Fault diagnosis of rolling bearing based on empirical wavelet transform and fuzzy function

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Abstract. The vibration signal of rolling bearing in mechanical equipment is nonlinear and nonstationary under the influence of various excitation sources. This paper combines empirical wavelet transform (EWT) with the fuzzy function and gives a method of fault signal recognition. Several modal components of the original signal can be obtained by decomposition. Components with more features of the original signal can represent some features of the original signal. The mutual information between each modal component and the original signal can be calculated. The noise and useful information can be identified according to the value of the mutual information, and then the noise of the signal can be filtered out to reconstruct the original signal. The fuzzy functions of the known class signals and the signals to be identified are calculated, and the correlation coefficients of the fuzzy functions of the signals to be identified and the signals to be identified are calculated.

1. Introduction

The vibration signal of rolling bearing in mechanical equipment is non-linear and non-stationary when it is affected by various excitation sources [1]. Therefore, it is difficult to diagnose the bearing fault by analyzing the vibration signal. It is necessary to select appropriate signal processing method according to this feature. Empirical mode decomposition (EMD) [2] is a non-stationary signal processing method which has been studied and applied. Some of scholars have applied it to the field of mechanical fault diagnosis [3]. However, there are some problems in EMD signal processing, such as modal aliasing, over envelope or under envelope [4]. In the method of empirical wavelet transform (EWT) [5], each frequency band of the original signal is separated by a orthogonal wavelet filter bank. This method inherits the advantages of EMD method and wavelet analysis method, and avoids the modal aliasing and endpoint effect of EMD [6]. On the other hand, the fuzzy function can be used as classifier [7]. Some modal components of the original signal can be obtained by processing the rolling bearing vibration signal with EWT. The components with more characteristic information of the original signal can represent some features of the original signal. The mutual information between each modal component and the original signal can be obtained. The noise and useful information can be identified according to the value of the mutual information, and then the original signal can be reconstructed by filtering out the noise. Then the original signal can be reconstructed by combining the fuzzy theory Function and correlation coefficient construct classifier: calculate the fuzzy correlation coefficient of the signal to be identified, and compare the correlation coefficient values to give the classification of the signal to be detected.
2. Basic principles of EWT

2.1. Decomposition steps of EWT

The EWT method defines that the spectrum of the signal is divided into \( N \) consecutive frequency bands \( f(t) = \sum_{k=0}^{N} f_k(t) \ (\omega_0 = 0, \ \omega_\pi = \pi) \), where \( \omega_n \) represent the boundary between the frequency bands. After determining the divided frequency band \( \Lambda_n \), each frequency band \( \Lambda_n \) is defined through the method of the original literature. The empirical scale function \( \hat{\phi}_n(\omega) \) and the empirical wavelet function \( \hat{\psi}_n(\omega) \) can be given by the following formula:

\[
\hat{\phi}_n(\omega) = \begin{cases} 
1, & |\omega| \leq (1-\gamma)\omega_n \\
\cos\left[\frac{\pi}{2} \beta\left(\frac{1}{\gamma\omega_n}|\omega|\right)\right], & (1-\gamma)\omega_n \leq |\omega| \leq (1+\gamma)\omega_n \\
0, & \text{otherwise}
\end{cases}
\]

\[
|\hat{\psi}_n(\omega)| = \begin{cases} 
1, & (1+\gamma)\omega_n \leq |\omega| \leq (1-\gamma)\omega_{n+1} \\
\cos\left[rac{\pi}{2} \beta\left(\frac{1}{\gamma\omega_n}|\omega|\right)\right], & (1-\gamma)\omega_n \leq |\omega| \leq (1+\gamma)\omega_n \\
\sin\left[rac{\pi}{2} \beta\left(\frac{1}{\gamma\omega_n}|\omega|\right)\right], & (1+\gamma)\omega_{n+1} \leq |\omega| \leq (1+\gamma)\omega_n \\
0, & \text{otherwise}
\end{cases}
\]

where \( \hat{\phi}_n(\omega) \) and \( \hat{\psi}_n(\omega) \) represent empirical scaling function and empirical wavelet function. We usually define that \( F[.] \) represents the Fourier transformation. So we can get their expression as follows:

\[
W^f_{f}(n,t) = \mathcal{F}\{f(t)\psi_n(t)\} = \int f(\tau)\psi_n(\tau-t)d\tau = F^{-1}\left\{f(\omega)\hat{\psi}_n(\omega)\right\}
\]

\[
W^f_{f}(0,t) = \mathcal{F}\{f(\tau)\phi(t)\} = \int f(\tau)\phi(\tau-t)d\tau = F^{-1}\left\{f(\omega)\hat{\phi}_n(\omega)\right\}
\]

\[
f(t) = W^f_{f}(0,t)\phi(t) + \sum_{n=1}^{N} W^f_{f}(n,t)\psi_n(t)
\]

