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Study on Adaptive PID Control Algorithm Based on RBF Neural Network

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Abstract

Aim at the limitation of traditional PID controller has certain limitation, the traditionalPID control is often difficult to obtain satisfactory control performance, and the RBF neural networkis difficult to meet the requirement ofreal-time control system.To overcome it, an adaptive PID control strategy based on (RBF) neural network isproposed in this paper. The resultsshow that the proposed controller is practical and effective, because of the adaptability, strong robustness and satisfactory controlperformance.It is also revealed from simulation results that the proposed control algorithm is valid for DC motor and also provides the theoretical and experimental basis.

Keywords: *adaptive PID controller, RBF neural network, DC motor*

1. Introduction

PID controllers are the most common industrial process controller, its structure is simple, good robustness and high reliability, and the PID controller is widely used industrial process control [1]. However, the conventional PID controller has a certain limiting, especially the controlled object contains a nonlinear and time-varying characteristics,the traditionalPID control is often difficult to obtain satisfactory control performance [2]. Since the parameters empirical formula of PID controller is proposed by the Ziegler andNiehols, and the many methods have been used for the parameter setting of the PID controller. With the development of intelligent control theory, the intelligent control technology was introduced in PID control by many scholars, and provided new method means for the PID controltechnology.In recent years, the artificial neural network has been used in complex process control, and has attracted widespread attention [3, 4]. Because the neural network has adaptive learning, parallel processing and the strong ability of fault tolerance.The neural network adaptivePID control scheme which is locally approximated by the RBFnetworkis adopted in this paper, and in order to improve the system accuracy, robustness and adaptiveness [5].

2. RBF function

The Radial Basis Function (RBF) is a neural network which was put forward by J.Moodyand C.Darken in the late 1980s, it is a three layer feed forward network with single hidden layer (Figure 1), is a kind of local approximation of the neural network. The RBFis a kind of three layer forward network. The mapping which is from the input to the output is nonlinear, and the mapping which is from hidden layer space to the output space is linear [6]. It simulates the neural network structure for the partial adjustment of the human brain and each receiving domain. RBF is a kind of local approximation network, which has been proved that the any precision approximates any continuous function. This kind of network characteristics is that it onlyhas a few output of connection power influence aim at local input space, so that local approximation network has the advantages of fasterlearning speed [7]. Therefore, the RBF network can significantly accelerate the learning speed and avoid local minimum problem, which is suitable for the real-time control.

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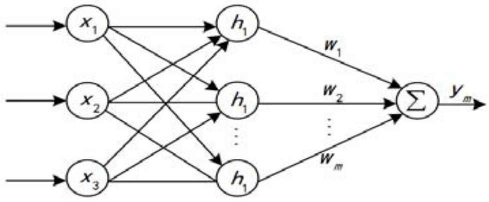

Figure 1. Three layer feed forward network with single hidden layer

In the structure of RBF network, $X=[x_1,x_2,\cdots x_n]^T$ is the input vector of network. Assuming the radial basis vectors of the RBF network is $H=[h_1,h_2,\cdots h_n]^T$. Where h_j isgaussian basis function:

$$h_j=\exp(-\frac{\left\|X-C_j\right\|^2}{2b_j^2}),\ j=1,2,\cdots m. \tag{1}$$

The j network node of center vector is $C_{i,j}=[c_{1j},c_{2j},\cdots c_{i,j}\cdots c_{n,j}]^T$. Assuming the basis width vector of network is $B=[b_1,b_2,\cdots b_m]^T$, b_j is the basis width parameter of node, and is greater than zero. The weight vector of network is $W=[w_1,w_2,\cdots w_m]$.The output of the network is given as:

$$y_m(k)=wh=w_1h_1+w_2h_2+\cdots+w_mh_m \tag{2}$$

Assuming the ideal output is $y(k)$, the performance index function is:

$$E(k)=\frac{1}{2}(y(k)-y_m(k))^2 \tag{3}$$

Based on the gradient descent method, the iterative algorithm of output power, node center and base width parameterare:

$$w_j(k)=w_j(k-1)+\eta(y(k)-y_m(k))h_j+\alpha(w_j(k-1)-w_j(k-2)) \tag{4}$$

$$\Delta b_j=(y(k)-y_m(k))w_jh_j\frac{\left\|X-C_j\right\|^2}{b_j^3} \tag{5}$$

$$b_j(k)=b_j(k-1)+\eta\Delta b_j+\alpha(b_j(k-1)-b_j(k-2)) \tag{6}$$

$$\Delta c_{j,i}=(y(k)-y_m(k))w_j\frac{x_j-c_{ji}}{b_j^2} \tag{7}$$

$$c_{ij}(k)=c_{ij}(k-1)+\eta\Delta c_{ij}+\alpha(c_{ij}(k-1)-c_{ij}(k-2)) \tag{8}$$

Where η is learning rate, α is momentum factor.

