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A neural network-based direct adaptive fault tolerance flight control for control surface damage

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Abstract

In order to enhance the reliability of flight control systems, a new neural network-based direct adaptive fault tolerance control was proposed for flight control system in the presence of control surface damage. Based on the accuracy approach of neural network, a fault parameter identification models were built to constitute hybrid compensator in order to ensure the strictly positive real of the failure flight control systems in the inner control loop. In the outer loop, a common direct adaptive controller was designed. The scheme was illustrated through simulations using an aircraft. The results show that an aircraft has also good dynamic performance in the control surface damage.

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Keywords: neural network; direct adaptive control; fault tolerance control; flight control systems

1. Introduction

With the complex flight mission and enhancing maneuver ability, the aircraft could undergo damage in certain situations. The control surface failures will bring accident for aircraft, so it is important to design fault tolerance flight control systems to improve reliability and safety. When failures occur, flight control system usually takes on uncertainty and nonlinear. So fault-tolerant control aims at possessing adaptive ability and making the system stable and retaining acceptable performance under the system faults. Direct adaptive control (DAC) theory can deal with uncertainty control problem, so it is used to flight control, robot, and motor control system[1-4]. Muhammad Yasser etc had widely researched neural network-based direct adaptive control method[5].

There are many advantages for using direct adaptive control to design control systems, but the systems must ensure the positive real which restrict the application field of direct adaptive control. At the same time, control surface failure will influence flight control system's state and output, so it is the key problem of fault tolerance control system how to compensate the uncertainty in order to realize the positive real. Considered above problems, in this paper the neural network is used to compensate the

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influence of failure so that the flight control system fulfils the positive real and gradually stability. The performance of the scheme was validated by the nonlinear simulation for a flight control system. As a conclusion, adaptive fault tolerance flight control is achieved.

2. Problem statement

In general, aircraft dynamics are inherently nonlinear. In the fault-free case, the flight control system dynamics can be described by the state-space model as following

$$\begin{cases} x(t)=A(x)x(t)+B(x)u(t)+d_i(x,t) \\ y(t)=C(x)x(t)+D(x)u(t)+d_0(x,t) \end{cases} \quad (1)$$

Here, $x(t) \in R^n$ is the state vector, $u(t) \in R^m$ is the input vector, $y(t) \in \mathrm{R}^l$ is the output vector. The matrices A , B , C and D are uniformly bounded. $\boldsymbol{d_i}(t)$ and $\boldsymbol{d_0}(t)$ are some bounded input and output disturbance. According to flight control aerodynamic function, the elevator δ_e , aileron δ_a , rudder δ_r , and thrust δ_t as input, body-axis roll rates q , pitch rates p , and yaw rates r as state, the aircraft state-space model become as following

$$\begin{cases} \overline{q}SbC_l(\alpha,\beta,p,q,r,\delta)=\dot{p}I_x-\dot{r}I_{xz}+qr(I_z-I_y)-pqI_{xz} \\ \overline{q}ScC_m(\alpha,\beta,p,q,r,\delta)=\dot{q}I_y+pq(I_x-I_z)+(p^2-r^2)I_{xz} \\ \overline{q}ScC_n(\alpha,\beta,p,q,r,\delta)=\dot{r}I_z-\dot{p}I_{xz}+pq(I_y-I_x)+qrI_{xz} \end{cases} \quad (2)$$

Here, $\overline{q}$ is dynamic pressure, α and β are angle of attack and sideslip angle. b and S are wing span and wing reference area. I_x , I_y , I_z , and I_{xz} are mass moments of inertia. C_l , C_m , and C_n are body-axis non-dimensional aerodynamic moment coefficients.

Actuator damage can cause the presence of variations in aerodynamic coefficients or control effectiveness deficiencies. In the fault case, the aircraft state-space model become as following

$$\dot{x}(t) = (A(x) + \Delta A(x))x(t) + (B(x) + \Delta B(x))u(t) + d_i(x,t) \quad (3)$$

Here, $\dot{x} = [\dot{p}, \dot{q}, \dot{r}]^{\mathrm{T}}$, $u = \left[\delta_e, \delta_a, \delta_r, \delta_t\right]^{\mathrm{T}}$, $\Delta A(x)$ is the change of state matrix because of control surface failure. $\Delta B(x)$ is the change of input matrix because of control surface failure.

In this paper fault tolerance control design objective is that used neural network to compensate $\Delta A(x)$ and $\Delta B(x)$ in order to assure the output of fault aircraft can perfectly track the trajectory of the reference model, and maintain flight control system stability and dynamic performance.

