Gear Fault Diagnosis based on LMD and Mathematical Morphological Filtering

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Abstract

As a common and vital component in gearboxes, gears are widely used in modern industry and manufacturing. Relevant research shows that the proportion of transmission system failures caused by gears in gearboxes is extremely large. Therefore, it is of great significance to diagnose faults on gears. The key to fault diagnosis of gears is to extract the characteristics of the fault signal. The fault types and damaged parts of the gear can be distinguished through the extracted fault characteristics. In this paper, theoretical methods such as mathematical morphology filtering and LMD local mean decomposition are studied, and they are applied in gear fault feature extraction and fault identification. The signal is morphologically filtered to achieve noise reduction processing. At the same time, the effectiveness of the method proposed in the paper is verified through simulation signals and experimental data. The results obtained show the effectiveness of the method and the value of engineering application.

Keywords

Mathematical morphology filter; Local Mean Decomposition (LMD); Fault diagnosis.

1. Introduction

Gears and gearboxes are common parts used by motors to transmit power and change speed. Once a failure occurs, the entire set of equipment may not operate normally. Therefore, the fault diagnosis of gears is very important. Due to the harsh operating environment of gears and gearboxes, various influencing factors and links, and early failures are not easy to find, it is easy to cause gear wear or tooth breakage. The gear fault vibration signal has the characteristics of non-stationary, multi-component amplitude modulation, periodic repetitive impact, etc., and it is also mixed with complex noise signals. Based on the characteristic frequency of the gear fault, the author constructs a multi-structure, multi-scale mathematical morphological filter to filter out the background noise, and extracts the impact signal. On this basis, the gear signal is decomposed by the local mean method to obtain several PF components; The PF component including the main fault information component is further analyzed, and its energy characteristic parameters are extracted to form the fault characteristic vector; finally, it is used as the input sample of the neural network, and the neural network is trained and fault identification, so as to realize the gear fault diagnosis.

2. LMD method

LMD (Local Mean Decomposition) was applied by Smith in 2005 as a new adaptive time-frequency analysis method for nonlinear and non-stationary signals. It can decompose the signal into multiple PF (Product Function, PF) based on the information of the signal itself. The sum of the components, the time-frequency distribution of the PF component can effectively reflect the energy distribution of the signal on the spatial scale [1], the amplitude-frequency characteristics of the original signal can be obtained by demodulating and analyzing the time-frequency information of the PF component, which is especially suitable Fault signal related to the gear. LMD decomposition is particularly suitable for adaptive analysis of non-stationary and nonlinear signals at the time-frequency level [1]. Its significant advantage is that any complex signal can be decomposed and converted into a set of multiple PF components and residual components R. The specific operation of the decomposition process is as follows [2]:

(1) Calculate all local extreme values of the signal to be analyzed, that is, all local maximum points and local minimum points, count all adjacent extreme points, and calculate the mean m_i and envelope estimates α_i one by one:

$$m_i = \frac{n_i + n_{i+1}}{2} \tag{1}$$

$$\alpha_i = \left| \frac{n_i - n_{i+1}}{2} \right| \tag{2}$$

(2) Count the calculation results of the first step, connect all m_i and α_i, and use moving average to smooth them to obtain the local envelope estimation function $a_{11}(t)$ and the local mean function $m_{11}(t)$.

(3) Remove $m_{11}(t)$ from the signal to be analyzed, and then get $h_{11}(t)$:

$$h_{11}(t) = x(t) - m_{11}(t) \tag{3}$$

(4) Divide the $h_{11}(t)$ obtained in the previous step by the local envelope estimation function $a_{11}(t)$ to obtain the FM signal $s_{11}(t)$, namely:

$$s_{11}(t) = \frac{h_{11}(t)}{a_{11}(t)} \tag{4}$$

(5) To make $s_{11}(t)$ a standard FM signal, you need to meet $a_{12}(t) = 1$; when $a_{12}(t) \neq 1$, you need to use $s_{11}(t)$ as the original data and repeat the above steps until $s_{1n}(t)$ becomes a standard pure frequency signal, that is,$a_{1(n+1)}(t) = 1$, so we know:

From $h_{11}(t) = x(t) - m_{11}(t)$, the following can be obtained:

$$\begin{cases} h_{11}(t) = x(t) - m_{11}(t) \\ h_{12}(t) = s_{11}(t) - m_{12}(t) \\ \vdots \\ h_{1n}(t) = s_{1(n-1)}(t) - m_{1n}(t) \end{cases} \tag{5}$$

Among them, we can see from $s_{11}(t) = h_{11}(t)/a_{11}(t)$:

$$\begin{cases} s_{11}(t) = h_{11}(t)/a_{11}(t) \\ s_{12}(t) = h_{12}(t)/a_{12}(t) \\ \vdots \\ s_{1n}(t) = h_{1n}(t)/a_{1n}(t) \end{cases} \tag{6}$$

To achieve the expectation, the condition $a_{1(n+1)}(t) = 1$ must be satisfied. However, in order to improve the calculation efficiency in practical applications, a variable θ ($0 < \theta < 1$) is usually given. When $1 - \theta < a_{1n}(t) < 1 + \theta$ is established, the calculation process described above can be ended. To multiply all $a_{1j}(j = 1,2, n)$ obtained by calculation in turn, the packet signal can be obtained, which is expressed as follows:

$$a_{1(t)} = a_{11}(t)a_{12}(t)\cdots a_{1n}(t) = \prod_{q}^{n} a_{1q}(t) \tag{7}$$

(6) The product of the envelope signal $a_{1(t)}$ and the pure FM signal $s_{1n}(t)$ obtained first after calculation is essentially the first PF component, which is expressed as follows:

$$PF_1(t) = a_{1(t)} s_{1n}(t) \tag{8}$$

(7) Use the initial signal x(t) to subtract the first decomposed FP componentPF_1, the resulting signal is expressed as $u_1(t)$, and then use $u_1(t)$ as the initial signal and continue to calculate according to the previous procedure, and calculate to $u_k(t)$ is monotonic, that is:

$$\begin{cases} u_1(t) = x(t) - PF_1(t) \\ u_2(t) = u_1(t) - PF_2(t) \\ \quad\vdots \\ u_k(t) = u_{k\text{-}1}(t) - PF_k(t) \end{cases} \tag{9}$$

(8) Finally, the original signal to be analyzed is decomposed into k PF components and the form of the sum of $u_k(t)$, namely:

$$x(t) = \sum_{p=1}^{k} PF_p(t) + u_k(t) \tag{10}$$

3. Mathematical morphological filtering

Mathematical morphology was originally used in the field of image analysis and research. It has a complete theoretical system. It is one of the effective methods for analysis and processing of non-stationary signals [3]. It has good noise reduction and impulse suppression capabilities, and can Compared with other processing methods, the algorithm is simple and efficient for noise reduction and feature extraction for nonlinear and non-stationary signals. Corrosion and expansion are the basic operators of mathematical morphology, which are specifically defined by the intersection and union algorithm. The combination of corrosion and expansion operations mainly includes opening and closing operations. Set f(n) as the discrete distribution function on $\mathrm{F} = (0,1,2,\mathrm{N}-1)$, and treat the structural element g(m) as $\mathrm{G} = (0,1,2,\mathrm{M}-1)$. Discrete function, which also conforms to the global definition of $\mathrm{N} \geq \mathrm{M}$ and f(n) for the corrosion of g(m) and the Minkowski difference sum of expansion [4].

$$(f \oplus g)(n) = min[f_{-m}(n) - g(m)], m \in G \tag{11}$$

$$(f \oplus g)(n) = \max[f_m(n) + g(m)], m \in G \tag{12}$$

It can be seen from the above equation that the advantage of corrosion and expansion calculations is that the calculation speed is fast , and the idea is:

Take each point in the domain G of the structural element as a reference point,

and move the signal data relative to each point by -m or m.

Each time the signal data is shifted, a corresponding value will be obtained, and

then the difference and sum of this value and the value of the structure element will be performed, so each point of the structure element domain G will get a signal value, and the poles corresponding to all points will be counted successively. The value can be the result of the corrosion expansion calculation.

