Identification of fatigue crack Acoustic Emission signal of Axle based on depth belief Network

Linli

College of locomotives and rolling stock，Dalian Jiaotong University,Dalian,China

LIZhinong

Key Laboratory of Nondestructive Testing, Ministry of Education, Nanchang Hangkong University, Nanchang 330063, China

Zhouyong

Software institute,Dalian University of Technology,Dalian,China

Jiayuheng

College of locomotives and rolling stock，Dalian Jiaotong University,Dalian,China

Abstract—**The axle is the key component of the running part of the railway vehicle, and it is the key component to bear the dynamic load of the vehicle. Due to its own factors and the bad working environment, it will often lead to cracks, surface damage, and even breakage when the axle is running. In this paper, the acoustic emission signal of fatigue crack of axle based on depth belief network is proposed which gives a new method to help identifying the fatigue crack online by acoustic emission detection technology. Firstly, the fatigue crack signal of axle is processed by using the time domain statistical characteristic parameters, and then the processed characteristic data was input into the depth belief network for learning and training. As a new type of mechanical learning intelligent network, deep belief network can realize the training calculation of multi-hidden layer, and multi-hidden layer can mine the feature of data more autonomously and deeply. Therefore, the accuracy of the results obtained from the operation is high.The experimental results show that the classification and recognition of fatigue crack signals obtained from acoustic emission experiments by depth belief network is very effective.**

Keywords-DBN; Failure Recognition; Acoustic emission

I. INTRODUCTION

The axle is an important bearing part in the railway train bogie. The wear, crack and even fracture often occur in the bad working environment, and the running state of the train directly affects the safety of the train running safety[1]. When the axle is overloaded, because of its internal defects or uneven tissue, the stress of the axle will be concentrated, which leads to a certain deformation of the axle, thus burying the hidden trouble of the accident. In the process of the deformation of the axle, the local deformation causes the energy to be released rapidly in the form of transient elastic wave, and the elastic wave, which is released by the deformation, is the acoustic emission signal[2]. The working environment of the axle is complicated. The sound emission detection of fatigue crack in the running axle will often be disturbed by the vibration and aerodynamic noise of the train. Therefore, it is a problem to identify the characteristics of the axle crack from the acoustic emission signal of the acquired number. With the rapid development of computer technology, AI technology has been widely applied in various fields. In 2006, Geoffrey Hinton first proposed the Deep Learning theory[3] in Science. The classification and recognition of faults by depth learning theory is the process of identifying the indication parameters of the fault from the state of the unknown fault to the learning training. Deep belief network is the most widely used model in deep learning theory. Its network model is based on the restricted Boltzmann machine (RBM). The computing power of DBN network is stronger, the generalization ability and the fault-tolerant performance are high. The data layer processing method used in the network can extract different features from each hidden layer inside the network, and set up the mapping network from the bottom to the high level by layer by layer, and optimizes the network error by the backward tuning of the network error, so that the network itself is reduced. The ability to interfere with the low human intervention, and for a large number of unlearned test samples, can also be abstracted from the training set by layer by layer to dig out the characteristics of the data in depth[4].

Deep learning theory was first applied to the field of computer image recognition. Hinton and others[5] put forward the theory of depth learning in the image classification and recognition of handwritten numbers, and use the model algorithm in it to reduce the dimension of the image effectively, reduce the operation time and improve the accuracy of the operation. In the field of speech classification and recognition, Hinton et al.[6] establishes a

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deep learning model through acoustic models and identifies four types of speech signals.

Deep learning theory also have the application of in the field of fault intelligent recognition and diagnosis. The fault signals obtained are generally one dimension or lower dimension. Before the input depth learning algorithm or the network training in the depth learning network, the fault signals need to be preprocessed to strengthen the network transportation. Tamilselva et al.[7] used DBN network to identify the running state of the engine structure. Huang Haibo et al.[8] used DBN network to identify and diagnose the vehicle suspension shock absorber. Tran and other[9] apply DBN model algorithm and Teager-Kaiser energy operator to the fault diagnosis of compressor valve, and use acoustic emission technology to collect experimental data under different pressure, and extract the multi variable characteristics of time domain, frequency domain and entropy, and make fault diagnosis.

