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Deep learning based on rolling bearing fault diagnosis method

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Abstract. With the continuous development of industrial automation, rolling bearings play a crucial role in many fields as key mechanical components, and the fault diagnosis of rolling bearings have great significance. This paper discusses a deep learning based rolling bearing fault diagnosis method, aiming to improve the accuracy and efficiency of fault detection. Firstly, the vibration signals of rolling bearings are pre-processed to extract the feature information that helps fault diagnosis. Then, the features were automatically learned and classified by using BP neural network. Finally, the effectiveness and robustness of the method were verified through experiments. Compared with the traditional fault diagnosis method, the deep learning-based rolling bearing fault diagnosis method has higher accuracy and practicality, which provides strong support for the fault detection and preventive maintenance of rolling bearings.

Keywords: Deep learning; BP neural networks; feature extraction; bearing fault diagnosis.

1. Introduction

Rolling bearing is an indispensable part in mechanical equipment, due to the complexity of the working environment and the characteristics of the bearing itself, the failure of the bearing is inevitable. Bearing defect or failure can cause abnormal vibration or even damage to the equipment. Through fault diagnosis of rolling bearings, potential problems, such as wear, crack, fracture, can be found in time, so as to avoid equipment accidents caused by bearing faults. Rolling bearing fault diagnosis is helpful to extend the service life of the equipment. Through regular fault diagnosis, the bearing can be repaired and replaced targeted, so as to reduce the wear degree of the equipment, and then extend the overall life of the equipment. Fault diagnosis of rolling bearing is of great significance in ensuring equipment operation safety, prolonging equipment life and improving equipment operation efficiency. Rolling bearing fault diagnosis has a more critical role in some key fields, such as aero-engine, nuclear power plant, etc. In these areas, the failure of rolling bearings may lead to serious safety accidents and even endanger the life safety of people. Therefore, in these critical equipment, it is particularly important to conduct fine rolling bearing fault diagnosis to ensure the safe and reliable operation of the equipment.

2. The fault analysis method of rolling bearings

Bearing fault diagnosis identify the state of the bearing by measuring, analysis and processing of the signal that can reflect the working state of the bearing, including the following links: signal detection, feature extraction, state identification, fault diagnosis and decision intervention[1]. At present, the research methods for rolling bearing fault diagnosis at home and abroad mainly focus on time-domain analysis, frequency-domain analysis, time-frequency analysis and intelligent diagnosis. Traditional diagnostic techniques, such as vibration sound, oil analysis, acoustic emission, optical fiber, temperature diagnosis, and each has its own characteristics[2]。

The common failure modes of rolling bearing are: wear, fatigue, corrosion, fracture, indentation, bonding and so on. Early damage may occur due to material defects, improper processing or assembly, poor lubrication, moisture or foreign body intrusion, corrosion and overload of rolling bearings[3]. Usually, due to improper assembly or improper use of the retention frame deformation, which may increase the friction between the holder and the rolling body, and even make some rolling body stuck and can not roll, or the holder and the internal and external roller friction can cause the retention frame damage, which also makes the vibration, noise and heat increase[4]. Generally, according to the state variables used in the monitoring and diagnosis, the rolling bearing working condition monitoring and fault diagnosis are divided into temperature detection technology, oil sample analysis technology, ferrospectral diagnosis technology, oil film resistance diagnosis technology and vibration detection technology[5]。

Fault feature extraction is generally performed in time, frequency and frequency domain. Time domain analysis is an early and intuitive diagnosis method, and the time domain characteristics are taken as the basis for fault diagnosis of rolling bearing[6-8]. The frequency domain analysis method first transforms the time domain signal to the frequency domain, and then extracts the feature parameters for fault diagnosis[9]. Because the vibration signal of the rolling bearing is non-stable and nonlinear, the time-frequency analysis method can comprehensively extract the characteristics of the time domain and the frequency domain, mainly including the wavelet transform[10], Short-time Fourier transform[11], Experience-mode decomposition[12]And so on method. In terms of classifier application research, experts and scholars at home and abroad gradually apply machine learning and other artificial intelligence technologies to the fault identification of rolling bearings, and the machine learning algorithm mainly includes support vector machine (SVM)[13], random forest (RF)[14], artificial neural network (ANN)[15]class.

