Research on an Adaptive Maneuvering Target Tracking Algorithm

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Abstract: The maneuverability of modern targets becomes more and more complex and variable, which raises higher requirements on the tracking performance of detection systems. Especially the stable and accurate tracking of maneuvering targets is more critical. For the problem that statistical properties of detection system noise are unknown and the state of motion of targets is complex and variable, a new adaptive maneuvering target tracking algorithm is proposed. The algorithm adopts the combination of adaptive Kalman filtering under the spherical coordinate system and its counterpart under the Cartesian coordinate system. The adaptive Kalman filtering algorithm under the spherical coordinate system is based on Sage-Husa noise statistics estimator to estimate the statistical property of measurement noise. In the Cartesian coordinate system, the Singer model is used to describe the target motion. Relevant results of the adaptive Kalman filtering algorithm under the spherical coordinate system are used to achieve high-precision estimation of target motion information. Simulation results show that the proposed algorithm has satisfactory tracking accuracy.

Key words: Maneuvering target tracking, adaptive Kalman filtering, noise statistics estimator, singer model.

1. Introduction

Maneuvering target tracking technology is very important for the tracking performance of detection systems. The technology is to map and filter different observation sets generated by various uncertain information sources and target maneuvering motion signals received by detection systems. Motion parameters of corresponding maneuvering targets can be predicted during the filtering process [1].

As the state of motion of targets becomes more and more complex and variable, the research on conventional maneuvering targets has no longer met demand. Moving targets can be freely switched under various different states of motion, and some targets can also change their trajectories autonomously, which makes measurement data of detection systems uncertain, changeable and conflicting [2]. In addition, nonlinearity of the observation equation and equations of target motion become more and more serious, which leads to that conventional models of target motion and state estimation method cannot accurately track the targets [3].

In this paper, a new adaptive maneuvering target tracking algorithm is proposed for the problem that statistical properties of detection system noise are unknown and the state of motion of targets is complex and variable. The algorithm adopts the combination of adaptive Kalman filtering under the spherical coordinate system and its counterpart under the Cartesian coordinate system. The adaptive Kalman filtering algorithm under the spherical coordinate system is based on Sage-Husa noise statistics estimator to achieve measurement noise statistical property estimation. In the Cartesian coordinate system, the Singer model is used to describe the target motion, and relevant results of the adaptive Kalman filtering algorithm under the spherical coordinate system is used to achieve high-precision estimation of target motion information.

2. Tracking Mathematical Modelling for Maneuvering Targets

2.1. Review Stage State Equation and Observation Equation under the Spherical Coordinate System

Select the target elevation angle and its angular rate, the target azimuth angle and its angular rate, and the target distance and its rate of change as state variables, and establish a CV model under the spherical coordinate system [4]:

$$\begin{bmatrix} \dot{\varepsilon}_t \\ \ddot{\varepsilon}_t \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \dot{\varepsilon}_t \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} w_{\varepsilon t}(t)$$

$$\begin{bmatrix} \dot{\beta}_t \\ \ddot{\beta}_t \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \beta_t \\ \dot{\beta}_t \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} w_{\beta t}(t)$$

$$\begin{bmatrix} \dot{R}_t \\ \ddot{R}_t \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} R_t \\ \dot{R}_t \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} w_{Rt}(t)$$

where $w_{\varepsilon t}$ —Gaussian white noise with mean zero and variance ; $Q_{\varepsilon t}$ —Gaussian white noise with mean zero and variance $Q_{\beta t}$; w_{Rt} —Gaussian white noise with mean zero and variance Q_{Rt} .

