[[1]](#footnote-1)

**Multi-modal Feature Fusion based Deep Learning Method for Frequency-type Fault Diagnosis**

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**Abstract:** Rotating mechanical equipment usually suffer from frequency-type fault which cannot be well diagnosed in the time domain since frequency feature is not well extracted. On the other hand, diagnosis in frequency can only results in offline fault classification not online fault diagnosis. To solve this problem, multi-modal feature fusion based deep learning method for frequency-type fault diagnosis is proposed in this paper. Multi-modal feature corresponding to the original data, slope data and curvature data are firstly extracted by 3 separate deep neural networks, respectively. Then multi-modal feature fusion is developed to get a new combined feature which can characterize the potential frequency feature involved in time domain data. Lastly, use the fused new feature as the input of the softmax classifier to get online diagnosis result of frequency-type fault. Simulation experiment and case study of rolling bearing shows the efficiency of the method proposed in this paper.

**Key Words:** Fault diagnosis; Deep learning; Multi-modal feature; DNN; 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]. As a core part of rotating machinery, bearings are used in a wide range of industrial field. In the whole life of bearing, different degree of wear phenomenon is inevitable, timely monitoring of the bearing failure is significant in the sense of avoiding serious losses or even risk of the operator life. In this regard, research on bearing fault diagnosis has attracted widely attention from experts both in academic and application [6-7, 9-18]. Therefore, bearing fault diagnosis in the actual industrial production process is a promising research field.

In general, the methods of fault diagnosis can be categorized into 3 classes: physical model based method, knowledge based method, and data-driven based method. 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 [19–24]. Principal component analysis (PCA), support vector machine (SVM), and artificial neural network (ANN) are the popular data-driven techniques for fault diagnosis [25–32]. Data-driven methods include statistical feature extraction and Neural network method [33-35]. 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.

Neural network based methods are the most advanced data-driven method for fault diagnosis. Wang et al. used WPT to extract non-stationary characteristics of the bearing’s vibration signal as the pre-extracted feature of ANN. The method uses the nonlinear learning classification ability and self-organizing ability of ANN to classify and diagnose bearing faults. 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 [21, 22]. 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 [36, 37]. When the number of samples is limited 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 [38]. 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. Fault diagnosis based on combination of WPT and SVM, can improve the accuracy of fault diagnosis [39]. 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 [40]. Yang and Tang etc. Proposed a method that combined the expert system with the Back Propagation neural network (BPNN), which fully utilized the advantages of the expert system and ANN and successfully detected the bearing failure [41]; Jiang et al. Propose 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 [42]. 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 multi-classification and large sample problems. In addition, expert experience is required to choose suitable kernel function and scale parameter. SVM method cannot be real-time monitoring and diagnosis, which make it unavailable to meet the performance requirement of real-time diagnosis. ANN also has some congenital defects: (1) As a shallow neural network, the convergence of ANN is easy to fall into local optimum, thus it cannot well characterize the signal characteristic; (2) Low efficiency of ANN learning and inaccuracy of feature extraction is another shortcoming of ANN. In summary, as a shallow learning method, SVM and ANN have not been able to effectively extract features involved in high-dimensional and non-steady data [43]. Deep learning is a promising feature extraction tool and has aroused widespread concern of scholars [14-17, 20, 21]. Compared with shallow learning, deep learning can perform well feature extraction and in-depth study on nonlinear big data [44, 45].

As one of the most popular and hot machine learning methods in the world today, deep learning has revolutionized artificial intelligence. Deep 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 deep learning in 2006. DNN can obtain a more abstract high-level representation of the input data by combining lower-level features which is a nonlinear transformations of its previous layer. So that DNN can discover the distribution of data without artificial feature selection, and can learn complex function [46]. Due to its excellent feature extraction capabilities, deep learning (DL) quickly attracted the attention of fault diagnosis researchers. Lu et al. used the good feature extraction ability of deep neural network to successfully diagnose the bearing fault with the innovation to diagnose the unknown type fault timely and effectively [47]; Jia et al. used deep neural network to detect rolling shaft bearing health status [48].But the above mentioned DNN fault diagnosis methods didn’t take the data’s multi-modal feature into consideration.

