APPROACHES TO AN ADAPTIVE TARGET TRACKING REAL–TIME FILTER IN IFFC SYSTEM

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Abstract

Based on Kalman filtering theory, this paper presents an adaptive target tracking real–time filter used in Integrated Fire / Flight Control (IFFC) system. First of all, a target maneuvering acceleration model is assumed, in this paper, as a second–order Gauss–Makove process which can follow the target maneuvering automatically. And a nonlinear time–varying target tracking filter model is described in the roll–stable line–of–sight (LOS) coordinate system. Then, in order to meet the requirements of real–time, the filter model is decoupled and linearized into three channels' filter models, and the measurement values are preprocessed before the filtering calculations start. Thirdly, with the Kalman filtering theory used, an adaptive target tracking real–time filter is designed. Finally, a lot of simulations are performed in accordance with the estimating accurancy, filtering convergent rate, adaptability to target maneuvering, real–time requirements, etc. of the filter. The simulation conclusions show that the adaptive target tracking filter developed in this paper has satisfactory performances.

I .Nomenclature

Symbols

a_F	chase aircraft acceleration
a_T	target acceleration
D	target range
H	measurement matrix
K	gain matrix
k	integer which takes on all values from 1 through N (N = duration of run / sampling rate)
P	predictive error matrix
Q	system noise variance matrix
R	measurement noise variance matrix
T	filter sampling rate
t	time
u	control
V_F	chase aircraft velocity
V_T	target velocity
X	target state
Y	measurement value
ω_F	chase aircraft angular velocity in LOS coordinate system
ω_L	LOS angular velocity in LOS coordinate system
υ	azimuth angle
μ	elevation angle
Δ	increment of a variable
δ_{kj}	Kronecker function
$\delta(*)$	Dirac function
λ,Ω	adaptive factors based on target states

Superscripts

$\cdot$	first derivative with respect to time
$\cdot\cdot$	second derivative with respect to time
T	transpose of matrix or vector
$\wedge$	estimator
$\rightarrow$	vector

Subscripts

x,y,z	direction of vector component in LOS coordinate system

II .Introduction

At present, all of the fighter aircraft with high performances are equiped with a fire control system which can perform weapon delivery calculations with high accuracy. Besides the chase aircraft states, the target states including target position,velocity and acceleration are needed in fire control solutions. But being limited by present technical conditions, airborne tracking systems can not provide all of the target state parameters directly. And the target states obtained by the present trackers (e.g. radar, electro–optical tracker,etc.) contain a lot of measurement noises, which can not be used in fire control calculations directly and have to be processed by filters. Therefore,there must be target tracking filters in advanced airborne fire cnotrol systems, especially in IFFC systems.

So called aerial target tracking filter is actually a filtering algorithm accomplished by airborne fire control computers, which provides the accurate estimations of target position,velocity and acceleration by processing the chase aircraft states and the noisy measurements of target states. The algorithm has been studied for many years not only for improving the accuracy of estimation, but also for meeting the requirements of real–time computation.[1~8] This paper presents an adaptive real–time filtering algorithm with high convergent rate and high estimating accuracy.

III.Description of the Filter Model

According to the second–order motional equations of an aerial maneuvering target and the relative geometry between the chase aircraft and target, a nonlinear time–varying target tracking filter model is described in the roll–stable line–of–sight (LOS) coordinate system.

The relative motional math. model of an aerial maneuvering target in LOS coordinate system is : [5,8]

$$\begin{bmatrix} \ddot{D} \\ \dot{\omega}_{LY} \\ \dot{\omega}_{LZ} \end{bmatrix} = \begin{bmatrix} (\omega_{LY}^2 + \omega_{LZ}^2)D + (a_{TX} - a_{FX}) \\ -2\omega_{LY}\dot{D}/D - (a_{TZ} - a_{FZ})/D \\ -2\omega_{LZ}\dot{D}/D + (a_{TY} - a_{FY})/D \end{bmatrix} \tag{1}$$

For a fighter with fixed weapon delivery system, the weapon line angular velocity $\vec{\omega}_W$ is as same as the chase aircraft angular velocity $\vec{\omega}_F$. So the weapon line motional model is: [7,8]

$$\begin{cases} \dot{\mu} = \omega_{LZ} - \omega_{FZ} \\ \dot{\nu} = \omega_{LY} - \omega_{FY} \end{cases} \tag{2}$$

