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High Maneuvering Target Tracking Using Fuzzy Covariance Presetting

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Abstract: In this study, a new covariance presetting scheme is presented to overcome some drawbacks of the high maneuvering target tracking problems by using the Fuzzy logic method for evaluating the elements of the covariance matrix presetting. This scheme includes an estimation part that uses a modified Kalman filter and a fuzzy logic part to improve the tracking performance of the high maneuvering targets. The result is compared with the conventional covariance matrix presetting method. Simulation results show a superior performance of the proposed covariance presetting when a target either moves with high maneuver or with constant velocity.

Key words: High maneuvering targets, fisher and Bayesian uncertainty models, Kalman filtering, matrix covariance presetting, fuzzy systems

INTRODUCTION

There exist many approaches for tracking a maneuvering target (Chan *et al*., 1979; Bogler, 1987; Bar-Shalom and Birmiwal, 1982; Shiryayev, 1963). For example, equivalent noise that its basic assumption is: the maneuver effect can be modeled by a white or color noise process, input detection and estimation that estimates acceleration as an unknown control input and then estimates the state using the estimated input, switching-model that consist of two classes of models: maneuver and nonmaneuver model; tracking is done by a filter that uses one model (maneuver or nonmaneuver) at one time. Singer (1970) modeled target acceleration as a random process with known exponential autocorrelation. This model is capable of tracking a maneuvering target, but the performance of the estimation is reduced when target moves at a constant velocity. In (Nordsjo and Dynamics, 2005), have developed an Extended Kalman Filter combined with an algorithm for recursive estimation of the measurement noise variance and the variance of the target acceleration. An input estimation method was presented at (Khaloozadeh and Karsaz, 2004) using augmented state technique and standard Kalman filter to estimate the parameters of a maneuvering target. The results indicate that the above technique is degraded when targets move with high maneuver. To improve the results in high maneuver state, Khaloozadeh and Karsaz (2006) has presented a matrix covariance presetting method but it's degraded when targets move at constant velocity. Recently, fuzzy logic was applied to maneuvering target tracking with intelligent adaptation capabilities (Lalk, 1994; McGinnity and Irwin, 1998).

In this study a new fuzzy tracking algorithm is proposed for high maneuvering target. High maneuvering targets are modeled using jerk modeling approach (Karsaz *et al*., 2007). To reach high performance tracking for high maneuvering target, a new fuzzy covariance presetting method is proposed.

MODELS OF UNCERTAINTY

The basic uncertainties models (Schweppe, 1973) to be considered in this study are the Bayesian and Fisher models which have used in (Khaloozadeh and Karsaz, 2004). Theses models are specific cases of the state space structure-white process.

The Bayesian models are one of the most important and common used models of uncertainty. In Bayesian models, uncertainty are modeled by random variables and/or stochastic processes with completely specified either probability distributions or completely specified first and second moments. The complete definition of the Bayesian, discrete time model for linear systems is summarized now.

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

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Where:

- X(n) = State
- z(n) = Observation
- v(n) = White observation uncertainty
- w(n) = White system driving uncertainty
- X(0) = Initial condition

$$E\{v(n_1)v^T(n_2)\} = \begin{cases} R(n_1) & n_1 = n_2 \\ 0 & n_1 \neq n_2 \end{cases}, \quad E\{w(n_1)w^T(n_2)\} = \begin{cases} Q(n_1) & n_1 = n_2 \\ 0 & n_1 \neq n_2 \end{cases}$$
$$E\{x(0)x^T(0)\} = \psi, \; E\{x(0)\} = 0, \; E\{w(n)\} = 0, \; E\{v(n)\} = 0$$

In many applications, the input disturbance, w(.) can be modeled as being completely unknown. A model where w(.) is completely unknown is a type of Fisher model. Of course, conceptually such Fisher models have to be handled in a different fashion from Bayesian models where w(.) is viewed as a random vector with known covariance matrix Q(.). For some applications the Fisher modeling of w(.), can be viewed as the limiting Bayesian case, where, Q(.)∞I.

