The research of electromotor control based on optimized RBF neural network

Ni-qin Jing*, Lin-na Wang

Beijing polytechnic, Beijing 100015, China

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Abstract

RBF neural network suits to control electromotors, which have uncertainty and highly nonlinear systems. However, in practice, RBF neural network also have some obvious defects. For example, the strong dependence on the initial parameter and the poor quality of clustering algorithm. For the above defects, this paper is going to build an optimized RBF neural network through the combination of ant colony optimization algorithms, chaos ergodicity optimization theory and traditional K-means algorithm. On this basis, the optimized RBF neural network will be applied to PID control and then the dynamic performance of the electromotor will be simulationally tested by the designed PID controller. The simulation results show that in the control of electromotor, the optimized RBF neutral network has the characteristic of high control accuracy and strong traceability and also it has the ability to guarantee electromotor control system with steady and dynamic performance.

Keywords: RBF neural network, ant colony optimization algorithms, chaos ergodicity optimization, chaos ant colony optimization algorithms, electromotor control

1 Introduction

The development of artificial neural network has experienced more than half a century. There emerges dozens of major structures of neural network. At present, the application of RBF neural network to PID control has become a hot issue, because RBF neural network has the ability to approximate any nonlinear function. It is able to learn parallel distributed processing and has a strong fault tolerance and robustness. Many training algorithms of RBF neural network support both online and offline training determine the network structure and the centre of the hidden layer units and width dynamically. And its learning speed is so fast that it is easy to model and control some complex nonlinear control systems.

However, RBF neural network is not omnipotent. It has a strong dependence on the set of the initial parameter. Once the initial parameter is given wrong, it will not get the optimized neural network structure. Another difficulty of RBF neural network is that the clustering quality of the traditional clustering algorithm is not high. Although the traditional clustering algorithm, like K-means algorithm, has a fast global searching speed, it is just a rough searching process, and in order to achieve optimal global searching effect, it needs to explore a new algorithm and then combine with it. Therefore, we introduce the ant colony algorithm and chaos colony algorithm based on the theory of chaos ergodicity to solve the initial parameter set and improve the traditional clustering algorithm.

We design the optimized RBF neural network PID controller under the Matlab in order to make the research of algorithm significant. We use this PID controller to make real-time status control of brushless direct current electromotor. And we test the feasibility and reliability of algorithm through the simulational experiment under the Matlab, making algorithm a new sublimation from theory to practice.

2 The Optimization of the RBF Neural Network

2.1 OPTIMIZED RBF NETWORK BASED ON ANT COLONY ALGORITHM

According to the advantages and disadvantages of K-means algorithm and ant clustering algorithm, we integrate these two algorithms to optimize RBF neural network jointly. By using the fast characteristic of K-means algorithm and the strong local searching ability of ant clustering algorithm, we design the improvement of RBF network clustering algorithm based on ant clustering algorithm. The main idea is using K-means algorithm and ant clustering algorithm to cluster the samples [5]. First, we use K-means algorithm to calculate the initial clustering centre of ant algorithm. Then we define the pheromone left by ant from sample X_i to the clustering centre $c_j(k)$ as τ_{ij}. The K in $c_j(k)$ is the Kth calculated clustering centre. The probability of ant (M) from X_i to $c_j(k)$ is:

Corresponding author e-mail: jnqddd@163.com

$$p_{ij}^{m}=\frac{\left|\tau_{ij}\lambda_{ij}^{\beta}\right|}{\left|\sum_{i\in alloeedn}\tau_{ij}\lambda_{ij}^{\beta}\right|}\quad , \tag{1}$$

where $i \in alloeedn$ is the samples which ant(M) can choose except the taboo table.

The followings are the updating equation of pheromone:

$$\tau_{ij}(k+1)=\rho\tau_{ij}(k)+\Delta\tau_{ij}\quad , \tag{2}$$

$$\Delta\tau_{ij}=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}\quad , \tag{3}$$

$$\Delta\tau_{ij}^{k}=\frac{Q}{d_{ij}}\quad , \tag{4}$$

where τ_{ij}^{k} is the pheromone of $X_i \to c_j(k)$, ρ is the persistence coefficient of strength, usually takes about 0.5-0.9 Q is the positive constant.

