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Research Article

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An improved BP neural network algorithm for competitive sports evaluation

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ABSTRACT

BP neural network algorithm is easy to get a local optimum and fall into local loop in calculation, which makes slow training speed and unstable calculation, so the development and application of the algorithm are restricted. This paper uses genetic algorithm to improve the generalization ability of ordinary BP algorithm to overcome the above problems. After analyzing the root causes of the defects of BP algorithm, specific calculation steps of genetic algorithm is improved when used to improve BP algorithm first. Then the calculation flows of new algorithm are redesigned. Finally the improved algorithm is used in region competitive sports evaluation and the experimental results show the superiorities of the improved algorithm. The superiorities include simple algorithm process, fast convergence speed, get out local minimum easily, small oscillation and so on.

Keywords: BP neural network algorithm, genetic algorithm, generalization ability, competitive sports evaluation.

INTRODUCTION

As the important subfield and the quintessence of artificial neural network, BP neural network accelerates the development in this field. In 1985，Rumelhart and some other scholars advanced the Error Back Propagation theory that was improved as BP Neural Network theory today. BP neural network has integrated system, explicit algorithmic process, data identification and simulation function. BP algorithm also owns the excellent ability to solve nonlinear problem, therefore, the value of practical application is outstanding. Along with researching deeply, the defects of BP neural network have been found. such as low convergence speed, long training time, falling into local minimum easily, bad generalization ability, few principle to build network structure. These defects can depress the accuracy of BP neural network and damage the practical effect. So, improving BP neural network step by step is significant not only for theory, but also for practical application[1].

According to the result of BP function experiment, this paper explored the flaws in training network and found the root of various flaws through studying BP theory. In order to conquer the defects in training, this paper consulted foreign document, then advanced a new method to improve BP training process. The mathematic approaches of this method had been given in this paper clearly. For confirming the practicability, contrasting the new method with the other algorithms is necessary. The comparison indicates that the new algorithm has many superiorities than ordinary BP algorithm. This superiorities include: simple algorithm process, fast convergence speed, get out local minimum easily, small oscillation and so on. In brief, this new algorithms can make the whole BP training process fast and stable.

EXPERIMENTAL SECTION

Working Principle of BP Algorithm

Up till now, hundreds of artificial neural network models are put forward from different views of research, among which multi-hierarchy feed forward error back propagation BP neural network is the most-widely used network model in actual research. Basic three-layer BP neural network structure is shown as figure 1[2,3].

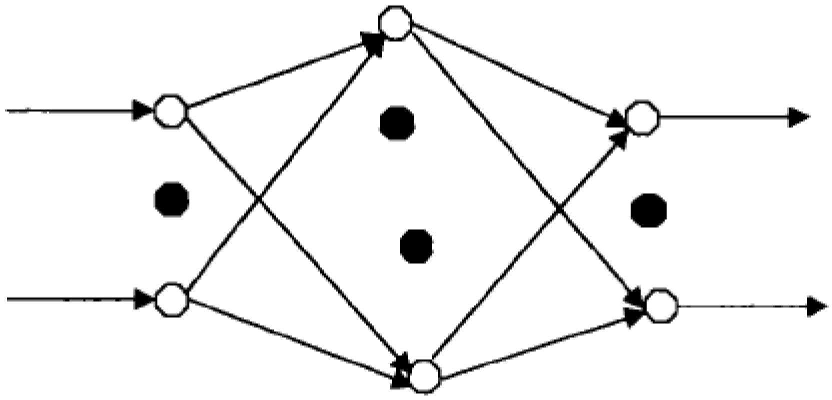

Fig. 1 Basic structure of BP neural network algorithm

From the picture we can see that 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 $Y_i(k)$, 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 neural network can be described as Formula 2.

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

$$\gamma_j(k) = f(x_i(k), \omega) \tag{2}$$

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[4].

