Research on the 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 traditional PID control is often difficult to obtain satisfactory control performance, and the RBF neural network is difficult to meet the requirement of real-time control system. To overcome it, an adaptive PID control strategy based on (RBF) neural network is proposed in this paper. The results show that the proposed controller is practical and effective, because of the adaptability, strong robustness and satisfactory control performance. 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: PID; 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 traditional PID control is often difficult to obtain satisfactory control performance [2].Since the parameters empirical formula of PID controller is proposed by the Ziegler and Nichols, 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 control technology. 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 adaptive PID control scheme which is locally approximated by the RBF network is adopted in this paper, and in order to improve the system accuracy, robustness and addictiveness [5].

A proportional-integral-derivative controller (the PID controller) is a control loop feedback mechanism (controller) widely used in industrial control systems. A PID controller calculates an error value as the difference between a measured process variable and a desired set point. The controller attempts to minimize the error by adjusting the process through use of a manipulated variable.

The PID controller algorithm involves three separate constant parameters, and is accordingly sometimes called three-term control: the proportional, the integral and derivative values, denoted P, I, and D. Simply put, these values can be interpreted in terms of time: P depends on the present error, I on the accumulation of past errors, and D is a prediction of future errors, based on current rate of change [6]. The weighted sum of these three actions is used to adjust the process via a control element such as the position of a control valve, a damper, or the power supplied to a heating element.

In the absence of knowledge of the underlying process, a PID controller has historically been considered to be the best controller [7]. By tuning the three parameters in the PID controller algorithm, the controller can provide control action designed for specific process requirements. The response of the controller can be described in terms of the responsiveness of the controller to an error, the degree to which the controller overshoots the set point, and the degree of system oscillation. Note that the use of the PID algorithm for control does not guarantee optimal control of the system or system stability.

Some applications may require using only one or two actions to provide the appropriate system control. This is achieved by setting the other parameters to zero. A PID controller will be called a PI, PD, P or I controller in the absence of the respective control actions. PI controllers are fairly common, since derivative action is sensitive to measurement noise, whereas the absence of an integral term may prevent the system from reaching its target value due to the control action [8].

A neural network for handwriting recognition is defined by a set of input neurons which may be activated by the pixels of an input image. After being weighted and transformed by a function (determined by the network's designer), the activations of these neurons are then passed on to other neurons. This process is repeated until finally, an output neuron is activated. This determines which character was read.

Like other machine learning methods – systems that learn from data – neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule-based programming, including computer vision and speech recognition. Computational devices have been created in CMOS, for both biophysical simulation and neuromorphic computing. More recent efforts show promise for creating Nano-devices [9] for very large scale principal components analyses and convolution. If successful, these efforts could usher in a new era of neural computing [10] that is a step beyond digital computing, because it depends on learning rather than programming and because it is fundamentally analog rather than digital even though the first instantiations may in fact be with CMOS digital devices [11].

2 RBF Function

The Radial Basis Function (RBF) is a neural network which was put forward by J.Moody and C.Darken in the late 1980s, it is a three layer feed forward network with single hidden layer (Fig.1), is a kind of local approximation of the neural network. The RBF is 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. 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 are that it only has a few output of connection power influence aim at local input space, so that local approximation network has the advantages of faster learning speed. Therefore, the RBF network can significantly accelerate the learning speed and avoid local minimum problem, which is suitable for the real-time control [12-13].

BP network three Layer nodes are represented, m input nodes x_i (each two indicators in Table 1 Value), in a hidden layer node h_j, 1 output node y (University Library Assess the level of information). Network power input nodes and hidden layer nodes Value w_{ij}, network nodes and the output power hidden layer nodes is t_j.

Each index can score from reviewer's subjective scoring method after obtaining. The data to be using equation (1) is normalized.

$$\overline{x_i} = \frac{x_i - b_i}{a_i - b_i} \qquad (1)$$

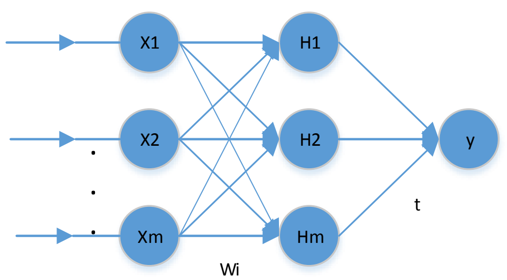

FIGURE 1 Three layer feed forward network with single hidden layer

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

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

The j network node of center vector is: $C_{i,j} = [c_{1,j}, c_{2,j}, ..., c_{i,j}, ..., c_{n,j}]^T$.

Assuming the basis width vector of network is: $B = [b_1, b_2, ..., b_m]^T$, where b_j is the basis width parameter of node, and is greater than zero.

The weight vector of network is: $W = [w_1, w_2, ..., w_m]^T$.

