BP Neural Network PID Control of Stable Platform

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Abstract: Stable platform has been widely used in modern weapons and civil equipment due to its ability to isolate carrier interference, and research on key technologies for stable platforms has very important practical significance and application value. In this paper, the three-axis stabilized platform is taken as the research object. A control system based on multi-loop control structure is designed around the mathematical model of DC torque motor. The design and implementation of servo control system are carried out by using classical PID and BP neural network PID control algorithm respectively. The BP neural network PID control algorithm is verified by MATLAB simulation. Compared with classical PID control algorithm, it has higher control precision and anti-interference ability.

1 INTRODUNCTION

This topic is based on the design of the control system of stable platforms, focusing on the design of the attitude control loop controller, and comparing the difference of the tracking effect of the stable platform when the controller adopts the classical PID control method and the BP neural network PID control method respectively.

2 DESIGN OF STABLE PLATFORM SERVO STSTEM

The main function of the three-axis stabilized platform control system is to isolate the carrier's disturbance. The system control structure is shown in Fig. 1. The stability loop uses dual-loop control, the inner loop is the frame angle control loop of the three-axis turntable, and the outer loop passes the fiber. The inner loop controller adopts the series lead correction design method to make its tracking performance meet the requirements of the double ten index (Wang Z S, Nian li LU, 2005). The outer loop controller adopts the classic PID controller and the adaptive PID controller, so that the stable turntable can isolate the carrier's disturbance f.

2.1 Design of Frame Angle Control Loop

In order to obtain the transfer function of the loaded motor, the third-order transfer function is fitted to the open-loop frequency characteristic of the loaded motor through the MATLAB system identification toolbox. The obtained identification result is shown in Fig. 2.

The frame angle control loop controller adopts the series correction controller, which respectively adds the inertia link, the lead link, the delay link, the input sinusoidal signal with the amplitude of 0. 5V and the frequency of 1Hz, the tracking amplitude error of the frame angle control loop is 3. 62%, obtained by the FFT analysis of the signal and the phase error is -4. 52°, which satisfies the double ten index (Deng K, Cong S, Shen H, 2011).

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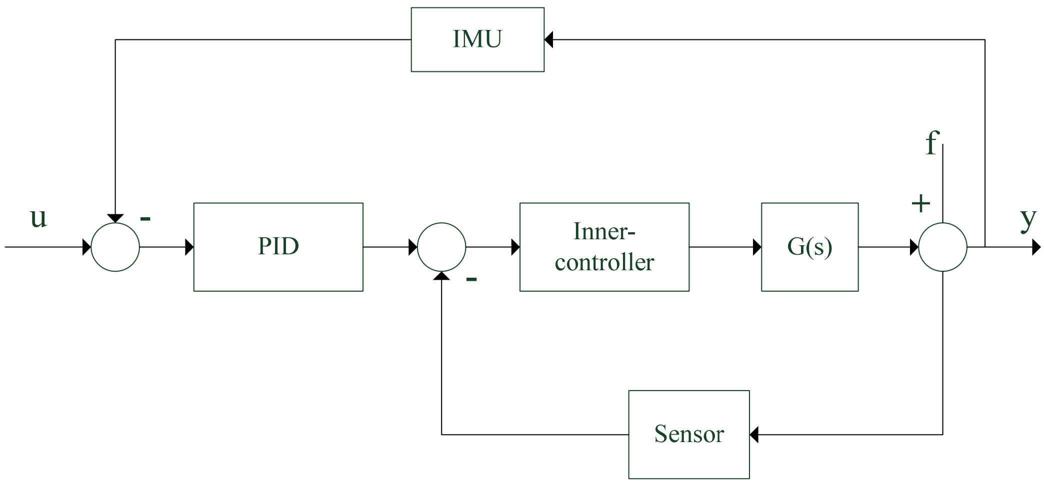

Figure 1. Dual-loop control structure.

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Process model with transfer function:
                    Kp
  G(s) = ------------------
         s(1+Tp1*s)(1+Tp2*s)

         Kp = 16.888
        Tp1 = 2.7372e-09
        Tp2 = 0.084752
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Figure 2. Loaded motor transfer function identification result.

2.2 Design of Attitude Control Loop

The design method of the attitude control loop controller is similar to the design method of the frame angle control loop. The frame angle control loop is regarded as the controlled object, and the output of the attitude control loop can isolate the effect of the interference f through the design of the controller, thereby maintaining the stable platform. The orientation in the inertial space is unchanged. The next chapter will focus on the principles of BP neural network control and combine it with classic PID.

