The Research on PID Control Ways to Improve RBF Neural Network

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Abstract. PID control has been a hot topic and it is a control technology which is widely used in industrial control process. In this paper we researchon PID controller structure and algorithm which based on RBF neural network. It is difficult to determine the clustering radius for the traditional RBF neural network algorithm with the shortcomings of poor stability and low learning efficiency.We improved the nearest clustering algorithm and combine it with the gradient descent to make the mixed learning algorithms and build neural network structure, while adjustthe network parameters and improved PID control method based on RBF neural network. At last we make the verification for its effectiveness and advantages by simulation experiments.

Introduction

PID control has been a hot topic, is a widely used industrial control process control technology. PID controller algorithm in the control sector is one of the earliest development of control algorithms, the algorithm is simple, robu-st, high reliability, are chemical, thermal and light industrial sites and many other important uses[1]. But the classic PID control parameters fixed, changes cannot be entered in nonlinear systems real-time adjustments in nonlinear system control is difficult to achieve good results, so the traditional control algorithm is difficult to achieve the desired control effect [2].

Because neural network adaptive control algorithm with a strong approach and self-learning ability, the neural network PID control, and constantly adjust the parameters of the PID controller to improve the control effect, make PID controller with fast learning ability and strong adaptation capacity, and parameter tuning and optimizing online robustness. Therefore neural network PID control algorithm in the control fields has been widely used [3-4].

RBF neural network PID controller

Neural network PID control is a neural network PID control and improved control method combines with traditional PID control, the overall performance is determined by the neural network model, and the characteristics of neurons, neural network topology and learning rules determine the neural network as a whole performance. Figure 1 shows the RBF neural network PID controller works. The $r_{in}(k)$ in figure is for a given signal that is the input signal, $y_{out}(k)$ is the output signal. Based on RBF Neural Network Identification PID controller is composed of two parts classic incremental digital PID controller and RBF neural network, the RBF neural network through self-learning and non-linear approximation ability to adjust the PID controller parameters online.

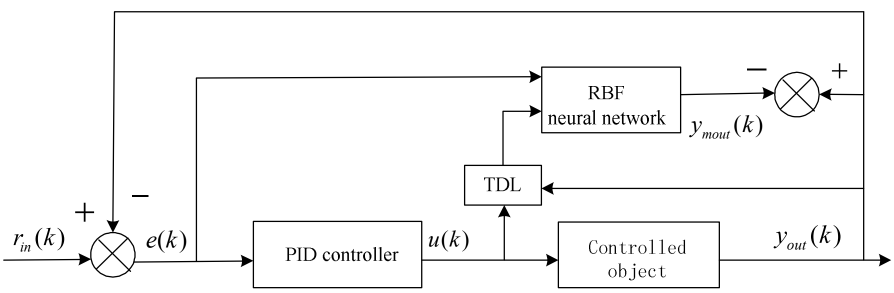

Figure.1: The PID control principle which based on RBF neural network

The improved nearest clustering algorithm

Nearest neighbor clustering algorithm have a lot of advantages: no pre-determined number of hidden units and the network automatically adjust training speed quickly in the training process. Width of the Gaussian function plays a big role, able to measure the distance between the input data and the existing Gaussian function centers. Nearest neighbor clustering algorithm, to a pre-specified width of the Gaussian function, Gaussian function center and the right values will need to go through training. Nearest neighbor clustering learning algorithm has a short time, a small amount of calculation and a series of advantages, but there are also some disadvantages: (1) when the data for the different attributes of traditional Euclidean distance clustering algorithm; (2) reduce the value of the immobilized cluster radius, reducing the learning efficiency [5].

