimation algorithm proposed in [4] and enhanced input estimation algorithm proposed in [5] aimed to overcome the major deficiency of original IE due to ignoring the uncertainty in the maneuver onset time. The Generalized Input Estimation (GIE) algorithm, proposed in [6], intends to relax the restrictive assumption concerning the input modeling, by assuming the input as a linear combination of known basic time functions. In the work of Wang et al. [7] the predicted and estimated states for a maneuvering target are related to the corresponding states without maneuvering, based on Constant Acceleration (CA) assumption. Therefore, the performance of estimation is shrunk when the target moves without CA. The input estimation techniques based on CA assumption have not been successful because the real targets do not move with a constant acceleration. Recently, a modified input estimation (MIE) technique for tracking a maneuvering target has been introduced by Khaloozadeh and Karsaz [8]. In this approach, the acceleration is treated as an additive input term in the corresponding state equation. The proposed modeling is a special augmentation in the state space model which considers both the states vector and unknown input vector as a new augmented state. This tracking algorithm operates in both maneuvering and non-maneuvering modes. However, its performance is not still satisfying when the target highly maneuvers or jerks.

On the other hand, different capabilities of intelligent systems such as intelligent information fusion and intelligent adaptation, makes them popular in various applications including target tracking [9-12]. A successful algorithm called self-constructing neural fuzzy inference network (SONFIN) has been proposed in [13] recently. The SONFIN can find a set of proper fuzzy logic rules dynamically. However, using neural network is computationally expensive. In addition, radial velocity (range rate) measurement of the pulsed Doppler radar has been applied in their method, which may be unavailable in some situations.

In this paper, we present a new intelligent algorithm for tracking high maneuvering targets. In this algorithm, a fuzzy state estimator is combined with the standard KF synergistically. This combination provides a new hybrid tracker (HT), which not only benefit from different advantages of KF such as fast initial convergence and optimal mean-square-error (MSE) estimation for non-maneuvering targets but also enjoys experts' knowledge on target maneuver dynamics and operates well in maneuvering and jerking modes.

2. **Problem Statement and Preliminaries.**

The problem of interest is described by the following discretized equation set.

$$X_{k+1} = A_k X_k + B_k U_k + W_k \tag{1}$$

$$Z_k = H_k X_k + V_k \tag{2}$$

where, $X_k \in R^n$, $U_k \in R^m$ and $Z_k \in R^p$ are system state, the input acceleration and the measurement vectors, respectively. Matrices A_k, B_k and H_k are assumed to be known functions of the time interval k and are of appropriate dimensions. The process noise W_k and the measurement noise V_k are zero-mean white Gaussian sequences with the following covariances: $E[W_k(W_l)'] = Q_k^x \delta_{kl}$, $E[V_k V_l'] = R_k \delta_{kl}$, $E[W_k V_l'] = 0$ and where the sign $'$ denotes transpose and δ_{kl} denotes the Kronecker delta function. The initial states X_0 and U_0 are assumed to be uncorrelated with the sequences W_k and V_k. The initial conditions are assumed to be Gaussian random variables with $E[X_0] = \hat{X}_0$, $E[X_0X_0'] = P_0^x$, $E[U_0] = \hat{U}_0$, $E[U_0U_0'] = P_0^u$, $E[X_0U_0'] = P_0^{xu}$.

The matrices H_k, A_k and B_k in (1) are assumed to be known function of time T (T is the time interval between two consecutive measurements) and are

$$A_k = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad B_k = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix}, \quad H_k = \begin{bmatrix} 0 & 1 \\ 0 & 0 \\ 1 & 0 \\ 0 & 0 \end{bmatrix}' \tag{3}$$

It is assumed that the acceleration U_k is a completely unknown input and models the target maneuver.

3. **Proposed Hybrid Tracker (HT).** In this section, a new hybrid KF-fuzzy logic method is proposed for tracking high maneuvering targets. The conventional KFs enjoy fast initial convergence rate. In addition, they have optimal MSE filtering process under certain assumptions including target constant velocity. However, its performance may degrade seriously in existence of maneuver. As we know, simple KF only uses kinematics information to estimate the target state. However, kinematics information is a small subset of available information for the tracker. The main contribution of this research is to append some information about the target maneuver dynamics to the KF in order to enhance its performance. However, due to mathematical limitations of KFs structure, appending more information to them is impossible or very difficult. In order to append some more information to the KF, we employed fuzzy logic with ability to incorporate experts' knowledge into the system. In fact, in this method, the fuzzy logic is used in order to detect the target maneuver based on the target maneuver dynamics. To have an accurate target tracking system in a stressful environment the following procedure is performed:

1. Partitioning a fuzzy maneuver estimator based on the target maneuver dynamics.
2. Designing a state estimator utilizing the fuzzy target maneuver estimator.
3. Combining the standard KF with the designed fuzzy state estimator synergistically.