Nowadays, many scholars have introduced deep learning technology into the bearing fault diagnosis task, and the bearing fault diagnosis model based on deep learning can adaptively extract fault-sensitive features from the original vibration signal, overcoming the inherent limitations of traditional data-driven methods. In addition, when facing massive vibration signals, the deep learning model can accurately fit the miscellaneous nonlinear relationship between the original bearing signal characteristics and the fault mode with the powerful computing ability of the computer equipment, so as to realize the intelligent fault diagnosis of rolling bearings in the era of big data.

3. BP neural network

BP neural network is also from the basis of single-layer neural network development, with BP neural network nonlinear problems, need to superposition the hidden layer to enhance the data processing ability of the network, the hidden layer according to the actual problems to analysis, after the network add multiple hidden layer will become multilayer network, through the network in the training to update the model backpropagation error signal weight and threshold to make the training output results better, three layers of BP neural network as shown in Figure 1.

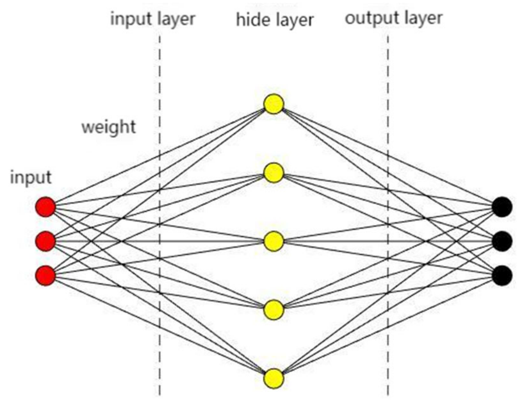

Fig. 1 The BP neural network structure diagram

The x_i in figure 1 is the input data, is the weighted value, is the bias, is the output. w_i θ y The training process of the BP neural network is divided into two stages. The first is the input data forward transfer stage, the input information output operations through weights and thresholds, the second stage is the error back propagation stage, if the training iterations does not reach the set value, or the model output does not meet the desired accuracy, then the network model error back propagation, and through the direction of error reduction. The algorithm steps of the BP neural network are:

Step1:Initialize the model parameters, and set other parameters, such as the number of input layer, hidden layer and output layer nodes;

Step2:Calculate the output of each layer of the network model by initializing the weight and threshold of the model;

Step3:Calculate the error value of the network model through the output and expected output of the network model;

Step4:If the output error does not meet the accuracy, the error backpropagation will be carried out to update the weights and thresholds;

Step5:If the conditions are not met step 4 and the maximum number of iterations is not reached, return to step 2 and continue the calculation.

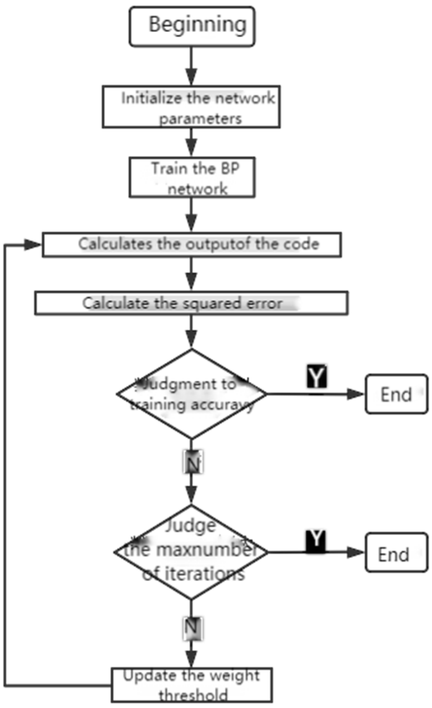

Fig. 2 The flow chart of BP neural network

The timing signal of rolling bearing is complex, and the starting phase is usually inconsistent when sampling, so the signal is different in similar samples. Therefore, before using the timing information of rolling bearing, some important characteristics of different bearing conditions are needed. The most common method to obtaining the bearing information characteristics is analyze the time area, frequency area and time-frequency area, and then input these characteristics as sample information to BP neural network for fault discrimination[16], BP neural network uses the implicit layer set in the model to process the input value, and then uses the output layer of the network model to obtain the processing results. If the deviation between the output value and the expected value does not meet the expected accuracy, the weights and thresholds of each layer can be adjusted by error back propagation until the output result reaches the expectation.

