Disturbance Rejection Attitude Controller Design for Launch Vehicle based on Orthogonal Function Neural Network

Wang Pei1,2, Lv Mei Bo1,2, Ge Zhi Lei1,2, Zhang Zi Qi1

1 College of Astronautics, Northwestern Polytechnical University, Xi’an 710072China
2 National Key Laboratory of Aerospace Flight Dynamics, Northwestern Polytechnical University, Xi’an 710072 China

E-mail: jimmy5579@163.com

Abstract. A disturbance rejection attitude controller of launch vehicle based on chebyshev orthogonal function (COF) neural network and proportional-differential (PD) control is proposed to attenuate effect of parameter variation and disturbances of launch vehicle on attitude control accuracy and stability. The chebyshev orthogonal function (COF) neural network is used to estimate and compensate impact of parametric uncertainties and disturbances by taking full advantage of information of gyros and attitude sensors. The designed controller applies proportional-differential control to realize attitude control. Simulation results show that the controller exhibits good dynamic performance, high ability and strong robustness against external disturbance and parameter uncertainty.

1. Introduction

The structure of launch vehicle is more and more complex, launch vehicle has become a highly complex nonlinear system and its attributes are aerodynamically unstable. Meantime the mass properties and aerodynamic parameters vary substantially throughout the flight regime that makes a challenging task to design its control systems, so numerous nonlinear control methods have been used to design the attitude control system of launch vehicle.

$H_\infty$ synthesis has been providing efficient scheduled controllers for launcher vehicle in atmospheric ascent [1]. But depending on the augmented model, the controller order is commonly very high and has to be reduced before implementation. Nonlinear Dynamic Inversion (NDI) control law is formulated to eliminate system’s nonlinearities by means of feedback. To make the NDI robust against model uncertainties and unknown but bounded external disturbances, dynamic constraint is defined and an additional Sliding Mode Control based loop is augmented [2]. Due to the ground test limitation and the complexity of hypersonic aerodynamics, the aerodynamics coefficients of Reusable Launch Vehicle may have large uncertainty. Thus an in-flight parameter identification method for lateral control departure parameter is proposed utilizing the retrospective cost optimization and an adaptive controller is applied to control the lateral motion of launch vehicle. But the real-time character is not discussed [3]. By design the extended state observer to compensate model disturbances and uncertainty, active disturbance rejection control (ADRC) is well suited for design launch vehicle attitude control system and obtains good control effect [4]. How to tuning parameters quickly and effectively has become a very important issue of the application of ADRC.

Considering the internal and external interference and parameters uncertainties imposed on launch vehicle attitude dynamic model, a disturbance rejection controller was proposed for launch vehicle attitude control. This new controller scheme contains two components, which were based on PD control
and COF neural network respectively. Simulation results show that the proposed controller is effective and robust in launch vehicle attitude control.

2. Attitude dynamic model of launch vehicle

Given the symmetry properties of launch vehicle, the longitudinal motion is adopted in subsequent sections. The longitudinal model is represented by three parts, including rigid body model, flexible body model and attitude information detect model [5].

The rigid body model of launch vehicle is expressed as

$$\Delta \dot{\theta} = c_i \Delta \alpha + c_2 \Delta \theta + c_3 \dot{\delta}_x + c_{30} \hat{\theta} + \sum \left( c_i \dot{q}_i + c_j q_j \right) + c_{30} \alpha_e - \bar{F}_m,$$
$$\Delta \ddot{\theta} = b_i \Delta \dot{\alpha} + b_j \Delta \theta + b_{35} \ddot{\delta}_x \Delta \alpha + \sum \left( b_i \ddot{q}_i + b_j q_j \right) + b_{30} \alpha_e = \bar{M}_{11}$$ \hspace{1cm} (1)

The flexible-body model of launch vehicle is given by the following expressions:

$$\ddot{q}_i + 2 \zeta_i \omega_i \dot{q}_i + \omega_i^2 \dot{q}_i = D_i \Delta \dot{\alpha} + D_{i1} \Delta \alpha + D_{i2} \Delta \delta_x + D_{i3} \Delta \delta_y + D_{i4} \Delta \delta_z + \bar{Q}_j$$ \hspace{1cm} (2)

