[[1]](#footnote-1)

**Differential Geometric Features fusion based Deep Learning Method of Fault Diagnosis**

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**Abstract:** During the operation of mechanical equipment, various types of faults need to be monitored in real time. Some frequency faults cannot be well detected in the time domain, which makes accurate real-time detection of mechanical equipment impossible. To solve this problem, a fault diagnosis method based on DNN fusion of geometric features is proposed. By introducing the geometric features of the raw data, the problem of the time domain detection being inaccurate when the frequency class faults exist in similar amplitudes is solved. The original, slope and curvature data are respectively constructed into an automatic encoder model to fully excavate the implied frequency information of the data. The experimental results of the rolling bearing show that the method proposed in this paper can detect the frequency fault well.

**Key Words:** Fault diagnosis; DNN; Differential geometric feature fusion

1. **Introduction**

At present, mechanical equipment is more and more inclined to large-scale and complicated. Since various parts of the mechanical equipment are closely connected, failure of any part may cause breakdown of the entire mechanical equipment or even led to large industrial accidents, accurate and timely fault diagnosis is a challenging issue [1-8]. Bearings are the core parts of rotating machinery, be used in a wide range of industrial field. Due to the bearing in use process will appear different degree of wear phenomenon, if not timely monitoring of the bearing failure will result in serious losses, and even endanger the lives of the operator. In this regard, research on bearing fault diagnosis has wide attention from experts both in academic and application [2-6, 8-14]. Therefore, bearing fault diagnosis in the actual industrial production process is very necessary. (故障诊断的意义)

In general, the methods of fault diagnosis can be mainly categorized into 3 classes: physical model based method, knowledge based method, and data-driven based method [7]. Since the precise physical model is unavailable, physical model based methods are difficult to adapt to increasingly complex mechanical equipment fault diagnosis. Quantity of prior knowledge is difficult to process which would invalidate the knowledge based fault diagnosis methods. The data-driven techniques are widely applied in industry for process monitoring and fault diagnosis [9–14]. Principal component analysis (PCA), support vector machine (SVM), and artificial neural network (ANN) are the popular data-driven techniques for fault diagnosis [15–22]. Data-driven methods include statistical feature extraction and Neural network method [8-11]. The method based on statistical feature extraction can only detect faults but not diagnose faults. In recent years, due to the rise of Neural network method, Neural network based methods are widely used in the fault diagnosis of complex systems. （介绍现有的故障诊断方法（数据驱动））

Neural network based methods are the most advanced data-driven method for fault diagnosis. However, due to the non-linearity, instability, high latitude and the large amount of noise pollution, the failure characteristics of mechanical equipment make it impossible to accurately diagnose mechanical equipment [12-14]. Some scholars put forward the use of signal processing feature extraction methods combined with machine learning methods for mechanical equipment failure diagnosis. Widodo and Yang extract frequency-domain features as SVM data sources to detect mechanical problems [13-17]. When the number of samples is small and the signal is non-stationary, Yu et al. Propose a method of rolling bearing fault diagnosis using a combination of SVM and EMD methods [10]. Hu et al. extracted the energy of each node of Wavelet Packet Transform (WPT) from the vibration signal as the characteristic parameter of bearing fault diagnosis, which greatly preserved the time-frequency characteristic of the characteristic information. The combination of WPT and SVM Fault diagnosis, improve the accuracy of fault diagnosis [18-21]. Based on the non-stationary characteristics of vibration signals of rolling bearings, Wang et al. Used WPT to de-noise the collected signals and extract the energy characteristics of wavelet bands of each frequency band as the input characteristics of Artificial Neural Network (ANN) Learning classification ability and self-organization ability to bearing fault classification and diagnosis [22-26]. Yang and Tang etc. Proposed a method that combined the expert system with the BP neural network (BPNN), which fully utilized the advantages of the expert system and ANN and successfully detected the bearing failure [27]; Jiang et al. Proposed a method using a combination of high-order cumulants with BPNN. This method uses high-order statistics as the eigenvector to improve the accuracy of BPNN in bearing fault diagnosis [28,29]. However, in these studies, SVM and BPNN have many shortcomings as a shallow learning method: the essence of SVM is a dichotomizer, which has low learning efficiency in many classification and large sample problems, how to choose suitable kernel function and scale parameter often need to experience, SVM method cannot be real-time monitoring and diagnosis, cannot meet the current real-time monitoring of machinery and fault diagnosis requirements; ANN also has some congenital defects: (1) ANN as a shallow neural network, The convergence speed is slow, easily fall into the local optimum, cannot well characterize the signal characteristic information; (2) learning complex non-linear data has the disadvantage of low efficiency and low classification accuracy. In summary, as a shallow learning method, SVM and BPNN have not been able to effectively extract features under high-dimensional non-steady-state data [30]. Deep learning is a promising feature extraction tool and has aroused widespread concern of scholars [21,28-30]. Compared with shallow learning, deep learning can perform well feature extraction and in-depth study on nonlinear big data [31,32]. (分析基于数据驱动的方法，引入深度学习的方法)