In air battles, targets are usurally in highly maneuvering movement, and the maneuvering model is multiform and stochastic. So, it's difficult to develop the math. model of the target acceleration $\vec{a}_T$. But it's very important to select the model of $\vec{a}_T$ with respect to the improvement of filtering accuracy. Today, the widely used assumption is that the target acceleration is fit in a first–order Gauss–Makove process.[1~5,7] In order to improve the estimating accuracy of target acceleration and for the convenience of making smooth estimation, the target maneuvering acceleration model is assumed, in this paper, as a second–order Gauss–Makove process.[6,8]

The target acceleration model is:

$$\begin{bmatrix} \dot{a}_{TX} \\ \dot{a}_{TY} \\ \dot{a}_{TZ} \end{bmatrix} = \begin{bmatrix} -\lambda a_{TX} - \Omega(\dot{D} + V_{FX}) - \omega_{LY} a_{TZ} + \omega_{LZ} a_{TY} \\ -\lambda a_{TY} - \Omega(V_{FY} + \omega_{LZ} D) - \omega_{LZ} a_{TX} \\ -\lambda a_{TZ} - \Omega(V_{FZ} - \omega_{LY} D) + \omega_{LY} a_{TX} \end{bmatrix} + \vec{W}(t) \tag{3}$$

where,

$$\lambda = -2\frac{(\vec{a}_T \cdot \vec{V}_T)}{(\vec{V}_T \cdot \vec{V}_T)};$$

$$\Omega = \frac{(\vec{a}_T \cdot \vec{a}_T)}{(\vec{V}_T \cdot \vec{V}_T)} + \left(\frac{\lambda}{2}\right)^2;$$

$$\vec{W}(t) = \vec{V}_T + \vec{\omega}_L \times \vec{V}_T.$$

$\vec{W}(t)$ is related to the forces and moments acted on the target, and it is considered as a zero–means white noise whose varance is $E[\vec{W}(t)\vec{W}^T(\tau)] = Q(t)\delta(t-\tau)$.

Combine the Eq. (1), (2) and (3), we can obtain the nonlinear time–varying state equation of target in LOS coordinate system.

$$\dot{\vec{X}}(t) = F(\vec{X}) + \vec{W}(t) \tag{4}$$

where,

$$\vec{X}(t) = [D \;\; \dot{D} \;\; a_{TX} \;\; \nu \;\; \omega_{LY} \;\; a_{TZ} \;\; \mu \;\; \omega_{LZ} \;\; a_{TY}]^T \tag{5}$$

$$F(\vec{X})=\begin{bmatrix} \dot{D} \\ (\omega_{LY}^2+\omega_{LZ}^2)D+a_{TX}-a_{FX} \\ -\lambda a_{TX}-\Omega(V_{FX}+\dot{D})-\omega_{LY}a_{TZ}+\omega_{LZ}a_{TY} \\ \omega_{LY}-\omega_{FY} \\ -2\omega_{LY}\dot{D}/D-(a_{TZ}-a_{FZ})/D \\ -\lambda a_{TZ}-\Omega(V_{FZ}-\omega_{LY}D)+\omega_{LY}a_{TX} \\ \omega_{LZ}-\omega_{FZ} \\ -2\omega_{LZ}\dot{D}/D+(a_{TY}-a_{FY})/D \\ -\lambda a_{TY}-\Omega(V_{FY}+\omega_{LZ}D)-\omega_{LZ}a_{TX} \end{bmatrix} \tag{6}$$

$$\vec{W}(t)=[0\quad 0\quad W_X\quad 0\quad 0\quad W_Y\quad 0\quad 0\quad W_Z]^T \tag{7}$$

For the airborne equipments of a typical fighter aircraft, the target informations available are: target range D, range rate $\dot{D}$, azimuth angle v, elevation angle μ, azimuth angular velocity ω_{LY} and elevation angular velocity ω_{LZ}, so the linear normal measurement equation is:

$$\vec{Y}(t)=H\vec{X}(t)+\vec{V}(t) \tag{8}$$

where,

$$H=\begin{bmatrix} 1&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&1&0 \end{bmatrix} \tag{9}$$

$\vec{V}(t)$ is the measurement noise vector. It is also considered as a zero–means white noise whose varance is

$E[\vec{V}(t)\vec{V}^T(\tau)]=R(t)\delta(t-\tau)$.

Eq.(4) and (8) form the nonlinear time–varying filter model of an aerial maneuvering target.