The followings are the steps of RBF neural network C and B confirmed by the detailed K-means algorithm and ant colony optimization algorithms [6].

Step1 Initialization algorithm: choose k different initial clustering centres

Step2 calculate the distance between all the sample inputs and clustering centre $\left\|X_i-c_j(k)\right\|$, i=1, 2…, n; j=1, 2……, k.

Step3 average the classified samples to get a new clustering centre $c_j(k+1)$. If k + 1< N, then do step2. If not, then do ***Step4.***

Step4 initialization process: suppose when $k=0$, NC=0, $\tau_{ij}(0)$=c (c is a constant), $\Delta\tau_{ij}=0$, $\lambda_{ij}=\frac{1}{d_{ij}}$ (an expected factor) $tabu_m(s)=\phi$, $s=0$ (the initial stage of *taboo* table of every ant is empty), place m ants on n samples randomly. Then put the initial sample position of every ant in the current taboo table, and set s=1. S is taboo table index. Last, put the ant's initial city in the current taboo table.

Step5 repeat until the taboo table is full. Repeat (n-1) times.

Step 6 calculate $d_{ij}=\left\|X_i-c_j(k)\right\|$, i=1, 2.., n; j=1, 2..,k.

Step7 according to the distance between every clustering centre above, then determine the base width vector of hidden nodes.

2.2 SIMULATIONAL EXPERIMENT

Based on the above improved clustering algorithm, we will approximate to a nonlinear system in order to compare the effect of the improved algorithm RBF network and the traditional RBF network. First of all, in order to verify the feasibility of the algorithm [7], we can randomly choose 100 arrays between 0 and 1 as input samples. Overlap coefficient $\sigma=1$, number of clusters $k=8$, number of ants $m=30$, $Q=100$, iterations NC=200. Now through the simulational experiment of nonlinear system $f(x)=e^{x}+x\bullet x+\sin(x)$, we can get Figure1 and Figure2.

The experiment proves that it is feasible for ant algorithm to improve clustering algorithm and the effect of clustering is very good. After comparing these two figures, we can see that the ability of the improved algorithm RBF network to approximate nonlinear system is stronger, and also it is able to solve nonlinear system problems and put forward good solutions to the control of nonlinear system, such as electromotor.

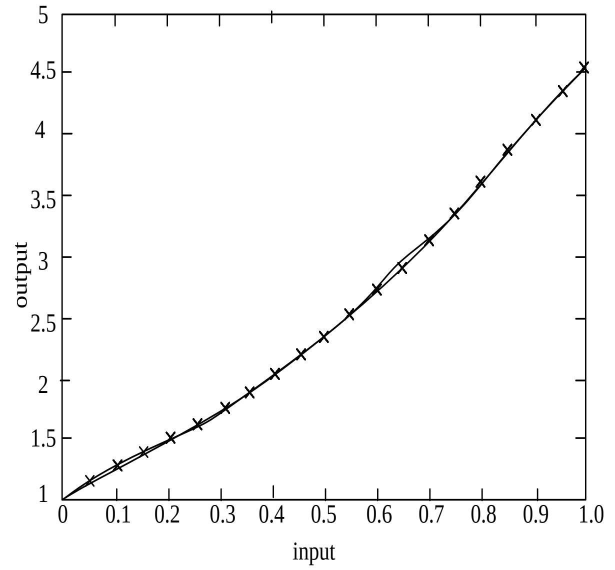

FIGURE 1 The functional effect figure of the improved algorithm RBF network approximation