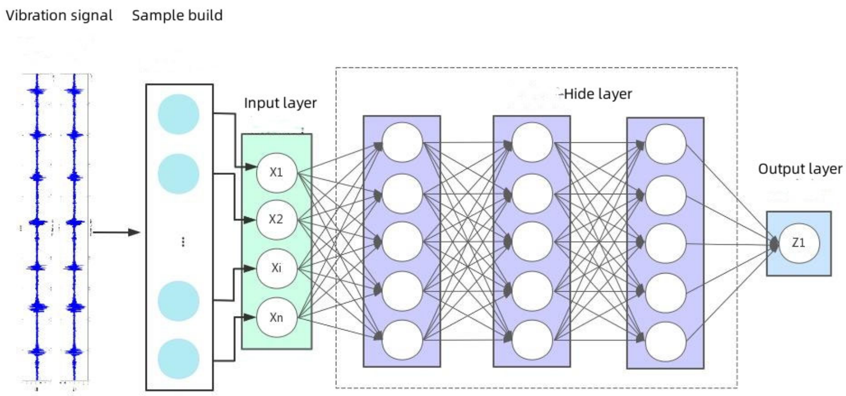

Fig. 3 Schematic diagram of the typical BPNN diagnostic flow

In the test, the bearing vibration signal from the Western Reserve University as the original signal is preprocessed before analysis to improve the reliability and authenticity of the data and check the randomness of the signal, so as to correctly select the analytical processing method. The data was imported into MATLAB, signal preprocessing——zero averaging, time domain analysis and eigenvalue extraction, frequency domain analysis and eigenvalue extraction (FFT), eigenvalue normalization, and BP neural network for pattern recognition. The following data pre-processing, fault bearing G301 as an example, normal bearing Z301 as an example, observe the changes of the original data before and after processing by different methods.

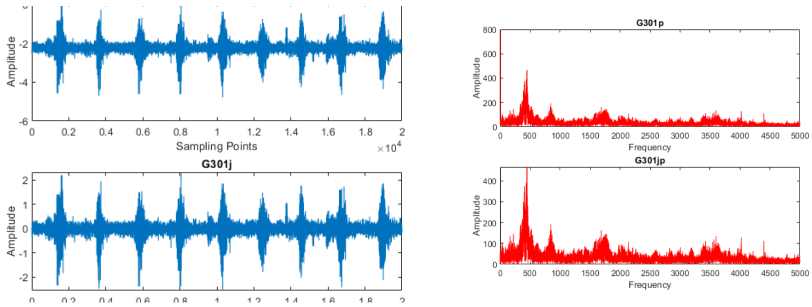

Fig. 4 Data preprocessing:Amplitude and the frequency domain map

In the same method, the characteristics of 10 sets of normal bearings and 10 sets of fault bearings are also extracted, and the following histogram is drawn:

X direction: features of each time domain (1~9, mean, variance, root mean square, peak, cliff coefficient, peak factor, margin factor, pulse factor, waveform factor), frequency domain feature, fft feature value, etc