Each step is elaborated in details as follows.

3.1. **Fuzzy maneuver estimator.** There is no explicit mathematical relationship between the radar output signal and the target maneuver. However, there exists a complex stochastic nonlinear mapping between them. In this paper, fuzzy maneuver estimator provides this mapping in each iteration. However, to estimate the target acceleration, it is needed to find important features of radar output signal. In the proposed method, two effective features of radar output signal are used as inputs of fuzzy acceleration estimator system.

A. *Absolute value of difference between the tracker course* ($\psi_{k|k}$) *and the observation target course* ($\xi_{k+1|k}$) :

Figure 1 shows the target movement geometry in Cartesian coordinates. In this figure, Z_{k+1} is the observation of sensor for $(k+1)$-*th* sample, $\hat{X}_{k|k}^{HT}$ denotes the state estimation by the HT at the *k-th* sample point given the measurement up to and including the *k-th*, and $\hat{X}_{k-1|k}^{HT}$ denotes the state estimation of HT at the $(k-1)$-*th* sample point given the measurement up to and including the *k-th*. $\Delta\theta_{k+1|k}$ is one of the most useful elements to detect the target maneuver [14,15]. $\left|\Delta\theta_{k+1|k}\right|$, $\psi_{k|k}$ and $\xi_{k+1|k}$ are calculated with the use of following equations.

$$\psi_{k|k} = angle\left(H_k \hat{X}_{k|k}^{HT} - H_k \hat{X}_{k-1|k}^{HT}\right) \tag{4}$$

$$\xi_{k+1|k} = angle\left(Z_{k+1} - H_k \hat{X}_{k|k}^{HT}\right) \tag{5}$$

$$\left|\Delta\theta_{k+1|k}\right| = abs\left(\psi_{k|k} - \xi_{k+1|k}\right) \tag{6}$$

Observably, when $\left|\Delta\theta_{k+1|k}\right|$ is low then the target is more likely to move around its last direction, and when $\left|\Delta\theta_{k+1|k}\right|$ is high then the target is more likely to move toward observation of the sensor. These facts were used as fuzzy rules in the fuzzy maneuver estimator of hybrid system.

B. *Autocorrelation of measurement residual* $(\Re_k)$:

$\Re_k$ is obtained from the following relations.

$$\begin{aligned} \tilde{Z}_{k+1} &= Z_{k+1} - H_{k+1}\hat{X}_{k+1|k}^{HT} \\ E\left[\tilde{Z}_k(\tilde{Z}_l)'\right] &= \Re_k \delta_{kl} \end{aligned} \tag{7}$$

where, $\Re(.)$ denotes the autocorrelation of measurement residual matrix.

The objective is to develop a maneuver detection algorithm with ability to detect the acceleration and jerk of a maneuvering target. Similar idea of quickest detection and change detection algorithm only for a constant acceleration has been investigated in the [7]. The standard KF is an efficient and unbiased filter. The measurement residue for the non-maneuvering targets is a stochastic zero mean white process. i.e.,