Gan et al. proposed a fault classification method based on hierarchical neural network [49]. By constructing a two-layer neural network, the method not only could locate the position of bearing fault, but also effectively mine the fault size of the bearing in the same position. Li et al. addresses a multi-modal deep support vector classification (MDSVC) approach in to propose a separation-fusion based deep learning method for gearboxes fault diagnosis [50]. The main innovation of this method is to fuse the multi-modal feature extracted in time domain, frequency domain and wavelet domain respectively. But it is not a real-time fault diagnosis method since Fourier transform is used to get the frequency data for the reason that Fourier transform is a full-time domain to frequency domain transformation. At present, existed studies about bearing fault diagnosis have not completely solved the problem of frequency-type faults with high diagnosis accuracy and real-time performance. The method considering the multi-modality of features, but it cannot guarantee real-time performance.

There are many zero-crossing values in the bearing data since they are mostly vibration signal. So bearing is common to suffer frequency fault whose fault size may be very larger in frequency value but very small in amplitude value. This character of frequency makes DNN available to distinguish frequency fault type based simply on the amplitude value of the observation data for the reason that multi-modal feature involves in vibration signal. On the other hand, differential geometry feature of the vibration signal, such as slope and curvature, can reveal the frequency fault feature in time domain. So research on real-time and accurate fault diagnosis method for bearing fault diagnosis is required to develop an efficient multi-modal feature fusion mechanism in time domain.

In order to resolve the limitation stated above, this paper developed an online differential geometric feature fusion based DNN (DGFFDNN) fault diagnosis method to improve the accuracy of frequency-type fault diagnosis. State of the art of this research is to design a fusion mechanism by combining multi-modal differential geometric feature. By this means, frequency failure can be well detected online which is significant to real-time frequency fault diagnosis. The main innovation is to solve the problem of inaccurate time-domain detection when frequency faults have similar amplitudes and frequent zero crossings by fusing the geometric features of the raw data. The original, slope and curvature data are respectively constructed into an Automatic Encoder (AE) model to fully excavate the implied frequency information of the data in time domain. Then, the obtained multi-modal 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 the extraction of different multi-modal. The third step is to fuse the obtained features. The final step is to use the well trained network to diagnose the new samples in real time.

The remainder of this paper is organized as follows: Section 2 is the review of deep learning. 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.

1. **Review of deep learning theory**

Deep learning is an unsupervised learning method. By multi-layer nonlinear transformation, low-level features are combined to form more abstract high-level representation, making the learning system cannot find the distributed representation of the data without relying on artificial feature selection. 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. In this paper, DNNs are pre-trained by stacking Auto Encoders (AE).

Auto-Encoder is a three-layer unsupervised neural network that is the input layer, multiple hidden layer and output layer. Among them, the input layer and the hidden layer constitute the coding network, while the hidden layer and the output layer constitute 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 unlabeled datasetconsisting of variable, each variable hassamples. The encoder network encodes the sampleto the hidden activate valuewith an activation function. The encoder process is described as follows:

 (1)

Where  is the encoder function, Sigmoid functionis usually taken as the activation function in the encoder process. *W* is the weight matrix of the network between input layer and the hidden layer, *b* is the bias vector generated by the encoder network, is the connection parameter between the input layer and the hidden layer. The Sigmoid function can be depicted via Eq. (2)

 (2)

Similarly, for the decoder network, the feature matrixobtained from encoder network is used to reconstructthrough the decoder network such that the reconstructedis equal to the input. The decoder process is described as follows:

 (3)

where is the decoder function, is the activation function of the decoder process, represents the weight matrix between the hidden layer and the output layer of the network , *d* is the bias vector generated by the decoder process.

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 can be shown in Equation 4.

 (4)

Where  denotes predictive value, denotes actual value.

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 feature potentially involved in the raw input data. The structure of DNN can be 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 as the feature extracted on the first layer. 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 .  is the hidden layer of , which can be seen as a feature representation of . This process is repeated to obtain the feature of the  automatic encoder  and the corresponding network training parameter.

