Single Neuron Adaptive PID Control of Seeker Stabilized Platform Speed Loop

Bin Pu[a], Jing Wang[b] and Huhai Jiang[c]

South-west institute of technical physics, Chengdu, 610041, China

[a]913152992@qq.com, [b]1522468472@qq.com, [c]835916113@qq.com

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Abstract: In order to effectively improve the dynamic performance of the seeker stable platform speed loop control system, a single neuron adaptive PID control method is proposed. Because the single neuron network has the characteristics of simple structure and self-learning, it can be combined with classic PID control to achieve adaptive parameter tuning. At the same time, this paper introduces the idea of quadratic performance index in the optimal control theory, and designs an improved single neuron adaptive PID control algorithm. Classical PID control, single neuron adaptive PID control and improved single neuron adaptive PID control method were used to simulate the speed loop control system of seeker stable platform. The results show that the improved single neuron adaptive PID control algorithm can not only adjust the adaptive parameters, but also has strong robustness and anti-jamming performance.

1. Introduction

The seeker stable platform speed loop control system mostly uses the classic PID control method. This method is based on frequency domain design. On the accurate model of the known controlled object, the system meets the design requirements through series-parallel correction [1]. However, in engineering practice, the application environment is often complicated and the mathematical model of the accurately controlled object cannot be obtained. At the same time, once this classic PID method is tuned, the parameters are fixed, and it is difficult to adapt to the complex characteristics of industrial process objects such as time-varying and nonlinear. Therefore, it is imperative to improve the control method in the seeker servo system.

With the advancement of science and technology, many advanced intelligent control methods have made great progress, such as neural networks with strong nonlinear mapping capabilities, self-learning adaptability, parallel information processing methods, and excellent fault-tolerant performance [2]. As the basic unit of neural network, single neuron has strong self-learning and self-adaptive ability. The adaptive controller composed of it has a simple structure, is easy to implement, has a small amount of calculation, and can adapt to changes in the external environment, and has strong robustness, so it has been widely used. Therefore, this paper takes the seeker stable platform speed loop control system as the object and combines the single neuron algorithm with the classic PID [3] algorithm to form a single neuron adaptive PID control algorithm, which realizes the parameter self-Adapt to setting. At the same time, the idea of quadratic performance index is introduced into the adjustment of the weighting coefficient of the single neuron learning algorithm to form an improved single neuron adaptive PID control algorithm. The results show that the improved algorithm has a better control effect on the stable platform speed loop control system.

2. Modeling of the speed loop control system of seeker stable platform

The seeker stabilization platform must ensure that the target is captured and tracked in the case of carrier movement. In order to effectively isolate the carrier movement and overcome the impact of the friction torque and other disturbances on the control performance, the speed loop is required to have adaptive parameters The goals of tuning and strong servo characteristics are also increasingly

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necessary, such as fast response, strong robustness, and isolation and interference performance. The speed loop suppresses the system nonlinearity and external disturbances by increasing the stiffness of the system, ensuring the stability of the system.

Therefore, based on the structure principle of the single-axis double-closed loop control system of seeker stabilization platform, this paper mainly focuses on the research of single neuron adaptive PID control for the seeker stabilization platform's rate loop. In the seeker stable platform speed loop control system, the most important actuator is generally a torque motor. The torque motor controls the movement of the frame to make corresponding movements, thereby counteracting the disturbance. Assuming that there is no coupling effect between the two channels of the frame, the mathematical model of the seeker stable platform speed loop control system can be established as follows:

(1) Model of motor and load platform.

According to the balance equation of the torque motor:

$$U_{a=}i_aR_a + L_a d_i/d_t + e \tag{1}$$

Among them, is the motor armature voltage; e is the motor back electromotive force; L_a is the motor armature inductance;R_a is the motor armature resistance; i_a is the motor armature current.

The transfer function of the equivalent torque motor from armature voltage U_a to M_m output torque is:

$$\frac{M_m(s)}{U_a(s)-C_e w'(s)} = \frac{C_m}{R_a}\frac{1}{T_e+1} = \frac{C_m}{L_a S + R_a} \tag{2}$$

Among them, C_m is the motor torque coefficient; C_e is the motor back electromotive force coefficient; T_e is the time constant, there is $T_e = L_a/R_a$

Taking angular velocity w as the output, ignoring the non-rigid factors between the motor and the load, assuming that the total rotational inertia of the motor and the load converted to the motor shaft is J, the equivalent load transfer function can be obtained from the dynamic principle:

$$\frac{w'(s)}{M_m(s)} = \frac{1}{Js} \tag{3}$$

Furthermore, the mathematical model of the motor and load system is shown in Figure 1.