Take the target elevation angle, the target azimuth angle and the relative distance between the observation station and the target which are all measured by ground radars as the observation variables, and establish a observation equation:

$$Z_{\varepsilon t} = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \dot{\varepsilon}_t \end{bmatrix} + v_{\varepsilon t}(t)$$

$$Z_{\beta t} = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} \beta_t \\ \dot{\beta}_t \end{bmatrix} + v_{\beta t}(t)$$

$$Z_{Rt} = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} R_t \\ \dot{R}_t \end{bmatrix} + v_{Rt}(t)$$

where $v_{\varepsilon t}$ —observation noise with mean zero and variance $\sigma^2{}_{\varepsilon t}$; $v_{\beta t}$ —observation noise with mean zero and variance $\sigma^2{}_{\beta t}$; v_{Rt} —observation noise with mean zero and variance $\sigma^2{}_{Rt}$.

2.2. State Equation and Observation Equation under the Cartesian Coordinate System

The Singer model [5] describing the target motion is established in the Cartesian coordinate system. According to characteristics of relevant functions of the stationary stochastic process, such as symmetry, decay, etc., Assume that the time-correlation function of maneuver acceleration is exponentially decayed:

$$R_a(\tau) = E\{a(t)a(t+\tau)\} = \sigma_a^2 e^{-\alpha|\tau|} \qquad (\alpha \geq 0)$$

where σ_a^2 and α are undetermined parameters that determine target maneuverability within the interval $(t, t+\tau)$. σ_a^2 is the maneuvering acceleration variance; α is the reciprocal of maneuvering time constant, that is, maneuvering frequency, and usually its empirical range is: turning maneuver $\alpha=1/60$, escape maneuver, atmospheric disturbance $\alpha=1$, and its explicit value can only be determined by real-time measurement.

It is assumed that the probability density function of maneuvering acceleration approximates a uniform distribution. The mean value of maneuvering acceleration is zero, and the variance σ_a^2 is calculated from the probability density model shown in Fig. 1, that is,

$$\sigma_a^2 = \frac{A^2{}_{\max}}{3}\left[1+4P_{\max}-P_0\right]$$

where $A_{\max}$ is the maximum maneuvering acceleration and P_0 is the non-maneuvering probability.

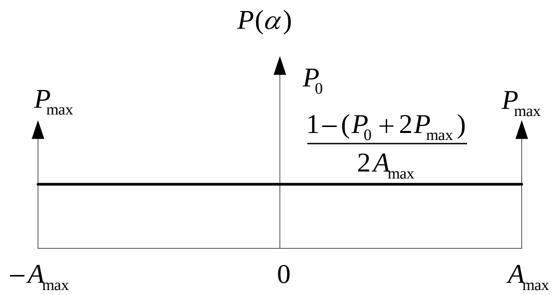

Fig. 1. Probability density function of target acceleration in the singer model.

After the time-correlation function $R_a(t)$ is processed by the Wiener-Kolmogorov whitening program, maneuvering acceleration $a(t)$ can be expressed by the first-order time-correlation model whose input is white noise, that is

$$\dot{a}(t) = -\alpha a(t) + \omega(t)$$

where $\omega(t)$ is Gaussian white noise with mean zero and variance $2\alpha\sigma_a^2$.Finally, when n=2, m=1, the maneuvering target model becomes the following first-order time-correlation model, that is, the Singer model:

$$\begin{bmatrix} \dot{x} \\ \ddot{x} \\ \dddot{x} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -a \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \omega(t)$$

$$\begin{bmatrix} \dot{y} \\ \ddot{y} \\ \dddot{y} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -a \end{bmatrix} \begin{bmatrix} y \\ \dot{y} \\ \ddot{y} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \omega_y(t)$$

$$\begin{bmatrix} \dot{z} \\ \ddot{z} \\ \dddot{z} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -a \end{bmatrix} \begin{bmatrix} z \\ \dot{z} \\ \ddot{z} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \omega_z(t)$$

where $\omega_x(t)$、$\omega_y(t)$、$\omega_z(t)$ are Gaussian white noise with mean zero and variance $2\alpha\sigma_a^2$; σ_a^2 is maneuver acceleration variance; α is the reciprocal of maneuver time constant, that is, maneuver frequency.

