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Fault diagnosis and isolation for diesel engine combustion chambers based on Autoencoder and BP neural network

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Abstract In order to improve the efficiency and accuracy of diesel engine combustion chamber fault isolation, a method of combining the feature dimension reduction of AutoEncoder network and the fault isolation of BP neural network was proposed based on acoustic emission signals. Taking a Z6170 diesel engine of China ZICHAI company as an example, some fault simulation tests of exhaust valve and piston rings under experimental environments were carried out, and the acoustic emission signals of the cylinder head were collected, then the time-domain, frequency-domain and other characteristic parameters of different section signals in the whole cycle were extracted. The dimension of characteristic parameters was reduced by using AutoEncoder network, then the fault diagnosis and fault isolation was carried out by using BP neural network, so that a fault diagnosis and fault isolation model of combustion chamber components was established. After training and verification of the model, it shows that the proposed diagnosis and isolation method is effective with capability of identifying the faults of exhaust valve and piston ring for the combustion chamber parts of diesel engines, therefore, it is promising to detect and isolate the condition of combustion components automatically.

Keywords Diesel engine; Fault diagnosis; AutoEncoder network; BP neural network; Acoustic emission

1 Introduction

Economy, high efficiency, long life and intelligence are the themes of the development of modern marine diesel engine. The marine diesel engine is the heart of the ship ’s power, its reliability directly affects the economics and reliability of related equipment and systems. The sea conditions faced by ships are complex and changeable, and the working environment of diesel engines is harsh. If a marine diesel engine fails during navigation and is not repaired in a timely and effective manner, it may cause economic loss in light situations, may even cause the ship to lose power due to shutdown, it causes severe economic loss and even endangers the life safety of the crew on board. Therefore, the reliability requirements of marine diesel engines are higher. The working environment of the ship's diesel engine combustion chamber components is the worst, and the probability of failures accounts for the largest proportion in the entire diesel engine. Therefore, the fault diagnosis of the combustion chamber components is a prerequisite for the development of diesel engines towards intelligence. The acoustic emission signals of marine diesel engines contain rich information of its running condition. Acoustic emission monitoring technology has the unique advantages of non-destructive and high signal-to-noise ratio. The application research of acoustic emission monitoring technology in diesel engine monitoring and diagnosis has been paid more and more attention. Most of the traditional diesel engine fault diagnosis methods are "shallow learning methods", their learning ability has certain limitations, and they cannot fully dig deep into the data, for high-dimensional data samples, there is a problem of low accuracy of fault classification [1]. In summary, this paper proposes a method for diesel engine combustion chamber fault diagnosis and fault isolation based on AutoEncoder and BP neural network. On the basis of extracting the characteristic parameters of multi-dimensional acoustic emission signals, the feature parameter set is normalized, then the data set is reconstructed and reduced by the AutoEncoder network, and the fault is identified by the BP neural network. The effectiveness of the method is verified by experiments.

2 Artificial faults simulation and test

Taking Weichai Z6170 diesel engine as an example, the acoustic emission signals of cylinder head under normal, air leakage of exhaust valve and worn piston rings were measured at 1000r / min, 0%, 25% and 50% load of diesel engine, and the characteristic parameters of energy in specific time domain and power in specific frequency domain of acoustic emission signals were extracted, as shown in Table 1.

Table 1. Acoustic emission signal characteristic parameters

Characteristic parameter	Parameter implication
N	Speed
L	Load
P_e	Signal power of combustion section 340 ~ 380 ° CA signal in frequency section 8 ~ 41kHz
P_r	Signal power within 8-39.7kHz of 425-500 ° CA section
r_b	ratio of signal energy between 340 ~ 355 ° CA and normal value of corresponding working condition
r_s	ratio of signal energy between 355 ~ 370° CA and normal value of corresponding working condition
r_a	ratio of signal energy between 370 ~ 420 ° CA and normal value of corresponding working condition
r_o	ratio of signal energy between 340 ~ 420 ° CA and normal value of corresponding working condition

