A New Tracking Algorithm for Strong-Maneuvering Target with Two-Layer Nested Model of CS and CL

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Abstract

A new tracking algorithm is proposed for strong-maneuvering target, which is based on a two-layer nested model with Improved Current Statistical (ICS) model and Curvilinear (CL) model as the inner and outer layer respectively. The inner layer use ICS model to construct statistics with filtering residuals to detect target's maneuver and thus correcting the parameters of CS model in real time in order to adapt to target's real motion. The outer layer uses the estimate of acceleration obtained from the inner layer as its input and in this way conduct better performance of target tracking by taking advantage of CL model, which can better correspond to the curvilinear motion of target. Simulation results show the practicability of the algorithm proposed in this article and demonstrate good tracking performance.

Keywords: *strong-maneuvering target; two-layer nested model; improved current statistical model; Curvilinear model; maneuver detection*

1. Introduction

The improving maneuver ability of aerial vehicles along with the fast development of modern technology turns the motion model construction of target into a crucial as well as difficult part in the target tracking technology of modern air combat. Therefore, the design of tracking algorithms for strong-maneuver target counts a lot in conducting good tracking performance [1].

The Current Statistical (CS) model proposed by Zhou Hongren in 1983 is widely used in target tracking. However, the values of angular acceleration limits $a_{\pm \max}$ and maneuver frequency $\alpha(k)$ are both decided empirically and fixed during the whole filtering process, which would result in considerably decrease of tracking accuracy. Improved CS (ICS) model using Activation Function constructed by filtering residuals is designed in [2-3] to correct the variance of acceleration and maneuver frequency. Curvilinear model, which contains constant velocity, constant acceleration and constant angular velocity motion models under different model parameters, is proposed in [4] to better correspond with the real motion of target.

To conduct better tracking performance, a new tracking algorithm with two-layer nested model is proposed in this article, the inner and outer layer of which are respectively ICS model and CL model. As the inner layer, ICS model uses adaptive-adjustment algorithm to estimate the acceleration of target in real time. Then the CL model of the outer layer uses this

estimate to better approximate the curvilinear motion of target. Through the combination of CS and CL model, stable target tracking with high accuracy is realized.

2. System Configuration of the Two-Layer Models

In Figure 1, $z(k)$ is the measurement set, $v(k)$ is the filtering residual, $\alpha(k)$ is the maneuvering frequency, $Q(k)$ is the error covariance of the acceleration, $\hat{a}_t(k)$ is the tangential acceleration estimate, $\hat{x}_T(k)$ is target state estimate.

Figure 1. The Block Diagram of the Two-layer Model

The two-layer model is composed of ICS model and CL model. The inner model is Improved Current Statistical (ICS) model, and it uses the self-adaptive adjustment algorithm to adjust the parameters, so it can estimate the target acceleration with greater accuracy. The outer model is CL model which takes the acceleration estimate from ICS as one of the inputs. And because CL model has a great approximation to the target curve motion, so it can track the target precisely.

3. Improved CS Model

3.1. Maneuver Detecting Algorithm of Target

In standard CS model, the maneuvering frequency ($\alpha(k)$) and the minimum and the maximum accelerate ($a_{\pm \max}$) of target can directly influence the state transition matrix ($F(k)$), turbulence transfer matrix ($U(k)$) and the variance of acceleration error ($Q(k)$) of the CS model, thus changing the target tracking accuracy. The values of $\alpha(k)$ and $a_{\pm \max}$ in standard CS model are usually fixed and empirical, which can conduct good tracking performance only when the values happen to be in accord with the target's real maneuver, which is often supposed to be weak. However, as the vehicles used in modern combat are generally good at maneuvering, it is obviously that fixed model parameters can't conduct tracking performance that is satisfactory enough.

Based on that the statistical characters of filtering residual would change when target maneuvers, we designed a maneuver detecting algorithm of target.

