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Algorithm to Determine Target Angle Coordinates with Maneuvering Detection of Self-Guided Head on the Basis of State Model Parameter Recognition

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Abstract— *On the basis of the tracking multi-loop target angle coordinate system, the article propose a method to synthesize adaptive filtering algorithm with maneuvering detection on the basis of state model parameter recognition to improve the quality of the target phase coordinates filter. The algorithm is capable of adapting to the diverse maneuverability in the actual of the target, as the evaluation process progresses to the most suitable model. As a result, the target phase coordinate evaluation quality is improved. Because the forecast matrix is continuously recognized, the state forecast will be more accurate. Because the algorithm does not increase the amplification factor, it does not increase the influence of observations noise to the state evaluation. Therefore, the state evaluation accuracy of the algorithm is advanced. The structure of the filter is simple, the evaluation error is small. The results are verified through the simulation, ensure in all cases the target changes maneuvering form, including the uncertainty related to the maneuvering moment with different maneuvering intensity and maneuvering frequency, the line of sight angle coordinate filter always accurately determines the target angle coordinates.*

Keywords— *Self-guided head, Target, Maneuvering, The line of sight angle, Adaptive filter, Parameter recognition.*

I. INTRODUCTION

To control the missile, it is necessary to determine the target coordinates or evaluate the phase coordinates [3]. Includes evaluation of their positions and derivative components. This information will be used in the trajectory control algorithms of the missile.

In radar stations and self-guided heads, the determination of target coordinates is done by tracking systems [3]. Including, angle tracking channels and distance tracking channels. The maneuverability of the target causes the appearance of higher-order derivative components of the coordinates to be tracked (input of the tracking systems) [1], [2]. As a result, the tracking error will increase and may lead to loss of tracking. Especially the angle coordinate tracking channels. Because, in angle tracking channels, it is required to control the antenna towards the target through a drive system with high inertia [8].

In the case of a maneuvering target, the tracking systems used to determine the target angle coordinates used on current self-guided systems have low accuracy. Because the tracking system uses directly the information from the antenna drive system as a signal to evaluate the target coordinates [3], [7].

Applying the linear Kalman filter technique [5], [6], [10], the maneuvering frequency and maneuvering intensity parameters are only selected by constants. Therefore, these parameters are not representative of every maneuvering motion of the target. The tracking error will increase when the actual movement of the target does not suitable for the hypothetical model.

Adaptive filtering algorithm with maneuvering detection based on amplification factor correction according to tracking error signal [6], the amplification factor increase when the target is maneuvering will increase the influence of observe noise on the result of evaluation. Therefore, the evaluation accuracy is not high, especially for the line of sight angular speed component. Although simple algorithms but need improvements when used [2].

Therefore, this article proposes a method to synthesize adaptive filtering algorithms with maneuvering detection on the basis of state model parameter recognition to improve the quality of the target angle coordinate filter.

II. ALGORITHM TO DETERMINE TARGET ANGLE COORDINATES WITH MANEUVERING DETECTION ON THE BASIS OF STATE MODEL PARAMETER RECOGNITION

The adaptive line-of-sight angle coordinate evaluation filter is performed on the forecast phase of the Kalman filter algorithm by defining (recognizing) the state model parameters (Φ - state transition matrix in the discrete time domain). The result of recognition is the generation of signals $\hat{\Phi}_{ij}$, $\hat{\Phi}_{ij}$ is the evaluation of the coefficient Φ_{ij} in the state transition matrix. If the target is not maneuvering, the evaluation signals $\hat{\Phi}_{ij}$ coincide with their prior values Φ_{ij}; this time the line-of-sight angle coordinate evaluation filter works according to the usual Kalman filter algorithm. If the target starts to maneuvering, then the difference appears between $\hat{\Phi}_{ij}$ and Φ_{ij}; then $\hat{\Phi}_{ij}$ will replace Φ_{ij} in the filter algorithm.

Maneuver moment detection rule:

The decision rule about when to start a maneuver is to check the condition:

$$\left|\Phi_{ij} - \hat{\Phi}_{ij}\right| > \lambda_{ij} \tag{1}$$

λ_{ij} - Define threshold for each coefficient of the matrix $\Phi(k,k-1)$.

If condition (1) is satisfied for at least one coefficient, then the decision on the start moment of maneuvering is accepted and begin the corresponding filter correction process.