The time-domain energy of the signal is shown in equation (1):

$$\mathrm{P} = \sum_{-\infty}^{\infty} |x(n)|^2 \qquad (1)$$

In addition to analyzing the time-domain signal of acoustic emission in a specific crank angle, the frequency-domain signal of the time-domain waveform corresponding to a certain working process can also be analyzed. The area of the PSD spectrum in a certain frequency range characterizes the energy in a certain frequency range of the signal. The definition of the energy P in the frequency range f_a-f_b is shown in equation (2) [2].

$$\mathrm{P} = \sum_{i=f_b}^{f_a} p(i) \triangle f \qquad (2)$$

Where P is the energy of the acoustic emission signal (V^2); f_a and f_b are the upper and lower limits of the frequency band (Hz); $p(i)$ is the power（$V^2 \cdot Hz^{-1}$）corresponding to frequency i; Δf is the frequency range (Hz).

Two failures of air leakage of exhaust valve and worn piston rings were simulated. The tests were carried out under 7 working conditions of normal, three kinds of air leakage of exhaust valve (one 1mm × 6mm groove, two 1mm × 6mm grooves and three 1mm × 6mm grooves) and three kinds of worn piston rings (the inner ring radius and gap of the first piston ring were 0.2mm × 1mm, 0.4mm × 2mm and 0.6mm × 3mm respectively), Then 773 samples were formed. The characteristic parameters of some samples are shown in Table 2.

Table 2. Partial feature parameter set

Number	Fault location	n	L	P_e	P_r	r_b	r_s	r_a	r_o	Category
1	Normal	1000	0	0.291	0.0295	1	1	1	1	0
2	Normal	999	25	1.053	0.0357	1	1	1	1	0
3	Normal	1000	50	1.364	0.0267	1	1	1	1	0
4	Air leakage of exhaust valve	1000	0	0.127	0.00250	0.0721	0.432	0.506	0.395	1
5	Air leakage of exhaust valve	1000	25	0.515	0.00696	0.131	0.528	0.611	0.517	1
6	Air leakage of exhaust valve	1000	50	0.443	0.00724	0.219	0.335	0.823	0.364	1
7	Worn piston rings	1000	0	0.091	0.00981	0.217	0.318	0.934	0.362	2
8	Worn piston rings	1000	25	0.474	0.0229	0.459	0.441	1.265	0.514	2
9	Worn piston rings	1000	50	0.658	0.0135	0.440	0.492	1.086	0.540	2

Encoding the category as a label set, as shown in Table 3.

Table 3. Code fault category

Category	Encode
Normal	100
Air leakage of exhaust valve	010
Worn piston rings	001

The six characteristic parameters under different states and different loads are shown in Fig. 1. It can be seen that each characteristic parameter can basically distinguish two conditions, but it is difficult to directly classify under normal conditions, air leakage of exhaust valve and worn piston rings. Therefore, it is necessary to reduce and reconstruct the characteristic parameters before fault diagnosis and fault isolation.

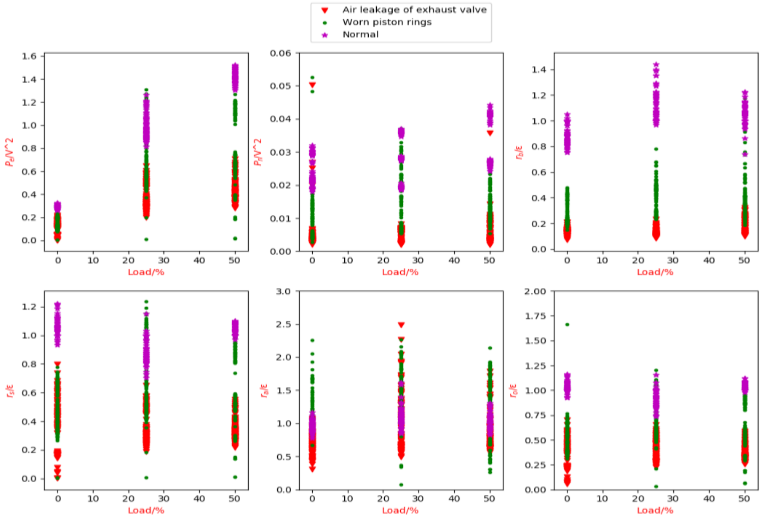

Fig. 1. Characteristics parameters dispersion comparison

In order to eliminate the dimensional influence between feature parameters and accelerate convergence, the sample data of feature parameters are normalized, as shown in equation (3);

$$y = \frac{x - MinValue}{MaxValue - MinValue} \tag{3}$$

Where: x is the original sample data, y is the converted sample data, and MinValue and MaxValue are the minimum and maximum value in the sample respectively.