$$E\{\tilde{Z}_{k+1}\} = 0 \tag{8}$$

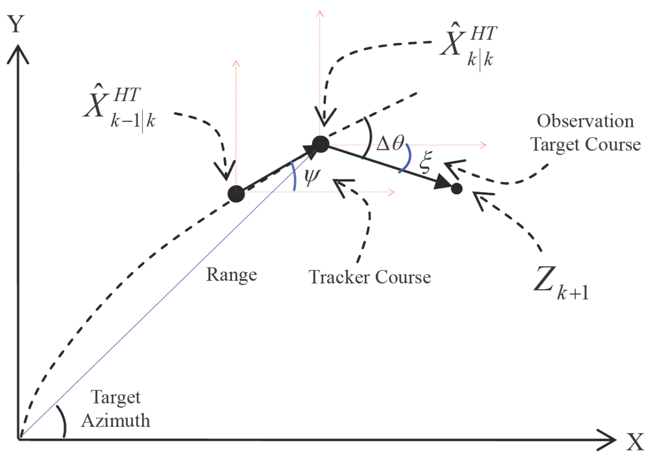

FIGURE 1. Target movement geometry in Cartesian coordinates

Therefore, for a non-maneuvering target, the mean of this sequence $(\tilde{Z}_{k+1})$ is zero. However, in a maneuvering target case, the mean of this sequence is no longer zero and contains more information. In fact, acceleration term leads to a bias in measurement residue. The amount of this bias, supply some information about the acceleration existence. So that, when $\Re_k$ is low then the target is more likely to move with constant speed with respect to the tracker. When $\Re_k$ is high then the target is more likely to move with acceleration with respect to the tracker. These facts were used as another fuzzy rule in fuzzy acceleration estimator system for target maneuver detection and estimation.

The proposed method is illustrated in Figure 2. In this figure, block 1, calculates $\Delta\theta_{k|k}$ and $\Re_k$. Block 2 is the fuzzy maneuver estimator. The fuzzy system has two inputs and one output. The input variables of fuzzy system are $\left|\Delta\theta_{k+1|k}\right|$ and $\Re_k$ and the output is estimation of the target acceleration magnitude ($\left\|\hat{U}_{k+1|k}\right\|_2$). Inputs and output fuzzy sets all have three Gaussian membership functions.

3.2. **Fuzzy state estimator.** Block 3 estimates the new state based on the output of fuzzy maneuver estimator as follows.

$$\begin{aligned} \hat{X}^{fuzzy}_{k+1|k} &= A_k \hat{X}^{fuzzy}_{k|k} + B_k \begin{bmatrix} \hat{U}^x_{k+1|k} \\ \hat{U}^y_{k+1|k} \end{bmatrix} \\ \hat{U}^x_{k+1|k} &= \hat{U}_{k+1|k} \cos\left(\xi_{k+1|k}\right) \\ \hat{U}^y_{k+1|k} &= \hat{U}_{k+1|k} \sin\left(\xi_{k+1|k}\right) \end{aligned} \tag{9}$$

where, $\hat{U}_{k+1|k}$, $\hat{U}^x_{k+1|k}$ and $\hat{U}^y_{k+1|k}$ denote estimation of the target acceleration magnitude, estimation of the x-axis target acceleration magnitude and estimation of the y-axis target acceleration magnitude, respectively. In relation 9, $\hat{X}^{fuzzy}_{k+1|k}$ represent the state estimation of fuzzy tracker at the $(k+1)$-th sample point given the measurement up to and including the k-th, whilst $\hat{X}^{fuzzy}_{k|k}$ denotes the state estimation of the fuzzy state estimator at the k-th sample point given the measurement up to and including the k-th. The output of block 3, $\hat{X}^{fuzzy}_{k+1|k}$, is the new state calculated by fuzzy logic based on the new information about the target maneuver dynamics.