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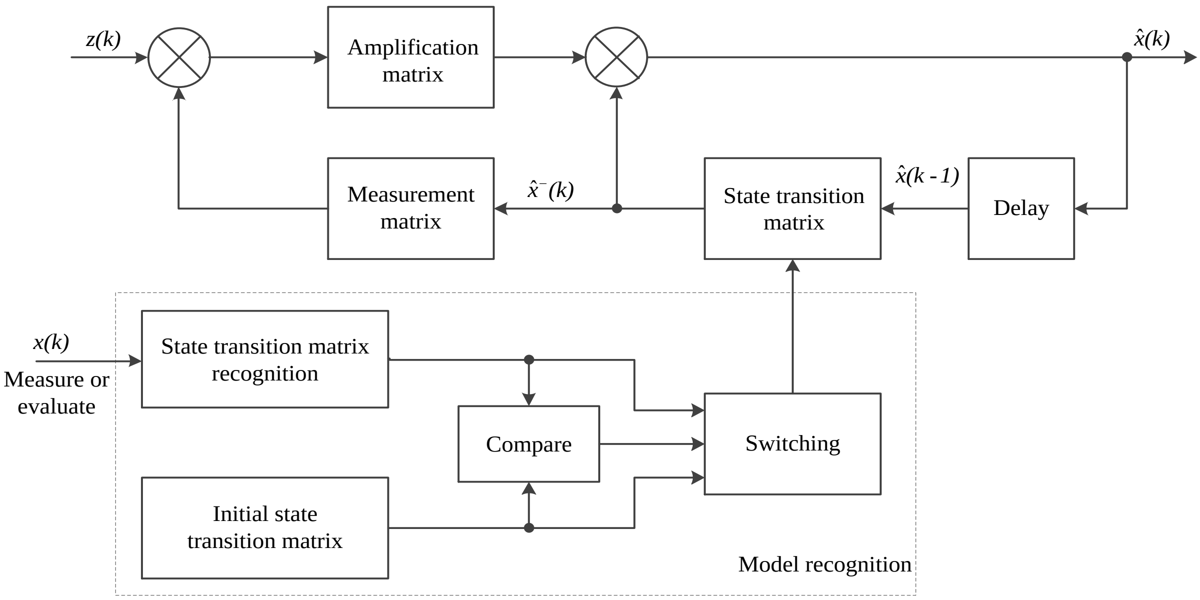

Fig. 1. Structure diagram of adaptive filter based on state model recognition.

A more complete rule for deciding to the start moment an acceptable maneuver is:

$$I = \sum_{\substack{i=1 \\ j=1}}^{N,N} Q_{ij}(\Phi_{ij} - \hat{\Phi}_{ij})^2 > \lambda_n \quad (2)$$

Q_{ij} - Factor;

λ_n - Threshold is selected from experiment or simulation.

2.1. Kalman filter algorithm with intermittent processes

Considering the process described by equation of state [5], [6], [9], [10]:

$$x(k) = \Phi(k-1)x(k-1) + \Gamma(k-1)u(k-1) + \xi_x(k-1) \quad (3)$$

The observation equation has the form:

$$z(k) = H(k)x(k) + \xi_z(k) \quad (4)$$

k - Discrete time;

$x(k)$ - State vector, size $(n \times 1)$;

$u(k)$ - Predestination input signal vector, size $(r \times 1)$;

$z(k)$ - Observation vector, size $(m \times 1)$, $(m \leq n)$;

$\xi_x(k), \xi_z(k)$ - Central Gaussian discrete white noise, uncorrelated;

$\Phi(k)$ - State transition matrix, size $(n \times n)$;

$\Gamma(k)$ - Input signal amplification matrix, size $(n \times r)$;

$H(k)$ - Observation matrix, size $(m \times n)$.

The Kalman filter algorithm is determined according to the retrieval expressions, which have the form [5], [6], [9], [10]:

$$\hat{x}(k) = \hat{x}^-(k) + K(k)\left[z(k) - H(k)\hat{x}^-(k)\right] \quad (5)$$

$$\hat{x}^-(k) = \Phi(k-1)\hat{x}(k-1) + \Gamma(k-1)u(k-1); \hat{x}(0) = x_0 \quad (6)$$

$$\begin{aligned} K(k) &= D(k)H^T(k)Q_z^{-1}(k) \\ &= D^-(k)H^T(k).\left[H(k)D^-(k)H^T(k) + Q_z(k)\right]^{-1} \end{aligned} \quad (7)$$

$$D(k) = \left[E - K(k)H(k)\right].D^-(k) \quad (8)$$

$$\begin{aligned} &D^-(k) = S(k)\Phi(k,k-1)D(k-1)\Phi^T(k,k-1) + Q_x(k-1); \\ &D(0) = D_0 \end{aligned} \quad (9)$$

$\hat{x}$ - State evaluation;

$\hat{x}^-$ - State forecast;

K - Amplification factor matrix;

D - The posterior error correlation matrix, symmetric, positive definite;

D^- - The prior error correlation matrix, symmetric, positive definite;

Q_z - The intensity matrix of observed noise $\xi_z(k)$, positive definite;

Q_x - The intensity matrix of process noise $\xi_x(k)$, positive definite.

