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Application of Improved Neural Network in the Automotive Engine Fault Diagnosis

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Abstract

Back Propagation neural network is a network, which is a multilayer feedforward network of according to the error back propagation algorithm training, i.e., BP neural network. The good nonlinear mapping ability of BP neural network can be a good application in engine fault diagnosis, but the traditional BP network has the trend of forgetting old samples during the training process when learning new samples ,and exists the drawback of low training accuracy. Therefore, a model of improved BP neural network is constructed. A neural network algorithm of increased state feedback in the output layer is designed in this paper. The simulation results show the proposed algorithm can effectively improve the BP neural network training accuracy, and achieve misfire diagnosis more accurately.

Keywords: *improved BP neural network, fault diagnosis, training accuracy*

1. Introduction

Automotive engines involve complex operating conditions and their faults are generally nonlinear. No sufficiently accurate model is currently available to characterize the faults. Therefore, an intelligent diagnosis system must be constructed to diagnose engine faults. Currently, engine fault diagnosis algorithms come under two categories: intelligent algorithms and recognition theories. For example, experts such as Zhang Wei [1] rely on a confidence rule database expert system to diagnose engine faults and the diagnostic accuracy depends on the depth of knowledge on the part of the experts in the knowledge base; experts such as Chen Jinhui [2] use a simulated annealing algorithm capable of global search to optimize and increase the stability of the BP neural network. However, the algorithm varies according to parameters and provides poor global search performance. The ant colony optimization (ACO) model stated in the document [3] features positive feedback, distributed calculation, global convergence, and heuristic learning. The ACO model and the neural network are combined to increase operation efficiency, but the algorithm generates a high calculation overhead and is only suitable for finding paths on a drawing. In the document [4], a heuristic value reduction algorithm based on the importance of attributes is used to reduce attributes and therefore establish a fault diagnosis method that combines a method of finding fuzzy information with the particle swarm optimization (PSO) to optimize the BP network. As a global optimization algorithm, the PSO algorithm takes a long time for training. Supported by the D-S theory, Wei Xiaodan [5] places the results of BP network diagnosis, RBF network diagnosis and ANFS diagnosis into different evidence groups, calculates the degree of conflict between these groups, and solves the problem of the D-S algorithm in failing to integrate highly conflicting evidence. Another fault diagnosis based on the Bayesian

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network model adopted by Cao Huajin [6] and Bu Yujun [7] , which should obtain the prior probability of fault causes and the conditional probability between each cause and effect.

As an error back propagation algorithm, the BP neural network has addressed the problem of inertia weight adjustment with a neural network [8]. However, the BP network uses a method of gradient descent, which may easily leads the network to a local minimum during training, thereby reducing the network training accuracy and effectiveness. Failure by the neural network to find suitable weights for calculation may cause the network training process to fail in convergence and weaken its generalization ability [9]. Moreover, traditional BP neural networks easily forget old samples when learning new samples. When available in small quantities, sample data cannot be fully utilized, which in turn may reduce the network training accuracy. This paper proposes a neural network algorithm of increasing state feedback in the output layer to solve the problem above. The proposed solution can increase the accuracy of neural network training despite the scarcity of samples.

2. Improved BP Neural Network

A BP neural network consists of three layers: input layer, hidden layer and output layer. A correlation layer is added to the above structure. At the layer, each node is connected with one node at the output layer to receive the previous output result from the output layer. Outputs from the correlation layer serves as additional inputs to the hidden layer and are connected along with the original input layer to the hidden layer. Hence, the correlation layer stores the memory the moment before network output, so that old samples at the previous point of time continue to be used. The Enhanced BP neural network is referred to as "Output-Feedback BP neural network" and improved BP in short. Figure 1 shows the structure of the improved BP neural network.