FILTERING OF THE BAYESIAN MODELS

The desired form of the filtering solution is a difference equation (recursive relationship) expressing $\hat{X}(n+1|n+1)$ in terms of $\hat{X}(n|n)$ on $z(n+1)$.

The solution of the filtering problem is the Kalman filter with equations:

$$\begin{aligned}
&\hat{X}(n+1|n+1) = F(n)\hat{X}(n|n) + K(n+1)[z(n+1) - H(n+1)F(n)\hat{X}(n|n)] \\
&K(n+1) = \Sigma(n+1|n+1)H^T(n+1)R^{-1}(n+1) \\
&\Sigma(n+1|n+1)) = \Sigma(n+1|n) - \Sigma(n+1|n)H^T(n+1) \\
&[R(n+1) + H(n+1)\Sigma(n+1|n)H(n+1)^T]^{-1}H(n+1)\Sigma(n+1|n) \\
&\Sigma(n+1|n) = F(n)\Sigma(n|n)F^T(n) + G(n)Q(n)G^T(n) \\
&\Sigma(0|0) = \psi, \hat{X}(0|0) = 0
\end{aligned} \tag{2}$$

where, K(N) is the Kalman gain and notation $\hat{X}(n+1|n)$ denotes the prediction at the (n+1)th sample point given the measurement up to and including the nth whilst $\hat{X}(n|n)$ denotes the estimation at the sample point given the measurement up to and including the nth. $\Sigma(n|n)$ is the error covariance matrix and is $\Sigma(n+1|n)$ the error covariance matrix of the one-step prediction.

Maneuvering targets are difficult to track with Kalman filter since the target model of tracking filter might not fit the real target trajectory (Kawase *et al*., 1998).

TRACKING ALGORITHMS

Some researches in detection and quick detection have been explored in the references (Bar-Shalom and Birmiwal, 1982; Shiryayev, 1963). It is assumed that the target moves in a plane, which is the two-dimensional case, such as a ship. The state and the measurement equations for non-maneuvering model is given by:

$$\begin{aligned} X(n+1) &= F(n)X(n) + G(n)w(n) \\ z(n) &= H(n)X(n) + v(n) \end{aligned} \tag{3}$$

where, $X = [x \;\; \dot{x} \;\; y \;\; \dot{y}]^T$ is the state vector. F is the state transition matrix, G is the plant noise system matrix and w (n) is the plant noise, assumed to be white with variance σ_p^2. The expression for G and F as functions of the update time T (T is the time interval between two consecutive measurements.) are:

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

H is the measurement matrix and v(n) is the measurement noise, assumed Gaussian with covariance matrix R. The matrix H is given by:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

The input estimation approach for tracking a maneuvering target is proposed by Chan *et al.* (1979). In this approach, the magnitude of the acceleration is identified by the least-squares estimation when a maneuver is detected. The estimated acceleration is then used in conjunction with a standard Kalman filter to compensate the state estimate of the target.

In input estimation techniques the maneuvering model treats the acceleration as an additive term:

$$X(n+1) = FX(n) + Cu(n) + Gw(n) \tag{4}$$

There are several methods to estimate and predict the states of maneuvering target (Bogler, 1987; Chan *et al*., 1979; Wang and Varshney, 1993; Bar-Shalom and Fotman, 1988) but the results demonstrate the performance of these techniques are degraded when targets move with high maneuver.

