Target State Estimation Based on Kalman Filter in Terminal Guidance

Zhong-nan TANG, Yu-jie WANG*, Bing-jie ZHU and Zhong-xi HOU
College of Aerospace Science and Engineering, National University of Defense Technology
Changsha, China
*Corresponding author

Keywords: Terminal Guidance, Target Localization, LOS Rate Estimation, EKF.

Abstract. In order to settle the requirement of target location and line-of-sight (LOS) rate estimation with multi-angle measurement in terminal guidance process, the state estimation algorithm based on Kalman filter is proposed in this paper. The linearized system model is established, and the extended Kalman filter is used to estimate the position and LOS rate of the target. The simulation results show that this method exhibits high accuracy for position estimation, and it can precisely track the change of LOS angular rate in real time. The algorithm is simple in principle, easy to implement and of high value in practice.

Introduction

As a new type of unmanned aerial vehicle with high cost-efficiency, portability, and one-time damage or reuse[1], Small Unmanned Combat Aerial Vehicles (SUCAVs) have good complementarity with medium or large UAVs(Unmanned Aerial Vehicles)[2]. As a new type of unmanned aerial vehicle, SUCAV has many technical bottlenecks. One of the key technologies in terminal guidance is target state estimation, including target location and line-of-sight angular rate estimation.

Active positioning method based on attitude information/laser ranging positioning model has high positioning accuracy, which requires UAV to be equipped with laser rangefinder[3]. However, SUCAVs have strict control over load and cost, and usually only carry visible/infrared seekers to measure the angle information of the target[4], which brings some challenges to the terminal guidance application of SUCAVs. On the one hand, the optimal strike route cannot be planned in real time after the target is found, for that the distance information cannot be obtained directly. The application of some terminal guidance laws containing distance information in terminal guidance is also limited. On the other hand, infrared seeker cannot directly measure the angular rate information of line of sight[5] (LOS) needed by most classical guidance laws. It can only be obtained by processing the original measurement data with certain methods (such as differential processing, which will introduce a lot of noise and may even lead to divergence of guidance and control process.).

To meet the needs of the above two practical problems, in this paper, the classical Kalman filtering method is used to filter the original LOS angle information. The three-dimensional position estimation of the target is realized based on angle measurement once the target is locked, which provides a basis for the optimal attack route planning. In the process of target strike, the LOS angular rate is estimated accurately in real time, so that it can be used in the subsequent terminal guidance algorithm, and it can realize stable tracking of target and fast recapture after losing lock.

Target State Estimation Algorithm

Extended Kalman Filter

The Kalman filtering process consists of two parts: the state updating process and the covariance updating process [6].

The equation of state updating includes the following equations:
A priori estimation equation of state,
\[ \hat{X}(k+1|k) = F(k)\hat{X}(k|k) + G(k)u(k) \]  
A posteriori estimation equation of state,
\[ X(k+1|k+1) = F(k)\hat{X}(k+1|k) + K(k+1)v(k+1) \]  
\( v(k+1) \) is the difference between the measured values and the predicted-measured values.  
The covariance updating process mainly includes the following equations:  
A priori estimation equation of covariance,
\[ P(k+1|k) = F(k)P(k|k)F^T(k) + Q(k) \]  
Filtering gain,
\[ K(k+1|k) = P(k+1|k)H^T(k+1)S^{-1}(k+1) \]  
\( S(k+1) \) is the covariance of \( v(k+1) \).  
A posterior estimation equation of covariance,
\[ P(k+1|k+1) = P(k+1|k) - K(k+1)S(k+1)K^T(k+1) \]  
For linear systems, the state transition function of the system can be written directly as \( F(k)X(k) \), where \( F(k) \) is the state transition matrix of the system. Similarly, for linear measurement processes, the measurement function can be written as \( H(k)X(k) \), where \( H(k) \) is the measurement matrix.  
But in engineering practice, the state description and dynamic parameter measurement of many systems are non-linear. In order to deal with the problem of non-linear filtering, the linearization method is used to linearize the non-linear system and the non-linear measurement. Based on the classical Kalman filter, an extended Kalman filter (EKF) is developed\[7\]. The EKF method is based on Taylor series theory. It expands the Taylor series of the non-linear functions to obtain the first order terms.

After that, the system can be filtered by referring to the algorithm flow.

3-D Position Estimation

In the process of searching, tracking and identifying targets, the SUCAV moves along the preset route. The servo system of the airborne photoelectric platform keeps the seeker's line of sight pointing to the target all the time\[8\]. For a limited period of time, the relative position between the SUCAV and the target is changed because of the SUCAV's movement. As shown in Fig. 1, multiple sets of line of sight angle measurement data can be obtained.

