Fault diagnosis of rolling bearing based on multi-scale one-dimensional convolutional neural network

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Abstract. Aiming at the typical non-stationary and nonlinear characteristics of rolling bearing vibration signals, a multi-scale convolutional neural network method for bearing fault diagnosis based on wavelet transform and one-dimensional convolutional neural network is proposed. First, the signal is decomposed into multi scale components with wavelet transform, and then each scale component is reconstructed. The reconstructed signal is subjected to the Fourier transform to obtain the frequency spectrum representation, which is used as the input of the one-dimensional convolutional neural network. Finally, one-dimensional convolution neural network is used to learn the features of the input data and recognize the bearing fault. The performance of the model is verified by using data sets of rolling bearing. The results show that this method can intelligent feature extraction and obtain 99.94% diagnostic accuracy.

1. Introduction
Rolling bearing is one of the most vulnerable parts of rotating machinery, and about 1/3 of the mechanical faults in rotating machinery are caused by rolling bearings [1]. In order to avoid the economic losses and security risks caused by bearing faults, it is particularly important to monitor, analyze and diagnose the rolling bearing faults in time.

At present, the process of bearing fault diagnosis mainly includes three aspects: data preprocessing, feature extraction and feature classification [2]. Traditional fault diagnosis mainly uses time domain, frequency domain and time-frequency domain analysis to obtain features. Multi-dimensional fault features are extracted by time-frequency domain analysis methods such as local feature scale decomposition, wavelet transform (WT), empirical mode decomposition (EMD) and so on, which are used as the basis of pattern recognition [3]. Among them, wavelet transform (WT) has solid mathematic foundation, and can decompose the vibration signals into multi-scale. Wang et al. [4] used discrete wavelet transform and sparse
representation to obtain new sparse wavelet energy features to identify rolling bearing faults. Shen et al. [5] developed a bearing intelligent fault diagnosis method based on wavelet transform and support vector regression. All of the above methods need to extract features manually, which depends on professional experience.

Recently, deep learning is widely used in pattern reorganization, especially in image processing, computer vision [6]. Deep learning model can directly extract abstract features from the original signal without manual feature extraction. With its powerful nonlinear modeling and feature representation ability, deep learning shows great potential in any aspects, many scholars have applied deep learning to mechanical equipment fault diagnosis [7][8].

Deep convolution neural network (CNN) is a typical deep learning model. Compared with other models, CNN has good generalization ability and robustness [9]. At present, CNN has been applied in bearing fault diagnosis methods, mainly including one-dimensional and two-dimensional convolutional neural network. In the fault diagnosis of bearing, because the input signal is one-dimensional, the classical two-dimensional CNN model needs to convert one-dimensional signal into two-dimensional image, so the one-dimensional convolution neural network model is used to diagnose the one-dimensional vibration signal of bearing. In order to avoid the influence of learning only one-dimension feature on the diagnosis accuracy, it is necessary to use wavelet transform to decompose the original signal into multi-scale components, reconstruct each scale component of the obtained signal, and construct a spectrum representation conducive to feature learning, so as to learn more useful fault feature information.

To sum up, aiming at the non-stationary and non-linear characteristics of rolling bearing vibration signal, wavelet transform is used for multi-scale analysis to accurately extract the different fault state feature information contained in time-frequency domain, and then it is brought into the one-dimensional convolution neural network model for feature learning and classification to realize intelligent fault diagnosis.

2. Theoretical Basis
2.1 Wavelet Transform
In the squared integrable real number space $L^2(R)$, if the function $\psi(t)$ satisfies the admissible condition:

$$C_{\psi} = \int_{-\infty}^{\infty} \frac{\vert \psi(t) \vert^2}{t} dt < \infty$$  \hspace{1cm} (1)

Then $\psi(t)$ can be used as the basic wavelet. $\psi(t)$ generates a family of functions $\{\psi_{a,b}(t)\}$ through scaling and translation, which is called wavelet function:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right)$$  \hspace{1cm} (2)

where $a$ is the scale factor and $b$ is the displacement factor wavelet transform of signal $x(t)$ is defined as:

$$WT_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \times \psi^\ast\left(\frac{t-b}{a}\right) dt$$  \hspace{1cm} (3)

where $\psi^\ast(t)$ is a conjugate of the wavelet function $\psi(t)$.

