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An interacting Fuzzy-Fading-Memory-based Augmented Kalman Filtering method for maneuvering target tracking

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ABSTRACT

In this paper, the interaction and combination of Fuzzy Fading Memory (FFM) technique and Augmented Kalman Filtering (AUKF) method are presented for the state estimation of non-linear dynamic systems in presence of maneuver. It is shown that the AUKF method in conjunction with the FFM technique (FFM-AUKF) can estimate the target states appropriately since the FFM tunes the covariance matrix of the AUKF method in presence of unknown target accelerations by using a fuzzy system. In addition, the benefits of both FFM technique and AUKF method are employed in the scheme of well-known Interacting Multiple Model (IMM) algorithm. The proposed Fuzzy IMM (FIMM) algorithm does not need the predefinition and adjustment of sub-filters with respect to the target maneuver and reduces the number of required sub-filters to cover the wide range of unknown target accelerations. The Monte Carlo simulation analysis shows the effectiveness of the above-mentioned methods in maneuvering target tracking.

1. Introduction

Standard Kalman Filtering (SKF) methods such as Linear Kalman Filter (LKF) and Extended Kalman Filter (EKF) produce reasonable results for tracking non-maneuvering targets, but they may not yield desirable accuracy in presence of maneuver [1–3]. There are two main approaches to handle this problem [3]: the Input Estimation (IE) approach and the Multiple Model (MM) approach.

1.1. The Input Estimation approach

The IE approach was developed to improve the estimation accuracy of the SKF methods in presence of unknown target accelerations [4]. One method that simultaneously combines the benefits of both SKF method and IE approach is a SKF-based target tracker with IE approach [5]. This method changes the maneuvering target model to the non-maneuvering one by using a state augmentation technique to create the standard Bayesian model. By applying the LKF or EKF to this model, one yields an Augmented Kalman Filtering (AUKF) method, which can estimate the unknown target acceleration along with the original target states. The AUKF method eliminates the need for a separate maneuver detector system and provides better performance with respect to the LKF or EKF in tracking non-maneuvering and low maneuvering targets.

However, the AUKF cannot produce acceptable state estimation in presence of high maneuvers due to the poor modeling of target acceleration dynamics [6,7]. To cope with this problem, several methods have been proposed in recent years with varying degrees of success [7–13]. Unfortunately, most of these techniques have some major problems. The fading memory factor proposed in [8] and forgetting factor proposed in [9] are determined off-line and remained unvarying during the operation, so the performance of these methods is obviously degraded with the changes of target acceleration. To deal with this trouble, a soft computing approach has been proposed in [10,11], which resets the covariance matrix at each sampling time based on the values of target acceleration. However, due to the deficiency of its maneuver detector system, this method has not increased the performance of AUKF method effectively. In [12], the authors tried to handle this dilemma by proposing an intelligent approach based on the fuzzy logic for covariance matrix resetting. Unfortunately, the fuzzy system used in this approach is not accurate enough. Among the above-mentioned methods, the Fuzzy Fading Memory (FFM) technique [13] is reasonably successful. During the maneuver, the FFM technique corrects the covariance matrix using a suitable fuzzy system. This modification enables the filtering algorithm to produce reasonable state estimation in presence of unknown target accelerations.

In this paper, by choosing the EKF as the filtering algorithm, it is shown that the FFM-based AUKF (FFM-AUKF) method yields more accurate results than the standard EKF and AUKF methods for the state estimation of non-linear dynamic systems in presence of maneuver.

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1.2. The Multiple Model approach

The second approach to overcome the shortcoming of the SKF methods during the maneuver includes the MM algorithms. These approaches have been developed because a single model cannot specify the behavior of a moving target completely. Among different MM approaches [14–16], the Interacting Multiple Model (IMM) algorithm provides an excellent compromise between computational burden and performance [17]. This algorithm has been utilized to solve many important problems including tactical ballistic missile tracking [18], underwater target tracking [19], traffic forecasts [20], and ground target tracking [21].

The IMM algorithm includes a bank of sub-filters such as LKF or EKF [22] so that each sub-filter can individually estimate the target states. The major prerequisite of this algorithm is that at least one sub-filter should match the real target state at each sampling instant [23]. On the other hand, the estimation error produced by one sub-filter should be as small as possible at each time step, otherwise the IMM algorithm may diverge and the estimation error of this algorithm goes beyond the limit of acceptability. This limitation is due to the inaccurate sub-filters state estimation, which implies the choice of imprecise filtering methods [24].

Motivated by the above observations, this paper proposes a novel Fuzzy IMM (FIMM) algorithm for the combination of FFM technique and AUKF method. In this algorithm, the standard EKF method used by the sub-filters of the conventional IMM algorithm [25] is replaced by the AUKF method. This change improves the tracking accuracy of IMM algorithm in tracking non-maneuvering and low maneuvering targets. Afterward, the covariance matrix of all sub-filters is modified at each time step according to the amount of target acceleration using the FFM technique. As a result, the proposed FIMM can effectively deal with the target maneuver and reduces the number of required sub-filters to cover the wide range of unknown target accelerations. In addition, the proposed method yields more accurate results than conventional IMM algorithms with a large number of sub-filters. The Monte Carlo analysis demonstrates the effectiveness of the FFM-AUKF and FIMM methods for the state estimation of non-linear dynamic systems in presence of maneuver.