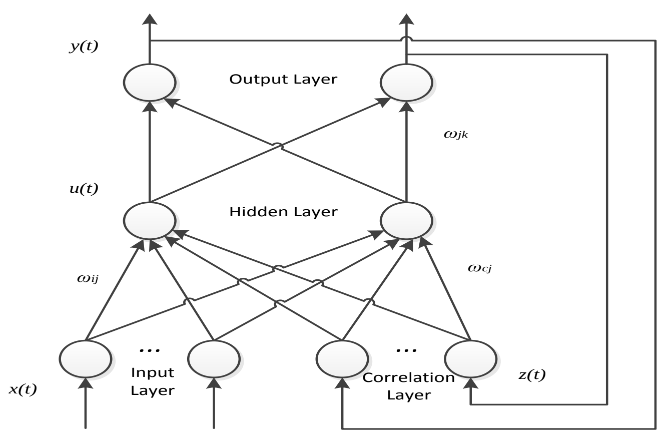

Figure 1. Structure of the improved BP neural network

Wherein: ω_{ij} indicates the weight for connection between the input and hidden units; ω_{cj} represents the weight for connection between the correlation and hidden units; ω_{jk} denotes the weight for connection between the hidden and output units. $x(t)$ is an input unit; $z(t)$ represents output from the correlation layer; $u(t)$ indicates output from the hidden layer; $y(t)$ denotes output from the output unit.

For simplicity, the mathematic model for improved BP neural network is defined below without threshold calculation:

$$y(t) = g\left(\sum_{j,k} \omega_{jk} u(t)\right) \tag{1}$$

$$u(t) = f\left(\sum_{i,j} \omega_{ij} x(t) + \sum_{i,j} \omega_{cj} z(t)\right) \tag{2}$$

$$z(t) = y(t-1) \tag{3}$$

Wherein $f(x)$ and $g(x)$ are transfer functions.

Only the inference process is provided herein for the weight correction formula for the connection weight between the correlation and hidden layer units ω_{cj} .Assuming that the ideal network output during t iterations is $d(t)$, actual output $y(t)$, wherein $i = 1, 2, \ldots\ldots n$ (n indicates the number of input nodes), $j = 1, 2, \ldots\ldots m$ (m indicates the number of neurons, $k = 1, 2, \ldots\ldots l$, $c = 1, 2, \ldots\ldots l$ (l indicates the number of output neurons), $p = 1, 2, \ldots\ldots P$ (P indicates the number of learned samples), the error function for the BP network during t iterations can be expressed as follows:

$$E(t) = \frac{1}{2} \sum_{p} \sum_{k} \left[d_k^{(p)}(t) - y_k^{(p)}(t) \right]^2 \tag{4}$$

Based on the method of gradient descent, obtain the partial derivative of ω_{cj} in the function as follows:

$$\frac{\partial E}{\partial \omega_{cj}} = \sum_{k} \frac{\partial E}{\partial y_k} \frac{\partial y_k}{\partial u_j} \frac{\partial u_j}{\partial \omega_{cj}} \tag{5}$$

Wherein d_k indicates the ideal output from the *k*th node at the output layer; y_k indicates the actual output from the *k*th node at the output layer; u_j indicates the output from the jth node at the hidden layer; x_i indicates the input to the *j*th node at the input layer; and z_c indicates the input to the *c*th node at the correlation layer.

$$\frac{\partial E}{\partial y_k} = \frac{1}{2}\left[2(d_k - y_k) \right] \cdot (-1) = -(d_k - y_k) \tag{6}$$

$$\frac{\partial y_k}{\partial u_j} = \frac{\partial y_k}{\partial net_k} \cdot \frac{\partial net_k}{\partial u_j} = g'(net_k) \cdot \frac{\partial net_k}{\partial u_j} = g'(net_k) \cdot \omega_{jk} \tag{7}$$

$$net_k = \sum_{j} \omega_{jk} u_j \tag{8}$$

$$\frac{\partial u_j}{\partial \omega_{cj}} = \frac{\partial u_j}{\partial net_j} \cdot \frac{\partial net_j}{\partial \omega_{cj}} = f^{'}\left(net_j\right) \cdot z_c \tag{9}$$

$$net_j = \sum_i \omega_{ij} x_i + \sum_c \omega_{cj} z_c \tag{10}$$

Then,

$$\frac{\partial E}{\partial \omega_{cj}} = -\sum_k \left(d_k - y_k\right) g^{'}\left(net_k\right) \omega_{jk} f^{'}\left(net_j\right) z_c \tag{11}$$