The output of the network is given as:

$$y_m(k) = wh = w_1h_1 + w_2h_2 + ... + w_mh_m. \qquad (3)$$

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

$$E(k) = \frac{1}{2}\left(y(k) - y_m(k)\right)^2. \qquad (4)$$

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

$$\begin{aligned} w_j(k) &= w_j(k-1) + \eta\left(y(k) - y_m(k)\right)h_j \\ &+ \alpha\left(w_j(k-1) - w_j(k-2)\right) \end{aligned}, \qquad (5)$$

$$\Delta b_j = \left(y(k) - y_m(k)\right)w_j h_j \left(\frac{\|X - C_j\|^2}{b_j^3}\right), \qquad (6)$$

$$\begin{aligned} b_j(k) &= b_j(k-1) + \eta\Delta b_j \\ &+ \alpha\left(b_j(k-1) - b_j(k-2)\right) \end{aligned}, \qquad (7)$$

$$\Delta c_{j,i} = \left(y(k) - y_m(k)\right)w_j \frac{x_j - c_{j,i}}{b_j^2}, \qquad (8)$$

$$\begin{aligned} c_{ij}(k) &= c_{ij}(k-1) + \eta\Delta c_{ij} \\ &+ \alpha\left(c_{ij}(k-1) - c_{ij}(k-2)\right) \end{aligned}, \qquad (9)$$

where η is learning rate, α is momentum factor.

Jacobian matrix algorithm is as follows:

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

where $x_1 = u(k)$.

There are many function form of RBF neural network, Gauss function was selected in this article as the hidden layer node function according to its unique advantages. 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 output as the objective function. The PID controller is applied to the controlled object, and makes the system output close to the given input of system [14-15].

The control error of PID controller is given as following:

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

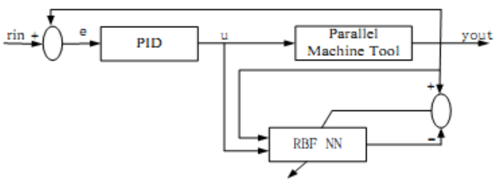

FIGURE Adaptive PID controller based on the BRF neural network

The three inputs of PID are 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:

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

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

where k_p, k_i, k_d are the 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

$$\begin{aligned}\Delta k_p &= -\eta \frac{\partial E}{\partial k_p} = -\eta \frac{\partial E}{\partial y} \frac{\partial y}{\partial \Delta u} \frac{\partial \Delta u}{\partial k_p} \\ &= \eta error(k) \frac{\partial y}{\partial \Delta u} xc(1)\end{aligned}, \tag{18}$$

$$\begin{aligned}\Delta k_i &= -\eta \frac{\partial E}{\partial k_i} = -\eta \frac{\partial E}{\partial y} \frac{\partial y}{\partial \Delta u} \frac{\partial \Delta u}{\partial k_i} \\ &= \eta error(k) \frac{\partial y}{\partial \Delta u} xc(2)\end{aligned}, \tag{19}$$

$$\begin{aligned}\Delta k_d &= -\eta \frac{\partial E}{\partial k_d} = -\eta \frac{\partial E}{\partial y} \frac{\partial y}{\partial \Delta u} \frac{\partial \Delta u}{\partial k_i} \\ &= \eta error(k) \frac{\partial y}{\partial \Delta u} xc(3)\end{aligned}. \tag{20}$$

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

STEP 1: Identified neurons. First, the output value of the item types and expectation input of cloud computing systems, types is analyzed in accordance with the requirements of BP neural network, specifically with the type of data corresponding to neurons, the input and output neurons.

STEP 2: Training sample set. Through the sample set (selected by the rule set of samples described in the next section), it can be learnt how to adjust the connection weights based on the size and direction of the error. The output mode and network mode is the same as the expected output, so as to enable the prediction of the model of system parameters.

STEP 3: Trigger switch. Changes occur in real-time monitoring by the load monitoring module task requests, when the module detects when an outbreak of type task request arrives, the trigger switches and makes BP neural network retrieval task requests and cloud computing underlying resource-related information.

STEP 4: Quantify BW value. By quantifying the value of an outbreak of type task requests, it can make them more adapted to BP neural network input and can speed up the data disposal process.

STEP 5: Quantify the resource pool indicators. The underlying resource pool information which is collected from cloud computing system should be standardized. Quantitative analysis of neural networks can change the underlying resources and to provide protection for the next parameter prediction.

STEP 6: Parameter prediction. Parameter prediction is core mission for the oriented model. By model training, input information collection, processing, the deployment model parameters with real-time forecasting resource deployment capabilities can be used to optimize cloud computing system capacity to respond to required busty workloads and to meet the requirement of dynamic and scalable cloud computing system.