3. A novel neural network-based direct adaptive fault tolerance flight control

3.1. system architecture

A scheme of a novel neural network-based direct adaptive fault tolerance flight control (NDAC) is introduced (illustrated in Fig.1). The online learning BP neural network identification model is designed by using BP neural network adjusting its weights for the purpose of making the error small. A failure parameter model is built by using neural network approximation performance in order to bring the combination feedforward compensator. Thus the control system will satisfy the positive real. At the same time, in the outer loop, a nominal direct adaptive controller is designed, which keeps common structure.

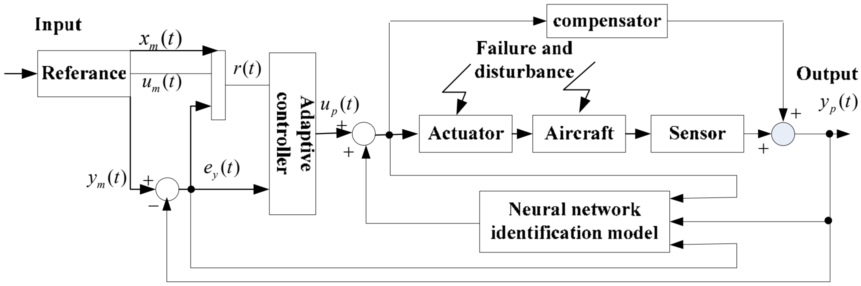


Fig.1. Neural network-based direct adaptive fault tolerance flight control

3.2. direct adaptive control

The direct adaptive control based on the command generator tracker. It is assumed that plant is almost strictly passive. Direct adaptive control algorithms can perfectly track the trajectory of the reference model and maintain control system stability. In many realistic environments, the controlled aircraft has the formula (1). The output of the aircraft must follow the output of the reference model.

$$\begin{cases} \dot{x}_m(t)=A_m(x_m)x_m(t)+B_m(x_m)u_m(t) \\ y_m(t)=C_m(x_m)x_m(t)+D_m(x_m)u_m(t) \end{cases} \quad (4)$$

This model incorporates the desired input-output behaviour of the plant. Let the output tracking error be defined as $e_y(t) = y_m(t) - y(t)$.

And use the following direct adaptive control algorithm

$$u_p(t) = k_e(t)e_y(t) + k_x(t)x_m(t) + k_u(t)u_m(t) = k(t)r(t) \quad (5)$$

Here, $k(t) = [k_e(t), k_x(t), k_u(t)] = k_p(t) + k_i(t)$, $r(t) = [e_y^{\mathrm{T}}(t), x_m^{\mathrm{T}}(t), u_m^{\mathrm{T}}(t)]$

The adaptive gains are a combination of proportional and integral gains which can be adaptive adjustment online. The detailed direct adaptive control algorithm can see the reference [1].

$$\begin{cases} k_p(t)=e_y(t)r^{\mathrm{T}}(t)T_p \\ k_i(t)=e_y(t)r^{\mathrm{T}}(t)T_i-\sigma k_i(t) \end{cases} \quad (6)$$

Here, T_p and T_i are constant parameter matrix， σ is error compensation coefficient. Control system design aim is that the tracking errors approach the zero so that it tracks completely.

3.3. neural Network training

BP neural networks can approximate any a continuous function to satisfy precision by choosing reasonable network structure. BP algorithm is a propagation-training method of weight in neural network which is along the error direction. In order to get the online identification model, a gradient descend algorithm based iterative is introduced. In this paper, the neural network acts as identification model, which hidden transfer function is Sigmoid and output transfer function is line function. Defining neural network input layers nodes as x_i, hidden layers nodes as h_j, output layers nodes as y_l. w_{ji} denotes the linear coefficients between input and hidden layers. w_{li} denotes the linear coefficients between hidden layers and output.

That, the training algorithm of the neural network weight is defined as following

$$\begin{cases} \Delta x_{k+1} = \eta \Delta x_k + \xi(1-\eta) g_k \\ x_{k+1} = x_k + \Delta x_{k+1} \end{cases} \quad (7)$$

Here x_k is network weight, η is learning ratio, ξ is the additional momentum.

According to cost function, the gradient of weight is as following

$$g_k = \frac{\partial e(k)}{\partial x(k)} = \frac{\partial e(k)}{\partial y(k)} \frac{\partial y(k)}{\partial u(k)} \frac{\partial u(k)}{\partial o(k)} \frac{\partial o(k)}{\partial net(k)} \frac{\partial net(k)}{\partial x(k)} \quad (8)$$

That, the training algorithm of the output weight is defined as following

$$\Delta w_{lj}(k) = \eta \Delta w_{lj}(k-1) + \xi(1-\eta)\delta_1 o_1(k) \quad (9)$$

Here $o_1(k)$ is the output of network hidden layers. $\delta_1 = e(k) \cdot \frac{\partial y(k)}{\partial u(k)} \cdot (e(k) - e(k-1)) \cdot g'(net(k))$.