But deep learning theory applying to the field of acoustic emission technology especially to the axle fatigue crack acoustic emission signal was few. This paper uses the depth belief network to excavate the data from the low to the high level, and applies this method to the fault identification of the fatigue crack acoustic emission signals of train axle, in order to detect the possible fatigue cracks of the train axle.

II. THE PROPOSED METHOD

A. Acoustic emission signal recognition method for train axle crack based on deep belief network

In order to classify the axles acoustic emission signals collected by the experiment, this paper adopts the fault feature recognition method combining the time domain statistical special diagnosis parameters and the depth belief network. Through this method, the fault feature extraction and identification of the train axle acoustic emission signal are extracted and identified. The following is a flow chart for identifying the fatigue crack acoustic emission signals of train axle based on deep belief network, as shown in Figure 1.

The main contents of the process are as follows: first, the fatigue crack acoustic emission signal, the axle knocking signal and the background noise signal obtained by the experiment are preprocessed, and the data length is selected to group the experimental data. At the same time, 12 kinds of time domain statistical characteristic parameters are selected to feature extraction and processing of the data after the grouping, and then the data are extracted and processed. According to the characteristics of the data, the corresponding depth belief network model is established. Finally, the time domain statistical eigenvectors are input into the depth belief network for classification and analysis. Finally, the type of the acoustic emission signal of the axle crack is identified under the axle knocking and the background noise interference.

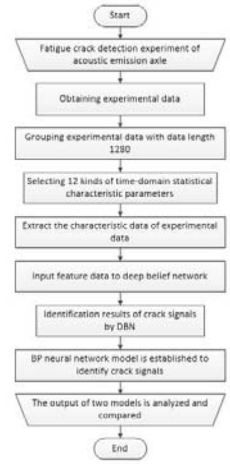


Fig. 1 flow chart of acoustic emission signal recognition method for train axle crack based on deep belief network

B. Time domain statistical feature extraction method

In the study of the intelligent identification of fatigue crack signals of the axle, a large number of samples should be trained to establish the neural network model, and these training samples should contain various parameters of the data, and also include the characteristic data that can be distinguished from other classes of data. In the engineering of signal processing and analysis, the most basic way of signal expression is the form of time domain. Using time as a variable and using mathematical expressions or waveforms to represent signals is the time domain form of signals. The time domain statistical characteristic parameters are more sensitive to the fatigue crack of the axle, which can reflect the fatigue crack of the axle well, which is influenced by the amplitude probability density function of the signal. This paper selects 12 time domain statistical parameters, which are peak, average, standard deviation, rectifying mean, kurtosis, variance, root mean square, wave factor, peak factor, kurtosis factor, pulse factor and margin index.

C. Theoretical research on fault recognition algorithm based on deep belief network

The learning process of deep belief network consists of two parts: the forward stack learning from the bottom to the top, and the backward fine tuning from the high level to the bottom. The deep belief network is a multilayer perceptron neural network[10] composed of multiple restricted Boltzmann machines (Restricted Boltzmann Machine, RBM). Each RBM unit is composed of a visual layer and a hidden layer. The layer and layer are connected by the weight value, and each node in the layer is not connected.

