Fault Detection of UAV Fault Based on a SFUKF

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Abstract. The UAV system is a typical closed-loop control system. Its good robustness can inhibit the fault signal, which poses certain difficulties for the detection of early or small amplitude faults. In this paper, a nonlinear longitudinal control system model of a class of UAVs is established, and a fault detection method based on the suboptimal fading unscented Kalman filter (SFUKF) is designed. Aiming at the common failure of actuators and sensors of the drone, this paper proves that the method realizes the fault detection of the airspeed tube blockage and the elevator part failure by simulation.

1. Introduction
As technology advances and demand increases, drone systems become more complex. If an accident occurs, it will cause significant economic losses. Moreover, due to the special working environment of the drone, once the fault occurs, the crash may occur. Hence, the fault detection technology of the drone has great engineering value. Generally, UAVs are particularly prone to failures with sensors and actuators.

Liu Xiaodong et al. [1] proposed a method to generate residuals by expanding Kalman filter (EKF) for the failure of UAV airspeed tube and elevator, and designed the residual evaluation function and threshold to determine whether it is faulty. However, EKF needs to calculate the Jacobian matrix (sometimes it is difficult to solve), and the calculation accuracy is only first-order precision, meanwhile the error caused by its linearization even makes the filter diverge. The unscented Kalman filter (UKF), as a newer Kalman filter technique, outperforms EKF in this respect: it does not need to solve the Jacobian matrix, and the accuracy also achieves second-order accuracy. K. Xiong et al. [2] used UKF for fault diagnosis. Due to low robustness and poor tracking performance, this method can only detect the slow-varying-type fault signal, and the detection effect on the abrupt-type fault signal is not ideal.

Zhou Donghua et al. [3] proposed an extended Kalman filter with suboptimal fading factor, and introduced a suboptimal fading factor, which is used to weaken the influence of old data and improve the tracking performance of the filter. Chang Wen Zheng et al. [4] optimized the calculation steps of the suboptimal fading factor, and derived the equivalent formula of covariance and cross covariance to calculate the suboptimal fading factor. However, some equations lack the derivation source, and the result is debatable.

In this paper, the suboptimal fading factor and the unscented Kalman filter are combined to re-derive the equivalent of the suboptimal fading factor calculation, and a nonlinear longitudinal control system model of the UAV is established. The failure of the airspeed tube blockage and the partial failure of the elevator was simulated, and the new test method was verified.
2. Failure Model of UAV Nonlinear Longitudinal Control System

The UAV longitudinal control system consists of a height control channel and a speed control channel. The height channel controls the altitude and pitch attitude by controlling the elevator steering gear, which mainly includes an attitude control loop (inner loop) and a highly stable loop (outer loop). The speed control channel controls the speed by controlling the opening of the throttle. The control law is as follows:

\[
\begin{align*}
\delta_e &= K_p^H(K_p^H(H_r - H_m) + K_i^H\int(H_r - H_m)dt - K_d^H\dot{H} - \theta_m) - K_p^q q_w \\
\delta_p &= K_p^V(V_r - V_m) + K_i^V\int(V_r - V_m)dt
\end{align*}
\]

(2.1)

Where, \(\delta_e\) and \(\delta_p\) are the deflection amounts of the elevator and throttle stick; \(H_r\) and \(V_r\) are the command values of altitude and speed; \(H_m\), \(\theta_m\), \(q_m\) and \(V_m\) are the measured values of altitude, pitch angle, pitch angular velocity and airspeed; \(K_p^H\), \(K_i^H\) and \(K_p^q\) are the corresponding ratios, integrals, and differential coefficients.

