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On Non-Stationary Signal Transformation and Feature Extraction

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Abstract
With the continuous development of the current society, the national economic level has been improving, and the people's material demand is higher and higher. Currently, it is necessary to improve the output and efficiency of materials. Therefore, mechanical automation equipment is also developing at a high speed, and the production efficiency is constantly improving. However, there are many important large-scale mechanical equipment, such as steam turbine or large ball bearing. If they work in a harsh environment for a long time, it is easy to cause damage. Whether it is the fault caused by manual disoperation or the fault caused by bearing damage, the shutdown may cause economic losses, or casualties and environmental damage. From the beginning of human beings, signal is the carrier of language and the medium of all kinds of things. According to human experience, the signal is divided into two parts, deterministic signal, and uncertain signal. Uncertain signals are divided into two kinds, stationary signals, and non-stationary signals. Nonstationary signals will follow time to transform, and the statistical feature is a function of time. For example, fault diagnosis can prevent and avoid bearing faults by transforming the non-stationary signals in various random signals generated by noise during the operation of equipment and engineering systems and extracting the required fault diagnosis features for diagnosis. If China can vigorously promote the use of non-stationary signal fault diagnosis, and many large equipment can be detected through fault diagnosis, it is likely to avoid the occurrence of faults. Because the loss of shutdown is sometimes very large, especially in the processing industry. For example, for a large synthetic fertilizer machine, the loss caused by shutdown for one day can be as high as several million yuan. If the system fault is diagnosed through non-stationary signals, it can completely prevent economic losses and even casualties. Therefore, the study of non-stationary signals is very meaningful, and it is also a subject that the country should vigorously develop.

Keywords: Wavelet Transform, Wavelet Packet Decomposition, Fault signal, Wavelet Analysis

Introduction
The methods of studying stationary signals are divided into two categories: one is time domain analysis method and the other is frequency domain analysis method. The time domain analysis method is relatively simple and direct. The results can be obtained by directly using the time domain signal analysis. Frequency domain analysis takes Fourier transform as the central point to obtain the spectrum and then extract the features, which will more intuitively see the characteristics of the signal than time domain analysis [1].

Because the traditional Fourier transform only shows the characteristics of the signal in the frequency domain, but it is a global transform, which only shows the signal in the form of different frequency components [2]. It separates time and frequency to analyze the signal. It builds a bridge from time domain to frequency domain and does not perfectly connect time domain and frequency domain, the most important property of non-stationary signal is the localization of signal in time domain and frequency domain. It cannot be seen that a certain frequency component appears at that time, that is, it is impossible to locate non-stationary signal in time and frequency at the same time. Therefore, the traditional Fourier transform is not suitable for the study of non-stationary signals, but only suitable for the study of periodic signals [3].

In order to study and analyze non-stationary signals, human beings began the research of non-stationary signals in the 1940s and 1950s based on the general short-time Fourier transform and put forward the concepts of short-time Fourier transform and Gabor transform, so as to establish the relationship between time domain and frequency domain of non-stationary signals and start the research of joint analysis. What's more, in the late 1980s, wavelet transform developed. Wavelet transform not only expanded and improved the joint analysis of signal time domain and frequency domain, but also has certain characteristics to adapt to signal resolution [4].

Since the advent of wavelet theory, many researchers have attached great importance to it. Therefore, wavelet theory has also developed very rapidly. They all believe that this is an important breakthrough in the study of non-stationary signals. Wavelet transform, known as "mathematical microscope", is a milestone in the history of harmonic analysis [5]. In the 1990s, the American Mathematical Society praised wavelet transform as one of the eight important topics of Applied Mathematics in the 1990s; China pays more attention and invests a lot in this field every year. Although the domestic development started late, it has developed rapidly and made great progress in mechanical fault diagnosis and detection. At present, many key universities and research institutes in China have carried out relevant research projects and achieved remarkable results [6].

Because of the advantages of wavelet transform in studying non-stationary signals, this paper studies non-stationary signal transformation and feature extraction through wavelet analysis [7].

Introduction to Non-Stationary Signals

Definition of signal

All things in nature are in the process of continuous movement. In a broad sense, the movement or reflected form of all things is a kind of signal. Nature relies on signals to transmit all kinds of information, which contains the characteristics of all things. To some extent, we can identify this information by extracting this feature. In other words, the specific content of the signal is information, and the process of feature extraction is the process of extracting the feature signal from the signal [8].