Jacobian matrix algorithm is as follows:

$$\frac{\partial y(k)}{\partial u(k)} \approx \frac{\partial y_m(k)}{\partial u(k)} = \sum_{j=1}^{m} w_j h_j \frac{c_{1j} - x_1}{b_j^2} \tag{10}$$

Where $x_1 = u(k)$.

3. Design of Adaptive PID Controller Based on the BRF Neural Network

There are many function form of RBF neural network, Gauss function was selected inthis article as the hidden layer node function according to its unique advantages [8]. Based on the RBF neural network, the adaptive PID control system structure is as shown in Figure 2. Neural network adaptive PID controller adjusts the connection weights of neural network NN and the three parameters of PID according to the square error of the given input and system outputas the objective function [9]. The PID controller is applied to the controlled object, and makes the system output close to the given input of system.

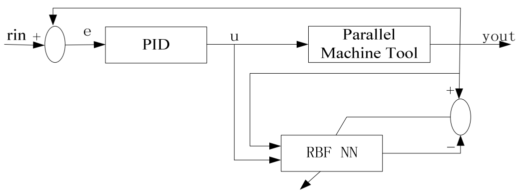

Figure 2. Adaptive PID Controller based on the BRF neural network

The control error of PID controlleris given as following:

$$error(k) = rin(k) - yout(k) \tag{11}$$

The three inputs of PID is given following as:

$$xc(1) = error(k) - error(k-1) \tag{12}$$

$$xc(2) = error(k) \tag{13}$$

$$xc(3) = error(k) - 2error(k-1) + error(k-2) \tag{14}$$

Control algorithm is given as:

$$u(k) = u(k-1) + \Delta u(k) \tag{15}$$

$$\begin{aligned}\Delta u(k) = {} & k_p(error(k)error(k-1)) + k_i error(k) \\ & + k_d(error(k) - 2error(k-1) + error(k-2))\end{aligned} \tag{16}$$

Where k_p, k_i, k_d arethe proportion, integral and differential parameters respectively.
The tuning index of neural network is selected as:

$$E(k) = \frac{1}{2} error(k)^2 \tag{17}$$

The gradient descent method is used for adjustment of k_p, k_i, k_d.

$$\Delta k_p = -\eta \frac{\partial E}{\partial k_p} = -\eta \frac{\partial E}{\partial y} \frac{\partial y}{\partial \Delta u} \frac{\partial \Delta u}{\partial k_p} = \eta error(k) \frac{\partial y}{\partial \Delta u} xc(1) \quad (18)$$

$$\Delta k_i = -\eta \frac{\partial E}{\partial k_i} = -\eta \frac{\partial E}{\partial y} \frac{\partial y}{\partial \Delta u} \frac{\partial \Delta u}{\partial k_i} = \eta error(k) \frac{\partial y}{\partial \Delta u} xc(2) \quad (19)$$

$$\Delta k_d = -\eta \frac{\partial E}{\partial k_d} = -\eta \frac{\partial E}{\partial y} \frac{\partial y}{\partial \Delta u} \frac{\partial \Delta u}{\partial k_d} = \eta error(k) \frac{\partial y}{\partial \Delta u} xc(3) \quad (20)$$

The $\frac{\partial y}{\partial \Delta u}$ can be obtained by the identification of neural network.