After the above formula is discretized, one has

$$\begin{bmatrix} x(k+1) \\ \dot{x}(k+1) \\ \ddot{x}(k+1) \end{bmatrix} = \begin{bmatrix} 1 & T & (\alpha T - 1 + e^{-\alpha T})/\alpha^2 \\ 0 & 1 & (1-e^{-\alpha T})/\alpha \\ 0 & 0 & e^{-\alpha T} \end{bmatrix} \begin{bmatrix} x(k) \\ \dot{x}(k) \\ \ddot{x}(k) \end{bmatrix} + \mathbf{w}(k)$$

where T is sampling time.

Take position components of targets in the Cartesian coordinate system detected by ground radars as the observation variable, and establish the following observation equation:

$$\begin{aligned} x_m(k) &= x(k) + v_x(k) \\ y_m(k) &= y(k) + v_y(k) \\ z_m(k) &= z(k) + v_z(k) \end{aligned}$$

where x、y、z are the position components of moving targets in the Cartesian coordinate system, respectively; $v_x(k)$, $v_y(k)$, $v_z(k)$ are the noise of target position components detected by ground radars, which are Gaussian white noise with mean zero and variance R_x^2、R_y^2、R_z^2, respectively.

3. Design of an Adaptive Maneuvering Target Tracking Algorithm

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The design procedures of the proposed adaptive maneuvering target tracking algorithm based on the combination of adaptive extended Kalman filtering under the spherical coordinate system and extended Kalman filtering under the Cartesian coordinate system include:

- Using the adaptive Kalman filtering algorithm based on Sage-Husa noise statistics estimator, measurement noise variance of each observation variable is estimated in real time under the spherical coordinate system to obtain approximate σ^2_{Rt}, $\sigma^2_{\varepsilon t}$ and $\sigma^2_{\beta t}$;
- Use the conversion formula between the observation noise variance under the Cartesian coordinate system and its counterpart under the spherical coordinate system again, and one obtains σ^2_{xt}, σ^2_{yt} and σ^2_{zt} by calculation.
- Select target position, velocity and acceleration in the Cartesian coordinate system as state variables, establish the Singer model, and bring the estimate of observation noise variance into the model for Kalman filtering so as to conduct maneuvering tracking for the targets.

3.1. Adaptive Extended Kalman Filtering under the Spherical Coordinate System Based on Sage-Husa Noise Statistics Estimator

Kalman filter algorithms require priori noise statistics, nevertheless the statistical properties of nose are unknown or inaccurate sometimes, or may even be time-varying. Using wrong noise statistics will produce filtering errors and even make filtering divergent, which is the limitation of Kalman filtering algorithms. Moreover, extended Kalman filtering algorithms need that nonlinear state equations or observation equations are expanded into Taylor series based on current estimates, and the first-order term of the Taylor series is taken thus to obtain linearization equations, which requires the reference trajectories close to actual trajectories. This requirement is difficult to be satisfied in the initial filtering phase [6].

The linearization error of nonlinear systems can be classified as a kind of noise in linear system models to some extent. Therefore, adaptive filtering can be used to estimate statistical properties of noise on-line to solve the problem that statistical properties of noise are unknown or inaccurate, to reduce the influence of linearization error on filtering performance, and to improve accuracy of nonlinear filtering.

The so-called adaptive filtering is to continuously estimate or correct unknown or inaccurate statistical properties of noise while filtering with measurement data. The adaptive filtering algorithm used here is based on Sage-Husa noise statistics estimator. When observation noise variance of systems is unknown, the adaptive filtering algorithm can be adopted to estimate the variance online.