Wherein $f\left(x\right)$ and $g\left(x\right)$ are both Sigmoid functions as expressed in Formula (12):

$$f\left(x\right) = g\left(x\right) = \frac{1}{1+e^{-x}} \tag{12}$$

Then,

$$\begin{aligned} g^{'}\left(net_k\right) &= y_k\left(1-y_k\right) \\ f^{'}\left(net_j\right) &= u_j\left(1-u_j\right) \end{aligned} \tag{13}$$

The weight increment is:

$$\Delta\omega_{cj}\left(t\right) = -\eta \frac{\partial E}{\partial \omega_{cj}} = \eta \sum_k \left(d_k - y_k\right) y_k \left(1-y_k\right) \omega_{jk} u_j \left(1-u_j\right) z_c \tag{14}$$

Then calculate the partial derivates of for other weights. indicates the learning rate, which ranges between 0 and 1. The network learning algorithm is shown below and used to adjust network weights during the process of improved BP neural network training.

The connection weights between the hidden layer and the output layer are adjusted based on the following formula:

$$\omega_{jk}\left(t+1\right) = \omega_{jk}\left(t\right) + \Delta\omega_{jk}\left(t\right) \tag{15}$$

Wherein,

$$\Delta\omega_{jk}\left(t\right) = -\eta \delta_{jk} u_j \tag{16}$$

$$\delta_{jk} = -\sum_k \left(d_k - y_k\right) y_k \left(1-y_k\right) \tag{17}$$

The connection weights between the input layer and the hidden layer are adjusted based on the following formula:

$$\omega_{ij}\left(t+1\right) = \omega_{ij}\left(t\right) + \Delta\omega_{ij}\left(t\right) \tag{18}$$

Wherein:

$$\Delta\omega_{ij}\left(t\right) = -\eta\delta_{ij}x_i \tag{19}$$

$$\delta_{ij} = \delta_{jk}\omega_{jk}u_j\left(1-u_j\right) \tag{20}$$

The connection weights between the correlation layer and the output layer are adjusted based on the following formula:

$$\omega_{cj}\left(t+1\right) = \omega_{cj}\left(t\right) + \Delta\omega_{cj}\left(t\right) \tag{21}$$

Wherein:

$$\Delta\omega_{cj}\left(t\right) = -\eta\delta_{cj}z_c \tag{22}$$

$$\delta_{cj} = \delta_{jk}\omega_{jk}u_j\left(1-u_j\right) \tag{23}$$

3. Engine Misfire Diagnosis Based on Improved BP Network

Automobile exhaust gas can be examined for the following engine faults: abnormal air-fuel ratio, injector fault, exhaust manifold leak, inaccurate angle of advance for the ignition system, and intermittent misfire. The automobile exhaust gas contains harmless gases such as CO_2, O_2 and H_2O as well as harmful gases such as CO, HC and NO_X. The content of each gas in the exhaust must meet a given standard. When a component of the exhaust exceeds the standard, the engine is partly abnormal or faulty. Data collation on the components of the automobile exhaust gas helps identify the cause of fault.

