Application of Improved Adaptive UKF Algorithm on Aircraft Attitude Estimation System

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Abstract: For the problem of aircraft attitude estimation system, Unscented Kalman Filter (UKF) algorithm is easy to be disturbed. Therefore, an improved adaptive UKF algorithm which can overcome disturbance well by introducing adaptive factors to adjust the state gain matrix is proposed in this paper. The simulation results show the effectiveness of the proposed algorithm.

Introduction

Aircraft attitude estimation system is an important part of aircraft attitude control system, which directly affects the accuracy of aircraft attitude control system. Aircraft attitude estimation system commonly uses filtering method to optimally estimate aircraft's attitude from the perspective of probability and statistics. Because the structure of aircraft attitude estimate on system is nonlinear, therefore it need to use nonlinear filtering method to get the optimal estimation of system's state variables.

As one of the earliest proposed nonlinear filtering methods, EKF method is widely used in engineering[1], but a first order approximate processing of the nonlinear equation, its drawback is ignorance of the higher-order terms, and bringing a rounding deviation, it may cause instability on EKF when system is strongly nonlinear, in addition EKF is very complex and time-consuming when calculates the Jacobian matrix[2]. In order to solve the above problems, Julier et al proposed a new nonlinear filtering method ——UKF, which can estimate more accurate than EKF by using the mean and variance of approximate nonlinear function. But UKF has strict requirements on the prior noise distribution of system, its good performance is based on the exact distribution of known noise, it can not adapt to the changing circumstances when the state system and measurement system are disturbed[3]. The actual operation environment of aircraft is complex, the state system and measurement system are often subject to unknown disturbances, it would make a decline in the estimation performance of UKF. For this problem, Zhou Donghua et al put forward strong tracking filter (STF), STF has good uncertainty and robustness on model and strong tracking capability on mutation status[4]. Reference[5] combining STF with UKF had successfully applied to astronomical autonomous navigation, and improves reliability of system. However, these two methods are similar with EKF, they all have the first order approximate processing of the nonlinear system, there are still some shortcomings such as calculating the Jacobian matrix of nonlinear function, which limits the application of this method.

For the above problems, this paper presents an improved strong tracking UKF algorithm which had been applied to aircraft attitude estimation system for simulation.

Improved adaptive UKF algorithm

Aircraft attitude determination system is discreted with 4-order Runge-Kutta method, we obtain the following nonlinear discrete system:

$$\begin{cases} \boldsymbol{x}_{k+1} = \boldsymbol{f}(\boldsymbol{x}_k, \boldsymbol{u}_k) + \boldsymbol{w}_k \\ \boldsymbol{z}_k = \boldsymbol{h}(\boldsymbol{x}_k) + \boldsymbol{v}_k \end{cases} \tag{1}$$

In Eq.1, x_k is the system state vector, $\boldsymbol{u}_k$ is the control input vector, z_k is the measurement vector, $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ are respectively Gaussian white noise of the state system and Gaussian white noise of measurement system, and their covariance are respectively $\boldsymbol{Q}_k$ and $\boldsymbol{R}_k$.

UKF algorithm for the aircraft attitude determination system described above is as follows:

1) Initialization

$$\hat{\boldsymbol{x}}_0 = \mathrm{E}[\boldsymbol{x}_0] \tag{2}$$

$$\boldsymbol{P}_0 = \mathrm{E}[(\boldsymbol{x}_0 - \hat{\boldsymbol{x}}_0)(\boldsymbol{x}_0 - \hat{\boldsymbol{x}}_0)^T] \tag{3}$$

2) Calculation of sigma point

$$\boldsymbol{\xi}_k = [\hat{\boldsymbol{x}}_k \quad \hat{\boldsymbol{x}}_k + \sqrt{(n+\lambda)(\boldsymbol{P}_k)_i} \quad \hat{\boldsymbol{x}}_k - \sqrt{(n+\lambda)(\boldsymbol{P}_k)_i}] \tag{4}$$

