

Research on bearing diagnosis technology based on wavelet transform and one-dimensional convolutional neural network

Dazhi Guo¹, Qiang Wang^{1,*}, Fengyan Wu², Jun Li¹, Mo Li¹, and Yan Jia¹

¹Department of Power Engineering, Naval University of Engineering, Wuhan 430000, China

²Unit 91315, China

Abstract. Aiming at the fault diagnosis of rolling element bearings, propose a method for fine diagnosis of bearings based on wavelet transform and one-dimensional convolutional neural network. First use wavelet transform to decompose the experimental data; Use the resulting low-frequency signal as a one-dimensional convolutional neural network input, bearing fault identification. The experiment uses the deep groove ball bearing of Case Western Reserve University as the research object, Use this method to identify the normal and outer ring faults of the bearing. the result shows: This method can be effectively applied to the precise identification of bearings.

1 Introduction

Bearings are one of the important components in rotating machinery systems, it is widely used in major fields. Because of its importance, how to find the type and location of the fault early and eliminate it is particularly important. P.D. McFadden and M.M. Toozhy combined the time-domain synchronous averaging technique with the high-frequency resonance demodulation technique to analyze the vibration signal of rolling bearings [1]. YF. Wang and P.J. KOotsookOS proposed envelope autocorrelation technology for low-speed rolling bearing fault diagnosis [2]. S. Prabhakar et al. Used Discrete Wavelet Transform (DWT) to analyze the outer ring and inner ring faults of rolling bearings [3]. R. Rubini et al. Used continuous wavelets to extract the excellent characteristics of pulses, and used several frequency cross-section average amplitude spectra to monitor the development trend of rolling bearing faults [4]. Zhou Yuanlong, Dongyang Dou, etc [5-6] select sensitive time and frequency domain indicators to form a fault feature set, and then input the feature set into a probabilistic neural network to efficiently classify single bearing faults. Li Heng, An Jing, etc [7-8] convert time-domain signals into frequency-domain signals through short-time Fourier transform and combine with DCNN network to achieve accurate prediction of bearing failure. In this paper, a combination of wavelet decomposition and one-dimensional convolutional neural network is proposed. The db10 wavelet is used to perform triple wavelet decomposition on the signal, and the resulting low-frequency

* Corresponding authors: 572465625@qq.com

coefficients are used as input to the neural network for fault recognition. Computer simulation of bearing data from Case Western Reserve University was conducted to verify the correctness of the method.

2 Algorithm

2.1 Experimental procedure

First use wavelet decomposition to triple decompose the original signal to obtain triple low-frequency signal and one, two, triple high-frequency signal; then use the obtained low-frequency signal as the input of one-dimensional convolutional neural network for fault recognition; the final result is using wavelet decomposition Comparison of the original data input, and found that this method can effectively improve the recognition accuracy.

2.2 Wavelet transform

Like Fourier transform, wavelet is based on the basis function to fit the measured signal. Different from the Fourier transform, wavelet adopts non-periodic signal. The scaling of different scales of this basis function is used to fit the different frequencies of the measured signal, and then the shift basis function is used to fit different frequency components in the time series (also It is called the position on the space), and finally the coefficients of the basis function after zooming and translation transformation are obtained to form a time-frequency scale map in order to analyze the position and frequency of the abrupt signal. The decomposition process is shown in Figure 1.

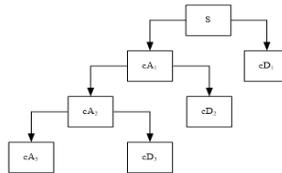


Fig. 1. Decomposition process.

2.3 One-dimensional convolutional neural network

A typical CNN network usually includes an input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer. In the early feature extraction algorithm of CNN, the convolutional layer and the pooling layer are used alternately to extract the input data features layer by layer, and the common output neural network is used to approach the output layer. In the convolutional layer, the convolution kernel performs a convolution operation on the feature vector output from the previous layer, and uses a nonlinear activation function to construct the output feature vector. The output of each layer is the convolution result of the multi-input feature. The input of a 1D CNN network is one-dimensional data, so its convolution kernel also adopts a one-dimensional structure, and the output of each convolutional layer and pooling layer also corresponds to a one-dimensional feature vector. The model is shown in Figure 2.