2. Problem statement

This paper deals with the state estimation of systems with non-linear dynamics. Most target tracking methods have been developed based on the mathematical models. The model considered in this article has the following discrete state-space equation with additive noise [26]:

$$\begin{aligned} X(k+1) &= f\big(X(k), k\big) + w(k) \\ z(k) &= h\big(X(k), k\big) + v(k) \end{aligned} \tag{1}$$

where the (possibly non-linear) functions $f(.)$ and $h(.)$ are system transition and measurement functions, respectively. In this model, $X(.)$ and $z(.)$ are the state and the observation vectors. The initial state $X(0)$ is assumed to be a Gaussian random variable with $E\{X(0)X^T(0)\} = \psi$ and $E\{X(0)\} = 0$. The measurement noise $v(.)$ and the process noise $w(.)$ are mutually uncorrelated zero-mean white Gaussian processes with covariance matrices R and Q, respectively.

$$\begin{aligned} &E\big\{v(k_1)v^T(k_2)\big\} = R(k_1)\delta(k_1 - k_2) \\ &E\big\{w(k_1)w^T(k_2)\big\} = Q(k_1)\delta(k_1 - k_2) \\ &E\big\{w(k)\big\} = E\big\{v(k)\big\} = 0 \quad \text{for all } k \end{aligned}$$

where the signs T and δ represent the transpose and Kronecker delta function. In the non-maneuvering mode, the state vector of a moving target in a two-dimensional plane at time step k is:

$$X(k) = \big[x(k)v_x(k)y(k)v_y(k)\big]^T \tag{2}$$

where $x(k)$, $v_x(k)$ and $y(k)$, $v_y(k)$ are target positions and velocities in x and y directions, respectively. In presence of maneuver, a new term is added to (1) and modifies this model as follows:

$$\begin{aligned} X(k+1) &= f\big(X(k), u(k), k\big) + w(k) \\ z(k) &= h\big(X(k), k\big) + v(k) \end{aligned} \tag{3}$$

where $u(k)$ denotes the unknown target acceleration, which is shown by the following vector:

$$u(k) = \big[u_x(k)u_y(k)\big]^T \tag{4}$$

The linear counterpart of model (3) has the following set of equations [26]:

$$\begin{aligned} X(k+1) &= F(k)X(k) + C(k)u(k) + G(k)w(k) \\ z(k) &= H(k)X(k) + v(k) \end{aligned} \tag{5}$$

At time step k, $F(k)$, $C(k)$, and $G(k)$ are the Jacobian matrices of the partial derivatives of f with respect to X, u, and w, respectively, and $H(k)$ is the Jacobian matrix of the partial derivatives of h with respect to X.

3. Fuzzy Fading Memory technique

Tracking a maneuvering target is difficult due to the uncertainty of unknown acceleration vector in Eq. (3). To solve this problem, Khaloozadeh and Karsaz have proposed a new scheme based on the combination of Bayesian and Fisher uncertainty models [5]. This so-called AUKF method provides better tracking accuracy in comparison with the SKF methods such as LKF and EKF in tracking non-maneuvering and low maneuvering targets. Unfortunately, the AUKF method cannot produce desirable performance in presence of high maneuvers. This problem is due to the limitation of this estimator to model the target acceleration dynamics correctly and completely, which causes the covariance matrix $(\hat{P}_{Aug}(n \mid n))$ becomes small after a few iterations. In recent years, several techniques have been proposed to deal with this trouble [7–13]. Among them, the fading memory method [9] is noteworthy because of its efficiency and easy implementation. This method uses the fading memory factor (α, $\alpha \geqslant 1$) to correct the covariance matrix in the filtering algorithm. Unfortunately, this factor is determined off-line so that it stays constant during the process. This dilemma leads to the over fading information in non-maneuvering mode or imperfect compensation in presence of maneuver. To solve this problem, a FFM technique has been proposed by Bahari et al. [13], which modifies the covariance matrix with respect to the amount of target acceleration in each iteration. During the maneuver, this technique aids the AUKF method to estimate the unknown target acceleration suitably.

In this section, the FFM-AUKF method is presented for the state estimation of non-linear system (3), where the EKF has been chosen as the filtering algorithm. In this method, the maneuvering model (3) is converted to a non-maneuvering model to construct a standard Bayesian model. In this method, the unknown deterministic term $u(k)$ is added to the state vector, which forms an augmented state-space equation as described below.

$$\begin{aligned} X_{Aug}(k+1) &= f\big(X_{Aug}(k), k\big) + W_{Aug}(k) \\ Z_{Aug}(k) &= h\big(X_{Aug}(k), k\big) + V_{Aug}(k) \\ X_{Aug}(k) &= \begin{bmatrix} X(k) \\ u(k) \end{bmatrix} \end{aligned} \tag{6}$$

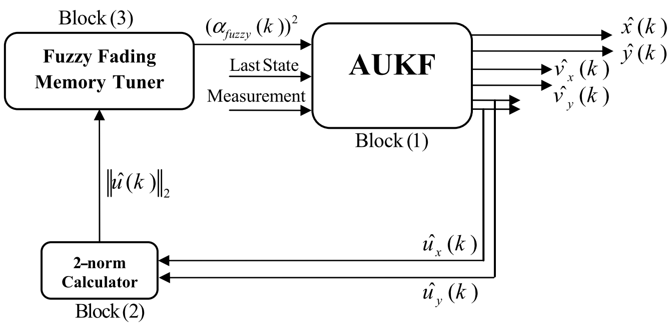

Fig. 1. The structure of FFM-AUKF method.

The linear approximation of this system is expressed by Eq. (7):

$$X_{Aug}(k+1) = F_{Aug}(k)X_{Aug}(k) + G_{Aug}(k)W_{Aug}(k)$$
$$Z_{Aug}(k) = H_{Aug}(k)X_{Aug}(k) + V_{Aug}(k) \tag{7}$$

The state estimation of the FFM-AUKF method is divided into two main stages: the prediction stage and the update stage, which are summarized as below.

