Fault Diagnosis of Rolling Bearing Based on Local Mean Decomposition and Transient Extracting Transform

ZhiChuan Zhao¹, ZhiGang Chen¹,²*, Long Chai³, YunLong Jang⁴

¹. School of Mechanical-Electronic Engineering, Beijing University of Civil Engineering and Architecture, Beijing 100044, China
². Beijing Engineering Research Center of Monitoring for Construction Safety, Beijing 100044, China
³. Changqing Downhole Technology Company, CNPC Chuanqing Engineering Company Limited Xi’an 710021, China

*Corresponding author’s e-mail: chenzhigang@bucea.edu.cn

Abstract: To solve the problem of inconspicuous feature extraction when LMD method is used to extract rolling bearing fault characteristic signals, A fault feature extraction method based on Local Mean Decomposition (LMD) and Transient-Extracting Transform (TET) was proposed. Firstly, the rolling bearing fault signals were processed by LMD and the feature components with rich fault information were screened out by using the kurtosis values. Then, the secondary feature extraction and envelope analysis of the acquired components were carried out by using TET method. The experimental results showing that this method can extract the pulse characteristics of the impact signal of rolling bearings efficiently, and is suitable for the fault diagnosis of rolling bearing.

1 Introduction
Rolling bearings are widely used in several kinds of mechanical equipment[1], and under the condition of high load and high speed, they are prone to damage. Therefore, the study of its fault problem is of great significance for the smooth progress of industrial production.

The detection of bearing faults is often achieved by acquiring the vibration signal of the bearing and subsequently using signal analysis to determine the type of faults. However, in actual diagnosis, the vibration signals we obtained are always containing some noise signal due to the influence of working conditions, environment and other factors, which makes it difficult to obtain fault information directly from the signals. Therefore, it is necessary to extract the fault feature information from the signal by some feature extraction methods for fault analysis.

Bearing vibration signals are often unsteady and nonlinear, and the short-time Fourier transform has low time-frequency resolution and the Wigner-Ville distribution existing cross-term interference in dealing with nonstationary signals[2]. Empirical Mode Decomposition (EMD)[3] can perform signal processing adaptively, but also suffers from problems such as modal mixing. The local mean decomposition[4] is also an adaptive signal processing method, and its problems in terms of modal aliasing are greatly reduced compared to EMD, which is suitable for processing bearing vibration signals.

The Synchrosqueezed wavelet transforms[5] has been widely used in feature extraction of various signals in recent years, but it is sensitive to noise and thus not suitable for processing strong pulse signals.
Based on the simultaneous squeezing transform, Yu Gang et al. proposed the transient-extracting transform\([6]\), which is suitable for extracting the strong pulse components in vibration signals, while the rolling bearing vibration signal has more Pulse characteristics.

Only using one single method such as LMD to extract part of the fault shock signal, there is still the existing problem that the extracted features are not obvious to analysis. Based on this, this paper combines the local mean decomposition with the transient-extracting transform, and applies this combined method to the bearing vibration signal decomposition. After obtaining the PF components containing rich fault information using LMD, the components are screening by using kurtosis\([7]\), and subsequently transformed using TET to further enhance the impulse characteristics of the signal and obtain the final signal for fault analysis.

Through the analysis and processing of the simulated signals, the ability of the proposed method in extracting the signal time-frequency information and obtaining the pulse characteristics is verified. Meanwhile, based on this, the method is applied to the fault analysis of the simulated fault vibration signals of rolling bearings, the accurate extraction of relevant fault features is successfully achieved, and the diagnosis analysis is completed.

2 Local Mean Decomposition

The local mean decomposition is a signal processing method that aims to extract the "best-fit" product function (PF component) of a set of pure FM and envelope signals from the signal, and to obtain all the PF components through a mathematical iterative loop for signal analysis. For the signal \(x(t)\), the decomposition process is as follows:

First, calculate all local extremum points of signal \(x(t)\), denote the extremum point as \(e_i\) and calculate the average value \(m_i\) of two adjacent points \(e_i\) and \(e_{i+1}\). The calculation formula is shown in (1):

\[
m_i = \frac{e_i + e_{i+1}}{2}
\]

(1)

The envelope estimate \(a_i\) is calculated according to the extreme point, and the calculation process is shown in (2):

\[
a_i = \frac{|e_i - e_{i+1}|}{2}
\]

(2)

By connecting all the points directly and using the moving average method, the local mean function \(m_{11}(t)\) and the envelope estimation function \(a_{11}(t)\) can be obtained. According to these two functions, the demodulation signal can be calculated as follows:

\[
s_{11}(t) = \frac{x(t) - m_{11}(t)}{a_{11}(t)}
\]

(3)