Ⅳ.Processing for Real–Time Requirements

Eq.(4) and (8) form a nine–dimensional nonlinear filtering model. If, with the nonlinear Kalman filtering theory used, the nonlinear filtering model is not linearized and decoupled before filtering calculations are performed, but is applied to filtering calculations directly, we will obtain an adaptive target tracking nonlinear filter with high convergent rate and high estimating accuracy and high adaptability to target maneuvering.[8] But the nonlinear filter has nine–dimensional matrix calculations of plus, minues, multiplication and matrix converse. The calculations is too much for us to put the filter into practice. This paper takes two efficient methods to solve the problem of real–time.

Decouple and linearization

The nine–dimensional nonlinear time–varying coupled filter model obtained above is divided into three filter models in range channel, azimuth angle channel and elevation angle channel respectively. And let the coupled values be substituted by corresponding estimators. So we can obtain the linear and decoupled filter models of three channels.

Range channel:

$$\begin{bmatrix} \dot{D} \\ \ddot{D} \\ \dot{a}_{TX} \end{bmatrix}=\begin{bmatrix} 0 & 1 & 0 \\ \hat{\omega}_{LY}^2+\hat{\omega}_{LZ}^2 & 0 & 1 \\ 0 & -\Omega & -\lambda \end{bmatrix}\begin{bmatrix} D \\ \dot{D} \\ a_{TX} \end{bmatrix}+\begin{bmatrix} 0 \\ -a_{FX} \\ -\Omega V_{FX}-\hat{\omega}_{LY}\hat{a}_{TZ}+\hat{\omega}_{LZ}\hat{a}_{TY} \end{bmatrix}+\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}W_X(t) \tag{10}$$

$$\vec{Y_1}(t)=\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}\begin{bmatrix} D \\ D \\ a_{TX} \end{bmatrix}+\vec{V_1}(t) \tag{11}$$

Azimuth angle channel:

$$\begin{bmatrix} \dot{v} \\ \dot{\omega}_{LY} \\ \dot{a}_{TZ} \end{bmatrix}=\begin{bmatrix} 0 & 1 & 0 \\ 0 & -2\hat{\dot{D}}/\hat{D} & -1/\hat{D} \\ 0 & \Omega\hat{D}+\hat{a}_{TX} & -\lambda \end{bmatrix}\begin{bmatrix} v \\ \omega_{LY} \\ a_{TZ} \end{bmatrix}+\begin{bmatrix} -\omega_{FY} \\ a_{FZ}/\hat{D} \\ -\Omega V_{FZ} \end{bmatrix}+\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}W_Z(t) \tag{12}$$

$$\overrightarrow{Y_2}(t)=\begin{bmatrix}1&0&0\\0&1&0\end{bmatrix}\begin{bmatrix}v\\\omega_{LY}\\a_{TZ}\end{bmatrix}+\overrightarrow{V_2}(t) \tag{13}$$

Elevation angle channel:

$$\begin{bmatrix}\dot{\mu}\\\dot{\omega}_{LZ}\\\dot{a}_{TY}\end{bmatrix}=\begin{bmatrix}0&1&0\\0&-2\hat{\dot{D}}/\hat{D}&1/\hat{D}\\0&-(\Omega\hat{D}+\hat{a}_{TX})&-\lambda\end{bmatrix}\begin{bmatrix}\mu\\\omega_{LZ}\\a_{TY}\end{bmatrix}$$

$$+\begin{bmatrix}-\omega_{FZ}\\-a_{FY}/\hat{D}\\-\Omega V_{FY}\end{bmatrix}+\begin{bmatrix}0\\0\\1\end{bmatrix}W_Y(t) \tag{14}$$

$$\overrightarrow{Y_3}(t)=\begin{bmatrix}1&0&0\\0&1&0\end{bmatrix}\begin{bmatrix}\mu\\\omega_{LZ}\\a_{TY}\end{bmatrix}+\overrightarrow{V_3}(t) \tag{15}$$

The filter models in three channels are similear in form, so they can be described in the general form as follews:

$$\begin{cases}\dot{\vec{X}}(t)=A(t)\vec{X}(t)+B\vec{U}(t)+G\vec{W}(t)\\ \vec{Y}(t)=H\vec{X}(t)+\vec{V}(t)\end{cases} \tag{16}$$

$\vec{W}$(t) is the system noise vector, and it is considered as a zero–means white noise whose varance is $E[\vec{W}(t)\vec{W}^T(\tau)]=Q(t)\delta(t-\tau)$. $\vec{V}$(t) is the measurement noise vector. It is also considered as a zero–means white noise whose varance is $E[\vec{V}(t)\vec{V}^T(\tau)]=R(t)\delta(t-\tau)$.