In Khaloozadeh and Karsaz (2004), an algorithm was proposed to develop a maneuver detection model, which detects the maneuver effectively. There considered the additive maneuver term u (n) as a deterministic signal in the maneuvering Eq. 4, then we deal with two mixed uncertainties, w(n) as a stochastic plant noise and u(n) as an unknown but bounded additive maneuver term where C is:

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

Also in Khaloozadeh and Karsaz (2004) the additive maneuver term u(n) is introduced as a new state and the maneuvering model Eq. 4 was converted to a non-maneuvering model with an augmented state equation in the form of the standard Bayesian model with Eq. 1 and 2 as:

$$\begin{gathered} \begin{bmatrix} X(n+1) \\ u(n+1) \end{bmatrix} = \begin{bmatrix} F & C \\ 0 & I \end{bmatrix} \begin{bmatrix} X(n) \\ u(n) \end{bmatrix} + \begin{bmatrix} G \\ 0 \end{bmatrix} w(n) \\ z(n) = H(n)X(n) + v(n) \\ X_{Aug}(n) = [X(n) \quad u(n)]^T;\ F_{Aug} = \begin{bmatrix} F & C \\ 0 & I \end{bmatrix};\ G_{Aug} = \begin{bmatrix} G \\ 0 \end{bmatrix} \end{gathered} \tag{5}$$

Define a posterior measurement z(n+1),

$$\begin{gathered} z(n+1) = HX(n+1) + v(n+1) = \\ H\{FX(n) + Cu(n) + Gw(n)\} + v(n+1) \\ z(n+1) = [HF \quad HC] \begin{bmatrix} X(n) \\ u(n) \end{bmatrix} + HGw(n) + v(n+1) \Rightarrow \\ H_{Aug} = [HF \quad HC]\ ;\ V_{Aug} = HGw(n) + v(n+1) \end{gathered} \tag{6}$$

Using this algorithm one can estimate X and u simultaneously with the standard Kalman filter by using the equations:

$$\begin{gathered} X_{Aug}(n+1) = F_{Aug} X_{Aug}(n) + G_{Aug} w(n) \\ Z_{Aug}(n) = z(n+1) = H_{Aug}(n) X_{Aug}(n) + V_{Aug}(n) \end{gathered} \tag{7}$$

Since v(n) and w(n) are uncorrelated, we can obtain the new covariance matrix of the measurement noise $V_{aug}(n)$ for the augmented state equation as:

$$\begin{gathered} R_{Aug} = E\{V_{Aug} V_{Aug}^T\} = E\{(HGw(n) + v(n+1)) \\ (HGw(n) + v(n+1))^T\} = HGE\{w(n)w(n)^T\} \\ G^T H^T + E\{v(n+1)v(n+1)^T\} \\ R_{Aug} = E\{V_{Aug} V_{Aug}^T\} = E\{(HGw(n) + v(n+1)) \\ (HGw(n) + v(n+1))^T\} = HGE\{w(n)w(n)^T\} \\ G^T H^T + E\{v(n+1)v(n+1)^T\} \\ \Rightarrow R_{Aug} = E\{V_{Aug}(n) V_{Aug}^T(n)\} = HGQG^T H^T + R \end{gathered} \tag{8}$$

In Karsaz *et al.* (2007) another augmented state model that also estimates the jerk of a maneuvering target has been proposed to increase the performance of tracking algorithm. In this case the maneuvering model is:

$$X(n+1) = FX(n) + C_{new} u_{new}(n) + Gw(n) \tag{9}$$

In Eq. 9 the new input $u_{new}(n)$ is consist of acceleration and time-derivative of it and C_{new} is as follows:

$$C_{new} = \begin{bmatrix} T^2/2 & 0 & T^3/6 & 0 \\ T & 0 & T^2/2 & 0 \\ 0 & T^2/2 & 0 & T^3/6 \\ 0 & T & 0 & T^2/2 \end{bmatrix}$$

Therefore the tracking algorithm changes to

$$\begin{gathered} X_{new}(n+1) = F_{new} X_{new}(n) + G_{new} w(n) \\ Z_{new}(n) = z(n+1) = H_{new}(n) X_{new}(n) + V_{Aug}(n) \end{gathered} \tag{10}$$