Where \( W^f_{f}(0,t) \) is the Fourier transformations of \( W^f_{f}(0,t) \), and in the same way \( \hat{W}^f_{f}(n,\omega) \) is is the Fourier transformations of \( W^f_{f}(n,\omega) \). Thus, So we can get every component of the original signal. So the singal can be expressed as follows:

\[
\begin{cases} 
f_k(t) = W^f_{f}(k,t)\times \psi_k(t) \\
f_n(t) = W^f_{f}(0,t)\times \phi(t)
\end{cases}
\]

2.2. Simulation experiment

In this section, we will construct some signals that have the characteristics of generation, and use these signals to analyze the characteristics of EMD and EWT. These signals can be expressed as follows:
\[ f_1(t) = 6t^2 \]
\[ f_2(t) = \cos(10\pi t + 10\pi t^2) \]
\[ f_3(t) = \begin{cases} 
\cos(80\pi t - 15\pi), & t > 0.5 \\
\cos(60\pi t), & \text{otherwise}
\end{cases} \]
\[ f(t) = f_1(t) + f_2(t) + f_3(t) \]  \hspace{1cm} (7)

Where \( f_1(t) \) stands for trend signal, \( f_2(t) \) stands for frequency modulation signal, \( f_3(t) \) stands a segmented signal composed of two different frequency signals, and \( f(t) \) is a mixture of these three signals.

At the same time, we use EWT and EMD to decompose \( f(t) \) separately. The results are shown in Fig 2 and 3, respectively.

**Figure 1.** Signal simulation

**Figure 2.** The decomposition results of EWT

**Figure 3.** The decomposition results of EMD

Figure 2 is the decomposition result of EWT. From the figure, we can see that this method decomposes the original signal into different components according to its characteristics. Figure 3 is the decomposition result of EMD. From the figure, we can see that the six different components decomposed by this method do not well reflect the characteristics of the original signal.

### 3. Basic principles of classifier

The correlation coefficient can well represent the similarity between two random signals, and the large correlation coefficient indicates the high correlation between signals. Thus, the paper gives a fuzzy correlation classifier through the advantages of correlation coefficient. The construction process of classifier is as follows:
(1) Find the correlation function of fuzzy function between random variables.
(2) Normalize the correlation function.
(3) Take the correlation coefficient of or respectively.
(4) Calculate the fuzzy correlation coefficient.

The basic working principle of the classifier can be described as follows: first, we would use the EWT method to decompose the signal to obtain the modal component, and then the noise is identified and filtered out by calculating the mutual information between the modal component and the original signal; then the fuzzy function of the signal is calculated, that is, the fuzzy function of class a signal, class B signal and the signal C to be identified; then the fuzzy function is calculated Correlation coefficient: set the correlation coefficient value of class a signal and signal C to be identified as I, and the correlation coefficient value of class B signal and signal C to be identified as II. Compare the size of class I and II. The flow diagram of classifier is shown in Figure 4.

![Figure 4. Theory of Fuzzy Classifier](image)

4. Experimental study

4.1. Experimental data

![Figure 5. The vibration signals: (a) normal signal (b) outer ring fault signal (c) inner ring fault signal.](image)

The experiment used the data of the rolling bearings in the electrical engineering test conducted by the Case Western Reserve University (Washington, U.S.) for processing. The bearing on the drive end of the deep groove ball bearing served as the test bearing with its model of SKF6205. An electric discharge machine was used to cause local damage to the bearing by artificial fabrication of the inner and outer bearing rings. The three signals collected are shown in Fig. 5.
4.2. Experimental analysis