Second, add a classifier to the top of the three 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 new feature as input of softmax, and the labeled data as output of Softmax classifier. The probability of each type can be calculated by the following hypothetical function:

 (7)

 (8)

Where, is the feature vector,  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:

 (9)

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.

 (10)

 (11)

, can be calculated by (7) - (8), is the number of samples. indicates the output of , is the learning rate of the reverse trimming process.

Third, 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 update of training parameters through (12) - (13).

 (12)

 (13)

where  represents the actual output value,  is a parameter set generated from the whole network training, , gradient descent algorithm is used to update the network parameter, and  is the learning rate in the process of deep learning.

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

There are many frequency-type faults in the rotating mechanical system. For the processing of such faults, the main method is Fourier transform to obtain the frequency domain information and then diagnose fault based on frequency information. Although frequency-type fault can be well recognized in the frequency domain, it is difficult to online diagnose in the time domain. To ensure online fault diagnosis, it is required to diagnose such faults in the time domain. And frequency feature should also be characterized in time domain. This section first analyzes frequency-type faults and then describes in detail of the required feature extraction and fault diagnosis 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 line represents the data for fault 1, and red line for fault 2. The normal data’s amplitude is expected to be zero. Point “a” and point “b” are the zero-crossing points of fault 2 and fault 1, and their amplitudes are 0. These two zero-cross points cannot be distinguished based simply on the amplitude information. But if slope data is considered, we can clearly distinguish these two faults since their slopes are 1.73 and 3.73, respectively. So the method based on differential geometric feature fusion proposed in this paper can provide an efficient means to increase the frequency information of the data so as to maximize the utilization of useful information.



**Fig.3.** Slope feature describe

It can be seen from Fig. 4. Fault data 1 and fault data 2 cannot be well separated in the time domain, so diagnosis effect based simply on amplitude is greatly reduced. On the other hand, and the difference between the two data’s frequency is more obvious. This makes the diagnostic effect in the frequency domain greatly improved. However, this diagnostic effect is of no practical significance, because real-time diagnosis is the first requirement of health monitoring of actual industrial systems, which can minimize the security risks. The method based on differential geometric feature fusion proposed in this paper is of much significance in the sense of accomplishing accurate and real-time fault diagnosisusing Fourier transform. This also provides an innovative way of real-time monitoring of equipment health.



**Fig.4.** Two different failure types in the time domain



**Fig.5.** Two different failure types in the frequency domain

* 1. **DGFFDNN-based online fault diagnosis method**

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

* + 1. **Multi-modal feature extraction**

The first step of DGFFDNN proposed in this paper is to extract multi-modal feature involved in the data. This article uses a stacking AE to extract data features. The multi-modal feature extraction algorithm is as follows:

***Step* 1:** obtain data that characterize the differential geometric features of raw data. Therefore, this paper first calculates the slope and curvature values of the raw data via Eq. (14)-Eq. (15).

 (14)

 (15)

Where  is the number of raw data.  is sampling interval.  is the raw data set.  is slope values of the raw data the raw data set.  is the original data set.

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

Reorganize  into a matrix of n rows and m columnsrespectively. .Construct  variable, each variable has  samples. This can make more adequate use of deep learning feature mining capabilities. Construct three DNN networks with N hidden layers, and initialize DNN training parameters.

 (16)

Where  is number of neurons in the first hidden layer,  is number of neurons in the last hidden layer. Among them, **is the weight matrix of raw data, similarly, **is the weight matrix of the slope data, ** is the weight matrix of the curvature data. For simplicity, in the rese part, only the original data will be used as an example for description later. **is bias vector,  represent raw data set. Network configuration is saved in. The number of input neurons of DNN is expressed by using (17).

 (17)

And the parameters of DNN are initialized by Eq. (18) - (19)

 (18)

 (19)

Apply unsupervised layer-by-layer feature extraction by DNN parameters training.

 (20)

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

Build DNN network model of slope and curvature data in the same manner. Repeat the above AE encoding process to extract multi-modal feature corresponding to original data, slope data, and curvature data, respectively.

 (21)

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 Eq. (22).

