High Maneuver Target Tracking Based on Combined Kalman Filter and Fuzzy Logic

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Abstract

In this paper, a new combined scheme is presented to overcome some drawbacks of the high maneuvering target tracking problems by using the mixed Fuzzy logic and the standard Kalman filter. This scheme is consist of two important aspects; at first absolute value of difference between last target course and the present observation target course and the second aspect is the absolute value of measurement residual. The results compared with the augmented method and another combined fuzzy logic method which have been reported in [8] and [16], respectively. Simulation results show a high performance of the proposed innovation method and effectiveness of this scheme in high maneuvering targets tracking problems.

1. INTRODUCTION

The Kalman filter has been used in many radar processors as an adaptive tracking filter to estimate the position, the velocity and the acceleration of a target; however its performance may be seriously degraded in presence of manoeuvre. Even a short-term acceleration can cause a bias in the measurement sequence. There exist many approaches and methods for tracking manoeuvring targets, which try to solve this problem [1]-[3]. For example, switching between Kalman filters of different order, estimation of acceleration as input during a manoeuvre and to correct the state using batch least squares methods or recursive estimation for on-line implementation. An Extended Kalman Filter combined with an algorithm for recursive estimation of the measurement noise variance and the variance of the target acceleration is proposed in [13]. Lanka [4] and Korn, Gully and Willsky [5] have developed an extended Kalman filter using a circular model of motion. Singer [6] modeled target acceleration as a random process with known exponential autocorrelation. This model is capable of tracking a manoeuvring target, but the performance of the estimation is reduced when target moves at a constant velocity. A generalized likelihood ratio (GLR) method for manoeuvre detection and estimation was presented by Korn, Gully and Willsky [5]. This algorithm proposed the use of two hypotheses, null hypothesis for a target without manoeuvre, and alternative hypothesis for a target with manoeuvre. When the log likelihood ratio is over a threshold, a manoeuvre is detected. This system needs a bank of correlators to detect the manoeuvre onset time. In some situations, the Kalman filter solves the target tracking problem by including the parameters as part of an augmented state to be estimated [8, 11, 12]. In many papers such filters are called "full state" estimator.

Recently, fuzzy logic was applied to manoeuvring target tracking with intelligent adaptation capabilities [14, 15]. However it is not easy to find effective parameter on manoeuvre detection and partition them.

[16] presents a method which used Kalman filter and fuzzy logic in order to track a manoeuvre target, but the only input of its fuzzy system was heading change. In this work we find more effective parameter on acceleration estimation and partition a new fuzzy system. This parameter leads us to an immediate manoeuvre detection and a more accurate estimation.

2. MODELS OF UNCERTAINTY [7]

The basic models to be considered in this paper are the Bayesian and Fisher models which have used in [8]. 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.

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The complete definition of the Bayesian, discrete time model for linear systems is summarized now.

$$
\begin{array}{lll}
X(n+1) = F(n)X(n) + G(n)w(n) & & \\
z(n) = H(n)X(n) + v(n) & & \\
X(n) & state & \\
z(n) & observation & \\
v(n) & white\ \ observation\ \ uncertianty & \\
w(n) & white\ \ system\ \ driving\ \ uncertianty & \\
X(0) & initial\ \ condition &
\end{array} \tag{1}
$$

$$
E\{v(n_1)v^T(n_2)\} = \begin{cases} \Re(n_1) & n_1 = n_2 \\ 0 & n_1 \neq n_2 \end{cases}
$$

$$
E\{w(n_1)w^T(n_2)\} = \begin{cases} Q(n_1) & n_1 = n_2 \\ 0 & n_1 \neq n_2 \end{cases}
$$

$$
E\{x(0)x^T(0)\} = \psi
$$

$$
E\{x(0)\} = 0 \quad , \quad E\{w(0)\} = 0 \quad , \quad E\{v(0)\} = 0
$$

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.

3. FILTERING OF THE BAYESIAN MODELS

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

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

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

where $K(N)$ is the Kalman gain and notation $\hat{X}(N+1 \mid N)$ denotes the prediction at the $(N+1)^{th}$ sample point given the measurement up to and including the N^{th} whilst $\hat{X}(N \mid N)$ denotes the estimation at the N^{th} sample point given the measurement up to and including the N^{th}. $\Sigma(N \mid N)$ is the error covariance matrix and $\Sigma(N+1 \mid N)$ is 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 [9].