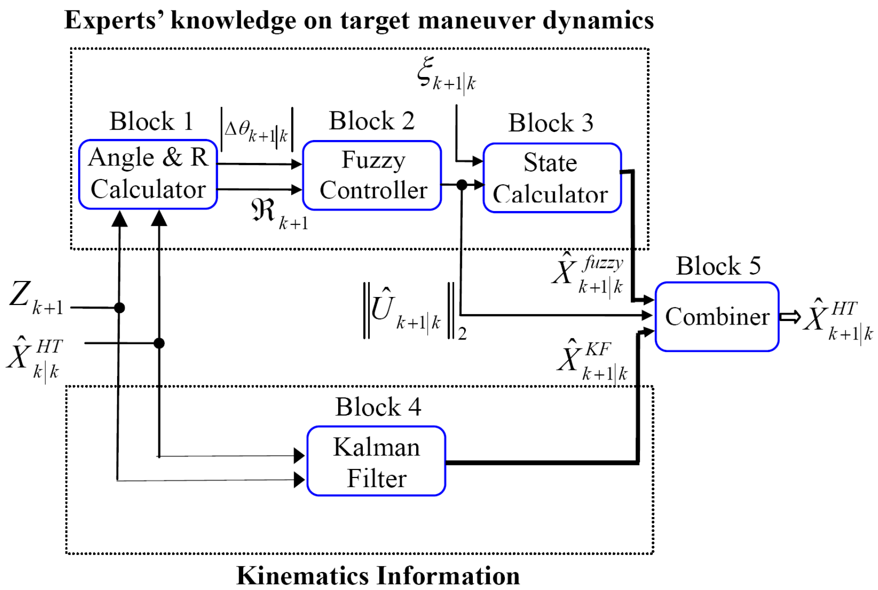

FIGURE 2. The proposed hybrid maneuvering target tracking structure

3.3. **Combining fuzzy state estimator with Kalman filter.** Block 4 in Figure 2 is a standard KF, which uses solely kinematics information to estimate the new state. As mentioned, the KF is used in order to enjoy its different advantages including optimal filtering ability in non-maneuvering mode and fast initial convergence rate. At the end of process, a method is needed to combine the output of fuzzy state estimator, $\hat{X}^{fuzzy}_{k+1|k}$, and the output of KF tracker, $\hat{X}^{KF}_{k+1|k}$, considering their advantages and disadvantages. The most important advantage of fuzzy tracker is that it performs well in maneuvering mode and, evidently, the advantage of KF is that it presents optimal tracking performance in non-maneuvering mode. Regarding the advantages and disadvantages of fuzzy tracker and KF tracker, $\hat{X}^{fuzzy}_{k+1|k}$ and $\hat{X}^{KF}_{k+1|k}$ can be combined in block 5 using the following relation:

$$\hat{X}^{HT}_{k+1|k} = \frac{\hat{U}_{k+1|k}\hat{X}^{fuzzy}_{k+1|k} + (\hat{U}_{\max} - \hat{U}_{k+1|k})\hat{X}^{KF}_{k+1|k}}{\hat{U}_{\max}} \tag{10}$$

In relation 10, $\hat{U}_{\max}$ is the maximum possible value of target acceleration magnitude. This value should be predefined for the HT.

As it can be interpreted from Figure 2, the HT enjoys both kinematics information and experts' knowledge on the target maneuver dynamics. Since the proposed architecture applies more information in comparison with previous classic methods such as [7,8] or intelligent methods such as [16], a superior performance is achieved.

4. **Simulation Results.** In this section, the improvement of state estimation carried out by the proposed method is demonstrated. To evaluate the new tracking scheme and compare it with two other existing methods, a MIE technique [8] and a CA approach [7], three case studies are considered.

In all case studies of this paper the sampling time is $T = 0.015(s)$ and the elements of covariance matrices of system and measurement noise are selected as $Q^x_k = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}$ and $R_k = \begin{bmatrix} (100)^2 \text{ m}^2 & 0 \\ 0 & (100)^2 \text{ m}^2 \end{bmatrix}$. Furthermore, the initial position and speed of target are unknown for the trackers.

First Case Study:

In this case study, our intention is to evaluate the HT in non-maneuvering mode and low maneuvering target case.

The initial position of target is given by $[x_0, y_0] = [4330(m), 2500(m)]$ with an initial speed of $[V_{x_0}, V_{y_0}] = [13(ms^{-1}), 7.5(ms^{-1})]$. The target moves with this constant speed until $t = 75(s)$. Then, its speed increases with a constant acceleration leading to no change in its course. To be more precise, after $t = 75(s)$, the target starts to accelerate with value of $[U_{x_{5001}}, U_{y_{5001}}] = [3.4641(ms^{-2}), 2(ms^{-2})]$. This acceleration causes no change in the target course. The target moves with this acceleration till the end of this simulation at $t = 135(s)$.

Figure 3 shows the target trajectory estimation by all afore-mentioned methods in this case study. In order to highlight the fast initial convergence ability of proposed method we place Figure 4 representing the target trajectory until $t = 45(s)$. Figure 5 indicates the target azimuth estimation of all three methods. High accurate estimation and initial fast convergence can be seen in the target azimuth estimation of new scheme. In order to compare the proposed method with the other two methods a Mont Carlo simulation of 50 runs was performed. The Standard Deviations (STDs) of estimation error in different target parameters are represented in Table 1.

Second Case Study:

In this case study, our intention is to evaluate the HT in high-maneuvering target case.

