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A New BP Neural Network Algorithm and Its Application in University Innovation Education Evaluation

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Abstract: BP neural network algorithm has one of the most important algorithms in intelligence field for its powerful nonlinear mapping ability and many other advantages. But BP neural network algorithm has the disadvantages such as low convergence which limits the application of the algorithm. The paper improves the original BP neural network algorithm through Fourier basis function and uses it to evaluate university innovation education. First the disadvantages and its sources of original BP neural network algorithm is analyzed; Second Fourier basis function and BP neural network algorithm are integrated and the calculation flow is redesigned to simplify the algorithm structure and speed up the calculation efficiency of the presented algorithm. Finally data of innovation education from three universities are selected to confirm the performance of the improved BP algorithm and experimental results show that the algorithm can be used practically in evaluating innovation education for different universities and guarantee the evaluation effectiveness and validity.

Key words: BP neural network, fourier basis function, algorithm performance, university innovation education evaluation

INTRODUCTION

With the rapid development of science and technology, artificial neural network has also experienced great improvement in theory and application and in which BP neural network as a typical algorithm has already extensively applied to many fields, such as handle singles, mode identify, machine control, expert system because the algorithm has very strong nonlinear mapping ability and many other advantages, its network topology structure is simple, it has high margin precision, it is easy to program and it has very strong maneuver ability, etc. Therefore, the application of BP neural network becomes more extensive and it has become one of the most important algorithms in intelligence field. Although Standard BP neural network has many advantages, also it has many disadvantages and the disadvantages hinder the application of the BP neural network. So how to overcome the disadvantages of BP neural network has become a hotspot in the fields related for the researchers (Wang *et al*., 2012).

LITERATURE REVIEW

Studies on the improvement of the studies on the improvement of the theory of BP neural network are comprised of the following five aspects. ① Improve the gradient of excitation function, standard BP algorithm adopts sigmoid non-linear function as characteristic function of neuron, so if the net input of neuron becomes too large or too small, the output will enter saturation region, the error at this time may be very large. Error curved surface will show non-convergence. Therefore, rate of convergence of the model can be accelerated through improving excitation function; ② Improve error curved surface; Standard BP algorithm adopts square-error as objective function and uses gradient descent to minimize the total error function. With the increase of learning times, function slows in approximation velocity, failing to guarantee the approximation accuracy of height non-linear sample. If only considering that error term may have over-fitting phenomenon, causing poor generalization ability of network, many scholars have put forward improvement methods; ③ Selection of initial weight value of network; Under normal conditions, the selection of initial weight value of BP algorithm is a set of random numbers among [0,1], through repeated adjustment, obtaining stable weight value. But such kind of selection method may cause the network to fall into local minimum, resulting in failing to get optimal solution. Therefore, many scholars optimize the initial value through composite algorithm, also achieving favorable

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effects; ③ Improving and optimizing algorithm; Standard BP algorithm adopts gradient descent to adjust weight value, making the training easy to fall into local minimum and slow in rate of convergence; such kind of method to improve and optimize algorithm is widely used at home and abroad, basically carrying out the improvement through the optimization theory of applied mathematics.

This study, starting from the problem that BP neural network is complicated in network structure and poor in calculation convergence, fourier basis function is used to improve original BP neural network algorithm to overcome the disadvantages of the original BP algorithm (Zhang *et al*., 2012).

ALGORITHM DESIGN

BP neural network algorithm: Multi-hierarchy feed forward error back propagation neural network is the most-widely used network model in actual research. Three- layer BP neural network is mainly comprised of input layer, hidden layer and output layer. Adjustable weight ω connects the layers. There can be several hidden layers, forming multi-layer BP neural network. The input of BP neural network is recorded as x_i (k), the actual output of network is recorded as y_j (k), the ideal output of network is recorded as Y_j (k), the subscripts i, j indicate the nodes of input layer of network respectively and k is the running iterations of BP neural network. Its approximation error is defined as Formula 1 in which L is the quantity of output layer nodes; in this way, the function characteristic of BP model can be described as Formula 2 (Liu *et al*., 2013).

$$E = \frac{1}{2}\sum_{j=1}^{L}(Y_j(k) - \gamma_j(k))^2 \qquad (1)$$

$$\gamma_j(k) = f(x_i(k), \omega) \qquad (2)$$

In Formula 2, function f is obtained through the composition of weights of each network layer and node function, generally being very complicated non-linear function BP neural network training is to dynamically adjust the connecting weight ω to make Formula 3 workable. The learning of weight ω adopts the fastest grads descent principle, i.e. the variable quantity of weights is in proportion to the negative gradient direction of approximation error E. See reference 2 for specific calculation (Scott, 2010).