The filtering residual in UKF is as following:

$$v(k) = Z(k) - \bar{Z}(k/k-1) \quad (1)$$

Considering that $v(k)$ is a White Gaussian when there's no maneuver, the variance matrix of $v(k)$ is as follows:

$$S(k) = \sum_{l=0}^{2n} \{ w_l^{(c)} [(Z^l(k+1/k) - \bar{Z}^l(k+1/k))^T (Z^l(k+1/k) - \bar{Z}^l(k+1/k))] + R(k+1) \} \quad (1)$$

Construct a statistical scale $d(k)$ as:

$$d(k) = v(k)^T S(k)^{-1} v(k) \quad (2)$$

From the statistical characters of filtering residual, we know that:

$$d(k) \sim \chi^2(m) \quad (3)$$

Where m stands for observation dimension. While $v(k)$ is no longer a white Gaussian when the target begins to maneuver. Moreover, the stronger the target's maneuver is, the larger $d(k)$ becomes. The maneuver detecting algorithm designed based on this character is as following.

Set a false alarm probability as λ_{Ta} , then the corresponding threshold Ta can be got by reference of distribution table of $\chi^2(m)$.

$$P\{d(k) > Ta\} \geq \lambda_{Ta} \quad (4)$$

If the equation (5) is true, that means there's a probability of $(1 - \lambda_{Ta})$ that target has made a strong maneuver. In order to guarantee the tracking accuracy and that the model can still adapt to target's maneuvering, $\alpha(k)$ and $a_{\pm \max}$ should be improved at the same time.

If not, it illustrate that the target moves without or with just very week maneuvering, in which case tracking performance can be remained without changing $\alpha(k)$ or $a_{\pm \max}$.

3.2. Adaptive Parameters Algorithm

Define the calculation of the average acceleration of target as:

$$\bar{a}_p = \frac{1}{l} \sum_{i=k-l}^{k-1} \ddot{x}(i) \quad (5)$$

Where l stands for step length, the recommended values of which usually range from 3 to 10, $\ddot{x}(i)$ is the estimate of target's acceleration at the moment of i , $\bar{a}_p$ is a fixed constant when $k \leq l$.

When equation (5) is true, i.e. the target's maneuver is detected to be strong, in 3.1, the model parameters should be updated as:

$$\sigma_a^2 = \begin{cases} \frac{4-\pi}{\pi} [\sqrt{d(k)-2a_{\max}} - \bar{a}_p(k)]^2 & \bar{a}_p(k) \geq 0 \\ \frac{4-\pi}{\pi} [\sqrt{d(k)-2} + \bar{a}_p(k)]^2 & \bar{a}_p(k) < 0 \end{cases} \quad (6)$$

$$\alpha = \sqrt{d(k) - 2\alpha_0} \quad (7)$$

Therefore, the parameters of CS model can be adaptive according to equation (7)~(8), and then match the real maneuvering of target, and finally improve the target tracking accuracy.

4. Filtering Algorithm of CL Model

4.1. CL Model of Target Motion

Assume that the target is making curve motion in the X-Y plane at the moment of k with the state vector, centripetal acceleration and normal acceleration respectively of $[x \dot{x} \ddot{x} y \dot{y} \ddot{y}]^T$, a_n and a_t . While ϕ is the angle between the direction of velocity and north (clockwise stands for positive), R presents turning radius. The relationships of variables mentioned above are as follow:

$$v(k) = R\omega(k) \quad (8)$$

$$a_t(k) = \frac{dv(t)}{dt} \Big|_{t=k} = R\beta(k) \quad (9)$$

$$a_n = R\omega(k)^2 = v(k)\omega(k) \quad (10)$$

Figure 2. X-Y Plane Graph of Target Curve Motion

Where $\omega(k)$, $\beta(k)$ stands for angular velocity and angular acceleration of the target respectively.