 (22)

Then gradient descent method is used for AE parameter optimization, the specific update process of network parameters can be formulated as Eq. (5) - (6). When the reconstruction error reaches a minimum, it means that the trained AE parameters can be a good representation of the characteristics of the data., and , corresponding to raw data, slope data and curvature data, respectively. Lastly, add a softmax classifier to the top layer of the DNN network.

* + 1. **Multi-modal feature fusion**

Based on original data, slope data and curvature data, respectively, 3 DNN models is established to extract the multi-modal local frequency feature in time domain. As illustrate in Fig.5 the slope of different fault data may also equal, that is, we cannot well classify different faults by simply use slope feature either. Thus, fusing different multi-modal feature to get a new combined feature is necessary. In this paper different feature is fused by stacked form to get new combined feature. By this fusion process, the feature is augmented to a higher dimensional feature, which can integrate the multi-modal feature to capture the local frequency feature in time domain, The features extracted from the above model are recombined to obtain a new feature vector, just as described in Eq. (23).

 (23)



**Fig. 5.** Feature fusion network structure

The whole feature fusion process can be shown in Fig.5. The purpose of feature fusion is to recombine the high-level features extracted by these three automatic encoders. The combination of features is as Fig. 6.



**Fig.6.** Stacked Fusion to get new feature vector

In the final step, use the fused feature as input and the fault label of each sample as the output to train the Softmax classifier.

* + 1. **Online diagnosis**

Online diagnosis is the use of off-line learned model parameters to identify faults in real-time data collection. DNN for mechanical equipment fault diagnosis steps shown in Fig. 7.



**Fig. 7.** DNN based fault diagnosis

The online fault diagnosis process is as follows:

**Step1:** Online data multi-modal feature extraction

When online observation at time , denoted as, is available, use the well trained DNN1 to extract the amplitude feature of the online original data via Eq. (24)

 (24)

Where function  is used to illustrate, the online amplitude feature is the output of the trained network (Net, Tr) when  is the input of the network.

Then, waiting for the observation at time, once is available, the slope at time  can be firstly computed via Eq. (25)

 (25)

Where  is the sample interval

Similar as the manner in Eq. (15), the slope feature can be extracted by the well trained DNN2 via Eq.(26)

 (26)

Waiting for the observation at time, once is available, the slope at time  can be firstly computed via Eq. (27)-Eq. (28)

 (27)

 (28)

Also the curvature feature can be extracted by the well trained DNN2 via Eq. (29)

 (29)

**Step2:** Online data multimodal feature fusion

Multi-modal feature at time t is used to obtain the fusion feature after the expansion, via Eq. (30)

 (30)

**Step 3:** Online diagnosis

According to the design of Softmax classifier, the type that maximizes the probability is the result of on-line diagnosis of online samples, via Eq. (31)-(32)

 (31)

 (32)

Whereis the number of fault，is well trained parameter of softmax. is result of fault diagnosis.

The flow chart of the entire algorithm is shown in Fig. 8.



**Fig.8.** Fault Diagnosis Flowchart Based on GFFDNN

1. **Experiment and analysis**

Rolling bearings play a crucial role in rotating machinery, bearing health will directly affect the reliability and stability of the entire system. In general, rolling bearing is easy to suffer from frequency-type fault. In this paper simulation study and rolling bearing case study are both illustrated to validate the efficiency of the DGFFDNN algorithm proposed. The proposed method is compared with the neural network method without feature fusion.

**4.1 Simulation Study**

This article mainly solves the problem that frequency-type ~~class~~ faults are difficult to detect effectively in the time domain. When such fault occurs in the mechanical system, ~~signals appear,~~ it is difficult for traditional learning methods to effectively identify different types of faults. This paper validates the effectiveness of the proposed algorithm by simulating multiple sets of different types of test data. Analysis of 3 typical experiment scenes are illustrated in detail: ~~Among them, there are data with~~ different amplitudes with ~~of the~~ same frequency, ~~data with~~ different frequency ~~amplitude~~s of the with same amplitude, ~~and data with~~ different amplitudes with ~~and~~ different frequencies.