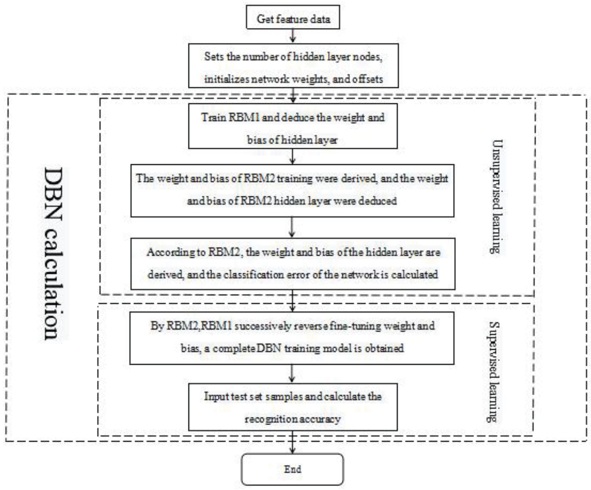


Figure 2 DBN algorithm flow chart

As shown in figure 2, after initializing the parameters of the DBN model, the data is input into the DBN model. The input layer of the DBN model is the visual layer of the first RBM. After the data input, the weight and bias of the first RBM hidden layer can be derived after the training of RBM, and then the weights and biases of the second RBM visual layers are derived by the training of the hidden layer. By analogy, the offset and weight of the last RBM hidden layer are finally obtained. The error range of the preset is contrasted, and the inverse optimization and fine-tuning calculation is carried out. The error is adjusted to layer by layer until the network requirement is satisfied, and the classification and recognition rate of the signal is obtained.

D. Restricted Boltzmann Machine RBM

In 1986, Hinton and Sejnowski proposed the concept of Boltzmann Machine (BM). Boltzmann machine is a stochastic neural network evolved from thermal dynamic energy model. It is an undirected graph model. The internal information of the network defines[11] through the state of each node and the weight of the connection weight. Each Boltzmann network model is composed of a visual layer and a hidden layer. The nodes of the layer and layer are connected by weight, connected by each node in the layer, and belong to the completely connected neural network. Boltzmann machine has powerful data processing capability, but its training time is long and its computation cost is huge. In order to improve this situation, Smolensky combined with Markov model, the layer and layer are still connected with the weight, but the interlayer interconnected structure is cancelled, and the nodes in each layer are independent and become restricted Boltzmann machine (Restricted Boltzmann Machine, RBM). The model connection structure is shown in Figure 3.

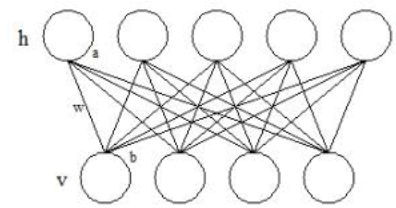


Figure 3 RBM model

III. IDENTIFICATION OF ACOUSTIC EMISSION SIGNALS OF FATIGUE CRACKS ON AXLE BASED ON DEEP BELIEF NETWORK

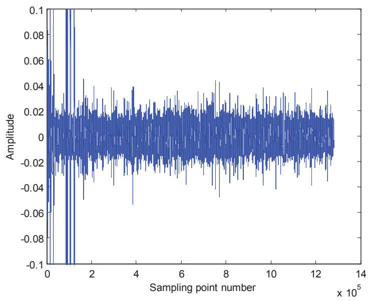
The main experimental equipment and materials of the train axle acoustic emission signal shown in figure 4 include: (1) acoustic emission test bench (2) acoustic emission system (3) a variety of different fault state of the train axle test specimen (4) toolbox;

Figure 4 acoustic emission test bench

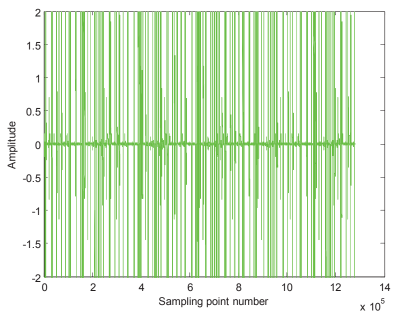
Because of the actual operation of the train, with many interference factors, such as vibration, knocking, friction, and so on, the characteristics of the fatigue crack signal of the axle are very weak. In order to simulate the actual running condition of the train, this experiment has also added the percussion signal and noise signal as the background interference while simulating the fatigue crack initiation and development process of the axle. In the later stage of identifying fatigue cracks in axles, the percussion signals and background noise signals are also discussed.