3 AutoEncoder network and BP neural network

AutoEncoder network belongs to the field of unsupervised learning [3], which is a forward neural network aiming at reconstructing input signals. It can give a better feature description than the original data, and has a strong feature learning ability. In learning, AutoEncoder network is often used to reduce the dimension of original data to get better results. AutoEncoder network takes the feature parameters as input, projects the high-dimensional feature data into the low-dimensional space through the hidden layer, and reconstructs the high-dimensional data[4]; Then fault diagnosis and isolation are carried out by BP neural network.

3.1 AutoEncoder network

The most basic model of AutoEncoder network can be regarded as three layers of neural network, i.e. input layer, hidden layer and output layer. The sample of the input layer acts as the label of the output layer. The network structure is shown in Fig. 2.

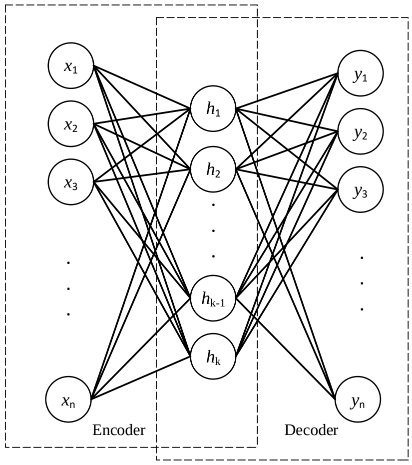

Fig. 2. AutoEncoder network structure

In AutoEncoder network, the process from input to intermediate state is called encoder, and the process from intermediate state to output is called decoder. Let the training sample set X={$x_{(1)}$, $x_{(2)}$, $x_{(3)}$, $x_{(N)}$}, and each sample x is an n-dimensional vector.

In the encoder, the n-dimensional vector is nonlinearly mapped to the k-dimensional vector h by equation (4).

$$h = f(wx + b) \tag{4}$$

In the decoder, the k-dimensional vector h is reconstructed to the input n-dimensional sample data y by equation (5).

$$y = f(\mathrm{w}'\mathrm{h} + \mathrm{b}') \tag{5}$$

The sigmoid function is selected as the activation function, as shown in equation (6), w,b represents the weight and bias of the encoder stage respectively; w' and b' represents the weight and bias of the decoder stage respectively. The parameter of the AutoEncoder network is recorded as θ. The goal of the AutoEncoder network is to optimize the parameter θ of the model so as to minimize the reconstruction error and achieve the purpose of dimension reduction. The loss function is the mean error function, as shown in equation (7).

$$sigmoid(x) = \frac{1}{1+e^{-x}} \tag{6}$$

$$Loss = \frac{1}{n}\sum_{t=0}^{n}(y_t - \hat{y_t})^2 \tag{7}$$

3.2 BP neural network

BP neural network belongs to supervised learning, and its training process is completed by two stages: the forward propagation of input parameters and the backward propagation of errors. It constantly modifies the weight and bias between each layer, so that the optimization of the network is carried out along the direction of the fastest error reduction, and finally the error is minimized. At this time, the weight and bias of the network is the best, the network optimization stops, and the training ends [5].

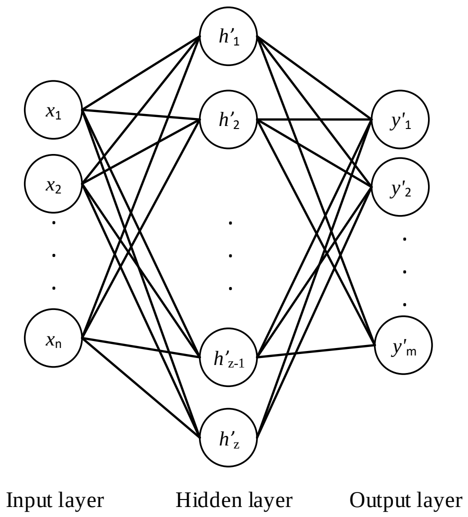

Fig. 3. BP neural network structure

（1）Forward propagation: the feature parameter set enters the network from the input layer, and is weighted and summed by neurons. Then, the output is generated through the activation function. In this way, the hidden layer is passed down layer by layer, and finally the output value is generated in the output layer. Sigmoid and relu functions are used as activation functions in the model, as shown in equation (9) and equation (10):

$$y = f(\widehat{w} \cdot x + \widehat{b}) \qquad (8)$$

$$sigmoid(x) = \frac{1}{1+e^{-x}} \qquad (9)$$

$$relu(x) = \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases} \qquad (10)$$