The prediction stage

In this stage, the predicted state estimate and the predicted estimate error covariance are described by Eqs. (8) and (9), respectively.

$$\hat{X}_{Aug}(k+1 \mid k) = f\left(\hat{X}_{Aug}(k \mid k), k\right) \tag{8}$$
$$\hat{P}_{Aug}(k+1 \mid k) = \left(\alpha_{Fuzzy}(k)\right)^2 F_{Aug}(k)\hat{P}_{Aug}(k \mid k)F^T_{Aug}(k) + G_{Aug}(k)Q_{Aug}(k)G^T_{Aug}(k) \tag{9}$$

where $(\alpha_{Fuzzy}(k))^2$ is determined by using the FFM technique at time step k.

The update stage

In this stage, the optimal state estimation of the augmented system (6) is obtained by applying the EKF.

$$\hat{X}_{Aug}(k+1 \mid k+1) = \hat{X}_{Aug}(k+1 \mid k) + K_{Aug}(k+1)\left[\hat{y}(k+1)\right] \tag{10}$$

$$\hat{y}(k+1) = Z_{Aug}(k+1) - h\left(\hat{X}_{Aug}(k+1 \mid k), k\right) \tag{11}$$

$$K_{Aug}(k+1) = \left[P_{Aug}(k+1 \mid k)H^T_{Aug}(k+1) + G_{Aug}(k+1)T_{Aug}(K+1)\right]R^{-1}_{Aug}(k+1) \tag{12}$$

$$\hat{P}_{Aug}(k+1 \mid k+1) = \hat{P}_{Aug}(k+1 \mid k) - \hat{P}_{Aug}(k+1 \mid k)H^T_{Aug}(k+1) \times \left[R_{Aug}(k+1) + H_{Aug}(k+1) \times \hat{P}_{Aug}(k+1 \mid k)H^T_{Aug}(k+1)\right]^{-1} \times H_{Aug}(k+1)\hat{P}_{Aug}(k+1 \mid k) \tag{13}$$

where the updated state estimate, the measurement residual, the Kalman gain, and the updated estimate error covariance have been determined by Eqs. (10), (11), (12), and (13), respectively. Ref. [5] includes the detailed information about the AUKF method.

Fig. 1 shows the structure of this method where block (1) is the AUKF. The inputs of this block are the previously estimated state, the measurement, and the fading memory factor; and the output of this block is the new state estimate. Block (2) is a 2-norm calculator that determines the target acceleration magnitude ($\|\hat{u}(k)\|_2 = \sqrt{(\hat{u}_x(k)^2 + \hat{u}_y(k)^2)}$) as its output. Block (3) is a fuzzy controller, which uses the output of block (2) to calculate the optimum value of $(\alpha_{Fuzzy}(k))^2$ at each time step. Finally, the output of block (3) is used to modify the covariance matrix $\hat{P}_{Aug}(k \mid k)$ in each iteration. This block uses a fuzzy controller, which has the following set of rules:

1. If $\|\hat{u}(k)\|_2$ is high then $(\alpha_{Fuzzy}(k))^2$ is high.
2. If $\|\hat{u}(k)\|_2$ is low then $(\alpha_{Fuzzy}(k))^2$ is low.

The input and output of fuzzy sets all have two Gaussian membership functions with the following membership grade:

$$g_i^j(x_i) = \exp\left[-\frac{1}{2}\left(\frac{x_i - c_i^j}{\sigma_i^j}\right)\right]^2 \tag{14}$$

where c_i^j and σ_i^j are the mean and standard deviation of the Gaussian membership function for the ith input variable of the jth fuzzy rule, respectively.

When target starts to maneuver and the tracker steps are not large enough, the FFM increases the value of $(\alpha_{Fuzzy}(k))^2$ to correct the estimated states by the AUKF method. Obviously, in the non-maneuvering mode, the tracker has suitable steps, and $(\alpha_{Fuzzy}(k))^2$ is chosen quite close to one [13]. The discussion about the convergence of estimators after resetting the covariance matrix can be found in [27].

4. The proposed Fuzzy IMM algorithm

Among different MM approaches [14–16,28–33], the IMM algorithm is a widely accepted method for the state estimation of a moving target. Conventional IMM algorithms require a set of predefined sub-filters with various dimensions and process noise values and the weighted sum of the estimates from these sub-filters yields the overall state estimate. The main limitation that influences the tracking accuracy of this algorithm is the mismatch between sub-filters and actual target motion types [23]. When at least one sub-filter cannot appropriately match the real target state, the IMM algorithm may not produce the desirable accuracy.

To reduce this problem, this paper proposes a FIMM algorithm including two main steps. In the first step, the standard EKF method used by each sub-filter of IMM algorithm is substituted with the AUKF method. This modification improves the performance of IMM algorithm due to the better accuracy of AUKF than EKF in tracking non-maneuvering and low maneuvering targets. In the second step, the FFM technique tunes the covariance matrix of each sub-filter based on the values of target acceleration in an intelligent manner using a fuzzy system. Fig. 2 shows the structure of proposed FIMM algorithm, where the index N indicates the number of sub-filters. Fig. 3 shows the structure of ith FFM block used in Fig. 2.