3 Simulation

In this section, using the PID control principle based on RBF neural network makes simulation for 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 :

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

Where the sampling time is 2ms, the input signal is step signal, network hidden layer neurons number is m=6.The Fig.3 shows the square wave response curve without the adaptive setting PID control strategy based on RBF neural network. The Fig.4 shows the square wave response curve with the adaptive setting PID control strategy based on RBF neural network .The Fig.5, Fig.6 and Fig.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 PID is greatly improved. This shows that aim at the controlled object which has nonlinear and time-varying parameters; the algorithm has trace ability and anti-interference ability.

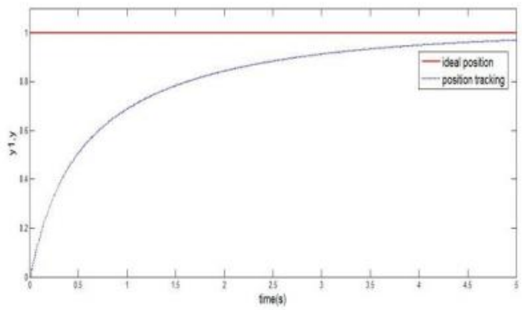

FIGURE 3 The step signal without the adaptive PID based on RBF NN

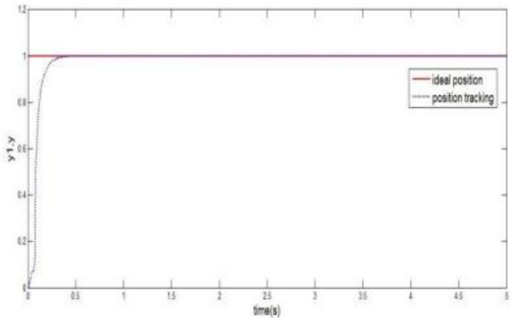

FIGURE 4 The step signal with the adaptive setting PID based on RBF NN

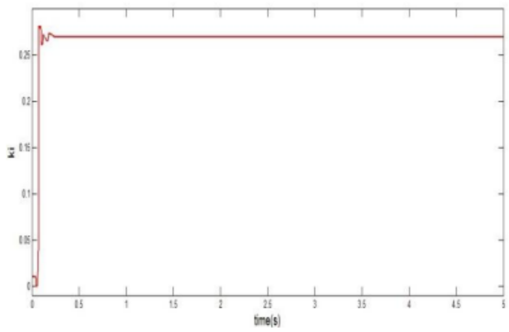

FIGURE 5 The adaptive setting curve of ki

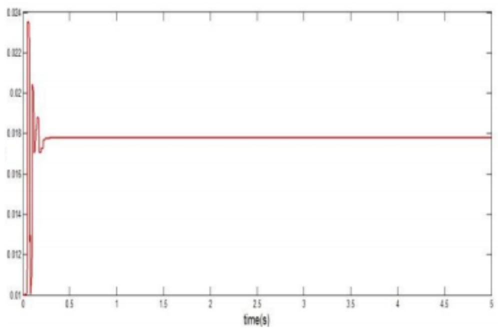

FIGURE 6 The adaptive setting curve of kp

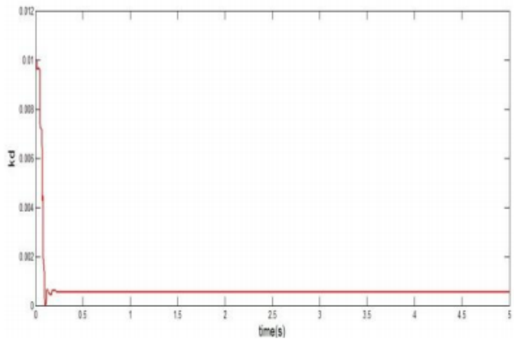

FIGURE 7 The adaptive setting curve of kd

When variation in a population of randomly selected individuals, mutation operator Loci child adoption, the basic steps are as follows: start with groups of individuals compiled Code string randomly selected one or more loci, and then follow the variation The probability of each generation after the completion of genetic manipulation, for a new generation of individual school Xi error and evaluate the fitness value, to identify the best individual, the optimal Individual two-step gradient descent local search, and put out a search of the Directly into the body of the new generation of the population, if the learning error achieve accuracy or up To specify the genetic algebra calculation is terminated. So after more than genetic luck Count, you can get BP neural network error minimum set of complete initial Weights and thresholds.

4 Conclusions

Aim at the limitation of traditional PID controller has certain limitation, the traditional PID control is often difficult to obtain satisfactory control performance, and the RBF neural network is difficult to meet the requirement of real-time control system. To overcome it, an adaptive PID control strategy based on (RBF) neural network is proposed in this paper. The results show that the proposed controller is practical and effective, because of the adaptability, strong robustness and satisfactory control performance. 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. In this paper, based on RBF neural network adaptive PID control strategy is 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. RBF Neural 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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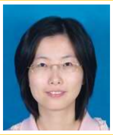

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