The change of line of sight angle coordinate φ_m and angular speed ω_m are determined by the initial state space model, which has the form [1], [2], [3]:

$$\begin{aligned} &\varphi_m(k) = \varphi_m(k-1) + \tau\omega_m(k-1),\ \varphi_m(0) = \varphi_{m0}; \\ &\omega_m(k) = (1 - \tau\alpha_m)\omega_m(k-1) + \xi_{\omega_m}(k-1),\ \omega_m(0) = \omega_{m0}; \end{aligned} \quad (10)$$

The Kalman filter algorithm observation equation [2], [3]:

$$z(k) = z_1(k) + K_\Delta\hat{\varphi}_a(k) = K_\Delta\varphi_m(k) + \xi_{\Delta 1}(k) \quad (11)$$

τ - Discrete time step;

$\hat{\varphi}_a$ - Evaluate the angular position of the antenna;

$\xi_{\Delta 1}$ - Equivalent central Gaussian white noise with variance $Q_{\xi_{\Delta 1}}$;

$$Q_{\xi_{\Delta 1}} = Q_{\xi_\Delta} + K_\Delta^2 D_{11}^{\hat{\varphi}_a};$$

$D_{11}^{\hat{\varphi}_a}$ - The variance of the error generating the evaluation signal $\hat{\varphi}_a$.

2.2. State model parameter recognition algorithm

The algorithm that can be used to determine Φ is the one algorithm proposed by Menor [3], [6]. It is the Kalman filter

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algorithm used to evaluate the model's parameter vector. To use this algorithm, control vector requirement must be known in advance, and the state vector must be measured or have received optimal evaluation of it by a separate filter [5].

Considering the process described by equation of state:

$$x_p(k) = \Phi_p(k-1)x_p(k-1) + \xi_p(k-1) \quad (12)$$

The vector needs to be evaluated:

$$a(k) = \left[\Phi_{p1}(k-1), \Phi_{p2}(k-1), ..., \Phi_{pn}(k-1)\right]^T \quad (13)$$

Observation equation:

$$z(k) = x_p(k) \quad (14)$$

Equation of state for a:

$$a(k) = a(k-1) + \xi_a(k-1) \quad (15)$$

The states and parameters are determined according to expression (3):

$x_p = \left[x^T \quad u^T\right]^T$ - Extended state vector $(n+r)$;

x - State vector, size $(n \times 1)$;

u - Predetermined input signal vector (control vector), size $(r \times 1)$;

$\Phi_p(k-1) = \left[\Phi(k-1) \quad \Gamma(k-1)\right]$ - Extended state transition matrix.

$\xi_p(k-1) = \left[\xi_x^T(k-1) \quad 0^T\right]^T$ - Center Gaussian white noise vector;

0 - Vector with zero elements, size $(r \times 1)$.

$Q_x(k) = M\left\{\xi_p(k)\xi_p^T(k)\right\}$ - Intensity of noise $\xi_p(k)$.

Φ_{pi} - Row matrix i^{th} of matrix Φ_p.

Using (12), (13) into (14), get:

$$z(k) = M_p(k)a(k) + \xi_p(k) \quad (16)$$

Where,

$$M_p(k) = \begin{bmatrix} x_p^T(k-1) & 0 & 0 & ... & 0 \\ 0 & x_p^T(k-1) & 0 & ... & 0 \\ 0 & 0 & x_p^T(k-1) & ... & 0 \\ ... & ... & ... & ... & ... \\ 0 & 0 & 0 & ... & x_p^T(k-1) \end{bmatrix} \quad (17)$$

$M_p(k)$ - Matrix $(n+r) \times (n+r).n$.

Usually, the coefficient Φ_{pii} of the model (12) is a slowly varying function over time compared to the phase coordinate parameters x_{pi}; therefore, during time the formation of the observations, might consider them to be constant. That is, the parameters a_j, ($j = 1,...,(n+r)^2$) are considered constant or almost constant. So, the equation of state for a can be expressed as:

$$a(k) = a(k-1) + \xi_a(k-1) \quad (18)$$

$\xi_a(k-1)$ - Center Gaussian white noise with intensity $Q_a(k-1)$;

$Q_a(k-1)$ - Selected very small.

