Fault diagnosis of fracturing truck based on ITD and TET

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Abstract. The power system is the core part of fracturing truck, and its running state will directly determine the operation efficiency of fracturing truck. Fracturing trucks often operate under heavy load and noisy conditions, so the power system is prone to faults and difficult to diagnose. In order to solve the difficult problem of fracturing vehicle power system diagnosis under noise and changing working conditions, one method based on intrinsic time-scale decomposition (ITD) and transient-extracting transform (TET) is proposed. Firstly, using the intrinsic time-scale decomposition to dealing the collected vibration signal of the fracturing vehicle power system, multiple related components have been obtained, and then perform transient-extracting transform to processing the components with larger correlations to the original signal. The local features of the signal are enhanced and the fault features are extracted to complete the fault diagnosis. The test results showing that the proposed fault diagnosis method can accurately identify the fault condition of the power system. The conclusions obtained can provide a certain reference for the research and development of the power system fault diagnosis method of fracturing truck.

1. Introduction

In oil extraction, fracturing operation is indispensable. Fracturing truck is the most important part of the fracturing operation[1]. It works by injecting large displacement and high pressure fracturing fluid into the well, jacking out the bottom layer and making it easier to collect oil and gas, and the increase the oil production. Therefore, the completion of fracturing operations will directly affect the efficiency of oil production.

The fracturing pump is the core component of the fracturing truck[2]. Due to the high pressure, high displacement and harsh working environment, the power system of fracturing pump is prone to be damaged. If the fracturing pump fails, the economic loss of the developer will be caused, and even will threaten the life safety of operators. The failure of a fracturing pump often goes through a long-term process from a tiny problem to a direct impact on construction operations. When the fault is found, most of the damage is irreversible, and the corresponding damaged part or even the whole system needs to be
replaced to ensure the fracturing truck can be used again. In recent two years, Only in Yulin, Qingcheng, the cost of repair, replacement and maintenance of fracturing pump power system has reached millions. Therefore, it is necessary to study the fault diagnosis method of power system of fracturing pump.

When the fracturing truck fails, its vibration signal is often mixed with the fault information we need to find. However, the collected fault signals themselves are Non-linear and Non-stationary, they are cannot be directly analyzed. Time-frequency domain analysis method is widely used in mechanical fault diagnosis because it can provide localized information of vibration signal in both time domain and frequency domain. At present, time-frequency analysis methods mainly include Fast Fourier Transform, Wigner Distribution Function, Wavelet Transform [3], but these methods are not self-adaptive and cannot effectively process non-stationary vibration signals. Empirical Mode Decomposition(EMD) is an adaptive signal processing method, but it also has a series of problems in signal processing, such as end effect and mode mixing [4].

Base on the EMD and Local mean Decomposition method (LMD), Intrinsic Time-Scale Decomposition[5] (ITD) is proposed by Frei et al.it can effectively deal with nonlinear, non-stationary signal, and widely used in the field of fault diagnosis. The algorithm is fast and efficient, and there is no interpolation or filtering process. It is suitable for dynamic characteristic extraction of non-stationary signal.

Transient-extracting reform(TET) is a new method proposed by Yu Gang [6]. It is based on short-time Fourier transform and does not require extending parameters. It can extract transient components with obvious kurtosis in fault vibration signal, and is suitable for mechanical fault diagnosis. Therefore, this method can use to dealing the component extracted by ITD, and the corresponding fault characteristics will be better obtained.

Some of the fault signal of the fracturing truck is analyzed by ITD method and TET method. the signal noise reduction and corresponding feature enhancement are completed after it, and the fault diagnosis of the related part of the fracturing truck's power system is succeeded.