3 THE CONTROL PRINCIPLE OF BP NEURAL NETWORK

Neural network control does not require precise mathematical models, easy parallel computing, good at learning from input and output, and nonlinear mapping capabilities. Combining it with PID control can make up for the lack of PID control, making the control of the stable platform more effective.

3.1 BP Neural Network Structure Model

The learning method of the neural network means that the information is transmitted from the input layer to the output layer layer by layer. If the output cannot reach the expected value, the error signal is transmitted back in the reverse direction, and the error signal is reduced by modifying the parameters of each layer, and then the forward propagation of information repeats the forward transmission of information and the reverse transmission of errors until the error is less than a given value. The main purpose of neural networks is to minimize errors in network output. This is the BP neural network algorithm, and the three-layer neural network structure is shown in Fig. 3.

x_1, x_2, $\cdots$, x_n is the input of thr network, y_1, y_2, …, y_{h} is the output of the hidden layer, t_1, t_2, …, t_m is the target output, the transfer function of the input layer to the hidden layer is f, hidden The transfer function from layer to output layer is g. So you can get:

$$y_i = f(\sum_{i=1}^{n} \omega_{ij} x_i) \qquad (1)$$

y_i represents the output of the j th neuron of the hidden layer. Output of the k th neuron of the output layer:

$$z_k = g(\sum_{j=1}^{h} \omega_{jk} y_i) \qquad (2)$$

At this point, the error between the actual output and the target output is:

$$\varepsilon = \frac{1}{2} \sum_{k=1}^{m} (t_k - z_k)^2 \qquad (3)$$

We call $f(x)$、$g(x)$ excitation functions, and there are several types of commonly used excitation functions:

Piecewise linear function, sigmoid function, Gaussian function (Qing Zhang, Zhenfan Tan, Ying Liang, 2008).

3.2 Neural Network PID

The control method obtained by combining the neural network and the PID is the neural network PID control (PIDNN). The control method has the advantages of neural network and PID control, and overcomes the shortcomings of the traditional PID control in the nonlinear time-varying system. . The structure of the PID control system based on BP neural network is shown in Fig. 4.

The controller consists of two parts:

Classic PID control: closed control of the controlled object directly.

BP neural network: the output state of the output layer neurons corresponds to the three adjustable parameters of the PID controller, k_p, k_d, k_i. The self-learning and weighting coefficients of the neural network are adjusted so that its steady state corresponds to the PID controller parameters under certain optimal control laws. Where is the transfer function of the frame angle control loop (Peng Meixiang, 2007).

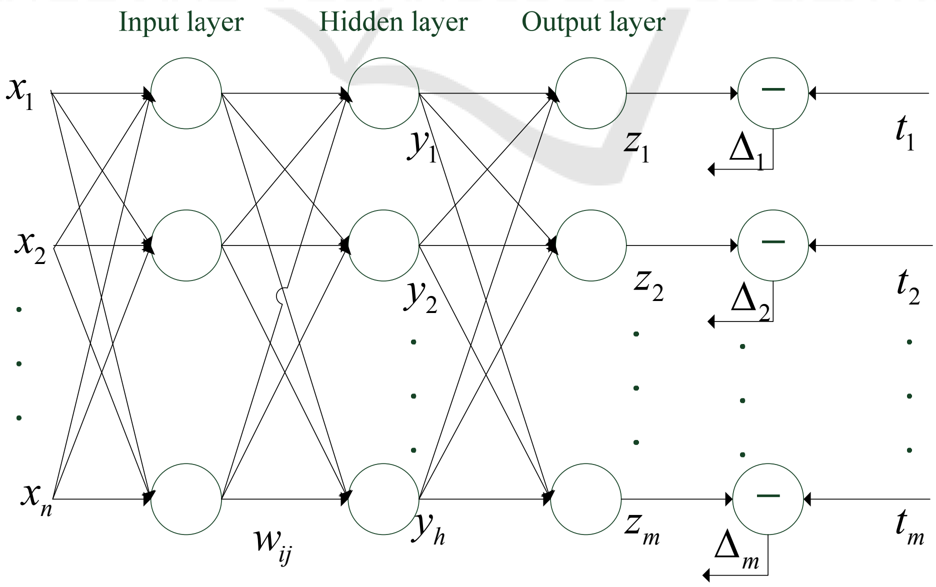


Figure 3. Three-layer neural network structure.