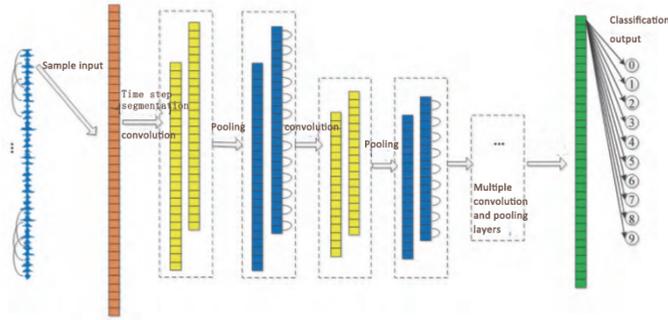


Fig. 2. One-dimensional convolutional neural network model.

3 Experimental data

In order to verify the effectiveness of the method in this chapter, this paper selects Case Western Reserve University (CWRU) as the verification data. The bearing is set to four sizes of fault diameter by EDM, which are 7, 14, 21, and 28 inches, respectively. In the experiment, an acceleration sensor was used to collect vibration signals. The sensors were placed on the motor drive end and the fan end, respectively. Because the vibration signal data collected by the drive end is comprehensive, and there is less interference from other components and environmental noise, this article selects the vibration signal collected by the drive end as the experimental data. The number of sampling points selected is 2048, the speed is unstable, but they are all maintained at about 1800rpm, and the normal and outer ring fault data are taken.

4 Simulation of rolling bearing fault diagnosis

4.1 Wavelet decomposition

The time and frequency domain diagrams of the original signal are shown in Figure 3.1-3.2. It can be clearly seen that the normal signal is relatively stable, the amplitude fluctuation is small, the amplitude of the fault signal increases, and periodic glitches appear on the time domain diagram. On the frequency domain diagram, the normal signal frequency is a single low frequency, and the fault signal has a resonance frequency, which is higher. The difference between the normal signal and the fault signal can be seen from the time-frequency diagram.

Using db10 as the fundamental wave, three-layer wavelet decomposition is performed on the original vibration signal to obtain the corresponding high-frequency coefficients and low-frequency coefficients, as shown in Figure 4.1-4.2. Among them, A3 is the low-frequency coefficient of the third layer, and D1, D2, and D3 are the high-frequency coefficients of the first, second, and third layers, respectively.