Three different vibration signals and the signals to be detected are reconstructed above, noise interference is filtered out, then three different vibration signals are calculated respectively, and use mean and standard deviation to express the fuzzy correlation coefficients characteristics. When the correlation coefficient is large, the signal to be detected belongs to this kind of signal. In order to further analyze the effect of the method proposed in this paper, according to the above ideas, EWT and EMD are used to calculate the fuzzy number and further calculate the mean value and standard deviation of the correlation coefficient. The calculation results are shown in Table 1 and table 2. According to table 1, as mentioned before, due to the interference of modal aliasing, the IMF component of signal obtained by EMD can not accurately express the information of original signal, so there is no clear distinction between the correlation coefficient of three categories: when the signal to be detected is a normal signal, it has a large correlation coefficient with the signal in normal state, so it can identify the category to be detected; when the signal to be detected is an external signal when circle fault or inner circle fault signal, the correlation coefficient can not identify the signal category well.EWT can accurately obtain the components of the original signal and effectively remove noise interference by using mutual information. The correlation coefficient between EWT and the signal to be detected is large. No matter what kind of signal to be detected is in Table 2, the correlation coefficient values of EWT and different types of signals are very different, which can effectively identify the types of signals to be detected.

| Table 1. Analysis results of EMD |
|-------------------------------|
| Groups | Environments | 0# | 1# | 2# |
|       |               | Normal | Outer ring fault | Inner ring fault |
| Normal | mean value    | 0.5104 | 0.4764 | 0.4102 |
|        | standard deviation | 0.0590 | 0.0729 | 0.0860 |
| Outer ring fault | mean value | 0.4664 | 0.2415 | 0.3650 |
|        | standard deviation | 0.0719 | 0.0540 | 0.0710 |
| Inner ring fault | mean value | 0.4042 | 0.3650 | 0.2789 |
|        | standard deviation | 0.0853 | 0.0710 | 0.0552 |

The method of BP and SVM, which are widely used, is compared with the method in this paper. Take Table 2. Analysis results of EWT

| Table 2. Analysis results of EWT |
|-------------------------------|
| Groups | Environments | 0# | 1# | 2# |
|       |               | Normal | Outer ring fault | Inner ring fault |
| Normal | mean value    | 0.6347 | 0.3134 | 0.1025 |
|        | standard deviation | 0.0395 | 0.1164 | 0.0969 |
| Outer ring fault | mean value | 0.3134 | 0.5407 | 0.0884 |
|        | standard deviation | 0.1164 | 0.0240 | 0.0533 |
| Inner ring fault | mean value | 0.1025 | 0.0685 | 0.2253 |
|        | standard deviation | 0.0969 | 0.0534 | 0.0452 |

20 groups of data respectively, 16 groups of data as training, test with 4 groups of data. The results and classification accuracy are shown in Table 3. Through the analysis of Table 3, it can be seen that the method proposed in this paper can identify different working states of rolling bearing well and has higher recognition rate compared with BP and SVM methods.
### Table 3. Recognition Rate of Different Classifiers

| Different environments | Method     | Groups |
|------------------------|------------|--------|
|                        |            | 0#     | 1#     | 2#     | 3#     |
| Normal                 | Proposed   | 91.6%  | 94.6%  | 100%   | 98.3%  |
|                        | BP         | 88.1%  | 82.8%  | 89.5%  | 80.0%  |
|                        | SVM        | 87.2%  | 83.2%  | 88.5%  | 80%    |
| Outer ring fault       | Proposed   | 96.2%  | 96.2%  | 100%   | 98.1%  |
|                        | BP         | 88.9%  | 82.9%  | 82.0%  | 84.6%  |
|                        | SVM        | 84.5%  | 76.0%  | 86.1%  | 84.6%  |
| Inner ring fault       | Proposed   | 91.5%  | 95.5%  | 100%   | 98.0%  |
|                        | BP         | 77.5%  | 82.5%  | 87.0%  | 84.0%  |
|                        | SVM        | 87.5%  | 87.0%  | 82.2%  | 77.5%  |

5. Conclusion

When rolling bearing fault occurs, the collected vibration signals often mix with a lot of environmental noise, resulting in the fault signal characteristics are not obvious. Therefore, this paper proposes a fault diagnosis method of rolling bearing based on EWT and fuzzy correlation classifier, and draws the following conclusions:(1) In view of the mode aliasing effect in EMD decomposition, the components of vibration signal are given by EWT, which can obtain accurate components.(2) The combination of fuzzy function and correlation coefficient is better than that of BP classifier and SVM classifier.

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