1) Processing of experimental data

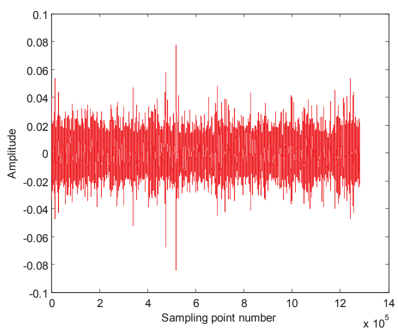
In this experiment, the acoustic emission signals of train axle under various conditions are analyzed and obtained from the experimental group. The data obtained from the fatigue crack test of the axle are extracted, and the whole signal is divided into three categories: axle crack signal, axle percussion signal and background noise signal. In the acoustic emission test of fatigue crack of the axle, 1 million 280 thousand data of three kinds of signal are obtained, with a total of 3 million 840 thousand data points, and all the data obtained by the experiment will be used in the follow-up study. Figure 5 below is a time domain signal of the three type of signal.



a) time domain diagram of axle crack signal



b) Time domain diagram of axle knocking signal



c) Time domain diagram of background noise signal

Figure 5 Time domain signal of three types of signals

From the time domain diagram of three kinds of signals, it is found that the amplitude range of the axle knocking signal varies between [-2,2], and the time domain amplitude range of the axle crack signal and the background noise signal is distinctly different, and the amplitude of the axle crack signal and the background noise signal are both [-0.1,0.1] and the axle. In addition to the local mutation of the amplitude (may be the change of the state of the crack), the crack signal is almost the same as the variation of the background noise signal, so it is difficult to distinguish. This indicates that the AE experiment of axle cracks is carried out under the background noise and strong impact.

2) The grouping experimental data

In order to extract more obvious and representative features, 1 million 280 thousand experimental data of three types of signals are grouped, each 1280 data is one group, and the last 640 data of each group are the same as the first 640 data of the next group, that is, a sliding zone with a step length of 640 is set here, and all the experimental data of the three types of signals are made in each group. It was divided into 2000 groups, with a total of 6000 groups. As the experimental data is a complete time series, each data point has relevance, so this setting can make the number of groups more, more able to explore the characteristics of data, without affecting the correlation between data.

3) Feature extraction experimental data

According to the principle of selecting characteristic parameters introduced in the previous article, this paper selects 12 time domain statistical parameters, which are peak, average, standard deviation, rectifying mean, kurtosis, variance, root mean square, wave factor, peak factor, kurtosis factor, pulse factor and margin index. The following table is the characteristic data of axle crack signal, axle percussion signal and background noise signal.

After grouping and extracting the characteristics of all the experimental data, a large number of original data samples are reduced obviously, and the effective data reduction is achieved. The data becomes the axle crack signal, the axle knocking signal and the background noise signal each 2000 groups. Each group is composed of the above 12 time domain parameters. The feature of the signal is more significant and more representative. It is well prepared for the next analysis of signal using neural network.

4) Normalization of feature data

Before input the experimental characteristic data to the network model operation, we should first normalize the data. Because the deep belief network is made up of multiple RBM stack, and the activation function of RBM is S type function, so the input data must be between [0,1]. The feature data after the extraction has a negative value or more than 1, so it is necessary to carry out numerical transformation of the data, that is, the data normalization processing, the input data range between [0,1] and the network algorithm, so this paper selects the linear normalization method for data processing.