Where:

$$X_{new}(n) = [X(n) \quad u(n) \quad \dot{u}(n)]^T$$

$$F_{new} = \begin{bmatrix} F & C_{new} \\ 0 & F_1 \end{bmatrix};\quad F_1 = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$G_{new} = \begin{bmatrix} G \\ 0_{4\times4} \end{bmatrix};\quad H_{new} = [HF \quad HC_{new}]$$

The covariance matrix of the measurement noise is the same as the earlier one:

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

In this study, we apply the above algorithm to estimate the parameters of a maneuvering target and a fuzzy covariance presetting method to increase the tracking performance.

A NEW FUZZY COVARIANCE PRESETTING METHOD

Nevertheless great efforts at above proposed methods, still there is a weakness for estimating high maneuver target parameters. In Khaloozadeh and Karsaz (2006) it has been explained that the weakness is because of the fast primary convergence rate of Kalman filter, in other words estimation error covariance matrix Σ(N|N) becomes small after some samples and it causes the algorithm not to be able to reach the optimal point. To overcome this problem, there is a conventional method (Goodwin and Sin, 1984) that increases error covariance matrix when the matrix magnitude becomes smaller than the critical limit, with this formula:

$$\sum(N|N) = k_f \times \sum(0|0)$$

where, k_f is a constant coefficient that is bigger than one. It causes the estimation error covariance matrix $\Sigma(N|N)$ becomes larger than critical limit, then the kalman filter doesn't lose the target direction and tracks the high maneuver target successfully. As it was mentioned before, kf is a constant coefficient in (Khaloozadeh and Karsaz, 2006). k_f will be changed during the target moves, for getting better results.

Here, it was present a new fuzzy logic algorithm to determine how much the covariance matrix must be changed (determine the value of k_f) and when. Finally we compare the performance effectiveness of these methods (Khaloozadeh and Karsaz, 2006) and fuzzy method.

The proposed fuzzy logic method calculates coefficient k_f with use of two features as inputs of fuzzy system:

- **Magnitude of error covariance matrix:** This is the norm of $\Sigma(N|N)$ matrix
- **Magnitude of jerk:** This is the norm of time-derivative of acceleration matrix

The output of fuzzy system is coefficient k_f that changes $\Sigma(N|N)$ matrix:

$$\sum_{new}(N+1|N+1) = k_f \times \sum(N|N)$$

The first input determines magnitude of error covariance matrix that must be change for avoidance of fast convergence and the second input indicates acceleration rate. When magnitude of error covariance matrix is low and the acceleration rate is high k_f should be high. The basic idea is used in the fuzzy inference rules is: If the acceleration changes with a large variation, the error covariance matrix must become large.

Figure 1 shows the membership functions of the inputs and the output of the fuzzy system. The rules of the fuzzy system are as follows:

- If norm (covariance) is S and jerk is S then coefficient k_f is VS
- If norm (covariance) is S and jerk is M then coefficient k_f is M
- If norm (covariance) is S and jerk is L then coefficient k_f is L