With the observation equation (16) and the process equation (18), applying the Kalman filter algorithm (5) - (9) to evaluate $a(k)$, we get:

$$\hat{a}(k) = \hat{a}(k-1) + K_a(k)\left[x_p(k) - M_p(k)\hat{a}(k-1)\right], \ \hat{a}(0) = a_0; \quad (19)$$

$$K_a(k) = D_a^-(k)M_p^T(k)\left[M_p(k)D_a^-(k)M_p^T(k) + Q_x(k)\right]^{-1}; \quad (20)$$

$$D_a(k) = \left[E - K(k)M_p(k)\right]D_a^-(k); \quad (21)$$

$$D_a^-(k) = D(k-1) + Q_a(k-1), \ D_a(0) = D_{ao}; \quad (22)$$

Where,

D_a - The posterior error correlation matrix of a;

D_a^- - The prior error correlation matrix of a;

a_0, D_{ao} - First condition;

In case x cannot be measured, in expressions (17), (19) - (22), x is replaced by $\hat{x}$, Q_x is replaced by $D(k)$; where, $\hat{x}$ is generated by the separate filter; $D(k)$ is the correlation matrix of $\hat{x}$.

2.3. Algorithm for evaluating the line of sight angle coordinates

The tracking error $\Delta z(k)$, the Kalman filter algorithm is determined by [3], [4]:

$$\Delta z(k) = z_1(k) - K_\Delta\left[\hat{\varphi}_m^-(k) - \hat{\varphi}_a(k)\right] \quad (23)$$

The prior correlation $D^-(k)$ is calculated according to (9):

$$\begin{aligned} &D_{11}^-(k) = S(k-1).[D_{11}(k-1) + 2\tau D_{21}(k-1) + \tau^2 D_{22}(k-1)] \\ &D_{11}(0) = D_{110} \end{aligned} \quad (24)$$

$$\begin{aligned} &D_{21}^-(k) = D_{12}^-(k) = S(k-1)\{(1-2\tau\alpha_m).[D_{21}(k-1) + \tau D_{22}(k-1)]\} \\ &D_{21}(0) = 0 \end{aligned} \quad (25)$$

$$\begin{aligned} &D_{22}^-(k,k-1) = S(k-1).\left\{(1-\tau\alpha_m)^2[D_{22}(k-1) + Q_{\xi_{\omega_m}}(k-1)]\right\} \\ &D_{22}(0) = D_{220} \end{aligned} \quad (26)$$

The posterior correlation $D(k)$ is determined according to (8):

$$D_{11}(k) = (1 - K_1K_\Delta)D_{11}^-(k) \quad (27)$$

$$D_{21}(k) = D_{12}(k) = D_{21}^-(k) - K_2K_\Delta D_{11}^-(k) \quad (28)$$

$$D_{22}(k) = D_{22}^-(k) - K_2K_\Delta D_{21}^-(k) \quad (29)$$

The amplification coefficients received under (7):

$$K_1 = D_{11}(k)K_\Delta / Q_{\xi_{\Delta 1}}; K_2 = D_{21}(k)K_\Delta / Q_{\xi_{\Delta 1}} \quad (30)$$

Replacing (23) and (30) into (5) and (6), get:

$$\begin{aligned} &\hat{\varphi}_m(k) = \hat{\varphi}_m^-(k) + K_1\Delta z(k); \quad \hat{\varphi}_m(0) = \varphi_{m0}; \\ &\hat{\omega}_m(k) = \hat{\omega}_m^-(k) + K_2\Delta z(k); \quad \hat{\omega}_m(0) = \omega_{m0}; \end{aligned} \quad (31)$$

$$\begin{aligned} &\hat{\varphi}_m^-(k) = \hat{\varphi}_m(k-1) + \tau\hat{\omega}_m(k-1); \\ &\hat{\omega}_m^-(k) = (1-\tau\alpha_m)\hat{\omega}_m(k-1); \end{aligned} \quad (32)$$

When using the state model (10) with observation (11), the filter synthesis algorithm is determined by the expressions (23) - (32) to generate the evaluations $\hat{\varphi}_m, \hat{\omega}_m$ with the condition $S = 1$ (in formula (9)).

The filter synthesized here differs from the above filter

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only in the following point: Replace the coefficients of the matrix $\Phi(k-1)$ (with constant (specific) values) in (6) by the general values Φ_{ij} $(i=1,2;\ j=1,2)$. Parameters Φ_{ij} are determined through the recognition process.

