Bearing fault diagnosis based on XWT-CEEMD noise reduction

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Abstract—In recent years, bearing fault diagnosis has been a research hotspot. In order to improve the reliability of acoustic fault diagnosis, this paper combines Cross Wavelet Transform (XWT) and complementary ensemble empirical mode decomposition (CEEMD) to extract bearing fault features from acoustic signals. Finally, the time-domain features and spectral centroid are input into the SVM for fault classification. The results show that the proposed method can effectively improve the reliability of acoustic fault diagnosis.

1. Introduction
Rolling bearing is the most common component in rotating machinery. The failure of traction motor bearing directly affects the operation safety of railway transportation system. When the bearing fails but is not found, it will lead to train derailment, resulting in disastrous accidents and huge economic losses. Therefore, it is necessary to monitor the condition of the train bearing to determine the fault condition of the bearing, and then decide whether to repair or replace the bearing.

The diagnosis method based on vibration signal has been gradually improved and has always been the mainstream of bearing diagnosis methods in China [1]. However, the vibration signal must be obtained by contact measurement, which is limited in some cases, especially for the test elements with irregular structural surface or in harsh test environment, such as high temperature, high humidity or corrosive environment. On the contrary, fault diagnosis based on sound signal is very useful in bad environment. Only acoustic emission sensors or microphones need to be placed around the equipment to collect fault data, which can avoid the impact of harsh environment.

Acoustic based diagnosis technology has the advantage of finding early faults. Under the conditions of normal load, rotating speed and good alignment, the surface damage begins with small cracks between the flat rail surface and the rolling element, which gradually expand and propagate to the surface to produce detectable acoustic emission signals [2]. Studies have shown that when a bearing fails, the fault feature is first reflected in the acoustic signal. Even before the fault defect is about to occur on the bearing surface, the fault sound feature has appeared [3]. Therefore, sound signal can be successfully applied to the field of fault diagnosis of rotating machinery. And Tandon and Chaudhary (1999) inferred that the diagnostic effect of sound signal is better than that of vibration signal [4]. MBA and Rao summarized the application of acoustic emission (AE) technology in rotating machinery, indicating that AE signal can be used in fault diagnosis, life prediction and other fields [5]. Alghamd and MBA studied the relationship between the time domain parameters of the collected sound signal and the fault size. The results show that the size of the fault size will change the statistical parameters of the corresponding AE signal [6]. In the process of practical application, due to the existence of noise, the effect of fault diagnosis based on acoustics will be affected. Noise reduction
of signal can effectively improve the reliability of fault diagnosis. Whether for acoustic-based diagnosis or vibration-based diagnosis, in essence, it is necessary to analyze the time-frequency domain of the signal and then extract the fault frequency feature[8].

In this paper, the work focuses on traction motor bearings fault diagnosis basing on sound signals collected with microphone. Sound signals are non-linear and non-stationary. EMD is one of the most widely used time-frequency analysis methods for processing non-linear and non-stationary signals[9]. In recent years, many scholars have proposed many bearing fault diagnosis methods based on EMD[10, 11]. Because EMD itself has some disadvantages, such as end effect and mode aliasing problems, many researchers have proposed some improved EMD methods, for example EEMD[12], CEEMD[13] and so on. These improvements have solved the defects of EMD to a certain extent. For every improvements, the calculation time cost are both large.

XWT was originally mainly used for local climate analysis[7]. In this paper, it is used in bearing fault diagnosis. The innovations and main contributions of this paper are as follows: the application of XWT in acoustic signal processing is studied, and CEEMD method is combined with XWT to identify fault features, and good results are achieved. This study provides ideas for subsequent scholars to use XWT for bearing fault diagnosis. In this paper, a complete machine learning fault diagnosis method of acoustic signal noise reduction is proposed. Firstly, the acoustic signals during motor operation are collected from four directions around the motor to obtain the comprehensive information characterizing the fault as much as possible. The noise frequency band and the main frequency division of the signal are identified by combining the cross wavelet transform, and then the frequency band of multi-channel signals is divided by ceemd. Signals in different frequency bands are selected based on wavelet coherence spectrum, and the denoised characteristic signals are reconstructed. Finally, SVM is used to classify the fault type to verify the effectiveness of the proposed method.