The longitudinal motion of the drone under varying wind fields can be described by the following differential equation [5]:

\[
\begin{align*}
\dot{V} &= \frac{1}{m}(P\cos\phi_p - D - mg\sin(\theta - \alpha)) - \dot{w}_x\cos(\theta - \alpha) - \dot{w}_y\sin(\theta - \alpha) \\
\dot{\alpha} &= \frac{1}{mV}(-L + P\sin\phi_p + mg\cos(\theta - \alpha)) + q - \dot{w}_x\frac{\sin(\theta - \alpha)}{V} + \dot{w}_y\frac{\cos(\theta - \alpha)}{V} \\
\dot{q} &= \frac{M_y}{I_y} \\
\dot{\theta} &= q \\
\dot{H} &= V\sin(\theta - \alpha) + w_y
\end{align*}
\]

(2.2)

Where, \(m\) is the mass of the body; \(g\) is the acceleration of gravity; \(V\) is the speed of vacuum; \(\alpha\) is the angle of attack; \(P\), \(D\) and \(L\) are engine thrust, air resistance and lift, respectively; \(M_y\) is the pitching moment; \(\phi_p\) is the engine mounting angle; \(I_y\) is the moment of inertia along the y-axis of the body coordinate system; \(w_x\) and \(w_y\) are the horizontal wind speed and the vertical wind speed; \(\dot{w}_x\) and \(\dot{w}_y\) are the rate of change of the horizontal wind speed and the vertical wind speed.

By the formula of [6], we can get the following expression:

\[
\begin{align*}
\dot{X}(t) &= F(X(t)) + B(X(t))u(t) + G(X(t))d(t) + B_f(t)f_1(t) + w(t) \\
\dot{y}(t) &= X(t) + D_f(t)f_2(t) + v(t)
\end{align*}
\]

(2.3)

Where,
\[
X(t) = \begin{bmatrix} V \\ \alpha \\ q \\ \theta \\ H \end{bmatrix}, 
F(X(t)) = \begin{bmatrix}
0 & \frac{K}{m} & -\frac{\rho V^2 S_w c_\delta}{2m} & 0 & -\rho V^2 S_w \left(C_{d0} + \epsilon (C_{l0} + C_{l_o} \alpha) \right) - g \sin(\theta - \alpha) \\
-\frac{\rho V^2 S_w c_\delta}{2m} & 0 & -\frac{\rho V^2 S_w \bar{c}_\delta}{2I_y} & 0 & \frac{1}{mV} \left(\frac{\rho V^2 S_w}{2} (C_{l_0} + C_{l_o} \alpha) + mg \cos(\theta - \alpha) + q \right) \\
0 & 0 & 0 & 0 & \frac{\rho V^2 S_w \bar{c}_\delta}{2I_y} (C_{a_r} + C_{a_r} \alpha + C_{a_r} \delta_e + \frac{cdq}{2V} C_{aq}) \\
0 & 0 & 0 & 0 & V \sin(\theta - \alpha)
\end{bmatrix}, 
\]

\[
B(X(t)) = \begin{bmatrix}
0 & 0 \\
\rho V S_w c_\delta & 0 \\
\rho V^2 S_w \bar{c}_\delta & 0 \\
0 & 0 \\
0 & 0
\end{bmatrix}, 
u(t) = \begin{bmatrix} \delta_e \\ \delta_p \end{bmatrix}, 
G(X(t)) = \begin{bmatrix}
-\cos(\theta - \alpha) & -\sin(\theta - \alpha) & 0 \\
-\sin(\theta - \alpha) & \cos(\theta - \alpha) & 0 \\
0 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & 1
\end{bmatrix}, 
\]

\[
d(t) = \begin{bmatrix} \dot{w}_x \\ \dot{w}_y \end{bmatrix}.
\]

\(X(t)\) is the input; \(y(t)\) is the output; \(d(t)\) is the interference; \(w(t)\) and \(v(t)\) are the process noise and the measurement noise; \(f_1(t)\) and \(f_2(t)\) are fault signals; \(\rho\) is the air density; \(S_w\) is the wing area; \(\bar{c}\) is the average aerodynamic chord length; \(C_{d0}\) is zero rise resistance coefficient; \(C_{a_r}\) is zero rising pitching moment coefficient; \(C_{l_0}\) is the lift when the angle of attack is 0; \(C_{l_o}\) and \(C_{a_r}\) are the partial derivatives of the lift coefficient and the pitching moment coefficient for each item (\(\alpha\) \(q\) \(\delta_e\)); \(K\) is a proportionality coefficient proportional element of the engine; \(\epsilon\) is downwash angle.