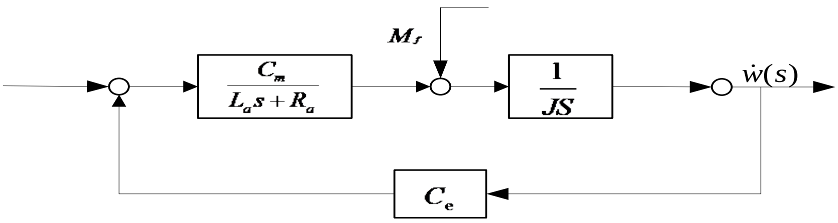

Figure 1. Model diagram of motor and load system

If the disturbance torque M_f received by the system is zero, the transfer function of the equivalent torque motor of the armature voltage u_a to the rotation angular velocity w is:

$$\frac{\dot{w}(s)}{U(s)} = \frac{\frac{C_m}{R_a J} * \frac{1}{s(T_e s+1)}}{1+\frac{C_m C_e}{R_a J} * \frac{1}{s(T_e s+1)}} = \frac{1}{C_e} * \frac{1}{T_m T_e s^2 + T_m s + 1} \tag{4}$$

The approximate ratios of the power amplifier and rate gyroscope are denoted as k_m and k_g, respectively. In summary, the speed loop control system model of the seeker stable platform is shown in Figure 2.

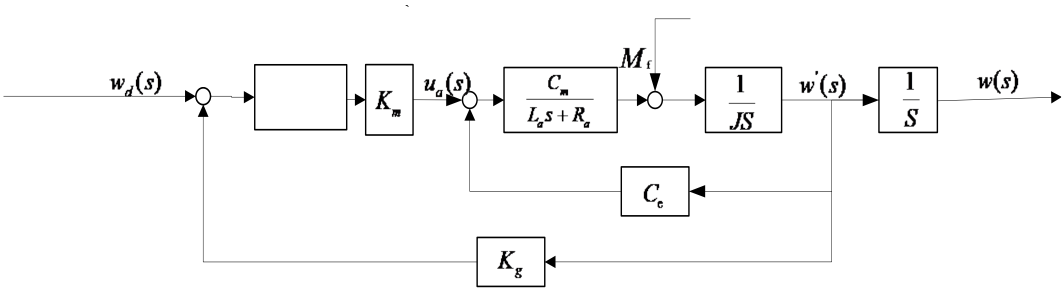

Figure 2. The model of the speed loop control system of the seeker stable platform is shown in the figure

Taking the rate gyro gain as 1, the transfer function of the rate loop control system of the seeker stable platform can be obtained from Figure 2:

$$G(s)=\frac{C_m K_m}{T_e R_a Js + R_a Js + C_e C_m} \tag{5}$$

3. Improved single neuron adaptive PID control method

3.1 Single neuron adaptive PID control

The single neuron adaptive PID control algorithm, which is composed of a single neuron network algorithm and a classic PID control algorithm, can realize automatic adjustment of parameters when the controlled system environment changes, and its controller structure schematic diagram See Figure3.

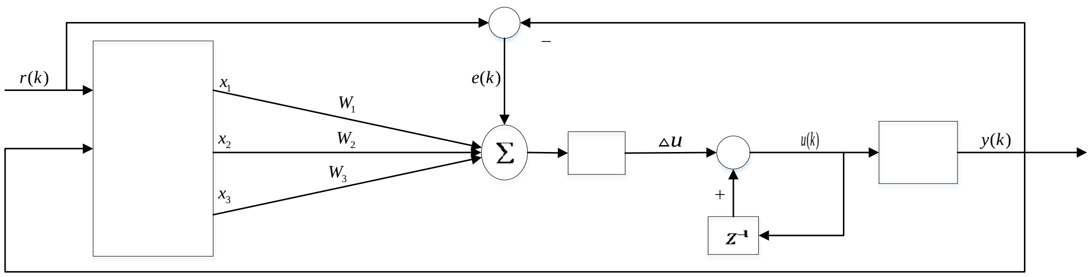

Figure 3. Schematic diagram of single neuron adaptive PID controller structure

The classic incremental digital PID control algorithm is:

$$\triangle u(k)=k_p \triangle e(k)+k_i e(k)+k_d[e(k)-2e(k-1)+e(k-2)] \tag{6}$$

Among them, kp is the scale factor; ki is the integral coefficient; kd is the differential coefficient; ki=kp*Ts/Ti; kd=kp*Td/Ts; kd is the sampling period.