If \(s_{11}(t)\) envelope estimation function to meet \(a_{12}(t) = 1\), then the \(s_{11}(t)\) as the original signal iteration to repeat the above process \(s_{1n}(t)\), until the resulting signals can meet \(-1 \leq s_{1n}(t) \leq 1\), its envelope estimation function \(a_{1(n+1)}(t)\) can meet:

\[
a_{1(n+1)}(t) = 1
\]

(4)

The envelope signal is then obtained by multiplying all the envelope estimation functions generated during the iteration process:

\[
a_i(t) = a_{11}(t)a_{12}(t) \cdots a_{12}(t) = \prod_{c=1}^{n} a_{1c}(t)
\]

(5)

The first PF component can be obtained by multiplying the envelope signal \(a_1(t)\) with the pure FM signal:

\[
PF_1(t) = a_1(t)s_{1n}(t)
\]

(6)

The component is separated from the original signal to obtain \(u_1(t) = x(t) - PF_1(t)\), which is used as the original signal to repeat the above process for \(k\), until the final obtained \(u_k\) is a monotone function.

Finally, multiple PF components can be obtained for signal analysis.
3 Transient-extracting Transform

The STFT result of signal $s(u)$ are as follows:

$$G(t, \omega) = \int_{-\infty}^{+\infty} g(u - t) \cdot s(u) \cdot e^{-i\omega u} du$$  \hspace{1cm} (7)

$g(u - t)$ is the sliding window, $\delta(t)$ is a function, its numerical value is 0 in the range of real numbers outside zero, and its integral is 1 in $\mathbb{R}$. $\delta(t)$ is written as $C \cdot \delta(u - t_0)$, take it calculated by (7) can get:

$$G(t, \omega) = \int_{-\infty}^{+\infty} g(u - t) \cdot C \cdot \delta(u - t_0) \cdot e^{-i\omega u} du = C \cdot g(t_0 - t) \cdot e^{-i\omega t_0}$$  \hspace{1cm} (8)

$C$ is the amplitude of the signal staying in time $t_0$.

The STFT result of $C \cdot \delta(u - t_0)$ can be seeing as several $\delta(t)$ with same delay $u$. the energy will be diverged after STFT, and the follow function is be proposed:

$$TEO(t, \omega) = \delta(t - t_0(t, \omega))$$  \hspace{1cm} (9)

(9) needs to satisfy:

$$t_0(t, \omega) = \begin{cases} t_0, & t \in [t - \Delta, t + \Delta], \omega \in \mathbb{R}^+ \\ 0, & otherwise. \end{cases}$$  \hspace{1cm} (10)

In $t_0$, it can be converted to

$$\delta(t - t_0(t, \omega)) = \delta(t - t_0)$$  \hspace{1cm} (11)

the value of TEO is 0 out of $t_0$ in $\mathbb{R}$, and the Transient-extracting transform is Multiply (7) and (9), which is represented like follows:

$$T_e(t, \omega) = G(t, \omega) \cdot TEO(t, \omega)$$  \hspace{1cm} (12)

4 Simulation signal analysis

In order to verify the signal processing capability of the proposed method, the method is studied and analyzed by experimental simulations, and the simulated signals used in the experiments are as follows:

$$\begin{align*}
\begin{cases} f(t) = f_1(t) + f_2(t) + f_3(t) \\
\hat{f_1}(t) = \cos(20\pi t) \\
f_2(t) = 0.64\cos(30\pi t) \\
f_3(t) = 0.32\cos[2\pi(5t + 0.5\sin(4t))] \end{cases}
\end{align*}$$

First, the signal was decomposed by LMD, and the first three components were selected for research. The obtained components are shown in Fig 1(a), Calculating the sum of the first three components obtained from the LMD, then use SST to observe its time-frequency distribution and compared with the theoretical instantaneous frequency characteristics, the results are shown in Fig 1(b).
Fig 1: PF components and the instantaneous frequency of the signal

Fig1(b) shows the obvious time-frequency characteristic frequencies of 10Hz and 15Hz, but some cross-term interference occurs at the remaining characteristic frequencies. This is not only caused by the incomplete decomposition of LMD, but also due to the cross-term interference in the processing of multi-component signals by the SST method itself. At the same time, the simulation results can basically reflect the instantaneous frequency characteristics of the original components, and in general, the method can effectively process the simulation signals.

Next, the PF component 2 is selected for the TET transform to verify its ability to extract the impulse signal using a Gaussian window with a window length of 100. The results obtained are shown in Fig 2.

The experimental results show that the TET method can effectively extract the pulse features in the signal, and the method is suitable for processing the fault signals of rolling bearings with many pulse elements.

Combined with the LMD decomposition method can get bet answers, next we will prove that through experiments.