Improved Euclidean distance by Entropy Method

Distance between data clustering in nearest neighbor algorithm commonly used to calculate the Euclidean distance. Is assumed to be a set of data objects as $A=\{x_1,x_2,\ldots,x_n\}$,Vector $x_i=\{x_{i1},x_{i2},\ldots,x_{im}\}$,The x_{ik} represented the k dimensionof x_i ,and m indicates the attributes dimension of the object properties.There are two vectors $x_i=(x_{i1},x_{i2},\cdots,x_{im})$, $x_j=(x_{j1},x_{j2},\cdots,x_{jm})$ represent two data objects, the Euclidean distance between the object x_i and the data x_j :

$$d(x_i,x_j)=(\sum_{k=1}^{m}(x_{ik}-x_{jk})^2)^{\frac{1}{2}} \tag{1}$$

This calculation Euclidean distance has the following two disadvantages: (1) does not consider the existence of a variety of different dimensions of the object attributes; (2) did not consider the different distribution of the various components (expectation, variance, etc.). This paper introduces entropy method to the traditional Euclidean distance which made innovation and improvement, to achieve the calculation of such data.

Entropy is a comprehensive evaluation method for multi-target and multi-variable. For the calculation of the Euclidean distance is based on the concept of information entropy to determine the properties of the weights. Thus we gained the empowerment of standardized Euclidean distance calculation formula. Entropy calculation is as follows:

(1)To be assumed that there are n clusters of data objects, each data object contains at the same time an m-dimensional attribute, then the attribute values of the matrix is expressed as:

$$X=\begin{vmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \vdots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{vmatrix} \tag{2}$$

Where x_{ij} denotes the jdimension attribute value of the object x_i .

(2) The j dimension attribute value of the attribute i-th data relative proportion of the object is calculated as follows:

$$r_{ij}=\frac{\max\limits_{1\le i\le n}(x_{ij})-x_{ij}}{\max\limits_{1\le i\le n}(x_{ij})-\min\limits_{1\le i\le n}(x_{ij})} \tag{3}$$

Where the r_{ij} representing the j-th dimension attributesproportion of the property value object x_i

The entropy of the j-dimensional attribute values are:

$$H_j=-\frac{1}{\ln n}\sum_{i=1}^{n}r_{ij}\ln r_{ij} \tag{4}$$

(3)The right value calculation of the j-dimensional attribute:

$$\theta_j=\frac{1-H_j}{\sum_{1}^{m}(1-H_j)},0\le\theta_j\le 1,\sum_{1}^{m}\theta_j=1 \tag{5}$$

(4) The definition of standardized Euclidean distance:

$$D(x_i, x_j) = (\sum_{k=1}^{m} (\frac{x_{ik} - x_{jk}}{s_k})^2)^{\frac{1}{2}} \tag{6}$$

The formula s_k represents a standard component of the k-th difference.

Euclidean distance is improved as follows:

$$D(x_i, x_j) = \theta_j \times (\sum_{k=1}^{m} (\frac{x_{ik} - x_{jk}}{s_k})^2)^{\frac{1}{2}} \tag{7}$$

According to the improved entropy method to calculate theaccuracy Euclidean distance between each data is greater, reaching the purpose of improving the accuracy of clustering.

The removal strategy of hidden node

Traditional learning nearest neighbor clustering algorithm, neural network hidden node is increasing. Hidden nodes resulted in the increasing complexity of the neural network structure, the calculation speed and calculation time increased significantly. Due to the harsh working environment of nonlinear systems, often cause data distortion, distortion of data will result in contributions to the output value of the network is not some hidden nodes, there is a kind of hidden nodes can severely affect the network's response speed and accuracy, so these nodes should be removed in the online and offline learning process, the complexity of such networks is greatly reduced, while the response speed and accuracy of network output has also been speeding up and improving.

Set the i learning samples as an example, the calculated output $O = (o_1, \cdots, o_k)$ and the connection weights matrix neurons $A = (\omega_1, \cdots, \omega_k)$ and the k hidden node to the j output value of the output node is written as:

$$o_{kj} = \omega_{kj} \exp(-\frac{\|x_i - c_k\|^2}{R^2}) \tag{8}$$

From the above equation, the impact of hidden layer nodes mainly due to the output of the network: the connection weights ω_{kj}, implicit distance $\|x_i - c_k\|$ between the node and the input and the base width R . So the removing of the hidden nodes should consider the overall contribution to delete hidden nodes on the network.