Signals are used to represent the physical quantity of information. In a broad sense, they can be roughly divided into the following categories: optical signals, acoustic signals, and electrical signals. People usually use mobile phones to communicate through radio waves, which belongs to electrical signals; In people's daily conversation, when sound waves reach other people's ears, others will understand what you mean. This is sound signal; Ancient people transmitted the news of war through the beacon tower, which is the light signal. Signals can be divided into deterministic signals and random signals according to their time characteristics; According to its own practical use, signal can be divided into TV broadcast signal, radar signal, communication network signal, etc [9]. Therefore, people need the help of signals to communicate and interact smoothly.

Signal Classification

There are many signal classification methods. We can divide signals into deterministic signals and uncertain signals. This paper studies the non-stationary signal in the non-deterministic signal, as shown in Figure 1

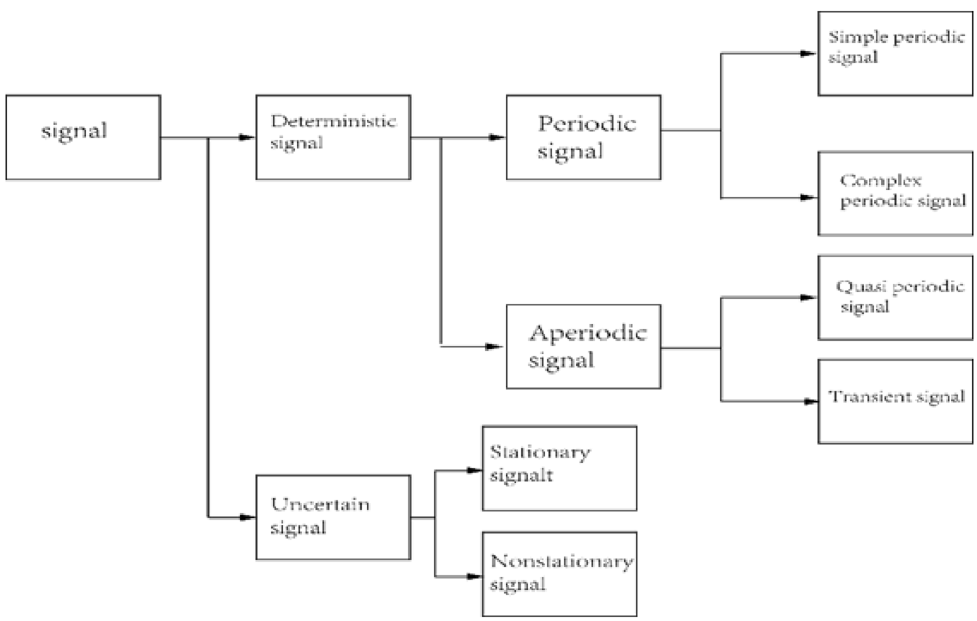

Figure 1: Signal Classification

According to the value characteristics, it can be divided into continuous signal and discrete signal; According to the characteristics of time function, it can be divided into time limit signal and frequency limit signal. According to different classification specifications, the types of signals are also different.

Definition of Non-Stationary Signal

Random non-stationary signal is called non-stationary signal for short. It refers to the parameter of random dispersion or the change signal generated by the change of distribution law with time. In fact, in a broad sense, the signals generated by nature and human society can be regarded as non-stationary signals. Nonstationary signals are included in all fields of life. The music signals in the songs people usually listen to, or the voice signals they usually chat with, or the signals sent by equipment failure, or even biological signals are nonstationary [10]. Therefore, non-stationary signal processing, feature extraction and research are very important and widely used in various fields. Over the years, the research on non-stationary signals has developed rapidly. For example, the method of simulating time-varying parameter signals. With people's continuous efforts, non-stationary signals must develop faster [10].

Short time Fourier transform

In the 1950s, people put forward the concept of short-time Fourier transform. In the short-time Fourier transform, a window function with a small span that can be moved on the time axis is applied to the signal, then the Fourier transform is performed, and then the window function is moved. This process is the short-time Fourier transform repeatedly. The expression is as follows:

$$STFT_x(\tau, f) = \int x(t)h * (t-\tau)e^{-j2\pi ft}dt \qquad (1)$$

Short time Fourier transform is the most common and common method in non-stationary signal processing. Non-stationary signals are regarded as composed of many short stationary signals. Based on the traditional Fourier transform, by adding a window in the time domain, constantly doing the Fourier transform, and then moving the window, the translation of the whole-time domain can be realized in this way [11]. However, short-time Fourier transform also has disadvantages, and its time-frequency resolution is limited by window function. That is, the higher the frequency resolution, the narrower the window function and the lower the frequency resolution. That is to say, the resolutions in time domain and frequency domain are always contradictory [12].