According to Figure 2, the projection of velocity in both X and Y direction are:

$$\dot{x}(t) = v(t)\sin(\phi(t)) \quad (11)$$

$$\dot{y}(t) = v(t)\cos(\phi(t)) \quad (12)$$

The second-order continuous differential state equation of the target can be deduced from equations (12)~(13) as:

$$\begin{bmatrix} \dot{x} \\ \ddot{x} \\ \dot{y} \\ \ddot{y} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ y \\ \dot{y} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \sin(\phi(t)) & \cos(\phi(t)) \\ 0 & 0 \\ \cos(\phi(t)) & \sin(\phi(t)) \end{bmatrix} \begin{bmatrix} a_t \\ a_n \end{bmatrix} \quad (13)$$

There are two conditions (15)~(16) hold for modern vehicles when the onboard radar keeps a normal scan frequency.

$$\left| \frac{\dot{a}_n(k)}{a_n(k)} \right| < \left| \frac{a_t(k)}{v(k)} \right| \quad (14)$$

$$\left| \frac{a_t(k)}{v(k)} \right| < \frac{2}{T} \quad (15)$$

Where k and T stands for sampling instant and sampling period.

The following equation (17) is the discrete form of the integration of equation (14) according to (13)~(14) under the conditions of (15)~(16):

$$\begin{bmatrix} x(k+1) \\ \dot{x}(k+1) \\ y(k+1) \\ \dot{y}(k+1) \end{bmatrix} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix} \begin{bmatrix} a_t(k) \\ a_n(k) \end{bmatrix} + \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix} \begin{bmatrix} a_t(k) \\ a_n(k) \end{bmatrix} \quad (16)$$

Where:

$$b_1 = \frac{\sin(\phi(k))}{w(k)^2} - \frac{\sin(\phi(k) + Tw(k))}{w(k)^2} + \frac{T \cos(\phi(k))}{w(k)} \quad (17)$$

$$b_2 = \frac{\cos(\phi(k))}{w(k)} - \frac{\cos(\phi(k) + Tw(k))}{w(k)} \quad (18)$$

$$b_3 = \frac{\cos(\phi(k))}{w(k)^2} - \frac{\cos(\phi(k) + Tw(k))}{w(k)^2} - \frac{T \sin(\phi(k))}{w(k)} \quad (19)$$

$$b_4 = -\frac{\sin(\phi(k))}{w(k)} + \frac{\sin(\phi(k) + Tw(k))}{w(k)} \quad (20)$$

$$c_1 = \frac{\cos(\phi(k))}{w(k)^2} - \frac{\cos(\phi(k) + Tw(k))}{w(k)^2} - \frac{T \sin(\phi(k))}{w(k)} \quad (21)$$

$$c_2 = -\frac{\sin(\phi(k))}{w(k)} + \frac{\sin(\phi(k) + Tw(k))}{w(k)} \quad (22)$$

$$c_3 = -\frac{\sin(\phi(k))}{w(k)^2} + \frac{\sin(\phi(k) + Tw(k))}{w(k)^2} - \frac{T \cos(\phi(k))}{w(k)} \quad (23)$$

$$c_4 = -\frac{\cos(\phi(k))}{w(k)} + \frac{\cos(\phi(k) + Tw(k))}{w(k)} \quad (24)$$

$$\phi(k) = \arctan \left(\frac{\dot{x}(k)}{\dot{y}(k)} \right) \quad (25)$$

Equation (17) indicates that:

when $a_t(k) = 0, a_n(k) = 0$, it represents CV model;

when $a_t(k) \neq 0, a_n(k) = 0$, it represents CA model;

when $a_t(k) = 0, a_n(k) \neq 0$, it represents CT model.

With equations (11)~(13), the third item on the right-hand side of equation (17) can be transformed into the form of $x(k), \dot{x}(k), y(k), \dot{y}(k)$ and thus can be simplified as:

$$\begin{bmatrix} x(k+1) \\ \dot{x}(k+1) \\ y(k+1) \\ \dot{y}(k+1) \end{bmatrix} = \begin{bmatrix} 1 & \frac{\sin(w(k)T)}{w(k)} & 0 & \frac{1 - \cos(w(k)T)}{w(k)} \\ 0 & \cos(w(k)T) & 0 & \sin(w(k)T) \\ 0 & \frac{\cos(w(k)T) - 1}{w(k)} & 1 & \frac{\sin(w(k)T)}{w(k)} \\ 0 & -\sin(w(k)T) & 0 & \cos(w(k)T) \end{bmatrix} \begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix} a_t(k) \quad (26)$$

