Fault diagnosis of rotating mechanical bearing based on adaptive noise-complete ensemble empirical modal decomposition and time-reallocated multisynchronous compression transform

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Abstract: Due to the noise interference in the original vibration signals measured from vibration sensors, it is necessary to noise reduce the signals before extracting fault features from them. This paper proposes a fault feature extraction method combining the adaptive noise-complete ensemble empirical modal decomposition (CEEMDAN) and the time-reallocated multisynchronous compression transform (TMSST), which first decomposes the original signal, then combines the relevant index values of the decomposed signal to filter the optimal signal components, and finally uses the TMSST to extract the fault features from the reconstructed signal. In this paper, a set of simulated signal data and two sets of experimental data are used to evaluate the performance of the method, and the results show that the method works well for rolling bearing fault signal identification.

1. Introduction

Due to the generally harsh working conditions of rotating machinery, and rolling bearings as the main operating components of rotating machinery, with the longer working time of the machinery, the damage rate of the bearings increases, and the failure point and failure range of the bearings will also increase\textsuperscript{[1-2]}. Fault diagnosis of rolling bearings is becoming increasingly important in order to avoid the negative consequences of accidents caused by damaged bearings and to save on repair and maintenance costs.

There are three methods of fault feature extraction for rotating machinery: time domain, frequency domain and time-frequency domain. In the time domain method, the root mean square, skewness and cliffness\textsuperscript{[3]} characterise the signal. During the operation of real production machinery, the vibration signals collected are always unstable and non-linear. Empirical Modal Decomposition (EMD) analyses non-linear and unsteady signals, but suffers from modal confounding. Integrated empirical modal decomposition (EEMD)\textsuperscript{[4]} improves modal aliasing to some extent, but the internal mode function still suffers from residual noise. CEEMDAN\textsuperscript{[5]} adds specific noise to each process of decomposition, avoiding the problem of final averaging. In fault signal pulse extraction, it is also of interest to enhance the energy focused representation of the signal. The synchronous compression transform and various improved versions\textsuperscript{[6-7]} can be good for processing the signal to produce a high energy focused TFA, but
the signal at bearing faults has a broadband nature and the SST has little effect in this case. G. Yu proposed a time redistribution synchronous compression transform based on a concentrated time-frequency analysis (TFA) method that can handle pulse-like signals better than other TFA methods.

In this paper, the rest of the paper is structured as follows: Section 2 introduces the principles of CEEMDAN, the screening criterion, and the implementation of TMSST, Section 3 performs the pulse extraction of the simulated signals, Section 4 troubleshoots the actual bearing inner ring signals, and Section 5 draws conclusions.

2. Theoretical algorithms

2.1 CEEMDAN

The specific algorithmic steps of CEEMDAN are as follows:

First add adaptive white noise \( v(t) \) to the original signal \( x(t) \)

\[
s(t) = x(t) + v(t)
\]  

(1)

Perform \( z \) EMD decompositions on \( s(t) \) and perform an overall average of the \( z \) resulting \( \text{imf}_1(t) \) to obtain the first modal component \( \text{imf}_1(t) \).

\[
\text{imf}_1(t) = \frac{1}{z} \sum_{i=1}^{z} \text{imf}^i(t)
\]  

(2)

\( i \) is the number of times adaptive white noise is added. The residual signal \( r_1(t) \) is then obtained as

\[
r_1(t) = x(t) - \text{imf}_1(t)
\]  

(3)

Finally, the steps i and ii are repeated until the algorithm ends when the residual signal cannot be EMD, giving the residual \( \text{imf} \). Assuming that the number of all modal components is \( k \) and the final residual signal is \( R(t) \), the original signal is decomposed as:

\[
x(t) = \sum_{i=1}^{k} \text{imf}^i + R(t)
\]  

(4)

In the series of IMF components obtained after the decomposition of the signal by the CEEMDAN algorithm, the main fault information exists in some of the components. In order to extract the fault information accurately, this paper combines the cliffness (K), slope (S) and correlation coefficient (COR) to filter the signal components. In order to make the criteria for each indicator the same, the data will be normalised. The criteria are as follows:

\[
Q = K + S + \text{COR}
\]  

(5)

2.2 TMSST

For a strong frequency varying signal, the expression is as follows.

\[
\hat{s}(\xi) = A(\omega) e^{i\phi(\omega) + \phi(\omega)(\xi - \omega) + 0.5\phi^{''}(\omega)(\xi - \omega)^2}
\]  

(6)