After decoupled and linearized, the nine–dimensional filter model is replaced by three three–dimensional filter models, which improve the system performance of real–time since the three–dimensional filter models need not nine–dimensional matrix calculations but three–dimensional matrix calculations, and the three channels can be processed in parallel.

When a sensor measures, it samples at a regular interval, and its measurement signals are discrete values, so the filter model (16) must be processed to discret form filter model as follows: [9]

$$\begin{cases}\vec{X}(k+1)=\Phi(k+1,k)\vec{X}(k)+\Gamma_1(k+1,k)\vec{u}(k)\\ \qquad +\Gamma_2(k+1,k)\vec{W}(k)\\ \vec{Y}(k)=H\vec{X}(k)+\vec{V}(k)\end{cases} \tag{17}$$

where

$$\Phi(k+1,k)=e^{AT}=\sum_{n=0}^{\infty}\frac{A^nT^n}{n!}\quad;$$

$$\Gamma_1(k+1,k)=\int_{t_k}^{t_{k+1}}B\Phi(k+1,\tau)d\tau\quad;$$

$$\Gamma_2(k+1,k)=\int_{t_k}^{t_{k+1}}G\Phi(k+1,\tau)d\tau\quad;$$

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

$\vec{W}$(k) represents the sum of the discretization errors and the uncertainty of dynamic system. Suppose $\vec{W}$(k) is a zero–means white noise series and $E[\vec{W}(k)\vec{W}^T(j)]=Q(k)\delta_{kj}$. $\vec{V}$(k) is also a zero–means white noise series and $E[\vec{V}(k)\vec{V}^T(j)]=R(k)\delta_{kj}$.

Preprocessing Technique of Measurement Values

In a filter, the higher the sensor sampling speed, the more the target movement informations measured, the higher the filtering accuracy. If the filter sampling speed is too high, it will increase the speed requirement of computerisation. And omitting parts of measurement values will affect the filtering accuracy. In order to solve the problem of filtering accuracy and real–time requirements, this paper takes the preprocessing technicque of measurement values, which measures at high speed and calculates at low speed after pressing data.Suppose the sensor measures M times in one filter sampling period and let

$$\overrightarrow{Y_{CP}}(k+1)=\frac{1}{M}\sum_{i=1}^{M}\vec{Y}(k+\frac{i}{M})$$

$$=\frac{1}{M}\sum_{i=1}^{M}\overrightarrow{Y^*}(k+\frac{i}{M})+\frac{1}{M}\sum_{i=1}^{M}\vec{V}(k+\frac{i}{M}) \tag{18}$$

where,

$\overrightarrow{Y_{CP}}(k+1)$ is average measurement value of M times,

$\overrightarrow{Y^*}(k+1)$ is accurate value,

$\overrightarrow{V}(k+1)$ is measurement error.

Since each measurement value has a certain noise, $\overrightarrow{Y_{CP}}(k+1)$ has certain error too. For improving input quality of filter, we must correct $\overrightarrow{Y_{CP}}(k+1)$. It's difficult to correct $\overrightarrow{Y_{CP}}(k+1)$ accurately with target maneuvering movement considered. And the filtering sampling speed is high enough (in this paper,T=40 ms) , so that we can suppose that the manruvering target moves rectilinearly in a filter sampling period.

Let

$$\overrightarrow{Y'}(k+1)=\overrightarrow{Y_{CP}}(k+1)+q[\overrightarrow{Y_{CP}}(k+1)-\overrightarrow{Y_{CP}}(k)]$$

$$=(1+q)\overrightarrow{Y_{CP}}(k+1)-q\overrightarrow{Y_{CP}}(k) \qquad (19)$$

where,

$$q=\frac{M-1}{2M}$$

be as the measurement value input filter at the time of k+1.

$$\overrightarrow{Y'}(k+1)=(1+q)\frac{1}{M}\sum_{i=1}^{M}\overrightarrow{Y^*}(k+\frac{i}{M})$$

$$+(1+q)\frac{1}{M}\sum_{i=1}^{M}\overrightarrow{V}(k+\frac{i}{M})$$

$$-q\frac{1}{M}\sum_{i=1}^{M}\overrightarrow{Y^*}(k-1+\frac{i}{M})$$

$$-q\frac{1}{M}\sum_{i=1}^{M}\overrightarrow{V}(k-1+\frac{i}{M})$$

$$=\frac{1}{M}(1+q)\sum_{i=1}^{M}\overrightarrow{Y^*}(k+\frac{i}{M})$$

$$-q\frac{1}{M}\sum_{i=1}^{M}\overrightarrow{Y^*}(k-1+\frac{i}{M})$$

$$+\frac{1}{M}\sum_{i=1}^{M}\overrightarrow{V}(k+\frac{i}{M})$$

The corresponding measurement varance matrix is:

$$R'(k+1)=E\left[\frac{1}{M}\sum_{i=1}^{M}\overrightarrow{V}(k+\frac{i}{M})\frac{1}{M}\sum_{i=1}^{M}\overrightarrow{V^T}(k+\frac{i}{M})\right]$$

$$=\frac{1}{M}R(k+1) \qquad (20)$$

V. Filter Design

This paper use Kalman filter theory to design the target tracking filter. Since Kalman filter is the linear minimal varance estimation and the optimal linear recurrence filtering and consider the statistical charactristics of the values estimated and measurement values, it can not only be used for steady stochastic process but also for unsteady stochastic process. For system (17), the general assumptions of Kalman filter are: system noises $\overrightarrow{W}(k)$ and measurement noises $\overrightarrow{V}(k)$ are zero−means Gauss−Makove white noise, and [W],[V] are uncorrelated each other, i.e.:

$$E[\overrightarrow{W}(k)]=0; \qquad E[\overrightarrow{W}(k)\overrightarrow{W}^T(j)]=Q(k)\delta_{Kj}$$

$$E[\overrightarrow{V}(k)]=0; \qquad E[\overrightarrow{V}(k)\overrightarrow{V}^T(j)]=R(k)\delta_{Kj}$$

$$E[\overrightarrow{W}(k)\overrightarrow{V}^T(j)]=0;$$

where , δ is Kronecker δ function which represents the statistical charactristics of the target acceleration and measurement noise. After the measurement signals are preprocessed ,the recurrence equations of estimating target movement statistical vector $\overrightarrow{X}$(k) according to measurement vector $\overrightarrow{Y}$(k) are: [7,9]

$$\hat{\overrightarrow{X}}(k+1|k)=\Phi(k+1,k)\hat{\overrightarrow{X}}(k|k)+\Gamma_1(k+1,k)\overrightarrow{u}(k)$$

$$P(k+1|k)=\Phi(k+1,k)P(k|k)\Phi^T(k+1,k)$$

$$+\Gamma_2(k+1,k)Q(k+1)\Gamma_2^T(k+1,k)$$

$$\overrightarrow{Y_{CP}}(k+1)=\frac{1}{M}\sum_{i=1}^{M}\overrightarrow{Y}(k+\frac{i}{M})$$

$$\overrightarrow{Y'}(k+1)=(1+q)\overrightarrow{Y_{CP}}(k+1)-q\overrightarrow{Y_{CP}}(k)$$

where,

$q = \frac{M-1}{2M}$ (in simulation, q can be adjusted optimally)

$$R'(k+1) = \frac{1}{M} R(k+1)$$

$$K(k+1) = P(k+1|k)H^T[HP(k+1|k)H^T + R'(k+1)]^{-1}$$

$$\hat{X}(k+1|k+1) = \hat{X}(k+1|k) + K(k+1)[\overline{Y'}(k+1) - H\hat{X}(k+1|k)]$$

$$P(k+1|k+1) = [I - K(k+1)H]P(k+1|k)$$

The structure block diagram of the three channels' target state estimator is shown in Figure 1.

VI.Simulation and Evaluation

In order to test the performances of the filter designed in this paper, a lot of digital simulations are carried out. In simulation, the target maneuvering regularity is assumed as:

$$D = 600 + 200T + 5T^2 \qquad (m) \tag{21}$$

$$v = 0.1 + 0.01T + 0.001T^2 \quad (rad) \tag{22}$$

$$\mu = 0.1 + 0.01T + 0.001T^2 \quad (rad) \tag{23}$$

The target acceleration is supposed to have a sudden change when the filter has run for 6 seconds so as to test the adaptability of the filter to target maneuvering. The measurement noise and system noise are simulated with Monte–Carlo method.

The simulation data are taken from FX aircraft. And the root–mean–square (RMS) error of the range measurement noise is 15 meters, the RMS error of the range rate measurement noise is 12 meters per second, the RMS error of the angle measurement noise is 5 milliradian, the RMS error of angular velocity noise is 5 milliradian per second, the filtering period is 40 milliseconds.