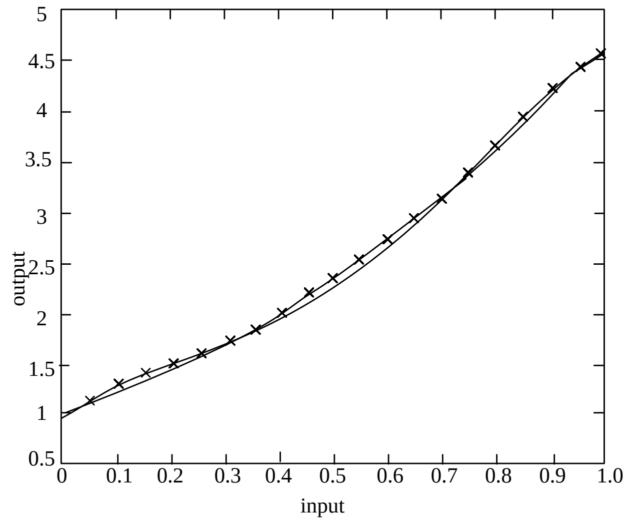

FIGURE 2 The functional effect figure of the traditional RBF network approximation

2.3 OPTIMIZED RBF NETWORK BASED ON CHAOS ANT COLONY ALGORITHM

In order to solve the problem of long time searching and local optimum of ant algorithm in optimization procedure, we adopt the good choice of the parameters in ant colony algorithm and the updated strategy of pheromone left in the path by the ant. We specifically introduce a chaotic disturbance in order to avoid the phenomenon of stagnation of ant colony algorithm in the optimization process. The chaos movement produced by Logistic mapping makes chaotic disturbance in pheromone of ant colony algorithm. The chaos movement produced by Logistic mapping can be defined like this:

$$h(n+1) = \mu h(n)\left[1-h(n)\right], \tag{5}$$

where n=0,1,2…, $0 < h(n) < 1$, n means the iteration. When $\mu = 4$, it is in chaos state. $h(n)$ experiences all the states between 0 and 1.

The main idea of chaos ant colony algorithm is first using subtractive clustering method to cluster the samples [8]. Then use K-means algorithm to calculate the initial clustering centre of ant algorithm. Then define the pheromone left by ant from sample X_i to the clustering centre $c_j(k)$ as τ_{ij} .The probability of ant (M) from X_i to $c_j(k)$ is:

$$p_{ij}^{m} = \frac{\left|\tau_{ij}\lambda_{ij}^{\beta}\right|}{\left|\sum_{i\in alloeedn} \tau_{ij}\lambda_{ij}^{\beta}\right|} mQ, \tag{6}$$

where $i \in alloeedn$ is the samples which ant(M) can choose except the taboo table (as in (1)).

The followings are the updating equation of pheromone:

$$\begin{cases} \tau_{ij}(k+1) = \rho\tau_{ij}(k) + \Delta\tau_{ij} \times 1.25 \times h(n) \\ \Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \\ \Delta\tau_{ij}^{k} = \dfrac{Q}{d_{ij}} \end{cases}. \tag{7}$$

$h(n)$ is the added chaotic disturbance of pheromone equation and n means iteration. This chaotic disturbance is in order to avoid the phenomenon of stagnation in searching optimization in ant colony algorithm and local extremum:

$$h(n+1) = 4h(n)\left[1-h(n)\right]. \tag{8}$$

In this equation, h(n) meets the formula (5). τ_{ij}^{k} is the pheromone of $X_i \to c_j(k)$, ρ is the persistence coefficient of strength, usually takes about 0.5-0.9, Q is the positive constant. Detailed chaos ant colony algorithm to calculate RBF neural network node centre c and node base width b are the same as the above steps, so we will not talk about it here.

2.4 SIMULATIONAL EXPERIMENT

Through the optimization of RBF neural network optimized by chaos ergodicity and the optimization of RBF optimized by chaos ant colony algorithm, we are going to make an approximation to a nonlinear function in order to test the approximation performance made by RBF neural network, which is optimized by two algorithms. Thus, we can compare the advancement and feasibility of these two algorithms. First input the samples as the following methods: the number of input samples is 100, in which the input sample X_i must obey the uniform distribution of interval [-4, 4]. Then calculate the number of initial clustering centre by using subtractive clustering method. Suppose the number of ant(m) is 30, iterations NC=200, overlap coefficient $\sigma = 1$. Through the approximation to the nonlinear function $f(x) = 1.1(1 - x + 2x^2)\exp(-x^2/2)$, we can get the simulation experiments Figure3 and Figure 4. From the comparison of these Figures, we can see that the training time needed for RBF neural network optimized by chaos ant colony algorithm is slightly more than RBF neural network optimized by chaos ergodicity, but its accuracy has a considerable improvement. We also can see that the nonlinear functional effects of RBF neural network optimized by chaos ant colony algorithm are better and more accurate.