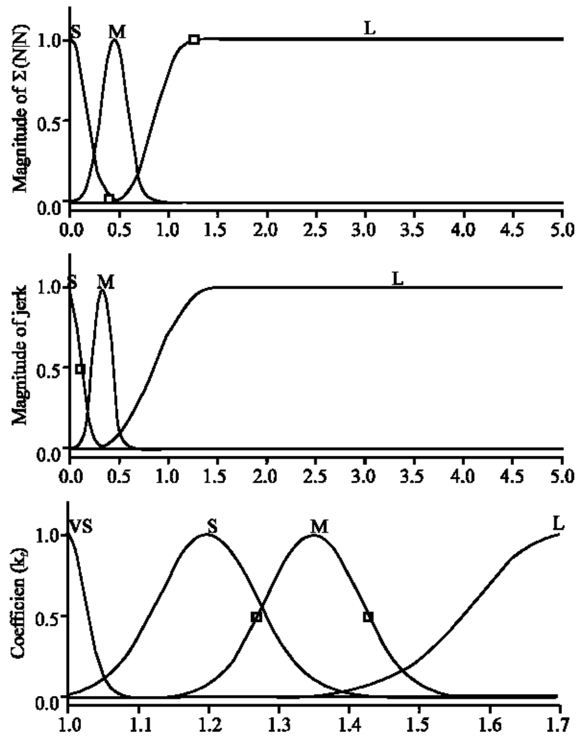

Fig. 1: The membership function of the fuzzy system

- If norm (covariance) is M and jerk is S then coefficient k_f is VS
- If norm (covariance) is M and jerk is M then coefficient k_f is VS
- If norm (covariance) is M and jerk is L then coefficient k_f is M
- If norm (covariance) is L and jerk is S then coefficient k_f is VS
- If norm (covariance) is L and jerk is M then coefficient k_f is VS
- If norm (covariance) is L and jerk is L then coefficient k_f is S

The result of proposed fuzzy method is: when target moves with a high maneuver, presetting method is performed with a large coefficient and when target moves at constant velocity presetting method is stopped.

SIMULATION RESULTS

The estimation improvement obtained by the proposed method is shown by the following examples. The sampling time is T = 0.1 (sec) and the number of the samples are 2000. Initial conditions are also:

$$x(0) = 10\text{ m};\quad y(0) = -10\text{ m};$$
$$v_x(0) = 10\text{ m sec}^{-1};\quad v_y(0) = 15\text{ m sec}^{-1}$$

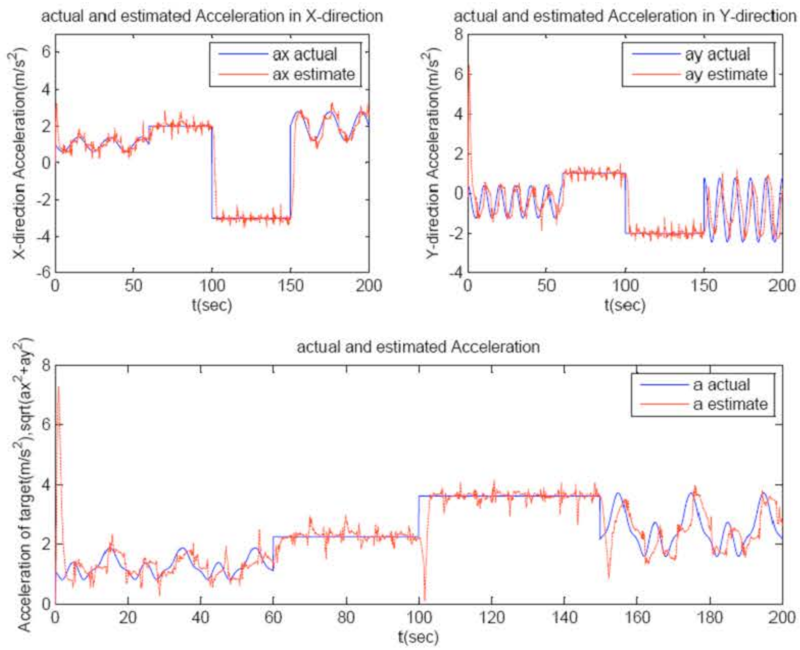

Fig. 2: The actual and the estimated acceleration by conventional presetting method, $k_f = 1.5$, the actual acceleration of target is shown with blue line