Deep learning, as one of the most popular and hot machine learning methods in the world today, has revolutionized artificial intelligence. Depth neural network (DNN) adopts unsupervised layer-by-layer greedy training algorithm and global parameter tuning based on BP algorithm, which can not only avoid local optimal problems, but also solve the restriction of the number of labels and samples. Hinton and Salakhutdinov first proposed the theory of depth learning in 2006. This theory is used to construct Deep Neural Network (DNN), which can form a more abstract high-level representation by combining nonlinear transformations of multiple layers and combining lower-level features, so that a learning system can discover the distribution of data without depending on artificial feature selection Expression of features, and learn complex expression function [33]. Due to its excellent feature extraction capabilities, it quickly attracted the attention of experts in the field of fault classification. Lu et al. used the good feature extraction ability of deep neural network and used it to diagnose the bearing fault successfully solved the problem that the traditional feature extraction method cannot find the unknown type fault timely and effectively [34]; Jia et al. Used deep neural network to detect rolling Shaft bearing health status [35]; Gan et al. Proposed a fault diagnosis method based on the characteristics of bearing faults [36]. Li et al. Addresses a multimodal deep support vector classification (MDSVC)approach, which employs separation-fusion based deep learning in order to perform fault diagnosis tasks for gearboxes [37]. The method is to fuse the data of time domain, frequency domain and wavelet domain. (介绍深度学习在故障诊断中的一些案例)

Since Many of the methods described above performs a full-time domain-to-frequency domain transformation, this method cannot diagnose a single point-in-time data. In other words, this method cannot achieve the purpose of real-time fault diagnosis. To ensure the real-time fault diagnosis can only use the signal of the time domain. However, fault diagnosis based on amplitude information in the time domain presents great problems. Since the bearing data is a vibration signal, there is a frequent zero-crossing value, which makes it impossible to distinguish the fault type based on the amplitude only at these points. At present, these studies about bearing fault diagnosis have not solved the problem that frequency-type faults are difficult to detect in the time domain and therefore cannot guarantee the real-time fault diagnosis.（目前这些研究都没有解决频率类故障在时域检测困难的问题，无法保证故障诊断的实时性)

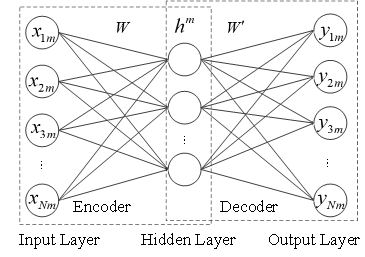
In order to resolve the limitation stated above, this paper developed a differential geometric feature fusion based DNN(DGFFDNN) fault detection method to achieve and improve the accuracy of frequency-type fault diagnosis. State of the art of this research is to design a fusion mechanism by combining differential geometric eigenvectors. By this means, frequency failure can be well detected which is significant to real-time frequency fault diagnosis. The main innovation is to solve the problem of inaccurate time-domain detection when frequency class faults have similar amplitudes and frequent zero crossings by introducing the geometric features of the raw data. The original, slope and curvature data are respectively constructed into an automatic encoder model, so as to fully excavate the implied frequency information of the data. Then, the obtained data features are fused and the feature dimension is increased to make the classification model training more accurate. First calculate the slope and curvature of the raw data that can represent the frequency characteristics of the value. The second step is to construct three DNN networks for training of each feature. The third step is to fuse the obtained features. The final step is to use the already trained network to diagnose the new samples in real time. (介绍本文所提出的方法)

