Control Allocation Reconstruction of Launch Vehicle Based on Neural Network

Zhu Li, Yaokun Zhang, Zhaowei Liang, Zhongtao Cheng, Lei Liu and Ye Yang

Abstract After the single engine thrust reduction fault of the launch vehicle, if the conventional fixed control allocation method is used, the actual control torque generated by the engine is difficult to meet the expected torque generated by the basic controller. Therefore, this paper proposes a neural network based control allocation method. The method learns the pseudo-inverse allocation method, so that the actual control torque can well track the desired control torque. Finally, the proposed neural network control allocation method is simulated and verified. The results show the feasibility and effectiveness of the proposed method.

Keywords Launch vehicle · Thrust reduction fault · Neural network control allocation · Pseudo-inverse method

1 Introduction

Control allocation is a key method to solve the redundant control of aircraft with multiple actuators. When control surfaces or actuators are fault or actuator efficiency changes, it can be done redistributing the control instruction to reconfigure the control system, which no longer need to readjust the complex flight control law, and greatly reduces the difficulty of the design of the control system comparing with the traditional reconfiguration control methods [1].

The main methods of control allocation include: generalized inverse method, Daisy Chaining method, direct allocation method, mathematical programming method and adaptive method. Among them, there are many studies on generalized inverse method, mathematical programming method and adaptive method [2]. For

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example, literature [3] compares the performance of the control allocation method based on generalized inverse, direct allocation method and fixed point method applied to the flight control system with uncertainty. Literature [4] studies the input constraint problem of control allocation method based on pseudo inverse. The literature [5] proposed a composited integrated guidance and control (IGC) algorithm to tackle the problem of inaccuracy information. The literature [6] proposed a disturbance observer-based gain adaptation high-order sliding mode control method.

For the launch vehicle control system with multiple engines, when the engine thrust reduction fault occurs, using fixed allocation method to allocate the equivalent oscillation angle instruction, the actual control torque generated by the engine cannot well meet the desired control torque. Aiming at this problem, use the methods of control allocation to reconfigure the control system.

In this paper, the control allocation method based on BP neural network is used to solve the reconfiguration control problem of launch vehicle with thrust reduction fault. Compared with the mathematical programming method, the neural network-based control allocation has the advantages of fast distribution speed and small calculation amount. Compared with the pseudo-inverse method, the pseudo-inverse method can not consider the physical constraints of the actuator. When the learning object of the neural network control allocation method is the control allocation method considering the actuator constraint, the neural network control allocation method will consider the actuator constraints. This paper mainly explores the learning ability of neural networks, so the pseudo-inverse control allocation method is used as the learning object of neural network.

2 Description of the Problem

This paper takes a certain type of launch vehicle as the research object. As shown in Fig. 1, the first stage engine of the launch vehicle consists of four strap-on engines and two core engines, each with its longitudinal axis parallel to the longitudinal axis

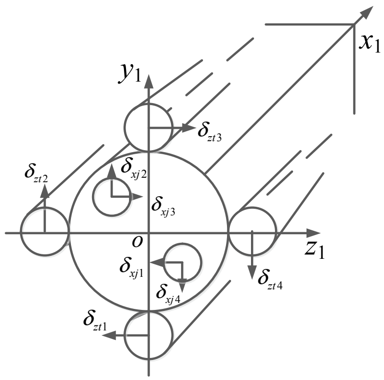


Fig. 1 Rear view of the rocket's primary engine layout

of the rocket. Two of the core engines are in a diagonal layout, and both can be used for two-way cross swing, and the oscillation angles in different directions are respectively recorded as δ_{xj1}, δ_{xj2}, δ_{xj3}, δ_{xj4}. The four strap-on engines are distributed symmetrically around the rocket and can be tangentially oscillated. The oscillation angles in different directions are recorded as δ_{zt1}, δ_{zt2}, δ_{zt3}, δ_{zt4}. The direction of the arrow shown in the figure is the positive direction of each engine swing [7].

The rocket forms a control torque through each engine oscillation angle, that is, the control of the flight attitude is finally achieved by adjusting the eight oscillation angles of the engine.

Generally, in the case of a rocket without failure, the oscillation angle control of each rocket engine is obtained by a fixed control allocation method.

