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Bridge Health Evaluation System based on the Optimal BP Neural Network

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Abstract

Neural network has strong ability of pattern recognition. In consideration of the problems of the traditional pure BP neural network, such as subjecting to the randomness of initial weights, slow convergence speed, low efficiency, easy to fall into local extreme value, in this paper we proposing an optimal BP network fusing with the genetic algorithm using in bridge health assessment. The optimized BP network algorithm has a good diagnosis effect, and improves the calculation accuracy and speed of the identification of bridge structure damage.

Keywords: *bridge health; genetic algorithm; optimal BP neural network; damage detection*

1. Introduction

With the progress of science and technology, as an infrastructure project, bridges' construction scale is more and more big, its cost is higher and higher. The large bridges play an important role in the national economy and social life. Because the existing bridges are in a real environment space, it is a complex dynamic system. For these uncertain factors and relationships, many of the existing bridge structure evaluation are still with the traditional detection methods [1]. In recent years, most of the developed bridge detection systems are just for test data acquisition and display, the analysis and the evaluation of collected data still have great progress space. Because neural network has strong ability of pattern recognition, this paper selects the BP neural network used for bridge health assessment, based on the introduction of the structure of the system hardware. The BP neural network can learn and store a lot of input-output model mapping, have the mathematical equation without describing the mapping relation before. It has strong accurate mapping function for solving complex nonlinear problems [2]. For these reasons, this paper select BP neural network using in bridge health assessment. And the hardware of data acquirement system mainly composed of fiber grating sensor made good preparation for data processing [3].

2. Hardware Composition and Function of the System

Acquisition system hardware includes: fiber Bragg grating strain sensor, optical fiber grating temperature sensor, optical fiber grating demodulator (BGD – 16M), switches, collection server, *etc.* Considering the strain sensor accuracy, sensitivity and anti-interference ability based on the request of the monitoring system, this paper selects the surface type GFRP packaging fiber grating strain sensors, CB-FBG-GFRP-W01. The fiber Bragg grating strain sensor adopts the without glue packaging technology, to overcome the durability of the traditional glue sealing fiber Bragg grating sensor, it can change the gage length according to

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the requirement, a minimum of 1 ~ 2 cm. The figure of the fiber Bragg grating sensor is shown in Figure 1.

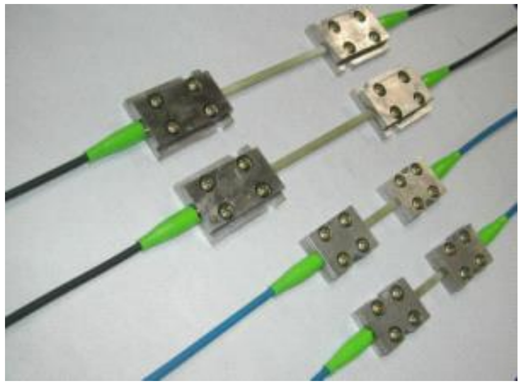

Figure 1. CB-FBG-GFRP-W01 FBG

At present, the demodulation instrument can access optical fiber 32 road at the same time, each road can be concatenated point reached 20. Each light signal will be wavelength demodulated into electrical signals at the same time by the fiber Bragg grating demodulator. Access the switches or directly connect to the computer. Constitute a distributed optical fiber sensing network. Each demodulation instrument network is assigned a single IP address, and realizes the data collection function by the collection server.

The basic construction of the hardware system is as shown in Figure 2.

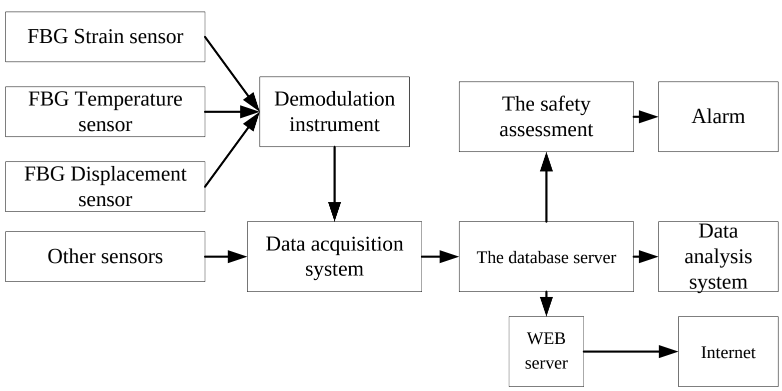

Figure 2. The construction of hardware system

3. Genetic Algorithm to Optimize the BP Neural Network

3.1. The traditional BP neural network

BP neural network (Back Propagation Neural Network) is a kind of no feedback foreword networks that correct error by reverse transfer. The structure of BP network includes input layer, hidden layer and output layer. It takes the all interconnected mode between layers. In BP neural network, it can approximate any functions at arbitrary precision [4]. The BP neural network topology is shown in Figure 3.