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

Defect Analysis of BP Algorithm

There are some shortages of BP neural network. ① It is small in the calculation of change of error gradient. Though the weight is large in adjustment amount, the error is descending slowly. So only with correct adjustment direction and long adjustment time can quit the flat site and enter some valley point, which causes a big increase in calculation training times, thus influencing rate of convergence. ② There are many minimum points. BP algorithm is a non-linear optimal method based on gradient descending method, inevitably having the problem of local minimum. And the solution space of actual problems is often extremely complicated multidimensional curved surface, having lots of local minimum points, leading to an increasing possibility of falling into local minimum point. Generally, while randomly set initial weight in BP algorithm, training of network is generally difficult to reach global optimum, which will make the algorithm training fall into local minimum, thus causing the training fail to converge to assigned error[5.6].

From the perspective of the characteristics of neural network BP and genetic algorithm, the training of BP algorithm is based on the weight modification principle of error gradient descending, inevitably having the problem of falling into local minimum point[7]; genetic algorithm is good at global search, while insufficient in local accurate search. Therefore, the combination of making use of genetic algorithm to optimize the initial weight and threshold of neural network with using neural network algorithm to finally complete network training realizes the complement of advantages, beneficial for better solving practical problems.

Specific Improvement Steps of Genetic Algorithm

An Ann (Artificial Neural Networks, ANN) model can be described by the connecting method of finite parameters such as neuron, network layers, neuron number of each layer and neuron, weight of each connection and transfer function. So we can encode an ANN model and realize the learning process of neural network with genetic algorithm.

Parameter setting. Input population size P, network layers (not including input layer), neuron number of each layer. Genetic algorithm has excellent robustness towards the setting of these parameters; changing these parameters won't exert great impact on obtained results.

Initialization and evaluation.① Randomly generate initial population $P=(x_1,x_2,...,x_n)$, any $x_i \in P$ being a neural network weight, which is comprised of a weight vector and a threshold vector, weight vector being n-dimensional real vector, n being the number of all the connection weights, threshold vector also being n-dimensional real vector (not including neuron of input layer). Each network weight x_i is equal to a chromosome; there are N such chromosomes, i.e. population size. The neurons are numbered from the bottom to the top, from the left to the right (including input neuron).

② According to corresponding neural network of randomly generated weight vector and threshold vector, as for the given input set and output set, calculate the global error of each neural network, as genetic algorithm can only evolve towards the direction of increasing fitness. So the fitness function can be formed according to formula 4 and formula 5, among which f_i is the adaptive value of the i th individual, $i=1,2,...,N$ being the number of chromosome, $k=1,2,...,n$ being the number of nodes of output layer, $p=1,2,...,m$ being the number of learning samples, v_{pk} being the output value of the k th node while inputting the p th training sample, T_{pk} being the anticipated output value[2,3].

$$f_i = 1/E_i \tag{4}$$

$$E_i = \sum_{p=1}^{m}\sum_{k=1}^{n}(v_{pk} - T_{pk}) \tag{5}$$

Selection operator. This paper adopts the mass selection operator combining spinning roulette wheel strategy with optimal retention strategy. Selecting process takes the spinning roulette wheel as basis, which is a kind of playback random sampling method. All the selections are to select good individual according to individual fitness from current population in the light of certain criterion to enter the next generation population, the basic ideal of which is that the selective probability of each individual is equal to the ratio of its fitness to the individual fitness among the entire population. The higher the individual fitness is, the greater the possibility to be selected is, and the greater the probability to enter next generation is. However, due to random operation, the selection error of this method is relatively big, sometimes even making the individual with high fitness be selected. In order to improve the convergence of genetic algorithm, this thesis adopts optimal retention strategy, selecting individual with the largest fitness as seeded player, directly retaining to the next generation. Substitute the worst individual in the population with the optimal individual recorded by the preceding generation while forming new population every time, so as to preventing the individual with optimal fitness in current population from being destroyed.