Mathematical morphological filtering has been gradually applied to signal processing from image processing in recent years, and has been rapidly developed in the field of signal processing. Mathematical morphological filtering is a filtering process based on basic morphological operations. It achieves the purpose of filtering by performing morphological operations on structural elements of a certain size and shape with the processed signal [5]. The core of morphological filtering of the analyzed signal is based on the characteristics of the signal itself, and the type of structural elements is preset in advance, which is equivalent to selecting a window function in wavelet analysis, and then performing the analysis on the geometric feature level Correspondingly cooperate or make minor corrections, so as to extract key information, and at the same time, it can suppress the noise to a certain extent [7].

4. Diagnosis method based on LMD and mathematical morphological filtering

On the premise of obtaining vibration signals:

1) Morphological filtering of the signal;

2) Perform LMD decomposition;

3) The first decomposed PF component with larger energy is selected for signal reconstruction, and envelope analysis is performed on the reconstructed signal to obtain the characteristic frequency.

The flow of the gear fault diagnosis analysis method based on LMD and mathematical morphological filtering is shown in Figure 1:

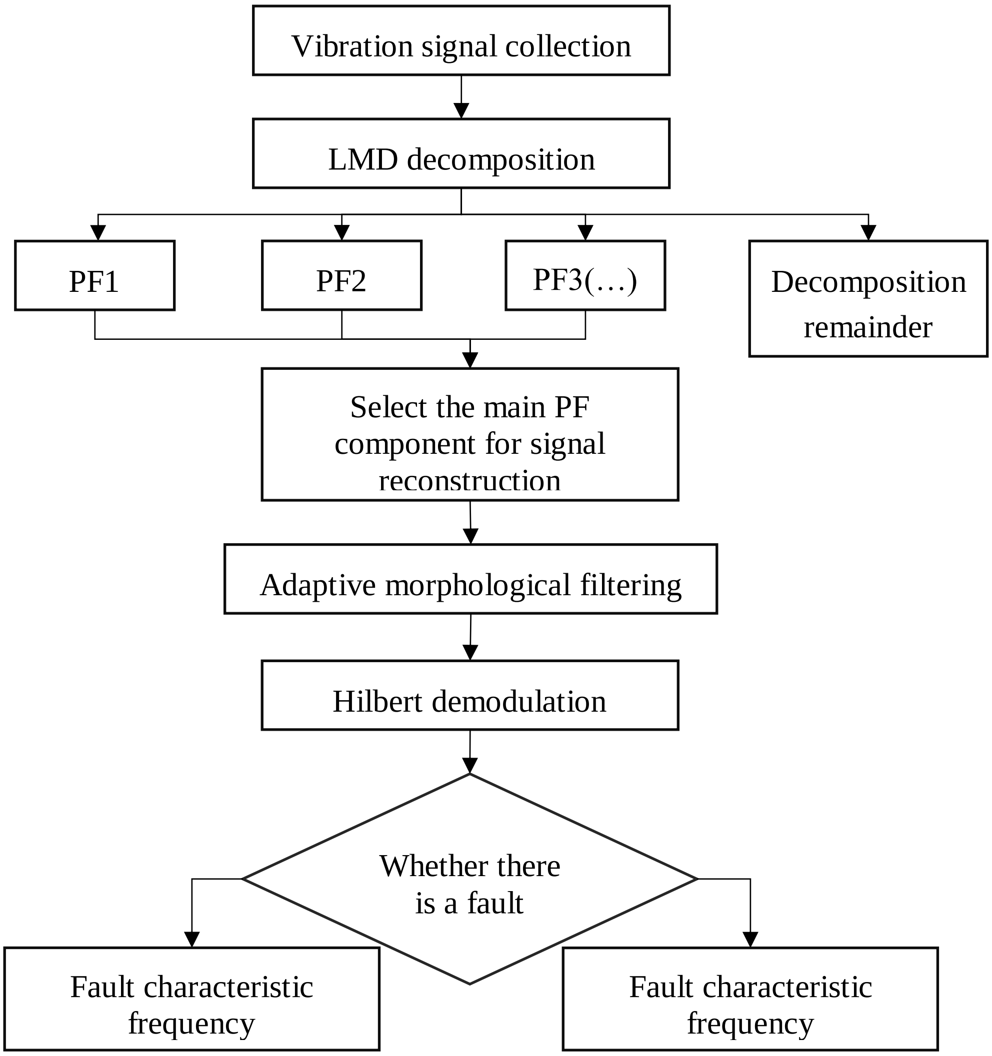

Fig 1. Gear fault diagnosis flowchart

5. Fault diagnosis of a certain transmission mechanism gear

The experimental data comes from the INV1618 transmission system typical failure simulation experimental device of Beijing Oriental Institute of Vibration and Noise Technology. The sampling frequency is 12.8KHz and the speed is 500r/min. The experimental device consists of a DC motor, a rotating shaft, and a sliding bearing. 4 rolling bearing supports, gear box, acceleration sensor and other components, as shown in Figure 2. In this experiment, two types of faults, broken teeth and wear, are arranged on the gears. The time-domain signal of the vibration acceleration of the measuring point in the wear fault state is shown in Figure 3.

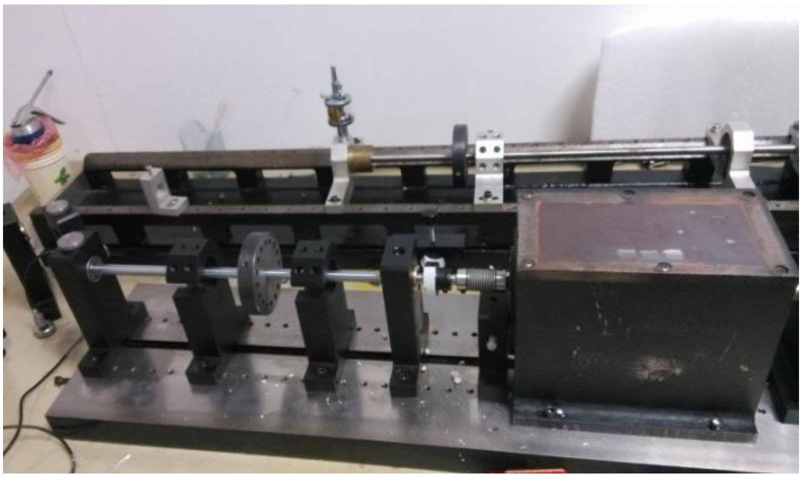

Fig 2 INV1618 type experimental device

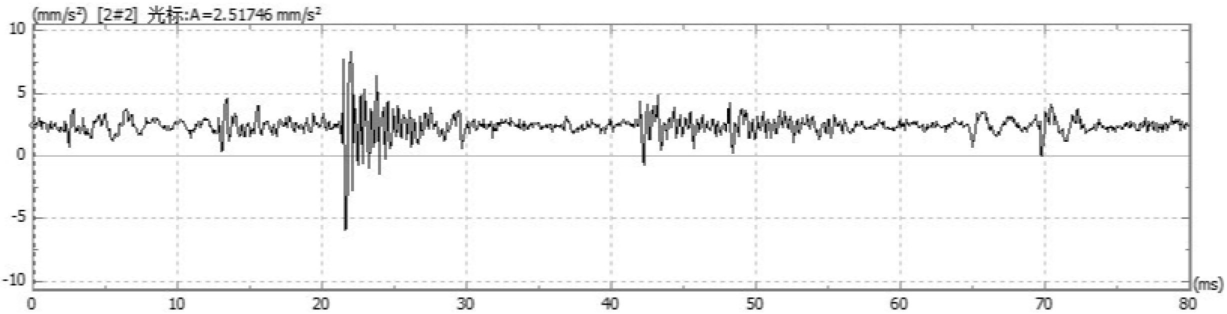

Fig 3 Time domain diagram of vibration acceleration of worn gear

It is obvious from the above figure that there are a lot of noise interference in the signal, which causes the fault characteristics to be completely submerged and cannot be displayed in the spectrogram. The analyzed signal is morphologically filtered and decomposed by LMD to obtain the components and remainder as shown in Figure 4:

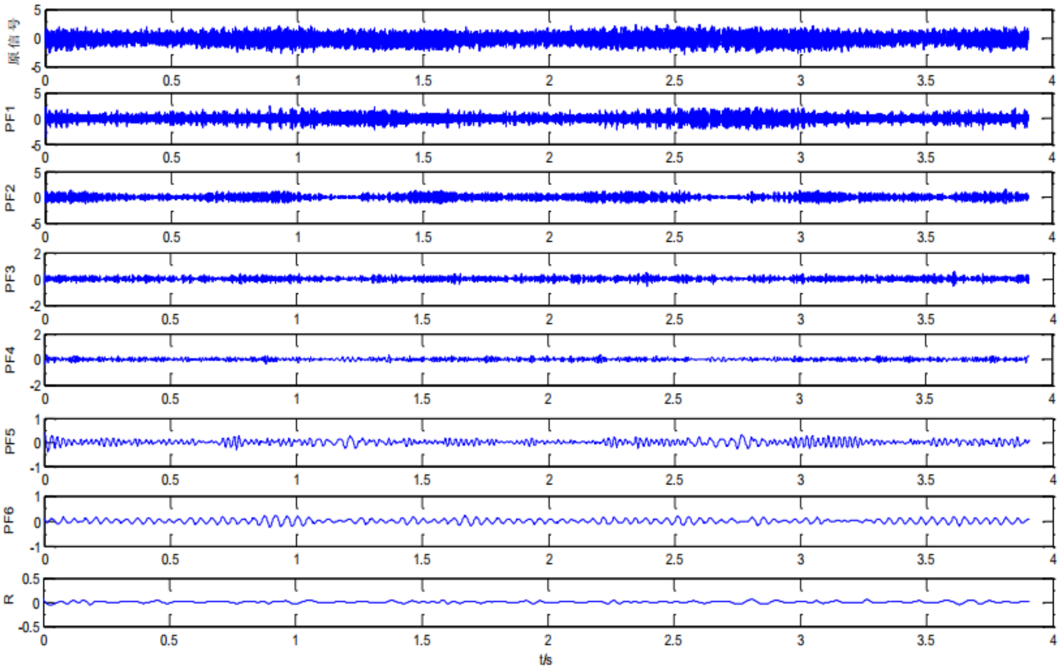

Fig 4 Decomposition of wear signal LMD

The 6 components and a residual term obtained by LMD decomposition. From the amplitude figure 4 we can see that the time-frequency characteristics contained in the first 4 PF components can approximate the characteristics of the source signal. Therefore, the first 4 main PF components are selected for signal analysis. Reconstruction and envelope the reconstructed signal to obtain the envelope spectrum as shown in Figure 5:

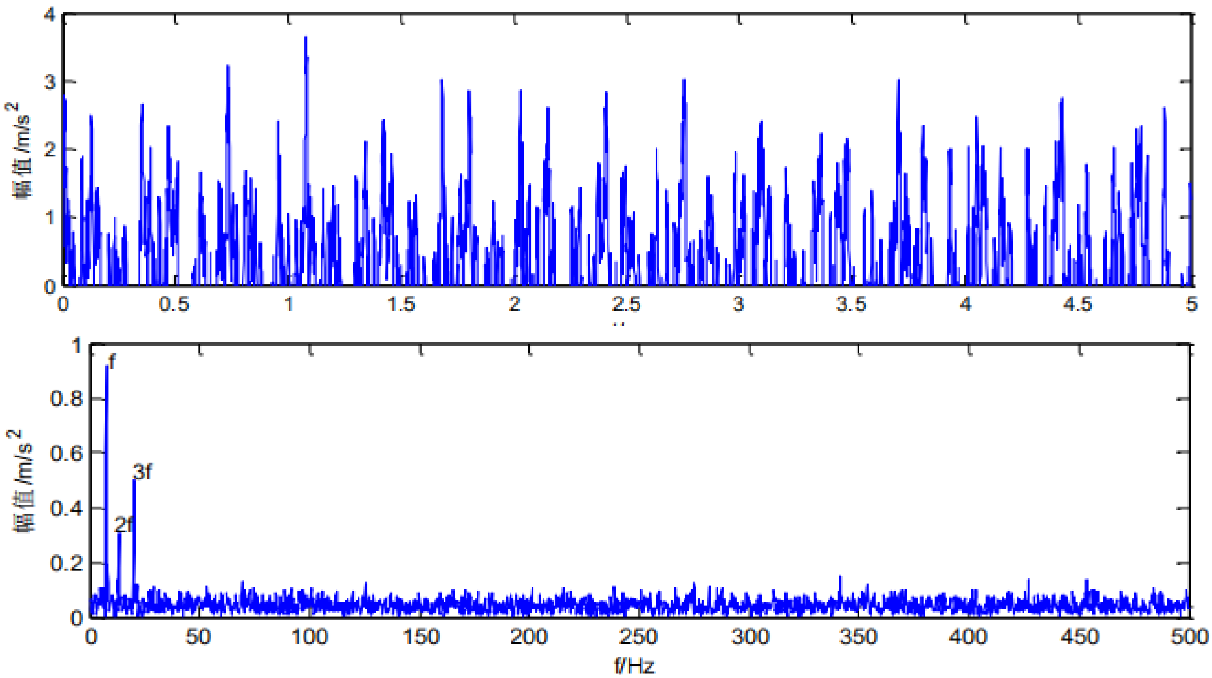

Fig 5 Time domain diagram and frequency domain diagram of reconstructed signal

From the figure, it can be clearly seen that the 5Hz shock signal is effectively extracted, and it is also found that there are obvious 2 times and 3 times equal frequency components. The sidebands that appear around the meshing frequency with the rotation frequency of the shaft as the spacing are consistent with the spacing of the reconstructed signal sidebands, which shows that the modulation of the meshing frequency by the frequency rotation occurs. The characteristic frequency of the gear wear fault calculated by theory is about 4.8 Hz, and it can be seen that the edge frequency information is uniformly distributed and the amount of information is huge, which is close to the gear wear fault frequency, indicating that gear tooth wear occurs in the meshing state of the gear. The actual state of the gear is consistent, the noise is effectively suppressed during the signal decomposition process, and the signal-to-noise ratio is improved at the same time, and the fault characteristics are clearly presented, which proves the effectiveness and practicability of the proposed method.

The time-domain signal of the vibration acceleration of the measuring point under the broken tooth fault state is shown in Figure 6:

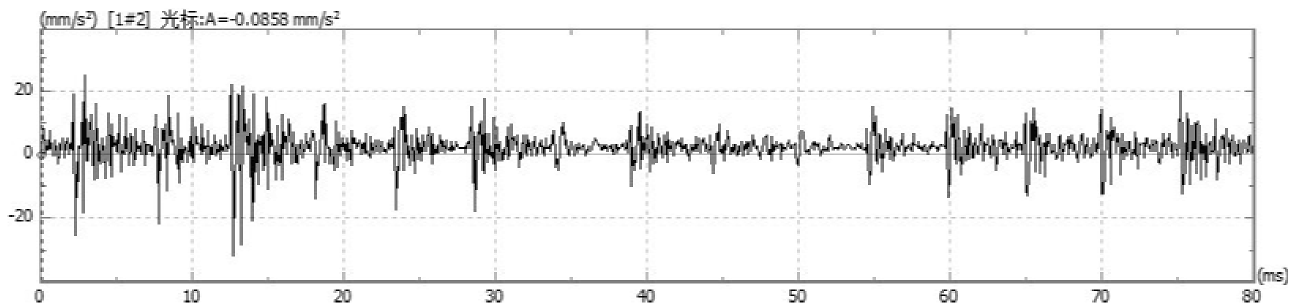

Fig 6 Multi-time domain diagram of broken tooth vibration acceleration

It can be seen from the signal time domain and spectrogram that the gear fault signal has obvious modulation phenomenon, and the frequency component contains a lot of low-frequency noise interference. The gear rotation frequency and its meshing frequency cannot be clearly expressed in the spectrogram. Therefore, the acquired state signal is first subjected to morphological filtering processing, and then LMD decomposition is performed to obtain the result as shown in Figure 7:

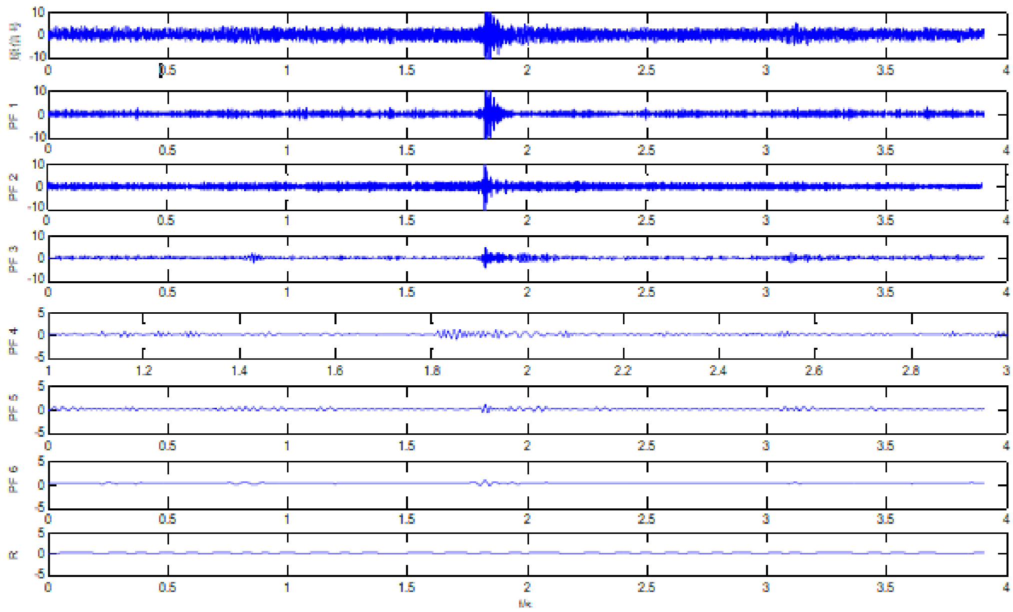

Fig 7 Decomposition of broken tooth LMD

It can be seen from Figure 7 that the gear tooth fractured fault signal is processed by LMD for 7-layer decomposition to obtain 6 PF components and one residual term. The time-frequency domain characteristics of the components clearly show that the components PF1, PF2, PF3, and PF4 almost cover the broken tooth. The most part of the signal is information, so the four PF components are selected for signal reconstruction. The reconstructed signal is morphologically filtered and enveloped demodulated to obtain the amplitude spectrum as shown in Figure 8:

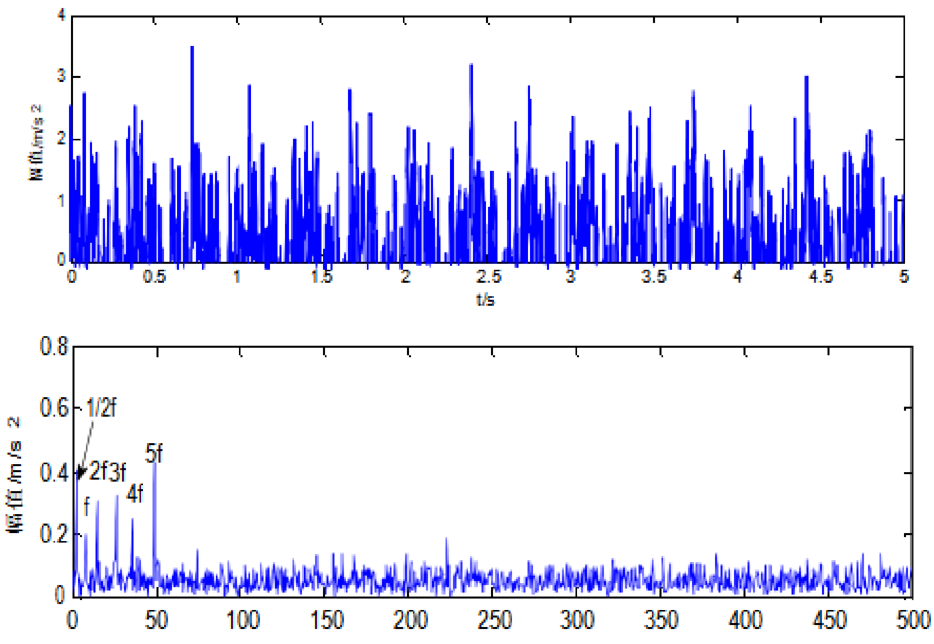

Fig 8 Time domain diagram and frequency domain diagram after demodulation

From the spectrogram of the reconstructed signal, the spectral lines at 0.5 times, 1 times, 2 times, 3 times, and 4 times the gear rotation frequency can be found. At the same time, the sidebands and the reconstructed signal are separated by the shaft rotation frequency near the meshing frequency. The spacing of the sidebands is consistent, which indicates that the frequency conversion has a modulation phenomenon on the meshing frequency. The characteristic frequency of the gear fault calculated by theory is about 10.2Hz, and the uniform distribution of the side frequency information and the huge amount of information are close to the gear broken tooth fault frequency, which can indicate that the gear running condition has a broken tooth, which is consistent with the actual situation of the gear In the same way, the noise spectrum is effectively suppressed in the signal processing process, the signal-to-noise ratio is improved, and the fault characteristics can be significantly displayed, which proves the effectiveness and practicability of the proposed method.

6. Conclusion

Under today's overall planning of intelligent manufacturing in major countries and macro trends, fault diagnosis for large-scale equipment has become more prominent in the industrial field as a practical and indispensable high-precision application technology, which can ensure the reliability of related machinery and equipment to a certain extent. Abnormal operation. Gearbox is an important equipment widely used in various military and civilian fields. Its operational safety and reliability are very important. As its key components, gears are under high load, high speed and complex load conditions for a long time. Failures will directly affect the safe and effective operation of the entire system. Therefore, it is extremely important to analyze, find, and resolve failures as early as possible and accurately. Starting from the reality of industrial applications, this article takes the gear as an essential part of the gearbox as the object of analysis and research, and conducts in-depth research on mathematical morphology filtering, local mean decomposition and other theories. From the perspective of time-frequency domain statistical parameters, the information of the gear's state is effectively stripped, and the fault category of the gear is identified consistent with the actual situation. It fully proves the effectiveness of LMD based on mathematical morphological filtering in gear fault diagnosis.

References

[1] Yang Bin, Cheng Junsheng. Gear damage identification method based on LMD and principal component analysis [J]. Vibration, Testing and Diagnosis, 2013, 33(5): 809-813.

[2] Chen Yanong, Bu Pugang, He Tian, et al. Application of local mean value decomposition in comprehensive diagnosis of rolling bearing faults[J]. Vibration and Shock, 2012, 31(3): 73-78.

[3] Hu Aijun, Xiang Ling, Tang Guiji, etc. Rotor fault feature extraction method based on mathematical morphology transformation[J]. Chinese Journal of Mechanical Engineering, 2011, 47(23): 92-96.

[4] Wu M T, Yong Y. The Research on Stock Price Forecast Model Based on Data Mining of BP Neural Networks[C]. Third International Conference on Intelligent System Design and Engineering Applications.2013:1526-1529.

[5] Xu Dong, An Jinzhi. Application of image salient extreme value detector based on attribute morphology analysis[J]. Journal of Aeronautics, 2006, 27(4): 692-696. Vibration and Shock, 2012, 31(3): 73-78.

[6] Wang Fengli. Research on nonlinear dynamic characteristics and application of rotor system based on local wave method: [Doctoral dissertation]. Dalian: Dalian University of Technology, 2003.

[7] Hu Aijun, Sun Jingjing, Xiang Ling, et al. Research on the frequency response characteristics of mathematical morphological filters in vibration signal processing[J]. Chinese Journal of Mechanical Engineering, 48(1): 99-103.