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An Improved Algorithm of BP Neural Network based on Genetic Clonal Selection Algorithm

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Abstract. Because of some defects of BP neural network, such as falling into local minimum easily, slow convergence, existing redundant nodes. it is improved by genetic clonal selection algorithm and dynamic theory and thus eliminates those defects. The experiment results confirm this algorithm's efficiency by using it to GIS aided location. And thus it has a more wider applicability in many fields.

Keywords: RBF BP neural network; genetic clonal selection algorithm; GIS aided location

1. Introduction

At present, BP neural network algorithm is widely used. It has many advantages, such as simple structure, good stability and nonlinear function approximation. It has been proved that a three layer BP network can realize any mapping from n-dimensional to m-dimensional. However, it has many defects, such as falling into local minimum easily, slow convergence, existing redundant nodes[1][3], which limits its further applications. Genetic algorithm has learned rules of biological evolution, which is a randomized search method and has the characteristics of inherent parallelism, global optimization and self-adaptive searching, so it is widely used to improve BP neural network. However, it also has many defects, such as slow convergence and premature convergence[4]. Therefore, it is not good enough only use genetic algorithm to improve BP network. On this basis, this paper use genetic clonal selection algorithm[5] to improve BP network.

High-frequency cloning variation, which is the main searching way of genetic clonal selection algorithm, can avoid many unexpected problems of genetic algorithms that are pattern convergence, population diversity destroying and prematurity because of crossover operator. Meanwhile, it can guarantee the global optimization, which reflects the strong ability of global optimization. So this paper use it to train the weights and thresholds of BP network. Moreover, there is lack of theoretical support on how to determine hidden layers and nodes. Too many hidden nodes will cause too much overhead and too few nodes won't achieve the accuracy and cause more training times. Appropriate hidden layer nodes is important for the solution of problems. So, this paper uses Dynamic self-adaptive strategy to adjust the hidden layer nodes. It can determine the least number of hidden layer nodes meanwhile the network has the best convergence.

2. Improved BP neural network algorithm

The basic steps of improving BP neural network with genetic clonal selection algorithm is as follows. Building the relationship between GA chromosome structure and weights of BP network; Determining the fitness function and affinity function, which determines the degree of affinity between training results and

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expected results; Determining the genetic cloning strategy, such as population scale, selection, crossover, clone and mutation so as to train BP network. The flowchart is showed as "Fig. 1".

1)Coding: the common coding ways are binary coding and real coding. In order to reduce troubles from this process, this paper uses real coding that directly associates weights and thresholds of every node with related gene segments. Every weight of network is represented with a set of real number.

2)Computing the affinity: according to the above neural network and inputing studying sample, it can compute the error(inversely with the affinity) between actual output and expected output results, which is showed as (1).

$$ff(a) = \frac{1}{\left(\frac{1}{M}\sum_{i=1}^{M}\left[Y_e(i) - Y(i)\right]^2\right) \times K} \tag{1}$$

In (1), Y is the network actual output and Ye is the expected output, M is the training sample and $0 < K \leq 1$.

At this stage, there should be dynamic adjustment for the hidden nodes according to the weights and thresholds. In the practical application of BP network, the nodes of input layer and output layer are usually determined by specific conditions. Too many hidden nodes will cause too much overhead and too few nodes won't achieve the accuracy and cause more training times. So appropriate hidden layer nodes is important for the solution of problems. Dynamic self-adaptive strategy, which means more hidden layer nodes at first and then gradually remove the hidden nodes which is not important for the problem in the processing, can determine the least number of hidden layer nodes meanwhile the network has the best convergence.

3)Selecting and crossover: estimating the affinity, the aim is to generate individuals with the most appropriate weights and thresholds.

4)Selecting, cloning and mutation: crossover (recombination) and clone operating for the optimal value. The better affinity the more Cloning. The main purpose is to generate individuals with more better weights and thresholds. The method to calculate clone scale is showed as (2).

$$Q_a = round(\beta \times ff(a) / \sum ff(a)) \tag{2}$$

In (3),β is the clone coefficient, which is used to control the clone scale.

In order to use high-frequency variation clone, it uses self-adaptive Cauchy mutation function(as showed in (3). Mutation probability is determined by parent affinity of clonal immune cells.

$$q' = \begin{cases} q + \alpha \times c(t), & t(k+1) = 0.8 \times t(k) \\ q + c(t) \end{cases} \tag{3}$$

In (3), q' is q's variant, c(t) is Cauchy random variable,α is a parameter to control the decay of c(t), t(k+1) is Cauchy variation parameter and t(k) is Cauchy parameter.

5)Estimating affinity: determining whether it meets the requirements of stopping iterations according to affinity. If meets, then stop; else go to next step.

6)Rebuilding population: rebuilding population and add some new individuals randomly so as to increase the diversity of antibodies, then go to step 2).

According to the above steps, we can realize the aim that using genetic clonal selection algorithm to improve BP neural network.