5) Recognition of fatigue crack of axle based on deep belief network

5-1) The establishment DBN network model

The structure of deep belief network is composed of multiple RBM stack. The main parameter of RBM is the weight of the connection between layers and the bias of each layer. In the previous study, a random minimum value was taken when the connection weight value W, the visual layer offset a, and the hidden layer offset B initialization parameters were taken, so according to the formula [12]

$$W = 0.1 \times randn(n,m) \quad (1)$$

$$a = 0.1 \times randn(1,n) \quad (2)$$

$$b = 0.1 \times randn(1,m) \quad (3)$$

The training of deep belief network is divided into two processes. There are two different learning rates in forward stacking learning and backward tuning. The forward RBM stack learning rate is ε, and the backward tuning learning rate is α, and the two learning rate can be calculated according to the experience value of 0.1. This paper mainly selects two RBM stacked depth belief networks, one input layer, one output layer and two hidden layer structures, and the number of hidden layer nodes is also selected as 12-12. In the process of recognition and classification using deep belief networks, a loss function is often set up to control the stability of the network operation process. In this paper, cross entropy is used as a loss function in the neural network. The cross entropy loss function can measure the similarity between the distribution of real output and the distribution of prediction after the model training and improve the speed of network training.

5-2) Experimental results and analysis

The data after the warp normalization is entered into the DBN network, and the first 80% of the three types of signal data are used as the training sample set in the way of the previous text, and the latter 20% is the test sample set to perform the network operation in order to obtain the recognition accuracy of the DBN network for the signals of the class.

In order to obtain the recognition accuracy of three kinds of signals by dbn network. We iterate the dbn network from 1 iteration to 200 times, and repeat the experiment 20 times, and then extract the calculated results of each iteration to get the average value. The results of the comprehensive recognition rate of the three kinds of signals are shown in figure 6.

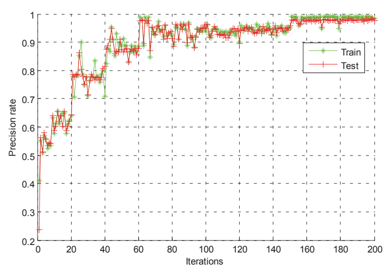
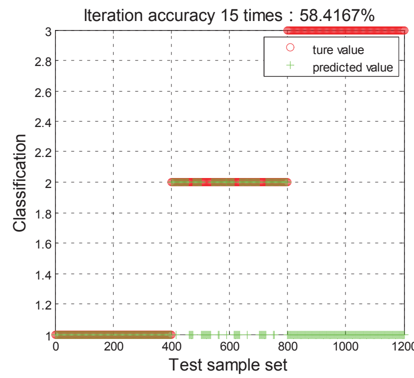


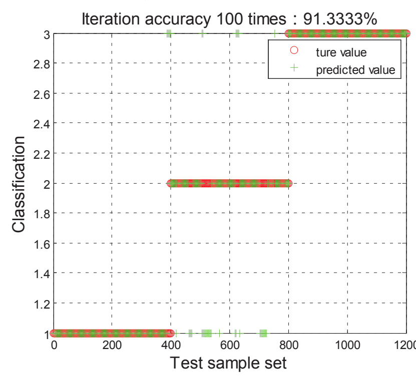
Figure 6 relation diagram of recognition rate and iteration number

It can be seen from figure 6 that the accuracy rate is less than 60% when the number of iterations is between [1,15], and the accuracy rate of the overall recognition of the three types of signals increases to about 80% when the number of iterations is between [16,40], which indicates that the overall learning ability of the DBN network is greatly enhanced, and the accuracy of the memory and calculation results of the old and new samples is accurate. When the number of iterations is at [50,140], the accuracy rate rises to about 95%, indicating that the recognition ability of the three types of signals has been basically improved. In this process, a certain number of experimental results have reached the recognition rate of nearly 99%, but in this process the rate of accuracy rises and fluctuates, and the experimental results have many oscillations, which can not be determined as the optimal number of iterations. When the number of iterations is between [150,200], the recognition accuracy of the training set and the test set increases to more than 98%, and the trend is in the process. The DBN network is perfect for all data samples, and the result is the best.