4. COMBINED KALMAN FILTER-FUZZY LOGIC METHOD

In this section, combined Kalman filter-fuzzy logic (CKF) method is proposed for tracking a high manoeuvring target. The main idea of the proposed method is adding some information to Bayesian model in order to obtain better performance. Because of mathematical limitations of standard Kalman filter, it is pretty impossible or very difficult to adding more information on it. As we know, fuzzy systems do not require a mathematical model of how system outputs depend on inputs. Therefore in this research fuzzy logic is employed in order to add some more information to the tracker. In fact, in this method Fuzzy logic is used in order to detect high manoeuvre of the target.

Radar output signal has no exact mathematical relation with target manoeuvre, but with no doubt there exist a complex nonlinear mapping between them. To map the input vector to target acceleration vector it is important to find the effective input elements. In the proposed method two features is used as inputs of fuzzy acceleration estimator system.

1. *Absolute value of difference between last target course (ψ) and observation target course (ξ):* this is shown as $\Delta\theta$ in Fig .1. $\Delta\theta$ is one of the most useful elements to detect the target manoeuvre [16].

When $|\Delta\theta|$ is low, then the target with high probability is moving around its last direction and when $|\Delta\theta|$ is high, then the target with high probability is moving toward sensor's observation. This fact was used as a fuzzy rule in fuzzy controller of CKF.

$|\Delta\theta|$, ψ and ξ are calculated by the following equations.

$$
\Delta\theta = \psi - \xi \tag{3}
$$

where:

ψ = *Last Target Course*

ξ = *Observation Target Course*

$$
\begin{aligned}
&\text{Last Target Course} = \text{angle}(H\hat{X}(N-1|N) - H\hat{X}(N-2|N)) \\
&\textit{Observation}\ \text{Target Course} = \text{angle}(\hat{Z}(N|N) - H\hat{X}(N-1|N))
\end{aligned} \tag{4}
$$

2. *Absolute value of measurement residual* (R): The objective in this section is to develop a manoeuvre detection algorithm which detects the acceleration and jerk of a manoeuvring target. Similar idea of quickest detection and change detection algorithm only for constant acceleration has been investigated in the [3]. The standard KF (equation (2)) is an efficient and unbias filter, so the sequence $\tilde{Z}(n+1) = Z(n+1) - \hat{Z}(n+1/n) = Z(n+1) - H(n+1)\hat{X}(n+1/n)$,which is the residue of the observation is a stochastic zero mean white process. i.e.,

$$E\{\widetilde{Z}(n+1)\}=0$$

$$E\{\widetilde{Z}(n_1)\widetilde{Z}(n_2)^T\}=\Re\delta(n_1-n_2)$$

Thus, for non-manoeuvring targets, the mean of this sequence ($\widetilde{Z}(n+1)$) is zero. But for manoeuvring target case this sequence is no longer zero, using Kalman filter.

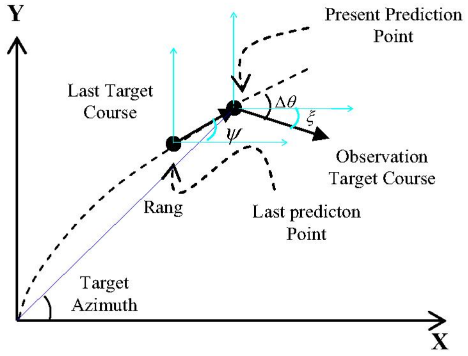

Fig. 1: Target movement geometry

Considering this fact, one can use this idea for manoeuvre detection by using the measurement residue in the manoeuvring case, which is not longer white zero mean and it contains more information which can use for manoeuvre detection procedure. This fact is used as another fuzzy rule in fuzzy acceleration estimator system.