One cycle of the proposed FIMM method is similar to the conventional IMM algorithm [14] and is summarized as follows:

Step 1: Mixing of estimates

In the first step, the estimated states of all sub-filters and their corresponding covariance are combined together. In the following equations, the $\hat{X}^i_{Aug}(k-1 \mid k-1)$ and $\hat{P}^i_{Aug}(k-1 \mid k-1)$ are the estimated state and the state error covariance of the ith filter ($i = 1, 2, \ldots, N$; $N =$ number of sub-filters), respectively. These variables are calculated by using the AUKF method at time step $k-1$ after the measurement update. One cycle of this step can be expressed as below:

$$\mu^{(i|j)}(k-1 \mid k-1) = \frac{1}{\bar{C}^j} p^{ij}\mu^i(k-1) \tag{15}$$

$$\bar{C}^j = \sum_{i=1}^{N} p^{ij}\mu^i(k-1) \tag{16}$$

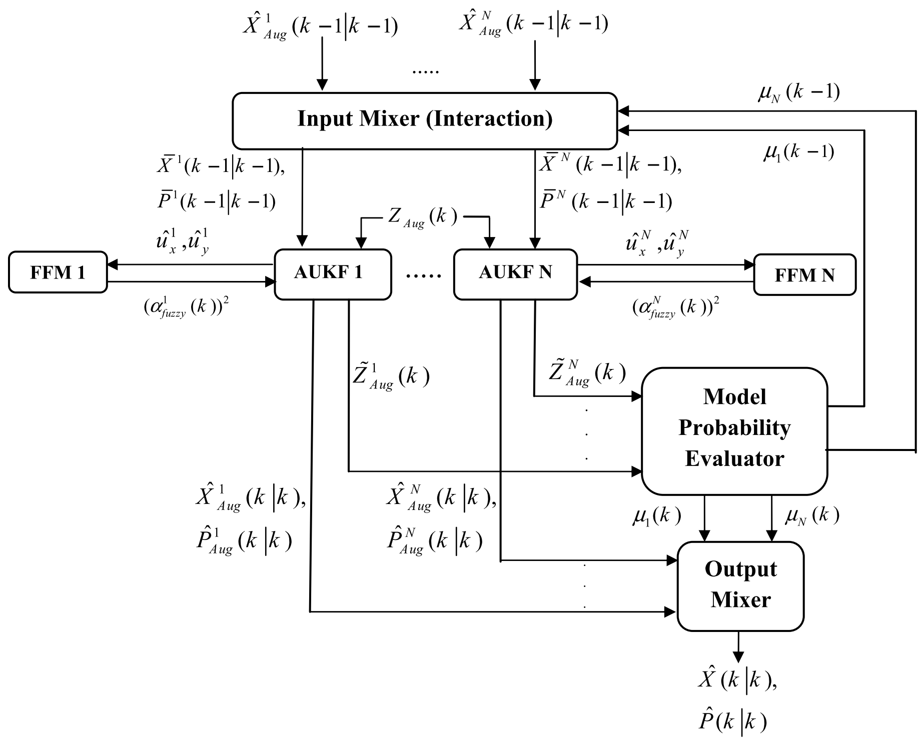

Fig. 2. The structure of proposed FIMM algorithm.

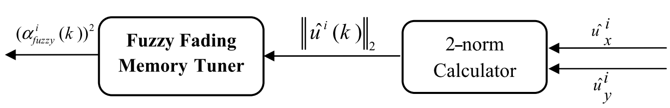

Fig. 3. The structure of ith FFM block in Fig. 2.

$$\bar{X}^j(k-1 \mid k-1) = \sum_{i=1}^{N} \hat{X}^i_{Aug}(k-1 \mid k-1)\mu^{(i|j)}(k-1 \mid k-1) \tag{17}$$

$$\begin{aligned}\bar{P}^j(k-1 \mid k-1) &= \sum_{i=1}^{N} \mu^{(i|j)}(k-1 \mid k-1)\bigl\{\hat{P}^i_{Aug}(k-1 \mid k-1) \\ &\quad + \bigl(\hat{X}^i_{Aug}(k-1 \mid k-1) - \bar{X}^j_{Aug}(k-1 \mid k-1)\bigr) \\ &\quad \times \bigl(\hat{X}^i_{Aug}(k-1 \mid k-1) - \bar{X}^j_{Aug}(k-1 \mid k-1)\bigr)^T\bigr\}\end{aligned} \tag{18}$$

where $\mu^{(i|j)}(k-1 \mid k-1)$, p^{ij}, $\bar{C}^j$, $\mu^i(k-1)$, $\bar{X}^j(k-1 \mid k-1)$, and $\bar{P}^j(k-1 \mid k-1)$ are the mixing probability, the model transition probability for switching from the ith filter to the jth one, the normalization constant, the probability of the ith filter at time step $k-1$, the mixed state estimate and its corresponding mixed error covariance at time step $k-1$, respectively.

Step 2: Filtering algorithm

The update equations for each sub-filter of the proposed FIMM algorithm are performed using the FFM-AUKF method.

Step 3: Update filter probability

The probability of the mode in effect is determined by means of a likelihood function $\Lambda^j(k)$. The likelihood function and the updated probability of the jth filter, $\mu^j(k)$, are calculated as:

$$\Lambda^j(k) = \frac{1}{\sqrt{2\pi |S^j_{Aug}(k)|}} \exp\bigl(-0.5\bigl(\tilde{Z}^j_{Aug}(k)\bigr)^T \bigl(S^j_{Aug}(k)\bigr)^{-1} \tilde{Z}^j_{Aug}(k)\bigr) \tag{19}$$

$$\mu^j(k) = \frac{\Lambda^j(k)\bar{C}^j}{\sum_{i=1}^{N} \Lambda^i(k)\bar{C}^i} \tag{20}$$

where $\tilde{Z}^j_{Aug}(k)$ and $S^j_{Aug}(k)$ are the measurement residual and residual covariance of the jth sub-filter. These variables are calculated in Step 2.