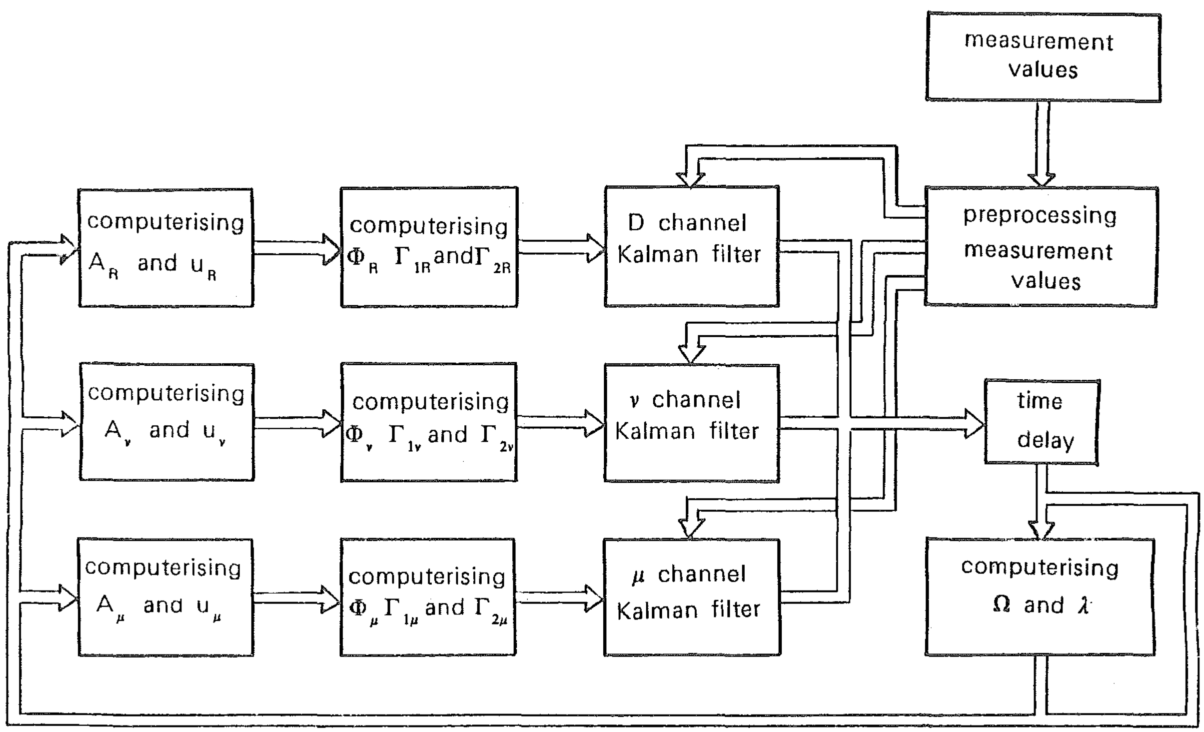


Figure 1. The Structure Block Diagram of the Three Channel' Target State Estimator

The estimating error curves of the target states are used in evaluation of the filtering results. The diffinition of the estimating errors is:

$$\Delta X_i(k) = X_i(k) - \hat{X}_i(k), \qquad i = 1,2,3.$$

Some of the simulation conclusion curves are given in follows to dermonstrate that the filtering algorithm developed in this paper has high performances.

Since each element in the filtering gain matrix has similear characteristics, only one gain curve is given in discuss. As shown in Figure 2, in the initial period, the magnititude of the gain is high and has fluctuations, which means that the correction to the state prediction is strong and the filtering system works not stable yet. After 2 seconds, K becomes stable, i.e., the filtering system becomes stable.