3) Time update

$$\boldsymbol{\xi}_{k+1|k} = \boldsymbol{f}(\boldsymbol{\xi}_k, \boldsymbol{u}_k) \tag{5}$$

$$\hat{\boldsymbol{x}}_{k+1|k} = \sum_{i=0}^{2n} W_i^m \boldsymbol{\xi}_{k+1|k,i} \tag{6}$$

$$\boldsymbol{P}_{k+1|k} = \sum_{i=0}^{2n+1} W_i^c (\boldsymbol{\xi}_{i,k+1|k} - \hat{\boldsymbol{x}}_{k+1|k})(\boldsymbol{\xi}_{i,k+1|k} - \hat{\boldsymbol{x}}_{k+1|k})^T + \boldsymbol{Q}_{k+1} \tag{7}$$

4）Calculation of residual factor $\boldsymbol{\gamma}_k$ and adaptive factor $\boldsymbol{\lambda}_k$

$$\boldsymbol{\chi}_{i,k+1|k} = \boldsymbol{h}(\boldsymbol{\xi}_{i,k+1|k}) \tag{8}$$

$$\hat{\boldsymbol{z}}_{k+1|k} = \sum_{i=0}^{2n} W_i^m \boldsymbol{\chi}_{i,k+1|k} \tag{9}$$

$$\boldsymbol{\gamma}_k = \boldsymbol{z}_{k+1} - \hat{\boldsymbol{z}}_{k+1|k} \tag{10}$$

$$\boldsymbol{\lambda}_{k,i} = \begin{cases} 1, \boldsymbol{\lambda}_{k,i} \le 1 \\ \boldsymbol{\lambda}_{k,i}, \boldsymbol{\lambda}_{k,i} \ge 1 i = 1,2,3,\cdots,n \end{cases} \tag{11}$$

$$\boldsymbol{\lambda}_{k,i} = \sqrt{\frac{\boldsymbol{N}_{k,ii}}{\boldsymbol{M}_{k,ii}}}, \tag{12}$$

$$\boldsymbol{N}_k = \boldsymbol{V}_k - l\boldsymbol{R}_k \tag{13}$$

$$M_k = W_i^c (\boldsymbol{\chi}_{i,k+1|k} - \hat{\boldsymbol{z}}_{k+1|k})(\boldsymbol{\chi}_{i,k+1|k} - \hat{\boldsymbol{z}}_{k+1|k})^T \tag{14}$$

$$V_{k+1} = \begin{cases} \boldsymbol{\gamma}_k \boldsymbol{\gamma}_k^T \\ \dfrac{\rho V_k + \boldsymbol{\gamma}_k \boldsymbol{\gamma}_k^T}{1+\rho} \end{cases} \tag{15}$$

In Eq.13 and Eq.15, l and ρ are adjustment coefficients, less than 1.

5) Measurement update

$$\boldsymbol{P}_{xz,k+1} = \sum_{i-0}^{2n+1} W_i^c (\boldsymbol{\xi}_{i,k+1|k} - \hat{\boldsymbol{x}}_{k+1|k})(\boldsymbol{\chi}_{i,k+1|k} - \hat{\boldsymbol{z}}_{k+1|k})^T \tag{16}$$

$$\boldsymbol{P}_{z,k+1} = \sum_{i-0}^{2n+1} W_i^c (\boldsymbol{\chi}_{i,k+1|k} - \hat{\boldsymbol{z}}_{k+1|k})(\boldsymbol{\chi}_{i,k+1|k} - \hat{\boldsymbol{z}}_{k+1|k})^T + \boldsymbol{R} \tag{17}$$

$$\boldsymbol{K}_k = \boldsymbol{P}_{xz,k+1} \boldsymbol{\lambda}_k \boldsymbol{P}_{z,k+1}^{-1} \boldsymbol{\lambda}_k^T \tag{18}$$

$$\hat{\boldsymbol{x}}_{k+1|k+1} = \hat{\boldsymbol{x}}_{k+1|k} + \boldsymbol{K}(\boldsymbol{z}_{k+1} - \hat{\boldsymbol{z}}_{k+1|k}) \tag{19}$$

$$\boldsymbol{P}_{k+1} = \boldsymbol{P}_{k+1|k} - \boldsymbol{K}_{k+1} \boldsymbol{P}_{z,k+1} \boldsymbol{K}_{k+1}^T \tag{20}$$

