Fault Diagnosis of Fracturing Vehicle Based on Local Mean Decomposition and Synchroextracting Transform

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Abstract. The power end of a fracturing truck is a key component that provides kinetic energy during pressure operations. Its vibration signal is collected during operation because of the complex working conditions and heavy loads, resulting in the collected signal being filled with a large amount of noise, for which it is difficult to perform effective fault feature extraction. To address this problem, a new fault diagnosis method is proposed. This method combines local mean decomposition (LMD) and synchroextracting transform (SET) for signal processing. First, LMD processing is done on the acquired signal to obtain several product function (PF) components. The cross-correlation coefficient and kurtosis value are used as references to select the true PF components. After that, the SET method is used to process the real PF components, extract the energy that is most correlated with the time-varying features of the signal, remove the fuzzy energy, improve the time-frequency resolution, and enhance the fault features contained in the signal to facilitate accurate fault diagnosis. Finally, the vibration signals collected from the power end of the fracturing vehicle are experimentally verified. The results show that the method can accurately extract the fault characteristics of bearing failure in the power end, and provide some useful reference for the diagnosis method of fracturing vehicle power system.

1. Introduction

The fracturing truck injects large displacement and high-pressure fluid into the well to squeeze the proppant into the fracture, which is characterized by large discharge capacity and high pressure, and the health of its components will directly affect the working performance of the fracturing truck. Because of the construction requirements, fracturing trucks always have to operate under some harsh conditions. In such an operating environment, fracturing trucks can be easily damaged or scrapped, which in turn can cause incalculable damage. Due to the demands of construction, frac trucks often operate in harsh conditions where they can easily break down or become obsolete, resulting in incalculable damage. In order to minimize losses and avoid fracting truck failures during operation, the power system of the fracting truck needs to be fault diagnosed in a timely manner\textsuperscript{[1]}. Currently, there are few diagnostic studies related to the power system of fracturing trucks. Wang Chuan\textsuperscript{[2]} et al. conducted a simulation analysis of the coupled vibration of the power system during fracturing truck operation, which provided a certain theoretical basis for fracturing truck fault diagnosis, but not for the power end fault analysis. Zhang Junling\textsuperscript{[3]} et al. combined local mean decomposition sample entropy with support vector machine for fault diagnosis to solve the problem of difficulty in
extracting fault features at the hydraulic end of fracturing vehicles, but the sample entropy features have a selection problem and the support vector machine also faces the dimensionality problem, which makes it difficult to clearly indicate the complex mapping relationship between the measured signal and the health state of the fracturing vehicle power system. The accuracy of diagnosis needs to be improved for feature extraction of signals containing strong noise and the presence of a wide range of variations in rotational speed or load bearing.

Therefore, an effective time-frequency joint analysis method is required to accurately extract the fault characteristics of the fracturing vehicle power system. Synchroextracting transform (SET) is a new time-frequency analysis method proposed by Yu et al. It is essentially a post-processing step of STFT. The algorithm removes most of the divergent energy by retaining only the time-frequency coefficients on the time-frequency ridges in the STFT results, thus obtaining a higher resolution time-frequency distribution and allowing signal reconstruction. However, SET has a condition that should not be neglected when processing multi-component signals: there should be a certain interval between the instantaneous frequencies of each component. The actual working conditions of the signal, such as the instantaneous frequency interval of each component, are not constant, and SET is not applicable. Thus, SET has not been widely used. But for the multi-component non-stationary signal such as the fault signal of the fracturing vehicle dynamic system, it is necessary to carry out high-precision time-frequency analysis.

Local mean decomposition (LMD) is a new nonlinear non-stationary signal analysis method. This method is proposed to further improve the problems of under-envelope, over-envelope and endpoint effect in the empirical mode decomposition method. To improve the diagnostic effectiveness of SET in analyzing multi-component signals, the signal is first decomposed adaptively into several PF components by the LMD method. Rejecting spurious PF components by the number of interrelationships and cliff values and selecting the true PF components. The real PF components are SET processed to concentrate the energy of the signal, obtain the time-frequency demodulation spectrum of the signal, and identify the fault characteristics. This combined LMD and SET method was used to analyze the fault vibration signal of the power end part of the fracturing vehicle to achieve an effective extraction of the fault characteristics.