（2）Back propagation: the basic idea of back propagation is to calculate the loss between the output value and the expected value through the loss function, and adjust the network parameters through the back propagation to reduce the error. The loss calculation of BP neural network is shown in equation (11):

$$Loss = \frac{1}{2}(y_t' - \widehat{y_t}')^2 \qquad (11)$$

（3）The accuracy calculation is shown in equation (12):

$$Accuracy = \frac{number(Correct\ \ classification)}{total\ \ number} \qquad (12)$$

3.3 Adam optimizes AutoEncoder-BP neural network

In order to optimize the AutoEncoder-BP neural network, update the weight and bias, the Adam optimization algorithm [6] is used to replace the gradient descent (GD) algorithm to minimize the loss function. The gradient descent algorithm keeps a single learning rate (ε) to update all weights, and the learning rate does not change in the process of network training, while the Adam optimization algorithm designs independent adaptive learning rates for different parameters by calculating the first and second moment estimates of the gradient. Adam algorithm combines the advantages of AdaGrad [7] algorithm and RMSPro algorithm. It has high computational efficiency and low memory requirements. Moreover, the diagonal scaling of Adam algorithm gradient is invariant. The algorithm principle can be expressed as [8]:

$$g_t = \nabla J(w_t) \qquad (13)$$

$$m_t = \beta_1 * m_{t-1} + (1 -) * g_t \quad (14)$$

$$v_t = \beta_2 * v_{t-1} + (1 - \beta_2) * {g_t}^2 \quad (15)$$

$$m_t{'} = \frac{m_t}{1-\beta_1{'}} \quad (16)$$

$$v_t{'} = \frac{v_t}{1-\beta_2{'}} \quad (17)$$

$$w_{t+1} = w_t - \frac{\varepsilon}{\sqrt{v_t{'}} + \alpha} * m_t{'} \quad (18)$$

m_t and v_t are the first and second order momentum terms respectively, and β_1 and β_2 are the exponential decay rates of the first and second moment estimates respectively, generally 0.9 and 0.999 respectively, $m_t{'}$ and $v_t{'}$ are respective correction values. w_t represents the weight matrix of the t time step, g_t represents the gradient of the loss function of the t time step to the weight matrix; ε is the learning rate, α is a small number (generally 1e-8) to avoid denominator 0.

Therefore, the adopted AutoEncoder-BP neural network structure is shown in Fig. 4.