The SFUKF filter designed in this paper needs to discretize the system as well as the general UKF method, and the method estimate and predict the system state through the discretized model. So we also need to discretize the system. Here we use the Euler discrete method to get the system under no-fault conditions. The model is shown as follow:

\[
\begin{cases}
X(k+1) = X(k) + TF(X(k)) + TB(X(k))u(k) + TG(X(k))d(k) + Tw(k) \\
y(k) = X(k) + v(k)
\end{cases}
\]

(2.4)

Where, \(T\) is a discrete period.

### 3. Unscented Transformation (UT)

The unscented transform is a method of calculating the statistic of a random variable after nonlinear transformation. The method which based on the initial mean and covariance of the state variables, selects discrete sample points, ie sigma points. Then each sample is subjected to nonlinear transformation, and the estimated values of the original nonlinear transformation are calculated by the transformation results of these samples.

It is known that the mean value of the dimensional random variable is \(\bar{x}\), the variance is \(P\), and \(y\) is a nonlinear mapping of \(x\), which satisfies the nonlinear function \(y = f(x,u)\).

The sigma points based on the mean and variance of the state variables are selected.
\begin{equation}
\begin{cases}
X_0 = \bar{x} \\
X_i = \bar{x} + \Delta X_i & i = 1, \cdots, 2M
\end{cases}
\end{equation}

Where, 
\begin{align*}
\Delta X_i = (\sqrt{cP_x})_i & i = 1, \cdots, M \\
\Delta X_{M+i} = -(\sqrt{cP_x})_i & i = 1, \cdots, M
\end{align*}

in which \((\sqrt{cP_x})_i\) represents the \(i\) column of matrix \(\sqrt{cP_x}\), \(c = \alpha^2(M + \kappa)\). \(\alpha\) determines the degree of dispersion of the sigma point around the state mean, the smaller the value, the closer the sigma point is to the mean value, so \(\alpha\) usually takes a small positive value; \(\kappa\) is also a parameter indicating the degree of sigma dot spread, and the degree of dispersion is proportional to its square, and is generally taken as 0.

The mapping of each sigma point is \(\gamma_i = f(X_i) \quad i = 0, \cdots, 2M\).

The mean\((\bar{y})\), covariance variance\((P_y)\), and cross covariance\((P_{xy})\) of \(y\) can be approximated as follows:
\begin{align*}
\bar{y} & \approx \sum_{i=0}^{2M} W_i^m \gamma_i \\
P_y & \approx \sum_{i=0}^{2M} W_i^c (\gamma_i - \bar{y})(\gamma_i - \bar{y})' \\
P_{xy} & \approx \sum_{i=0}^{2M} W_i^c (X_i - \bar{x})(\gamma_i - \bar{y})'
\end{align*}

Where, \(W_i^m\) and \(W_i^c\) are the weighting coefficients of the first-order statistical properties and the weighting coefficients of the second-order statistical properties, respectively. The calculation method is as follows:
\begin{equation}
\begin{cases}
W_0^m = 1 - \frac{M}{\alpha^2(M + \kappa)} \\
W_i^m = \frac{1}{2\alpha^2(M + \kappa)} & i = 1, \cdots, 2M \\
W_0^c = (2 - \alpha^2 + \beta) - \frac{M}{\alpha^2(M + \kappa)} \\
W_i^c = \frac{1}{2\alpha^2(M + \kappa)} & i = 1, \cdots, 2M
\end{cases}
\end{equation}

Where, \(\beta\) is characterization of the state distribution that is used to adjust weights of transformed sigma points, specified as a scalar value greater than or equal to 0. For Gaussian distributions, \(\beta=2\) is an optimal choice.

4. Strong Tracking Filtering Method

Although the traditional unscented Kalman filter shows good adaptability to nonlinear problems, its robustness is poor. When there is a sudden change, the traditional UKF is difficult to track. Because as the system becomes stable, the Kalman gain \(K_{k+1}\) tends to zero. If the system suddenly changes at this time, although the residual\((y_{k+1} - \hat{y}_{k+1})\) of the measured and estimated values of the output continue to
become large, the change of $K_{k+1}(y_{k+1} - \hat{y}_{k+1})$ is small, and the state estimate $\hat{x}_{k+1|k+1}$ of the next step is almost unchanged.