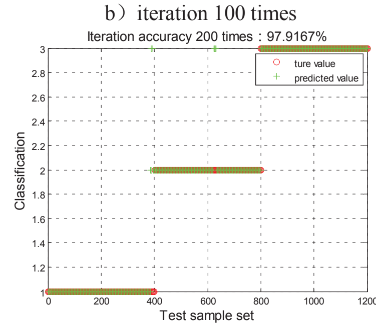
Figure 7 shows three kinds of signal recognition accuracy rates. The longitudinal coordinate 1 represents the axle crack signal, 2 represents the axle knocking signal, and 3 represents the background noise signal; the abscissa [1,400] represents the number of data points of the axle crack signal, [401,800] represents the number of data points of the axle knocking signal, and the [801,1200] represents the number of data points of the background noise signal; "O" is the expected output of the network in the figure 7. "+" is the predictive output of the network. If the actual output and the expected output overlap in the region of the various signals, we think that the DBN model identifies three types of signal classification, that is, to identify the axle crack signal in the axle knocking signal and the background noise signal.



a）iteration 15 times



b）iteration 100 times



c）iteration 200 times

Figure 7 recognition accuracy at different iterations

When the DBN network is iterated to 15 times, the average recognition rate is 58.42%. The network has already identified the percussion signal of the axle initially, but has not completely identified it. For the removal of the crack signal and the background noise signal, the similarity of the original experimental data of the two is high, and the two are not completely distinguished by the feature extraction, so the model can not classify the two.

When the DBN network is iterated to 100 times, the average recognition rate is 91.3% and the comprehensive recognition rate after multiple experiments is 91.33%. At this time, the network model not only has a certain recognition ability, but also can recognize the classification of the three types of signals, and the stability of the output results is higher. The network structure and network training is already in phase. For maturity.

When the DBN network is iterated to 200 times, the average recognition rate is 97.9%, and the comprehensive recognition rate after many experiments is 98.957%. When the number of iterations reaches 200 times, except for a few data points, the three kinds of signals have been distinctly separated. At the same time, from Figure 6, the output of the network has been stable after 170 iterations, which indicates that the training of the DBN network model has been completed and the recognition rate is not rising. From this we can conclude that the maximum number of iterations of the DBN model is 200 times, and the highest recognition rate is 98.957% through repeated 20 experiments.

5-3) Comparison and analysis of recognition results with BP neural network as classifier

BP neural network is a feedforward neural network with error back propagation ability. It can combine a number of nodes with simple processing ability and can complete complex nonlinear mapping. The biggest characteristic is that it has strong adaptive ability. The network can not only learn self adaptively, but also adapt self adaptively. The size of the whole network has a good fault tolerance, but in practice, it will often encounter local minimum and network oscillation problems [16,17]. The advantage of BP neural network is that the three layer BP neural network is applied to the nonlinear transformation function, its precision can approximate any nonlinear function, and the operation effect is good. At present, the BP neural network has widely used [18] in the fields of signal processing, pattern recognition and so on.

The number of nodes in input layer and output layer of BP neural network is determined by the number of input characteristic parameters and the number of output signals. The number of nodes in the input layer is 12, the number of nodes in the output layer is 3, and the number of hidden layers is 1. In this paper, the learning rate is 0.1, the number of iterations is 1000 times, and the expected error is 0.0001. At present, there is no unified standard for the selection of the number of nodes in the hidden layer. Most of them are [19] determined by the number of iterations and the final output results after many calculations by experience or through the number of nodes of different nodes. Therefore, the range of the number of nodes in the hidden layer is [6,20].

The input data of the BP neural network are 2000 groups of three types of signals, in which 80% groups of training samples are randomly selected as the training samples of the network, and the remaining 20% are used as the test sample sets of the network. 20 experiments are carried out repeatedly on different hidden layer nodes, and the average value is taken as the recognition result of each node number network.