The remainder of this paper is organized as follows: Section 2 review of deep learning based fault diagnosis. In Section 3, a new DGFFDNN fault online diagnosis method is originally developed; In Section 4, the validity of the proposed fault diagnosis method is obtained through experiments and simulation analysis; Sections 5 is the conclusion and future work of this paper. (文章剩余部分组织结构)

1. **Review of deep learning theory**

Deep learning is an unsupervised learning method. By multi-layer nonlinear transformation, low-level features combined to form more abstract high-level representation, making the learning system cannot rely on artificial feature selection, to find the distributed representation of the data, and to learn complex expression functions. Deep learning adopts unsupervised learning to pre-train DNN layer by layer, which helps DNN effectively excavate the fault features in mechanical signals. Then, DNN is fine-tuned by supervised learning to optimize the expression of DNN's fault features and make them have monitoring and diagnostic capabilities. DNNs are pre-trained by stacking Auto Encoders (AE).

Auto-Encoder is a three-layer unsupervised neural network, which is the input layer, hidden layer and output layer. Among them, the input layer and the hidden layer make up the coding network, and the hidden layer and the output layer make up the decoding network. As shown in Fig.1, the input and output of the AE are the same. AE converts input data in a high-dimensional space into coded vectors in a low-dimensional space through a coding network, and coded vectors in a low-dimensional space are reconstructed into raw input data by a decoding network. Since the input signal can be reconstructed at the output layer, the encoded vector becomes a representation of the input data.



**Fig. 1.** The model of Auto-encoder

Given an untagged data set consisting ofobservation features or variables, each observation variable has  samples. the encoding and decoding process of auto-encoder can be expressed as:

 (1)

 (2)

Where  is the activation function for the encoding network, is the weight of the input layer and the hidden layer,  is the bias vector of the encoding network,  is the activation value of the hidden layer, which is the features of input data ; is the activation function of decoding network, is connected to the hidden layer and output layer weights, is the bias vector for the decoding network, is the network output, which is the reconstruction value of input . and is Sigmoid function. The Sigmoid function can be depicted as follows:

 (3)

The essence of training AE is to train and optimize the network parametersand. In order to make the output as close as possible to the input, we need to optimize the network training parameters. Describe the proximity between input and output by minimizing the reconstruction error.The reconstruction error as shown in Equation 4:

 (4)

In training process, gradient descent method is used for AE parameter optimization, the concrete update form of network parameters can be formulated as formula (5) - (6).

 (5)

 (6)

Where is the learning rate, and  can be calculated by BP algorithm.

DNN can be simply seen as a multi-hidden layer neural network in which multiple AE layers are stacked. The bottom-up unsupervised learning method is used to extract features layer-by-layer and fine-tune the entire network with supervised learning methods. So that the DNN can extract the most essential characteristic attribute of some state of the object from the raw data. DNN structure shown in Fig. 2.



**Fig. 2.** The structure of DNN

First, the DNN network is pre-trained by the unsupervised layer-by-layer greedy training algorithm. Given an untagged input data set as the input to the coding network to practice the first automatic encoder, the coded vector is obtained. Training parameter is obtained by setting x as the output of.is then used as the input to the second automatic encoder  and trained on the network parameter  of .  as hidden layer data of  can be seen as a characteristic representation of . This process is repeated to obtain the hidden layer feature of the  automatic encoder  and the corresponding network training parameter.

Second, add a classifier to the top of the DNN network. The DNN pre-training process is completed through unsupervised training layer by layer, and the layers of feature information are extracted. However, DNN at this time does not have the classification function, in order to achieve the output classification function, but also need to add a DNN classifier on the top. In this paper, we use the Softmax classifier as the output layer of DNN. Use feature of the last hidden layer and the labeled data to train the Softmax classifier. BP algorithm is used to update the network parameter of deep learning. The fine-tuning process uses the labeled data to improve the performance of DNN.

1. **Differential geometric feature fusion based DNN fault detection method**

There are many frequency-type faults in the actual system. For the processing of such faults, the main method is fourier transformed to obtain the frequency domain information and then processed. Although it is easily detected in the frequency domain, it is difficult to detect in the time domain. To ensure real-time fault detection, need to be able to effectively detect such faults in the time domain. This section first analyzes frequency-type faults and then describes in detail of the methods proposed in this paper.