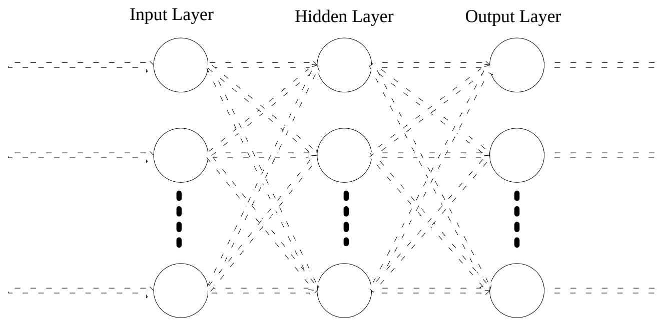

Figure 3. The BP neural network topology

In practical applications, sometimes the effect the standard BP algorithm is not very ideal, there are a lot of problems: such as falling into local minima, low speed of learning algorithm convergence speed, the randomness of the initial value, and there is no theoretical evidence for the selection of the numbers of hidden layer and of hidden nodes [5]. Learning efficiency and the momentum factors need to be given by experience.

3.2 The principle of genetic algorithm

Genetic algorithm is a kind of parallel random search optimization method. It introduces the principle of the natural biological evolution into coding series group formed by the optimization parameters. According to the selected fitness function, and screening by selection, crossover and mutation, it makes individual with good fitness value retained, with not good fitness obsoleted [6]. The new groups inherit the information of last generation, and are better than the last generation. Repeat the cycle until meet the end conditions.

Genetic algorithm is a search algorithm with iterative process. The basic process is shown in Figure 4.

Genetic algorithm is an operation of population size, taking all members in the group as the objects [7].

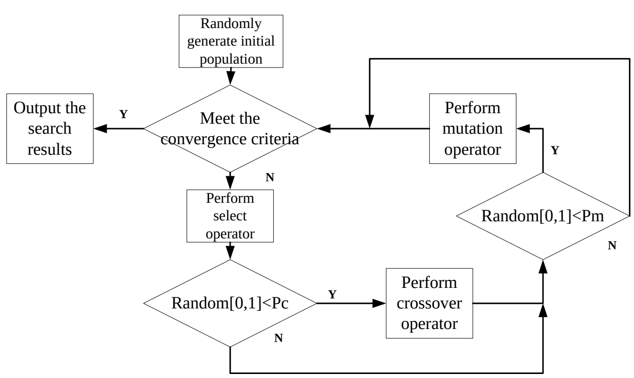

Figure 4. Basic process of genetic algorithm

3.3 Genetic algorithm optimizes the BP neural network

Genetic algorithm optimizing is to use genetic algorithm to optimize BP neural network's weights and thresholds, making the optimized BP neural network predict the output better. The BP neural network optimized by genetic algorithm can be divided into three parts:

determining BP neural network's structure; the optimization; BP neural network prediction. The overall diagram is as shown in Figure 5.

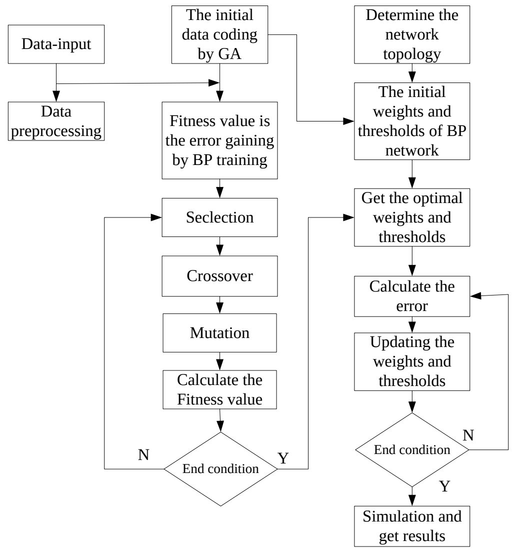

Figure 5. Overall diagram of optimization

3.3.1 Determination of BP neural network's structure: According to the number of input and output parameters of fitting function, we can confirm the BP neural network's structure, and the length of the individual of genetic algorithm. Genetic algorithm optimization uses BP neural network's weights and threshold value [8].