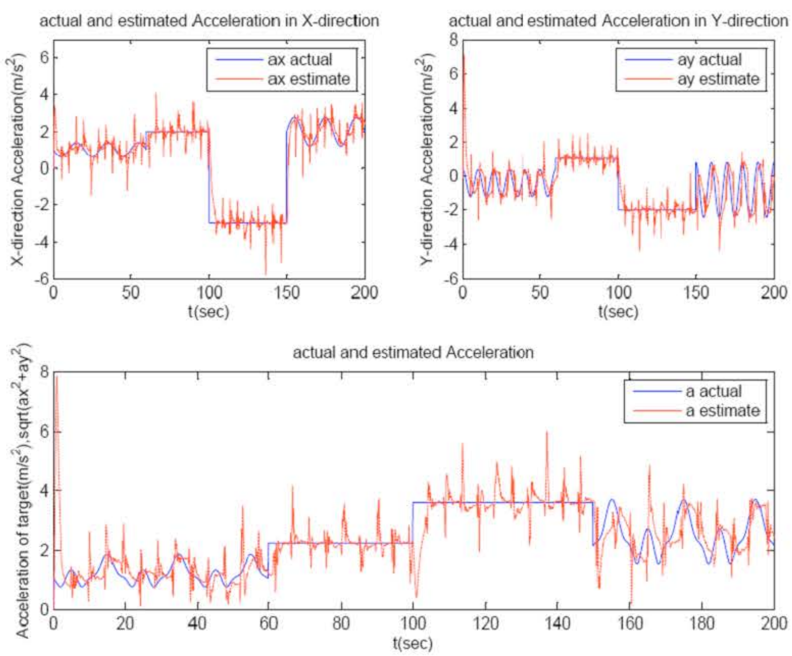

Fig. 3: The actual and the estimated acceleration by conventional covariance presetting method, $k_f = 10$, the actual acceleration of target is shown with blue line

where, m denoted meter and s denoted second.

Figure 2 shows the estimated and the actual acceleration that obtain by the conventional covariance presetting method which was proposed by Khaloozadeh and Karsaz (2006) with $k_f = 1.5$. Figure 3 also shows the estimated and the actual acceleration by the conventional covariance presetting method (Khaloozadeh and Karsaz, 2006) for $k_f = 10$.

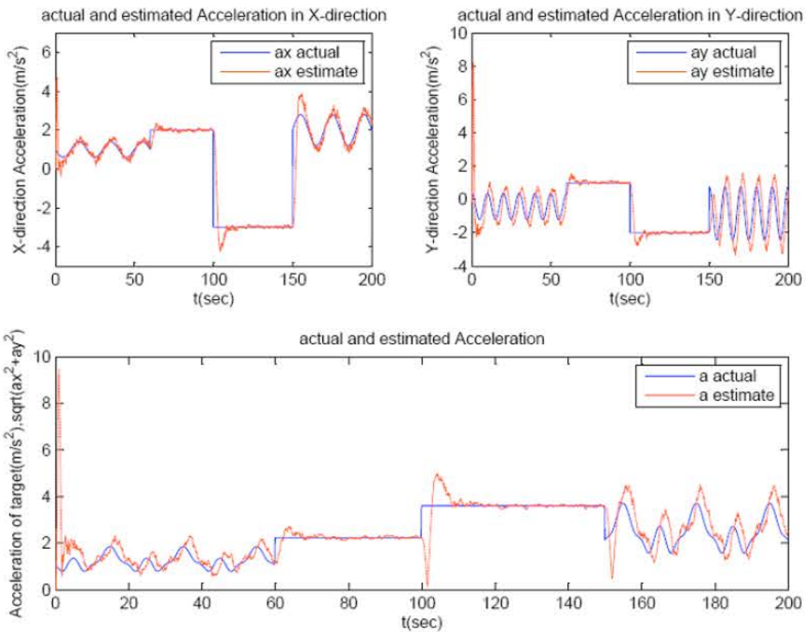

Fig. 4: The actual and the estimated acceleration by the proposed fuzzy covariance presetting method