The attitude information measurement model is the following:

$$\Delta \dot{\theta}_{gc} = \Delta \dot{\theta} - \sum W_i (X_{gc}) q_i,$$
$$\Delta \dot{\theta}_{sa} = \Delta \dot{\theta} - \sum W_i (X_{sa}) \dot{q}_i$$ \hspace{1cm} (3)

Where, $\Delta \theta$ is the trajectory inclination angle deviation of launch vehicle. $\Delta \alpha$ is the attack of angle deviation of launch vehicle. $\Delta \delta_x$ is swing angle of longitudinal pitch channel motor. $\Delta \delta_y$ is swing angle acceleration of longitudinal pitch channel motor. $\alpha_e$ is the angle of attack caused by wind. $\bar{F}_m$ is the linearized disturbance force of launch vehicle. $\bar{M}_{11}$ is the linearized disturbance moment of launch vehicle. $\Delta \theta$ is pitch angle deviation. $\Delta \theta_{gc}$ and $\Delta \theta_{sa}$ are pitch angle and angle velocity which are measured by inertial integrated navigation platform under the influence of elastic vibration respectively. The definition of the rest parameters and expression can be found in [5].

3. Compensator design based on orthogonal function neural network

Chebyshev orthogonal function neural network has strong capability of nonlinear approximation with high reconstructing accuracy and fast training rate. So the adaptive chebyshev orthogonal function neural network is design to approach the disturbance and uncertainties of the system.

The chebyshev orthogonal function neural network is augmented as

$$\hat{f} = \sum_{i=1}^{N} w_i \phi_i + \varepsilon = W^T \hat{\Phi}(X) + \varepsilon$$ \hspace{1cm} (4)

Where, $x = (x_1, \cdots, x_n)^T$ is the input of network, $N$ is the number of network input. $\phi_i(X) = P_{i1}(x_1) P_{i2}(x_2) \cdots P_{in}(x_n) = \prod_{j=1}^{n} P_{ji}(x_j)$, $P_{ji}(x_j)$ is the chebyshev orthogonal function. The expression of chebyshev orthogonal function are

$$P_{ij}(x_j) = 1, \quad P_{i2}(x_j) = x_j, \quad P_{i3}(x_j) = 2x_j P_{i2}(x_j) - P_{i1}(x_j), \quad j = 1, 2, \cdots, N, i \leq 3.$$

$\hat{\Phi} = [\phi_1 \phi_2 \cdots \phi_N]^T$ is the network output vector of chebyshev orthogonal function. $w$ is neural network weight. The network input are selected as $x = [e \quad \dot{e}]^T$.

The chebyshev orthogonal function network can approximate nonlinear continuous system to any degree of accuracy based on following assumptions [6].

1) Network output $f(x, W)$ is continuous;

2) For a small positive number $\varepsilon_0$, there is the ideal

3) Approximation network output $f(x, W^*)$, satisfaction
are control input. So the launch vehicle, \( x_M \) is swing angle coefficient in longitudinal channel can be represented as

\[
\Delta \ddot{\theta} = -b_1 \dot{\theta} \Delta \theta - b_2 \Delta \alpha \dot{\theta} - b_3 \Delta \dot{\theta} - b_4 \Delta \ddot{\theta} - \sum_i (b_i \dot{\theta}_i + b_{i1} q_{b_i}) \alpha \dot{\alpha}_i + \Delta \theta_i \delta_i - b_5 \Delta \ddot{\theta} - \sum_i (b_i \dot{\theta}_i + b_{i1} q_{b_i}) \alpha \dot{\alpha}_i + \Delta \theta_i \delta_i
\]

(7)

The swing angle coefficient can be described as \( b_i = b_{i0} + b_{i1} \). \( b_{i0} \) is swing angle coefficient in nominal model, \( b_{i1} \) is the uncertainty of swing angle coefficient. By treating \( f(x) = -b_1 \Delta \theta - b_2 \dot{\theta} \Delta \alpha - b_3 \Delta \dot{\theta} - b_4 \Delta \ddot{\theta} - \sum_i (b_i \dot{\theta}_i + b_{i1} q_{b_i}) \alpha \dot{\alpha}_i + \Delta \theta_i \delta_i \) as unknown part of equation, and \( g(x) = -b_5 \). So the launch vehicle longitudinal channel can be represented as

\[
\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= f(x) + b_{i0} \delta_i
\end{align*}
\]

(8)

Where, \( x_1 = \Delta \theta, x_2 = \Delta \ddot{\theta} \), \( u \in \mathbb{R} \) are control input.

