A NEW STATE AUGMENTATION FOR MANEUVERING TARGETS DETECTION

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ABSTRACT

In this paper, an innovation model is presented to transform the maneuvering target tracking problems to the standard Bayesian model, therefore a standard Kalman filter can be applied to them. The modeling is based on mixed Bayesian- fisher uncertainties and a special augmentation in state space. In this model, target position and velocity are conventional states and the acceleration is treated as an additive input term, which has been augmented in the corresponding state equation. The results have been compared with the work of [7]. The simulation results show a high performance of the proposed innovation model and effectiveness of this scheme in tracking maneuvering targets.

1. INTRODUCTION

There exist many approaches and methods for target tracking with maneuver, for example, switching between Kalman filters of different order, acceleration input estimate during a maneuver and correct the state accordingly using batch least squares methods or recursive estimation for on-line implementation. Singer [1] has been assumed that the target acceleration is modeled as a random process with known exponential autocorrelation. This model is capable to tracks a maneuvering target, but the performance of the estimation is reduced when the target move at a constant velocity. A generalized likelihood ratio (GLR) method for maneuver detection was presented by Korn, et. al. [2]. This algorithm proposed the use of two hypotheses, null hypothesis for a target without maneuver, and alternative hypothesis for a target with maneuver. When the log likelihood ratio is over a threshold, a maneuver is detected. This system needs a bank of correlators to detect the maneuver onset time.

In this Paper, we presented a new modified algorithm for tracking of maneuvering targets based on the mixed Fisher and the standard Bayesian uncertainties models by some matrix manipulation on the state equations.

2. MODELS OF UNCERTAINTY

The two basic uncertainty models to be considered in this paper are the Bayesian and Fisher models [3]. Theses models are specific cases of the state space structure-white process. The Bayesian models are one the most important and common used models of uncertainty. In Bayesian models, uncertainty is 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 as

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

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

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

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

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

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 $Q(.) = \infty I$.

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 $\hat{X}(N|N)$ based on $z(N+1)$.

The logic, which yields the desired equation, can be summarized in the following steps:

1. Assume that $\hat{X}(N+1|N+1)$ is to be calculate just $\hat{X}(N|N)$ and $z(N+1)$.

2. Use the one-step prediction logic to change the problem to calculate $\hat{X}(N+1|N+1)$ from $\hat{X}(N+1|N)$ and $z(N+1)$.

3. Solve a Fisher estimation problem where $\hat{X}(N+1|N+1)$ and $z(N+1)$ are considered on an unknown vector $X(N+1)$.

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In the Bayesian model, stochastic probabilistic models are used for all the uncertainties. Thus $x(0)$, $v(n)$ and $w(n)$ are modeled as zero mean uncertainty random variables.

The matrix $H(n)$, $F(n)$ and $G(n)$ *in Eq. (1)* assumed to be known function of time n. The problem to be considered is, how to use the observation up to time n_2, z(1),...,z(n_2), to estimate the state $X(n_1)$ at some time n_1.

The solution of the problem filtering, after some manipulation leads us to the Kalman filter with equations:

$$\hat{X}(N+1|N+1)=F(N)\hat{X}(N|N)+K(N+1)[z(N+1) - H(N+1)F(N)\hat{X}(N|N)] \quad (2)$$

$$K(N+1)=\Sigma(N+1|N+1)H^T(N+1)R^{-1}(N+1)$$

$$\Sigma(N+1|N+1))=\Sigma(N+1|N)- \Sigma(N+1|N)H^T(N+1)[R(N+1)+H(N+1) \Sigma(N+1|N)H(N+1)^T]^{-1}H(N+1)\Sigma(N+1)$$

$$\Sigma(N+1|N)=F(N)\Sigma(N|N)F^T(N) +G(N)Q(N)G^T(N)$$

$$\Sigma(0|0)=\psi, \hat{X}(0|0)=0$$

where, $\Sigma(N|N)$ is the error covariance matrix and $\Sigma(N+1|N)$ is the error covariance matrix of the one-step prediction.