**4.1.1 Description of simulation experimental data**

Simulation data generation method is shown in ~~as~~ Table 1. And the generated observation data ~~Waveform~~ is shown in Fig. 9, Fig.11, and Fig.13, respectively, red line represents the normal observation and the blue line represents the fault observation. ~~are different fault signals in the waveform diagram.~~

**Tab.1.** Simulation data

|  |  |  |  |
| --- | --- | --- | --- |
| Different experimental scenes | Sampling interval | Normal observation | Fault observation |
| different amplitudes with same frequency | 0.1 |  |  |
| different frequency with same amplitude | 0.1 |  |  |
| different amplitudes with different frequencies | 0.1 |  |  |

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 2.

**Tab.2.** 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 |

**4.1.2 Analysis of simulation experiment result**

In order to verify the effectiveness of the algorithm, different types of simulation data are used to illustrate the experiment result.  ~~also verified in this paper. The situation when the signal frequency has same frequency with different amplitudes is shown in~~ Category label of fault diagnosis is illustrated in Fig.10, Fig.12 and Fig.14. Fig.10 shows the fault diagnosis result corresponding to experiment case 1: different amplitudes with same frequency. In Fig.10, red star represents the fault diagnosis label of each online sample, and blue circle represents the real label of each sample. At each sample time, coincident of red circle and blue star means that the online observation at this sample time is correctly diagnosed. Fault diagnosis result based on 4 different methods are illustrated in Fig.10. Fig.10(a)-(d) illustrates the fault diagnosis result corresponding to DGFFDNN, DNN, DGFFBP and BP, respectively.

Comparing the result of Fig.10(a) and Fig.10(c) with that of Fig.10(b) and Fig.10(d), it can be easily seen that the diagnosis accuracy of DGFFDNN is higher than traditional DNN, which tells us that differential geometry feature fusion based method is an efficient means to diagnose frequency-type fault. The first row and the second of Fig.10 compared the fault diagnosis result based on DNN and BP, respectively. It can be concluded that DNN does well in feature extraction. From the above analysis of Fig.10, it can be concluded that DGFDNN is significant superior to other 3 methods. The accuracy of DGFFDNN, DNN, DGFFBP and BP is 94.34%, 92.01%, 90.69% and 87.04%, respectively.



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



**Fig.11.** Same frequency with different amplitudes result

Fig.12 shows the fault diagnosis result corresponding to experiment case 2: same amplitudes with different frequency. The interpretation of Fig.12 is similar to Fig.10. The accuracy of DGFFDNN, DNN, DGFFBP and BP are 93.06%, 73.54%, 62.87% and 54.36%, respectively. Comparing Fig.12 (a) with Fig.10(a), it can be seen that when the fault size is very small in time domain, traditional DNN method fails to diagnose fault accurately, while DGFFDNN proposed in this paper does very well in real-time and accurate diagnosis for frequency-type fault.



**Fig.12.** Same amplitudes with different frequency



**Fig.13.** Same amplitudes with different frequency result

Fig.14 shows the fault diagnosis result corresponding to experiment case 3: different amplitudes with different frequency. The interpretation of Fig.14 is similar to Fig.10.The accuracy of DGFFDNN, DNN, DGFFBP and BP are 98.4%, 94.24%, 92.36% and 90.86%, respectively.

Comparing Fig.14 (a) with Fig.12(a) and Fig.10(a), it can be seen that if the fault size is larger in both time domain and frequency domain, even traditional shallow learning method can come to a relatively satisfactory diagnosis result. In the case when fault size is only large in amplitude, traditional DNN can come to a relatively satisfactory diagnosis result, but traditional BP, which is a shallow learning method, cannot come to a very satisfactory diagnosis result. As for the case when fault size is large in frequency but very small in amplitude, which is a typical frequency-type fault, accuracy of the traditional shallow learning method is only 54.36% cannot meet the engineering requirement. Even DNN can only come to the diagnosis accuracy of 73.54%, while our method proposed in this paper can greatly improve the diagnosis accuracy to a rather higher value 93.06%. All the above analysis shows that DGFDNN is an efficient online diagnosis method for frequency-type fault.