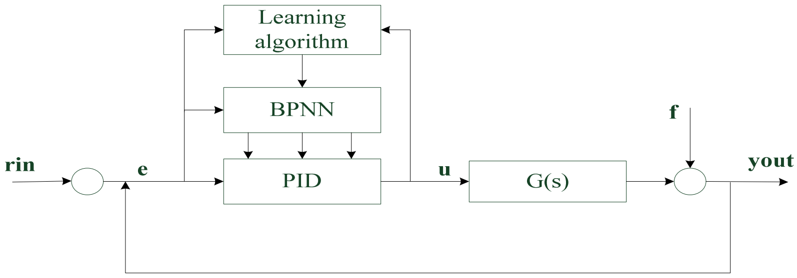


Figure 4. Control block diagram of stable platform based on BP neural network algorithm.

Let BP neural network NN be a three-layer BP structure. It has m input nodes, q hidden nodes and 3 output nodes. The input node corresponds to the operating state quantity of the selected system, and the input quantity and output quantity at different times as shown in the figure below are normalized if necessary.

The output nodes correspond to the three parameters of the PID controller k_p, k_i, k_d. Since k_p, k_i, k_d cannot be negative, the output layer neuron activation function takes a non-negative Sigmoid function.

The input of the BP neural network is $O_j^{(1)} = x(j)$, and $j = 1, 2, \cdots, m$.

Where m is the number of input variables, depending on the complexity of the controlled system. The network hidden layer input and output are respectively

$$net_i^{(2)}(k) = \sum_{j=0}^{m} \omega_{ij}^{(2)} o_j^{(1)} \tag{4}$$

$$O_i^{(2)}(k) = f(net_i^{(2)}(k)) \qquad i = 1, 2, \cdots, q \tag{5}$$

In the formula(5), $\{\omega_{ij}^{(2)}\}$ is hidden layer weighting factor, the superscripts (1), (2), and (3) represent the input layer, the hidden layer, and the output layer.

Finally, the input and output of the three nodes of the network output layer are:

$$net_l^{(3)}(k) = \sum_{i=0}^{q} \omega_{li}^{(3)} o_i^{(2)}(k) \tag{6}$$

$$O_l^{(3)}(k) = g(net_l^{(3)}(k)) \qquad l = 1, 2, 3 \tag{7}$$

In the formula, $\{\omega_{li}^{(3)}\}$ is output layer weighting factor.

Correcting the weight coefficient of the network by the steepest descent method, that is, searching and adjusting the negative gradient direction of the weighting coefficient by $E(k) = \frac{1}{2}(rin(k) - yout(k))^2$, and adding an inertial term that makes the search quickly converge globally, and then,

$$\Delta\omega_{li}^{(3)}(k) = -\rho \cdot \partial[\frac{1}{2}(rin(k) - yout(k))^2] / \partial\omega_{li}^{(3)} + \gamma\Delta\omega_{li}^{(3)}(k-1) \tag{8}$$

ρ is learning rate, γ is inertia coefficient (usually the value of ρ, γ is between 0 and 1),while

$$\frac{\partial E(k)}{\partial\omega_{li}^{(3)}} = \frac{\partial E(k)}{\partial y(k)} \cdot \frac{\partial y(k)}{\partial u(k)} \cdot \frac{\partial u(k)}{\partial O_l^{(3)}(k)} \cdot \frac{\partial O_l^{(3)}(k)}{\partial net_l^{(3)}(k)} \cdot \frac{\partial net_l^{(3)}(k)}{\partial\omega_{li}^{(3)}} \tag{9}$$

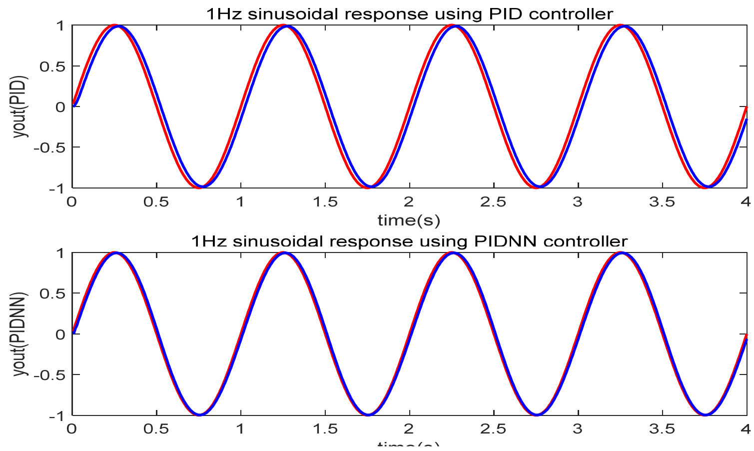
In this way, the BP neural network output layer weight calculation formula is:

$$\Delta\omega_{li}^{(3)}(k) = \rho \cdot e(k) \frac{\partial\hat{y}(k)}{\partial u(k)} \cdot \frac{\partial u(k)}{\partial o_l^{(3)}(k)} \cdot g'(net_l^{(3)}(k)) \cdot o_i^{(2)}(k) + \gamma\Delta\omega_{li}^{(3)}(k-1) \tag{10}$$