4. TRACKING ALGORITHMS

Some researches in detection and quick detection have been explored in the references [4-6]. It is assumed that the target moves in a plane, which is the two-dimensional case, such as a ship. The state equation for the non-maneuvering model is given by

$$X(n+1)=F(n)X(n)+G(n)w(n) \quad (3)$$

where

$$X = [x \quad \dot{x} \quad y \quad \dot{y}]^T$$

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

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

The measurement equation is given by

$$z(n) = H(n)X(n)+v(n)$$

where H is measurement matrix and $v(k)$ 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 maneuvering model treats the acceleration as an additive term:

$$X(n+1)=FX(n)+Cu(n)+Gw(n) \quad (4)$$

In the work of (Wang et., al., IEEE Transactions On Aerospace and Electronics Systems, 1993) the predicted and estimated states for the maneuvering target are related to the corresponding states without maneuvering according to the following equation:

$$\hat{X}^m(n+1|n)=\hat{X}(n+1|n)+M(n+1|n)u(n) \quad (5)$$

$$\hat{X}^m(n|n)=X(n|n)+N(n)u(n-1)$$

where,

$$M(n+1) = FN(n)+C(n) \quad (6)$$

$$N(n) = [I - K(n)H]M(n)$$

$K(n)$ 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 n^{th} whilst $\hat{X}(n|n)$ denotes the estimation at the n^{th} sample point given the measurement up to and including the n^{th}.

The estimate $\hat{u}(n)$ of the acceleration input $u(n)$ can be expressed in terms of the residual $r^m(n)$ from the maneuvering filter

$$\hat{u}(n)=\hat{u}(n-1)+G_u(n)r^m(n) \quad (7)$$

where

$$G_u(n)=P_u(n-1)W \quad (8)$$

$$W=M^T(n)H^T(HM(n)P_u(n-1)M^T(n)H^T+R^m(n)^{-1}$$

$$P_u(n)=P_u(n-1)-P_u(n-1)WHM(n)P_u^T(n-1)$$

In Eq. (8) $R^m(n)$ is the modified measurement covariance, given by

$$R^m(n)=HP^m(n|n-1)H^T+R \quad (9)$$

The estimated and prediction error covariances for the maneuvering model are respectively by

$$P^m(n|n)=P(n|n)+N(n)P_u(n)N^T(n) \quad (10)$$

$$P^m(n+1|n)=P(n+1|n)+M(n+1)P_u(n)M^T(n+1)$$

5. PROPOSED TRACKING ALGORITHM (MIXED FISHER AND BAYESIAN MODELS)

The objective in this section is to develop a maneuver detection model, which detects the maneuver effectively.

If we consider the additive maneuver term $u(n)$ as a deterministic signal in the maneuvering equation (4), then we deal with two mixed uncertainties, one $w(n)$ as a stochastic plant noise and $u(n)$ as a deterministic but unknown additive maneuver term where C is as follows

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

Now, we propose the additive maneuver term $u(n)$ as a new state and convert the maneuvering model Eq. (4) to a non-maneuvering model with an augmented state equation in the form of the standard Bayesian model with Eqs. (1), (2) as

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

$$z(n) = H(n)X(n)+v(n)$$

$$X_{Aug}(n)=[X(n) \quad u(n)]^T; F_{Aug}=\begin{bmatrix}F & C\\ 0 & I\end{bmatrix}; G_{Aug}=\begin{bmatrix}G\\ 0\end{bmatrix}$$

$$z(n+1) = HX(n+1) + v(n+1)$$
$$= H\{FX(n) + Cu(n) + Gw(n)\} + v(n+1) \qquad (11)$$
$$z(n+1) = [HF \quad HC]\begin{bmatrix} X(n) \\ u(n) \end{bmatrix} + HGw(n) + v(n+1) \Rightarrow$$
$$H_{Aug} = [HF \quad HC]; V_{Aug} = HGw(n) + v(n+1)$$

Now we have a standard Bayesian model, and use kalman filter to estimate X, u .

In fact, we can estimate X and u simultaneously with the standard Kalman filter by using the equations:

$$X_{Aug}(n+1) = F_{Aug}X(n) + G_{Aug}w(n)$$
$$Z_{Aug}(n) = z(n+1) = H_{Aug}(n)X_{Aug}(n) + V_{Aug}(n) \qquad (12)$$

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 equations as

$$R_{Aug} = E\{V_{Aug}V_{Aug}^{T}\} =$$
$$E\{(HGw(n) + v(n+1))(HGw(n) + v(n+1))^{T}\}$$
$$= HGE\{w(n)w(n)^{T}\}G^{T}H^{T} + E\{v(n+1)v(n+1)^{T}\}$$
$$\Rightarrow R_{Aug} = E\{V_{Aug}(n)V_{Aug}^{T}(n)\} \qquad (13)$$
$$= HGQG^{T}H^{T} + R$$

6. SIMULATION RESULTS

It is assumed that the target moves in a plane, which is the two-dimensional case, such as a ship.