3.1. Neural Network Structure and Parameters

A sample for fault analysis represents the volume fractions of CO, CO_2, HC and O_2. Therefore, the number of neurons at the input layer is 4 and these neurons are described as x_1, x_2, x_3 and x_4. There are six nodes at the output layer, indicating the following faults respectively: intermittent misfire, low air-fuel ratio, high air-fuel ratio, premature ignition, late ignition, and exhaust manifold leak. These faults are described as y_1, y_2, y_3, y_4, y_5 and y_6. The number of nodes at the correlation layer is also six. According to the Kolmogorov theorem, set the number of nodes at the hidden layer to 9. Outputs for engine misfire fault diagnosis are expressed in binary codes that range between 0 and 1. Therefore, a Sigmoid function is used, as it has the feature of monotonic increasing and provides a range that meets the training data criteria. Learning rate η is 0.02. Initial weight is a random number in the range of -1 to +1.

3.2. Emulation Result and Analysis

Sample data is divided into two parts, one for training and one for prediction. Prediction samples should be evenly distributed to cover each type of fault. The number of such samples is generally no less than 10% of the total number. Herein, 42 of the 60 samples are used for network training. Figure 3 and Figure 4 illustrate the error training curves for a traditional BP network and an improved BP neural network. The maximum number of iterations is 1,000. Change in error is barely noticeable due to small order of magnitude in Figure 3 when the number of training result iterations exceeds 300 and in Figure 4 when the number of iterations on the error curve exceeds 100. To make the earlier error change process clearer on the training error curve, only a training error curve involving 500 iterations is given. The training error is 1.8940e-004 shown in Figure 3 and 1.2506e-004 shown in Figure 4.

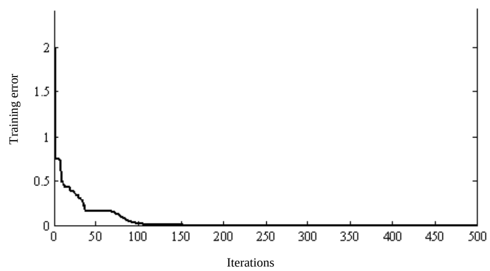

Figure 3. Training error curve for a traditional BP neural network

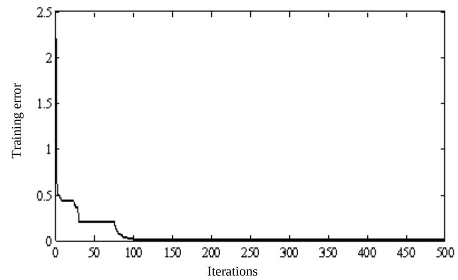

Figure 4. Training error curve for a impoved BP neural network

For both the trained improved BP neural network and traditional BP neural network, 18 groups of non-training sample data shown in Table 1 are used as prediction samples, which are diagnosed in three batches. Samples are allocated as follows: Data in Sample 1 are numbered as 1, 5, 7, 12, 14 and 16; data in Sample 2 are numbered as 2, 4, 9, 11, 13 and 17; data in Sample 3 are numbered as 3, 6, 8, 10, 15 and 18.Table 2 and Table 3 show the mean value of three prediction output results respectively on the traditional BP neural network and the improved BP neural network and the mean value of fault types and mean squared errors corresponding to the output results.

Table 1. Prediction sample data

No.	Misfire Fault Sample				Fault Type					
	$CO(x_1)$	CO_2 (x_2)	$HC(x_3)$	$O_2(x_4)$	y_1	y_2	y_3	y_4	y_5	y_6
1	0.50	0.42	0.80	0.63	1	0	0	0	0	0
2	0.60	0.44	0.80	0.60	1	0	0	0	0	0
3	0.50	0.40	1.00	0.60	1	0	0	0	0	0
4	1.00	0.60	0.50	0.10	0	1	0	0	0	0
5	1.00	0.60	0.50	0.10	0	1	0	0	0	0
6	0.92	0.68	0.50	0.10	0	1	0	0	0	0
7	0.20	0.40	0.80	1.00	0	0	1	0	0	0
8	0.10	0.46	0.80	1.00	0	0	1	0	0	0
9	0.10	0.44	0.60	1.00	0	0	1	0	0	0
10	0.80	1.00	0.10	0.30	0	0	0	1	0	0
11	0.80	1.00	0.10	0.30	0	0	0	1	0	0
12	0.80	1.00	0.10	0.30	0	0	0	1	0	0
13	0.50	1.00	0.50	0.30	0	0	0	0	1	0
14	0.40	1.00	0.50	0.30	0	0	0	0	1	0
15	0.50	1.00	0.42	0.30	0	0	0	0	1	0
16	0.30	0.60	0.10	0.60	0	0	0	0	0	1
17	0.40	0.60	0.10	0.60	0	0	0	0	0	1
18	0.40	0.50	0.10	0.60	0	0	0	0	0	1