Step 4: Estimate fusion

Finally, all the state estimates and the error covariances from individual sub-filters are merged according to the following equations:

$$\hat{X}(k \mid k) = \sum_{j=1}^{N} X^j_{Aug}(k \mid k)\mu^j(k) \tag{21}$$

$$\begin{aligned}\hat{P}(k \mid k) = \sum_{j=1}^{N} \mu^j(k)\bigl\{P^j_{Aug}(k \mid k) &+ \bigl[X^j_{Aug}(k \mid k) - \hat{X}(k \mid k)\bigr] \\ &\times \bigl[X^j_{Aug}(k \mid k) - \hat{X}(k \mid k)\bigr]^T\bigr\}\end{aligned} \tag{22}$$

where $X^j_{Aug}(k \mid k)$, $P^j_{Aug}(k \mid k)$, $\hat{X}(k \mid k)$, and $\hat{P}(k \mid k)$ are the estimated state and the covariance of the jth filter of Step 2, the combined state estimate and its corresponding covariance, respectively.

The proposed FIMM algorithm provides some advantages, which are described here briefly. This algorithm shows better tracking performance than conventional IMM algorithms with a large number of sub-filters. In the proposed algorithm, the predefinition and adjustment of sub-filters with respect to the target maneuver properties are not required since the FFM technique corrects the covariance matrix of each sub-filter at each sampling time using a fuzzy system. Additionally, the FIMM algorithm reduces the number of required sub-filters to cover the wide range of unknown target accelerations.

5. Simulation tests

In this section, simulation tests are performed on the problem of maneuvering target tracking in two-dimensional space. In order to evaluate the effectiveness of the FFM-AUKF and FIMM methods, the following Root Mean Square Error (RMSE) of the estimated state (S) is defined as:

$$RMSE(S) := \sqrt{\frac{\sum_{k=1}^{L}(S^X_{True}(k) - S^X_{Estimated}(k))^2 + (S^Y_{True}(k) - S^Y_{Estimated}(k))^2}{L}} \quad (23)$$

where $S^X_{True}(k)$, $S^Y_{True}(k)$ and $S^X_{Estimated}(k)$, $S^Y_{Estimated}(k)$ denote the true and the estimated state (S = position, velocity, and acceleration) of target for each axis at the kth step ($k = 1, 2, \ldots, L$), and L is the total number of scans (time steps). In addition, due to the large estimation errors corresponding to some of the filtering algorithms used in this paper, the following equation is defined to normalize the RMSE of each estimated state.

$$Error := \frac{RMSE(S)}{Max(RMSE(S))} \quad (24)$$

Eq. (24) is utilized to show the estimation error corresponding to the filtering algorithms used for simulation (Figs. 4–7). The following target movement model is considered for the simulation test regarding Eq. (5):

$$X(k+1) = FX(k) + Cu(k) + Gw(k)$$

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

$$C = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix}$$

where T is the time interval between two successive measurements. The measurement/observation model in the polar coordinates is governed by the following equation:

$$Z(k) = \begin{bmatrix} r(k) \\ \phi(k) \end{bmatrix} = \begin{bmatrix} \sqrt{((x(k))^2 + (y(k))^2)} \\ \tan^{-1}(\frac{y(k)}{x(k)}) \end{bmatrix} + \begin{bmatrix} v_r \\ v_\phi \end{bmatrix}$$

where $r(k)$, $\phi(k)$, and v are range, bearing, and a zero-mean Gaussian measurement noise vector, respectively. The covariance matrix of the measurement noise v is R_k.

$$R_k = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_\phi^2 \end{bmatrix}$$

For the simulation analysis, the values of $\sigma_r = 300$ m and $\sigma_\phi = 0.1$ rad are chosen for R_k.

Now, the test parameters of different filtering algorithms used in this paper are described. The EKF method uses one Constant Velocity (CV) model with the covariance matrix of $Q_{EKF} = 5^2 I_2$ and the error covariance matrix of $P_{EKF}(0, -1) = 10^4 I_4$, the AUKF and FFM-AUKF methods use $Q_{AUKF} = Q_{FFM\text{-}AUKF} = 5^2 I_2$ and $P_{AUKF}(0, -1) = P_{FFM\text{-}AUKF}(0, -1) = 10^4 I_6$, respectively.

Most IMM trackers use one low acceleration filter and one high acceleration filter assuming the transition matrix is stationary and known [5]. Therefore, two sub-filters are considered for the proposed FIMM algorithm. These two sub-filters (M_1 and M_2) have the following parameters:

M_1: The covariance matrix and the augmented state error covariance of this sub-filter are $Q_{M_1} = 5^2 I_2$ and $P^{M_1}_{Aug}(0, -1) = 10^4 I_6$, respectively.

M_2: The covariance matrix and the augmented state error covariance of this sub-filter are $Q_{M_2} = (40)^2 I_2$ and $P^{M_2}_{Aug}(0, -1) = 10^4 I_6$, respectively.