The performance of the new modeling maneuvering target detection is evaluated by simulation some examples. To evaluate the proposed algorithm, an example of a target, which turns, in two-dimensional space are simulated.

In first example we consider a target which is traveling at initial velocity in X and Y direction as $v_x(0) = 10m/sec., v_y(0) = 15m/sec.$ and acceleration $u(t) = [a_x(t) \quad a_y(t)]^T$ in X and Y direction as $a_x(t) = 0\ m/s^2$, $a_y(t) = 0\ m/s^2$ until $t=15$ sec. In this simulation, the sampling time is $T=0.1$ second and the elements of the Q and R matrices are 0.025

Figure 1, shows the actual and estimation of $x(t)$, $y(t)$, $v_x(t)$ and $v_y(t)$ of the proposed method in the present of target maneuvering.

Figure 2, shows the actual and estimation of the acceleration in X and Y direction in the present of target maneuvering..

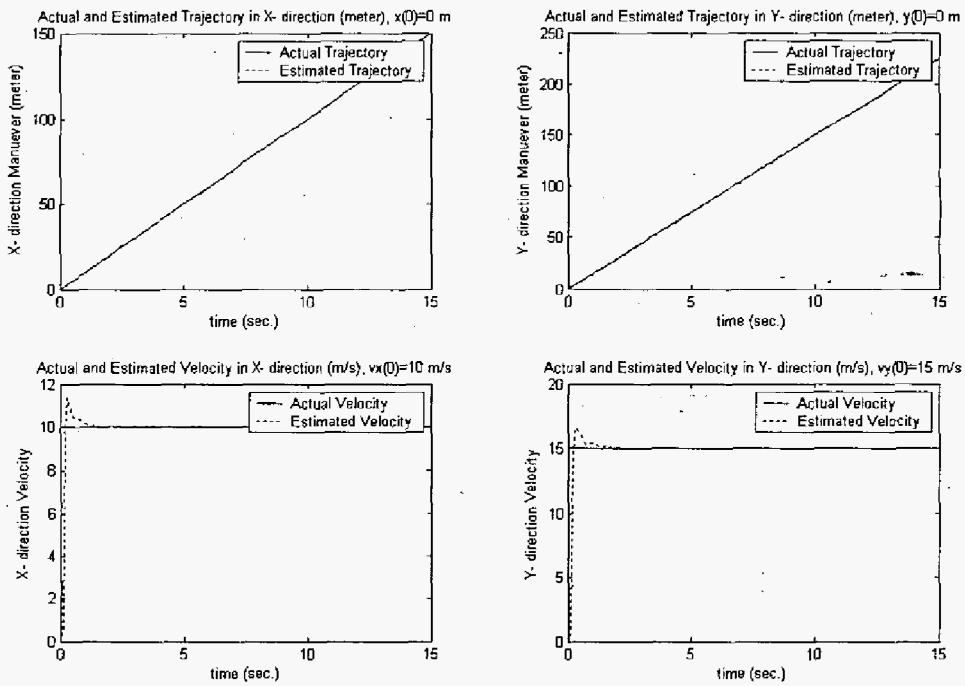

Figure 1: Actual and estimation of $x(t)$, $y(t)$, $v_x(t)$ and $v_y(t)$ of the proposed method ($a_x(t) = a_y(t) = 0$ m/s^2)