2.2 One-dimensional convolutional neural network
The network is composed of input layer, convolution layer, batch normalization (BN), pooling
layer, full connection layer, dropout layer and output layer. The training process can be divided into two parts. The forward propagation is a neural network to calculate the predicted value according to the samples; Back propagation uses gradient descent method to update the weights.

1) Forward propagation calculation process

One-dimensional convolution process can be expressed:

\[ x_j^l = F\left(\sum_N \text{Conv1D}(x_{i-1}^j, k^j_l) + b^j_l\right) \]  

(4)

where \( k \) is the convolution kernel, \( j \) is the number of convolution kernels, \( N \) is the convolution calculation area, \( i \) is the it data, \( x_{i-1}^l \) is the convolution input of the first \( l \) layer, \( x^l \) is the convolution output, \( \text{Conv1D}() \) is one-dimensional convolution calculation, \( b^l \) is the bias, \( F() \) is the activation function. The activation function is Relu function.

2) Error reverses propagation process

The chain derivation rule is used to update the parameters. Assuming that the error of convolution transfer is known to be \( \nabla x^l \), then the error \( \nabla x^{l-1} \) of the upper layer and the error \( \nabla w^l \) of the parameter to be updated are as follows:

\[ \nabla x^{l-1} = \frac{\partial L}{\partial x^{l-1}} = \nabla x^l \cdot \frac{\partial x^l}{\partial x^{l-1}} \]  

(5)

\[ \nabla w^l = \sum_i \frac{\partial L}{\partial w^l} = \sum_i (\nabla x^l \cdot \nabla w_{i,p-1}) \]  

(6)

where, \( L \) is the objective function, \( x^{l-1} \) is the original value of the upper layer, \( w \) is the parameter to be updated.

3. WT-1DCNN diagnosis model and process

The intelligent diagnosis of rolling bearing using the diagnosis model based on multi-scale one-dimensional convolutional neural network can be divided into the following 8 steps, as is shown in Figure 1.

**Figure 1. Fault diagnosis process**

1) The time domain signals of rolling bearing working state are collected by sensors;
2) The multi-scale representation of the signal is obtained by wavelet transform;
3) Each layer of wavelet signal is reconstructed by a single branch;
4) The amplitude spectrum of the reconstructed signal is obtained by Fast Fourier Transform;
5) Normalize the obtained amplitude data, and construct each scale data into a one-dimensional feature vector;
6) The feature samples are divided into training samples, verification samples and testing samples according to a certain proportion;
7) Construct a one-dimensional convolutional neural network model, use training samples to train the model, and verify with verification samples, and finally get a diagnosis model;
8) Input the testing sample into the model for verification, and get the final diagnosis accuracy.

4. Experimental verification and analysis

4.1 Data Description
The experimental data comes from CWRU [10]. The experimental platform consists of a motor, a coupling and a load motor, the bearing to be tested is the motor drive end bearing. The failure of the bearing is a single point damage simulated by EDM. The state of the bearing can be divided into normal (N), inner ring failure (IF), rolling element failure (BF) and outer ring failure (OF), according to the damage degree of the failure (fault diameter), each type of failure can be divided into mild (fault diameter 0.18mm), moderate (fault diameter 0.36mm), and severe (fault diameter 0.53mm) three different degrees of failure. The motor runs under four loads of 0, 1, 2, and 3 hp, and the speed is 1800 rpm. The experiment contains two sampling frequency: 12 kHz and 48 kHz. This article uses the data collected under the sampling frequency of 12 kHz as the experimental data. In this experiment, the data set is divided into 10 health states; each health state has a total of 400 data samples, a total of 4000 data samples. 70% of the characteristic samples are randomly selected as training samples, the remaining 30% as test samples, and 30% of the training samples as verification set.

4.2 Model building
According to the 10 state data samples of rolling bearings, db5 wavelet is used for 3-layers decomposition, then the wavelet signal of each layer is reconstructed into a single branch, and the reconstructed signal is subjected to fast Fourier transform to obtain a spectrum representation. The obtained spectrum data is normalized and constructed into a one-dimensional feature vector, which is used as the input of the 1DCNN model.