2. Motor bearing fault experiment
The schematic diagram of the test bench is shown in figure 1. The experimental platform includes a yq-625kw traction motor with a maximum speed of 5600rpm, four microphones and electronic controller (not indicated in the figure 1).

![Diagram of experimental platform](image)

**Figure 1. Experimental platform**

Bearing to be inspected: The bearing installed at the drive end of the motor is NU214 cylindrical roller bearing. Bearing specifications are as below table:

| Number of rollers | External diameter | 120mm |
|------------------|-------------------|-------|
| Roller diameter  | Internal diameter | 55mm  |
| Pitch diameter   | Width             | 29mm  |

Fault setting: severe single point damage was produced by laser etching. Damage occurs at the cage, inner ring, outer ring and roller of the bearing respectively. There are 4 faults in total.

Signal acquisition: Install the processed fault bearing into the motor, set the motor speed to 2414 rpm, and the electronic controller controls the electrical frequency to 80.5hz to simulate the operation of the train at 160km / h. Due to the motor structure, the sound heard in different directions of the motor will be a little different. Place 4 microphones at 0, 3, 6 and 9 o'clock at the far end respectively.
The sampling frequency is set to 54.94 kHz. The test bench is used to collect the data of the four fault types. The length of collected data is shown in table 2.

| Fault type                  | Sampling duration /s | Sampling points sum       |
|-----------------------------|----------------------|---------------------------|
| Cage severe fault           | 205                  | 11262700                  |
| Roller severe fault         | 210                  | 11537400                  |
| Inner ring severe fault     | 180                  | 9889200                   |
| Outer ring severe fault     | 195                  | 10713300                  |
| Total                       | 790                  | 43402600                  |

3. Signal noise reduction principle

3.1 Wavelet coherence analysis

For time domain signal $x(t)$, its continuous wavelet transform is defined as follows:

$$W_x(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^*(t - \tau/a) dt$$

Where, $a$ is the scale factor, $\tau$ is the translation factor, $*$ represents its complex conjugate, $\omega_0$ is the initial phase angle of $x(t)$, $\psi(t)$ is usually Morlet wavelet function, and $\psi(t)$ expression is as follows:

$$\psi(t) = \pi^{-1/4}(e^{-\omega_0^2} - e^{-\omega_0^2/2})e^{-t^2/2}$$

The process of wavelet cross transform for channel $i$ and channel $j$ collected signals is as follows:

$$W_{x_i \& x_j}(a, \tau) = |W_{x_i}(a, \tau) \cdot W^*_x(a, \tau)|$$

Where $W_{x_i \& x_j}(a, \tau)$ is the cross wavelet power spectral density. The greater its value, the greater the correlation between the two signals. The wavelet coherence spectrum between the two channel signals can reflect the correlation of the original signal in time-frequency domain. Due to the randomness of noise, the coherence of noise signal is far less than that of principal components in the signal. In the wavelet coherent spectrum, the coherence will be represented by the brightness of the color. The brighter the color, the greater the coherence of the corresponding frequency band. It contains more information. The darker the color, the more noise of the corresponding frequency band. The less noise contained in the signal, the more obvious the fault characteristics will be. It is necessary to remove the frequency band with low coherence (frequency band in dark color) during noise reduction.

3.2 CEEMD signal decomposition

Empirical mode decomposition (EMD) is a signal decomposition method. Its idea is to adaptively decompose the original signal into the superposition of each independent component without basis function. Each independent component is called intrinsic mode function (IMF). As an algorithm derived from EMD, ensemble empirical mode decomposition (EEMD) suppresses the frequency aliasing between IMF by adding auxiliary white noise many times in the decomposition process and averaging the IMF, and its performance has been greatly improved. Complementary ensemble empirical mode decomposition (CEEMD) is a further optimization of EEMD and reduces the residual auxiliary noise of EEMD. In order to distinguish the noise band from the principal component band, ceemd is used to decompose the original signal into many sub-band signals. The decomposed signal can be expressed as the following formula:

$$x(t) = \sum_{i=1}^{n} IMF_i + \text{residual}$$
After CEEMD decomposition of a signal, n IMF are obtained. With the increase of i, the frequency band frequency of IMFi will decrease as a whole. These IMF include not only the frequency bands that can reflect fault feature, but also the frequency bands of noise signals.