* 1. **Frequency-type fault analysis**

Since the bearing data is a periodic vibration signal, there will be a large amount of zero-crossing data. These zero-crossing data are equal in amplitude, which makes it difficult to discriminate the health of the bearing based only on the amplitude data. Fig. 3.illustrates fault 1 and fault 2 as an example, where blue is data for fault 1, and red is data for fault 2. In a and b points are the zero-crossing points of fault 2 and fault 1, and their amplitudes are 0. At this time, these two points cannot be distinguished based on the amplitude information. But if considering their slope data, we can clearly distinguish these two fault types. So the method based on differential geometric feature fusion proposed in this paper is essentially to increase the frequency domain information of the data in order to maximize the utilization of useful information. Therefore, this paper first calculates the slope and curvature values of the raw data as characteristics of the frequency domain information.



**Fig.3.** Slope feature describe

It can be seen from Fig. 4.The difference between the fault data 1 and the fault data 2 in the time domain is small, so that the diagnosis effect based on the time domain amplitude is greatly reduced, and the difference between the two is more obvious in the frequency domain. This makes the diagnostic effect in the frequency domain greatly improved. However, this diagnostic effect is of no practical significance, because in the health monitoring of actual industrial systems, people hope that the real-time performance of the system is high, which can minimize the security risks. The method based on differential geometric feature fusion proposed in this paper is very practical. This method can obtain higher bearing fault diagnosis accuracy without using Fourier transform and time domain to frequency domain transform. This also provides an innovative way of real-time monitoring of equipment health.



**Fig.4.** Comparison between time domain and frequency domain

* 1. **DGFFDNN-based fault online detection method**  (基于DGFFDNN的在线故障检测方法)

The DGFFDNN fault online diagnosis method is presented in this section. This section is divided into three parts to introduce the algorithm step by step: DNN-based multi-class feature extraction, multi-class feature fusion, fault online diagnosis. The complete fault diagnosis algorithm is as follows:

* + 1. **DNN-based multi-class feature extraction** （基于dnn的多类特征抽取）

The first step of DGFFDNN proposed in this paper is to extract data feature. This article uses a stacking Auto Encoders to extract data features. The feature extraction algorithm is as follows:

***Step* 1:** obtain data that characterize the differential geometric features of raw data. Summarized in algorithm 1.

|  |
| --- |
| **Algorithm 1** Get data that characterizes the differential geometric features of the raw data. |
| **Require:**  : Raw vibration signal data with N fault data sets  : Data preprocessing function, with parameters |
| 1:**function**  2: for n=1:N  calculate the slope of  calculate the curvature of  5:  6:  7: **return** |

***Step* 2:** Training DNN network model.

Respectively reorganize  into a matrix of n rows and m columns:.Construct observation, each observation has  samples. This can make more efficient use of deep learning feature mining capabilities. Construct a DNN network with N hidden layers, and initialize DNN training parameters.

 (7)

Among them,**is the weight matrix, ** is bias vector is the number of DNN hidden layer neurons. Network configuration saved in.  represent raw data set. The number of input neurons of DNN is expressed by using (8).

 (8)

The parameters of DNN are initialized by (9) - (10)

 (9)

 (10)

Applying unsupervised layer-by-layer feature extraction to datasets by training DNN for parameters

 (11)

Layer-by-layer feature extraction as shown in Fig. 2. get the characteristics of the top.

Similarly build DNN network model of slope and curvature data. Repeat the above AE forward encoding process to extract the characteristic values of the original data slope data and curvature data as follows:

 (12)

Whereis the features of raw data;is the features of slope data;is the features of curvature data ;

Calculate the reconstruction error of the original data, slope data, and curvature data separately according to Equation 13.

 (13)

Then gradient descent method is used for AE parameter optimization, the concrete update form of network parameters can be formulated as formula (5) - (6). When the reconstruction error reaches a minimum, it means that the AE-trained parameters can be a good representation of the characteristics of the data.,and  respectively represents the feature values of AE extracted from raw data, slope data and curvature data. The corresponding auto encoder are respectively constructed to extract the features of the raw data, the slope data and the curvature data. Then add a classifier to the top of the DNN network.