Table 2. Fault prediction on a traditional BP neural network

Output from Traditional Neural Network	Fault Type	Error
0.9687 0.0145 0.0100 0.0000 0.0003 0.0002	Intermittent misfire (y_1)	2.4724e-004
0.0025 0.9828 0.0000 0.0034 0.0079 0.0000	Low air-fuel ratio (y_2)	
0.0294 0.0000 0.9632 0.0003 0.0023 0.0118	High air-fuel ratio (y_3)	
0.0000 0.0024 0.0000 0.9786 0.0155 0.0081	Premature ignition (y_4)	
0.0006 0.0119 0.0027 0.0109 0.9584 0.0028	Late ignition (y_5)	
0.0011 0.0000 0.0131 0.0164 0.0037 0.9825	Exhaust manifold leak(y_6)	

Table 3. Fault prediction on improved BP neural network

Output from improved BP Neural Network	Fault Type	Error
0.9748 0.0098 0.0074 0.0001 0.0012 0.0000	Intermittent misfire (y_1)	1.4736 e-004
0.0061 0.9858 0.0000 0.0083 0.0035 0.0004	Low air-fuel ratio (y_2)	
0.0124 0.0000 0.9779 0.0000 0.0065 0.0091	High air-fuel ratio (y_3)	
0.0000 0.0061 0.0000 0.9853 0.0041 0.0062	Premature ignition (y_4)	
0.0043 0.0028 0.0042 0.0064 0.9819 0.0043	Late ignition (y_5)	
0.0000 0.0002 0.0064 0.0081 0.0011 0.9863	Exhaust manifold leak (y_6)	

Judging from the emulation results shown in Figures 3 and 4, and Tables 2 and 3, the BP and improved BP neural networks are equally effective in fault prediction. Both the improved BP method and the traditional BP network can predict all types of faults.

Now reduce the number of training sample groups to 40, 38, 34, 30, 24, and 20. Samples should be evenly distributed. It is a false alarm when the actual output value is lower than 0.5 compared with an ideal output of 1 or the actual output value exceeds 0.5 compared with an ideal output of 0. Table 4 lists the numbers of errors reported by the BP and improved BP neural networks in the case of different sample quantities.

Table 4. Falsely reported prediction results

Number of Samples	40	38	34	30	24	20
BP neural network	0	1	1	1	2	3
Improved BP neural network	0	0	1	0	1	2

Table 4 shows that the improved BP neural network provides a lower rate of false alarm than a traditional BP neural network when the number of training samples is reduced. The improved BP neural network is more reliable than a traditional BP neural network when it is difficult to obtain fault data.

4. Conclusion

The improved BP neural network model proposed herein eliminates the defect of forgetting old samples when learning new ones, and therefore can fully utilize existing samples for neural network training, especially when samples are scarce. Therefore, the improved BP neural network is suitable for scenarios where training samples for fault analysis are hardly available. The improved BP neural network generates a lower rate of false alarm than a traditional BP network and thus increases the accuracy in predicting misfire faults when training samples are scarce. However, the improved BP has the following disadvantages:

1. The additional correlation layer may inevitably increase the network computing time;

2. This paper only adds a layer for output data feedback from the output layer to the hidden layer and draws a conclusion in the form of emulation tests, but does not theoretically verify the effectiveness of the improved BP network method.

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