The total equivalent control oscillation angle of the pitch channel, the yaw channel and the roll channel is δ_{ϕ}, δ_{Ψ}, δ_{γ}; The equivalent control oscillation angle of the three channels of the strap-on engine is $\delta_{\phi zt}$, $\delta_{\Psi zt}$, $\delta_{\gamma zt}$; The equivalent control oscillation angle of the three channels of the core engine is $\delta_{\phi xj}$, $\delta_{\Psi xj}$, $\delta_{\gamma xj}$. If the relationship between the total equivalent control oscillation angle command and the equivalent control oscillation angle command of the core engine and the strap-on engine is λ and 1. In general, set $\lambda = 2$. then:

$$\begin{cases} \lambda\Delta\delta_{\varphi xj} = \Delta\delta_{\varphi zt} = \Delta\delta_{\varphi} \\ \lambda\delta_{\psi xj} = \delta_{\psi zt} = \delta_{\psi} \\ \lambda\delta_{\gamma xj} = \delta_{\gamma zt} = \delta_{\gamma} \end{cases} \tag{1}$$

When using the fixed control allocation method, the oscillation angle control amount of each engine is obtained by:

$$\begin{cases} \delta_{ztI} = -\delta_{\psi\mathrm{zt}} + \delta_{\gamma\mathrm{zt}} \\ \delta_{ztII} = -\Delta\delta_{\varphi zt} + \delta_{\gamma\mathrm{zt}} \\ \delta_{ztIII} = \delta_{\psi zt} + \delta_{\gamma zt} \\ \delta_{ztIV} = \Delta\delta_{\varphi zt} + \delta_{\gamma zt} \end{cases}, \begin{cases} \delta_{xjI} = (-\delta_{\psi xj} + \delta_{\gamma xj}) \\ \delta_{xjII} = (-\Delta\delta_{\varphi xj} + \delta_{\gamma xj}) \\ \delta_{xjIII} = (\delta_{\psi xj} + \delta_{\gamma xj}) \\ \delta_{xjIV} = (\Delta\delta_{\varphi xj} + \delta_{\gamma xj}) \end{cases} \tag{2}$$

When studying the influence of the engine thrust reduction fault on the rocket motion, the actual thrust of the engine under the thrust reduction fault is the partial value of the rated thrust, then:

$$\begin{cases} P_{\mathrm{zt1}} = k_{zt1}P_{\mathrm{zt}} \\ P_{\mathrm{zt2}} = k_{zt2}P_{\mathrm{zt}} \\ P_{\mathrm{zt3}} = k_{zt3}P_{\mathrm{zt}} \\ P_{\mathrm{zt4}} = k_{zt4}P_{\mathrm{zt}} \end{cases}, \quad \begin{cases} P_{xj1} = k_{xj1}P_{xj} \\ P_{xj2} = k_{xj2}P_{xj} \end{cases} \tag{3}$$

Among them, P_{zt}, P_{xj} is the current rated thrust of the strap-on and core engine, $P_{zt1} \sim P_{zt4}$, P_{xj1}, P_{xj2} are the actual thrust values of each engine output after the failure; $k_{zt1} \sim k_{zt4}$, k_{xj1}, k_{xj2} are scale factors that reflect the magnitude of thrust reduction after engine failure. Taking the No. 1 strap-on engine as an example, as shown in Fig. 2,

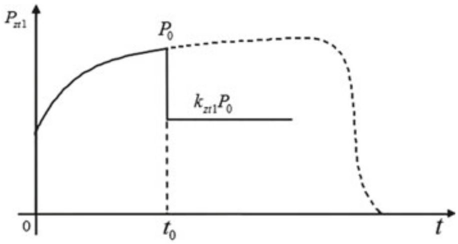


Fig. 2 Schematic diagram of thrust under engine thrust reduction failure

at the time t_0, the engine has a thrust reduction failure, and the actual thrust rapidly drops to a certain fixed value [8].

Considering the engine thrust reduction failure, the actual control torque generated by the engine is:

$$\begin{aligned}
M_{C_{X_1}} &= -P_{zt}r_{zt}\left(k_{zt1}\delta_{ztI} + k_{zt2}\delta_{ztII} + k_{zt3}\delta_{ztIII} + k_{zt4}\delta_{ztIV}\right) \\
&\quad - P_{xj}r_{xj}\left(k_{xj1}\delta_{xjI} + k_{xj2}\delta_{xjII} + k_{xj2}\delta_{xjIII} + k_{xj4}\delta_{xjIV}\right) \\
M_{C_{Y_1}} &= P_{zt}(X_R - X_Z)\left(k_{zt1}\delta_{ztI} - k_{zt2}\delta_{ztIII}\right) + P_{xj}(X_R - X_Z)\left(k_{xj1}\delta_{xjtI} - k_{xj2}\delta_{xjIII}\right) \\
M_{C_{Z_1}} &= P_{zt}(X_R - X_Z)\left(k_{zt2}\delta_{ztII} - k_{zt4}\delta_{ztIV}\right) + P_{xj}(X_R - X_Z)\left(k_{xj2}\delta_{xjII} - k_{xj1}\delta_{xjIV}\right)
\end{aligned} \tag{4}$$

Among them, X_R is the distance from the engine's swing point to the theoretical tip of the rocket; X_Z is the distance from the rocket's centroid to the theoretical tip of the rocket; r_{zt} is the distance from the rocker strap-on engine swing point to the longitudinal axis of the rocket; r_{xj} is the distance from the rocker core engine swing point to the longitudinal axis of the rocket.