Moreover, because the short-time Fourier transform assumes that the signal is very stable in the window, but some signals transform faster with time, it is difficult to ensure that the signal is stable in the window. However, if the window is enlarged, the local stability of the signal cannot be guaranteed. It will be much better to process it with wavelet analysis, because it can analyze the time domain and frequency domain at the same time [13].

Wavelet Analysis

The origin of wavelet analysis can be traced back to the early stage of last century, but this concept was accidentally put forward by German scientists in the 1980s to facilitate the study of seismic signals, and then developed rapidly later. Because the short-time Fourier transform has defects, because the size and shape of its window are fixed, it can only be said to be an improvement of the traditional Fourier transform, but it cannot fundamentally change the defects of the Fourier transform. At this time, the spectrum analysis and wavelet analysis of the adjustable window should be shipped out. In popular terms, it automatically adjusts the window size with the change of non-stationary signal to form wavelet.

1) Definition of wavelet transform

Definition of wavelet transform it is assumed that its Fourier transform meets the following conditions:

$$C_\varphi = \int R \frac{|\varphi(\omega)|^2}{|\omega|} d\omega < \infty \qquad (2)$$

We call φ(t)one of his mother wavelets. From the above formula, we can get the conclusion that if we want to produce better results, the selection of mother wavelet is best a regular real or complex function.

$$\varphi_{a,\tau}(t) = \frac{1}{\sqrt{a}} \varphi(\frac{t-\tau}{a}) a, \tau \in R; a > 0 \qquad (3)$$

a is the scaling factor and τ is the translation factor. We call φ_(α,τ)(t) the wavelet basis function dependent on a and α, that is, it determines the scaling level of wavelet transform, and τ value determines the change of position.

Wavelet transform has many advantages. It can focus on any detail of the signal. It is a significant improvement and breakthrough in short-time Fourier transform.

Characteristics of wavelet transform it can carry out multi-resolution analysis of signals, and finally achieve time subdivision at high frequency and frequency subdivision at low frequency by controlling stretching and translation, which can perfectly combine time domain and frequency domain for analysis, and wavelet analysis can carry out local analysis of spatial frequency, so as to solve the shortcomings of traditional Fourier and short-time Fourier, Is a major breakthrough.

2) Continuous Wavelets Transform

Arbitrarily expand a function f (T) contained in L2 (R) under wavelet basis, as follows:

$$WT_f(a, \tau) = \langle f(t), \varphi_{a,t}(t) \rangle = \frac{1}{\sqrt{a}} \int R\, f(t) \varphi * (\frac{t-\tau}{a}) dt \qquad (4)$$

This is the wavelet transform CWT. From the above formula, the wavelet transform is essentially a change of integral. To some extent, it is like the Fourier transform. However, the wavelet transforms project a time function onto a two-dimensional time-scale surface, so it will be convenient to extract some features.

3) Discrete Wavelets Transform

To reduce the adverse effects of redundancy in the process of wavelet transform, we discretize the displacement and scale, that is, limit αand τ. At present, the commonly used method is power series discrete method:

$$a_0^{\frac{-j}{2}} \varphi\left[a_0^{-j}(t-\tau)\right], \; j = 0,1,2... \qquad (5)$$

In the above formula, a=a_0,a_0>0.

Generally, to include the whole period, the average discrete value of τ should be taken. For the premise that the scale size is j, the width of the basis function after discrete transformation is the original a on the premise that the scale size is α_0^j times. Although the sampling interval becomes large, the original information is still retained, in this way, the discrete wavelet becomes:

$$WT_f(a_0^j, k\tau_0) = \int f(t) \varphi *_{a_0^i, kz_0}(t) dt \qquad (6)$$

4) Wavelet packet decomposition

Wavelet packet transform is an orthogonal decomposition method, which is carried out based on multi-resolution, so it is more accurate. It decomposes the frequency band of the signal layer by layer in the frequency domain. This method not only saves the time-domain characteristics of the wavelet transform, but also decomposes the higher frequency part that the wavelet transform does not decompose, that is, it improves the frequency resolution.