It can be seen that the incremental PID control only needs to correct the proportional coefficient, integral coefficient and differential coefficient through repeated experiments to achieve effective control. The PID control algorithm composed of a single neuron:

$$\triangle u(k)=w_1 e(k-1)+w_2[e(k)-e(k-1)]+w_3[e(k)-2e(k-1)+e(k-2)] \tag{7}$$

Formula (6) and formula (7) are identical in form, the essence is that the adjustable proportional, integral and differential coefficients in formula (6) are fixed after correction, while the weight coefficients w_1, w_2, w_3 in formula (7) are determined by neurons Learn to adjust instead of fixing in advance.

Therefore, it can be said that the single neuron adaptive PID control algorithm has adaptive characteristics. Its core is to correct the weight coefficients through certain learning rules. Different learning rules constitute different control algorithm cores. Three typical learning rules are commonly used, unsupervised Hebb learning rules, supervised Delta, Hebb learning rules. Supervised Hebb learning rule is a combination of unsupervised Hebb learning rule and supervised Delta learning rule. Therefore, this paper uses supervised Hebb to form a single neuron adaptive PID control algorithm, and its learning rules generate control signals through self-organization related search. The standardized learning algorithm is as follows:

$$\begin{cases} u(k) = u(k-1) + K\sum_{i=1}^{3} w_i(k)x_i(k) / \sum_{i=1}^{3} | w_i(k) | \\ w_1(k) = w_1(k-1) + \eta_i e(k)u(k)x_1(k) \\ w_2(k) = w_2(k-1) + \eta_p e(k)u(k)x_1(k) \\ w_3(k) = w_3(k-1) + \eta_d e(k)u(k)x_1(k) \end{cases} \tag{8}$$

In formula (8), e(k) is the system error; the output of the converter is the state quantity required for neuron self-learning x_i;K is the adjustable proportional coefficient of neuron; n_i, n_p, n_d is the learning efficiency; u(k) is the output of the controller, its function law:

$$u(k) = u(k-1) + K\sum_{i=1}^{3} w_i^{'}(k)x_i(k) \tag{9}$$

The weighting factor $w_i(k)$ corresponding to $x_i(k)$:

$$w_i^{'}(k) = w_i(k) / \sum_{i=1}^{3} | w_i(k) | \tag{10}$$

State variable x_i can be expressed as

$$\begin{cases} x_1(k) = r(k) - y(k) = e(k) \\ x_2(k) = \triangle e(k) = e(k) - e(k-1) \\ x_3(k) = e(k) - 2e(k-1) + e(k-2) \end{cases} \tag{11}$$

The single neuron adaptive PID control is essentially a variable coefficient proportional integral differential compound controller. Through its own learning process, it understands the structure, parameters and uncertainties of the system, and changes the control parameters accordingly, so it is very robust. In the single neuron adaptive PID control algorithm, the initial value of the weighting coefficient, the learning rate and the proportional coefficient of the neuron are the coefficients to be selected. The selection of the initial value of the weighting coefficient can be determined according to the parameters of the conventional PID controller when the parameters are unchanged.

For the learning rate coefficient of a single neuron, the degree of freedom of the value of the learning rate after normalization is quite large. Simulation experiments show that the value of the learning rate has little effect on the quality of the neuron system. The proportional coefficient K plays a very important role, and its value is closely related to the dynamic response and stability of the system.

Therefore, different learning rates were adopted n_i, n_p, n_d, In order to adjust different weights separately:

1) The choice of K value is very important. The larger the K, the better the rapidity, but the larger the amount of overshoot may even make the system unstable. The K value should be reduced. If the transition time is too long, the K value should be increased.

2) If the process transition time is too long, increase by n_p, n_d ;If the overshoot quickly drops to a stable value, and then the steady-state time for the appreciation is too long, it can reduce the increase of the integral effect; for a large delay system, to reduce overshoot, n_p, n_d can be appropriately larger; if the system transition time is too long, it can be appropriately increased by n_i.

3.2 Single neuron adaptive PID control using quadratic performance indicators

According to the linear quadratic optimal control theory [6], the quadratic performance index is introduced into the single neuron controller. With the idea of the quadratic performance in optimal control, the output error and the control increment are weighted the sum of squares is the smallest to adjust the weighting coefficient, so as to indirectly realize the constrained control of the output error and control increment weighting. The introduced performance indicators are:

$$J(k)=\frac{1}{2}[\mathrm{P}(y_d(k)-y(k))]^2+Q\vartriangle^2 u(k)\} \tag{12}$$

among them:$y_d(k)$, $y(k)$ is the output of the process at time k; P and Q are the weighting coefficients of the output error and the control increment. d is the total lag of the process.

