Research on Optimal Control Method of Four Rotor UAV Based on BP Neural Network

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Abstract. With the development of related technical fields, the application scenarios of four rotor unmanned aerial vehicle (UAV) is becoming wider and wider. Especially in the field of power inspection, UAV inspection has gradually replaced manual inspection, forming a new working mode. At present, the unmanned aerial vehicle inspection technology applied to transmission lines has become increasingly mature. However, UAV technology has only been gradually applied to the patrol inspection of overhead power distribution network in recent years. The traditional proportional integral derivative (PID) control method of unmanned aerial vehicle (UAV) is difficult to meet the needs of UAV patrol inspection work in terms of control accuracy and response speed. To solve this problem, this paper uses back propagation neural net to optimize the traditional control method. Appropriate control parameters are trained by online learning. The improved control core unit has the function of automatic setting of control parameters. This enables the UAV to adapt to the changing flight environment and fly more smoothly. Finally, the improved back propagation neural net PID controller is used to simulate the system model. The research results have a positive role in promoting the development of unmanned aerial vehicle inspection technology for distribution lines.

Keywords: Four Rotor Unmanned Aerial Vehicle · BP Neural net · Proportional Integral Derivative · Control Method

1 Introduction

Four rotor UAV has outstanding advantages such as small size, easy to carry, high quality and low price. In recent years, four rotor unmanned aerial vehicles have attracted more and more attention. Especially in the field of power inspection, unmanned aerial vehicle inspection has gradually replaced manual inspection, forming a new working mode [1, 2]. The performance of the control core unit directly determines the flight state of the four rotor UAV [3]. The control core unit of the four rotor UAV has four input signals, but it controls six outputs. The six outputs of the control core unit include three position

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motion control signals and three attitude angle motion control signals [4]. Therefore, the four rotor UAV has the characteristics of underdrive. At the same time, the mechanical structure of the four rotor UAV is relatively complex. Its control core unit is a nonlinear system. When it controls the attitude angle, it will also affect the position state of the UAV [5]. However, the control accuracy of classical PID control core unit is not high and the response speed is slow. When UAV needs to perform complex work tasks, its control method needs to be further optimized [6]. For example, in the daily inspection work scene of transmission lines, only drones need to fly and take photos at a constant speed along the smooth line channel. Classical PID control core unit can be used to perform such a simple task. However, the working scenario of lean inspection of distribution lines requires that UAVs can shuttle freely in rugged and complex line channels, and that UAVs can quickly avoid obstacles. When performing such complex tasks, it is necessary to improve the control accuracy and response speed of the four rotor UAV control core unit.

This paper studies the performance optimization of the flight control core unit of a four rotor UAV. Back propagation neural net is introduced into the PID control core unit of four rotor UAV. A self-tuning method of UAV flight control parameters is proposed. The improved four rotor UAV control core unit is simulated. The research results have a guiding role in improving the operation ability of UAV and expanding the application field of UAV.

2 Operation Principle of PID Control Core Unit Based on BP Neural Net

BP neural net has three levels from the perspective of structure, namely, input level, output level and hidden level. BP neural net is a network structure of forward feedback error. For a simple control core unit, only one hidden level is usually used. For complex system structures, multiple hidden levels may be used. Each hidden level can have multiple neurons. Figure 1 is the typical levels of BP neural net.

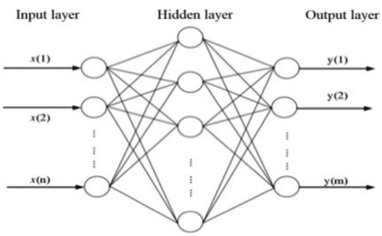

Fig. 1. Typical level of BP neural net

As shown in Fig. 1, the input signal is input through the input level. The signal is multiplied by the corresponding weight as the independent variable of the input activation function. Relevant variables are calculated in the hidden level. The signal enters the output level after being processed by the hidden level. At this time, the signal is multiplied by the corresponding weight as the independent variable of the output activation function. This variable is compared with the desired value. If there is a deviation between the two, the deviation signal of the two is fed back to the lower input level. The weight of each neuron is calculated by gradient descent method. When the deviation does not reach the set range, or the training times do not reach the set range, repeat the above process. By continuously training the above process, the appropriate weights of each neuron can be matched.