4. Simulation

In this section, using the PID control principle based onRBF neural networkmakes simulationfor DC motor in MATLAB. Parameters of the system for simulation are:KP=0.3, KD=0.3, KI=0.1,the transfer function of the DC motor is:

$$G(s) = \frac{103}{s^2 + 15s} \quad (21)$$

Where the sampling time is 2ms, the input signal is step signal, network hidden layer neurons number is m = 6.The Figure 3 shows the square wave response curve without the adaptive setting PID control strategy based on RBF neural network. The Figure 4 shows the square wave response curve with the adaptive setting PID control strategy based on RBF neural network. The Figure 5, Figure 6 and Figure 7 reflect the process of PID parameter adjustment. From the simulation curve we can see that the adjusted online PID controller based on the RBF neural network has good control effect, and the control effect comparing simple PIDis greatly improved. This shows that aim at the controlled object which has nonlinear and time-varying parameter, the algorithm has trace ability and anti-interference ability.

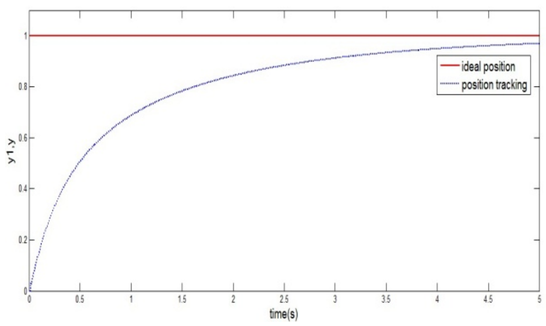

Figure 3. The step signal without the adaptive settingPID based on RBF NN

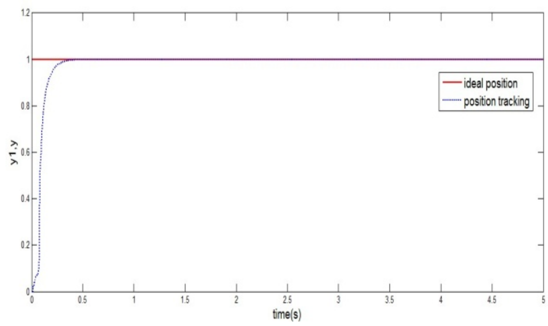

Figure 4. The step signal with the adaptive setting PID based on RBF NN

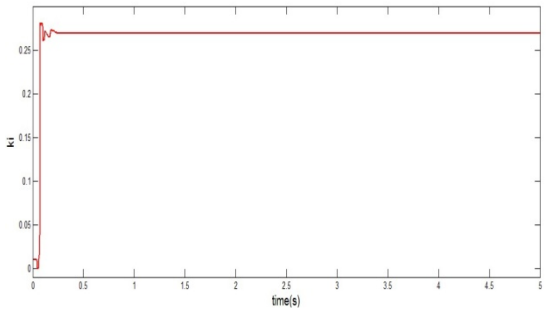

Figure 5. The adaptive setting curve of ki

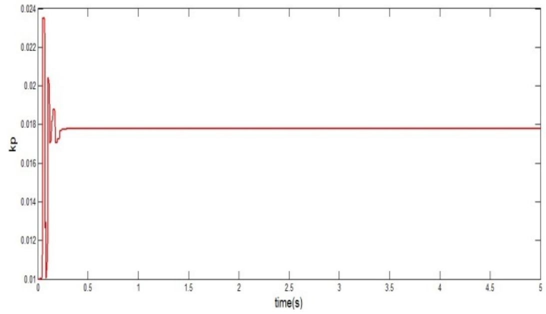

Figure 6. The adaptive setting curve of kp

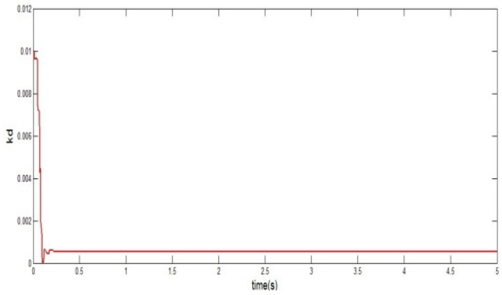

Figure 7. The adaptive setting curve of kd

5. Conclusion

In this paper, based on RBF neural network adaptive PID control strategyis proposed for the DC motor. The results show that the proposed controller is practical and effective, because of the adaptability, strong robustness and satisfactory control performance. RBFNeural network adaptive PID controller achieved good control effect. It is also revealed from simulation results that the proposed control algorithm is valid for DC motor and also provides the theoretical and experimental basis, and the controller is a kind of practical engineering.

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