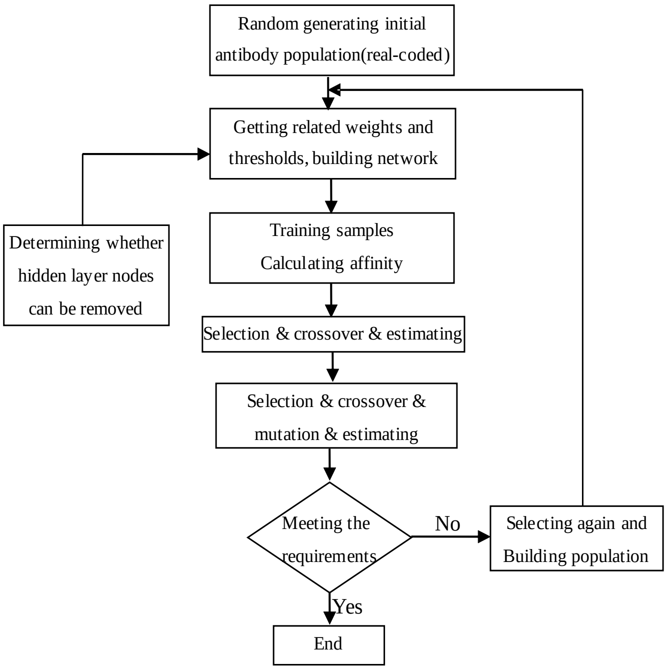

Fig. 1. Flowchart of improved BP neural network

3. Application of the improved BP algorithm on GIS location

This paper studies a three-tier highway in Chongqing of GIS aided location system with the improved BP algorithm(more details about the case can find in [2]). This paper only gives the results of the improved BP algorithm and the old BP algorithms. Selecting the first 30 raster objects as the investigated objects and the first 20 as the training input and the last 10 as validation input. Network is three-layer structure. There are 6 input nodes, which respectively represent land price, deviation, elevation, geological disasters, land use types, across facilities(V1、V2、V3、V4、V5、V6); 1 output node representing the final land price(also the training value of model); 25 hidden layer nodes at first. Then, this paper compares results from the improved BP algorithm with that from the old BP algorithm. In order to get a clear comparison, it gives two comparing ways that is when the error is less than or equal to 0.01% and the iteration time is 350. Results from two algorithms are showed in"Table 1"and the comparison result is showed in"Table 2".

TABLE 1. RESULTS FROM THREE ALGORITHMS

*(**Note**: land price 1 is from the old BP algorithm, which has iterated 350 times and the error is less than or equal to 0.01%; land price 2 is from the improvedl BP algorithm, which has iterated 263 times and the error is less than or equal to 0.01%; land price 3 is from the improved BP algorithm, which has iterated 350 times and the error is less than or equal to 0.001%)*

ID	V1	V2	V3	V4	V5	V6	Land price 1	Land price 2	Land price 3
21	82	0.78	0.49	1	4100	0	43.12	43.21	43.77
22	59	0.55	0.11	4	1180	0	36.46	35.99	35.86
23	67	0.1	0.54	3	670	0	9.9	9.99	9.98
24	52	0.64	0.31	5	52	0	24.79	24.21	24.32
25	54	0.97	0.36	4	54	0	38.65	39.19	39.15
26	98	0.409	1.86	1	98	0	20.57	20.57	20.59
27	105	0.486	1.94	1	105	1	42.49	42.59	42.72
28	95	0.122	0.11	3	950	0	9.87	9.74	9.74
29	84	0.208	0.39	2	84	0	13.12	13.17	13.27
30	64	0.695	1.35	1	640	1	28.15	28.99	28.88

TABLE 2. COMPARING RESULTS FROM THE TWO ALGORITHMS

(Note: the training value in table 2 is the land price in table 1; error 1 is from training value 1; iteration times of 263 from training value2)

ID	Expected output	Training value 1	Error 1 (%)	Training value 2	Iteration times	Training value 3	Error 3 (%)
21	43.83	43.12	1.63	43.21	263	43.77	0.1
22	35.75	36.46	-1.99	35.99	263	35.86	-0.3
23	9.984	9.9	0.84	9.99	263	9.98	0
24	24.44	24.79	-1.45	24.21	263	24.32	0.4
25	39.01	38.65	0.92	39.19	263	39.15	-0.4
26	20.62	20.57	0.25	20.57	263	20.59	0.2
27	42.67	42.49	0.42	42.59	263	42.72	-0.1
28	9.742	9.87	-1.3	9.74	263	9.74	0
29	13.24	13.12	0.92	13.17	263	13.27	-0.2
30	28.79	28.15	2.23	28.99	263	28.88	-0.3

As can be seen from the above data, in the premise of one indicator is determined, another indicator of the improved BP algorithm is significantly better than the old one. That is when the error is required less than or equal to 0.01%, the iteration time of improved BP is 263. However, the old BP algorithm is 350. When the iteration time is required equal to 350, the error of improved BP is 0.07% and the old BP is 2.23%. We can get a conclusion that the improved BP algorithm has a high generalization ability and it has a good estimation results using it to calculate land price. So, it is effective and high efficiency for GIS aided location. The final hidden layer nodes of the improved BP is 14. Obviously, the number of 25 at first is not the most appropriate number. Therefore, the idea of dynamic self-adaptive is very useful. At first, when we don't know how many hidden nodes is the most appropriate, we can give more hidden nodes. As the algorithm running, some nodes has less association can be deleted with dynamic self-adaptive idea, which can avoid redundant nodes and improve the algorithm's accuracy and efficiency.

4. Conclusion

Although BP algorithm has been widespread concern, the defects, such as falling into local minimum easily, slow convergence, existing redundant nodes, limit its further applications. This paper uses genetic clonal selection algorithm to improve BP network, such as using high-frequency variation clone, affinity estimating and hidden layer nodes dynamical deleting, which has improved the accuracy and the training speed obviously. The simulation results of GIS aided location show that genetic clonal selection algorithm can improve the learning capability of BP network and it has a wide applicability in many fields.

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