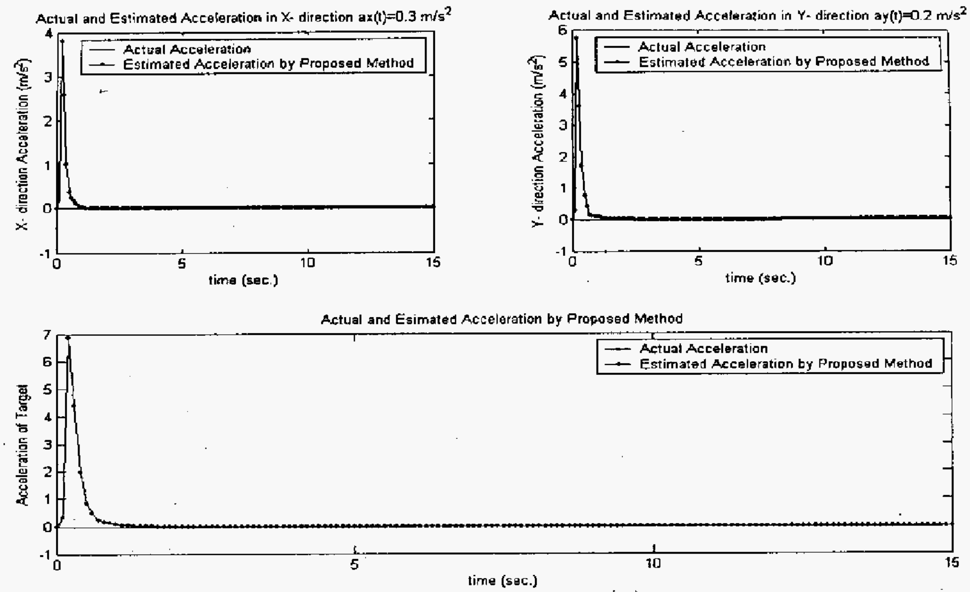

Figure 2: Actual and estimation of the acceleration in *X* and *Y* direction ($a_x(t)=a_y(t)=0\ \mathrm{m/s^2}$)

In second example we consider a target which is traveling at initial velocity $v_x(0)=5m/sec., v_y(0)=-3m/sec.$ and acceleration $u(t)=[a_x(t)\ \ a_y(t)]^T$ in *X* and *Y* direction as $a_x(t)=a1\,(m/s^2), a_y(t)=a2\,(m/s^2)$, where a1=0.3 m/s² and a2=0.5 m/s² until *t=15* second. The sampling time is *T=0.1* second and the elements of the *Q* and *R* matrices are *0.5*. Figure 3, shows the actual and estimation of *x(t)*, *y(t)*, $v_x(t)$ and $v_y(t)$ of the proposed method in the present of target maneuvering. Figure 4, illustrates the actual and estimation of the acceleration in *X* and *Y* direction.

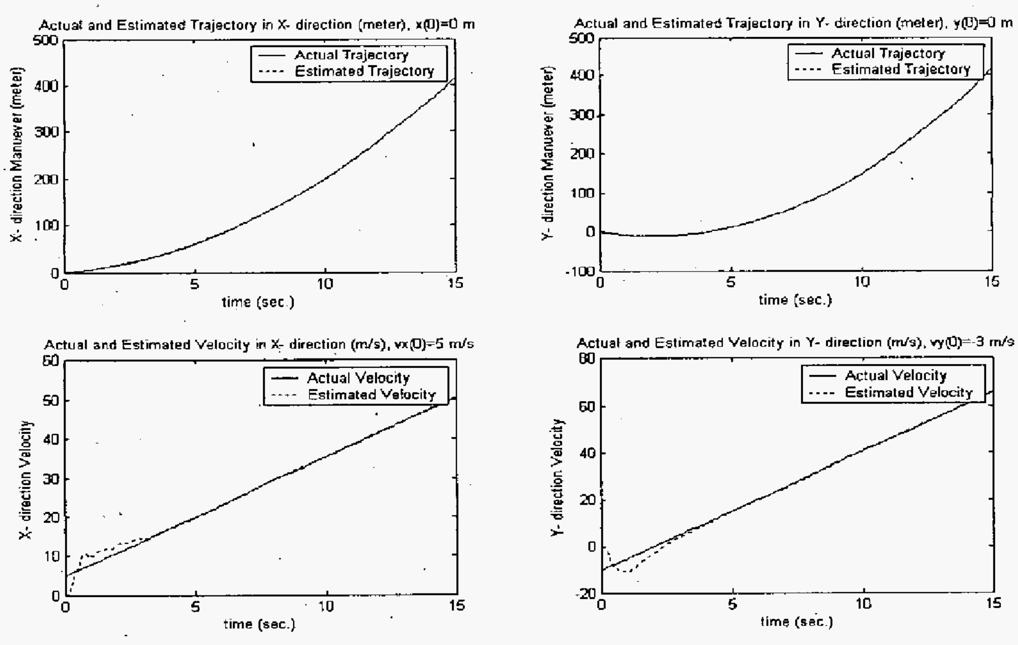

Figure 3: Actual and estimation of *x(t)*, *y(t)*, $v_x(t)$ and $v_y(t)$ of the proposed method ($a_x(t)=0.3\ \mathrm{m/s^2}, a_y(t)=0.5\ \mathrm{m/s^2}$)