Assume that the system state equation and the observation equation are:

$$\begin{cases}\mathbf{X}(k+1)=\boldsymbol{\varphi}\left(\mathbf{X}(k)\right)+\boldsymbol{\Gamma}(k)\mathbf{u}(k)+\boldsymbol{\omega}(k)\\ \mathbf{Z}(k)=\mathbf{h}\left(\mathbf{X}(k)\right)+\mathbf{v}(k)\end{cases}$$

The Taylor expansion of the observation equation gives that:

$$\mathbf{h}\left(\mathbf{X}(k+1)\right)=\mathbf{h}\left(\hat{\mathbf{X}}(k+1/k)\right)+\frac{\partial\mathbf{h}}{\partial\mathbf{X}}\Big|_{\mathbf{X}=\hat{\mathbf{X}}(k+1/k)}\left(\mathbf{X}(k+1)-\hat{\mathbf{X}}(k+1/k)\right)+\nabla^2\left(\mathbf{X}(k+1)-\hat{\mathbf{X}}(k+1/k)\right)$$

Then

$$\mathbf{Z}(k+1)=\mathbf{H}(k+1)\mathbf{X}(k+1)+\mathbf{h}(\hat{\mathbf{X}}(k+1/k))-\mathbf{H}(k+1)\hat{\mathbf{X}}(k+1/k)+\mathbf{v}^{'}(k+1)$$

where $\mathbf{v}^{'}(k+1)=\nabla^2\left(\mathbf{X}(k+1)-\hat{\mathbf{X}}(k+1/k)\right)+\mathbf{v}(k+1)$ is virtual observation noise, whose statistical property is unknown.

It can be seen from the above equation that the introduction of virtual noise compensates for linearized model errors, which is beneficial to the improvement of filtering performance. To this end, the Sage-Husa noise statistical estimator is used to estimate the virtual noise variance matrix online.

The Sage-Husa recursive suboptimal unbiased estimator is

$$\hat{\mathbf{R}}(k+1)=\frac{1}{k+1}[k\hat{\mathbf{R}}(k)+\boldsymbol{\gamma}(k+1)\boldsymbol{\gamma}^{\mathrm{T}}(k+1)-\mathbf{H}(k+1)\mathbf{P}(k+1/k)\mathbf{H}^{\mathrm{T}}(k+1)]$$

From a statistical point of view, it can be seen that the Sage-Husa noise statistics estimator is essentially an arithmetic mean operation, but it should highlight the role of new data and gradually weaken the impact of old data. This can be achieved by the attenuated memory method, which is to multiply weighting coefficients by the sum of the equations. According to this idea, the noise statistics estimator is given as:

$$\hat{\mathbf{R}}(k+1)=(1-d_k)\hat{\mathbf{R}}(k)+\left[d_k\boldsymbol{\gamma}(k+1)\boldsymbol{\gamma}^{\mathrm{T}}(k+1)-\mathbf{H}(k+1)\mathbf{P}(k+1/k)\mathbf{H}^{\mathrm{T}}(k+1)\right]$$

where $d_k=(1-b_f)\big/(1-b_f^{k+1})$, b_f is the forgetting factor with $0<b_f<1$.

It is observed that there exists subtraction among positive definite matrices in the estimation operation on $R(k+1)$. Due to improper selection of initial filtering values or a higher degree of nonlinearity of systems, $R(k+1)$ may become negative definite so that the filtering diverges. After deduction, the improved Sage-Husa time-varying observation noise estimator is:

$$\hat{\mathbf{R}}(k+1) = (1-d_k)\hat{\mathbf{R}}(k) + d_k \left\{ \left[\mathbf{I} - \mathbf{H}(k+1)\mathbf{K}(k+1) \right] \boldsymbol{\gamma}(k+1)\boldsymbol{\gamma}^{\mathrm{T}}(k+1) \right.$$
$$\left. \bullet \left[\mathbf{I} - \mathbf{H}(k+1)\mathbf{K}(k+1) \right]^{\mathrm{T}} + \mathbf{H}(k+1)\mathbf{P}(k+1/k+1)\mathbf{H}^{\mathrm{T}}(k+1) \right\}$$

There only exists addition among positive definite matrices in the estimation operation on $R(k+1)$. Therefore, the positive definiteness of $R(k+1)$ is guaranteed, which improves the stability of filtering. Combining the above formula with the basic equations of Kalman filtering constitutes the adaptive Kalman filtering algorithm (AKF) with unknown statistical properties of observation noise.