The strong tracking filtering method introduces a time-varying fading factor $\lambda$, which is used to weaken the influence of old data on the current filtered value, and adaptively adjust the state prediction covariance. Details as follows:

$$\lambda_{k+1} = \begin{cases} \lambda_y, & \lambda_y > 1 \\ 1, & \lambda_y \leq 1 \end{cases}$$

$$\lambda_y = \frac{tr(N_{k+1})}{tr(M_{k+1})}$$  \hspace{1cm} (4.1)

Where,

$$N_{k+1} = V_{k+1} - \sigma R(k) - H_{k+1}^*Q(k)H_{k+1}^*'$$

$$M_{k+1} = H_{k+1}^*P_{k+1|k}H_{k+1}^* + V_{k+1}$$

$$V_{k+1} = \begin{cases} \epsilon_e^T, & k = 0 \\ \rho V_k + \epsilon_{k+1}^T, & k \geq 1 \end{cases}$$

Here, $\rho$ is a forgetting factor, used to weaken the impact of old data, generally 0.95; $\sigma$ is a weakening factor, used to make the state estimate smoother.

$H_{k+1}$ can be expressed as the equivalent of the output prediction covariance $P_y$ and the cross covariance $P_{xy}$:

$$P_y = E[(y_{k+1} - \hat{y}_{k+1|k})(y_{k+1} - \hat{y}_{k+1|k})']$$

$$= E_h[(x_{k+1} - \hat{x}_{k+1|k})(x_{k+1} - \hat{x}_{k+1|k})'] + R(k)$$

$$= H_{k+1}E_h([x_{k+1} - \hat{x}_{k+1|k}](x_{k+1} - \hat{x}_{k+1|k})')H_{k+1}^* + R(k)$$

$$= H_{k+1}P_{k+1|k}H_{k+1}^* + R(k)$$

$$P_{xy} = E[(x_{k+1} - \hat{x}_{k+1|k})(y_{k+1} - \hat{y}_{k+1|k})']$$

$$= E_h([(x_{k+1} - \hat{x}_{k+1|k}][H_{k+1}(x_{k+1} - \hat{x}_{k+1|k})'])'$$

$$= E_h([(x_{k+1} - \hat{x}_{k+1|k})(x_{k+1} - \hat{x}_{k+1|k})']H_{k+1}^*$$

$$= P_{k+1|k}H_{k+1}^*$$

So we can get $H_{k+1} = P_{xy}^{-1}P_y^{-1}$, and further,

$$N_{k+1} = V_{k+1} - \sigma R(k) - P_{xy}^{-1}P_{k+1|k}Q(k)P_{k+1|k}^{-1}P_{xy}$$  \hspace{1cm} (4.2)

$$M_{k+1} = P_y - R(k)$$  \hspace{1cm} (4.3)

### 5. Suboptimal Fading Unscented Kalman Filter

The first step is to initialize the estimated state value $\hat{x}_{0|0}$ and covariance matrix $P_{0|0}$.

The second step is to predict the status:

The Sigma points is selected from the estimated state value $\hat{x}_{k|k}$ through (3.1), and the state $\hat{x}_{k+1|k}$ and state covariance $P_{k+1|k}$ at the time of $k+1$ are predicted.
\[ \hat{x}_{k+1|k} = f(\hat{x}_{k|k}, u_k) \quad i = 1, \ldots, 2M \]

\[ \hat{x}_{k+1|k} = \sum_{i=0}^{2M} W_i^m \hat{x}_{k+1|k} \]

\[ P_{k+1|k} = \sum_{i=0}^{2M} W_i^c [\hat{x}_{k+1|k} - \hat{x}_{k+1|k}][\hat{x}_{k+1|k} - \hat{x}_{k+1|k}]^T + Q(k) \]