Normalized output vector $r_k = (r_{k1}, \cdots, r_{kj})$ for the k node can be calculated as follows:

$$r_{kj} = \frac{\|o_{kj}\|}{\|o_{j,\max}\|} \tag{9}$$

Wherein $\|o_{j,\max}\|$ said when input samples i, the maximum absolute value of all the hidden j unit cell output: $\|o_{j,\max}\| = \max(\|o_{1j}\|, \|o_{2j}\|, \cdots, \|o_{kj}\|), (j = 1 \cdots n)$

Before training a pre-set threshold $\varepsilon_2 (0 \le \varepsilon_2 \le 1)$, if successive n samples the input, the output of a node normalized vector r_k of any one component of the whole is less than the threshold value ε_2, then say the contribution of implicitoutput node k of the network is necessary to remove the very small hidden nodes.

Algorithm steps

(1)Define the $s(l)$ storage output vector and different categories, custom counter $CT(l)$ to count the number of samples of different classes, which l is the number of categories. Using formulas $R_0 = \frac{s}{n}$ to determine the nearest neighbor clustering radius $R = R_0$.

(2)Start from the data (x^1, y^1),set x^1 as the first cluster , so that $c_1 = x^1$, $s(1) = y^1$, $CT(1) = 1$. At this point, only one neural network to establish the cluster center c_1, this right is implied unit output. $\omega_1 = s(1)/CT(1)$

(3)If the k input data sample is (x^k, y^k), calculated from the formula $H_j = -\frac{1}{\ln n}\sum_{i=1}^{n} r_{ij} \ln r_{ij}$ and the formula $\theta_j = \frac{1-H_j}{\sum_1^m (1-H_j)}$ for each dimension attribute data entropy and attribute weights.

Assuming already exists n cluster center $c_1, \cdots, c_n$. Using entropy method improved Euclidean distance formula $D(x^k, c_i)$ to the minimum distance a cluster center. If the distance is the minimum distance $d_{\min}$, compared with the nearest neighbor clustering.

If $d_{\min} > R$, then x^k as a new cluster center and provides that $c_{n+1} = x^k$, $s(n+1) = y^k$, $CT(n+1) = 1$,while the provisions and values $S(i)$ and $CT(i)$ remain unchanged, including $i = 1, \cdots, n+1$. Therefore, the neural network added an implicit unit. Network output weights can be expressed as the hidden layer $\omega_i = s(i)/CT(i)$.

If $d_{\min} \le R$,then $s(j) = s(j) + y^k$, $CT(j) = CT(j) + 1$, $c_n = \frac{1}{m}\sum_1^m x^k$ .At this hidden layer output vector network output weightsis $\omega_i = s(i)/CT(i)$.

(4)Using the formula $y_m(x^k) = \sum_1^n \omega(i)\exp(-\frac{\|x^k - c_i\|}{R^2}) / \sum_1^n \exp(-\frac{\|x^k - c_i\|}{R^2})$ to calculateRBF neural network output $y_m(k)$.

(5)Based on the performance index function $E = \frac{1}{2}\sum_{k=1}^{n}(y(k) - y_m(k))^2$ to calculate value E. If $E > \varepsilon$,According to the value of E to adjust the learning method using the ladder step the radius of the cluster, returning to step (3), otherwise go to step (7).

(6)Calculated for each node in a hidden input samples normalized output vector r_i , if m successive data samples $r_k < \varepsilon_2$, it is determined that the contribution of k hidden node network output is small, it is necessary to delete the nodes.

(7)End of clusters. Nearest neighbor clustering algorithm is improved compared to the traditional algorithm has the following advantages: (1) the initial cluster radius by the formula chosen, and the introduction of ladder-type step to accelerate the learning efficiency; (2)with a mean thought optimization clustering k- center; (3) calculate the entropy method using Euclidean distance, so that the calculation is more accurate; number (4) hidden layer can be adjusted online, while node removal strategy can eliminate redundant nodes, optimize network structure.

Simulation

Set of nonlinear controlled object is:

$$yout(k) = \frac{yout(k-1) + u(k-1)}{1 + yout(k-1)^2} \tag{10}$$

On RBF neural network PID controller and improved hybrid algorithm RBF Neural Network Control feature PID controller simulation study, where incremental PID controller with digital PID controller and the initial PID control parameters are selected randomly.