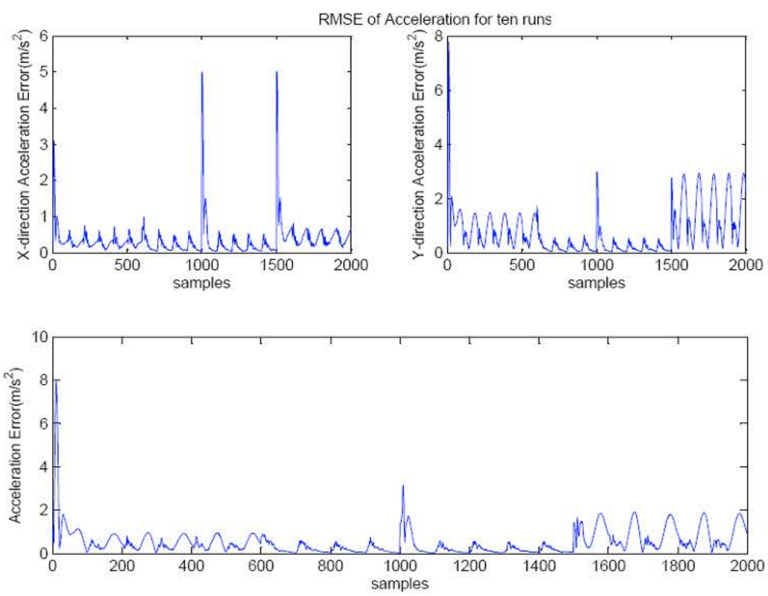

Fig. 5: RMSE of estimated acceleration by conventional covariance presetting method, $k_f = 1.5$

Figure 4 shows the estimated and actual acceleration obtained by fuzzy method that is reported in last part. The simulation results show that in contrast of Khaloozadeh and Karsaz (2006), the proposed method prevent of presetting when the target moves with constant velocity and start to preset the covariance matrix of the estimation when there exist high maneuver targets.

For better comparison the RMSE index (root mean square errors) of estimated acceleration is calculated by running the simulation ten times at the same initial conditions on position, velocity and acceleration of target for above methods. The simulation results are shown at Fig. 5-7.

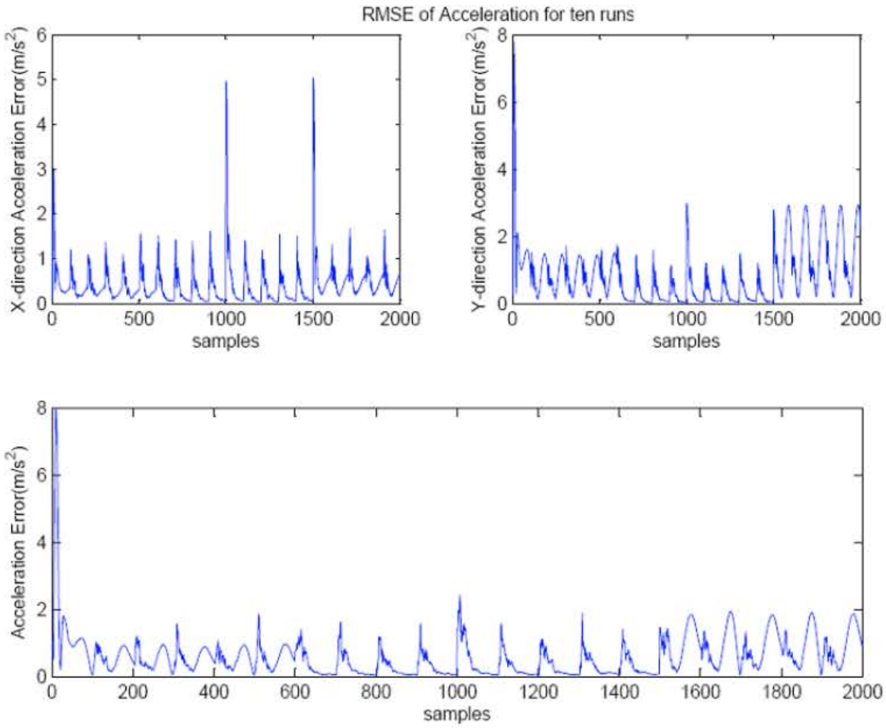

Fig. 6: RMSE of estimated acceleration by conventional covariance presetting method, $k_f = 10$