2. Theoretical method

2.1. Intrinsic Time-Scale Decomposition

The Intrinsic Time-Scale Decomposition will quickly and adaptively decompose the signal, and end getting several Proper Rotation (PR) components that are physically meaningful, and a monotonous trend component. These components are highly correlated with the original signal and contain most of the information we need to extract. The method first breaks the signal into the following forms:

\[ X_t = \varepsilon X_t + (1 - \varepsilon)X_t = L_t + H_t \]  
\[ X_t \] is the original signal, \( L_t = \varepsilon X_t \) is the baseline signal. \( H_t = (1 - \varepsilon)X_t \) is the inherent rotation component. is a custom baseline extraction operator. \( \varepsilon \) is a custom baseline extraction operator.

Presuming \( \{t_k | k = 1,2,\cdots\} \) is the local extreme point of the signal \( X_t \), define \( t_0 = 0 \). Using \( X_{k} \) and \( L_{k} \) to represent \( X(t_k) \) and \( L(t_k) \).can getting these:

\[ L_t = \varepsilon X_t = L_k + \left( \frac{L_{k+1} - L_k}{X_{k+1} - X_k} \right)(x_t - x_k) \]  
\[ L_{k+1} = \alpha \left[ x_k + \frac{t_{k+1} - t_k}{t_{k+2} - t_k}(X_{k+2} - x_k) \right] + (1 - \alpha)X_{k+1} \]

Among above, \( X_k \) is the extreme value, \( t_k \) is the related moment, \( k \) is the number of the extreme points. \( \alpha \) is to control component amplitude gain coefficient, we take it for 0.5.

After several calculations, the original signal was finally decomposed into the following signals:

\[ H_t = H_{k_1}^L + H_{k_2}^L + \cdots + H_{k_n}^L + L_t \]

Among above, \( H_{k_i}^L \) is the Kth PR component, we can using them to analyze the fault condition.

2.2. Transient- extracting transform

The STFT result of signal \( s(u) \) can be written as
\[ M(t, \omega) = \int_{-\infty}^{+\infty} a(u - t) \cdot s(u) \cdot e^{-i\omega u} \, du \] (5)

Above \( a(u - t) \) is the sliding window. \( \delta(t) \) is a function whose value is 0 out of zero in the field of R, and its integral in R is 1. \( \delta(t) \) can be written as \( A \cdot \delta(u - t_0) \), calculate by (5) can obtain:

\[ M(t, \omega) = \int_{-\infty}^{+\infty} a(u - t) \cdot A \cdot \delta(u - t_0) \cdot e^{-i\omega u} \, du = A \cdot a(t_0 - t) \cdot e^{-i\omega t_0} \] (M) (6)

The STFT result of \( A \cdot \delta(u - t_0) \) can be looked as A series of \( \delta(t) \) with the same delay \( c \). \( c \) is equal to \( t_0 \), it can be proved by derivate \( \omega \) in (6). But the energy will be diverged after STFT, so the follow transient feature extraction operator is be proposed:

\[ TEO(t, \omega) = \delta(t - t_0(t, \omega)) \] (7)

The operator properties are as follows:

\[ t_0(t, \omega) = \begin{cases} t_0, & t \in [t - \Delta, t + \Delta], \omega \in R^+ \\ 0, & otherwise \end{cases} \] (8)

In \( t_0 \), it can be written as

\[ \delta(t - t_0(t, \omega)) = \delta(t - t_0) \] (9)

the value of TEO is 0 out of \( t_0 \) in the field of R, and the Transient- extracting transform is Multiply the operator and the STFT result of the real signal, which is represented like follows:

\[ T_e(t, \omega) = M(t, \omega) \cdot TEO(t, \omega) \] (10)

What we need is \( T_e(t, \omega) \), and after the transformation represented by the above formula, the energy by time-frequency analysis will be more concentrated, and the signal can be reconstructed at the same time. The expression of the TET reconstructed signal can be written as:

\[ s(t) = (2\pi a(0))^{-1} \cdot \int_{-\infty}^{+\infty} T_e(t, \omega) \cdot e^{i\omega t} \, d\omega \] (11)