Y direction: 10 sets of fault bearings, 10 sets of normal bearings

Z direction: eigenvalue contribution

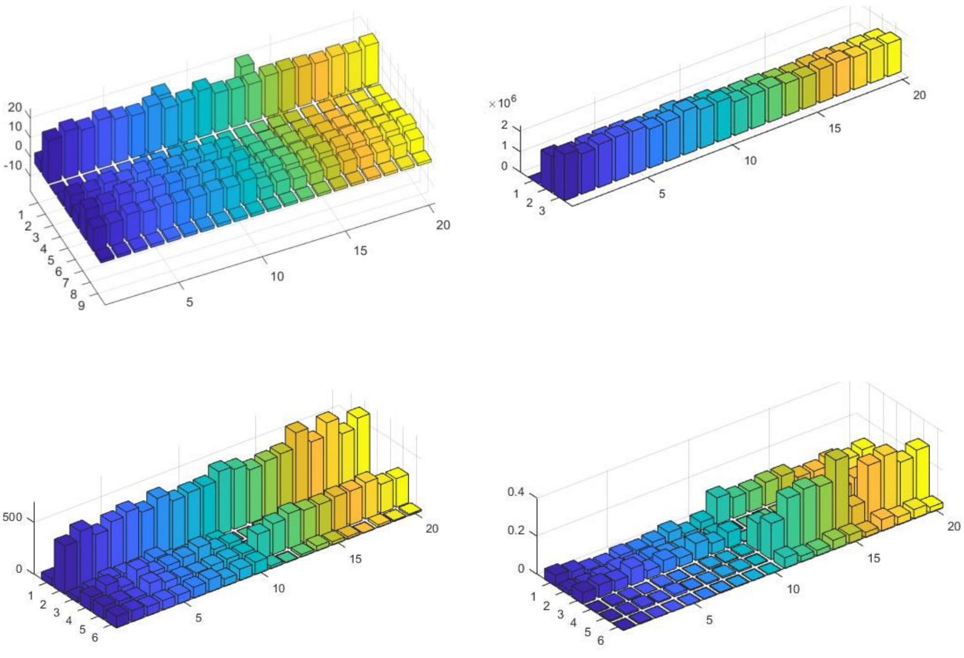

Fig. 5 Histogram of feature values for the top 20 sets of data

To comparing the difference scales between different samples of the same eigenvalue. And considering the input value size of the neural network, we need to normalize all feature values to the 0-1 interval.

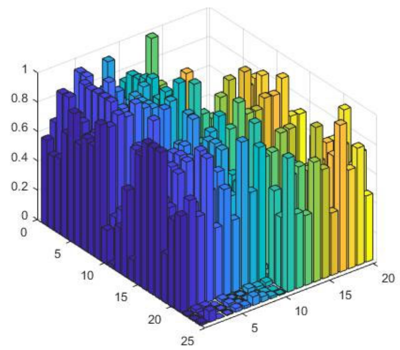

Fig. 6 20 histograms of 24 normalized feature values of data

0-24 the extracted feature values (time domain feature-FFT feature-frequency domain feature-power spectrum feature) can be obtained from the graph. Group 1 and group 11 are not very different in some groups, that is, the mean in the time domain feature and the [(360:450,1)] in the FFT are not very different. Therefore, these two sets of eigenvalues should not be considered when doing the neural network. The effective eigenvalues were 22.

4. Fault diagnosis method of rolling bearing based on BP neural network

During the bearing status monitoring process, the sample data are derived from the effective feature values extracted after the experimental data analysis. Therefore, the number of network input neurons is 22; the network output is bearing state, divided into normal bearing and fault bearing, with (0 1), (1 1) and normal bearing, so only two output neurons are designed in the network to represent these

2 states. In summary, the BP network has 22 neurons in the input layer and 2 neurons in the output layer.

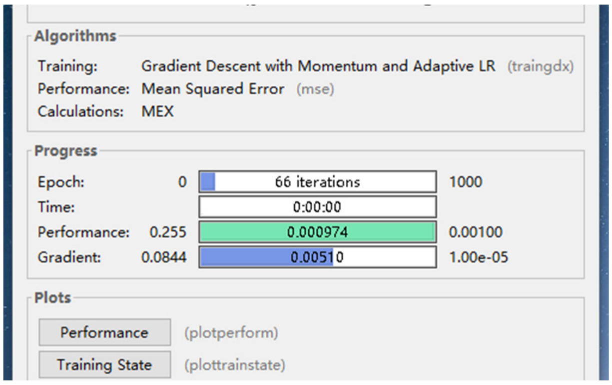

Fig. 7 The BP network structure

To identify the different states of the bearing, a neural network is established to train it. In the present paper, the BP network has 22 neurons in the input layer, 2 neurons in the output layer and 40 neurons in the hidden layer. The number of training steps was 66 steps, and the training error was 0.0009742.

Table 1 The structure of the BP network

Network structure	Number of cryptography	Training function	Target error	The number of input neurons	The number of output neurons
BP Three-tier network	40	traingdx	0.001	22	2