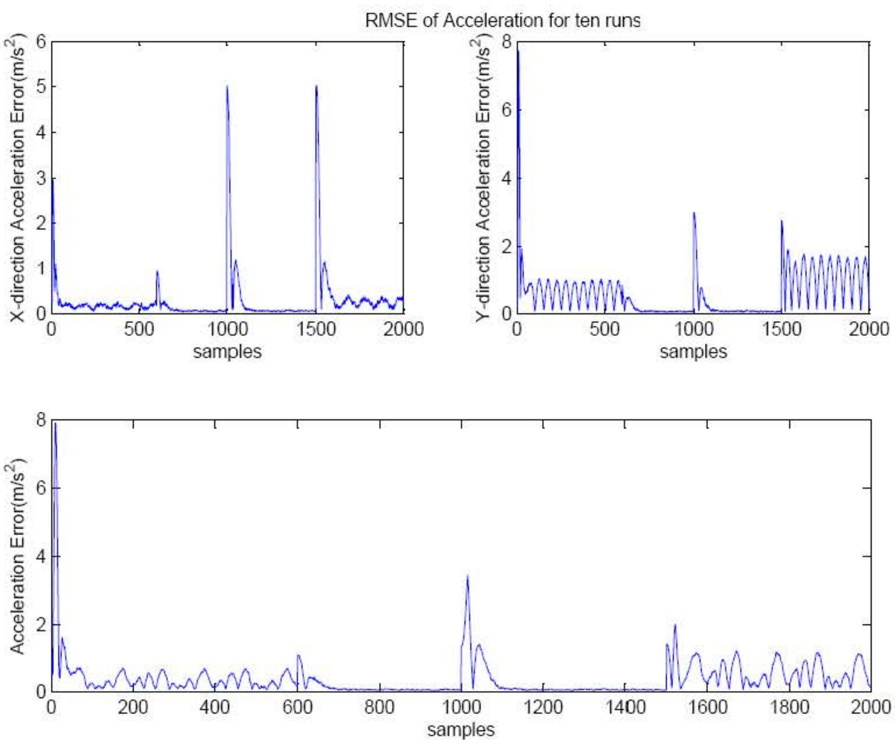

Fig. 7: RMSE of estimated acceleration by the proposed fuzzy covariance presetting method

Table 1: The total average error

	Error at a_x	Error at a_y	Error at a
Proposed method	0.2644	0.5688	0.6272
[13] Method, $k_f = 1.5$	0.3210	0.7436	0.8099
[13] Method, $k_f = 10$	0.3711	0.7716	0.8562

Also, we evaluate the total average error for above methods and compare them in Table 1. The total average error is defined as follows:

$$\text{Error at } a_x = \frac{1}{\text{samples}} \sum_{i=1}^{\text{samples}} |(a_{xi} - \hat{a}_{xi})|$$

$$\text{Error at } a_y = \frac{1}{\text{samples}} \sum_{i=1}^{\text{samples}} |(a_{yi} - \hat{a}_{yi})|$$

$$\text{Error at } a = \frac{1}{\text{samples}} \sum_{i=1}^{\text{samples}} |(a_i - \hat{a}_i)|$$

The errors are evaluated for ten runs.

CONCLUSIONS

In this study, a new covariance presetting scheme is presented to overcome the high maneuvering target tracking problems. The scheme is consist of Kalman filtering estimation and the new fuzzy logic presetting method to increase the performance of tracking algorithms. The simulation results show a better performance than the study by (Khaloozadeh and Karsaz (2006). If the acceleration changes with a large variation, the error covariance matrix must become large.

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