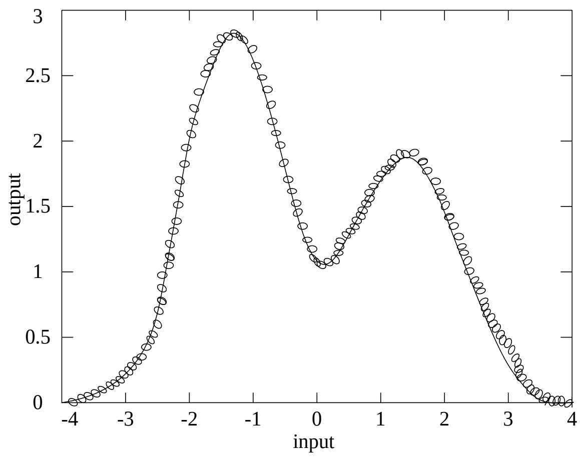

FIGURE 3 The nonlinear functional effect figure of RBF neural network optimized by chaos ant colony algorithm

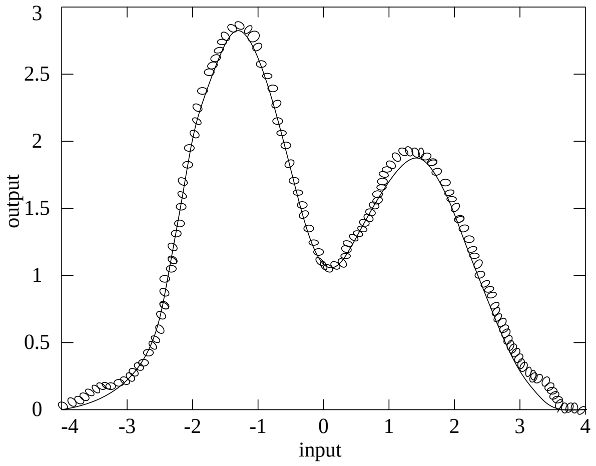

FIGURE 4 The nonlinear functional effect figure of RBF neural network optimized by chaos ergodicity

3 Brushless Direct Current Electromotor Control of the Optimized RBF Neural Network

3.1 PID CONTROL OF THE OPTIMIZED RBF NEURAL NETWORK

We adopt PID control of the optimized RBF neural network. The followings are the implementation of this control system.

We adopt the added PID control as the control system. The error control is:

$$e(k)=r(k)-y(k). \tag{9}$$

PID input is:

$$\begin{cases} xc(1)=e(k)-e(k-1) \\ xc(2)=e(k) \\ xc(3)=e(k)-2e(k-1)+e(k-2) \end{cases}, \tag{10}$$

The control algorithm is:

$$u(\mathrm{k})=u(k-1)+\Delta u(\mathrm{k}), \tag{11}$$

$$\begin{aligned}\Delta u(\mathrm{k})&=k_p(e(k)-e(k-1)+k_i e(k)\\&+k_d\left[e(k)-2e(k-1)+e(k-2)\right].\end{aligned} \tag{12}$$

Take the performance index function $J=(yout(k)-y_m(k))^2/2$, in which $yout(k)$ is the k times output of the control system, $y_m(k)$ is the k times output of RBF neural network. When using RBF network to identity the system's Jacobi matrix, we can get:

$$\frac{\partial yout(k)}{\partial u(k)}\approx\frac{\partial y_m(k)}{\partial u(k)}=\sum_{j=1}^{m}\omega_j h_j\frac{c_{ji}-x_1}{b_j^2}. \tag{13}$$

In the above equation, x_1 is the control input $u(k)$.