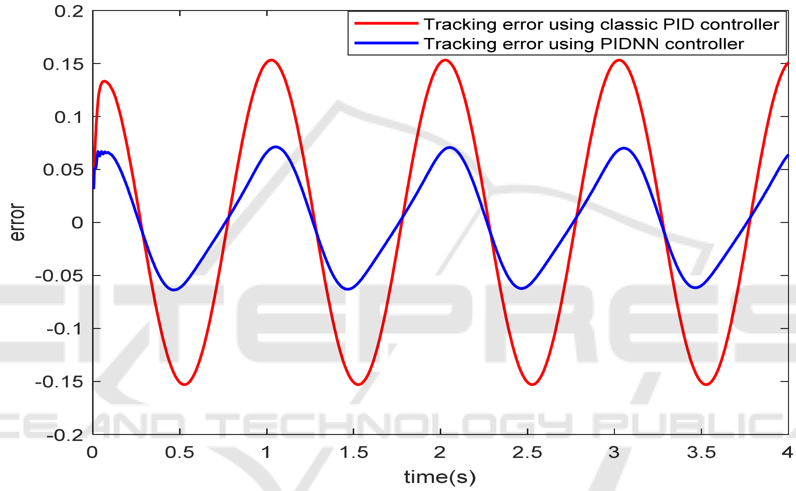
4 SIMULATION

Based on the previous sections, we analyzed the design method of BP neural network PID controller. The determination of BP neural network structure and the selection of activation function are studied. Below we design the angular control loop controller as the controlled object of the attitude control loop, and use the following parameters for simulation analysis.

1. BP neural network structure selects 4-5-3 structure, the input vector is: $x = [rin(k), yout(k), error(k), 1]$, the output vector is $y = [k_p, k_i, k_d]$;

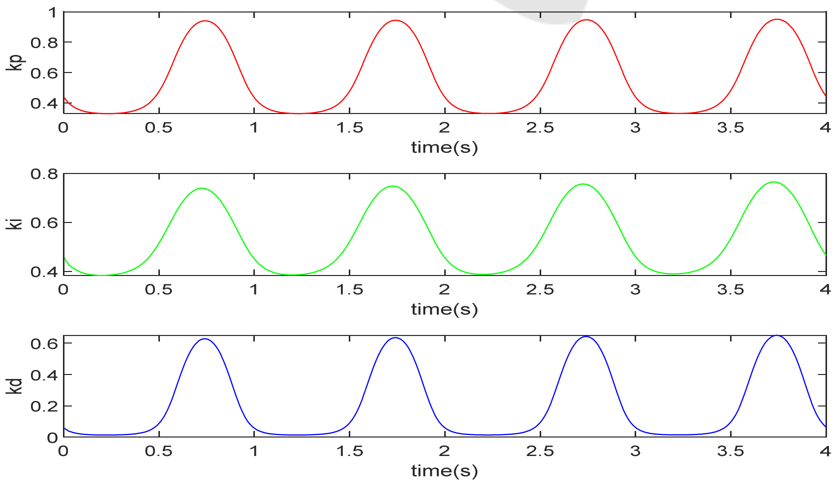


(a)



(b)

Figure 5. BP Neural Network PID Control Structure.



(c)

Figure 6. Curve of parameter change.

2. The activation function is selected as follows, the activation function of the hidden layer selects the hyperbolic tangent function:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{11}$$

3. The activation os the output layer selects the function:

$$g(x) = \frac{e^x}{e^x + e^{-x}} \tag{12}$$

4. Learning rate $xite = 0.16$;inertia factor $alfa = 0.10$; sampling time is 0. 005s.

The attitude control loop adopts BP neural network controller and classical PID controller respectively, and the sinusoidal response curve of the stable platform with sinusoidal signal input with amplitude of 0. 5V and frequency of 1Hz is shown in the Fig. 5(a).

The tracking error curve of the stable platform is shown in the Fig. 5(b).

The trend of k_p, k_i, k_d is as shown in Fig. 6.

Taking the pitch axis as an example, can be seen from the image obtained from the above simulation, the control system adopts classical PID control method, the input signal is a 1Hz sinusoidal signal. Using FFT spectrum analysis to obtain sinusoidal tracking error, the amplitude error is 5. 48% and the phase error is 2. 1. The control system adopts BP neural network PID control method, Using FFT spectrum analysis to obtain sinusoidal tracking error, the amplitude error is reduced to 3. 92% and the phase error is reduced to 1. 8, meet the requirements of the double ten indicator.

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