Correct the weighting coefficient $w_i(k)$ of the network according to the gradient descent method, and search and adjust the negative gradient direction of the weighting coefficient according to $J(k)$:

$$\vartriangle w_i(k)=-\eta_i(\frac{\partial J}{\partial w_i(k)})=-\eta_i(\frac{\partial J}{\partial y}*\frac{\partial y}{\partial u}*\frac{\partial u}{\partial w_i(\mathrm{k})}) \tag{13}$$

In the calculation: The error caused by the calculation needs to be compensated by adjusting the learning rate n_i. In the actual calculation, the first value b0 of the output response when the unit input is added to the process input at zero initial state is substituted, and its value can be obtained through experiment; e(k+d) is unmeasurable, you can use e (k) instead.

In summary, the improved single neuron adaptive PID control learning algorithm can be derived from equations (6), (7), (8), and (12):

$$\begin{cases} u(k)=u(k-1)+K\sum_{i=1}^{3} w_i^{'}(k)x_i(k) \\ w_i^{'}(k)=w_i(k)/\sum_{1}^{3}|w_i(k)| \\ w_1(k)=w_1(k-1)+\eta_i Ke(k)[Pb_0 z(k)x_1(k)-QK\sum_{i=1}^{3}(w_i^{'}(k)x_i(k))x_1(k) \\ w_2(k)=w_2(k-1)+\eta_p Ke(k)[Pb_0 z(k)x_2(k)-QK\sum_{i=1}^{3}(w_i^{'}(k)x_i(k))x_2(k) \\ w_3(k)=w_3(k-1)+\eta_d Ke(k)[Pb_0 z(k)x_2(k)-QK\sum_{i=1}^{3}(w_i^{'}(k)x_i(k))x_2(k) \end{cases} \tag{14}$$

Among them, the state variable x_i is the same as equation (13), and $z(k)=e(k)$ is the systematic error.

4. Simulation and comparative analysis

In Simulink, simulation comparison experiment of classic PID control, single neuron adaptive PID control and improved single neuron adaptive PID control method is carried out, and the equivalent transfer function of the speed loop control system of a certain seeker stable platform is, after Z transformation:

$$G(z)=\frac{0.1z^2+0.13z+0.0004.6}{z^3-2z^2+z-0.00001.2} \tag{15}$$

The initial value selection learning rule: the classic PID control parameters are obtained after correction by the Signal constaint module in the private placement forest, and the proportional integral differential coefficients are 3.5/28.78 and 0.08, respectively. The single neuron adaptive PID control algorithm and its improved algorithm, as long as it follows: the selection of initial weights is not too limited, but if all are assigned 0, it will fall into a local minimum and crash the controller. The initial weight is only used to start the controller, and has no effect on the weight adaptive adjustment process and system performance. When the gain factor K is small, the system has small overshoot, slow response, and high accuracy. Conversely, when the gain factor K is large, the overshoot is large, with fast response, poor accuracy, and long adjustment time. If it is too large, oscillation may occur. The algorithm adopts standardized learning rules, so the learning rate can take a large value. First choose K so that the overshoot of the system is not too large. Therefore, the initial learning rate n_i, n_p, n_d can be taken as 0.32, 0.34, 0.33; K=5; the sampling time is 1ms.

To build a simulation model in simulink, first perform the step response of the three methods, as shown in Figure 4.

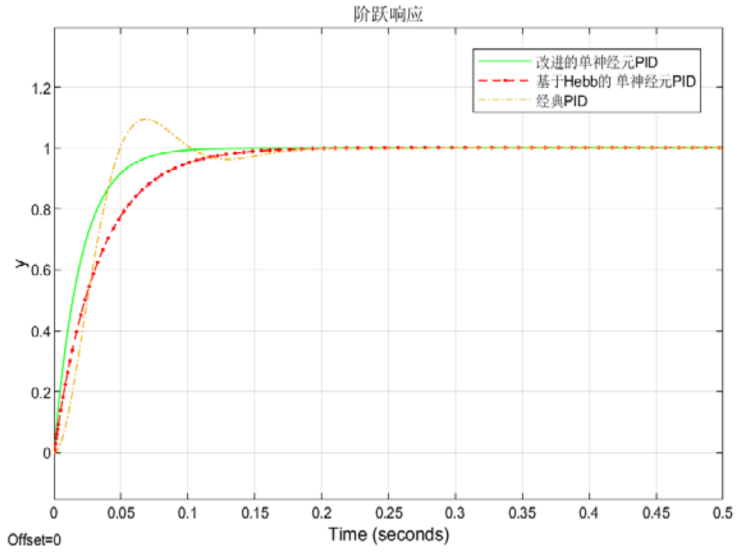

Figure 4. Step response of different algorithms

From the step response curve, the difference between classic PID control, single neuron adaptive PID control without overshoot, improved algorithm single neuron adaptive PID control, not only no overshoot, but also faster response speed, around 0.1S A steady state is reached.