The parameter recognition algorithm of the model (10) is determined by the expressions (19) - (21) with the following parameters:

Vector of the model's parameters:

$$a^T(k)=[\Phi_{11}(k-1)\quad \Phi_{12}(k-1)\quad \Phi_{21}(k-1)\quad \Phi_{22}(k-1)] \qquad (33)$$

+ When the target is not maneuvering:

$$\Phi_{11}(k-1)=1;\ \Phi_{12}(k-1)=\tau;\ \Phi_{21}(k-1)=0;\ \Phi_{22}(k-1)=1-\tau\alpha_m;$$

+ When the maneuvering target, according to (13), the change rule of $a(k)$ has the form:

$$a(k)=a(k-1)+\xi_a(k-1) \qquad (34)$$

The noise component $\xi_a(k)$ is used to increase adaptability in the case of a maneuvering target. For process (10), (34) and observation (11), can be evaluated simultaneously φ_m, ω_m and a by expanding the state vector $x=[\varphi_m\quad \omega_m\quad a^T]^T$; however, the computation mass will increase due to the very large state vector size. To overcome this shortcoming, separate the state evaluation problem and the parameter recognition problem.

The state evaluation problem is performed according to the algorithm (23) - (32) with weight $S(k)=1$, forming the tracking filter the line of sight coordinates.

- The problem of parameter recognition is done as follows: Using state evaluation signals as observation signals, the observation equation has the form:

$$\hat{x}(k)=[\hat{\varphi}_m(k)\quad \hat{\omega}_m(k)]^T = M(k)\,a(k)+\xi_{\hat{x}}(k) \qquad (35)$$

$\hat{x}(k)$ - Received from line of sight angle coordinate evaluation filter (31), (32).

$$M(k)=\begin{bmatrix} \hat{\varphi}_m(k-1) & \hat{\omega}_m(k-1) & 0 & 0 \\ 0 & 0 & \hat{\varphi}_m(k-1) & \hat{\omega}_m(k-1) \end{bmatrix} \qquad (36)$$

$\xi_{\hat{x}}(k)=\left[\xi_{\hat{\varphi}}(k-1)\quad \xi_{\hat{\omega}}(k-1)\right]^T$ - A central Gause process with a known correlation matrix Q_x.