3. Simulation signal analysis

In order to verify the signal processing capability of this method, the method is tested and studied by experimental simulation. Now a multi-component FM signal as follows is assumed to be tested:

\[ \begin{align*}
  f_1(t) &= f_1(t) + f_2(t) \\
  f_1(t) &= \sin(2\pi(60t - 5t^3)) \\
  f_2(t) &= \sin(2\pi(12t - 4\sin(1.5t)))
\end{align*} \] (12)

It was decomposed by ITD, then adding the sum of the first three components we obtained. the time frequency analysis by MSSF \(^7\) was carried out to compared with the original instantaneous frequency characteristics. Results are showing in Fig1:

![Fig 1 (ITD reconstruct results and original frequency)](image)
From Fig 1 we can see, due to the damage caused by ITD, ITD results coordinates have some interference at the intersection of instantaneous frequencies. Beyond that, the two profiles are nearly the same, it indicates that the ITD results can reflect the information of the original signal.

After ITD, the second PR component of the simulation signal is extracted by Transient-extracting transform., the component 2 and its TET results are showing in Fig2.

As can be seen from the Fig2, at 3s, the signal suddenly changed a little, and this feature is the enhanced by TET. The transient feature extraction of the signal is completed. Therefore, the result of ITD and TET reflects that the combination of ITD and TET method can extract the transient characteristics of signals, which also can attempt to be used in the processing of fault vibration signals.

4. fault diagnosis of fracturing truck power system

Fig 3 (fracturing truck)

Fig 4 (The sensor measuring points)
In order to see the extracting ability of the proposed method under actual conditions, we collected some fault signals in the power system of the fracturing truck. The fracturing truck used in experiment is shown in Fig 3.

The sampling frequency of the vibration sensor used in the test is 12000Hz, the sensor measuring points 1 and 2 are mainly used to measure the signals of the bearing sleeve inside the power port, as shown in Fig 4, the fault of the bearing sleeve is shown in Fig 5.

Under the condition that the engine speed is 1797R/min, pressure 44MPa. The information of normal working condition and the bearing sleeve fault have been obtained. The overall performance of the normalized signal is shown in Fig 6.

From Fig 6 we can see, the signal obvious contains external noise. Now taking the fault signal to verify the effect of the method. The characteristic frequency of the sleeve fault setting in the test is 89.7Hz.
Firstly, the fault signal is decomposed and denoised by ITD, and the correlation between the obtained components and the original signal is analyzed by cross-correlation function. The time domain diagram of the first five PR components is showing in Fig 7. The calculation results of the correlation between the PR components and the original signal are shown in Table 1.

If the correlation coefficient is above 0.9, the correlation is significant. According to the size of the correlation results, the component I is selected for Transient-extracting transform, and the extraction results are showing in Fig 8.

The upper part of the figure is the original PR1 component, and the lower part is its processing result of the TET. It can be seen that the original signal is clearly extracted after TET, the amplitude has been changed, but it will not affect the transient signal.

Taking the last transformed component signal to do envelope spectrum analysis, and the result is showing in Fig 9.

In the envelope spectrum, we can clearly see that the fault characteristic frequency is 89.6 Hz, and the related double and triple frequencies are also clearly displayed in the figure, which is basically the same to the set fault frequency mentioned before.

| PR components | correlation coefficient |
|---------------|------------------------|
| PR1           | 0.9215                 |
| PR2           | 0.4674                 |
| PR3           | 0.2869                 |
| PR4           | 0.1542                 |
| PR5           | 0.0648                 |
5. Conclusion

For the problem that fracturing truck power part fault difficult to identify and diagnosis. This paper proposed a fault diagnosis method based on ITD and TET to solve it. The experimental results showing this method can accurately extract the information of bearing sleeve faults in the power part of fracturing truck, and can reflect the internal faults in the power part to a certain extent.

There are many components in the power system of the fracturing truck, and different types of faults have different characteristics. Due to the limitation of fault samples, further research and analysis cannot be carried out, and it is a problem need to be solved in the next research work.

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