The CKF method is illustrated in Fig .2. In this figure, block 1, calculates $\Delta\theta$ and R. Block 2 is a fuzzy controller and the fuzzy system have two input and one output. The input variables of fuzzy system are $|\Delta\theta|$ and R. Inputs and output fuzzy sets all have three Gaussian membership functions with the following membership grade $u_i^j(x_i)$.

$$u_i^j(x_i)=\exp\left[-\frac{1}{2}\left(\frac{x_i-c_i^j}{\sigma_i^l}\right)^2\right] \quad (5)$$

where, c_i^j and x_i are the centre value and the standard deviation of Gaussian membership function for i th input variable of j-th fuzzy rule, respectively. The output of the fuzzy logic controller determines the estimated acceleration value of target deviation a_t from its last Target course based on $\Delta\theta$ input. Fuzzy inference rules support mentioned information. Block 3 estimates the new state based on the fuzzy logic output as follow.

$$\hat{Y}(N+1|N)=F(N)\hat{Y}(N|N)+G(N)\begin{bmatrix}a_{tx}\\ a_{ty}\end{bmatrix}$$

a_t : *Target Acceleration (*Output of block 2)

$$a_{tx}=a_t\mathrm{Cos}(\xi) \quad (6)$$

$$a_{ty}=a_t\,\mathrm{Sin}(\xi)$$

a_{tx} : x- axis Target acceleration

a_{ty} : y- axis Target acceleration

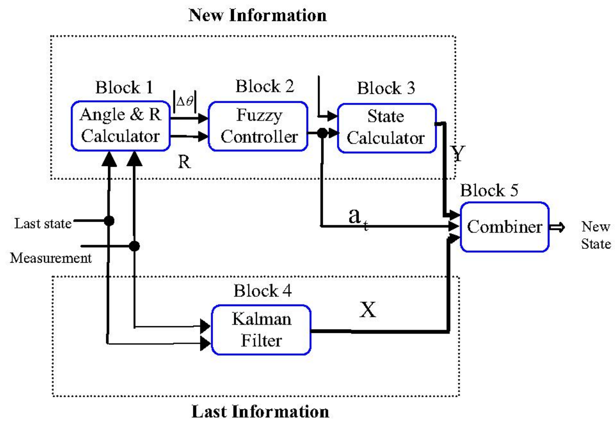

Fig. 2: The CKF method

$\hat{Y}(N+1|N)$ Denotes the fuzzy prediction at the $(N+1)^{th}$ sample point given the measurement up to and including the N^{th}, whilst $\hat{Y}(N|N)$ denotes the fuzzy estimation at the N^{th} sample point given the measurement up to and including the N^{th}. The output of block 3, $\hat{Y}$, is the new state which calculated by Fuzzy logic based on the new information.

Kalman filter facilitates the mean-square-error analysis of the system behaviour. This method has some advantages and works well in mild manoeuvres. For making use of the advantages of Kalman filter, block 4 uses it to estimate the new state. In the other words, the output of block 4, $\hat{X}$, is the new state which is estimated by Kalman filter based on the last information. At the end of the process a method is needed to combine output of the fuzzy estimator, $\hat{Y}$, and output of the Kalman estimator, $\hat{X}$, considering their advantages and disadvantages. Simulation result proves that fuzzy tracker performs better when the manoeuvre is high and Kalman Filter works better when manoeuvre is mild. Assuming the target manoeuvre is proportional to a_t, $\hat{Y}$ and $\hat{X}$ can be combined in block 5 using the following relation:

$$\overline{NX}=\frac{\left|a_t\hat{Y}+(a_{\max}-a_t)\hat{X}\right|}{a_{\max}} \quad (7)$$

In formula 7, $a_{\max}$ is the maximum value of a_t and $\overline{NX}$ is the output of block 5. As illustrated in figure 2, CKF uses both kinematics information and new information, which leads to a better performance.

5. SIMULATION RESULTS

The estimation improvement obtained by purposed method is illustrated by the following examples.

In experiments reported in this section, the following assumptions and parameter values are used. In this simulation, the sampling time is T=0.015 (sec). Covariance elements generated for R and θ axis are both Gaussian random variables; in addition the measurement noise vector in Cartesian coordinates is related to the measurement noise vector in polar coordinates by the following equation [10].

$$\begin{bmatrix} \delta_x^2 \\ \delta_y^2 \end{bmatrix} = \begin{bmatrix} \cos^2\theta_0 & R_0^2 \sin^2\theta_0 \\ \sin^2\theta_0 & R_0^2\cos^2\theta_0 \end{bmatrix} \begin{bmatrix} \delta_R^2 \\ \delta_\theta^2 \end{bmatrix} \tag{8}$$

where,

$\delta_R = 200, \quad \delta_\theta = 1$

$R_0 = 5000\,(\mathrm{m})$ and $\theta_0 = 30\,(\mathrm{deg})$

In order to evaluate the new tracking scheme and comparison with two existing method augmented Kalman filter [8] and method of [16], two scenarios were considered as follow.