Where,

\[ W_0^m = 1 - \frac{M}{\alpha^2 (M + \kappa)} \]

\[ W_i^m = \frac{1}{2\alpha^2 (M + \kappa)} \quad i = 1, \ldots, 2M \]

\[ P_{k+1|k} = \sum_{i=0}^{2M} W_i^c [\hat{x}_{k+1|k} - \hat{x}_{k+1|k}][\hat{x}_{k+1|k} - \hat{x}_{k+1|k}]^T + Q(k) \]

\[ W_0^c = (2 - \alpha^2 + \beta) - \frac{M}{\alpha^2 (M + \kappa)} \]

\[ W_i^c = \frac{1}{2\alpha^2 (M + \kappa)} \quad i = 1, \ldots, 2M \]

The third step is to update state estimation and covariance by measurement:

A sigma point is taken for \( \hat{x}_{k+1|k} \). Then, the output is evaluated value by measuring function.

\[ \hat{y}_{k+1} = \sum_{i=0}^{2M} W_i^m \hat{y}_{k+1|k} \]

\[ W_0^m = 1 - \frac{M}{\alpha^2 (M + \kappa)} \]

\[ W_i^m = \frac{1}{2\alpha^2 (M + \kappa)} \quad i = 1, \ldots, 2M \]

\[ P_y = \sum_{i=0}^{2M} W_i^c [\hat{y}_{k+1|k} - \hat{y}_{k+1|k}][\hat{y}_{k+1|k} - \hat{y}_{k+1}^c] + R(k) \]

\[ W_0^c = (2 - \alpha^2 + \beta) - \frac{M}{\alpha^2 (M + \kappa)} \]

\[ W_i^c = \frac{1}{2\alpha^2 (M + \kappa)} \quad i = 1, \ldots, 2M \]

\[ P_{yy} = \frac{1}{2\alpha^2 (M + \kappa)} \sum_{i=1}^{2M} [\hat{x}_{k+1|k} - \hat{x}_{k+1|k}][\hat{y}_{k+1|k} - \hat{y}_{k+1}]^T \]

Here, \( i \) starts from 1 because \( \hat{x}_{k+1|k} - \hat{x}_{k+1|k} = 0 \).

The output residual is \( e_{k+1} = y_{k+1} - \hat{y}_{k+1} \).

The suboptimal fading factor \( \lambda_{k+1} \) is calculated through (4.1), then state estimation and covariance are updated.
The fourth step, we order $k=k+1$, then go to the second step and continues to repeat the calculation.

6. Fault Diagnosis Method

This method supposes the modeling error is $\psi$, the actual measurement function is $h(x,u)$, and its model is $\bar{h}(x,u)$.

$$
\psi_k = h(x_k,u_k) - \bar{h}(x_k,u_k)
$$

$$
y_k = \bar{h}(x_k,u_k) + \psi_k + v_k
$$

Then the residual of the predicted and actual values of the output is

$$
\varepsilon_k = y_k - \hat{y}_k
$$

$$
= \bar{h}(x_k,u_k) + \psi_k + v_k - \bar{h}(\hat{x}_k,u_k)
$$

$$
= \psi_k + v_k + \phi_k
$$

Where, $\phi_k = \bar{h}(x_k,u_k) - \bar{h}(\hat{x}_k,u_k)$ is the estimated residual.

Using the residual generated by SFUKF, we can calculate the cumulative sum of the residuals of $m$ to determine whether or not the fault is present:

$$
D_m = \frac{1}{\sqrt{m}} \sum_{i=1}^{m} \varepsilon_k
$$

$$
= \frac{1}{\sqrt{m}} \sum_{i=1}^{m} \psi_k + \frac{1}{\sqrt{m}} \sum_{i=1}^{m} v_k + \frac{1}{\sqrt{m}} \sum_{i=1}^{m} \phi_k
$$

As long as the model is accurate enough, $\psi_k$ is almost 0, so $D_m$ is approximated as follows:

$$
D_m = \frac{1}{\sqrt{m}} \sum_{i=1}^{m} v_k + \frac{1}{\sqrt{m}} \sum_{i=1}^{m} \phi_k
$$

When there are only sensor failures, the residual is:

$$
\varepsilon_k = y_k + b_f - \hat{y}_k
$$

$$
= \psi_k + v_k + \phi_k + b_f
$$

As long as the filter is valid, $\lim_{k \to \infty} \phi_k = 0$; At the same time, the noise is white noise, that is $\lim_{k \to \infty} v_k = 0$. In the presence of a sensor failure, $D_m = \frac{1}{\sqrt{m}} \sum_{i=1}^{m} v_k + \frac{1}{\sqrt{m}} \sum_{i=1}^{m} \phi_k + \frac{1}{\sqrt{m}} \sum_{i=1}^{m} b_f$ will change from a normal 0-average unbiased distribution to a non-zero mean distribution.