The PID control core unit of four rotor UAV is a nonlinear system. If you want to obtain good control effect, you must adjust the appropriate control parameters. Relevant control parameters include proportional constant KP, differential time constant Ki and integral time constant KD. The training method can be optimized by BP neural net to match the three parameters of proportional constant KP, differential time constant Ki and integral time constant KD. The UAV controller optimized by BP neural net is mainly divided into PID control core unit and BP neural net. Figure 2 is BP neural net optimization control core unit.

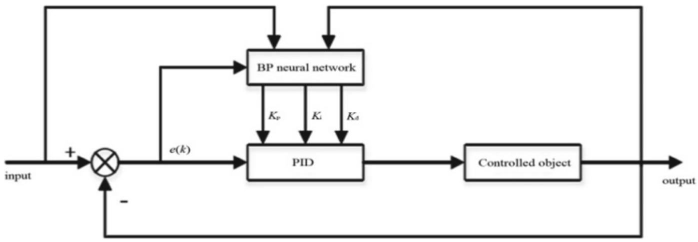

Fig. 2. BP neural net optimization control core unit

BP neural net is a network structure with multi-level forward feedback and error back propagation. The process of reverse calculation of weights between neurons in each level during Back propagation neural net training is as follows.

The output signal of the input level of the control core unit is the input signal. Therefore, the expression of the input signal of the hidden level is described by expression (1).

$$O_{\mathrm{j}}^{(1)} = x(j) \quad j = 1 \ldots\ldots N \tag{1}$$

In expression (1), N is the amount of input signals of the input level. N is related to the complexity of the control core unit. Generally speaking, the more complex the system is, the more input signals it has. The relationship between output signal and input signal of the hidden level is described by expression (2).

$$net_i^{(2)}(k) = \sum_{j=1}^{N} w_{ij}^{(2)} \mathrm{O}_{\mathrm{j}}^{(1)}(\mathrm{k}) \tag{2}$$

$$O_{\mathrm{i}}^{(2)}(k) = f(\mathrm{net}_i^{(2)}(k)) \qquad k = 1 \ldots\ldots Q \tag{3}$$

In expression (2) and expression (3), Q is the amount of neurons. The corner mark of the input level is (1). The corner mark of the hidden level is (1). The corner mark of the output level is (3). f (*) is the activation function. Sigmoid activation function can accurately fit any nonlinear function. Therefore, sigmoid function is described by expression (4) in this paper.

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} - e^{-x}} \tag{4}$$

The expression of input signal and output signal of BP neural net output level is described by expression (5).

$$net_{i}^{(3)}(k) = \sum_{i=1}^{Q} w_{ij}^{(3)} \mathrm{O}_{\mathrm{i}}^{(1)}(\mathrm{k}) \tag{5}$$

$$O_{l}^{(3)}(k) = g(net_{l}^{(3)}(k)), l = 1, 2, 3 \tag{6}$$

In expression (5), The output level designed in this paper consists of three neurons. The output signals of these three neurons correspond to K_{p}, K_{i} and K_{d} respectively. The sigmoid functions of output level are described by expression (7), expression (8), expression (9) and expression (10).

$$g(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

$$O_{i}^{(3)}(k) = K_{\mathrm{p}} \tag{8}$$

$$O_{2}^{(3)}(k) = K_{\mathrm{i}} \tag{9}$$

$$O_{3}^{(3)}(k) = K_{\mathrm{d}} \tag{10}$$

3 UAV Control Algorithm Based on BP Neural Net Optimization

This paper mainly studies the training weight through online training. The loss function expression of BP neural net is described by expression (11).