In the same way, the training algorithm of the hidden weight is defined as following

$$\Delta w_{ji}(k) = \eta \Delta w_{ji}(k-1) + \xi(1-\eta)\delta_2 o_2(k) \quad (10)$$

Here $o_2(k)$ The input of network input layers. $\delta_2 = f'(net(k)) \cdot \delta_1 \cdot \Delta w_{lj}(k)$.

4. simulation result

In this paper, the flight condition is a straight level flight condition at 5000~9000 m altitude and 0.5 mach. The sampling period is chosen to be 0.01 second, and simulation time is 50 second. Aircraft maneuvering is set as follows: firstly climb, then attitude holding, finally right turning. For the case 1 without fault, system response is shown in Fig.2. From the response of roll rates and normal load, the closed-loop response is fairly fast without overshoot. In addition the aircraft almost perfectly track the trajectory of reference model. But systems output fluctuated a little in the initiatory time when NDAC is used because the neural network learn algorithm is adjusted in online.

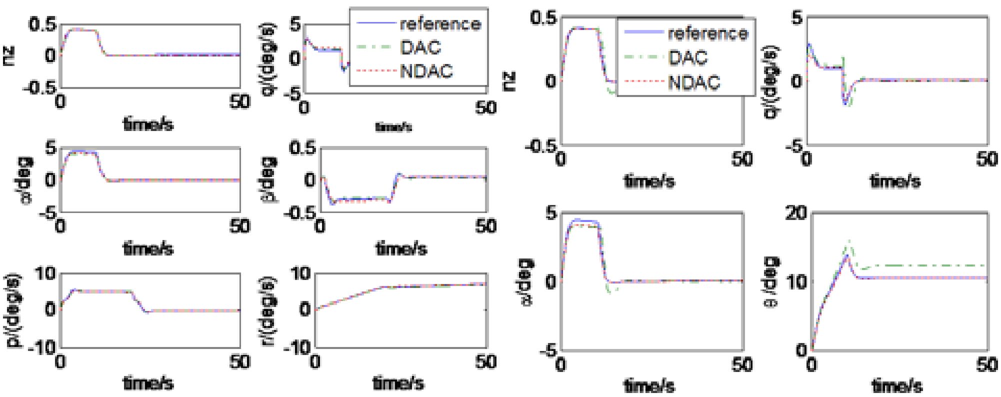
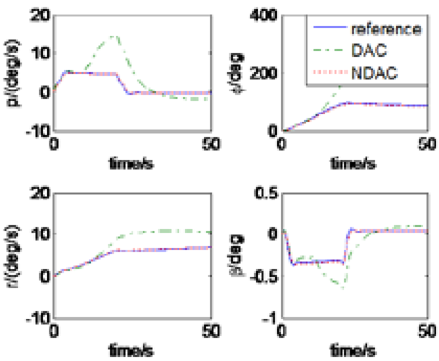


Fig.2. System response without failure

Fig.3. System response with 50% left elevator failure



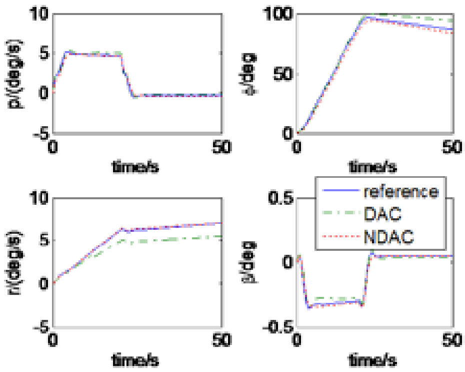


Fig.4. System response with 50% left aileron

Fig.5. System response with 50% rudder failure

The fault scenarios are control surface loss. All faults are simulated to occur at 10 second. The specific failures are a partial loss 50% of the rudder control surface, left aileron, and left elevator. When the sudden failure of control surface occurs at 10 second respectively, the system responses are shown in Fig.3-5. When failure occurs, system output is changed. But using the proposed adaptive scheme, the aircraft can keep stability and handling qualities, and reconfiguration process is rapid and in time. In conclusion, the proposed adaptive scheme is achieved.

5. Conclusion

Because actuator damages are occurred suddenly in the fly, the failure aircraft takes on usually uncertainty. In this paper a new neural network-based direct adaptive fault tolerance flight control algorithm is proposed for the presence of control surface damage. The positive real of failure control system is content by using online neural network method. The proposed algorithm is satisfying from the simulation, which failure information need not be known for reconfiguration actuator failures and the output of fault aircraft tracks perfectly trajectory of the reference model.

Acknowledgements

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