When there is only an actuator failure, the state function is changed due to a change in the process function of the actual system, which results in $\lim_{k \to \infty} \phi_k \neq 0$.

So, $D_m = \frac{1}{\sqrt{m}} \sum_{i=1}^{m} v_k + \frac{1}{\sqrt{m}} \sum_{i=1}^{m} \phi_k + \frac{1}{\sqrt{m}} \sum_{i=1}^{m} b_f$, $\phi_k$ is the estimated residual in the case of a fault. Obviously $D_m$ becomes a zero-mean distribution.
7. Simulation
In this paper, the overall parameters, aerodynamics and engine data of a certain type of UAV are used. The PID controller is designed according to the control law shown in the formula, and the fault detection simulation platform is established through Matlab.

We set the simulation time to 40s, the sampling period to 0.02s, and the evaluation function's moving time window to be 10; Initial state is $X_0 = [25 \ 0 \ 0 \ 0 \ 1000]$; Process noise and Measurement noise are $R(k) = Q(k) = \text{diag} \{0.01 \ 0.0001 \ 0.0001 \ 0.0001 \ 0.01\}$.

7.1. Airspeed tube blockage
This failure is very typical. Many air crashes, including the crash of the 6.1 Air France passenger plane, were caused by airspeed tube icing and other reasons, which eventually caused a tragedy. The air-speed pipe is generally blocked by the total pressure hole. The blockage will result in a constant total pressure in the capsule, which will cause the measured dynamic pressure and airspeed to be fixed when the height is constant or slightly changed, and cannot reflect the real state. In the case of a blockage of the airspeed tube, let $B_j(k) = 0$; $D_j(k) = I$; $f(k) = [V_f - V \ 0 \ 0 \ 0 \ 0]$‘ ($V_f$ is the speed of the faulty airspeed tube solution). The fault is injected at 20s, and the residual and evaluation function images are shown as follows:

![Figure 1. Residual(e) with airspeed tube blocked.](image)

![Figure 2. Cumulative residual(Dm) with airspeed tube blocked.](image)

Figure 1. Residual(e) with airspeed tube blocked. (a),(b),(c),(d) and (e) are the residuals of $V$, $\alpha$, $q$, $\theta$ and $H$ respectively.

Figure 2. Cumulative residual(Dm) with airspeed tube blocked. (a),(b),(c),(d) and (e) are the cumulative residuals of $V$, $\alpha$, $q$, $\theta$ and $H$ respectively.
As we can see in Figure 1, when the failure starts, only the airspeed residual is obvious, but it is still difficult to distinguish it from the normal situation. In Figure 2, at 20 seconds, $Dm$ has undergone a clearly distinguishable change.

7.2. Elevator Partial Failure

In the event of partial failure of the elevator, when the system is running for 20s and the failure of the elevator is injected by 10%, $B_f(k) = B_f(X(k))$, $D_f(k) = 0$, $f_i(k) = [-10\% \delta_e, 0]$. The obtained residual and evaluation function images are shown as follows:

![Figure 3. Residual(e) with partial failure of the elevator.](image)

![Figure 4. Cumulative residual(Dm) with partial failure of the elevator.](image)

It can be seen from Fig. 3 that it is difficult to distinguish faults by residuals. From the cumulative residual of Figure 4, the fault situation is obvious.

8. Conclusion

In this paper, the fault diagnosis method based on SFUKF is applied to the fault detection of the closed-loop nonlinear longitudinal control system of the UAV. The simulation experiment proves that the method used in this paper has good detection ability for actuator failure and sensor failure represented by airspeed tube blockage and partial failure of the servo. The method can realize the fault detection of the drone flight control system quickly and effectively, which provides reliable guarantee for flight safety of drones.
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