Improved single neuron adaptive PID control algorithm,The change of controller parameter n_i, n_p, n_d is shown in Figure 5.

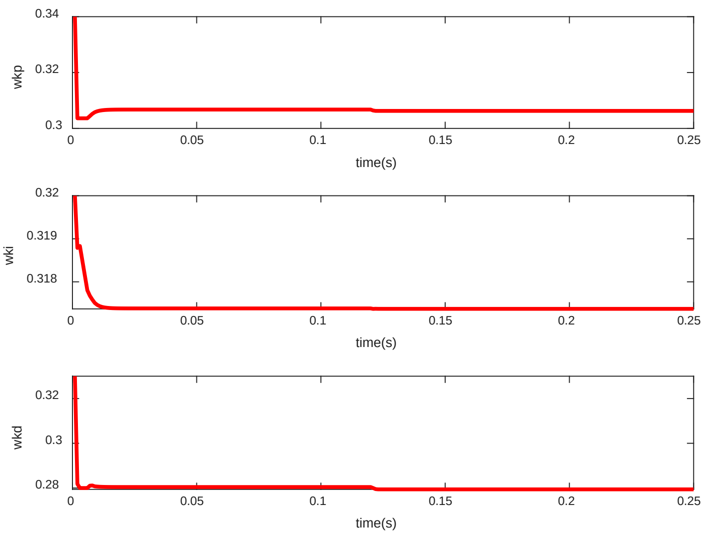

Figure 5. The parameter changes curve of the improved algorithm

The changes of the self-learning weight parameters of the improved algorithm according to FIG. 5 show that compared with the classic PID control algorithm, the improved single neuron adaptive PID control algorithm can indirectly realize the parameter adjustment, that is, the adaptive control can be realized, adjustable Parameters may not be fixed targets.

The parameters of the improved algorithm controller were perturbed by 15%, and a pulse with an amplitude of 0.1 was added as an interference signal at 0.12 seconds to verify the isolation and anti-interference ability of the improved algorithm controller. The simulation results are shown in Figure 6.

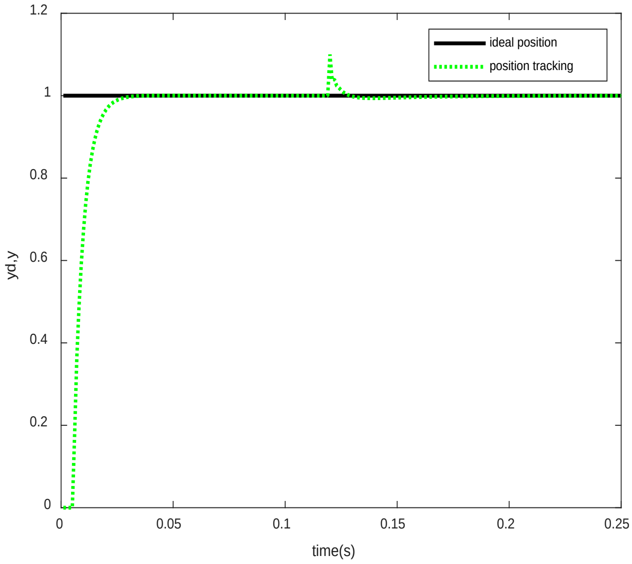

Figure 6. System immunity

Figure 6 shows that the quadratic index function that introduces the optimal theory improves the single neuron adaptive PID control algorithm based on supervised Hebb learning rules, and is able to maintain good isolation anti-interference and robustness.

5. Conclusion

This article takes the seeker stable platform rate loop servo system as the object. First, the simple structure of the single neuron network algorithm in the advanced intelligent control algorithm is combined with the classic PID control algorithm. The theoretical analysis and simulation comparison analysis show that the combined algorithm with the characteristics of the two algorithms, the parameter adaptive tuning is realized. Secondly, the fusion of the idea of optimal control and neural network control constitutes an improved single neuron adaptive PID control algorithm, which not only has a significant improvement in overshoot, steady state adjustment and control rate increment, but also effectively improves The robustness and isolation anti-disturbance capability of the seeker stable platform speed loop servo system are discussed. This research has certain theoretical research value and engineering application significance.

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