3.3 Signal denoising algorithm
(1) The signals collected by any two microphones are cross wavelet transformed to obtain the wavelet coherence spectrum, and the frequency band with the greatest coherence is obtained from the wavelet coherence spectrum.

(2) Several signals are obtained by CEEMD decomposition, and each IMF is cross wavelet transformed with the original signal. According to the coherent spectrum, the IMF (called IMFC) corresponding to the coincident coherent frequency band is retained, and the rest are eliminated.

(3) Reconstruct feature signal: \( x_{\text{feature}}(t) = \sum IMF_c \)

4. Signal noise reduction
Taking the serious fault cage as an example, take the 5-second signal (274700 sampling points) at the same time from channel 1 and channel 2 for XWT to obtain the wavelet coherence spectrum, as shown in figure 2. Apply CEEMD to the signal of channel 2 to generate 12 IMF (IMF1 ~ IMF12). Apply XWT to each IMF and the original signal to obtain the wavelet coherence spectrum, as shown in figure 3. It can be seen that with the increase of i, IMF can reflect the information from high frequency to low frequency of the original signal.

Figure 2. Wavelet coherence spectrum between signal of channel 1 and channel 2

Figure 3. Wavelet coherence spectrum between IMF1-IMF12 and signal of channel 2.
By comparing figure 2 with figure 3, it can be seen that the frequency bands contained in IMF₂, IMF₆, IMF₉, IMF₁₀ and IMF₁₁ coincide with the frequency band with the greatest coherence in the coherence spectrum between the original signals. These IMF can characterize the information of this frequency band of the original signal, while the other IMF is reflected as noise of the original signal. According to section 3.2, in addition to the residual vector, the original signal can be composed of the addition of all IMF. Therefore, in order to obtain the signal after noise reduction, the characteristic signal can be reconstructed according to section 3.3 as follows:

\[ x_{\text{feature}}(t) = IMF₂ + IMF₆ + IMF₉ + IMF₁₀ + IMF₁₁ \]

In the same way, reconstruct the feature signals of other fault types as shown in the table below:

| Fault type               | Feature signal                        |
|-------------------------|---------------------------------------|
| Roller severe fault     | \[ x_{\text{feature}}(t) = IMF₂ + IMF₆ + IMF₉ + IMF₁₀ + IMF₁₁ \] |
| Inner ring severe fault | \[ x_{\text{feature}}(t) = IMF₂ + IMF₆ + IMF₉ + IMF₁₀ + IMF₁₁ \] |
| Outer ring severe fault | \[ x_{\text{feature}}(t) = IMF₂ + IMF₆ + IMF₉ + IMF₁₀ + IMF₁₁ \] |

5. Machine learning fault diagnosis

In order to verify the effectiveness of the noise reduction and feature extraction method proposed in this paper, the time-domain features and spectral centroid of the feature signal and the time-domain features and spectral centroids of the original signal are input into the SVM for fault classification. Finally, the accuracy of fault classification is compared. Cut all the data in table 1 into samples with one second as the unit length. The time-domain feature and spectral centroids of these samples are input into SVM for fault classification. The test results are shown in the table below.

| Fault Type                     | Denoised | No Denosied | Number of samples |
|--------------------------------|----------|-------------|-------------------|
| Cage severe fault              | 197      | 171         | 205               |
| Roller severe fault            | 206      | 181         | 210               |
| Inner ring severe fault        | 173      | 160         | 180               |
| Outer ring severe fault        | 185      | 162         | 195               |
| Total                          | 761      | 674         | 790               |
| Accuracy                       | 96.33%   | 85.32%      |                   |

It can be seen from table 5.1 that when the time-domain feature of the feature signal are input into SVM, there are 761 correctly predicted samples and the accuracy reaches to 96.33%. On the contrary, when the time-domain feature of the original signal are input into SVM, only 674 are judged correctly and the accuracy only reaches to 85.32%.

6. Conclusion

In this paper, a acoustic signal denoising method based on Cross Wavelet Transform and CEEMD is proposed. The signal processed by this method can better reflect the bearing fault type. The results of fault classification by SVM show that the method proposed in this paper is effective.

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