3.3.2 Use genetic algorithm to optimize neural network: Using a genetic algorithm to optimize the BP neural network's initial weights and threshold, the optimized BP neural network can predict and output better [9]. The steps of optimizing are as follows.

(1) Initialize the population: Individual coding is real coding. Each individual is a real number including the connection weights of input layer and hidden layer, the threshold of hidden layer, the connection weights of hidden layer and output layer, the threshold of output layer. Individual contains the neural network's weights and threshold.

(2) The calculation of fitness function: According to BP neural network's weights and thresholds gained by individuals, predict system output after training the BP neural network by training data. The absolute value of error between the predicted output and the desired output and E are as the individual fitness value, the calculating formula is as following:

$$F = k\left(\sum_{i=1}^{n} abs\left(y_i - o_i\right)\right) \tag{1}$$

In the formula, n is the network output node number; y_i is the desired output of the i node of BP neural network; o_i is the predicted output of the i node; k is coefficient.

(3) Selection: Selection operation of genetic algorithm contains roulette method, tournament method and other method. This paper selects roulette method, namely the selection strategy based on fitness ratio. The choice probability of each individual f_i is:

$$f_i = \frac{k}{F_i} \tag{2}$$

$$p_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \tag{3}$$

In the formula, f_i is the fitness value of individual i. Due to the fitness is the smaller the better, calculate the reciprocal of the fitness value before the individual selection. k is coefficient, N is the individual's number of the population.

(4) Crossover: Because the individual uses real number coding, crossover operation methods uses real crossing method, the crossover operation of the first k in chromosomes and the first i in chromosomes is as follow:

$$\begin{cases} a_{kj} = a_{kj}(1-b) + a_{lj}b \\ a_{lj} = a_{lj}(1-b) + a_{kj}b \end{cases} \tag{4}$$

In the formula, b is a random number between 0 and 1.

(5) Mutation: Mutate with the i individual and j individual, the method of mutation operation is as follow:

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) * f(g), r \geq 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) * f(g), r < 0.5 \end{cases} \tag{5}$$

In the formula, $a_{\max}$ is the upper bound of gene a_{ij} □ $a_{\min}$ is the lower bound of gene a_{ij}; **Error! Reference source not found.**, r2 is a random number, g is the current number of iterations, $G_{\max}$ is the maximum number of evolutionary, r is a random number between 0 and 1.

(6) Calculate the fitness value F.

(7) If the fitness F is not end condition, then go back to Selection and repeat the process.

3.4 The optimized BP neural network training process

BP network need to be trained before the prediction, and then the network have the associative memory and ability to predict. Based on the optimal initial weights and thresholds that obtained by genetic algorithm, train the BP network [10]. The process is divided into the following several steps: (1) The weights and thresholds obtained by the genetic algorithm take as a new starting point; (2) Output calculation of hidden layer; (3) Output layer calculation; (4) Error calculation; (5) Weight updating; (6) Threshold updating; (7) Judge whether the iteration end, if it is not the end, return to step (2) and continue to repeat (2) to (7).

4. Project Instance Analysis

According to the result of a suspension bridge model and safety evaluation, convert the evaluation index into percentage format. The corresponding sample training data as shown in Table 1, the calibration data are shown in Table 2.