$$E = \frac{1}{2}\left[(r - \mathrm{y})(k + 1)\right]^{2} \tag{11}$$

The corresponding weights of each neuron are continuously adjusted by the method of gradient descent. Adjust the weight coefficient according to the direction in which the derivative of the loss function is less than zero. The expression of this process is as follows.

$$\Delta w_{li}^{(3)}(k + 1) = -\eta \frac{\partial E}{\partial w_{li}^{(3)}} \tag{12}$$

In expression (12), η is the rate of learning of the optimization algorithm in this paper. The control parameters of incremental PID can be calculated by chain rule.

$$u(k) = \Delta^2 e(k)+K_p \Delta e(k) + K_i e(k) + u(k-1) \tag{13}$$

Take K_i, K_p and K_p in the above formula as input variables. The expression (13) can be rewritten again.

$$u(k) = f\left[\Delta^2 e(k), \Delta e(k), K_i, K_p, K_d, u(k-1)\right] \tag{14}$$

The main purpose of BP neural net is to find the most suitable mapping relationship between output and input through learning and training. $\partial u(k)/\partial O_l^{(3)}(k)$ in expression (12) can be derived from the above expression.

$$\frac{\partial u(k)}{\partial O_1^{(3)}(k)} = -e(k-1)+e(k) \tag{15}$$

$$\frac{\partial u(k)}{\partial O_2^{(3)}(k)} = e(k) \tag{16}$$

$$\frac{\partial u(k)}{\partial O_3^{(3)}(k)} = e(k-2) - 2e(k-1) + e(k) \tag{17}$$

The weight adjustment expression of the channel between the output level and the hidden level is described by expression (18).

$$\frac{\partial E}{\partial w_{li}^{(3)}} = -\delta_l^{(3)} * O_i^{(2)}(k) \tag{18}$$

Bring expression (18) into expression (12). It can calculate the weight calculation expression from hidden level to output level.

$$\Delta w_{li}^{(3)}(k+1) = \eta \delta_l^{(3)} O_i^{(2)}(k) \tag{19}$$

The weight calculation expression of neurons from the input level to the hidden level is described by expression (20).

$$\begin{cases} \Delta w_{ij}^{(2)}(k+1) = \eta \delta_\mathrm{i}^{(2)} O_j^{(1)}(k) \\ \delta_i^{(2)} = f'(net_i^{(2)}(k)) \times \sum_{l=1}^{3} \delta_l^{(3)} w_{li}^{(3)}(k), i = 1, 2, \ldots, Q \end{cases} \tag{20}$$

Expression (18) and expression (20) are the weight coefficient expressions of each neuron in the optimal control algorithm.

4 Simulation Experiment of UAV Control Core Unit Based on BP Neural Net Optimization

4.1 Proportional Integral Derivative Controller

This paper constructs a Proportional Integral Derivative control core unit model based on BP neural net in Simulink environment. Firstly, the neural net with 3–5–3 structure is written by using S-Function in S-function module. Then the neural net is coupled with PID controller. This neural net can use the real-time feedback information of PID control core unit for online learning and training. By adjusting the weight between the neurons of each level, three appropriate PID control parameters can be matched. Figure 3 shows the logic structure of the optimized control core unit. Figure 4 shows the internal structure of S-function module input.