First scenario: The initial position of the target is given by (x,y)=(4330,2500) with an initial speed of (v_x, v_y)=(13,7.5) and on a constant course of 30° and speed until t= 75 s, then it starts to maneuver with acceleration value u_x=*-1 m/s*^{2} , u_y= *-1 m/s*^{2}. Target move with this acceleration up to end of this simulation at t=135 s. Fig. 3 shows, target trajectory estimation by proposed method and augmented Kalman filter in this scenario. Fig. 4 shows, target range estimation by two methods. Fig. 5 shows, target azimuth estimation by two methods. In order to compare CKF with augmented Kalman filter and method of [16], a Monte- Carlo simulation of 50 runs was performed. The standard deviation (std) of estimation error of range, azimuth, course and speed of all three methods in this scenario is compared in Table 1.

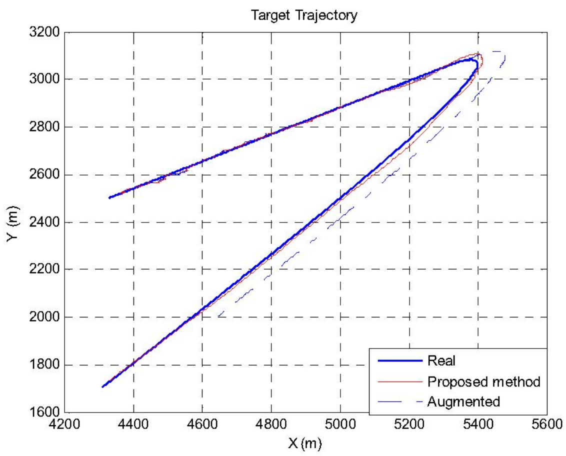

Fig. 3: Target's Trajectory in Cartesian coordinate and tracking result of CKF and augmented Kalman filter

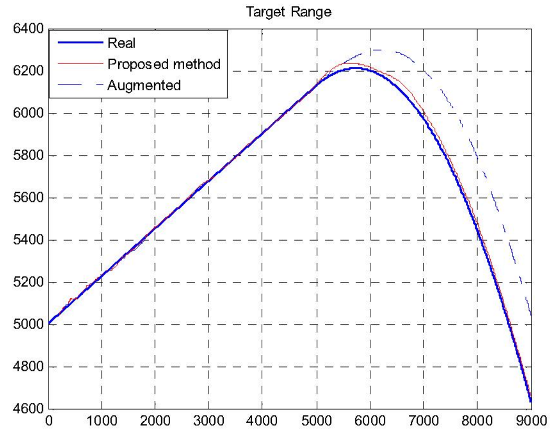

Fig. 4: Target's range estimation

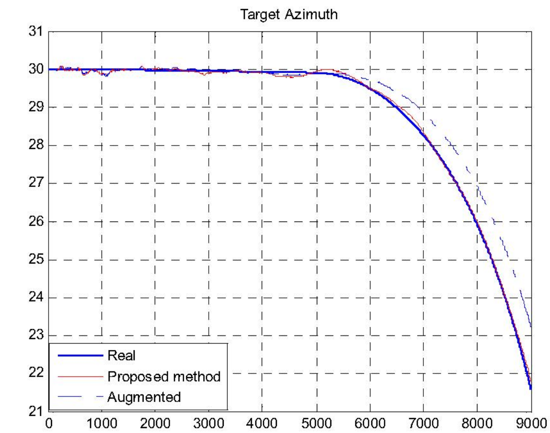

Fig. 5: Target's azimuth estimation

TABLE 1: RADAR FILTER ESTIMATION ERROR IN THE FIRST SCENARIO (std)

	Range	Azimut	Cours	Speed
CKF	11.6915	0.0653	12.123	2.383
Augmented Method	140.536	0.4474	35.076	13.865
Method of [16]	59.2162	0.1145	25.474	14.018

Second scenario: The initial position of the target is given by (x,y)=(4330,2500) with an initial speed of (v_x, v_y)=(13,7.5) and on a constant course of 30° and speed until t= 180 s, then it starts to maneuver with acceleration value u_x=*-1 m/s*^{2} , u_y=*-1 m/s*^{2}. This acceleration finish at t=225 s after that, target starts to maneuver at t=228s with acceleration of u_x=*1.6 m/s*^{2}, u_y=*1.6 m/s*^{2}. Target moves with this acceleration up to end of this simulation at t=300s. Fig. 6 shows, target trajectory estimation by proposed method and augmented Kalman filter in this scenario. Fig.7 shows, target range estimation by two methods. Fig.8 shows, target azimuth estimation by two methods.