Crossover and mutation operator. ① Improved Adaptive Crossover Probability and Mutation Probability. In the parameters of genetic algorithm, the selection of crossover probability P_c and mutation probability P_m is the key to influence the behavior and performance of genetic algorithm, exerting a direct impact on the convergence of algorithm. In the simple genetic algorithm, as the values of P_c and P_m are constant, it is not efficient enough to solve multivariable complication optimization problems, having the problems of prematurity or misconvergence. Srinivas and etc. put forward adaptive genetic algorithm, AGA, the basic idea of which is that the individual with fitness higher than average fitness in the population adopts the smaller crossover probability P_c and mutation probability P_m, aiming at retaining individual with favorable structure so as not to be destroyed and to enter the next generation; as for individual with fitness lower than average fitness, using higher crossover probability and mutation probability to facilitate the elimination of such individual. Although this method is improved compared with simple genetic algorithm, there are still some problems. For example, while the fitness is close to the largest fitness, the crossover probability and mutation probability are; while equal to the largest fitness, the crossover probability and mutation probability are zero, which makes AGA undesirable in the early stage of evolution. As in the population of early stage of evolution, more optimal individuals are in an unchangeable state, and the favorable individual at this time is not always the globally optimal solution, which is easy to make the evolution tend to be locally converged [4].

Hence, this paper, based on this, adopts improved adaptive algorithm, making the individual crossover probability and mutation probability of largest fitness in the population be not zero, as shown in formula 6 and formula7, in which f_{avg} represents the average fitness of population of each population; $f_{\max}$ represents the largest fitness in the population; $f^{'}$ represents larger fitness of two individuals to be crossed over; f represents the fitness of individual to be mutated in the population. p_{c1}, p_{c2}, p_{m1} and p_{m2} are design parameters, which are 0.9, 0.6, 0.1, 0.001 respectively[5,6].

$$P_c = \left\{ \begin{array}{ll} P_{c1} - \dfrac{(p_{c1} - p_{c2})(f^{'} - f_{\max})}{f_{\max} - f_{avg}}, & f^{'} \geq f_{avg} \\ p_{c1} & f \leq f_{avg} \end{array} \right\} \tag{6}$$

$$P_m = \left\{ \begin{array}{ll} P_{m1} - \dfrac{(p_{m1} - p_{m2})(f^{'} - f_{\max})}{f_{\max} - f_{avg}}, & f^{'} \geq f_{avg} \\ p_{m1} & f \leq f_{avg} \end{array} \right\} \tag{7}$$

Improved AGA not only keeps the adaptive advantage of AGA but also conquers the shortage of slow evolution of population in the early stage, having favorable optimization function.

② Crossover Operator. First, in the population, according to the crossover probability P_c obtained in the first step, randomly select certain quantity of chromosomes as parents, and randomly select a breakpoint, exchanging the gene strand on the right (or top) of the breakpoints of parents, generating new filial generation; finally, substitute the paternal chromosome with filial generation chromosome, generating new population[7].

③ Mutation. Similar to the selection of paternal generation in crossover process, as for each selected chromosome to be mutated, in order to get better mutation, multiple mutation is permitted. While mutating, first randomly generate a vector with the same dimension as each weight and threshold of chromosome, and add to the selected vector to be mutated. As to the result of each mutation, restore neural network and carry out performance evaluation. If the descendant is better than paternal generation, the mutation of paternal generation shall be ended; otherwise, carry out next mutation on paternal generation, until finding out descendant better than paternal generation.

Immigration operator. It is found through the test that in the search process of genetic algorithm, the individual with highest fitness in the population at present is possible to participate in crossover and mutation calculation, just with small probability; on the contrary, the lower the fitness of the individual is, the larger the probability to be selected to participate in crossover and mutation is, but the generated individual fitness is very low, and the global search performance on algorithm is not obviously increased. Therefore, this thesis introduces immigration operator which is a good method to avoid prematurity. In the immigration process, it can only accelerate the elimination of bad individual, but also increase the diversity of solution, further meeting the evolutionary mechanism of creatures. Immigration operator eliminates the worst individual with certain elimination rate (generally 15%~20%) in the evolutionary process of each generation, and generates part of excellent immigrants to supplement the population. Excellent immigrants here are mutated and generated through the multiple crossovers on those individuals to be eliminated. Thus, not only fully retain the good gene genetic pattern of paternal generation but also guarantee the diversity of population, improving the optimization searching performance of GA.