Suppose control command is \( y_w \), have \( e = y_w - \Delta \theta, e = (e, \dot{e})^T \). We use the chebyshev orthogonal function network to estimate the uncertainty part, the control law is designed as

\[
u = -\frac{1}{b} (e - \hat{F}(x,W) + \Delta \theta + \hat{K}^T e)
\]

(9)

Where, selecting \( \hat{K} = (k_2, k_3) \) can make the polynomial \( s^2 + k_2 s + k_3 = 0 \) satisfy Hurwitz criterion. Substituting (9) into (8), we obtain (10) as follows

\[
\dot{e} = Ae + b(W - W^*)^T \Delta \Phi(X) + \delta
\]

(10)

Where, \( A = \begin{bmatrix} 0 & 0 \\ -k_2 & -k_3 \end{bmatrix}, b = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \).

We define Lyapunov function as,

\[
V = \frac{1}{2} e^T P e + \frac{1}{2} \gamma_1 (W - W^*)^T (W - W^*)
\]

(11)

Where, \( \gamma_1 \) is a positive constant, \( P \) is a positive definite matrix and meet Lyapunov equation

\[
A^T P + PA = -Q
\]

(12)

Where, \( Q \) is a arbitrary \( 2 \times 2 \) positive definite matrix. Calculating the derivative of the Lyapunov function, so

\[
\dot{V} = \frac{1}{2} \dot{e}^T P \dot{e} + \frac{1}{2} e^T \dot{P} e + \frac{1}{2} (W - W^*)^T \dot{W}
\]

(13)

Substituting (10) into (11),

\[
\dot{V} = -\frac{1}{2} \dot{e}^T Q \dot{e} + \frac{1}{2} (W - W^*)^T (\gamma_1 \dot{e}^T P b \Phi(X) + \dot{W}) + \dot{e}^T P b \delta
\]

(14)

If we select chebyshev orthogonal function network weight adaptive law as,

\[
W = -\gamma_1 \Phi(X) \dot{e}^T P b
\]

(15)
The derivative of the Lyapunov function is obtained as
\[
\dot{V} = -\frac{1}{2} \dot{e}^T Q \dot{e} + \dot{e}^T P b \delta
\] (16)

Because the approximation error can be sufficiently small, so \(\dot{V} \leq 0\) is approximately satisfied. We can build a compensation control law for uncertainty based on COF network. The control signal of controller is
\[
u_{\text{control}} = -\frac{1}{b} (\dot{f}(x,W) + \dot{y}_m + u_{pd})
\]
\[
u_{pd} = K_2 \dot{e} + K_1 \ddot{e}
\]
\[
\dot{f}(x,W) = W^T \Phi(X) \quad \ddot{W} = -\gamma_1 \Phi(X) \dot{e}^T P b
\] (17)

Where, \(K_2\) and \(K_1\) are proportional and differential gains, respectively. They are the adjustable parameters. \(\dot{f}(x,W)\) is the estimation of the unknown disturbance item. The adjustable parameters include \(\gamma_1\) and \(Q\). Commonly the proposed controller parameters include \(K_1, K_2, q_{11}, q_{22}, \gamma_1\). Compared with ARDC method, the number of controller parameters dramatically reduced. It is convenient to design parameter.