**Fig.14.** Different amplitudes with different frequency



**Fig.15.** Different amplitudes with different frequency result

Table listed the fault diagnosis accuracy of the four fault diagnosis method in three different experiment cases. It can be seen from Table 3 that DGFFDNN method is greatly superior to other machine learning method for the real-time diagnosis of typical frequency-type fault.

**Tab.3.**~~Comparison of the~~ Simulation study: accuracy of different fault diagnosis methods

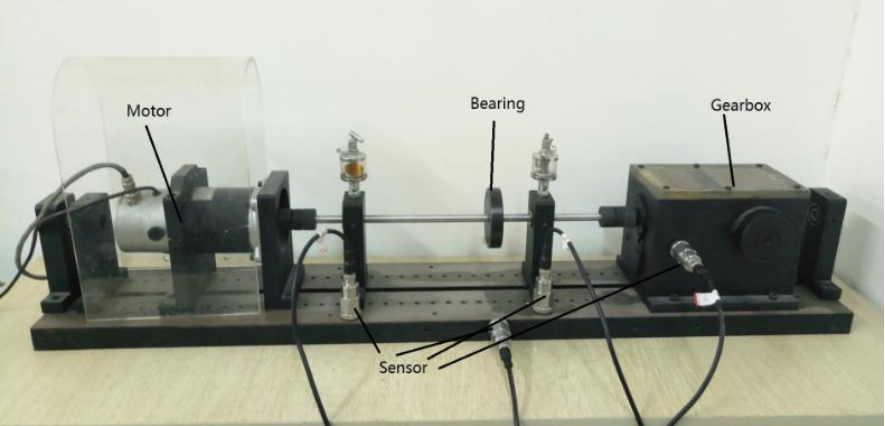
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Data | DGFFDNN | DNN | DGFFBP | BP |
| Same frequency with different amplitudes | 94.34 | 92.01 | 90.69 | 87.04 |
| Same amplitudes with different frequency | 93.06 | 73.54 | 62.87 | 54.36 |
| Different amplitudes with different frequency | 98.40 | 94.24 | 92.36 | 90.86 |

**4.2 Case study**

In order to further verify the algorithm validity in engineering practice, the rolling bearing ~~is used as an~~ experimental platform established by our research team and a benchmark rolling test data set provided by Western Reserve University are both used to verify the effectiveness of DGFFDNN. In our own test platform, we have carried out research on different fault diameter with same fault type, and different fault types with same fault diameter.

**4.2.1 Description of experimental platform**

The experimental data set is the bearing data that collected from bearing fault diagnosis test platform established 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 collected for ~~widely used in~~ bearing fault diagnosis. Acceleration sensor is used in the experiment platform 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 is shown in Fig.15.



**Fig. 15.** Experiment platform of rolling bearing

**4.2.2 Case study result analysis**

DGFFDNN method proposed in this paper ~~Our proposed deep learning based on differential 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.

This article selects three sets of fault data and a set of normal data, and the fault data are corresponding to internal fault with different fault size in the case when~~. The three sets of fault data are internal fault types, and the~~ load is 0. The fault size ~~ifference is that the fault diameter~~ is 0.007, 0.014, and 0.021, respectively. The four experiment case ~~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 methods. ~~signals. The time domain signal is shown in Fig.12.~~



**Fig.16.** Case studyresult for diagnosis of different fault size

Fig. 16 shows the diagnostic results of experiment 2: same fault size with different fault type. The interpretation of Fig.16 is similar to Fig.10. Comparing of Fig.16(a)-(d) can come to the conclusion that DGFFDNN diagnosis result shown in Fig.10(a) is better than other 3 methods. The accuracy of DGFFDNN, DNN, DGFFBP and BP are 98.54%, 90.14%, 88.16% and 80.13%, respectively. It can be seen from Fig.16that the proposed DGFFDNN method can even well distinguish different fault size, which will provide very useful information for Failure prediction maintenance. It indicates that the proposed method is effect in fault diagnosis of engineering application field.