Wavelet packet is composed of a pile of functions, which can be understood as a set composed of a pile of functions. A library is constructed: and the wavelet orthogonal basis is just a group in the set:

$$\varphi(t) = \sqrt{2} \sum_k h_{0k} \emptyset(2t-k) \qquad (7)$$

$$\varphi(t) = \sqrt{2}\sum_k h_1 \varphi(2t-k) \qquad (6) \qquad (8)$$

Through the knowledge of recursive spatial function and multi-resolution analysis, we can get the total energy formula of the signal as follows:

$$E = \int_{-\infty}^{+\infty} f^2\,(t)dt \qquad (9)$$

To sum up, wavelet decomposition decomposes the signal into many sub bands, and the bandwidth of each sub band is the same, which is equal to decomposing a pile of new signals, and then their energy can be calculated separately, normalized, and then compared together, so that the characteristics can be seen directly.

Rolling Bearing Signal

Overview of rolling bearing fault signal

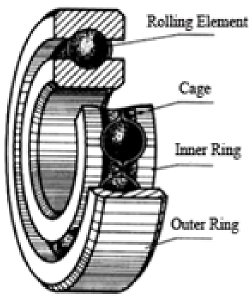

Figure 2: Rolling Bearing Structure

Vibration signals are often generated in the working process of the bearing. In the working process, the performance of the bearing is damaged due to long working time, structural deformation, corrosion, fracture, wear and other reasons. Finally, the bearing is damaged, and the normal operation of the equipment cannot be carried out. If the rolling bearing is not replaced after damage, but continues to work, irregular vibration and abnormal temperature change may occur in the subsequent process. The above phenomena can be used as an important diagnostic basis for rolling bearing faults. A series of practice and experiments have proved that the analysis of rolling bearing fault signal is the most effective means, which contains many advantages.

Characteristics of fault signal of rolling bearing

According to different working conditions, rolling bearing signals can be divided into four categories: normal signal, inner ring fault signal, outer ring fault signal, ball fault signal, and outer ring can be subdivided into 3 o'clock, 6 o'clock, 12 o'clock, etc.

When the rolling bearing is working, there is a collision between the ball and the inner ring, and a collision between the ball and the outer ring, so it makes each element vibrate. The mutual vibration of different components, even if the vibration is very weak, when the vibration frequency is similar, the vibration is more intense. It is only related to the bearing element itself, not to the bearing frequency and rotation speed. Because the bearing fault is unstable, there is no rule to summarize, and the fault signal will not be stable.

When a fault occurs, the bearing will produce the fault characteristic frequency, that is, the regular impact caused by repeated impact on the surface of the damaged part after it contacts with other parts during bearing operation. This characteristic can be extracted as recognition feature.

Non-stationary Signal Simulation Experiment

Simulation data and platform description

The data used in the simulation comes from the fault data collected by the bearing data center of Case Western Reserve University in the United States.

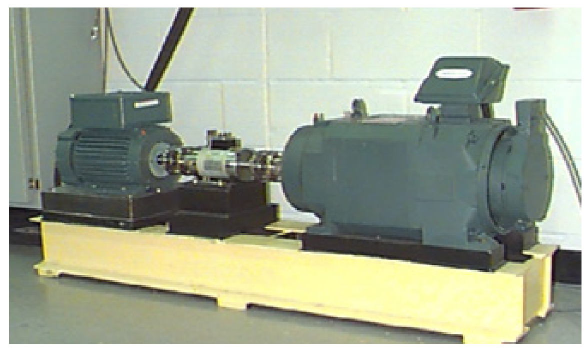

Figure 3: Bearing Test Bench of Western Reserve University

Simulation Data and Platform Description

1) Categories of wavelet functions

There are many categories of wavelet functions. It is very important to choose wavelet bases reasonably, because different wavelet bases will decompose, and the results and characteristics will be different.

There are many common basic wavelets, such as Haar wavelet, Morlet wavelet, Mexican Hat wavelet, Gaussian wavelet, DBN wavelet, etc.

Daubechies wavelet system is the general name of a series of binary wavelets proposed by Daubechies, a French scholar. It is recorded as DBN in MATLAB, where n is the series of wavelets, which is the vanishing moment of the wavelet function. The larger n is, the smoother it is. The wavelet used in this paper is db10.