Assuming that the coordinates of the ground stationary target \((x_t, y_t, z_t)\) are unknown and the coordinates of the SUCAV \((x_u, y_u, z_u)\) contain multiple sets of data in a limited time. In order to estimate the position of the target, select the state variable of the system as \( X(k) = [t_x, t_y, t_z] \), then the equation of state transition of the system is:
\[ X(k+1) = F(k)X(k) + V(k) \]  
where \( V(k) \) is additive zero-mean Gauss white noise with covariance \( Q(k) \).
Because the target is stationary, the state equation is linear and the state transition matrix is:

$$ F(k) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} $$

(7)

The measurement function includes the deflection of LOS and the inclination of LOS:

$$ h = \begin{bmatrix} h_\alpha \\ h_\beta \end{bmatrix} = \begin{bmatrix} \arctan\left(\frac{u_y-t_y}{u_x-t_x}\right) \\ \arctan\left(\frac{u_z-t_z}{\sqrt{(u_x-t_x)^2+(u_y-t_y)^2}}\right) \end{bmatrix} $$

(8)

It can be seen that the measurement function of the system is nonlinear. The first-order Taylor expansion of the measurement function is obtained as shown below:

$$ H_1 = \begin{bmatrix} \frac{\partial h_\alpha}{\partial t_x} & \frac{\partial h_\alpha}{\partial t_y} & \frac{\partial h_\alpha}{\partial t_z} \\ \frac{\partial h_\beta}{\partial t_x} & \frac{\partial h_\beta}{\partial t_y} & \frac{\partial h_\beta}{\partial t_z} \end{bmatrix} $$

(9)

Theoretically, this method can be free from terrain fluctuation as long as the target is always in the center of the seeker's field of view and the seeker can obtain the information of the LOS angle.

**LOS Rate Estimation**

For the estimation of LOS angle and angular rate, the LOS angle is regarded as a linear change of LOS rate in a finite time. The state variable of the system is $x = [\alpha \ \beta \ \dot{\alpha} \ \dot{\beta}]^T$, and the state transition matrix is as follows:

$$ F_2 = \begin{bmatrix} 1 & 0 & \Delta T & 0 \\ 0 & 1 & 0 & \Delta T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} $$

(10)

where $\Delta T$ represents the sampling time interval of measurement, since it is a direct measurement of line-of-sight angle information, the measurement function is:

$$ H_2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} $$

(11)
Simulation Results

Position Estimation Results

As shown in Fig. 2, $T$ is a stationary target and $U$ is the current position of SUCAV. The line of sight of SUCAV for a period of time is shown in the figure. The SUCAV is set to fly at a constant speed (30 m/s) in a circle with flying altitude of 100 m. The radius of curvature is 60m, centering at (400 m, 600 m, 100 m). The target position is set as (400 m, 600 m, 10 m).

![Figure 2. Positioning based on multi-angle measurements.](image)

The 3D position estimation result of the target based on extended Kalman filter is shown in Fig.3.

![Figure 3. Position estimation results based on Kalman filter.](image)

It shows that the estimated coordinates of each direction converge after about 30 times of calculation and are in good agreement with the true values. The positioning errors on North and East directions are within 5 m, and the height errors are within 2 m, which shows the effectiveness of the algorithms.

LOS Rate Estimation Results

Accurate estimation of LOS angle and angular rate during SUCAV downward strike can enable SUCAV to quickly recapture after losing its target.

Fig. 4 and Fig. 5 compare the angle measurement errors between the measurements of the analog seeker and the filtering values. It can be seen that the filtering algorithm converges faster and the measurement error decreases significantly after Kalman filtering.
In principle, infrared seeker usually acquires angular rate by differential processing the measured angle data in sampling time. The noise of the original angle measurement data is further magnified after the differential process, which would be up to the level of 50 deg/s. Therefore, the Kalman filter is used to estimate the LOS rate. As shown in Fig. 6 and Fig. 7, it can be observed that the convergence of the algorithm is faster, and the filtering result is better for tracking the actual angular rate.

Summary

Aiming at the application requirement of target location and LOS rate estimation in terminal guidance process of SUCAV, a target location method based on multi-angle observation is proposed in this paper. The extended Kalman filtering algorithm is used to estimate the three-dimensional coordinates of stationary target, as well as the LOS angle and LOS rate. The position estimation of the target is realized once the target is locked, and the LOS rate is estimated accurately in real time in the process of target strike. The algorithm is simple in principle, easy to implement and of high value in practice.

References

[1] Eid, B M, et al, Challenges of Integrating Unmanned Aerial Vehicles In Civil Application, IOP Conference Series: Materials Science and Engineering 53(2013).
[2] Cai, Guowei, Jorge Dias, and Lakmal Seneviratne, A survey of small-scale unmanned aerial vehicles: Recent advances and future development trends, Unmanned Systems 2.02 (2014): 175-199.
[3] Cheng, Z., and L. Zhang. An Aerial Image Mosaic Method Based on UAV Position and Attitude Information, Acta Geodaetica et Cartographica Sinica 45.6(2016):698-705.
[4] Yu, Yingrong, et al, Guidance information estimation of the semi-strapdown infrared imaging seeker, Chinese Control Conference IEEE, 2017.
[5] Sun, T., et al, Line-of-sight angular rate estimation of strapdown optical image seeker, Acta Optica Sinica 34.6(2014):0612010.
[6] You He, Radar Data Processing and Application, Electronic Industry Press, (2013) 10-34.
[7] Vatankhah, Ramin, F. Karami, and H. Salarieh. Observer-Based Vibration Control of Non-Classical Micro-Cantilevers Using Extended Kalman Filters, Applied Mathematical Modelling 39.19(2015).

[8] Yongliang, L. U., and F. Wenjun, Application of Pulse Width Modulation Amplifier SA03 in Speed Servo System on Unpiloted Airborne Platform, Aerospace Radar 29.4:51-54.