Table 1. Sample training data

NO.	Bridge Tower Deviation	Bridge Tower Stress	Main Beam Linear	Derrick Stress	Main Rope Linear	Anchor Span Stress	Assessment Result
1	100	90	100	93.33	100	100	94.49
2	100	100	100	100	95.24	93.33	94.78
3	94.74	90	95.24	86.67	100	93.33	90.85
4	94.74	95	85.71	83.33	90.48	86.67	86.81
5	94.74	75	76.19	80	76.19	86.67	78.96
6	92.63	70	83.81	81.33	80.95	80	78.57
7	89.47	85	71.43	73.33	71.43	76.67	75.55
8	82.11	65	61.90	63.33	64.76	68	66.49
9	75.79	70	57.14	56.67	63.81	63.33	63.94
10	73.68	50	52.38	53.33	66.67	65.33	59.49
11	75.79	40	47.62	50	61.90	63.33	56.03
12	73.68	40	42.86	46.67	61.90	56.67	53.26
13	71.58	35	45.71	48.67	52.38	48	49.10
14	69.47	35	43.81	50	46.67	46	46.60
15	68.42	36	40.95	46	42.86	43.33	44.83
16	68.42	25	36.19	49.33	33.33	34.67	39.52
17	61.05	22	28.57	43.33	33.33	20	33.38
18	47.34	15	19.25	36.67	37.19	43.33	29.10
19	42.11	5	7.62	33.33	23.81	14.67	18.67

Table 2. The corresponding sample

NO	Bridge Main Deviation	Bridge Tower Stress	Main Beam Linear	Derrick Stress	Main Rope Linear	Anchor Span Stress	Assessment Results
1	81	84.21	65	38.10	86.67	71.43	70.27
2	83	95.79	79	90.48	78	86.67	82.56
3	91	98.95	83	84.76	85.33	96.10	86.21
4	70	68.42	45	46.67	50	42.86	49.68
5	35	15.79	25	8.57	12.67	20	15.12

In order to test the performance and correctness of the optimal BP neural network, take the 1st to 19th set of data as the training samples from the standard sample library. The node n of network input layer is 7; the output layer nodes m is 1; hidden layer node l=5; accuracy k of network training error is 0.001; neural network's learning efficiency is 0.9; genetic algorithm population size N=19; the evolution number G=100; crossover probability is 0.65; the mutation probability is 0.05. Table II is the calibration data of testing network prediction accuracy.

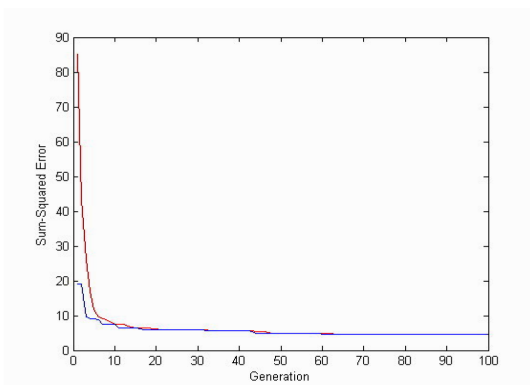

Figure 6. Genetic optimized neural network error curve

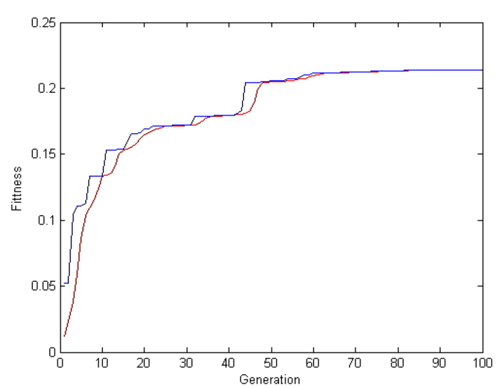

Figure 7. Genetic optimized neural network fitness curve

Figure 6 and Figure 7 is the error and fitness curve. The calculated results with traditional BP neural network have larger error. In comparison, the network optimized by genetic algorithm has higher prediction precision and better reliability. Particularly when the input node is large, the BP neural network optimized by genetic algorithm will greatly improve the efficiency.

5. Conclusion

This paper introduces the hardware system structure of the bridge health evaluation system based on fiber Bragg grating sensor, and puts forward the safety evaluation algorithm of BP neural network that is optimized by the integration of genetic algorithm. The algorithm not only has the function approximation ability of traditional neural network, but makes the neural network shorten the training time and avoid to falling into local extreme value with the weights and thresholds optimized by genetic algorithm. And verify the correctness and feasibility of the algorithm combining the safety evaluation of a suspension bridge. From the research, it can be concluded that the optimal BP neural network has higher prediction precision and better reliability than the traditional one. At the same time, it can be found out that in future applications, only when the data acquisition system can collect accurately the key parameters of the bridge and transfer back to data processing system completely, neural network damage identification methods can achieve its practical value and popularization meaning.

Acknowledgements

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