4.2. Filtering Algorithm of CL Model

The equation (27) indicates that the values of angular velocity $w(t)$ and normal angular acceleration $a_t(k)$ need to be updated in real time. Considering that the improved CS model can provide the estimate of $a_t(k)$, we designed a estimate algorithm (28) for angular velocity $w(t)$ based on a time varying model to avoid adding an external model to do the task.

$$w(k+1) = w(k) + \frac{w(k)T}{v(k)} a_t(k) \cong w(k) + \frac{\Delta\phi(k)}{v(k)} a_t(k) \quad (27)$$

$$\Delta\phi(k) = \phi(k) - \phi(k-1) \quad (28)$$

$$v(k) = \sqrt{\dot{x}(k)^2 + \dot{y}(k)^2} \quad (29)$$

With equation (26), (29) and (30), equation (28) can be transformed into (31):

$$w(k+1) = w(k) + \frac{\arctan \left(\frac{\dot{x}(k)}{\dot{y}(k)} \right) - \arctan \left(\frac{\dot{x}(k-1)}{\dot{y}(k-1)} \right)}{\sqrt{\dot{x}(k)^2 + \dot{y}(k)^2}} a_t(k) \quad (30)$$

The dimension of the state variables in equation (27) can be expanded by equation (31) and substituted into $w(k)$ to make:

$$\begin{bmatrix} x(k+1) \\ \dot{x}(k+1) \\ y(k+1) \\ \dot{y}(k+1) \\ w(k+1) \end{bmatrix} = \begin{bmatrix} 1 & \frac{\sin(w(k)T)}{w(k)} & 0 & \frac{1 - \cos(w(k)T)}{w(k)} & 0 \\ 0 & \cos(w(k)T) & 0 & \sin(w(k)T) & 0 \\ 0 & \frac{\cos(w(k)T) - 1}{w(k)} & 1 & \frac{\sin(w(k)T)}{w(k)} & 0 \\ 0 & -\sin(w(k)T) & 0 & \cos(w(k)T) & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \\ w(k) \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix} a_t(k) \quad (31)$$

Where:

$$b_s = \frac{\arctan\left(\frac{\dot{x}(k)}{\dot{y}(k)}\right) - \arctan\left(\frac{\dot{x}(k-1)}{\dot{y}(k-1)}\right)}{\sqrt{\dot{x}(k)^2 + \dot{y}(k)^2}} \quad (32)$$

By updating the values of $a_i(k)$ and $w(t)$ in real time using algorithms in Section 3 and equation (32) respectively, target tracking is realized.

5. Simulation Results

5.1. The Simulation Results of Acceleration Estimate in ICS Model

Simulation Scenario: Assume that the target's maneuvers are limited in a horizontal plan. The initial state of target is $X(0) = [x_0, \dot{x}_0, \ddot{x}_0, y_0, \dot{y}_0, \ddot{y}_0]^T = [1000, 120, 0, 2000, 100, 0]^T$, covariance of system noise $W(k)$ is: $Q(k) = \text{diag}\{[100 \ 10 \ 5 \ 100 \ 10 \ 5]^T\}$. The MSE of the measurement noise (two-coordinate radar) is: $\sigma_{xy} = \text{diag}[50, 50]^T$, i.e., covariance of measurement noise $V(k)$ is: $R(k) = \text{diag}[50, 50]^T$ m. The sample period and total simulation time is $T = 0.1s$ and 50s respectively. The maneuvers of target are listed in Table 1.