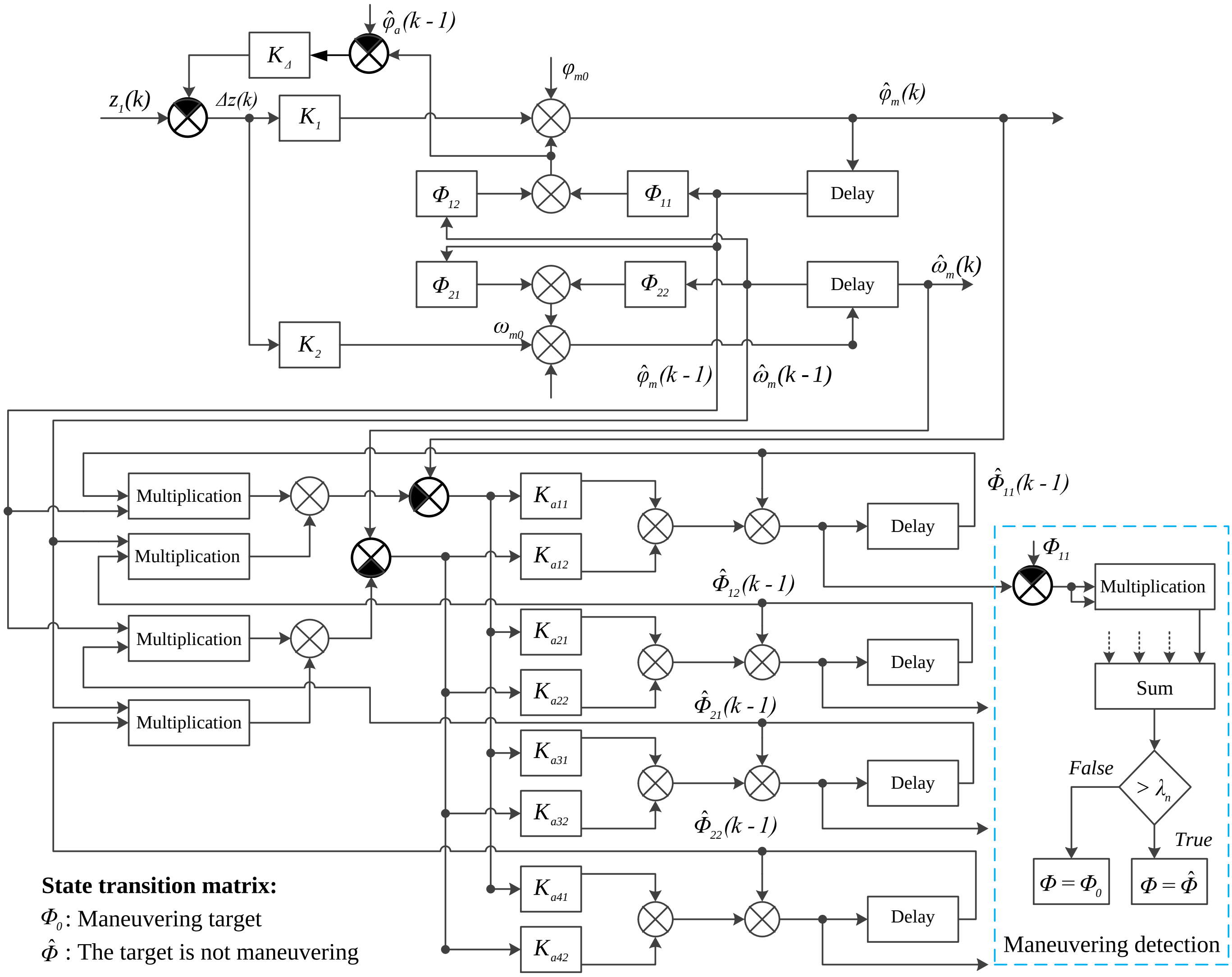

Fig. 2. Structure diagram of adaptive filter evaluating line of sight angle coordinates based on state model parameter recognition.

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The evaluation error correlation matrix of a and the intensity matrix Q_a of the noise $\xi_a(k)$ in general form:

$$D_a = \begin{bmatrix} D_{a11} & D_{a12} & D_{a13} & D_{a14} \\ D_{a21} & D_{a22} & D_{a23} & D_{a24} \\ D_{a31} & D_{a32} & D_{a33} & D_{a34} \\ D_{a41} & D_{a42} & D_{a43} & D_{a44} \end{bmatrix} \quad (37)$$

$$Q_a = \begin{bmatrix} Q_{a11} & Q_{a12} & Q_{a13} & Q_{a14} \\ Q_{a21} & Q_{a22} & Q_{a23} & Q_{a24} \\ Q_{a31} & Q_{a32} & Q_{a33} & Q_{a34} \\ Q_{a41} & Q_{a42} & Q_{a43} & Q_{a44} \end{bmatrix} \quad (38)$$

Replacing (37), (38) into the expressions (20) - (22), the amplification coefficient is determined:

$$K_a = \begin{bmatrix} K_{a11} & K_{a21} & K_{a31} & K_{a41} \\ K_{a12} & K_{a22} & K_{a32} & K_{a42} \end{bmatrix}^T \quad (39)$$

Replacing (33) - (36) and (39) into (19), get the algorithm to evaluate the parameters Φ_{ij} of the original model (10):

$$\begin{aligned} &\hat{\Phi}_{11}(k) = \hat{\Phi}_{11}(k-1) + K_{a11}\Delta z_1 + K_{a12}\Delta z_2;\ \hat{\Phi}_{11}(0) = \Phi_{11} = 1 \\ &\hat{\Phi}_{12}(k) = \hat{\Phi}_{12}(k-1) + K_{a21}\Delta z_1 + K_{a22}\Delta z_2;\ \hat{\Phi}_{12}(0) = \Phi_{12} = \tau \\ &\hat{\Phi}_{21}(k) = \hat{\Phi}_{21}(k-1) + K_{a31}\Delta z_1 + K_{a32}\Delta z_2;\ \hat{\Phi}_{21}(0) = \Phi_{21} = 0 \\ &\hat{\Phi}_{22}(k) = \hat{\Phi}_{22}(k-1) + K_{a41}\Delta z_1 + K_{a42}\Delta z_2;\ \hat{\Phi}_{22}(0) = \Phi_{22} = (1-\tau\alpha_{cd}) \end{aligned} \quad (40)$$

The tracking errors $\Delta z_1, \Delta z_2$ are determined by:

$$\begin{aligned} &\Delta z_1 = \hat{\varphi}_m(k) - \hat{\varphi}_m(k-1)\hat{\Phi}_{11}(k-1) - \hat{\omega}_m(k-1)\hat{\Phi}_{12}(k-1) \\ &\Delta z_2 = \hat{\omega}_m(k) - \hat{\varphi}_m(k-1)\hat{\Phi}_{21}(k-1) - \hat{\omega}_m(k-1)\hat{\Phi}_{22}(k-1) \end{aligned} \quad (41)$$

From algorithms (40) and (41), the structural diagram of the filter evaluates the line of sight angle coordinates based on the parameter recognition of the state model shown in Figure 2.