End of operation. If the network error meets the requirement or reaches certain evolution generations, the evolution shall be stopped and the evolution result shall be outputted; otherwise, turn to the third Step.

Calculation Flows of Improved Algorithm

The calculation flows of the improved algorithm can be listed as follows. ① Initial Population, including the population size and the initialization of each weight (generate according to the method for neural network to generate initial weight), and encode it; ② Calculate the selection probability of each individual and sort them; ③ Select good individual to enter next generation population according to spinning roulette wheel selection strategy; ④ In the new generation population, select adaptive individual to carry out crossover and mutation operation according to adaptive crossover probability and mutation probability to generate new individual; ⑤ Insert the new individual into the population and calculate the fitness of new individual; ⑥ Immigration operator operation. Judge whether there is "prematurity phenomenon", if there is, immigration strategy shall be adopted and turn to the second step ; ⑦ If the satisfactory individual is found, it shall be ended; otherwise, turn to the second step.

After reaching required performance indicator, decode the optimal individual in final population, then the optimized network connection weight can be obtained.

EXPERIMENTAL SECTION

Evaluation Indicator System Design for Competitive Sports Evaluation

The paper takes regional competitive sports evaluation for examples and, on the basis of referring to references, experts consultation and practice survey, designs a set of evaluation indicator system which includes 5 second-class indicators and 34 third-class indicators. 5 second-class indicators are competitive sports culture, administrative system, resource allocation, operation mechanism, benefit performance respectively. And second-class indicators competitive sports culture includes ideology and culture, method culture, artifact culture, administrative system includes organization system, and security system, the specific contents of rest three second-class indicators are omitted here.

Experimental Results and Analysis

Experimental data come from the database of some typical regions, Beijing, Shanghai, Liaoning, Shangxi, and Yunnan. Limited to paper space, the evaluation of intermediate results is omitted here, only providing evaluation results of second grade indicators and final comprehensive performances, see table 1.

Table 1 Evaluation results of second grade indicators and final performance

	Competitive sports culture	Administrative system	Resource allocation	Operation mechanism	Benefit performance	Final results
Beijing	4.662	4.091	4.031	4.232	4.571	4.389
Shanghai	4.669	3.988	3.989	4.001	4.386	4.223
Liaoning	4.221	3.785	3.861	3.889	4.109	3.981
Shanxi	3.624	3.189	3.287	3.229	3.573	3.376
Yunnan	3.118	2.899	2.901	2.866	3.102	2.941

As for the performance of the presented algorithm, this paper also realizes the application of the ordinary BP neural network[4] and ordinary fuzzy comprehensive evaluation algorithm[8], evaluation performances of different algorithms are shown in table 2. In table 2 evaluation results of training effects of different regions 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.

Table 2 Evaluation performance comparison of different algorithms

	Algorithm in the paper	Ordinary BP algorithm	Fuzzy algorithm
Evaluation Accuracy	94.65%	84.38%	76.11%
Time Consuming (S)	12	692	11

CONCLUSION

This paper, through improving genetic algorithm making use of the advantage in high system evaluation accuracy, also overcoming the actual defect in poor algorithm convergence, advances a new system evaluation model based on improved genetic algorithm, also analyzes and establishes a set of evaluation indicator system for evaluating competitive sports evaluation. The experimental results show that the model evaluation results are satisfactory. The model in this paper has the following superiorities compared with other methods.① Through self-study on samples involving in the comparison, genetic algorithm structure can be decided, repeatedly iterating according to the criterion of optimal training, constantly adjusting ant genetic algorithm structure, until reaching a relatively stable status, thus, the utilization of that method eliminates many human factors, helping to ensure the objectiveness of the evaluation results; ②High accuracy, able to make system error reach the requirement of any accuracy with convergence;③ Good dynamics, self-study and dynamic tracking ability will be stronger with the progress of time and the increase of samples involved in comparison. Hence, there is certain practical application value in that method.

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