Table 1. Maneuvers of Target

Time	Maneuver Type	Acceleration $[a_x, a_y]$
0~10s	CV(Constant Velocity)	$[0, 0]$
10~15s	CA(Constant Acceleration)	$[20, -20]$
15~30s	CV	$[0, 0]$
30~33s	CA	$[-20, 20]$
33~50s	CV	$[0, 0]$

The estimate results of acceleration are shown in Figure 3~5:

Figure 3. Acceleration in X Direction

Figure 4. Acceleration in Y Direction

Simulation results in Figure 3-4 show that both of CS model and ICS model would generate delay when estimating the acceleration of target. For example, when $t = 10s$ the target changes from CV motion into CA motion with acceleration of $[a_x, a_y] = [20, -20] m/s^2$. But their acceleration estimates cannot adapt to target's real acceleration until $t = 15s$, that's because the acceleration estimates of both CS and ICS model depend on the variance of estimate error $\hat{Q}(k)$, which changes with time delay, thus delaying the correction of estimate.

However, Figure 3-4 illustrate that ICS model takes less time than CS model to adjust its parameters to adapt to the true acceleration. For example, when target returns to CV motion at time $t = 15s$, ICS model tracks on the true acceleration close to $t = 23s$, but CS model does not catch up until $t = 27s$. At the same time, the ICS model has less overshoot than CS model, which indicates that the former conduct more stable tracking performance than the latter.

Figure 5. Acceleration Estimate RMSE (N=50)

As shown in Figure 5, the 50 sets of Monte Carlo simulation results show that the estimate RMSE (Root Mean Squared Error) of ICS model is much smaller than that of CS model. The average RMSE shown in Table 2 demonstrates that the tracking accuracy of ICS model improved by 35.81% than that of CS model.

Table 2. Average RMSE of Acceleration Estimate

RMSE	CS	ICS	Precision Improved
Acceleration Estimate	6.87	4.41	35.81%

5.2. The Two-Layer Nested Model Simulation Results

With the same simulation scenario in 5.1, target tracking results by ICS and CS-CL model are shown in Figure 6~11.

Figure 6. Tracking Trajectory

**Figure 7. Partial Enlargement
View of Figure 6**

Figure 6 shows that CSCL and ICS model can conduct similar extent of accuracy in target's tracking trajectory, but the partial enlargement view of Figure 6, as shown in Figure 7, shows that when target maneuvers with a large angular velocity, tracking results of CS-CL model is obviously smoother and closer to the true trajectory than ICS.

**Figure 8. Velocity Estimate in
X direction**

**Figure 9. Velocity Estimate in
Y direction**

The estimate of velocity in Figure 8 shows that when target returns to CV motion from CA motion at $t = 15s$, CS-CL and ICS model can approximately adapt to that at $t = 22s$ and $26s$ respectively, *i.e.*, the time delay is 7s by CS-CL model and 11s by ICS model. Similarly, as shown in Figure 9, when target returns to CV motion from CA motion at $t = 33s$, CS-CL model would produce a good tracking performance from $t = 35s$, but ICS at $t = 38s$. Results in Figure 8~9 indicate that CS-CL model conducts better dynamic performance than ICS model.

**Figure 10. Position Estimate
RMSE (N=50)**

**Figure 11. Velocity Estimate
RMSE (N=50)**

As shown in Figure 10~11, the 50 sets of Monte Carlo simulation results show that CS-CL model can conduct more accurate target tracking performance than ICS model, particularly when target makes strong maneuver during 10 ~ 23 s. Results in Table 2 further illustrate that CS-CL model makes the tracking precision in position and velocity improved by 36.22% and 58.38% respectively than ICS model.

Table 2. Average RMSE of Position & Velocity Estimate

RMSE	ICS	CSCL	Precision Improved
Position Estimate	9.28	5.92	36.22%
Velocity Estimate	9.72	6.13	58.38%

6. Conclusions

An improved CS (ICS) model is presented straightforwardly, which can simultaneously accommodate varying angular velocity of target in its possible maneuvering behavior. CL model is subsequently presented for its effectiveness in adjusting to target motion. Using ICS as inner model and CL model as outer model, a two-layer nested model is constructed. Based on this nested model, a novel algorithm is proposed to ameliorate tracking performance of strong maneuvering target. Simulation results validate the effectiveness of this novel algorithm.

Note that the success of the novel algorithm is mainly in tracking accuracy and stability, the development of the methodology to reduce time delay to achieve better efficiency can be involved into further research.

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