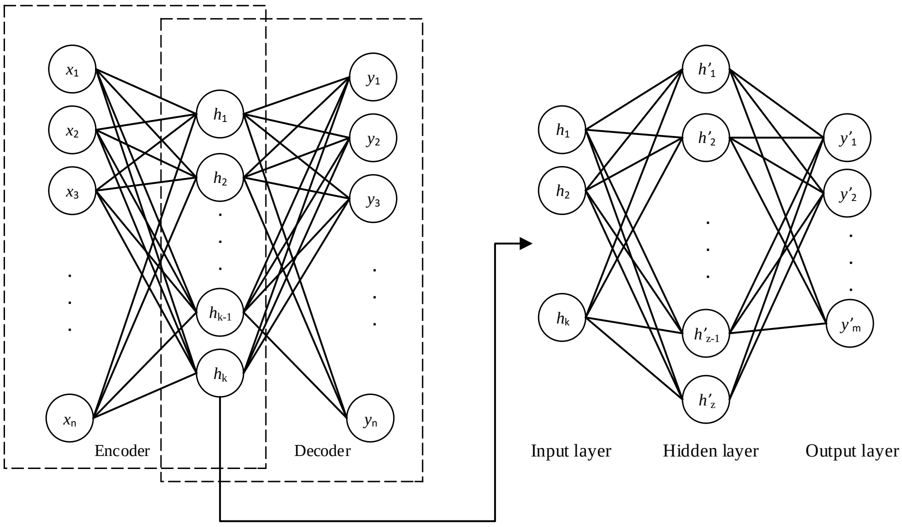

Fig. 4. Structure of AutoEncoder-BP neural network

4 Fault diagnosis and isolation method based on Auto Encoder-BP neural network

The fault diagnosis and isolation method based on AutoEncoder-BP neural network can be divided into four aspects: feature parameter extraction stage, data normalization stage, AutoEncoder network dimensionality reduction stage, and BP neural network fault diagnosis and isolation stage. The step flow chart is shown in Fig. 5.

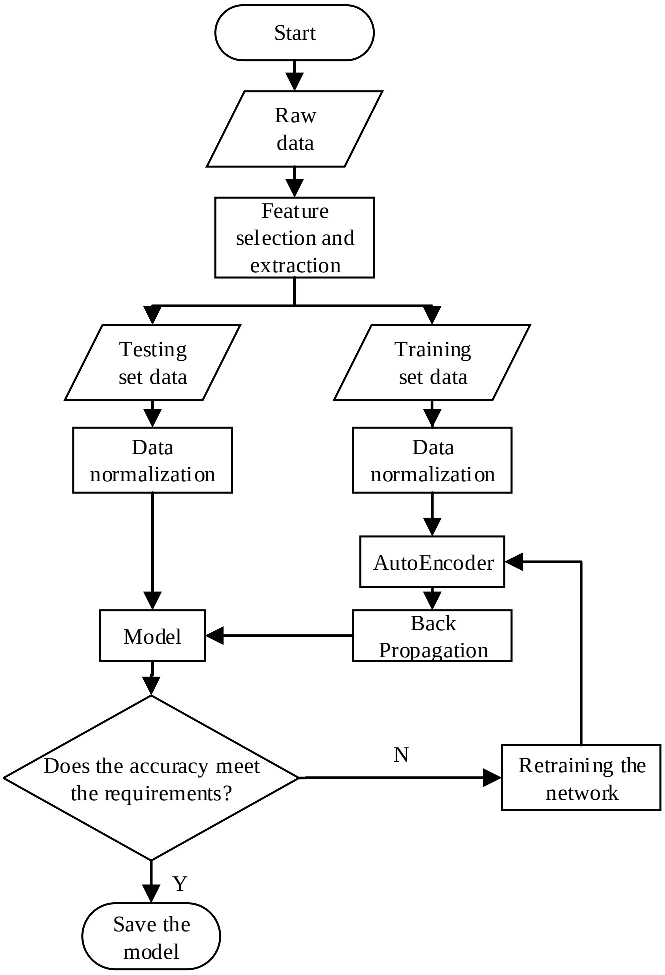

Fig. 5. Flow chart of fault diagnosis method

5 Experiment verification

5.1 Network parameter setting

In the training process of AutoEncoder-BP network, the setting of each network parameter will affect the network performance. The optimal network layers are determined by experiments. The initial parameter values are set as shown in Table 4.

Table 4. Parameter setting of AutoEncoder-BP network

	Parameter	Parameter value	Remarks
AutoEncoder network	w	N[0,1]	Weight
	b	0	Bias
	n~k	8-6-3	Number of nodes in network layer of Encoder part
	k~n	3-6-8	Number of nodes in network layer of Decoder part
	ε_1	0.01	Learning rate
	e_1	100000	Iteration times
	$\hat{w}$	U[-1,1]	Weight

BP network	$\hat{b}$	0	Bias
	k	3	Number of input layer nodes
	m	3	Number of output layer nodes
	ε_2	0.0001	Learning rate
	e_2	50000	Iteration times

AutoEncoder network uses the training set for dimension reduction training, and then reduces the dimension of the test set to obtain the 3D characteristic parameter distribution as shown in Fig. 6, where x, y and Z are the first, second and third dimensions of the reduced dimension data set respectively.