A maneuvering target tracking problem in a real situation, usually, deals with more complex cases. In the second case study, the initial position of target is given by $[x_0, y_0] = [200.27(m), 0(m)]$ with an initial speed of $[V_{x_0}, V_{y_0}] = [18(ms^{-1}), 0(ms^{-1})]$. The target moves with constant acceleration of $[U_{x_0}, U_{y_0}] = [1(ms^{-2}), 0(ms^{-2})]$ until $t = 75(s)$. Then, it starts to maneuver with acceleration of $[U_{x_{5001}}, U_{y_{5001}}] = [-4(ms^{-2}), -4(ms^{-2})]$. This

TABLE 1. Estimation error in the first case study (STD)

Parameter	*STD ERROR*			*Improvement Percentage to CA Approach*	*Improvement Percentage to MIE Technique*
	CA Approach	*MIE Technique*	*Proposed Method*		
Range	442.31	422.74	29.67	93.29	92.98
Azimuth	0.40	0.29	0.21	48.59	29.22
Course	34.87	27.68	22.86	34.43	17.42
Speed	49.61	42.86	8.62	82.62	79.89

acceleration continues to $t = 105(s)$. Then, the target starts to another maneuver with acceleration of $[U_{x7001}, U_{y7001}] = [8(ms^{-2}), 8(ms^{-2})]$. The target moves with this acceleration up to end of this simulation at $t = 150(s)$.

Figure 6 shows, the result of target trajectory estimation. The target speed estimation is indicated in Figure 7. As can be seen in this figure, proposed scheme tracks the target speed very accurately while two other methods could not follow fast changes in the target speed. Figure 8 illustrates the high performance of proposed method in tracking the target course in comparison with two other methods. Table 2 provides the result of three methods in estimating different target parameters. These results obtained from Mont Carlo simulation over 50 runs.

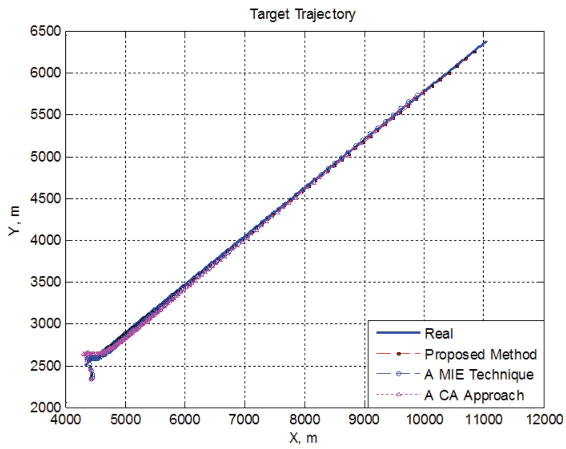

FIGURE 3. Target trajectory estimation in the first case study

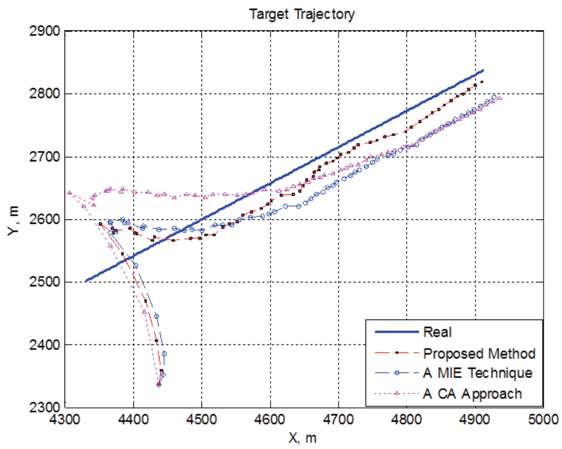

FIGURE 4. Target trajectory estimation in the first case study between $t = 0s$ and $t = 45s$

TABLE 2. Estimation error in the second case study (STD)

Parameter	*STD ERROR*			*Improvement Percentage to CA Approach*	*Improvement Percentage to MIE Technique*
	CA Approach	*MIE Technique*	*Proposed Method*		
Range	509.08	507.39	52.46	89.70	89.66
Azimuth	5.72	5.59	1.84	67.85	67.08
Course	44.70	43.20	14.22	68.19	67.08
Speed	78.41	77.73	10.98	86.00	85.87

Third Case Study:

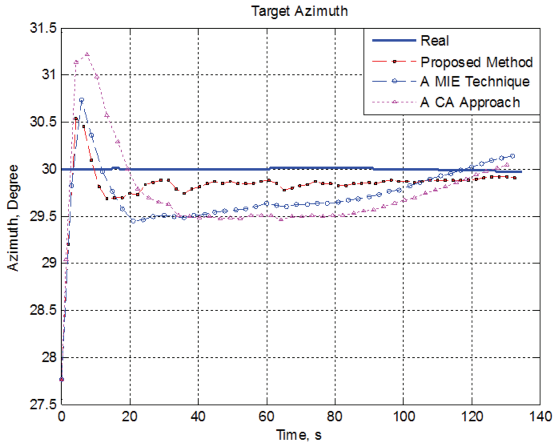

Figure 5. Target azimuth estimation in the first case study

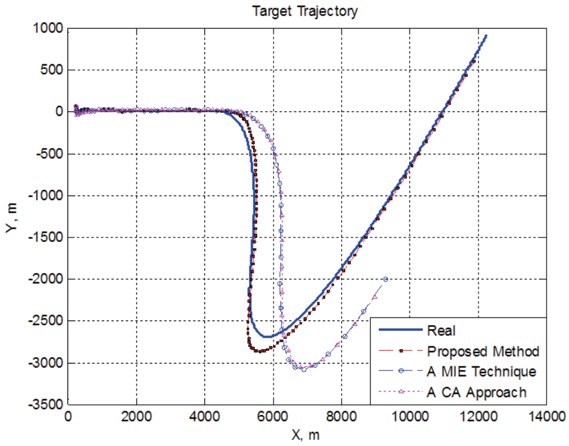

Figure 6. Target trajectory estimation in the second case study

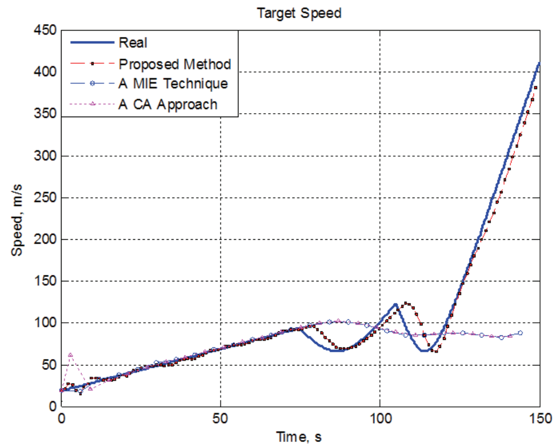

Figure 7. Target speed estimation in the second case study

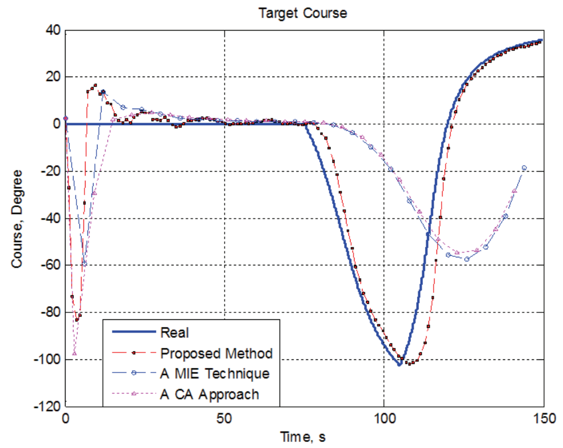

Figure 8. Target course estimation in the second case study

In this case study, our intention is to evaluate the HT in jerking mode.

In this simulation, the initial position of target is given by $[x_0, y_0] = [4330(m), 2500(m)]$ with an initial speed of $[V_{x0}, V_{y0}] = [13(ms^{-1}), 7.5(ms^{-1})]$. The target moves with this constant speed until $t = 75(s)$. Then, the target starts to maneuver with the jerk of $[J_x, J_y] = [4\cos(t/8)\,(ms^{-3}), 4\cos(t/8)\,(ms^{-3})]$. The target moves with mentioned jerk until $t = 129(s)$. Then, the target jerk changes to $[J_x, J_y] = [4\sin(t/8)\,(ms^{-3}), 4\sin(t/8)\,(ms^{-3})]$. The target continues to move with this jerk up to end of this simulation at $t = 195(s)$.

The trajectory of target in this case study is illustrated in Figure 9. This figure suggests the accuracy of proposed method in tracking a highly maneuvering target. Very quick maneuvers between $[x, y] = [4200(m), 1800(m)]$ and $[x, y] = [4600(m), 2000(m)]$ are detected by the proposed maneuver detector system leading to an accurate estimation result. The ability of proposed scheme in tracking the target azimuth and range in a very stressful situation is emphasized by Figures 10 and 11 respectively. Figure 12 shows the fast initial convergence of proposed method. Table 3 shows that the proposed scheme can significantly improve the state estimation result. The results mentioned in this table are calculated from performing Mont Carlo simulation over 50 runs.