Weights and parameters used in the above calculation process are as follows:

$$W_0^m = \frac{\lambda}{n+\lambda} \tag{21}$$

$$W_0^c = W_0^m + (1 - \alpha^2 + \beta) \tag{22}$$

In Eq.21 and Eq.22, $\lambda = \alpha^2(n+\kappa) - n$ is a composite scale parameter; α is a scaling factor that regulates the distribution of distance between the particles, the general value is 0.001 ~ 1; β is an adjustable parameter, the general value is 2; κ is a scale parameter, and general value is $\kappa = 3 - n$.

Reference[4]gives proof of this algorithm .The improvement done in this paper is mainly aimed at the calculation of adaptive factor matrix and the covariance matrix introduced by the adaptive factor matrix. This algorithm can ensure the adjustment of each channel by introducing two multiple adaptive fading factors, and also can guarantee the positive definiteness of the covariance matrix. It can improve the stability of the algorithm.

Simulation Results

In order to show the anti-interference ability of the algorithm proposed in this paper, the simulation introduces state mutation $\Delta x = [0 \quad 0 \quad 0 \quad 0.1 \quad 0.1 \quad 0.1]^T$ at 150s, and changes the statistical characteristics of the noise by expanding 100 times. Simulation results are shown in Fig.1 and Fig.2.

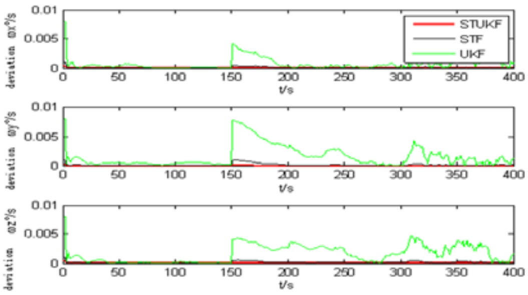

Fig.1 Aircraft three-axis attitude angular velocity estimation deviation curve

From Fig.1 and Fig.2, we can see that the estimation accuracy of the three methods are almost the same when the statistical characteristics of the system noise are accurate and the state does not exist mutation, and when the interference caused by state mutation is introduced into the system or the statistical characteristics of the system noise are inaccurate, the algorithm proposed in this paper which almost isn't influenced by the interference and inaccurate statistical characteristics of noise has the best tracking ability, followed by the STF algorithm, the worst is the UKF algorithm which has great fluctuation. This is because the adaptive factor that is introduced in STUKF and STF algorithm can adjust state gain matrix in real time, so as to track the state of the system better.

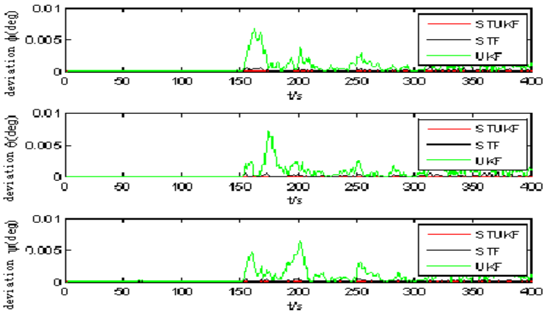

Fig.2 Aircraft three-axis attitude angle deviation curve

Conclusions

For the circumstances that aircraft attitude estimation system is affected by interference and exists inaccurate statistical characteristic of noise, and UKF exists the defect of low precision, This paper proposes an improved adaptive UKF algorithm which can adjust the state gain matrix in real time by introducing two multiple adaptive fading factors, thus can overcome the outside interference and inaccurate statistic characteristics of noise better. The simulation results show the effectiveness of the proposed algorithm.

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