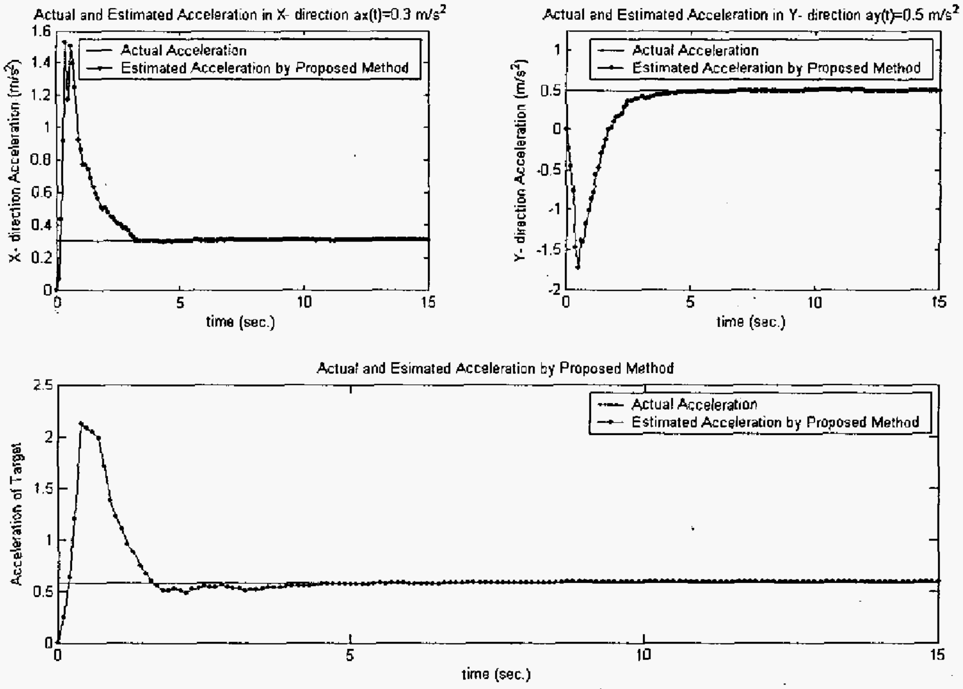

Figure 4: Actual and estimation of the acceleration in X and Y direction $(a_x(t)=0.3\ \mathrm{m/s^2}, a_y(t)=0.5\ \mathrm{m/s^2}, a(t)=\sqrt{a_x^2(t)+a_y^2(t)})$

In the end for second example also, the performance of proposed algorithm has been compared with the work of Wang. The simulation results show a very good performance for proposed method and effectiveness of this scheme in parameters tracking of the maneuvering targets. Figure 5, represents the actual acceleration, Wang's method and proposed method.

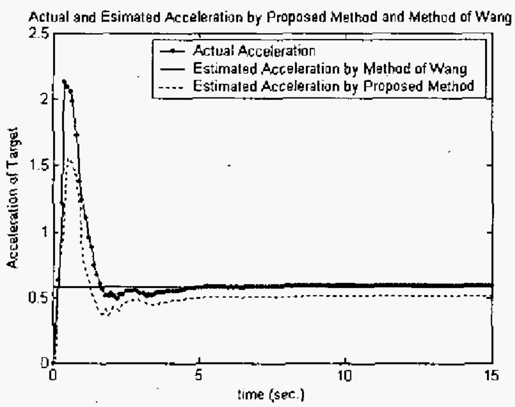

Figure 5: Actual acceleration, Wang's method and proposed method acceleration estimation $(a(t)=\sqrt{a_x^2(t)+a_y^2(t)})$

7. CONCLUSIONS

This paper deals with a new modeling to tracking-maneuvering detection. This method is based on a mixed Bayesian- fisher uncertainty models. Converting this augmented model to a standard Bayesian model, then a standard Kalman filter can be applied to this model. The results compared with the work of [7]. Simulation results show a high performance of the proposed innovation model and effectiveness of this scheme in parameter detection of the maneuvering targets.

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