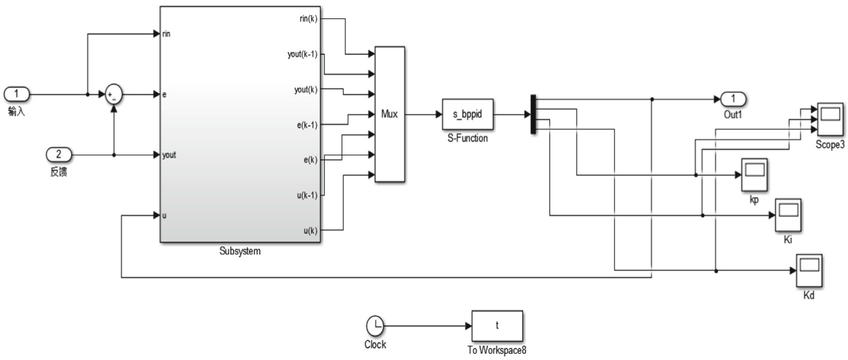

Fig. 3. Logic structure of the optimized control core unit

4.2 Simulation Analysis

The flight attitude is the most important control object. The four axis vehicle model is decoupled. The simulation of each attitude angle is carried out in Simulink. Figure 8 shows the changes of three control parameters of the PID control core unit when selecting the pitch angle control simulation (Fig. 5 , Fig. 6, Fig. 7).

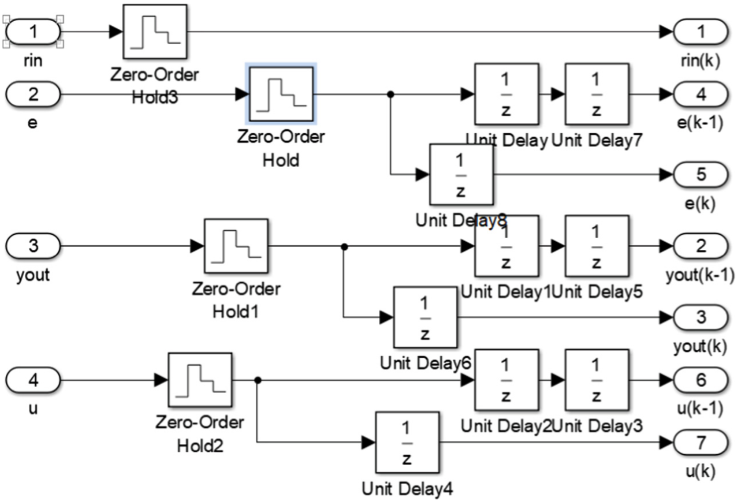

Fig. 4. Model of input subsystem

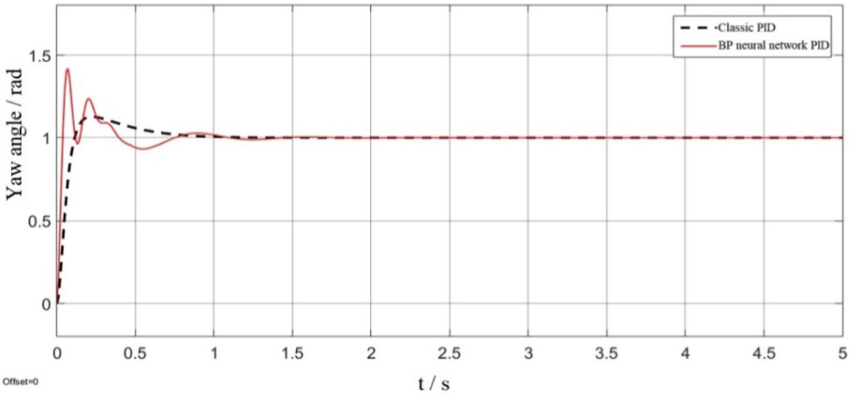

Fig. 5. Calculation and analysis result of yaw angle

The simulation results show that the optimization control method proposed in this research has good control effect on three attitude angles. The response speed and stability of the new method are obviously superior to the traditional PID control method. On the other hand, the three attitude angles fluctuated violently within one second of starting the control process. This is mainly because the neural net is constantly on-line training and learning, changing PID control parameters, resulting in the curve is not smooth.