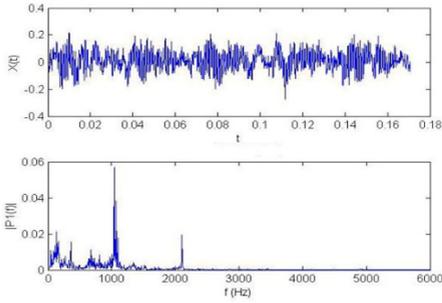


Fig. 3.1 Normal

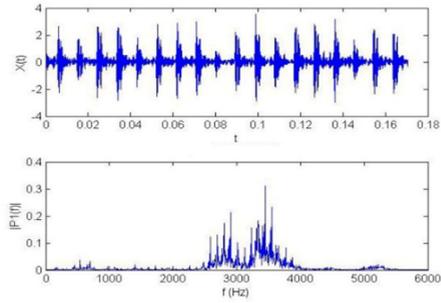


Fig. 3.2 Outer ring failure

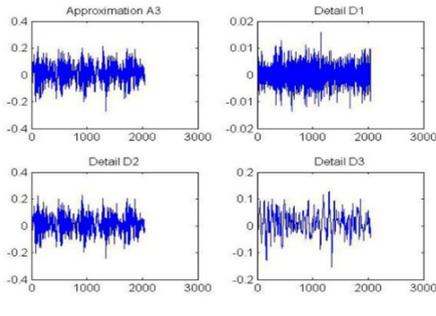


Fig. 4.1 Normal

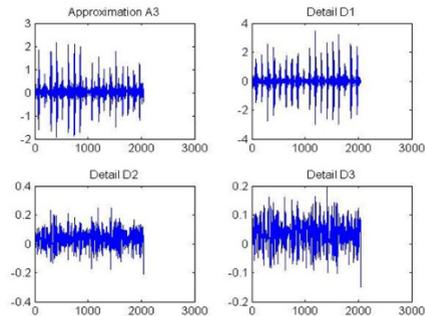


Fig. 4.2 Outer ring failure

As can be seen from A3, D1, D2, D3 in Figure 4.1-4.2, the impact amplitude of the normal signal is small, and the fault signal has a relatively large impact. The signals of different frequency bands obtained after wavelet decomposition can clearly see the noise. Through continuous decomposition of the signal, more and more high-frequency information is filtered out, and the noise is getting smaller and smaller. The resulting A3 low-frequency signal appears smoother than the original signal. Therefore, the A3 low-frequency signal is selected as the input of the one-dimensional convolutional neural network.

4.2 Fault recognition based on one-dimensional convolutional neural network

To further identify the fault, a one-dimensional convolutional neural network is used to process the time series of vibration. All the normal and outer ring fault data are obtained by the above method of this article to obtain the A3 low frequency coefficient, the data is divided with 6000 points as the step size, and the overlap degree is set to 80%. The classification label is shown in Table 1. Get a total of 800 pieces of data, select 600 pieces for training, and 200 pieces for testing.

Table 1. Sample data distribution.

Type of data	Fault size	Label	Training set	Test set
Normal	0 in	0	150	50
Outer ring failure	7 in	1	150	50
	14 in	2	150	50
	21 in	3	150	50

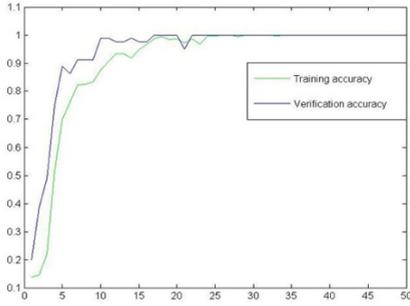


Fig. 5.1 training accuracy curve.

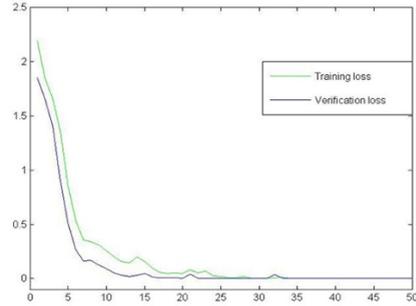


Fig. 5.2 training loss curve.

Table 2. 1DCNN model diagnosis results.

Type of data	Label	Accuracy
Normal	0	100%
Outer ring failure	1	99.8%
	2	100%
	3	100%

The one-dimensional convolutional neural network used in this article contains four convolutional layers, four pooling layers, a Dropout layer and a fully connected layer activated using Softmax. The Adam optimizer is selected through debugging, the learning rate is 0.0002, and the batch size is 20. The training results are shown in Figures 6.1-6.2. It can be seen from Figures 6.1-6.2 that after 20 iterations of training, the model network tends to be stable, the training accuracy reaches 100%, and the loss function tends to 0 ; the accuracy in the verification set also tends to 100%. The model is applied to the test set, and the average results of 10 tests are shown in Table 2, with an average accuracy rate of 99.95%. For the same model identification using the original data, the accuracy rate is 96% under the same number of iterations. The data results show that the method has high accuracy, and can be applied to accurately identify bearing faults.

5 Conclusion

This paper proposes a method based on the combination of wavelet transform and one-dimensional convolutional neural network. This method uses the denoised signal after wavelet transform as the input of the neural network to accurately classify the bearing fault size. The following conclusions are obtained through simulation :

- 1) Using low-frequency coefficients obtained by wavelet decomposition as neural network input can greatly improve training accuracy and reduce noise errors.
- 2) The 1DCNN model has a high fault recognition rate for the refined diagnosis of bearings, with an average accuracy rate of 99.95%.
- 3) The model combines the wavelet decomposition theory, and the accuracy of this method is improved compared with the original data recognition.

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