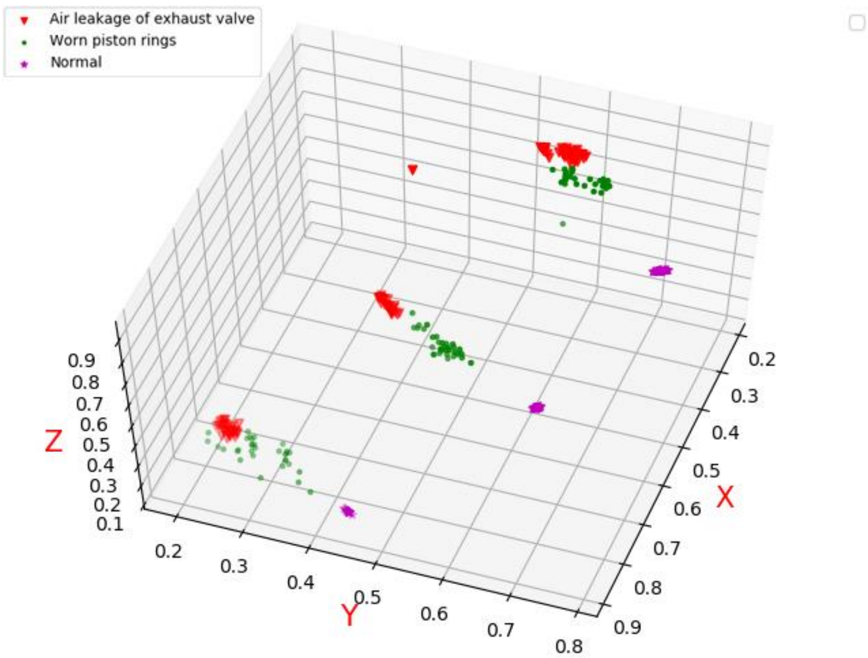

Fig. 6. Characteristics parameters dispersion after dimension reduction and reconstruction

It can be seen that after dimensionality reduction and reconstruction, the boundaries between the data under the three conditions of normal, air leakage of exhaust valve and worn piston rings are very clear from Fig. 6, and then through BP neural network classification, higher accuracy of fault classification can be obtained.

According to the method described above, it is necessary to optimize the network layers of BP network. In order to study the influence of different network layers on the accuracy of fault classification, 4 different BP neural network structures are set. It is found through experiments that the fault identification rate corresponding to different layers of BP neural network is shown in Table 5.

Table 5. Experimental results of different layers of BP neural network

Layers of BP neural network	Number of nodes corresponding to network layer	Failure identification rate
1	3-3	74.03
2	3-24-3	87.60
3	3-12-24-3	94.57
4	3-12-24-6-3	92.64

It can be seen from Table 5 that the recognition effect of single-layer BP neural network is poor due to its linear classification. With the increase of layers, the processing ability of BP neural network for nonlinear data is enhanced, and the fault recognition rate is increased, reaching the highest level in the third structure. However, the deepening of the network layer by layer will challenge the back propagation ability of the network. In the back propagation, the gradient of each layer is calculated on the basis of the previous layer, and the number of layers will cause the gradient to become smaller and smaller in the multi-layer propagation until the gradient disappears. So it can be seen from the table that the recognition rate of 4-layer BP neural network is lower than that of 3-layer BP neural network. Therefore, BP neural network is set as three layers.

5.2 Result analysis

After training the training set data through BP network, the loss value iteration diagram is obtained as shown in Fig. 7. After each iteration, the test set data is used to verify, and the accuracy iteration diagram is obtained as shown in Fig. 8.