3.2. Relationship between Observation Noise Variance under the Cartesian Coordinate System and Its Counterpart under the Spherical Coordinate System

The ground radar measurement equation is:

$$\begin{cases} R_t = R_{t0} + v_{Rt} \\ \varepsilon_t = \varepsilon_{t0} + v_{\varepsilon t} \\ \beta_t = \beta_{t0} + v_{\beta t} \end{cases}$$

The target components in the spherical coordinate system, which are measured by ground radars, are converted into position components in the Cartesian coordinate system, of which the calculation formula is:

$$\begin{cases} x_t = R_t \cos\varepsilon_t \cos\beta_t \\ y_t = R_t \sin\varepsilon_t \\ z_t = -R_t \cos\varepsilon_t \sin\beta_t \end{cases}$$

Relationship between the observation noise variance under the Cartesian coordinate system and its counterpart under the spherical coordinate system

$$\sigma^2{}_{xt} = \sigma^2{}_{\varepsilon t}(R_{t0}\sin\varepsilon_{t0}\cos\beta_{t0})^2 + \sigma^2{}_{\beta t}(R_{t0}\cos\varepsilon_{t0}\sin\beta_{t0})^2 + \sigma^2{}_{Rt}(\cos\varepsilon_{t0}\cos\beta_{t0})^2$$

$$\sigma^2{}_{yt} = \sigma^2{}_{\varepsilon t}(R_{t0}\cos\varepsilon_{t0})^2 + \sigma^2{}_{Rt}\sin^2\varepsilon_{t0}$$

$$\sigma^2{}_{zt} = \sigma^2{}_{\varepsilon t}(R_{t0}\sin\varepsilon_{t0}\sin\beta_{t0})^2 + \sigma^2{}_{\beta t}(R_{t0}\cos\varepsilon_{t0}\cos\beta_{t0})^2 + \sigma^2{}_{Rt}(\cos\varepsilon_{t0}\sin\beta_{t0})^2$$

3.3. Kalman Filtering Algorithm under the Cartesian Coordinate System

Consider the target state equation and the measurement equation as follows:

$$X(k+1) = \Phi(k+1,k)X(k) + G(k+1,k)W(k)$$
$$Y(k) = H(k)X(k) + V(k)$$

where $X(k)$ is an n-dimensional target state variable, $Y(k)$ is an m-dimensional measurement variable, and state noise $W(k)$ and measurement noise $V(k)$ are mutually uncorrelated Gaussian white noise sequences, of which statistical properties are:

$$E\left[W(k)\right]=O, E\left[W(k)W^T(j)\right]=Q(k)\delta_k,$$
$$E\left[V(k)\right]=O, E\left[V(k)V^T(j)\right]=R(k)\delta_k$$

And the initial state X_0 is independent of $W(k)$ and $V(k)$, that is

$$E\left[X_0W^T(k)\right]=O, E\left[X_0V^T(k)\right]=O$$

The Kalman filtering equation is:

$$\hat{X}(k/k-1)=\Phi(k/k-1)\hat{X}(k-1/k-1)$$

$$P(k/k-1)=\Phi(k,k-1)P(k-1/k-1)\Phi^T(k,k-1)+G(k-1)Q(k-1)G^T(k-1)$$

$$K(k)=P(k/k-1)H^T(k)\left[H(k)P(k/k-1)H^T(k)+\hat{\mathbf{R}}(k)\right]^{-1}$$

$$\gamma(k)=Y(k)-H(k)\hat{X}(k/k-1)$$

$$\hat{X}(k/k)=\hat{X}(k/k-1)+K(k)\gamma(k)$$

$$P(k/\mathrm{k})=\left[I-K(k)H(k)\right]P(k/k-1)$$

The initial state covariance matrix is taken as

$$P_0=\begin{bmatrix} 10^5 \bullet I_3 & 0_3 & 0_3 \\ 0_3 & 10^5 \bullet I_3 & 0_3 \\ 0_3 & 0_3 & 10^5 \bullet I_3 \end{bmatrix}$$