When the thrust reduction fault occurs in a single engine of a launch vehicle, if the fixed control allocation method is used, the actual control torque generated by the launch vehicle engine will not meet the desired control torque generated by the basic controller. Therefore, control allocation reconstruction is required so that the actual control torque can track the desired control torque.

3 Neural Network Control Allocation Reconstruction Design

The neural network can approximate continuous nonlinear functions with arbitrary precision and have the ability to adapt and self-learn for complex uncertain problems. Neural networks are widely used in system identification, system control, optimization calculation, and fault diagnosis and fault-tolerant control of control systems [9–13]. Therefore, the powerful data fitting ability of the neural network can be utilized to control the allocation of the launch vehicle under the condition of the thrust drop failure.

3.1 Construction of Neural Networks

In this paper, BP neural network is used to learn the control allocation data generated by pseudo-inverse method. The input-output mapping relationship is [14]:

$$y_{\rm i}=\sum_{\rm j=1}^{\rm N_2}\left[\omega_{ji}\sigma\left(\sum_{k=1}^{N_1}\upsilon_{jk}x_k+\theta_{\upsilon j}\right)+\theta_{\omega i}\right],\quad i=1,\ldots,N_3 \tag{5}$$

where $k = 1, 2,\ldots, N_1$. Here, N_1, N_2, and N_3 represent the number of neural network inputs, the number of hidden layer neurons, and the number of outputs. x_k is the i-th element of the network input, and y_i is the i-th element of the network output. $\sigma_{(x)}$ as a sigmoid excitation function is given by:

$$\sigma(x)=\frac{2}{\left(1+e^{-2x}\right)}-1 \tag{6}$$

Designed neural network input:

$$x=\left[\,\delta_{\varphi}\ \delta_{\psi}\ \delta_{\gamma}\ k_{zt1}\ k_{zt2}\ k_{zt3}\ k_{zt4}\ k_{xj1}\ k_{xj2}\,\right] \tag{7}$$

Among them, δ_ϕ, δ_Ψ, δ_γ are control commands generated by the PID controller. k_{zt1}, k_{zt2}, k_{zt3}, k_{zt4}, k_{xj1}, k_{xj2} are the degrees of thrust reduction of each engine.

Neural network output:

$$y=\left[\,\delta_{ztI}\ \delta_{ztII}\ \delta_{ztIII}\ \delta_{ztIV}\ \delta_{xjI}\ \delta_{xjII}\ \delta_{xjIII}\ \delta_{xjIV}\,\right] \tag{8}$$

Among them, δ_{ztI}, δ_{ztII}, δ_{ztIII}, δ_{ztIV}, δ_{xjI}, δ_{xjII}, δ_{xjIII}, δ_{xjIV} are the oscillation angles of the respective engines.

The number of hidden layer neurons in the designed neural network is 10, so the number of weights of the entire neural network is 188, including the threshold of neurons.

3.2 Learning of Neural Networks

Because the main purpose of this paper is to verify the feasibility of neural network control allocation in the case of single engine thrust reduction of the launch vehicle, so just select a feasible control allocation method for learning. Therefore, the learning object of the neural network designed in this paper is based on the pseudo-inverse method. In order to realize the neural network control allocation under the single engine thrust fault, it is necessary to first obtain the control input and output data based on the pseudo-inverse method, that is, the control command generated by the PID controller and the oscillation angle of each engine under different fault conditions. In order to simplify the training process, only the data of the No. 1 core engine and the No. 2 core engine under different thrust reduction were selected, The choice is that the thrust of the No. 1 core engine is reduced by 0, 20, 40, 60, 80, 100% at 50 s, and the thrust of the No. 2 core engine is reduced by 0, 20% at 50 s, 40, 60, 80, 100%.

4 Simulation Results and Analysis

The simulation process is as follows: the initial rocket pitch angle command is 90°, then gradually changes to 25° in 0–160 s, and maintains 25° to 165 s.