***Step* 3:** Add a classifier to the top of the DNN network.

The DNN pre-training process is completed through unsupervised training layer by layer, and the layers of feature information are extracted. Here need to add a DNN classifier on the top. In this paper, we use the Softmax classifier as the output layer of DNN. We use feature of the last hidden layer and the labeled data to train the Softmax classifier. The probability of each type can be calculated by the following hypothetical function:

 (14)

 (15)

Where,  is the model parameter of Softmax. The model parameters can also be optimized by the same means to minimize the cost function. The cost function of Softmax classifier can be defined as follows:

 (16)

Where is indicate function.

A softmax classifier is added at the top of DNN, and a limited set of labels  are used for the reverse adjustment of DNN.the update of training parameters through (12) - (13).

 (17)

 (18)

, can be calculated by (14) - (15), is the number of samples.  indicates the output of , is the learning rate of the reverse trimming process.

*Step* 4: Fine-tune the parameters.

For the accuracy of feature extraction and output layer classification, the entire DNN training parameters are supervised finely with a finite number of sample tags and a BP algorithm, and the fine tuning process is completed by minimizing the reconstruction error. The process of parameter update is as follows:

 (12)

 (13)

where  represents the actual output value,  is a parameter set generated from the whole network training, , BP algorithm is used to update the network parameter, and  is the learning rate in the process of deep learning. The fine-tuning process uses the labeled data to improve the performance of DNN.

We establish three DNN model to extract the fault characteristics of the raw data respectively. The DNN Network structure shown in Fig.5.



**Fig. 5.** Network structure

* + 1. **Multi-class feature fusion（多类特征融合）**

In this paper, the model of DNN which is established by the original, slope and curvature data respectively can fully extract the fault components of the frequency class contained in the fault signal. In order to make the final diagnosis accuracy higher, we must make full use of the trained network to extract the frequency and time domain features of the data. Feature fusion is to recombine the high-level features extracted by these three automatic encoders. Then use the trained softmax classifier to classify the recombined features. The combination of features is as Fig. 5.



**Fig.5.** New feature vector

The detailed steps of feature fusion are shown in Algorithm 2.

|  |
| --- |
| **Algorithm 2** Geometric Feature Fusion Core Algorithm. |
| **Require:**  num3: The number of neurons in the third hidden layer  Classes: Total number of fault data categories  : Network configuration parameters  : Automatic encoder trained parameters  Function reshape(T): Reorganize a one-dimensional array T into a matrix of M\*N  : Geometric feature fusion function, with parameters |
| 1:**function**  2:  Extract the original, slope, and curvature data from the training data  3:  4: for n=1:3                  for layer=1: depth        5:  6:  8: **return** |

* + 1. **Fault online diagnosis**

On-line diagnosis is the use of off-line learned model parameters to identify faults in real-time data collection. In order to accurately use the DNN model to extract the essential characteristics of the health status of mechanical equipment from the input samples, the following steps are required: First, the data of the collected vibration signals should be preprocessed. Secondly, the preprocessed data is used as the DNN model input unsupervised layer pre-training to extract the characteristics of mechanical equipment health status. Finally, based on the finite number of samples of the sample, the entire network is fine-tuned using the BP algorithm to update the entire network parameters. In this way we can carry out an effective diagnosis of the health status of mechanical equipment. Mechanical equipment fault diagnosis is usually divided into two processes: Offline learning and Online diagnosis. The purpose of offline learning is to train a DNN model using the collected historical data. First, the data is preprocessed on historical data, and then the forward training process of DNN is performed. Finally, the DNN network parameters are adjusted in reverse using labels, and the well trained network parameters are saved. On-line diagnosis is to use the well trained parameters and online data to perform corresponding calculations, and then determine whether the data is fault data. If there is a fault, an early warning is issued. If not, the data collection and diagnosis are continued. Usually, DNN for mechanical equipment fault diagnosis steps shown in Figure 3.



**Fig. 3.** DNN based fault diagnosis

DGFFDNN online fault diagnosis method is mainly divided into two parts, one is offline data modeling, and the other is online data fault diagnosis. The offline data modeling part is divided into data preprocessing, training DNN model, using parameters to fine-tune the DNN model parameters, and saving the reorganized parameters. On-line diagnosis is divided into on-line data acquisition, data preprocessing, multidimensional feature extraction, feature fusion, and fault type diagnosis. DGFFDNN based fault online diagnosis flowchart is shown in Fig.6.