TABLE 3. Estimation error in the third case study (STD)

Parameter	*STD ERROR*			*Improvement Percentage to CA Approach*	*Improvement Percentage to MIE Technique*
	CA Approach	*MIE Technique*	*Proposed Method*		
Range	414.89	410.91	53.49	87.11	86.98
Azimuth	1.57	1.54	0.26	83.46	83.14
Course	93.87	94.16	30.48	67.54	67.64
Speed	28.42	27.13	8.94	68.54	67.05

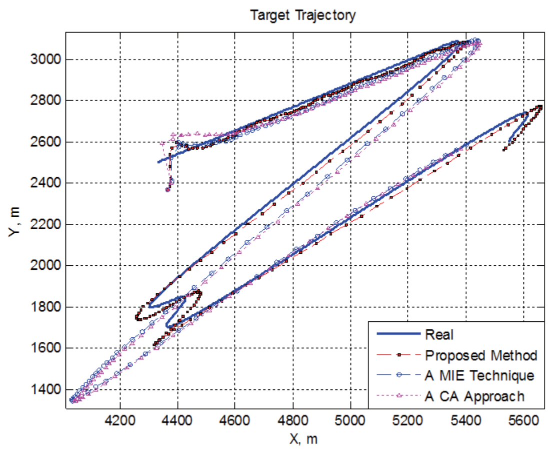

FIGURE 9. Target trajectory estimation in the third case study

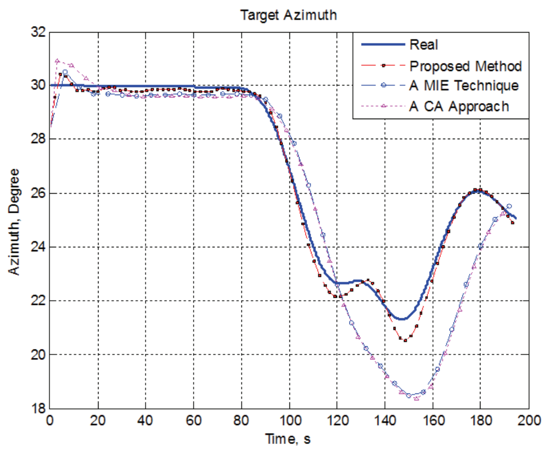

FIGURE 10. Target azimuth estimation in the third case study

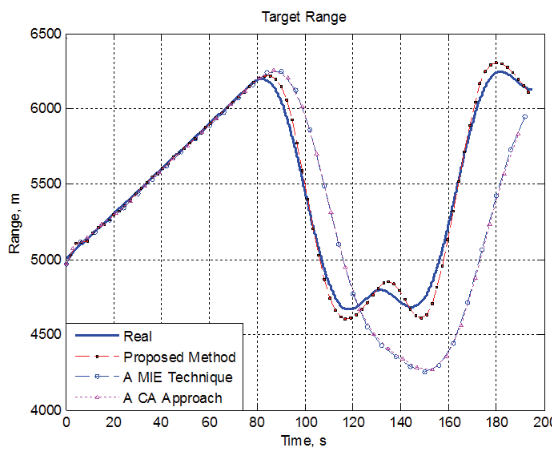

FIGURE 11. Target range estimation in the third case study

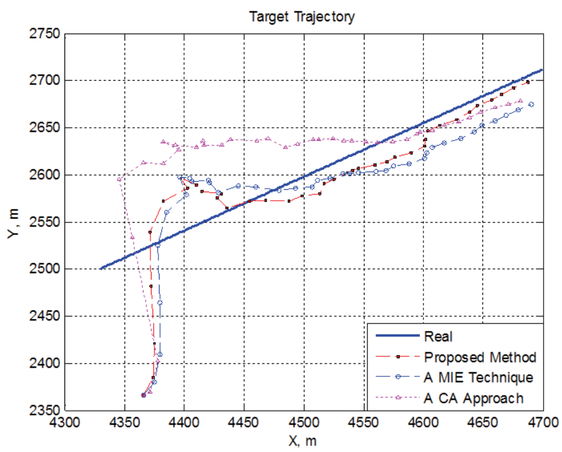

FIGURE 12. Target trajectory estimation in the third case study between $t = 0s$ and $t = 28.5s$

5. **Conclusions.** In this paper, a new hybrid Kalman filter-fuzzy logic architecture for tracking non-maneuvering, maneuvering, and high maneuvering targets has been introduced. The hybrid system is a synergistic combination of two different methodologies. The first methodology is a standard KF, which uses kinematics information and represents optimal MSE filtering process in non-maneuvering mode. The second methodology is a novel fuzzy state estimator, which uses experts' knowledge on the target maneuver dynamics and represents a very accurate tracking performance in maneuvering mode.