State noise covariance matrix is

$$\mathbf{Q}(k)=2\alpha\sigma_a^2\mathbf{q}=2\alpha\sigma_a^2\begin{bmatrix} q_{11}I_3 & q_{12}I_3 & q_{13}I_3 \\ q_{12}I_3 & q_{22}I_3 & q_{23}I_3 \\ q_{13}I_3 & q_{23}I_3 & q_{33}I_3 \end{bmatrix},$$

where α is chosen as 1, $\sigma_a^2=\begin{bmatrix} I_3 & 0_3 & 0_3 \\ 0_3 & I_3 & 0_3 \\ 0_3 & 0_3 & I_3 \end{bmatrix}$.

$$\begin{aligned} q_{11} &= \frac{1}{\alpha^4}\left[\frac{1-e^{-2\alpha T}}{2\alpha}+T-2\frac{1-e^{-\alpha T}}{\alpha}+\frac{\alpha^2T^3}{3}-\alpha T^2+\frac{2}{\alpha}(1-e^{-\alpha T}-\alpha Te^{-\alpha T})\right] \\ &= \frac{1}{2\alpha^5}\left[1-e^{-2\alpha T}+2\alpha T+\frac{2\alpha^3T^3}{3}-2\alpha^2T^2-4\alpha Te^{-\alpha T}\right] \end{aligned}$$

$$\begin{aligned} q_{12} &= \frac{1}{\alpha^3}[-\frac{1-e^{-2\alpha T}}{2\alpha}+2\frac{1-e^{-2\alpha T}}{\alpha}-\frac{1}{\alpha}(1-e^{-\alpha T}-\alpha Te^{-\alpha T})-T+\frac{\alpha T^2}{2}] \\ &= \frac{1}{2\alpha^4}(e^{-2\alpha T}+1-2e^{-\alpha T}+2\alpha Te^{-\alpha T}-2\alpha T+\alpha^2T^2) \end{aligned}$$

$$q_{13}=\frac{1}{\alpha^2}[\frac{1-e^{-2\alpha T}}{2\alpha}+\frac{e^{-\alpha T}-1}{\alpha}+\frac{1}{\alpha}(1-e^{-\alpha T}-\alpha Te^{-\alpha T})]=\frac{1}{2\alpha^3}(1-e^{-2\alpha T_s}-2\alpha T_s e^{-\alpha T_s})$$

$$q_{22}=\frac{1}{\alpha^2}[\frac{1-e^{-2\alpha T}}{2\alpha}+2\frac{e^{-\alpha T}-1}{\alpha}+T]=\frac{1}{2\alpha^3}(4e^{-2\alpha T}-3-e^{-2\alpha T})$$

$$q_{23}=\frac{1}{\alpha}[\frac{e^{-\alpha T}-1}{2\alpha}-\frac{e^{-\alpha T}-1}{\alpha}]=\frac{1}{2\alpha^2}(e^{-2\alpha T}+1-2e^{-\alpha T})$$

$$q_{33}=\frac{1}{2\alpha}(1-e^{-2\alpha T})$$

4. Numerical Simulation

Assume that the detection system has a ranging accuracy of 10m (1σ) for the target, and a measurement accuracy of 0.12° (1σ) for the azimuth angle. The adaptive Kalman filtering algorithm under the polar coordinate system based on the Sage-Husa noise statistics estimator is adopted to integrate with the Kalman filtering algorithm under the Cartesian coordinate system based on the Singer model. The resulting adaptive maneuvering target tracking algorithm is used to estimate the mean square error of target motion information and measurement noise. Simulation results are shown in Fig. 2 ~ Fig. 4.