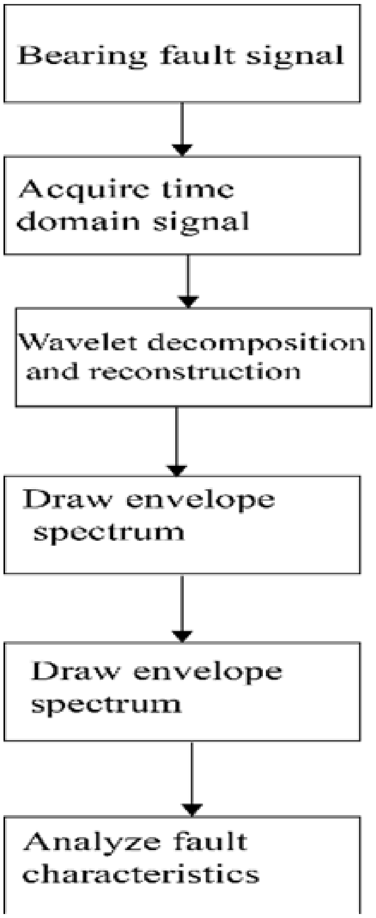

Figure 4: Wavelet Transform Analysis Process

When the normal working condition and fault diameter of the original signal are 0.1778mm, the motor load is 2 HP, and the speed is 1750r / min, the time domain signal analysis of inner ring, outer ring and ball fault is as follows:

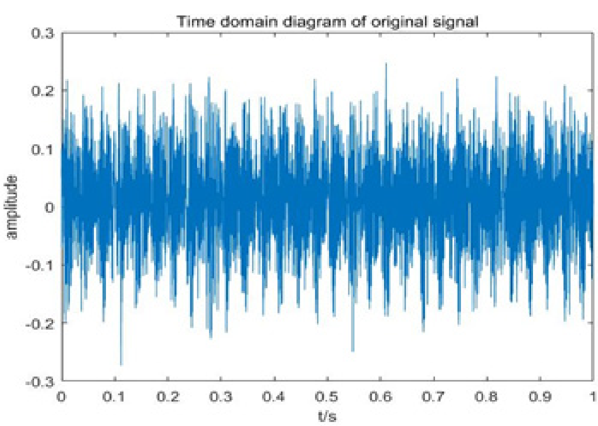

Figure 5: Signal of Bearing under Normal Working Conditions

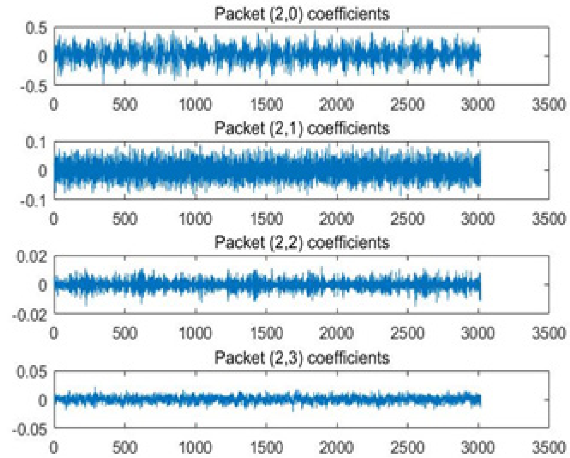

Figure 6: Normal signal db10 Wavelet Decomposition

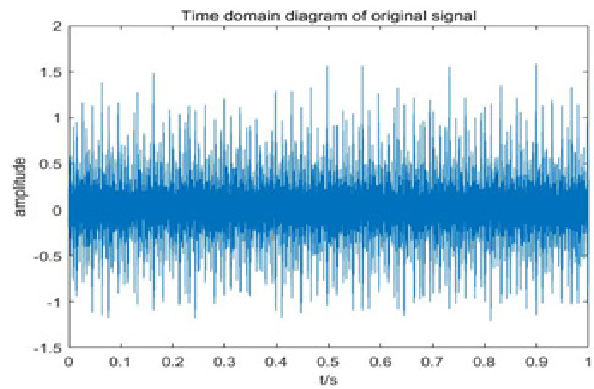

Figure 7: Signal of Bearing Cone Failure

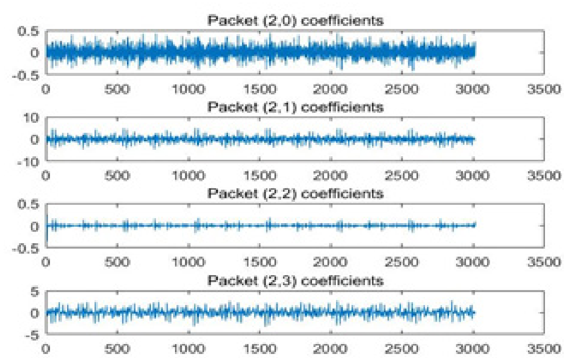

Figure 8: Inner Ring Fault db10 Wavelet Decomposition

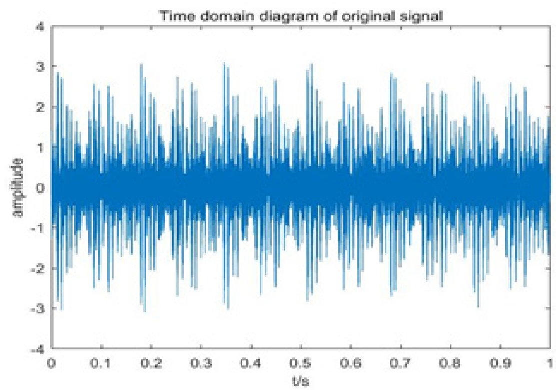

Figure 9: Signal of Bearing Cup Failure

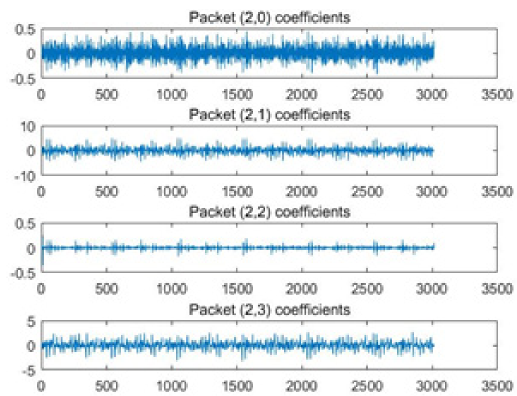

Figure 10: Outer Ring Fault db10 Wavelet Decomposition

Non-stationary Signal Feature Extraction Process

Then, we do the Hibert transform for the D1 layer of each working condition and analyze the signal of this layer in the frequency domain. The obtained spectrum diagram is shown in the figure:

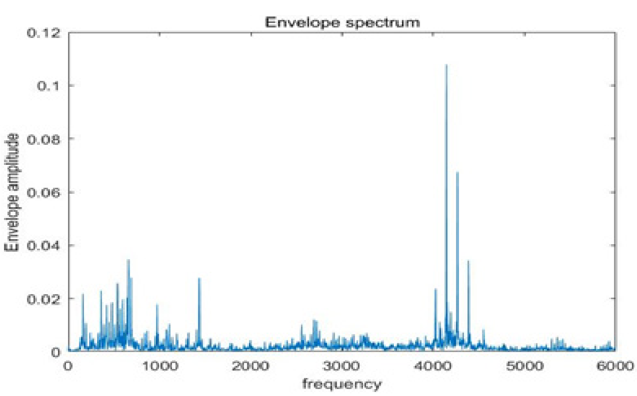

Figure 11: D1 Envelope Spectrum under Normal Working Conditions

However, the envelope spectrum is too dense. We refine the envelope spectrum so that we can intuitively see the change of the envelope spectrum, which improves the resolution of the envelope spectrum and makes it convenient for us to extract and analyze the characteristics of the signal after wavelet change from the envelope spectrum. Since the 1970s, frequency thinning has developed slowly. The so-called thinning is the operation of improving the spectrum and analyzing the physical resolution without lengthening the time domain length of the signal. If the envelope spectrum is as dense as the above, it is not easy for us to observe and extract the features of the signal. Therefore, at this time, we refine the envelope spectrum and take the first 600 to refine it to observe and extract the features. We have obtained high resolution and it is easy to observe, study and extract the features.