5. Simulation

In order to validate the proposed controller, simulations of attitude control for the launch vehicle in some flight second, are presented. Structural parameters and aerodynamic coefficients for the nominal case are from [4]. Considering the nominal situation without disturbance and uncertainty, the PD controller \((K_1 = 30, K_2 = 16)\) is designed based on Hurwitz criterion. The chebyshev orthogonal function network parameters are set as
\[
Q = \begin{bmatrix}
q_{11} & 0 \\
0 & q_{22}
\end{bmatrix} = \begin{bmatrix}
300 & 0 \\
0 & 100
\end{bmatrix}, \quad \gamma_1 = 100, N = 10.
\]

The performance of proposed controller was analyzed from response time, steady-state error and ITAE index.

Case 1: In nominal situation without disturbance and parameter perturbation, initial pitch angle deviation is \(5^\circ\). Simulation result is shown as Figures 1.

In nominal situation, the designed controller eliminates the initial attitude deviation fast and accurately. The rise time index is about 0.57 second, and the adjusting time index is about 0.92 second. The stable error is 0.005 deg, and the ITAE index is 1.08. The Table 1 shows that the proposed controller performance significantly better than PD controller.

| Controller  | Rise time | Adjusting time | Stable error | ITAE index |
|-------------|-----------|----------------|--------------|------------|
| PD+COF      | 0.57s     | 1.08s          | 0.005\(^\circ\) | 1.08       |
| PD          | 4.56s     | 6.91s          | 0.008\(^\circ\) | 23.6       |

Case 2: To validate the robustness of the controller under time-varying disturbance, which is mainly caused by inaccurate modeling of the aerodynamic data and external perturbations, in the case 2, all of the aerodynamic parameters used in modeling the plant are increase of 30\%. The wind attack of angle is \(a_w = 50^\circ \sin(t)\), pitch channel linearized force and torque disturbance are respectively \(\overline{F}_{by} = 0.4s^{-1}\sin(2t)\) and \(\overline{M}_{bc} = 0.3s^{-2}\sin(3t)\). Initial condition was the same as the case 1. Simulation result is shown as Fig. 4.
Figure 1. The curve of pitch angle varied with time in case 1.

Figure 2. The curve of Pitch angle varied with time in case 2.

Table 2. Control performance of different controller in Case 2

| Controller | Rise time | Adjusting time | Max Stable error | ITAE index |
|------------|-----------|----------------|------------------|------------|
| PD+ COF    | 0.59s     | 0.99s          | 0.0078°          | 0.91       |
| PD         | 4.38s     | 7.7s           | 0.151°           | 30.3       |

Under the time-varying disturbance situation, the response time index of PD controller is obvious degenerate. The control error presents the similar periodicity in changes of disturbance. Stable error peak value of PD controller is 0.15°. However, the proposed controller has a good response. Compared with case 1, the performance has slightly declines as shown in Table II. The dynamic performance and control precision are still much better than PD controller result. The simulation results show the strong robustness and interference resistance of proposed controller.

6. Conclusion

In view of the launch vehicle attitude control problem, the main controller based on PD control was designed for control attitude of launch vehicle and the compensator based on COF network was used to estimate and compensate impact of parametric uncertainties and disturbances. Simulations of attitude control for the launch vehicle in some flight second are presented. Adding the COF network compensator, the rapidity and precision of attitude control were significantly improved. Under the disturbance case, the designed controller still has good control performance. The robustness of the proposed control scheme is embodied.

References

[1] M. Knoblauch, D. Saussie, C. Berard 2012 American Control Conference pp 967-972
[2] Uzair Ansari, Abdulrahman H. Bajodah 2016 Proceedings of 2016 4th International Conference on Control Engineering & Information Technology pp 1-6
[3] Shicong Dai, Quanjun Liu, Ying Wang, Zhang Ren, Yudong Wang, Changwan Min 2017 Proceedings of the 36th Chinese Control Conference pp:3565-3569
[4] Haoyu C, Chaoyang D, Qing W 2015 J. Systems Engineering and Electronics 37 2109-2114
[5] Yanwang X 1999 Design and analysis on control system of the ballistic missile and launch vehicle (Beijing: Astronautic Publishing House) pp 63-65
[6] Bhargav Y, Vyas, Biswarup Das, Rudra Prakash Maheshwari 2016 J. IEEE Transactions on Neural Networks and Learning Systems 8 1631-1642.