2. Theoretical method

2.1. Local mean method

The LMD algorithm is a decomposition of the AM and FM signals into a PF component. This separation is achieved by smoothing the original signal, subtracting the smoothed signal from the original signal, and then using the amplitude demodulation results of the envelope estimation. Each PF component is the product of the envelope signal and the FM signal, from which the time-varying instantaneous phase and instantaneous frequency can be deduced. The basic principle is as follows:

Based on the original signal, determine the local extreme value points, calculate the mean value $m_i$ of the adjacent extreme value points, and calculate the envelope estimate $a_i$. Connect all $m_i$ with a straight line and smooth them by sliding average to obtain the local mean function $m_{11}(t)$ and $a_{11}(t)$. The local mean function $m_{11}(t)$ is separated from the original signal to obtain $h_{11}(t)$. Demodulate $h_{11}(t)$ to obtain $s_{11}(t)$.

If $s_{11}(t)$ does not meet the condition $a_{12}(t)=1$, then $s_{11}(t)$ is used as the original data to repeat the above process until a pure frequency modulation signal $s_{1n}(t)$ is obtained. The envelopes $s_{1n}(t)$ is obtained by equation (1), and the first PF component of the original signal is obtained by multiplying the envelope signal $a_{1}(t)$ and the pure FM signal $s_{1n}(t)$, as shown in Equation (2).

$$a_{1}(t) = a_{11}(t)a_{12}(t) = \prod_{q=1}^{n}a_{1q}$$

$$PF_{1}(t) = a_{1}(t)s_{1n}(t)$$

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The first component PF\textsubscript{1} is separated from the original signal \(x(t)\) to obtain a new signal \(u_1(t)\). \(u_1(t)\) is used as the original data to repeat the above steps, and cycle \(k\) times until \(u_k\) is a constant or monotone function. It can be seen that LMD is very effective in the processing of nonlinear and non-stationary signals, and can decompose signals more adaptively than empirical mode decomposition. The working environment of the power end of the fracturing truck is very complex, and the collected signals are nonlinear and non-stationary. Therefore, the signal of the power end of the fracturing truck is very suitable for LMD decomposition.

2.2. Synchroextracting transform

SET, as a newly proposed high-resolution time-frequency analysis method, has the advantages of good energy concentration and strong noise immunity in signal processing, and its fundamental purpose is to obtain higher precision time-frequency resolution. The basic principle is as follows:

Since SET is a post-processing process based on STFT, STFT is first analysed, and its expression is:

\[
G(t, \omega) = \int_{-\infty}^{\infty} g(u-t) \cdot s(u) \cdot e^{-i\omega u} du
\]  

(3)

Where: \(g(u-t)\) is a movable window, \(s(u)\) is the signal to be analyzed.

STFT extends one-dimensional time signal \(s(u)\) to two-dimensional Fourier plane to observe the time-frequency domain information of the extracted signal. For STFT multiplying phase factor \(e^{i\omega u}\), according to Parseval theorem, Formula (3) can be written as:

\[
G(t, \omega) = \int_{-\infty}^{\infty} \hat{s}(t) \cdot \hat{g}(u-t) \cdot e^{i\omega u} \cdot e^{i\omega u} du = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{s}(\xi) \cdot \hat{g}(\omega-\xi) \cdot e^{i\omega u} d\xi
\]  

(4)

Where: \((\cdot)^*\) Complex conjugate, \(\hat{s}(\xi)\) is the Fourier transform of \(s(u)\), \(\hat{g}(\omega-\xi)\) is the Fourier transform of \(g(u-t)\).

Taking a harmonic signal with frequency \(\omega=\omega_0\) and amplitude constant \(A\) as \(s(t)=Ae^{i\omega_0 t}\), the frequency domain expression is:

\[
\hat{s}(\xi) = 2\pi A \cdot \delta(\xi - \omega_0)
\]  

(5)

From Equation (4), the STFT of \(s(t)\) can be obtained as:

\[
G_\nu(t, \omega) = A \cdot \hat{g}(\omega-\omega_0) \cdot e^{i\omega_0 t}
\]  

(6)

According to Formula (6), it can be seen that the STFT expression of harmonic signal is composed of a series of harmonic signals with the same frequency \(\omega_0\) as the original signal. The original TF indicates that \([G_\nu(t, \omega)]\) reaches the maximum value on the IF trajectory, and the time-frequency coefficient \(G_\nu(t, \omega)\) will have the best noise robustness. Therefore, SEO is introduced into the STFT distribution to extract and retain the coefficients most relevant to the time-varying characteristics of the signal in the STFT results, and the remaining coefficients are directly removed, which ultimately improves the clustering of the time-frequency distribution. The calculation formula of SET is:

\[
T(t, \omega) = G_\nu(t, \omega) \cdot \delta(\omega - \omega_0(t, \omega))
\]  

(7)

Where: \(G_\nu(t, \omega)\) is the result of STFT, \(\delta(\omega - \omega_0(t, \omega))\) is SEO, \(\omega_0(t, \omega)\) is estimated IF.