The Fourier transform of the Gaussian window function used in STFT can be expressed as

\[
\hat{g}(\omega) = \sqrt{2\pi\sigma} e^{-0.5\omega^2}
\]  

(7)

\( G(t,\omega) \) is obtained, and then the estimated value of 2D GD is derived, and the immobile point iteration algorithm is used to reduce the error, and the 2D GD value is corrected by iteration after iteration to obtain the following expression.

\[
t^{[N]}(t,\omega) = \phi(\omega) + \left( \frac{\phi^{''}(\omega)}{\sigma^2 + \theta^2} \right)^N (t + \phi^{''}(\omega))
\]  

(8)

When the number of iterations is large enough,

\[
\lim_{N \to \infty} t^{[N]}(t,\omega) = \phi(\omega)
\]  

(9)

Replacing \( \hat{t}(t,\omega) \) by \( t^{[N]}(t,\omega) \), we finally derive

\[
\lim_{N \to \infty} Ts(u,\omega) = \hat{s}(\omega) \hat{g}(0) \delta(u + \phi^{''}(\omega))
\]  

(10)

From the above equation, it can be seen that after a sufficient number of iterations, the TF energy of the high frequency variation signal can also be well compressed into the GD trajectory.
3. Simulated signal analysis
Before the extraction of fault features, the original signal is decomposed using CEEMDAN. From Fig. 1 (a) and (c), we can obtain that IMF2 and IMF3 are the best components, and the reconstructed signal with relatively less noise. Comparing Figure 1 (b) of the original signal with Fig 1 (d) of the reconstructed signal, it can be seen that the CEEMDAN method can effectively reduce the noise of the original signal while maintaining the integrity of the signal as much as possible. It is convenient for subsequent pulse extraction of the signal.

![Fig 1 preprocessing of simulation signal](image1)

To illustrate the effectiveness of the TMSST method, the simulated signal after noise reduction is analysed with TMSST in Fig 2 (a), and the extracted pulse components are amplified, and the results are shown in Fig 2 (b) and (c), which shows that for each pulse component of the signal a TFR with a high concentration of energy can be generated.

![Fig. 2 TMSST result](image2)

4. Example of rolling bearing fault diagnosis
In order to verify the effectiveness of the proposed method, the data was collected by conducting experiments on a comprehensive mechanical fault simulation experimental platform (MFS-MG). The method in this paper will be used to analyse the collected vibration signal data. The sampling frequency in the experiment is 12.8 KHz, the rotation frequency is 19.89Hz, Combining the relevant parameters
and formulas it can be calculated that the inner loop fault frequency is 98.5Hz, the fault characteristic
cycle time is 10ms and the shaft rotation cycle time is 50ms.

The actual bearing outer ring fault signal is analysed, and it can be seen from Fig 3 that both STFT
and GCLT\cite{9} results have certain energy ambiguity problems, and TMSST can produce good energy
centration TFR, which illustrates the effectiveness of the method.

The original signal is decomposed using CEEMDN. From Fig. 4 (a) and (c), it can be seen that
IMF2 and IMF3 are the best components, and a signal with relatively less noise is obtained after
reconstruction. Comparing the original signal Fig. 4 (b) and the reconstructed signal Fig. 4 (d), it can be
seen that the CEEMDN method can effectively reduce the noise of the original signal while
maintaining the integrity of the signal as far as possible. It is convenient for subsequent pulse extraction
of the signal.

The TMSST method was used to extract pulse features from the reconstructed signal. Since the inner
ring fault point rotates with the shaft, there exists a rotation period of the shaft in addition to the inner
ring fault feature period, as can be seen in Fig 5 (a), the average value of the time interval between
successive pulses of the shaft is 48.9 ms, and Fig 5 (b) and (c) show that the average value of the time
interval between pulse features of the inner ring is 9.65 ms. Both are essentially equal to the theoretical values and are consistent with the inner ring fault characteristics, indicating that the method in this paper is able to extract accurate pulse characteristics for bearing fault diagnosis.

5. Conclusion
In this paper, for rotating machinery, a fault feature extraction method combining CEEMDAN and TMSST based on the cliffness-slope-correlation coefficient screening criterion is proposed, which can effectively improve the problem that the noise still exists in large quantities due to the extraction of IMF by only one decomposition, while ensuring that the original signal retains the fault information as much as possible, and the combination of TMSST can better extract the fault pulse. Finally, the feasibility of the method is demonstrated by applying it to simulation data and experimental data. Future work is needed to improve the efficiency of the algorithm and to optimise the iterative algorithm for rotating machines, which are diverse and complex.

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