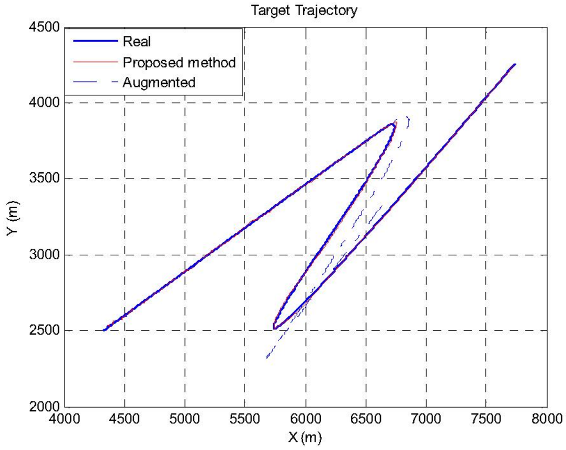

Fig. 6: Target's Trajectory in Cartesian coordinate and tracking result of CKF and augmented Kalman filter

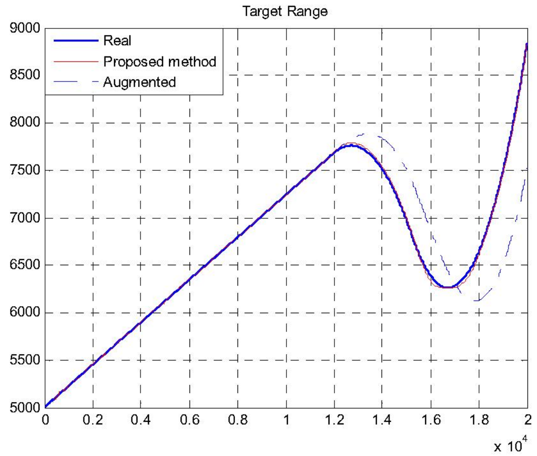

Fig. 7: Target's range estimation

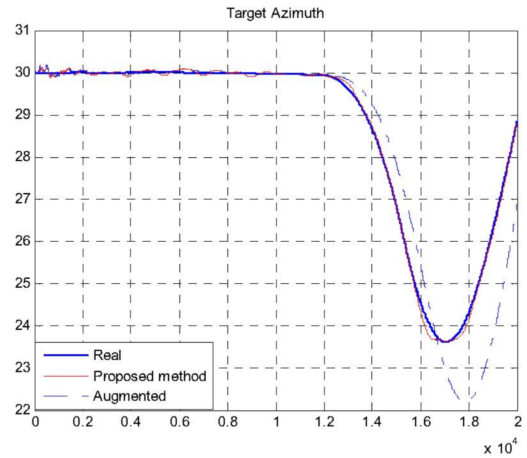

Fig. 8: Target's azimuth estimation

Table 2 shows comparison of the std of estimation error in second scenario. These results are the mean value over 50 runs.

TABLE 2: RADAR FILTER ESTIMATION ERROR IN THE SECOND SCENARIO (std)

	Range	Azimuth	Course	Speed
CKF	18.640	0.0690	20.0826	2.9348
Augmented Method	369.0760	0.8371	30.7829	23.4713
Method of [16]	62.7099	0.1214	21.0996	5.3662

6. CONCOLUSION

In this paper, a new combined scheme is presented to overcome the high maneuvering target tracking problems. This scheme is based on two important aspects; at first absolute value of difference between last target course and the present observation target course and the second aspect is the absolute value of measurement residual. The results compared with the works of augmented method proposed in [8] and the work was reported in [16]. Simulation results show a high performance of the proposed method and effectiveness of this scheme in tracking of high maneuvering targets.

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