During this time, the yaw angle, the roll angle command remains at 0°. Rocket strap-on engine oscillation angle range is −8° to 8°, core engine oscillation angle range is −6° to 6°.

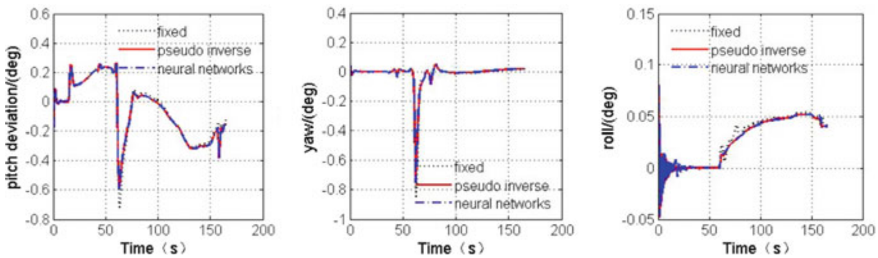
Based on the neural network learning data, the BP neural network control allocation reconstruction is simulated and verified. In order to verify the learning ability of neural network control allocation, the simulation situation needs to be different from the neural network training situation. Therefore, the simulation situation is that the thrust of the No. 1 core engine is reduced by 70%, and the thrust of the No. 2 core engine is reduced by 90%.

1. **The Thrust of the No. 1 Core Engine is Reduced by 70% at 60 s**

Figure 3 shows the flight attitude angle of the launch vehicle generated by fixed allocation, pseudo-inverse allocation, and neural network allocation. Figure 4 shows the Z-axis desired control torque generated by the PID controller under different allocation methods, the Z-axis actual control torque generated by different allocation methods, and the difference between the desired torque and the actual control torque.

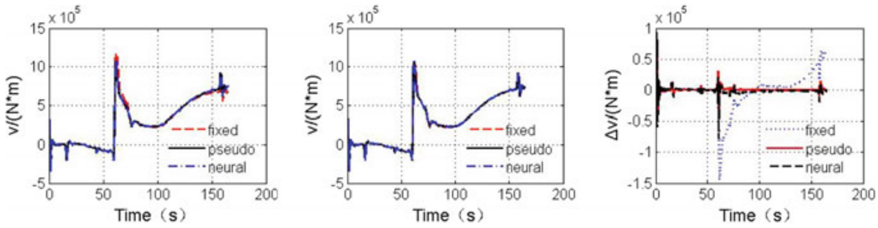
2. **The Thrust of the No. 2 Core Engine is Reduced by 90% at 60 s**

Figure 5 shows the flight attitude angle of the launch vehicle generated by fixed allocation, pseudo-inverse allocation, and neural network allocation. Figure 6 shows



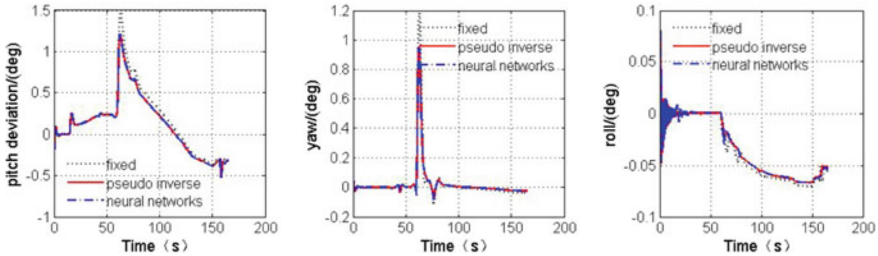
(a) Pitch angle error (b) Yaw angle error (c) Roll angle error

Fig. 3 Rocket attitude angle error diagram with 70% thrust reduction



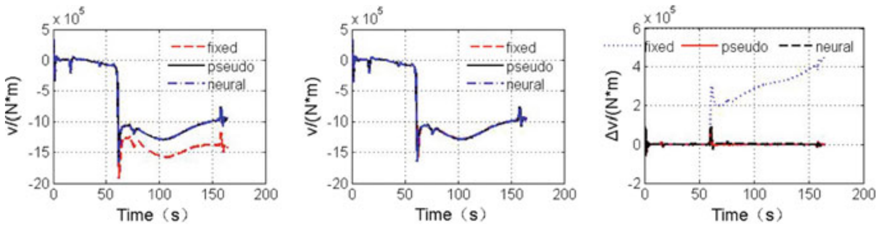
(a) Z-axis desired control torque (b) Z-axis actual control torque (c) Z-axis control torque error

Fig. 4 Z-axis torque comparison diagram with 70% thrust reduction



(a) Pitch angle error (b) Yaw angle error (c) Roll angle error

Fig. 5 Rocket attitude angle error diagram with 90% thrust reduction



(a) Z-axis desired control torque (b) Z-axis actual control torque (c) Z-axis control torque error

Fig. 6 Z-axis torque comparison diagram with 90% thrust reduction

the Z-axis desired control torque generated by the PID controller under different allocation methods, the Z-axis actual control torque generated by different allocation methods, and the difference between the desired torque and the actual control torque.