In RBF neural network PID controller, the neural network learning algorithm uses the gradient descent. Wherein the input layer nodes is 3, i.e. the control deviation $e(k)$, the amount of delay of the control signal $u(k-1)$, and outputs the delayed signal $y_{out}(k-1)$, an output layer node, i.e. $y_{mout}(k)$, the hidden layer nodes is 6. Initialization data center Cis taken as 30, the radius of the Gaussian function is taken as 40, the output power is taken as 8, the network learning efficiency is taken to be η=0.25, take the momentum factor α=0.01,

thelearning efficiency of PID control parameters are $\eta_p = \eta_i = \eta_d = 0.2$.

Figure 2 shows the RBF neural network PID control system unit step response. Figure 3 shows the RBF neural network PID control system improved hybrid algorithm unit step response.

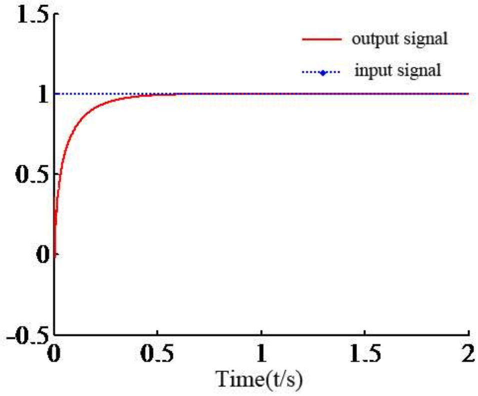

Figure.2:The RBF neural network PID control system step response

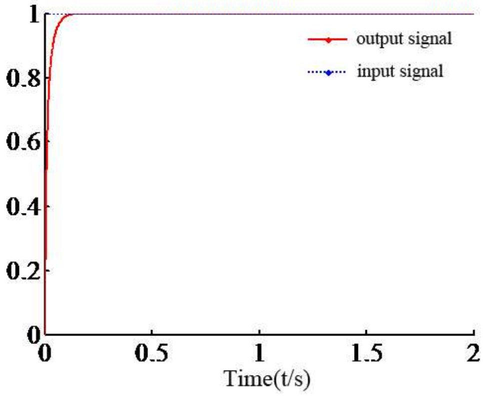

Figure.3: The Improved RBF neural network PID control system step response

As can be seen from Figures 2 and 3, the improved hybrid algorithm RBF neural network PID control system based on the step response time than the RBF neural network PID control system step response time is short. Thus shows improved hybrid algorithm based on RBF neural network not only apply to the control of nonlinear systems, and the algorithm can establish the appropriate neural network architecture based on the input signal. Therefore, this learning algorithm can not only shorten the calculation time and output precision network will be greatly improved.

The identification results RBF neural network identifier is shown in Figure 4. As can be seen from Figure 4, and achieved good recognition results improved hybrid algorithm based on RBF neural network PID control RBF neural network identifier, and the identification of interfering signals tracking curve after adding only small changes in the system, proving once again that this control the method of identification ability is strong, with good anti-jamming capability and tracking performance.

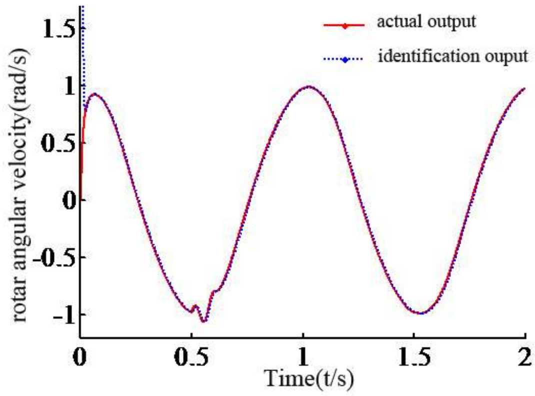

Figure.4: The Improved RBF neural network identification results

Conclusions

Because neural network control algorithm has a strong approximation and adaptive capability, using the RBF neural network with the PID control and improved its learning algorithm, so RBF neural network PID controller not only for control of nonlinear systems and can be based on the input signal automatic adjustment of the network structure, thereby improving the response speed and accuracy of the system. Nonlinear System Simulation results show that the PID controller is with high precision, robust and adaptive capabilities and provides an efficient algorithm for neural network PID control.

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