$$\lim_{k\to\infty} E = \lim_{k\to\infty}\frac{1}{2}\sum_{j=1}^{L}(Y_j(k) - \gamma_j(k))^2 = 0 \qquad (3)$$

BP neural network algorithm based on Fourier basis function Continuous-time Fourier series of periodic signal: As we all know, for signal f(t) that the period is T, it can be showed by continuous-time Fourier series, i.e. Formula 4:

$$f(t) = a_0 + \sum_{n=1}^{\infty} a_n \cos(n\omega_0 t) + \sum_{n=1}^{\infty} b_n \sin(n\omega_0 t) \qquad (4)$$

Of which:

$$\omega_0 = \frac{2\pi}{T}$$

is fundamental angular frequency, a_0 is DC component and a_n, b_n are Fourier series.

For time-limited nonperiodic signal f(t), 0≤t≤T, the periodic signal that f(t) is via continuation of period T is f_p (t), i.e. Formula 5:

$$f_p(t) = \sum_{m=-\infty}^{\infty} f(t - mT) \qquad (5)$$

Of which, m is a positive number. f_p (t) = f (t) occurs obviously when time t is 0≤t≤T. Therefore, the continuous-time series of periodic signal f_p (t) can be also showed by Formula 1 within the principal value period 0≤t≤T.

For bandlimited signal f(t) (0≤ω≤Nω), Formula 4 can be changed as Formula 5:

$$f(t) = a_0 + \sum_{n=1}^{N} a_n \cos(n\omega_0 t) + \sum_{n=1}^{N} b_n \sin(n\omega_0 t) \qquad (5)$$

For the numerical computation, Formula 4 is separated into Formula 7:

$$f(k) = a_0 + \sum_{n=1}^{N} a_n \cos(n\omega_0 kT_s) + \sum_{n=1}^{N} b_n \sin(n\omega_0 tkT_s) \qquad (7)$$

Of which, T_S is a sampling period and

$$T_s \le \frac{\pi}{N\omega_0} = \frac{T}{2N}$$

When

$$T_s = \frac{T}{2N}$$

Formula 8 can be changed as Formula 8 and k = 0, 1, 2, ..., 2N-1 in Formula 8:

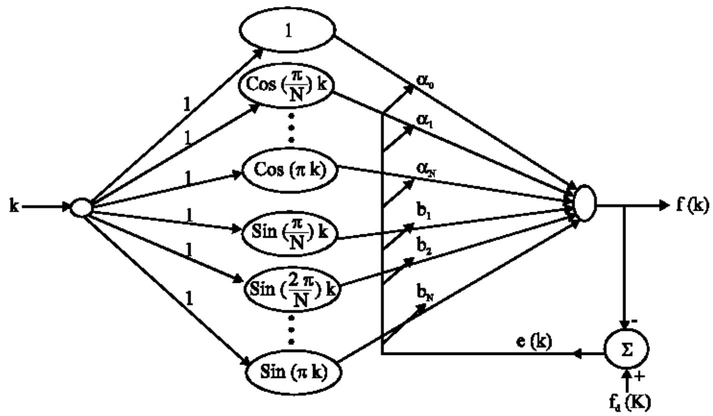

Fig. 1: Neural network model based on Fourier basis function

$$f(k) = a_0 + \sum_{n=1}^{N} a_n \cos(\frac{\pi}{N} nk) + \sum_{n=1}^{N} b_n \sin(\frac{\pi}{N} nk) \tag{8}$$

Neural network model based on Fourier basis function: In Formula 8, neural network model based on Fourier basis function is p roduced if f(k) is a neural network output, f_d (t) is a neural network training sample, a_n, b_n are neural network training weights and:

$$\cos(\frac{\pi}{N} nk) \text{ and } \sin(\frac{\pi}{N} nk)$$

are neural network excitation functions (Fig. 1).

The algorithm of neural network model based on Fourier is as follows.

