Feature extraction and recognition of rotating machinery fault noise based on convolutional neural networks

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Abstract. Rotating machines are common equipment in industrial production, which may cause failure for a long time. Because of its convenient use and non-destructive to itself, acoustic detection method is suitable for fault diagnosis of rotating machinery. The convolution neural network model is used to identify several typical rotating machine faults. The repeatability experiments and different training sets show that the method has good universality. A visual fault identification system is built, and the effect of the system is verified by experiments.

1. Introduction
With the continuous improvement of science and technology since the industrial revolution, mechanical equipment used in industrial production has become more and more complex. How to detect, diagnose and predict the life of each module of mechanical equipment has become an important research topic over the years[1]. And rotating machinery is basically the core component of all mechanical equipment[2]. It is widely used in many fields (such as aerospace, chemical industry, petroleum, manufacturing, transportation and energy). Once a component fails during operation, it will often involve the entire mechanical equipment and cause unpredictable losses[3]. In severe cases, catastrophic events and casualties occurs multiple times[4-5]. Therefore, fault diagnosis is of great significance to ensure the safe and reliable operation of mechanical equipment[6]. If the equipment operation can be monitored and diagnosed in real time through modern scientific and technological means, the faulty equipment can be alerted immediately or early warning before it occurs. For example, the sound sensor of the array collects the sound of the equipment running state, and diagnoses the location and severity of the fault through the sound[7].

2. Extraction of noise feature of rotating machinery failure

2.1. Sound signal preprocessing
Since the parameters of the equipment vary greatly during operation, even if the same sound sensor and computer recording equipment are used, the sound data collected each time also has a big change, and as the noise continues to be generated during the operation of the equipment, there will be differences between the collected sound samples. So we need to reduce the difference between different samples, so the normalization method is used to make the amplitude of the sound concentrated between 0 and 1, making the data more stable and convenient for calculation and processing.
Commonly used normalization methods include standard normalization and maximum and minimum normalization in others paper[22]. This paper uses maximum and minimum normalization in the experiment process, and the formula is shown in 1:

$$X_m = \frac{(x - x_{\min})}{x_{\max} - x_{\min}}$$  

(1)

In the formula $x_{\min}$ — Minimum signal amplitude  

$x_{\max}$ — Maximum signal amplitude

The sound signal collected when the equipment is running is an unsteady signal. However, in a very short period of time, the sound has the characteristics of stability, and the sound signal to be processed is required to be smooth and continuous when the short-time Fourier transform is subsequently performed. Therefore, this paper will process the sound signals collected by the capture card into frames.

Because the collected sound signals are affected by the environment, a silent experimental environment cannot be achieved. The abnormal sound reflected on the indoor wall and some other parts are mixed, which has strong noise pollution. Therefore, in order to improve the quality of the sound source, filtering and noise reduction before fault feature extraction becomes very important. The commonly used filtering methods mainly include singular value decomposition filtering[23], wavelet threshold filtering[24] and empirical mode filtering[25].

2.2. Wavelet transform

The wavelet transform turns it into a wavelet base with finite length and attenuation. In this way, the localizing time and frequency can be obtained at the same time. The process of continuous wavelet transform is to obtain a series of wavelet sequence $\psi_{\alpha,b}(t)$ through the translation and expansion of wavelet basis function $\psi(t)$, thereby decomposing the original signal into different frequency components, as shown in the formula:

$$\psi_{\alpha,b}(t) = \frac{1}{\sqrt{\alpha}} \psi \left( \frac{t - b}{\alpha} \right), \alpha > 0, b \in \mathbb{R}$$  

(2)

In the formula, parameter $a$ represents the scale factor to determine the position of the wavelet time-frequency window in the frequency domain. The parameter $b$ represents the translation factor, which determines the position of the wavelet time-frequency window in the time domain. Therefore, assuming $x(t) \in L^2(\mathbb{R})$, according to the wavelet sequence, the wavelet transform is as shown in the formula:

$$CWT_x(a,b) = \int_{-\infty}^{\infty} x(t) \psi_{\alpha,b}(t) dt = \frac{1}{\sqrt{\alpha}} \int_{-\infty}^{\infty} x(t) \bar{\psi} \left( \frac{t - b}{\alpha} \right) dt$$  

(3)

Where $\bar{\psi}_{\alpha,b}(t)$ is the complex conjugate of $\psi_{\alpha,b}(t)$, the wavelet transform is reversible, and the inverse of the wavelet transform is:

$$x(t) = \frac{1}{C_{\psi}} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \psi_{\alpha,b}(t)CWT_x(a,b) \frac{1}{\alpha} d\alpha db$$  

(4)

In the formula,$C_{\psi} = 2\pi \int_{-\infty}^{\infty} \frac{|\tilde{\psi}(\omega)|}{|\omega|} d\omega$.

Common wavelet functions include Haar wavelet, Daubechies (dbN) wavelet, Morlet wavelet, Coiflet wavelet, Meyer wavelet, etc.

2.3. Time-frequency characteristic performance

In order to analyse the time-frequency characteristic method of wavelet, this section collects a section of normal and abnormal sound signals of nuclear power plants for time-frequency analysis. The signal time-domain waveform diagram and frequency-domain waveform diagram of the rotating machinery in normal operation are shown in Figure 1:
Figure 1. Time domain and frequency domain waveforms of motor fault signal

It can be seen from the figure that if you only look at the relationship between time and amplitude or frequency and amplitude, less information can be obtained. It can only be seen that the signal frequency of the motor rotation is mainly concentrated in the low frequency band. Therefore, we use the wavelet time-frequency analysis method to analyze the signal.