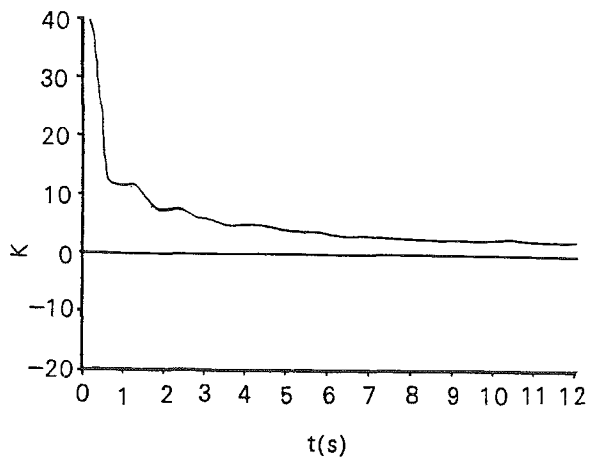
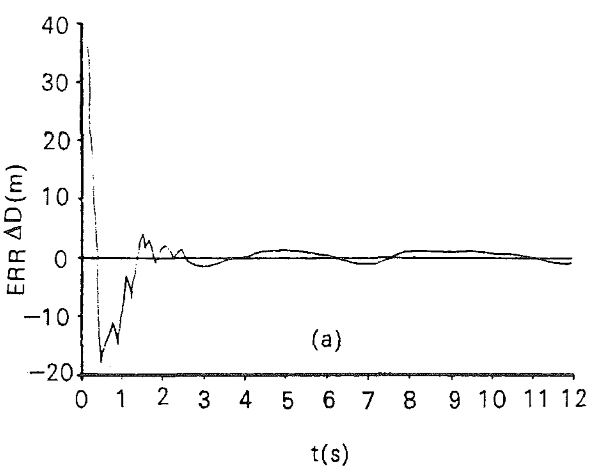
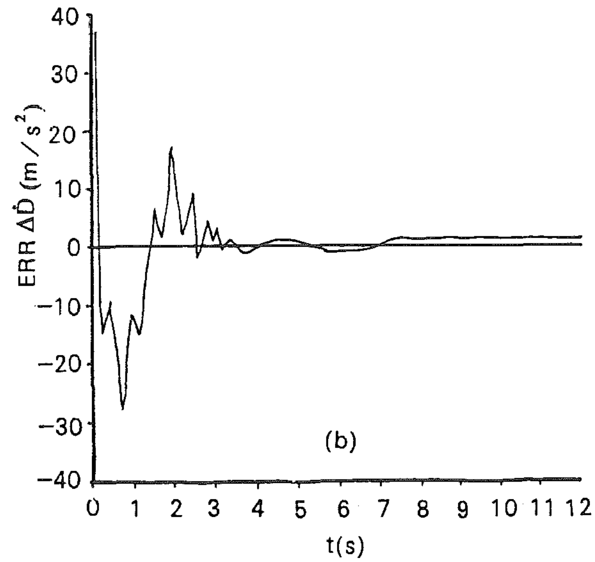
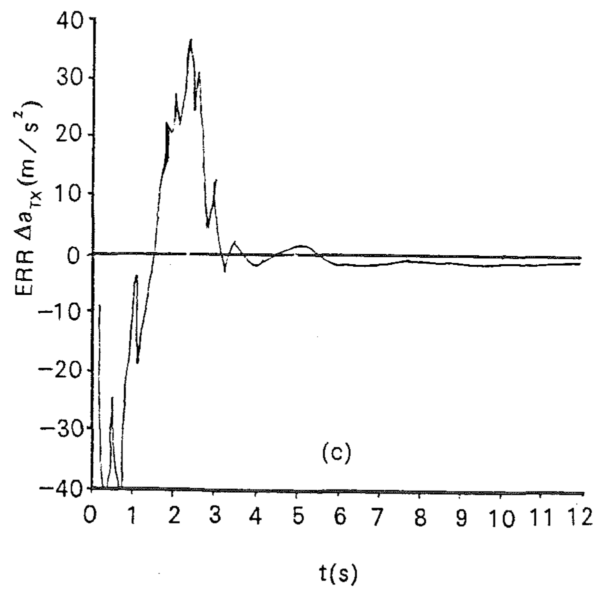
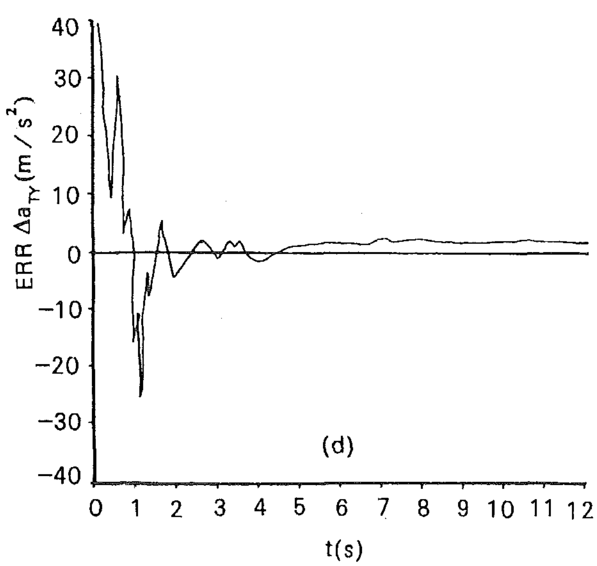