In addition, an IMM algorithm with ten EKFs (IMM-EKF10) is considered for comparison with the proposed FIMM algorithm. The IMM-EKF10 utilizes one CV model for constant velocity mode and nine Constant Acceleration (CA) models with different process noise levels for maneuvering mode ($Q^{CV}_{IMM\text{-}EKF10} = 5^2 I_2$, $Q^{CA1}_{IMM\text{-}EKF10} = 6.3^2 I_2$, $Q^{CA2}_{IMM\text{-}EKF10} = 6.75^2 I_2$, $Q^{CA3}_{IMM\text{-}EKF10} = 7.3^2 I_2$, $Q^{CA4}_{IMM\text{-}EKF10} = 8^2 I_2$, $Q^{CA5}_{IMM\text{-}EKF10} = 8.95^2 I_2$, $Q^{CA6}_{IMM\text{-}EKF10} = 10.3^2 I_2$, $Q^{CA7}_{IMM\text{-}EKF10} = 17.9^2 I_2$, $Q^{CA8}_{IMM\text{-}EKF10} = 28.3^2 I_2$, $Q^{CA9}_{IMM\text{-}EKF10} = 40^2 I_2$).

The description of CV and CA models can be found in [26,34]. In this paper, the initial state of all filters and sub-filters is selected similar to the initial state of the target. The ith sub-filter at time step $k-1$ can switch to the jth sub-filter at time step k according to the following transition probability matrix, which is governed by an underlying Markov chain.

$$P_{ij} = \begin{cases} 0.98 & \text{if } i = j \\ \frac{1-0.98}{N-1} & \text{otherwise} \end{cases}$$

where N is the number of sub-filters.

5.1. Case studies

5.1.1. Case study 1

In this simulation, the sampling time is $T = 0.25$ s. The initial state of the target is chosen as $[1000(\text{m})150(\text{m/s}) - 500(\text{m})150(\text{m/s})]^T$. Target moves with the constant acceleration of $[u_x, u_y] = [-1(\text{m/s}^2), 0(\text{m/s}^2)]$ until $t = 37.5(\text{s})$. Then, it changes its acceleration to $[u_x, u_y] = [0.3g(\text{m/s}^2), -0.2g(\text{m/s}^2)]$, $g = 9.8(\text{m/s}^2)$ and this acceleration continues until time $t = 75$ s. Finally, the target starts another maneuver with the acceleration of $[u_x, u_y] = [-2g(\text{m/s}^2), 3g(\text{m/s}^2)]$ up to the end of simulation at time $t = 100$ s.

Fig. 4 shows the actual value of target position and the Error obtained with the EKF, the AUKF, the FFM-AUKF, the IMM-EKF10, the FIMM algorithm.

Fig. 5 demonstrates the actual value of target velocity and the Error provided by the AUKF, the FFM-AUKF, and the FIMM compared with the EKF and the IMM-EKF10 algorithm.

5.1.2. Case study 2

In this simulation, the sampling time is $T = 0.25$ s. The initial state of the target is chosen as $[500(\text{m})100(\text{m/s}) - 400(\text{m})60(\text{m/s})]^T$ with the constant acceleration of $[u_x, u_y] = [1(\text{m/s}^2), -1(\text{m/s}^2)]$ until $t = 31.25$ s. Then, target changes its acceleration to $[u_x, u_y] = [2g * \sin(t/8)(\text{m/s}^2), 3g * \sin(t/4)(\text{m/s}^2)]$, $g = 9.8(\text{m/s}^2)$ up to the end of simulation at time $t = 100$ s.

Fig. 6 shows the actual value of target position and the Error obtained with the EKF, the AUKF, the FFM-AUKF, the IMM-EKF10, the FIMM algorithm.

Fig. 7 demonstrates the actual value of target velocity and the Error provided by the AUKF, the FFM-AUKF, and the FIMM compared with the EKF and the IMM-EKF10 algorithm.

The Error of case studies 1 and 2 is depicted in Figs. 4–7 (based on 100 Monte Carlo runs) and the corresponding RMSE of state estimation is shown in Table 1. Besides, the computational complexity of each method in terms of processing time for each scan (in milliseconds) is also shown in this table. All the results are obtained based on the simulations using the tic/toc functions of MATLAB software on a 2.00 GHz Intel P4 platform.

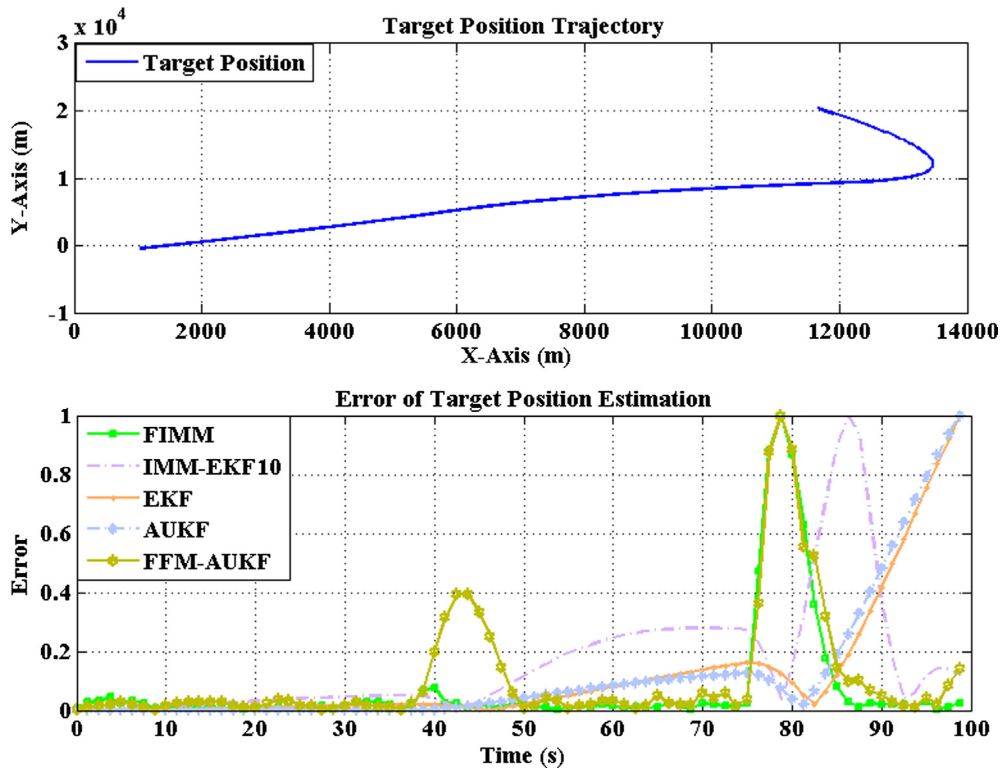

Fig. 4. The actual value of target position and the corresponding Error by different methods in case study 1.