The accomplished hybrid tracker enjoys advantages of both KF estimator and fuzzy estimator. As a result, the HT not only provides optimal MSE filtering process in non-maneuvering mode but also it tracks high maneuvering targets with fabulous accuracy. Simulation results in different case studies clearly visualize this claim and emphasize on the accuracy of new hybrid scheme in comparison with a MIE technique and a CA approach. Furthermore, faster initial convergence rate with respect to two afore-mentioned conventional methods is obtained.

REFERENCES

[1] A. Ohsumi, T. Kimura and M. Kono, Kalman filter-based identification of unknown exogenous input of stochastic linear systems via pseudomeasurement approach, *International Journal of Innovative Computing, Information and Control*, vol.5, no.1, pp.1-16, 2009.

[2] B. J. Lee, J. B. Park, Y. H. Joo and S. H. Jin, Intelligent Kalman filter for tracking a manoeuvring target, *IEE Proc. Radar, Sonar & Navig.*, vol.151, no.6, pp.344-350, 2004.

[3] Y. T. Chan, A. G. C. Hu and J. B. Plant, A Kalman filter based tracking scheme with input estimation, *IEEE Trans. Aerosp. Electron. Syst.*, vol.AES-15, no.2, pp.237-244, 1979.

[4] H. I. Whang, J. G. Lee and T. K. Sung, Modified input estimation technique using pseudoresiduals, *IEEE Trans. Aerosp. Electron. Syst.*, vol.30, no.1, pp.220-228, 1994.

[5] P. L. Bogler, Tracking a maneuvering target using input estimation, *IEEE Trans. Aerosp. Electron. Syst.*, vol.AES-23, no.3, pp.298-310, 1987.

[6] H. Lee and M. J. Tahk, Generalized input-estimation technique for tracking maneuvering targets, *IEEE Trans. Aerosp. Electron. Syst.*, vol.35, no.4, pp.1388-1402, 1999.

[7] T. C. Wang and P. K. Varshney, A tracking algorithm for maneuvering targets, *IEEE Trans. Aerosp. Electron. Syst.*, vol.29, no.3, pp.910-924, 1993.

[8] H. Khaloozadeh and A. Karsaz, Modified input estimation technique for tracking manoeuvring targets, *IEE Proc. Radar, Sonar & Navig.*, vol.3, no.1, pp.30-41, 2009.

[9] M. Wang, B. Chen and S. Tong, Adaptive fuzzy tracking control for strict-feedback nonlinear systems with unknown time delays, *International Journal of Innovative Computing, Information and Control*, vol.4, no.4, pp.829-838, 2008.

[10] C. Vairappan, S. Gao, H. Tamura and Z. Tang, An improved learning of local search for fuzzy controller network, *International Journal of Innovative Computing, Information and Control*, vol.5, no.4, pp.1101-1113, 2009.

[11] K. C. C. Chan, V. Lee and H. Leung, Radar tracking for air surveillance in a stressful environment using a fuzzy-gain filter, *IEEE Trans. Fuzzy Syst.*, vol.5, no.1, pp.80-89, 1997.

[12] M. H. Bahari and N. Pariz, High maneuvering target tracking using an input estimation technique associated with fuzzy forgetting factor, *Scientific Researches and Essays*, vol.4, no.10, pp.936-944, 2009.

[13] F. B. Duh and C. T. Lin, Tracking a maneuvering target using neural fuzzy network, *IEEE Trans. Syst. Man and Cybernet. – Part B*, vol.34, no.1, pp.16-33, 2004.

[14] M. H. Bahari, A. Karsaz and H. Khaloozadeh, High maneuver target tracking based on combined Kalman filter and fuzzy logic, *Proc. of the 1st Int. IEEE Conf. on Information, Decision and Control*, Adelaide, Qld., pp.59-64, 2007.

[15] M. H. Bahari, A. Karsaz and M. B. Naghibi-S, Intelligent error covariance matrix resetting for maneuver target tracking, *J. Applied Sciences*, vol.8, no.12, pp.2279-2285, 2008.

[16] M. H. Bahari, H. Fadishei and R. Rajayee, Intelligent error covariance matrix resetting for maneuver target tracking, *Int. J. Factory Automation, Robotics and Soft Computing*, vol.3, pp.45-50, 2009.