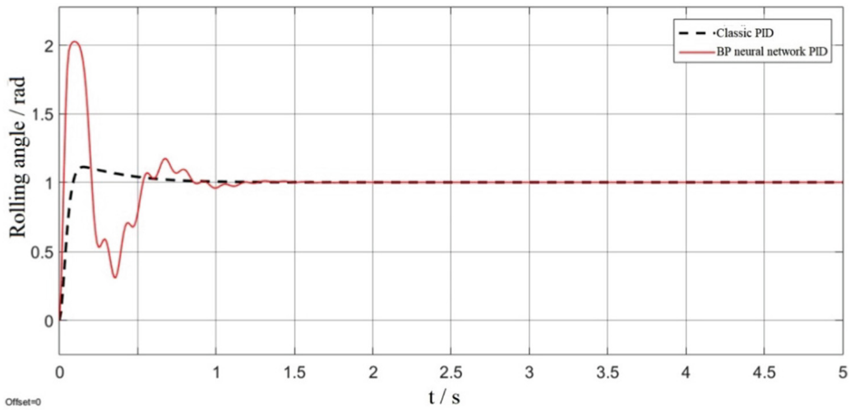

Fig. 6. Calculation and analysis result of rolling angle

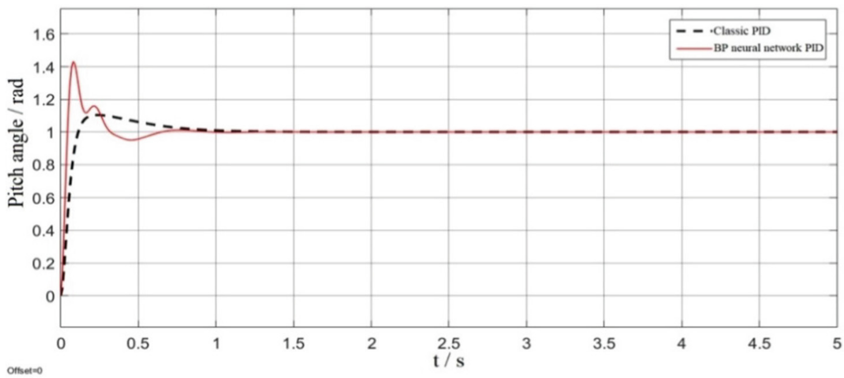

Fig. 7. Calculation and analysis result of pitch angle

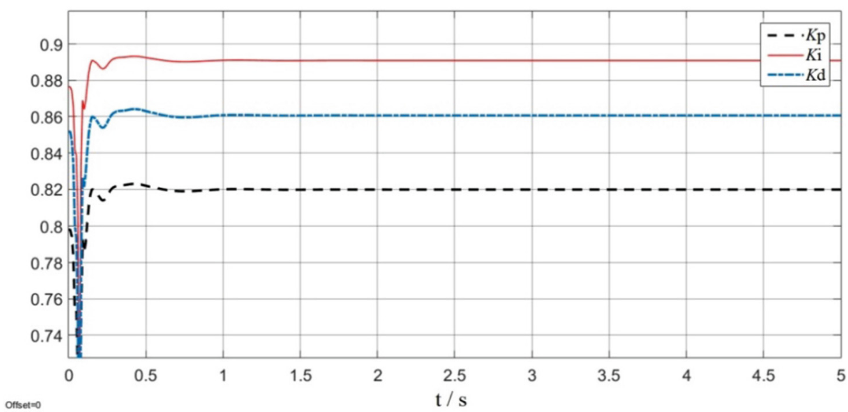

Fig. 8. Calculation and analysis result of three PID control parameters

5 Conclusion

This paper presents a control method of UAV based on neural net optimization. The method can be trained online and automatically set the appropriate system control parameters. According to the analysis of the research results, the new control method of UAV based on neural net optimization can basically achieve the desired control effect. In general, this optimization method has many advantages, such as parameter adaptation, high sensitivity, fast response and so on. It has certain guiding significance for the development of flight control technology of multi rotor UAV in the future.

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