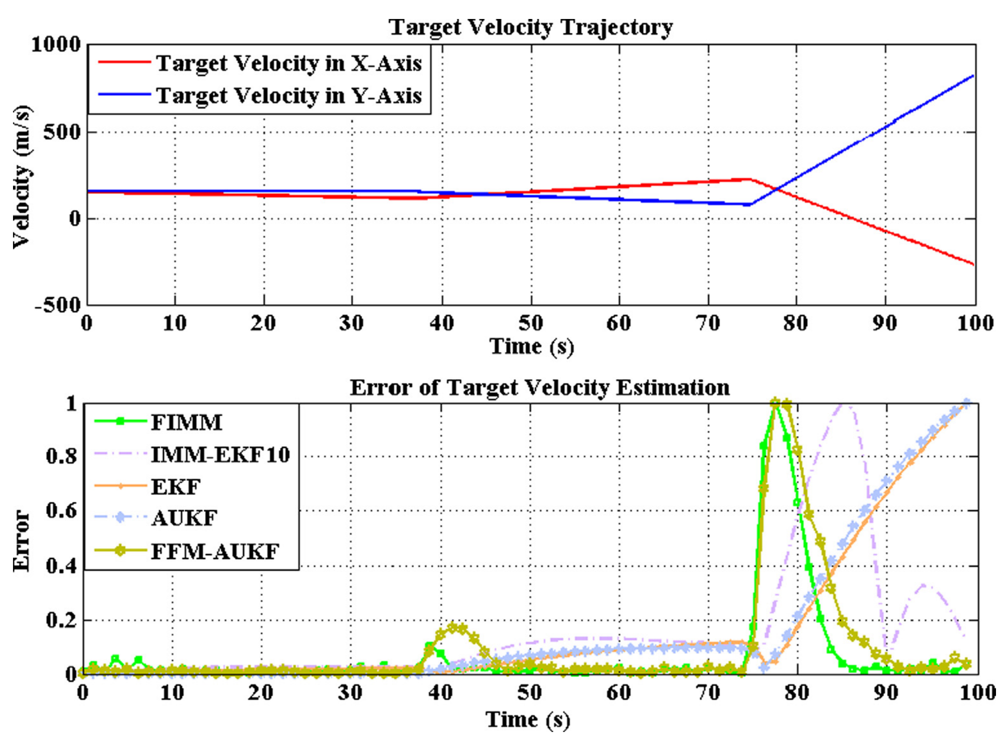

Fig. 5. The actual value of target velocity and the corresponding Error by different methods in case study 1.

5.2. *Simulation analysis*

Although the AUKF method provides good tracking accuracy in non-maneuvering mode, it shows a significant divergence in presence of high maneuvers. Our results show that the combination of FFM technique and AUKF method can effectively converge the response of this filter in presence of high maneuvers.

In addition, the proposed FIMM algorithm shows better tracking performance than conventional IMM algorithms with a large number of sub-filters at the price of higher computational cost. Based on the numerical results of current study, it is seen that filters with higher estimation precision require much more computation time than those with lower accuracy, reflecting that there is a trade-off between filtering accuracy and computational cost.

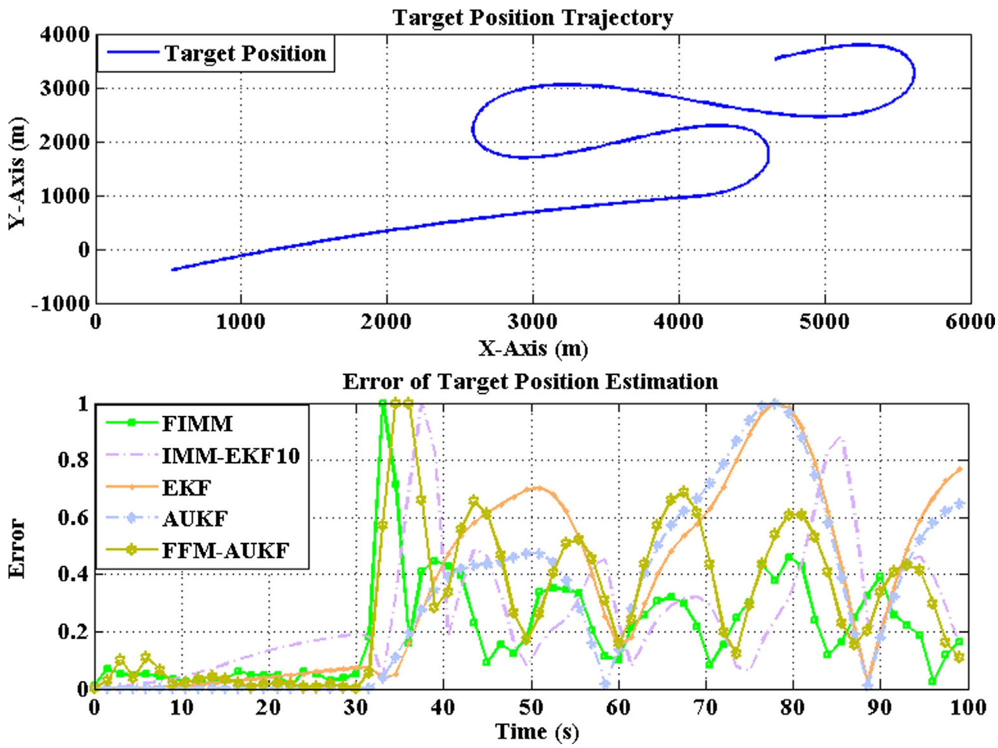

Fig. 6. The actual value of target position and the corresponding Error by different methods in case study 2.