We improve the resolution of envelope spectrum, and the results are shown in the figure below:

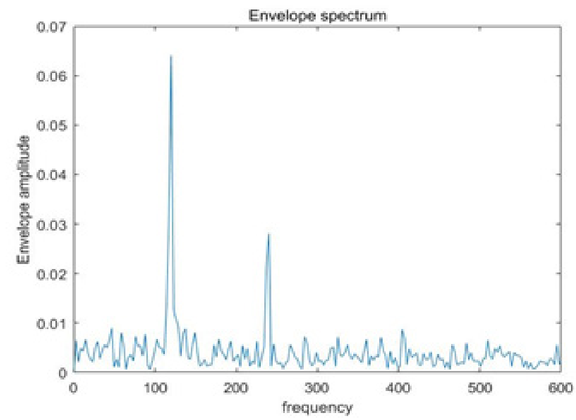

Figure 12: Refinement of Envelope Spectrum under Normal Working Conditions

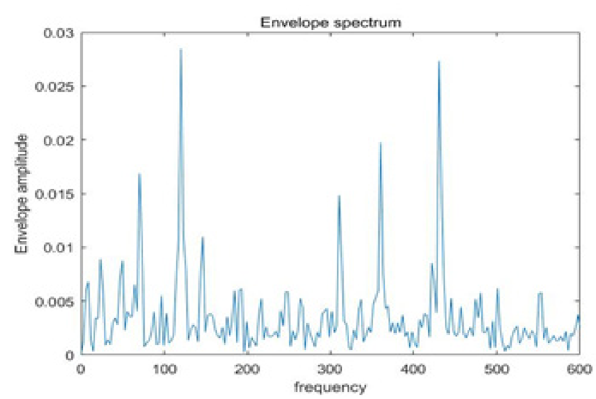

Figure 13: Inner Ring Fault Envelope Spectrum

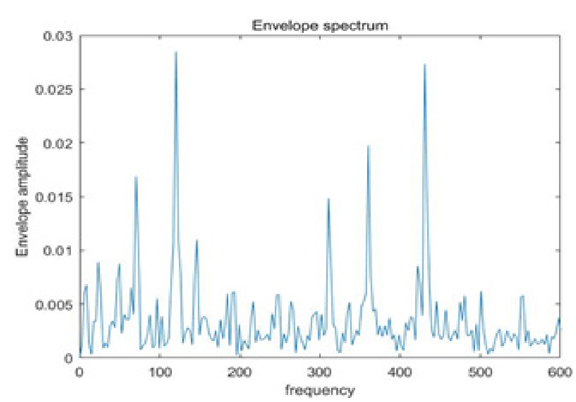

Figure 14: Outer Ring Fault Envelope Spectrum

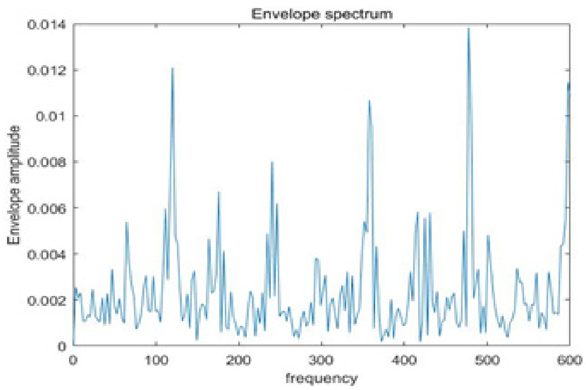

Figure 15: Ball Fault Envelope Spectrum

When the inner ring fault is 157hz, 316hz and 463hz, it is consistent with the characteristic frequency of the inner ring fault. The ball faults are 137hz, 390hz and 500Hz, which are basically consistent. When the outer ring fault is 105Hz, 315hz and 420hz, it is completely consistent with the fault characteristics of the outer ring.

Conclusion

Many signals are generated during the operation of the project or equipment. To diagnose the fault of the system, it is necessary to transform these non-stationary signals and extract the required characteristics. In this paper, the rolling bearing fault signal is selected as the research object, the wavelet analysis is selected as the research method, and the multi-scale analysis and envelope analysis of wavelet are used for research. This paper mainly summarizes the following aspects:

1. It is great to study the literature related to the subject, understand the development status at home and abroad, conduct more in-depth research on the subject, understand the significance and necessity of fault diagnosis, and learn and master more knowledge about non-stationary signals.
2. This paper introduces the basic definition and classification of signals, as well as some processing methods of non-stationary signals, understands the relevant knowledge, and lays a foundation for feature extraction by wavelet transform.
3. This paper introduces the basic definition and classification of signals, as well as some processing methods of non-stationary signals, understands the relevant knowledge, and lays a foundation for feature extraction by wavelet transform.
4. Taking wavelet transform as the core, the signal of ball bearing is analyzed, and MATLAB is used as the working platform. Through repeated experiments, the envelope spectrum is extracted, and then the characteristic frequency is extracted. Finally, the superiority of wavelet transform is verified.

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