Further analyzing the performance, this paper created a rotating mechanical load fault based on the original rotating mechanical operation, which also contains a normal signal and a fault signal. The time-frequency diagram of the wavelet transform of the fault signal is shown in the figure below:

Figure 2. Four time-frequency diagrams of wavelet transform
Through the analysis, it can be seen that the wavelet transform can see the difference between the normal and the fault of the motor, the signal affected by noise is small, it has good time and frequency resolution, and the energy is relatively concentrated, and the frequency fluctuation is small. Through the above analysis, it is shown that the time-frequency diagram can be used as the information of detecting signal failure, but it also has information that cannot be seen by the human eye. We use convolutional neural networks to learn, feature extraction and classification of the collected signal time-frequency maps, and finally achieve the purpose of classifying signal faults.

3. Fault noise classification based on convolutional neural networks

3.1. Neural network

Over the years, convolutional neural networks have been widely promoted in the fields of artificial intelligence, face recognition, voice interaction, and autonomous driving. Convolutional neural network is composed of input layer, convolutional layer, pooling layer and fully connected layer. This section will introduce the basic structure of neural network. Its basic structure is shown in Figure 3.

![Convolutional neural network structure diagram](image)

Figure 3. Convolutional neural network structure diagram

3.2. Data set

The experiment collected signals of different time and different conditions for bearing failure, load failure, coupling failure and normal conditions. When the bearing fails, it is considered that the bearing is wounded, and the same four bearings are wounded with depths of 2.0mm, 3.0mm, 4.0mm, and 5.0mm respectively. Load failures are mainly caused by loose fan blades, and fan blades have been wounded with depths of 1.0mm, 2.0mm, and 3.0mm. Coupling failures are mainly caused by wounds on the inner ring, ball and outer ring. The eleven states collected signals at different speeds of the species.

The eleven states are classified into four categories, the collected data is segmented, the sampling frequency is 44100, and the second is divided into one segment, and a time-frequency diagram is made every second. Since the pixel size of the image affects the calculation speed of the convolutional network, we save the time-frequency map as a pixel-by-pixel picture, which collects and analyzes a total of 6000 time-frequency maps of four types of faults and different states, and sets the labels. Among them, the training set is 4800 and the test set is 1200. The recognition rate Acc and the loss function loss are used as the recognition performance standard of the neural network algorithm. The fault types are shown in the following table:
### Table 1. Fault type setting

| Object      | Failure type         | Failure size | Number of fault points |
|-------------|----------------------|--------------|------------------------|
| Bearing     | Bearing wound        | 1 mm         | 1                      |
|             |                      | 2 mm         | 1                      |
|             |                      | 3 mm         | 2                      |
|             |                      | 4 mm         | 1                      |
|             |                      | 1 mm         | 1                      |
| Load        | Load fan loose       | 2 mm         | 1                      |
|             |                      | 3 mm         | 1                      |
|             | Inner ring wound     | 1 mm         | 1                      |
| Coupling    | Outer ring wound     | 2 mm         | 1                      |
|             | Ball wound           | 3 mm         | 1                      |
| Normal      | Normal               | None         | None                   |

3.3. Test and performance comparison

In order to demonstrate the applicability of the network proposed in this paper, without changing the network structure, this paper collects four states of different motors at different speeds. The same collection equipment as the previous sample has doubled the speed and collected a total of 8280 samples. The specific sample classifications are shown in the following table:

### Table 2. Data set collected in the experiment

| Failure type     | Training data | Verify the data | Test data |
|------------------|---------------|-----------------|-----------|
| Bearing failure  | 1500          | 250             | 258       |
| Load failure     | 1500          | 300             | 300       |
| Coupling fault   | 1400          | 300             | 300       |
| Normal fault     | 1600          | 250             | 250       |

In the previous experiments, the data set was divided into training set, test set, and verification set in sequence according to the sampling order. This time a crossover experiment is used to randomly select 1000 images from the training set, and then randomly select 200 images from the remaining time-frequency diagrams as the verification set. Repeat the experiment five times. The experimental results are shown in the figure below.

![Figure 4. Experimental results of the crossover experiments](image)

It can be seen that the neural network model constructed in this paper has good applicability for the identification of rotating machinery faults. It can also achieve a high recognition rate for different data sets, with high stability, and no messy recognition.

For this research on fault recognition, many scholars have proposed a variety of network model frameworks, such as: Yuan et al. proposed a mechanical fault diagnosis model based on HHT transformation and CNN algorithm. LinKai et al. proposed a fault diagnosis framework based on sparse autoencoders. Zhu et al. proposed a diagnosis method based on support vector machines and improved...
evidence theory to realize the diagnosis of different faults under mixed conditions. Xie et al. proposed a fault diagnosis method for nuclear detectors based on BP neural network, which effectively improves the fault diagnosis frequency of nuclear detectors. Chen et al. proposed a fault diagnosis model based on the PCA-KNN fusion algorithm. Adjust the parameters of the above algorithm to the optimal, use the data set collected and established in this paper to compare with the neural network model of this paper, the recognition accuracy rate corresponding to the test set is shown in the following table:

| The Algorithm     | Failure type | Accuracy rate: % |
|-------------------|--------------|------------------|
| SVM               | 4            | 93.24            |
| HHT-CNN           | 4            | 89.88            |
| BP                | 4            | 86.26            |
| PCA-KNN           | 4            | 90.12            |
| The framework in this paper | 4 | 96.05 |

4. Conclusion
By comparing several fault diagnosis algorithms, from the final recognition accuracy respectively, the algorithm framework in this paper has the highest recognition accuracy, which can reach 96.02%. And in terms of convergence speed, the network designed in this paper can reach convergence after more than 100 iterations, which can not only meet the needs of fault identification, but also achieve good results in different rotating mechanical sound signal training sets.

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