3.2 SIMULATIONAL EXPERIMENT OF ELECTROMOTOR PERFORMANCE

In this paper, we use Matlab2007 as the test platform. After the comparison of neural network PID electromotor control improved by two algorithms and normal PID electromotor control, we can get the following result. In figure5, line1 represents the effect of normal PID control electromotor; line2 represents the effect of RBF neural network PID control electromotor optimized by chaos ant colony algorithm; line3 represents the effect of RBF neural network PID control electromotor optimized by ant colony algorithm.

From Figure 5, we can see that the effects of RBF neural network improved by two algorithms are better than that of normal PID control. In starting process of electromotor, it can effectively avoid starting overshoot, which is brought by normal PID control. Moreover, the time needed for the electromotor from start to stable work becomes shorter, thus improve the electromotor's working efficiency.

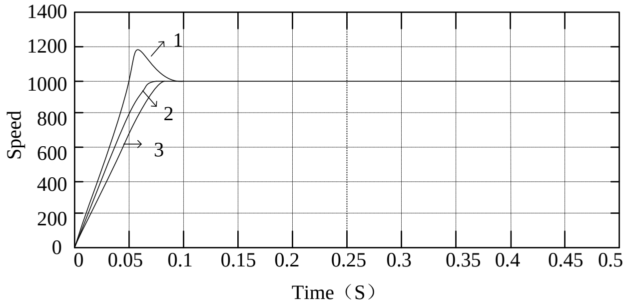

FIGURE 5 Operational process of electromotor under rated condition

From Figure 6, we can see that comparing to normal PID controller, RBF neural network PID controller improved by two algorithms have better speedy traceability when the given speed changes. As the rotated speed of electromotor changes, it can avoid overshoot shake, which is brought by normal PID control. Furthermore, the following speed are faster and that can reduce the energy consumption of the electromotor, so it is helpful to maintain the electromotor's stable working condition.

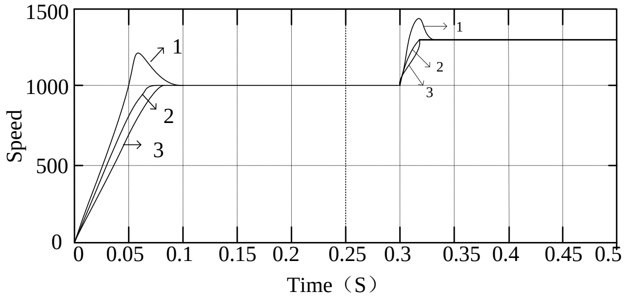

FIGURE 6 Electromotor's given speed from 1000 r/min to1300 r/min

4 Conclusions

We can draw the following conclusions through the research of electromotor control based on optimized RBF neural network.

We use ant colony algorithm to improve k-means algorithm. Then we design the improvement of ant colony algorithm RBF network clustering algorithm through the combination of the theory of ant colony algorithm and the characteristic of k-means algorithm. This principle uses k-means algorithm when the initial clustering begins. Because this algorithm operates fast and suits global rough search [9]. Then we use ant colony to avoid local extremum in searching. These two combined clustering quality of clustering algorithm improve more obviously than the traditional clustering algorithm, and it is more suitable for the approximation of nonlinear system.

Through the characteristics of Logistic mapping, we design the specific methods to calculate the hidden layer neuron of RBF neural network. The optimized chaotic searching is very fast. It can avoid minimums and easily implement [10]. The function of chaos ant algorithm in RBF neural network is very successful, which better develops the ability of strong local optimization of ant colony algorithm.

We do the simulational experiments by the designed neural network PID controller. In the experiment, we simulate the appearance of load and disturbance. We control the working state of electromotor through RBF neural network, which is improved by RBF control in neural network PID controller by using two optimized algorithms. RBF neural network improved by two algorithms achieves good control effect on electromotors, which is proved by the experiments.

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Authors

Niqin Jing, born in 1979, Shanxi Province of China

Current position, grades: lecturer
University studies: Master's degree was earned in major of software engineering, Beijing University of Technology in 2011.
Scientific interest: digital signal processing, Neural Network Algorithm, embedded system

Linna Wang, born in 1978, Henan Province of China

Current position, grades: lecturer
University studies: Master's degree was earned in major of signal and information processing, Tianjin University in 2011.
Scientific interest: digital signal processing