III. SIMULATION RESULTS AND ANALYSIS

- The sample trajectory is generated from the following kinetic model:

$$\begin{aligned} &\varphi_m(k) = \varphi_m(k-1) + \tau\,\omega_m(k-1) \\ &\omega_m(k) = (1-\tau\alpha_m)\omega_m(k-1) + \alpha_m\tau u \\ &z(k) = \varphi_m(k) + \xi_{z\varphi}(k) \end{aligned} \quad (42)$$

- Parameters for creating line of sight trajectory: $\tau = 0{,}001(s)$, $\alpha_m = 0{,}6\,(1/s)$, $\varphi_{m0} = 0\,(rad)$, $\omega_{m0} = 0\,(rad/s)$, $\sigma^2_{\xi_z} = 0{,}05^2(o^2)$, simulation time $t_\Sigma = 15(s)$, $u\ (^O/s) = \begin{cases} 0{,}5 & when\ t < 5\,s \\ 5 & when\ t \ge 5\,s \end{cases}$.

u - Characterizes the magnitude of the line of sight angle speed. When there is a change in the value of u, the angular speed of the line of sight will change from the current value to the new value of u;

α_m - Parameter that characterizes the speed of change of angular speed (angular acceleration); α_m greater, the larger the angular acceleration.

- Parameters of the model $\alpha_m = 0{,}6\,(1/s);\ \sigma^2_{\omega_m} = 0{,}0012\,(rad/s)^2$.

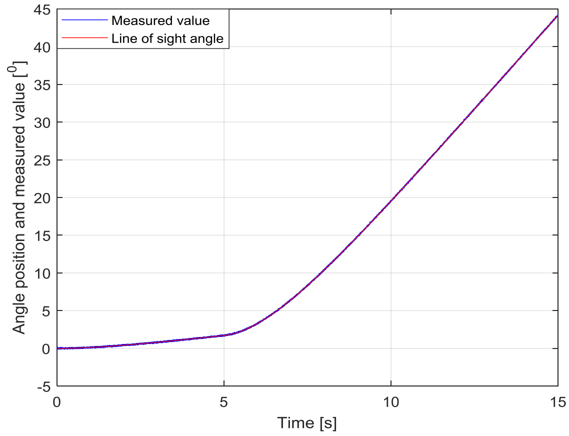

Fig. 3. Line of sight angle and measured value.

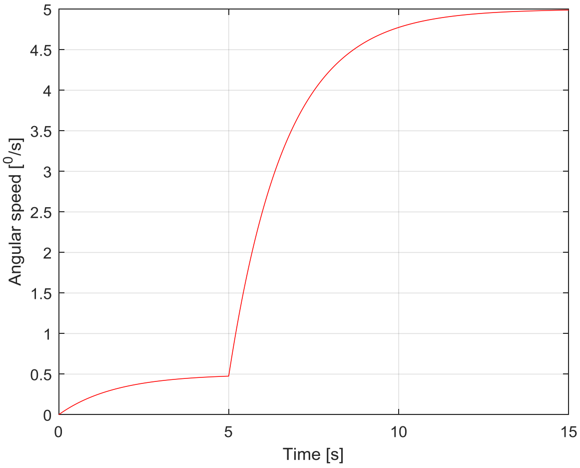

Fig. 4. Line of sight angle speed.

- Correlation matrix of process noise for parameter Φ:

$$Q_a = \begin{bmatrix} \tau^4/4 & \tau^3/2 & \tau^3/2 & \tau^2/2 \\ \tau^3/2 & \tau^2 & \tau^2 & \tau \\ \tau^3/2 & \tau^2 & \tau^2 & \tau \\ \tau^2/2 & \tau & \tau & 1 \end{bmatrix} \times \tau \times \sigma_a^2 \quad (43)$$

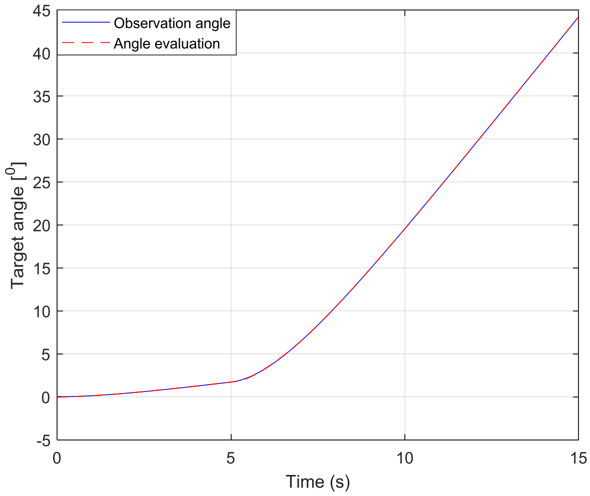

Fig. 5. Evaluation of angle coordinates $\hat{\varphi}_m$.