The BP neural network has a high accuracy rate of identifying the percussion signal of the axle, and the average recognition accuracy is over 96.5%. The recognition accuracy of the axle crack signal and the background noise signal is low. The recognition accuracy of the axle crack signal is 50%~60%, and the recognition accuracy of the background noise signal is between 65%~70%.

5-4) Comparison and analysis of experimental results

After the establishment of the deep belief network and the BP neural network model and the network training, it is concluded that the BP neural network output is optimal when the hidden layer node of the BP neural network is 13 and the network model is iterated 1000 times. When the hidden layer nodes of the DBN model are 12, and the network overlapped for 200 times, the DBN network recognition is obtained.

TABLE I. RESULTS OF THE TWO NEURAL NETWORKS WERE COMPARED

Categor y	Axle crack signal	Axle knock signal	Backgro und noise signal	Integrat ed signal
DBN	99.215%	99.097%	98.559%	98.957%
BP	61.281%	97.222%	68.294%	75.599%

We can see from table 1, apart from the axle noise signal, the recognition accuracy of the axle crack signal and the background noise signal is only about 60%~70%, and does not make a complete distinction.This shows that BP neural network is affected by its own limitations and can not distinguish the two similar signals completely. The recognition accuracy of DBN network for three kinds of signals is very high, especially the identification ability of axle fatigue crack signal is very strong, and the expected effect is achieved.

In the 20 repeated experiments, the recognition rate of the axle crack signal in the DBN network is about 99%, and the recognition rate of the background noise signal is more than 98%. The recognition rate of the axle crack signal by BP neural network is only 50%~70%, and the recognition rate of the background noise signal is between 60%~80%. Moreover, the recognition results of BP neural network are very unstable and fluctuate greatly. In the 20 repeated experiments, the recognition rate of the DBN network is more than 98% for the axle strike signal; the recognition rate of the BP neural network is above 95%, and the recognition rate of the axle knocking signals is very high in the two networks.

In the analysis of three kinds of signals, we also studied the time cost of the two networks. From the number of iterations, the recognition process of the three types of signals from the DBN network needs 200 iterations, and the recognition results are better. While the recognition results after the 1000 iteration of the BP neural network are not ideal, and the running time of the DBN network for the classification and recognition of the three types of signals is far higher than the operation time of the BP divine network. BP neural network and DBN network have similar operation process, but there are essential differences between the two. The transport process of BP neural network is the method of applying the gradient descent method to the nonlinear transformation of data. The DBN network is a number of RBM probability generation models to abstract the data, and use jisbos sampling method and contrast divergence to abstract the feature information in the abstract data continuously, so that the intelligence degree of the DBN network is constantly improved. Therefore, when there is a certain difference between the various input data, the BP neural network runs faster and takes less time. When the various data are relatively similar, the DBN network, although the cost of running time is high, is ideal for classification and recognition of all kinds of data. Therefore, in the study of fatigue crack of AE axle, DBN network can identify the axle crack signal from strong background noise.

IV. Conclusion

In this paper, an acoustic emission signal recognition method of train axle fatigue crack based on deep belief network is proposed. The method of extracting and identifying the fatigue characteristics of the axle fatigue crack proves that the method is effective and the conclusion is as follows:

Deep belief networks belong to multiple RBM stacked neural networks, and have strong data mining ability, so in the same working conditions, although the network runs longer, the accuracy of the classification and recognition of the three types of signals is very high. Therefore, the fault recognition method based on the deep belief network can effectively extract the fault information of the axles acoustic emission signal and use it as the fault feature of the type of identifying signal. At the same time, this method can accurately identify the type of the signal in a short time, which shows that the method can quickly, accurately and effectively diagnose the fatigue crack acoustic emission signal of train axle in real time.

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