Figure 2. A Curve of the Filtering Gain









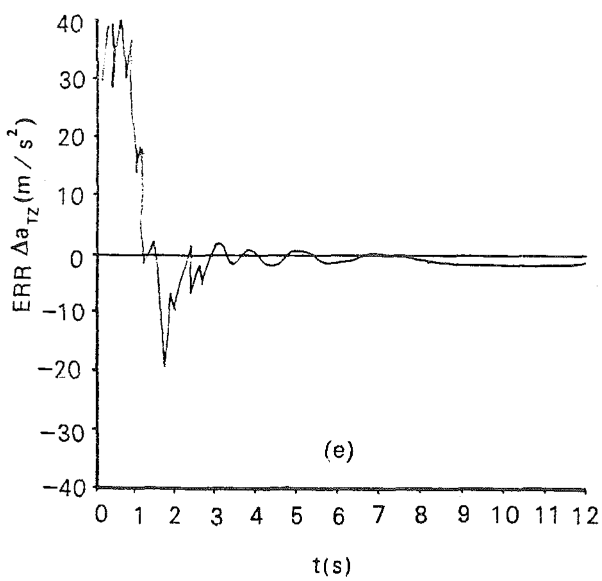


Figure 3. Filtering Error Curves Varying with Time

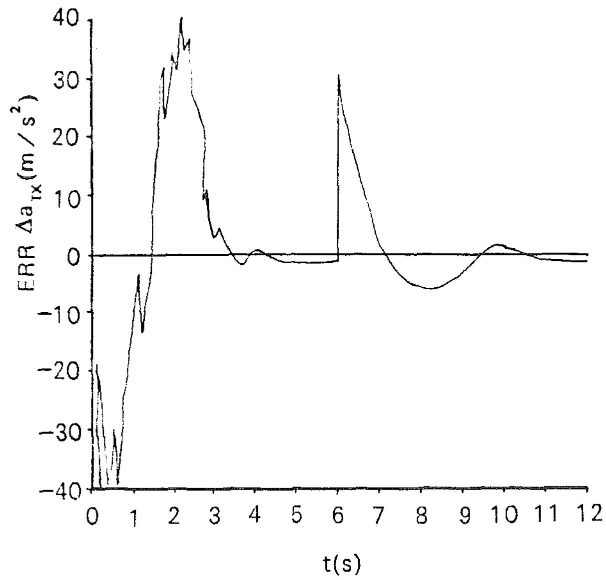


Figure 5. Filtering Error Curve When a_{TX} Changes Suddenly

In Figure 3, the filtering error curves varying with time are shown. When the filtering system is stable, the filtering errors are much less than the measurement varance, which means that the filtering accurancy is high.

When testing the adaptability of the filter to target maneuvering, this paper assums that the target acceleration a_{TX} changes suddenly at t = 6 seconds and the changeing regularity is shown in Figure 4.

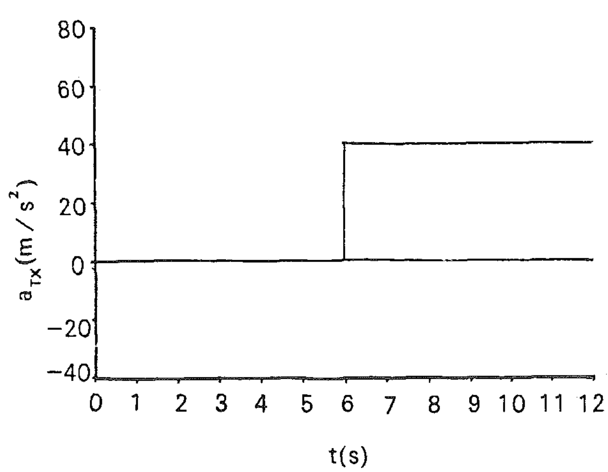


Figure 4. Target Acceleration Component a_{TX}

As shown in Figure 5. When the target acceleration a_{TX} changes suddenly at t = 6 seconds, Δa_{TX} (i.e. the estimating error of a_{TX}) increases suddenly. But Δa_{TX} decreases into the range of ± 10 m / s² in less than 2 seconds, which means that the filter has very good adaptability to the target maneuvering.

As disscussed above, the real–time filtering algorithm developed in this paper has high convergent rate and high estimating accuracy and high adaptability to the target maneuvering. And this paper is significient in prepairation to the target state estimator of airborne fire control system and in improving the accuracy of airborne fire control system and tracking maneuvering target.

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