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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 feed forward 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

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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 network model adopted by Cao Huajin[6] and Bu Yujun[7], whichshould 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 netwok 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

The improved BP neural network is shown in Fig.1,increasing the correlation layer.

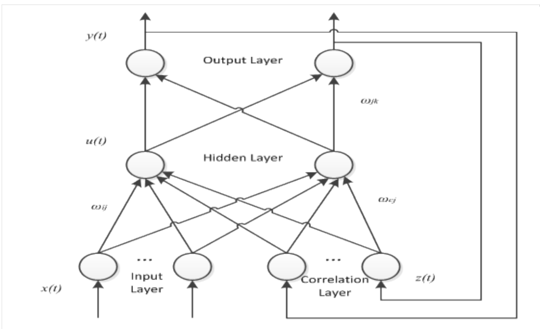

Fig. 1. Structure of the improved BP neural network

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

$$y(t)=g\left(\sum_{j,k}\omega_{jk}u(t)\right), \quad u(t)=f\left(\sum_{i,j}\omega_{ij}x(t)+\sum_{i,j}\omega_{ij}z(t)\right), \quad z(t)=y(t-1) \tag{1}$$

Assuming that the ideal network output during t iterations is $d(t)$,actual output $y(t)$, the error function for the BP network during iterations can be expressed as (2):

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

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

$$\frac{\partial E}{\partial \omega_{cj}}=\sum_{k}\frac{\partial E}{\partial y_k}\frac{\partial y_k}{\partial u_j}\frac{\partial u_j}{\partial \omega_{cj}} , \quad \frac{\partial E}{\partial \omega_{cj}}=-\sum_{k}(d_k-y_k)g^{'}(net_k)\omega_{jk}f^{'}(net_j)z_c . \tag{3}$$

Wherein $f(x)$ and $g(x)$ are both Sigmoid functions as expressed in Formula(4):

$$f(x)=g(x)=\frac{1}{1+e^{-x}} . \tag{4}$$

The weight increment is:

$$\Delta\omega_{cj}(t)=-\eta\frac{\partial E}{\partial \omega_{cj}}=\eta\sum_{k}(d_k-y_k)y_k(1-y_k)\omega_{jk}u_j(1-u_j)z_c . \tag{5}$$

3 Engine Misfire Diagnosis Based on Improved BP Network 2

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. Fig.2 and Fig.3 illustrate the error training curves for a traditional BP network and an improved BPnetwork.

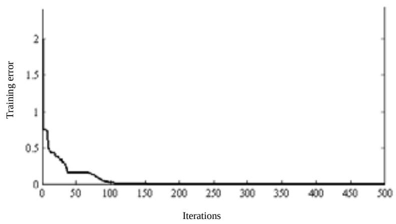

Fig. 2. Training error curve of BP

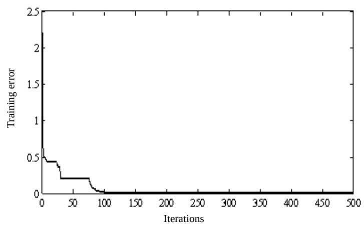

Fig. 3. Training error curve of improved BP

Table1 and Table2 show the mean value of three prediction output results respectively on the traditional BP network and the improved BP network and the mean value of fault types and mean squared errors corresponding to the output results.

Table 1. 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)	
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)	2.4724e-004
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 2. Fault prediction on inproved 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)	1.4736e-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)	

Table 3. 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

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.

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