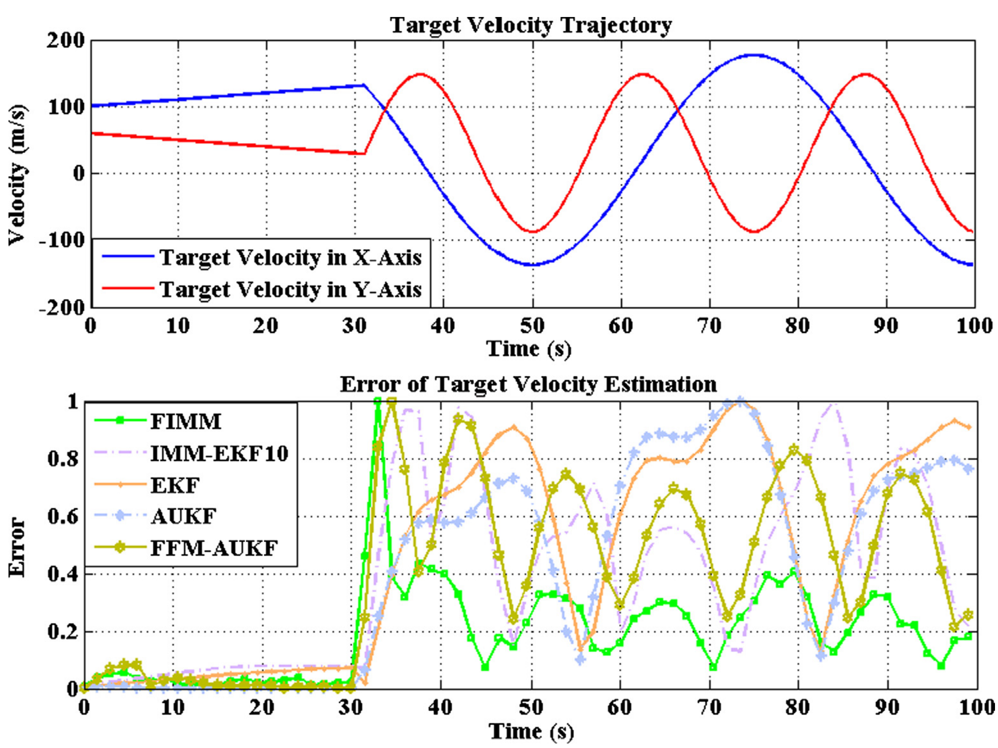

Fig. 7. The actual value of target velocity and the corresponding Error by different methods in case study 2.

6. Conclusion

In this paper, the higher performance of FFM-AUKF and FIMM methods has been shown in the state estimation of non-linear dynamic systems in presence of unknown target acceleration. The FFM technique adjusts the time-varying covariance matrix to deal with the unknown target maneuver utilizing a fuzzy system as a universal approximator. The FFM-AUKF method produces more accurate results than EKF and AUKF methods with higher computational cost.

In addition, a FIMM algorithm has been proposed for the interaction of FFM technique and AUKF method. In this algorithm, the predefinition and adjustment of sub-filters with respect to the target maneuver are not required since the FFM technique corrects the covariance matrix of each sub-filter intelligently. Moreover, this algorithm has decreased the number of required sub-filters to

Table 1
A comparison of RMSEs of different methods (based on 100 Monte Carlo runs) and the required computational time for each scan in case studies 1 and 2.

Case studies ↓	Performance (RMSE) ↓	EKF	AUKF	IMM-EKF10	FFM-AUKF	FIMM
Case study 1	X-position (m)	849.63	842.21	163.52	9.06	6.65
	Y-position (m)	961.75	934.46	197.16	11.95	9.05
	Max (*RMSE*(*Position*))	249.12	234.30	48.37	3.27	2.73
	X-velocity (m/s)	128.69	131.70	46.35	9.70	6.30
	Y-velocity (m/s)	169.04	167.93	59.59	13.31	8.72
	Max (*RMSE*(*Velocity*))	33.90	32.80	13.56	3.66	2.71
Case study 2	X-position (m)	541.13	565.98	50.68	14.05	2.82
	Y-position (m)	321.39	355.85	93.14	31.56	6.22
	Max (*RMSE*(*Position*))	65.24	75.00	15.26	3.96	1.26
	X-velocity (m/s)	113.82	122.29	27.08	15.47	3.93
	Y-velocity (m/s)	78.11	83.08	55.64	34.11	8.82
	Max (*RMSE*(*Velocity*))	11.72	13.29	6.11	3.48	1.87
The required computational time per scan (in milliseconds)		0.383	0.413	3.645	6.269	29.518

cover the wide range of unknown target accelerations. The experimental results have shown that the proposed FIMM algorithm provides better performance than conventional IMM algorithms with a large number of sub-filters.

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