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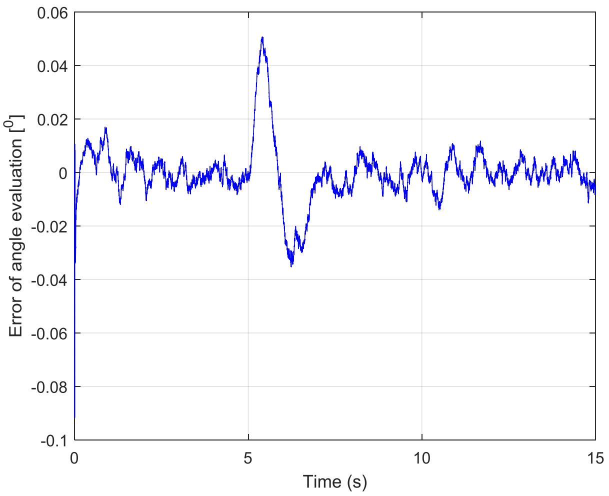

Fig. 6. Error of evaluation of angular coordinates.

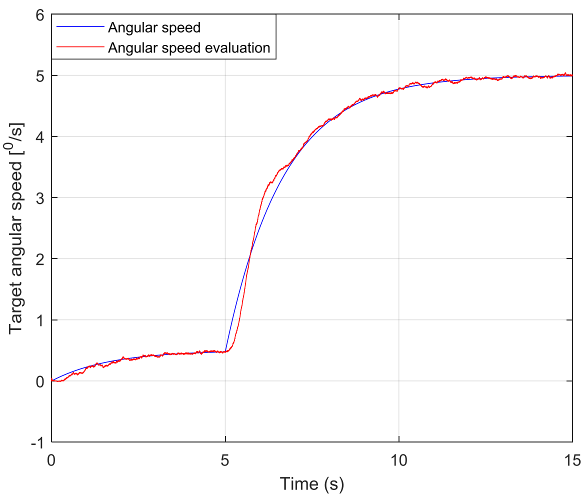

Fig. 7. Angular speed evaluation ω_m .

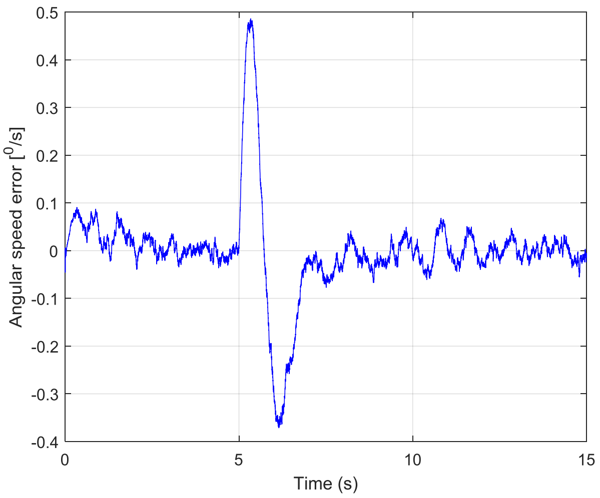

Fig. 8. Error of angular speed evaluation.

From the simulation results shown in figures 5, 6, 7 and 8, it is found that:

The error of evaluation of both angular coordinates and angular speed is small.

When the target starts to maneuvering, the state forecast matrix has not reached the desired value, so the error is larger, but this value is also very small ($|\Delta\varphi_m| < 0{,}04\ (^o)$, $|\Delta\omega_m| < 0{,}5\ (^o/s)$).

The state model parameter recognition adaptive algorithm significantly improves the evaluation accuracy compared to the conventional Kalman algorithm.

IV. Conclusion

The target angle coordinate determination system with maneuvering detection based on state model recognition has higher coordinate evaluation accuracy than the target angle coordinate determination system based on the optimal filtering algorithm in the case of a maneuvering target.

The target angle coordinate determination system has maneuvering detection based on state model recognition, accuracy is improved because it does not directly use the signal equilibrium direction as the target coordinate evaluation signal without use a separate line-of-sight angle coordinate evaluation filter; At the same time, the related states are evaluated by the Kalman filter algorithm in the tracking loop.

Because it is not possible to choose a target model suitable for all types of maneuvering, the optimal angle coordinate system with fixed parameters will have a large evaluation error, when in reality the maneuvering target is different from the model selected.

From the simulation results, can be seen that the system of determining the target angle coordinates based on the state model parameter recognition significantly reduces the tracking error when the target changes maneuvering form. Capable of adapting to target maneuvering when the evaluation process progresses to the most suitable model.

Adaptive filtering algorithm with maneuvering detection based on state model parameter recognition. Because the forecast matrix is continuously recognized, the state forecast will be more accurate. Because the algorithm does not increase the amplification factor, it does not increase the influence of observations noise to the state evaluation. Therefore, the state evaluation accuracy of the algorithm is advanced. However, because the state transition matrix adaptation does not use prior information about the different maneuverability of the target, the recognition accuracy for different maneuvering cases is different.

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