3. Fault diagnosis process based on LMD and SET

Diagnosing faults for non-smooth fault signals on the power side of fracturing trucks. A number of PF components are first decomposed using the adaptive decomposition of the LMD. The number of interrelationships and the cliff value are used as judgment indicators, and the components with interrelationships greater than 0.1 and cliff values greater than 3 are selected as the true PF components. Then SET processing is done on the real PF components, and the component signals are superimposed
to obtain the time-frequency demodulation spectrum of the signal. Finally, it is compared with the fault characteristic frequency for fault diagnosis. The specific process is shown in Figure 1.

![Figure 1. Fault diagnosis process](image)

**4. Experimental analysis**

In order to verify the feasibility of this method, the vibration signal of the power end of the 2000 fracturing truck is collected and preliminarily analysed. MDR-80 mobile data recording system (16 channels) was used for signal acquisition. The sampling frequency of the equipment was 12 kHz, and the acquisition sensor was a piezoelectric acceleration sensor. The fracturing truck is shown in Figure 2.

Since the working environment of the fracturing truck is very complex, the location selection of measuring points is also very important. As shown in Figure 4, a total of 8 measuring points are arranged, in which the radial and axial vibration signals of the dynamic input end are measured respectively for 1,2 measuring points. The other measuring points measured the axial and radial vibration signals of the piston rod of the fracturing pump.

![Figure 2. 2000 fracturing truck](image)

![Figure 3. Power end inner ring fault bearing](image)

![Figure 4. Measuring point distribution map](image)
The engine speed is 1600r/min, the pressure is about 40MPa. In this paper, the vibration signal of the bearing inner ring fault in the power end of the fracturing truck is selected for analysis, as shown in Figure 3. The theoretical calculation shows that the fundamental frequency $f_r$ is 30Hz and the inner ring fault characteristic frequency $f_{BPFI}$ is 152.5Hz.

The time domain diagram after normalization of normal vibration signal and inner ring fault signal is shown in Figure 5. It can be clearly seen that the fault signal is filled with noise. Firstly, the inner-loop fault signal is processed by LMD, and the correlation coefficient and kurtosis value are calculated to find the real PF component with high correlation with the original signal and kurtosis value greater than 3. The LMD decomposition diagram is shown in Figure 6, and the correlation coefficients and kurtosis values between each PF component and the original signal are shown in Table 1.

![Figure 5. Time domain of normal signal and inner ring fault signal](image1)

![Figure 6. LMD of inner ring fault signal](image2)

It can be seen from Table 1 that only the first two PF components reach the correlation coefficient greater than 0.1 and the kurtosis value is greater than 3. Therefore, the PF1 component is selected for SET processing, and the results are shown in Figure 7.

| PF  | Correlation coefficient | Kurtosis |
|-----|------------------------|----------|
| PF1 | 0.9344                 | 5.5770   |
| PF2 | 0.3839                 | 3.5844   |
| PF3 | 0.1476                 | 2.8464   |
| PF4 | 0.0278                 | 3.0746   |
| PF5 | 0.0022                 | 3.5966   |

The fault frequency of bearing inner ring can be clearly seen from Figure 7, and the double frequency and triple frequency can be clearly seen, realizing the accurate extraction of fault features. At the same time, in order to illustrate the advantages of this method, comparative experiments are added. Set analysis is directly performed on the signal without LMD decomposition. The results are shown in Figure 8. Almost no useful information can be obtained from the figure and the fault characteristics of the inner ring cannot be identified. It is proved again that the method proposed in this paper is feasible for fault diagnosis of bearing inner ring fault at the power end of fracturing truck.
5. Conclusion
In this paper, a fault diagnosis method based on LMD and SET is proposed. In the fault diagnosis of the signal collected from the power end of the fracturing vehicle, the PF component is firstly decomposed adaptively by LMD, and the real PF component with high correlation and cliff value greater than 3 is selected to eliminate the irrelevant frequency interference. The real PF component is SET processed to improve the time-frequency resolution, and the accurate extraction of fault information is successfully achieved. This paper only analyses the bearing failure signal at the power end of the fracturing vehicle. Further analysis is needed for the fault diagnosis of other mechanical structures of the fracturing vehicle, which deserves further study.

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