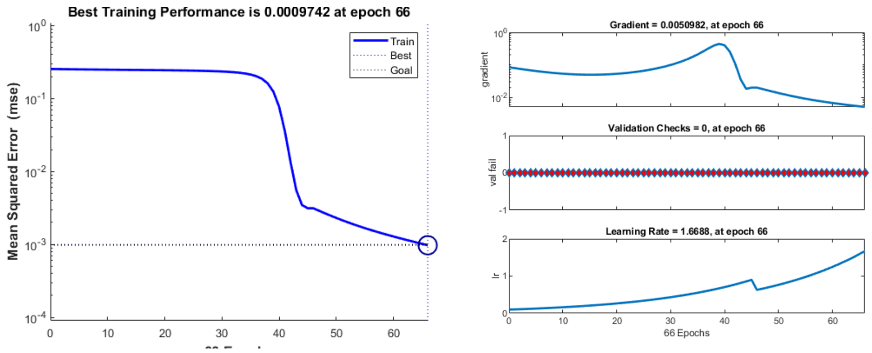

Fig. 8 The BP training status

In the existing related literature, most of the spectrum map or time-frequency map of the original signal conversion is used as the input of the network for fault diagnosis. However, due to the large size of the input image, the number of network model layers used in this method is generally deep. And the network model layer is relatively shallow, if also want to use the same image recognition, if the direct input network can not better extract the relevant features, if the image for certain compression processing will make the image lost some of the original features, also can make the network fault recognition effect is greatly reduced. Moreover, the process of multilayer feature extraction of time-frequency images of signals requires a lot of computing resources, and the model training time is relatively long. In this paper, the original vibration signal is taken as the input of the established network model without excessive processing, which not only realizes the fault diagnosis task well, but also saves some computing resources time relatively.

5. Summary

Based on the requirement of rolling bearing fault diagnosis, this paper presents a method of rolling bearing fault diagnosis based on neural network. Simple transformation of the original data generates a two-dimensional matrix as input, and the fault features are automatically extracted by the neural network, which can accurately identify the running state of the rolling bearing. Through multiple sets of experiments, under the data set used and the network model, the accuracy of the established model for the fault diagnosis and the rationality of the relevant parameters are verified. In the network model of this paper, only a simple transformation of the original data to generate a two-dimensional matrix can be used as input, and a more accurate diagnosis effect can be obtained, and the prediction function of the model can be realized. This method can simplify the process of fault diagnosis to some extent, and make full use of the advantages of the relevant network models to achieve efficient and accurate fault identification, to achieve a good diagnosis effect, and has a certain value of engineering application and theoretical research.

References

[1] Wang Jun. Rolling bearing fault diagnosis. China, 2002,24 (2):27~30.

[2] He Honglin, Feng Liyao, etc. Design of the diagnostic system of the rolling bearing based on the neuron network. Machine Tool and Hydraulic Pressure 2004, No.11.

[3] Zhou Ruifeng. Research and implementation of the intelligent diagnosis method of rolling bearing fault. Dalian University of Technology, 2009.

[4] Chen Jin. Vibration monitoring and fault diagnosis of mechanical equipment. Shanghai: Shanghai Jiao Tong University Press.1999.

[5] Mei Hongbin. Vibration monitoring and diagnosis of rolling bearings [M]. Beijing: Machinery Press, 1995.

[6] Cempel C.Diagnostically Oriented Measures of Vibroacoustical Processes[J].Journal of Sound and Vibration, 1980, 73(4): 547-561.

[7] Wan Shuting, Wu Meiling. Rolling bearing fault diagnosis based on temporal parameter trend analysis [J]. Mechanical Engineering and Automation, 2010 (03): 108-110.

[8] Li Wenfeng, Dai Haomin, Xu Aiqiang. Application of new time domain index and PNN in fault diagnosis of rolling bearing [J]. Mechanical Science and Technology, 2016,35 (9): 1382-1386.

[9] Yan Yuling， Shimogo Taro． Application of the impulseindex in rolling element beating fault diagn osis． Mechanical systems and signal processing,1992,6(2)．

[10] Qiu Xueqing, Zhang Xin. Domestic status and development of rolling bearing fault diagnosis research. Coal mine machinery 2007.6, No.6.

[11] Gustafsson G, Tallian T.Detection of Damage in Assembled Rolli-ng Bearings.Trans.of ASLE.1962

[12] D.Ho and R.B.Randall.Optimisation of bearing diagnostic techniques using simulated and actual bearing fault signals.Mechanical Systems and Signal Processing, 2000

[13] Huang Zhonghua, Xie Ya. Fault diagnosis of rolling bearing inner ring and outer ring based on Hilbert transform [J]. Journal of Central South University (Natural Science Edition), 2011,42 (07):1992-1996.

[14] S.J.Dong, B.P.Tang, R.X.Chen, Bearing Running State Recognition Based on Non-extensive Wavelet Feature Scale Entropy and Support Vector Machine[J], Measurement, 2013, 46(10):4189-4199.

[15] Tang Xianguang, Guo Yu, Ding Yanchun, Zheng Huawen. Rolling bearing envelope analysis based on short-time Fourier transform and independent component analysis [J]. Mechanical strength, 2012,34 (01):1-5.

[16] LI J, YAO X, WANG X, et al.Multiscale local features learning based on BP neural network for rolling bearing intelligent fault diagnosis[J].Measurement,2020,153:107419.