The neural network framework is keras. When constructing 1DCNN model, there are 11 layers of network, including input layer, 3 convolution layers, 3 BN layers, pooling layer, dropout layer, full connection layer and output layer, as shown in Table 1.

| Table 1. One-dimensional convolutional neural network structure |
|-------------|-----------------|------|
| Layer type   | Output Shape    | Param |
| Input        | (None, 2048)    | /     |
| Conv1D_1     | (None, 128,128) | 8320  |
| Batch Normalization_1 | (None, 128,128) | 512   |
| Conv1D_2     | (None, 128,64)  | 24640 |
| Batch Normalization_2 | (None, 128,64) | 256   |
| Conv1D_3     | (None, 128,32)  | 6176  |
| Batch Normalization_3 | (None, 128,32) | 128   |
| Max Pooling1D| (None, 64,32)   | /     |
| Flatten      | (None, 2048)    | /     |
| Dropout      | (None, 2048)    | /     |
| Output       | (None, 10)      | /     |

4.3 Result and discussion
For the testing samples, in order to avoid the error caused by one experiment data, 10
experiments were carried out. The accuracy of the test set is 99.74% to 100%, and the average accuracy of 10 experiments is 99.94%, which indicates that the model selected in this experiment has good stability.

In order to show that wavelet transform can accurately extract fault features for non-stationary vibration signals, the original signal is directly input into 1DCNN, and the feature samples after wavelet transform are input into the same 1DCNN model for comparison. After 10 experiments, as shown in Figure 2 the average accuracy of 1DCNN is 98.02%, while the average accuracy of WT-1DCNN is 99.94%.

In order to verify the superiority of the method proposed in this paper, the relative data sets are compared with different methods. Du et al [11]. developed a method for diagnosing rolling bearing faults (Wavelet Leaders) based on the multifractal features of wavelet leadership, and got 88.9% accuracy. Li et al [12]. proposed a fault diagnosis method based on short-time Fourier transform and CNN (STFE-CNN), which realized end-to-end fault pattern recognition, and the accuracy rate was 97.93%. Min et al [13][13]. proposed a CNN-based multi-sensor fusion method (MCNN), which fused the signals of multiple sensors and input them into CNN to diagnose the 10 health states of the bearing, with a 99.41% correct rate. Ding et al [14]. proposed a new energy fluctuation multi-scale feature mining method (WPE-2DCNN) based on wavelet packet energy (WPE) images and two-dimensional deep convolutional networks, which was used for bearing fault diagnosis, and the accuracy rate reached 98.8. %.

Comparing the five methods, the results are shown in Figure 3. It can be seen that the WT-1DCNN method used in this article has the highest fault diagnosis accuracy.

![Figure 2. 1DCNN and WT-1DCNN](image-url)
5. Conclusion

In order to solve the problem that the artificial feature extraction in bearing fault diagnosis depends on experience and has weak generalization and adaptability, a multi-scale one-dimensional convolution neural network is proposed for bearing fault diagnosis. Compared with other diagnosis methods, the method is as follows advantage.

Compared with traditional intelligent diagnosis methods, the use of wavelet transform to perform multi-scale analysis of signals can more effectively dig out the hidden feature distribution in fault data, and establish a complex nonlinear relationship between fault features and bearing faults.

One dimensional convolution neural network is used to train the input one-dimensional signal, which effectively integrates feature automatic learning and fault classification, avoids the dependence on complicated signal processing technology and rich diagnosis experience, simplifies the actual diagnosis process and achieves good diagnosis effect.

Acknowledgments

This work was supported by the National Nature Science Foundation of China (Grant No. U1804141), the Key Scientific Research Projects of Colleges and Universities in Henan Province (Grant No. 21A460033), the Foundation for University Key Teacher of Henan Educational Department (Grant No.2018GGJS091), the Program for Innovative Research Team in University of Henan Province (Grant No. 20IRTSTHN015), and the key specialized and development projects in Henan province(No.202102310257).

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