**Fig.17.** Case study for diagnosis of different fault type

Fig. 17 shows the diagnostic results of experiment 2: same fault size with different fault type. The fault size of this experiment 2 is 0.007, which is a rather small fault size. The interpretation of Fig.17 is similar to Fig.10. Comparing of Fig.17(a)-(d) can come to the conclusion that DGFFDNN diagnosis result shown in Fig.17(a) is better than other 3 methods. The accuracy of DGFFDNN, DNN, DGFFBP and BP are 97.63%, 89.53%, 86.42%, and70.84, respectively. It can be seen from Fig.17 that the proposed DGFFDNN method can even well distinguish different fault type when multiple faults occur in the rotation mechanical equipment. Especially for multiple small fault diagnosis, we can see from Fig.10(a) and Fig.10(d) that fault diagnosis accuracy of DGFFDNN is significantly prior to traditional BP.

**4.2.3 Benchmark data set testing**

In addition, we also use the data from the Case Western Reserve University Bearing Center as a benchmark data to test this algorithm[51].

Fig. 18 shows the diagnostic results of experiment 1: same fault size with different fault type. The fault size is set to 0.07, which is rather small. The interpretation of Fig.18 is similar to Fig.10. Comparing of Fig.18 (a)-(d), it is easily to be seen that DGFFDNN diagnosis result shown in Fig.18 (a) is better than other 3 methods. The accuracy of DGFFDNN, DNN, DGFFBP and BP are 97.73%, 89.2%, 86.37%, and 60.24%, respectively. Well distinguish of fault size will be very helpful for fault prognosis and maintenance.



**Fig.18.** Benchmark test for diagnosis of different small fault type

Fig. 19 shows the diagnostic results of experiment 2: same fault type with different fault size. The interpretation of Fig.19 is similar to Fig.10. Comparing of Fig.19 (a)-(d) can come to the conclusion that DGFFDNN diagnosis result shown in Fig.19 (a) can well diagnose multiple faults occurred in rotation mechanical equipment. The accuracy of DGFFDNN, DNN, DGFFBP and BP are 98.06%, 89.52%, 87.73%, and 73.56%, respectively.

**Fig.19.** Benchmark test for diagnosis of different fault size

From the above comparison, it can be concluded that differential geometry feature fusion based DNN method can be validated by simulation study as well as case study. Table 4 lists the diagnosis accuracy for case study. It can be seen from Table 4 that the diagnostic accuracy of the proposed method is an effect fault diagnosis method for rotation mechanical equipment.

**Tab.4.** Case study: accuracy of different fault diagnosis methods

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Data | DGFFDNN | DNN | DGFFBP | BP |
| Henan University Bearing Platform |  |  |  |  |
| Different fault size(0.007,0.014 0.021,0) | 98.54 | 90.14 | 88.16 | 80.13 |
| Different fault type(Inner race,Ball,Out race,normal) | 97.63 | 89.53 | 86.42 | 70.84 |
| Western Reserve University Bearing Platform |  |  |  |  |
| Different fault size(0.007,0.014 0.021,0) | 97.73 | 89.52 | 86.37 | 60.24 |
| Different fault type(Inner race,Ball,Out race,normal) | 98.06 | 89.52 | 87.73 | 73.56 |

1. **Conclusion and future work**

In this paper, aiming at the problem that frequency-type fault cannot be accurately diagnosed in the time domain, a new DGFFDNN method is developed to get an online fault diagnosis algorithm with high diagnosis accuracy. The main innovation of this method is to characterize the potential frequency feature involved in time domain data by exploring the dynamic trend feature characterizing ability of differential geometry feature. Frequency-type fault whose fault size is larger in frequency domain while very small in time domain can be well diagnosed by the proposed method. The main idea is to extract multi-modal feature corresponding to the original data, slope data and curvature data are firstly extracted by 3 separate deep neural networks, respectively; Then the extracted multi-modal features are merged to augment the feature dimension, so that the fault classifier can be trained more accurately. In addition, this method enables diagnosis of frequency-type faults in the time domain, which will facilitate the online health diagnosis of the mechanical equipment. The case study of rolling bearing test platform validates the effectiveness of the method.

How to effectively implement health monitoring of devices through self-learning algorithms without tagged data is a very important research direction in the future.

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