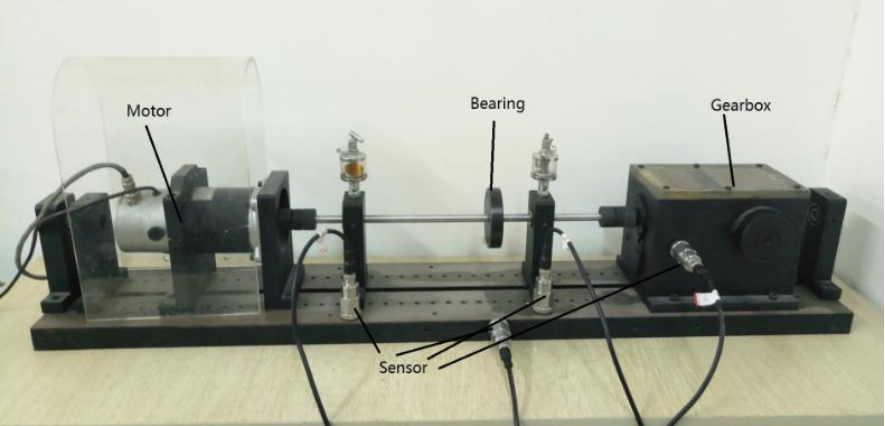
**Fig.6.** Fault Diagnosis Flowchart Based on GFFDNN

1. **Experiment and analysis of bearing faults**

Rolling bearings play a crucial role in rotating machinery, bearing health will directly affect the reliability and stability of the entire system. In this paper, the rolling bearing is used as an experimental platform to verify the effectiveness of the fault diagnosis method for geometric feature fusion. The proposed method is compared with the neural network method without feature fusion.

* 1. **Description of experimental platform**

The experimental data set is the bearing data that collected by Data-driven research team of Henan University built a bearing fault diagnosis test platform. In the bearing fault diagnosis, the vibration signal is the easiest to collect. And the vibration signal is more sensitive to bearing failure. Therefore, vibration signals are widely used in bearing fault diagnosis. In order to further verify the validity of the algorithm, this paper also uses American Western Reserve University Bearing Data Center data as a standard. Acceleration sensor is used in the experiment to collect the vibration signal of motor drive end as experimental data of bearing fault diagnosis. In this experiment, the acceleration sensor is used to collect the motor-driven vibration signal of 0hp, the sampling frequency is 48kHz. There are four types of fault diameter :(1)0.007, (2)0.014, (3)0.021 (4) normal condition. The experimental platform shown in Fig.5.



**Fig. 5.** Experiment platform of rolling bearing

* 1. **Description experimental data**

This article mainly solves the problem that frequency class faults are difficult to detect effectively in the time domain. When such fault signals appear, it is difficult for traditional learning methods to effectively identify different types of faults. This article selects three sets of fault data and a set of normal data. The three sets of fault data are internal fault types, and the load is 0. The difference is that the fault diameter is 0.007, 0.014, and 0.021. The four data types were chosen because these data types have similar amplitude and frequent zero crossings. It makes difficult to effectively distinguish fault types based on time domain signals. The time domain signal is shown in Fig.6.



**Fig. 6.** Observation of raw signals

In addition to using real bearing data, this paper also validates the effectiveness of the proposed algorithm by simulating multiple sets of different types of test data. Among them, there are data with different amplitudes of the same frequency, data with different amplitudes of the same amplitude, and data with different amplitudes and different frequencies, Simulation data generation method is shown as table 2.and the data as shown in Fig. 8, 9, and 10, respectively.

**Tab.2.** Simulation data

|  |  |  |  |
| --- | --- | --- | --- |
| Different experimental scenes | Sampling interval | Signal 1 | Signal 2 |
| different amplitudes with same frequency | 0.1 |  |  |
| different frequency with same amplitude | 0.1 |  |  |
| different amplitudes with different frequencies | 0.1 |  |  |

* 1. **Analysis of results**

Our proposed deep learning based on geometric features is applied to bearing fault diagnosis. There are 4,500 samples under each data type and 4 different data types to characterize the frequency fault types of rotating mechanical systems. In order to reduce the influence of randomness, Experiment repeated 10 times. DNN training uses a stochastic gradient descent method, and the maximum number of iterations of DNN in each layer is 1000, 800, 1000 times respectively. In this paper, DNN's pre-training initialization parameters are shown in Table 1.