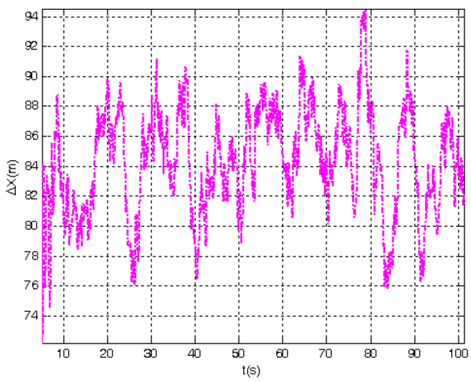

Fig. 2. Estimation error of target position along x-coordinate.

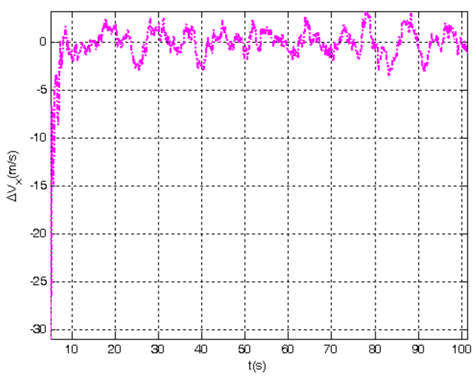

Fig. 3. Estimation error of target velocity along x-coordinate.

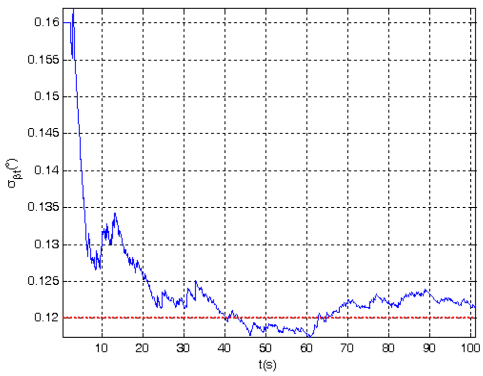

Fig. 4. Estimation of measurement noise MSE of azimuth angle.

5. Conclusion

In this paper, a new adaptive maneuvering target tracking algorithm is designed. Firstly, the CV model and the observation equation of maneuvering target motion are established in the spherical coordinate system. The adaptive Kalman filtering algorithm based on Sage-Husa noise statistics estimator is used to conduct real-time estimation for measurement noise variance of each observation variable; then the conversion formula between observation noise variance under the Cartesian coordinate system and its counterpart under the spherical coordinate system is used to achieve the observation noise variance under the Cartesian coordinate system; the target position, velocity and acceleration in the Cartesian coordinate system are selected as state variables to establish the Singer model, and the estimate of the observation noise variance in the Cartesian coordinate system is adopted to realize maneuver tracking of targets via Kalman filtering algorithms. Simulation results show that the proposed algorithm can achieve adaptive high-precision tracking for maneuvering targets under unknown noise characteristics of detection systems.

References

[1] Li, X. R., & Jilkov, V. P. (2003). Survey of maneuvering target tracking: Part I: Dynamic models. *IEEE Transactions on Aerospace and Electronic Systems, 39(4)*, 1333-1362.

[2] Cao, Y., Jiang, J., Wang, S., & Fan, Y. (2014). Tracking methods of high speed strong maneuvering targets in near space. *Proceedings of the 12th International Conference on Signal Processing (ICSP)* (pp. 1885-1889).

[3] Liu, C. (2014). Research on motion model and tracking algorithms of radar maneuvering target. PhD thesis, Xidian University, Xi'an, China.

[4] Pan, Q., Liang, Y., & Yang, F., *et al*. (2009). *Modern Target Tracking and Information Fusion*. Beijing: National Defense Industry Press.

[5] Singer, R. A. (1970). Estimating optimal tracking filter performance for manned maneuvering targets. *IEEE Transactions on Aerospace and Electronic Systems, 6(4)*, 473-483.

[6] Zhu, P., Chen, B., & Principe, J. C. (2011, July-August). Extended Kalman filter using a kernel recursive least squares observer. *Proceedings of International Joint Conference on Neural Networks* (pp. 1402-1408). California, USA.

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