It can be seen from Figs. 3 and 5 that the more severe the degree of the fault has an greater influence on the attitude angle. When using fixed allocation, the error of the attitude angle is greater than the error of using the neural network to control the allocation. It can be seen that the use of a neural network for control allocation is feasible and enables the launch vehicle to maintain a good flight state in the event of a fault. Moreover, the difference between the attitude angle error generated by the neural network control allocation and the attitude angle error generated by the pseudo-inverse control allocation is small, and it can be seen that the neural network has well learned the pseudo-inverse allocation method.

It can be seen from Figs. 4 and 6 that after the failure occurs, if the fixed allocation is used, the actual torque generated by the engine cannot satisfy the desired torque generated by the control law, and the neural network allocation can better track the desired torque. Moreover, the difference between the torque error generated by the neural network allocation and the torque error generated by the pseudo-inverse allocation is small.

5 Conclusion

The simulation results show that the control allocation based on neural network has better instruction tracking performance than the fixed allocation. And the neural network has a certain learning ability, and can learn the pseudo-inverse control allocation method. At the same time, after learning, it has good command tracking performance for unlearned fault conditions. It is foreseeable that the neural network will exhibit better instruction tracking performance when learning using a control allocation method that takes into account more factors.

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References

1. Oppenheimer, M.W., Doman, D.B., Bolender, M.A.: Control allocation for over-actuated systems. In: Mediterranean Conference on Control & Automation (2006)
2. Johansen, T.A., Fossen, T.I.: Control allocation—a survey. J. Automatica. **49**(5), 1087–1103 (2013)
3. Ma, J., Li, P., Li, W., et al.: Performance comparison of control allocation for aircraft with control effectiveness uncertainties. In: Asia Simulation conference 2008/the 7th International Conference on System Simulation and Scientific Computing (2008)
4. Hang, X., Duan, G.: A developed constrained control allocation approach based on pseudo inverse. In: Chinese Automation Congress. IEEE, New York (2018)
5. Ping, M., Denghui, Z., Songyan, W., et al.: Integrated guidance and control design method based on finite-time state observer. J. Syst. Eng. Electron. **29**(6), 1251–1262 (2018)
6. Yin, X., Wang, B., Liu, L., Wang, Y.: Disturbance observer-based gain adaptation high-order sliding mode control of hypersonic vehicles. J. Aerosp. Sci. Technol. **89**, 19–30 (2019)
7. Yanshen, W.: Attitude control technology of new-generation launch vehicles. J. Beijing Univ. Aeronaut. Astronaut. (2009)
8. Zhi-Xiang, W., Jia-wen, L., Dao-Kui, L.: Failure: simulation of thrust decline of launch vehicle based on six DOF model. J. Manned. Spaceflight. **23**(5), 650–657 (2017)

9. Huang, J., Qian, J., Liu, L., Wang, Y., Xiong, C., Ria, S.: Echo state network based predictive control with particle swarm optimization for pneumatic muscle actuator. J. Franklin Inst. **353**, 2761–2782 (2016)
10. Wu, Y.C., Feng, J.W.: Development and application of artificial neural network (2018)
11. Yao, L., Wang, H.: Fault diagnosis and fault tolerant control for the non-Gaussian nonlinear stochastic distribution control system using Takagi-Sugeno fuzzy model. Int. J. Model. Ident. Control **29**(1), 22–30 (2018)
12. Han, Y., Yu, J., Liu, Z., et al.: Command filter-based adaptive neural control for permanent magnet synchronous motor stochastic nonlinear systems with input saturation. Int. J. Model. Ident. Control **30**(1), 38–47 (2018)
13. Rahoui, A., Seddiki, H., Bechouche, A., et al.: Adaptive neural networks for AC voltage sensorless control of three-phase PWM rectifiers. Int. J. Model. Ident. Control **31**(2), 139–151 (2019)
14. Basheer, I.: Artificial neural networks: fundamentals, computing, design, and application. J. Microbiol. Methods **43**(1), 3–31 (2000)