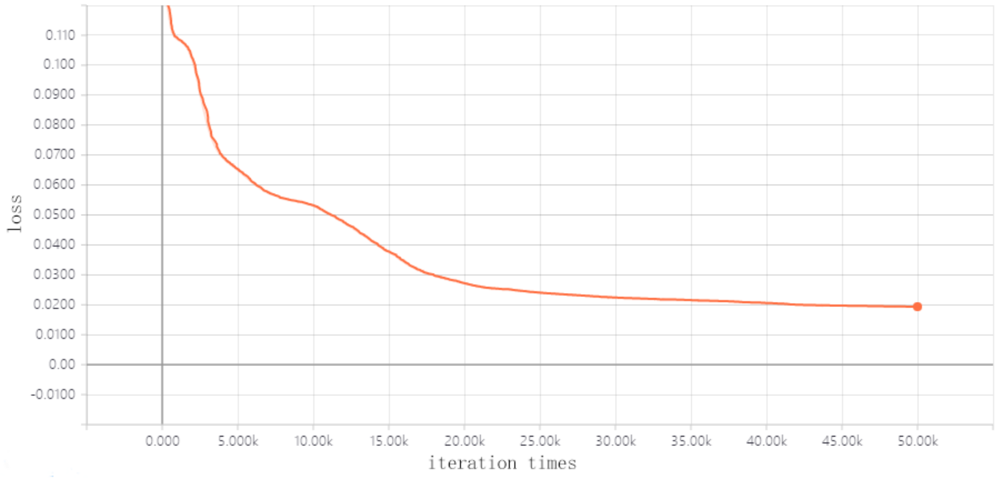

Fig. 7. Loss value iteration of training set

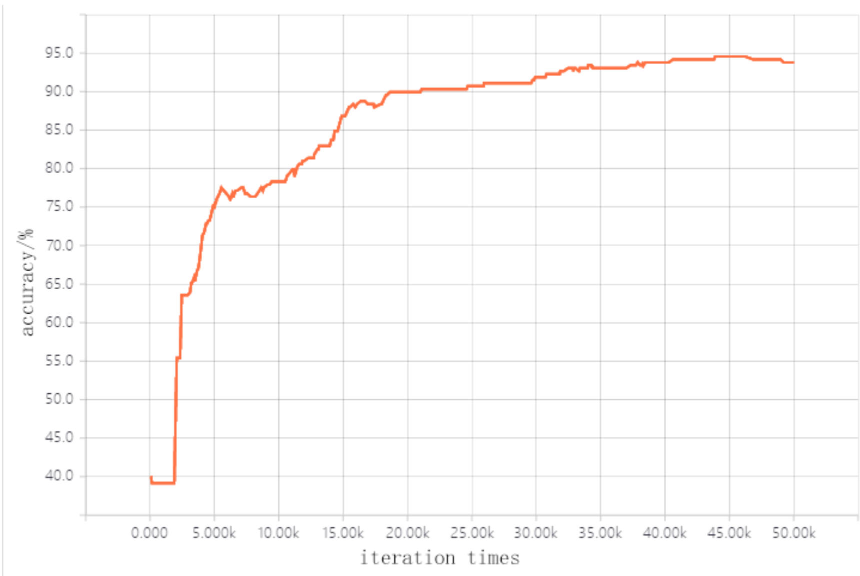

Fig. 8. Test set accuracy iteration chart

The loss value of BP neural network after training is close to 0 from figure 7. As shown in Figure 8, the accuracy of the test set reaches 94.57% after training, and the recognition rate under normal diesel engine, air leakage of exhaust valve and worn piston rings is shown in Table 6.

Table 6. Recognition rate of diesel engine under three conditions

Condition of diesel engine	Accuracy rate
Normal	100%
Air leakage of exhaust valve	93.07%
Worn piston rings	92.55%

It can be seen from Table 6 that the accuracy rate of AutoEncoder-BP neural network for fault diagnosis of diesel engine in normal condition reaches 100%, so as to avoid misjudgment in normal condition of diesel engine, and the accuracy rate of fault isolation for air leakage of exhaust valve and worn piston rings reaches more than 90%, which proves the effectiveness of this fault diagnosis and isolation method.

6 Summary and conclusion

(1) AutoEncoder network can effectively reduce the dimension of the extracted acoustic emission characteristic parameters, prevent over fitting, and accelerate the training speed of BP neural network. It is feasible to apply it to the acoustic emission fault diagnosis and isolation of diesel engine combustion chamber.

(2) The characteristic parameters of acoustic emission signals in different working conditions of diesel engine are extracted, the acoustic emission fault diagnosis and isolation model of diesel engine combustion chamber based on AutoEncoder BP neural network is established, and its classification performance is analyzed. The results show that the model is suitable for multi classification, and it can effectively realize the isolation of air leakage of exhaust valve and worn piston rings in different working conditions of diesel engine, and accurate diagnosis can be made for the normal conditions of different working conditions of diesel engine to avoid misjudgment.

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