- Formula 8 for neural network output
- Formula 9 for error function of network model

$$e(k) - f_d(k) - f(k) \tag{9}$$

- Formula 10 for network model performance index (Robert and John, 2009).

$$J = \frac{1}{2} \sum_{k=0}^{2N-1} e^2(k) \tag{10}$$

- Weight adjustment by gradient descent algorithm, See Formula 11 and 12 for weight adjustment quantity.

$$\Delta a_n^k = -\eta \frac{\partial J}{\partial a_n^k} = \eta e(k) \cos(\frac{\pi}{N} nk), \quad n = 0, 1, 2 \ldots N \tag{11}$$

$$\Delta b_n^k = -\eta \frac{\partial J}{\partial b_n^k} = \eta e(k) \sin(\frac{\pi}{N} nk), \quad n = 0, 1, 2 \ldots N \tag{12}$$

Formula 13 and 14 for weight adjustment, in which, η is a learning rate and $0<\eta<1$ (Beichner, 2009).

$$a_n^{k+1} = a_n^k + \eta e(k) \cos(\frac{\pi}{N} nk), \quad n = 0, 1, 2 \ldots N \tag{13}$$

$$b_n^{k+1} = b_n^k + \eta e(k) \sin(\frac{\pi}{N} nk), \quad n = 0, 1, 2 \ldots N \tag{14}$$

Convergence discussion of the new model: As we all know, the size of learning rate η affects neural network convergence significantly. If too small, the convergence speed of neural network is slow and the computation amount and time are increased; if too large, neural network shocks not to reach the convergence. For absolute convergence of neural network, a theorem of neural network convergence is given as below (Guo, 2013).

Theorem 1: Only when the learning rate η satisfies $0<\eta<4/3N+1$, neural network algorithm is convergent. Here 2N is the number of neural network training samples. For the space limitation, see Reference 8 for the detailed proof of Theorem 1.

EXPERIMENT CONFIRMATION

Evaluation indicator system design: While designing the indicator system of innovation education evaluation of higher institutions, this paper first takes the innovation education of higher institutions as characteristic. Higher education being a teaching activity transferring advanced knowledge and training senior professional talents, innovation education job in higher institutions, besides having the common characteristics of higher education job and common rules to be obeyed, has features different from ordinary education process. Therefore, this thesis

Table 1 Evaluation results of first grade indicators

	Peiking normal university	Shangxi normal university	Shanghai normal university
Schools side	4.172	4.113	4.099
Teacher side	4.641	3.992	4.602
Students side	4.601	3.883	4.271
Education effects	4.382	3.801	4.192
Final evaluation	4.541	3.821	4.299

Table 2: Evaluation performance comparison of different algorithms

Algorithm	Aalgorithm in this paper	Ordinary BP neural network algorithm	Comprehensive fuzzy algorithm
Accuracy rate	95.79 %	82.14%	65.68%
Time consuming (S)	17	462	18

first refers to literatures related to innovation education and experts' opinions, according to relevant principles of education and surveying, deciding the scope of influence of innovation education in higher institutions by combining area method with goal method and designing evaluation indicator system with such four perspectives of innovation education job as schools, teachers, students and effects. The system includes 4 first-grade indicators (that are university side, teacher side, student side and education effects), 12 second-grade indicators, 35 third-grade indicators, limited the space of the paper, the detailed indicators is omitted here (Li, 2011).

Experimental results analysis: Experimental data come from database of Peiking Normal University and Shangxi Normal University and Shanghai Normal University. Relevant data of 3000 learner of each university are selected as the basis for data training and experimental verification in the paper, totally 9000 learns' data for study data that come from practical investigation and visit of different students. In order to make the selected learners' data representatives, 1200 learners (400 learner from each university) with more than 3 years learning experience, 6000 learners with 2 years learning experience, 1800 learners with less than 2 years but more than one years learning experience. Limited to paper space, the evaluation of intermediate results is omitted here, only providing evaluation results of first grade indicators and final comprehensive evaluation results in Table 1.

As for the performance of the presented algorithm, this paper also realizes the application of the ordinary BP neural network (Liu *et al*., 2013) and comprehensive fuzzy evaluation (Li, 2011), evaluation performance of different algorithms is shown in Table 2. In Table 2 evaluation results of training effects of different students are selected and compared with artificial evaluation to calculate the evaluation accuracy. And the calculation platform as follows: hardware is Dell Poweredge R710, in which processor is E5506, memory 2G, hard disk 160G; software platform is Windows XP operating system, C programming language environment.

CONCLUSION

Although Standard BP neural network has many advantages, also it has many disadvantages. Its optimization algorithm is based on the most soon calculate way algorithm. The most soon calculate way algorithm has many disadvantages, such as slow convergence speed, easily run into local minimum dot. Therefore, in the side the standard BP calculate way has the same disadvantages and it leads to the shortage of study capability of network. The study aims at the disadvantages of BP algorithms and use fourier basis function to overcome the disadvantages of the original BP algorithm. Experimental results verify the efficiency and the validity of the improved algorithm when it used to evaluate university innovation education.

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