5 Diagnosis of bearing fault signal

5.1 The experimental device

In order to verify the ability of the combined method of local mean decomposition and transient extraction transform to extract fault impact features from original signals in practice. Now the actual bearing fault vibration signals are used for research and analysis. experimental platform including speed sensor and bearings. The fault simulated in the experiment is the fault of bearing inner ring processed by electric spark technology. The sampling frequency is 25.6KHz, the rotate speed is 1800r/min.

5.2 Fault diagnosis of rolling bearing inner ring

When the inner ring of a rolling bearing get faults, the position of the fault point often rotates with the rotation of the inner ring, and the vibration signal finally measured will be modulated. In this case, the difficulty of diagnosis is relatively high. The frequency of the failure signal of the bearing inner ring set by the experiment is 39.87Hz, and the failure frequency is 187.62Hz. The time domain diagram and spectrum diagram of the vibration signal of bearing inner ring fault are shown in Fig3(a).
Fig3: Inner ring fault and its PF components

From Fig3(a) cannot direct obtaining useful fault information, which is now analyzed using the combined method proposed in this paper. Firstly, LMD was used for signal modal decomposition to obtain multiple PF components. The kurtosis is used to distinguish the degree of correlation between each component and the original signal. The higher the kurtosis is, the more obvious the fault feature is. The calculation results of the kurtosis values of some components are shown in Table 1, and Fig.3(b) is the time domain diagram of the first three PF components of the inner circle:

| PF components | Kurtosis values |
|---------------|-----------------|
| PF1           | 13.0162         |
| PF2           | 5.6846          |
| PF3           | 3.1019          |
| PF4           | 2.6574          |
| PF5           | 2.9653          |

According to the kurtosis values, PF1 was selected for TET pulse extraction, and the window length set as 150. The results are shown in Fig. 4(a):

Fig4: PF1 signal and its TET results with the Envelope spectrum
Envelope spectrum analysis was performed on the final obtained signal, and the results are shown in Fig 4(b).

It can be founded that the fundamental frequency is 40.625Hz and the peak frequency is 184.4Hz. Four times the fundamental frequency can also be seeing, the results is close to the failure frequency set by the test. The proposed method can not only find the fundamental frequency, but also find the fault impact frequency, which has good ability in fault feature extraction.

6 Conclusion
In this paper, a fault diagnosis method based on local mean decomposition (LMD) and transient-extracting transform (TET) is proposed, and the results are verified by experiments. A accurate bearing fault feature extraction was achieved, and the mainly conclusions are as follows:

(1) Combining the local mean decomposition method with the transient extraction transform, the impulse components implied in the original signal can be extracted more accurately, which is suitable for processing rolling bearing vibration signals with more impulse features.

(2) When processing multi-component signals, the decomposed mode components have cross-term interference at similar instantaneous frequencies, which may cause problems when processing multiple fault signals with similar fault frequencies and it is worth further study.

Acknowledgements
This research was supported by Beijing University of Civil Engineering and Architecture Special fund support for basic scientific research business expenses of municipal Universities(X20061) and Project supported by research fund of Beijing Construction Safety Monitoring Engineering Technology Research Center.

References
[1] Wang G B, He Z J, Chen X F, Lai Y N. (2013) Basic research on mechanical fault diagnosis "where to go" [J]. Journal of mechanical engineering, 49(1): 63-72.
[2] Du X L, Chen Z G, Wang Y X. (2020) Bearing fault diagnosis based on the synchrosqueezed S transform and ensemble deep ridgelet auto-encoder [J]. Journal of Vibration and Shock, 39(14):59-68.
[3] Zhang L Z, Xu W X, Jing L Y, Tan J W. (2020) Fault Diagnosis of Rotating Machinery Based on EMD-SVD and CNN[J]. Vibration. Measurement & Diagnosis, 40(06):1063-1070+1228.
[4] Zhang S Q, Sun G X, Li L, Li X X, Jian X. (2013) Research on Mechanical Fault Diagnosis Based on LMD Approximate Entropy and CNN Clustering [J]. Chinese Journal of Scientific Instrument, 34(03):714-720.
[5] Daubechies I. et al. (2011) Synchrosqueezed wavelet transforms: An empirical mode decomposition-like tool[J]. Applied and Computational Harmonic Analysis, 30(2): 243-261.
[6] Pan H , Yang Y , Li X , et al. (2019) Symplectic geometry mode decomposition and its application to rotating machinery compound fault diagnosis[J]. Mechanical Systems and Signal Processing, 114(JAN.1):189-211.
[7] Mcdonald G L , Zhao Q , Zuo M J . (2012) Maximum correlated Kurtosis deconvolution and application on gear tooth chip fault detection[J]. Mechanical Systems and Signal Processing, 33(Complete):237-255.