**Tab.1.** DNN model parameters

|  |  |  |  |
| --- | --- | --- | --- |
| Training parameter |  |  |  |
| Hidden layers | 6 | 4 | 5 |
| Number of neurons | 500/400/200/100/50/10 | 500/100/50/20/10 | 500/200/100/50/20/10 |
| Max number of epochs | 1000 | 800 | 1000 |
| Learning rate | 0.01 | 0.02 | 0.01 |

In order to verify the effectiveness of the algorithm, different types of simulation data are also verified in this paper. The situation when the signal frequency has same frequency with different amplitudes is shown in Fig.8. On the left is the waveform of the signal. On the right is the diagnostic effect of the proposed algorithm. Red and blue are different fault signals in the waveform diagram. In the diagnostic effect chart, red represents the predicted category, and blue represents the real category.



**Fig.8.** Same frequency with different amplitudes

The situation when the signal same amplitudes with different frequency is shown in Fig.9. On the left is the waveform of the signal. On the right is the diagnostic effect of the proposed algorithm. Red and blue are different fault signals in the waveform diagram. In the diagnostic effect chart, red represents the predicted category, and blue represents the real category. It can be seen that frequency-type faults are difficult to detect in the time domain. Compared to other types of fault monitoring results, detailed data can be found in tab 2.



**Fig.9.** Same amplitudes with different frequency

The situation when the signal different amplitudes with different frequency is shown in Fig.10. On the left is the waveform of the signal. On the right is the diagnostic effect of the proposed algorithm. Red and blue are different fault signals in the waveform diagram. In the diagnostic effect chart, red represents the predicted category, and blue represents the real category.



**Fig.10.** Different amplitudes with different frequency

From the above simulation results, it can be seen that when the amplitude and frequency of the signal are not the same, the diagnostic effect is the best. In addition to the simulation data, this paper also uses the data collected in the test platform built by ourselves to verify. The diagnostic results are shown in Fig. 9. It can be seen that there is a good diagnostic accuracy for bearing data.



**Fig.11.** Detection accuracy of data-driven research team of Henan University data

In addition, we also use the data from the Xi'an University Bearing Data Center to verify this algorithm. The diagnostic results are shown in Figure 12. It can be seen that the proposed algorithm is effective.



**Fig.11.** Detection accuracy of Western Reserve University Bearing Data Center data

Compared with the simulation results without feature fusion, the proposed method is validated. It can be seen from Table 3 that the diagnostic accuracy of the proposed method in frequency class and other faults is higher than that of ordinary neural networks and traditional deep neural networks DNN.

**Tab.3.** Comparison of the accuracy of fault diagnosis

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Data | GFFDNN | DNN | GFFBP | BP |
| Western Reserve University Bearing Center | 98.06 | 89.52 | 87.73 | 81.56 |
| Henan University of Technology Bearing Data | 98.54 | 90.14 | 88.16 | 80.13 |
| Same frequency with different amplitudes | 94.34 | 93.01 | 92.69 | 91.04 |
| Same amplitudes with different frequency | 95.06 | 90.23 | 86.27 | 84.31 |
| Different amplitudes with different frequency | 98.40 | 95.24 | 94.36 | 92.86 |

1. **Conclusion and future work**

In this paper, aiming at the problem that frequency class fault cannot be effectively diagnosed in the time domain, a new DGFFDNN fault online diagnosis method is developed in detail. The main innovation is to solve the problem of difficulty in detecting frequency-type faults in the time domain by introducing the differential geometric characteristics of the original data. When the fault information has similar amplitude and frequent zero-crossing characteristics, the traditional diagnosis method will have the problem of inaccurate diagnosis. In this paper, the original data, slope data and curvature data are respectively constructed into an automatic encoder model to fully excavate the data implied frequency information. Then the obtained data features are merged to increase the feature dimension, so that the fault diagnosis model can be trained more accurately. In addition, this method enables detection of frequency-type faults in the time domain, which will facilitate the real-time detection of the health of the mechanical equipment. The rolling bearing test platform validates the effectiveness of the method.

Large-scale mechanical equipment is getting more and more complicated, and the requirements for fault diagnosis are getting higher and higher. How to implement health monitoring of devices through self-learning algorithms without tag data is a very important research direction in the future

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