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Working State of Diesel Engine Cylinder Based on Continuous Wavelet Transform Algorithm

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Abstract: In reality, discrete Fourier transform is a very important signal processing method. It is widely used in analysis and control systems. When the diesel engine starts, the excitation signal in the cylinder will reflect the basic principle of wavelet transform technology. In order to monitor the working state of diesel engine in real time, the continuous wavelet transform algorithm is studied in this paper. In this paper, we mainly use the fault detection experiment, use the continuous wavelet transform algorithm to process the data, and study the working state of the cylinder. The experimental results show that in most cases, the diesel engine cylinder is not working fully. The test accuracy of multi state fixed point signal is 85.28%, and the test accuracy of mobile acquisition signal is 87.41%.

1. Introduction

Continuous wavelet transform is a signal processing method. From the one-dimensional to two-dimensional transformation, we can see that the discretization is to decompose the signal into many wavelet coefficients and process each subband. This method has high practical value in practical application. It is analyzed that during the operation of diesel engine, the work pieces in the cylinder are affected in a certain period of time and cause vibration. This paper observes various power frequency signals of diesel engine cylinder under various working conditions, and judges whether there is correlation between them in time.

There are many theoretical achievements in the research of continuous wavelet transform algorithm and diesel engine cylinder working state detection. For example, someone artificially realized that the working state of armored vehicle diesel engine cylinder would not be disassembled for detection, simulated the misfire fault on the real vehicle, and measured the noise signal near the exhaust port under different states [1-2]. Some scholars also described the online monitoring method of Cummins engine cylinder working condition based on neural network [3-4]. Some scholars also analyzed the working principle of diesel engine cylinder working state detection and introduced the composition of the detection system [5-6]. Therefore, the research on the role of continuous wavelet transform in the detection of diesel engine cylinder working state has the significance of the times and practical value.

In this paper, the image edge detection algorithm based on wavelet transform is studied firstly, and its concept and algorithm are described. Secondly, the functions and structural characteristics of the cylinder block in the diesel engine are analyzed. Then, the vibration characteristics of diesel engine are analyzed, and it is pointed out that the amplitude of vibration signal will change suddenly when the inlet and exhaust valve clearance changes. Finally, the relevant conclusions are drawn through the diesel engine cylinder working fault detection experiment.

2. Detection of Diesel Engine Cylinder Working State Based on Continuous Wavelet Transform Algorithm

2.1. Image Edge Detection Algorithm Based on Wavelet Transform

Wavelet transform is based on multi-resolution analysis, and has good characteristics in time and frequency resolution. Wavelet analysis uses a group of orthogonal functions to represent or approximate functions or signals. Such functions are called wavelets, which are formed by the expansion of a wavelet basis function. Discrete wavelet transform is also taken as the priority object, because its description framework is not only effective, but also very intuitive. Image storage has the characteristic of multi resolution. Continuous wavelet transform is very helpful for people to deeply understand the characteristics of space domain and frequency domain. For image edge detection, 2-D wavelet transform is more widely used. Multiresolution analysis, also known as multi-scale analysis, is the essence of wavelet transform. The essence of wavelet transform is that wavelet transform plays a great role in the application of image processing [7-8].

Wavelet transform uses modulus and large value to detect edges, which is its fundamental principle. In a noisy image, after wavelet transform, the noise is in the high-frequency part, which is confused with high-frequency edge information, so we need to find a way to remove the noise edge. In wavelet transform, there is more than one choice of wavelet basis, and different wavelet bases will be different after transformation. Using wavelet transform to decompose the graph direction is a prerequisite step, which plays a decisive role in the decomposition effect. Therefore, this aspect is more important. After edge extraction by using wavelet transform modulus and large value, in order to further reduce noise and achieve better results, the key problem lies in the selection of threshold [9-10]. The detailed implementation process of this algorithm is as follows:

Multiscale wavelet transform is applied to the image to obtain the sum of vertical and horizontal components, $V^{\varepsilon^1} g(m,n)$ and $V^{\varepsilon^2} g(m,n)$ respectively. Then calculate the modulus of wavelet transform coefficients:

$$Xg(m,n)=\sqrt{\left|V^{\varepsilon^1} g(m,n)\right|^2+\left|V^{\varepsilon^2} g(m,n)\right|^2} \tag{1}$$

Find the argument of wavelet transform coefficient:

$$Pg(m,n) = \text{acrtan}\frac{V^{\varepsilon^2} g(m,n)}{V^{\varepsilon^1} g(m,n)} \tag{2}$$

Find the local modulus maximum. The local maximum points along the argument $Pg(m,n)$ are found by using the method of non-sum maximum suppression. Finally, the obtained candidate points are thresholded to extract image edges.

Because of the intake and exhaust valve clearance fault, injection advance angle fault and fuel supply fault signal of diesel engine, there is a strong impact component. Therefore, this paper chooses wavelet packet method to analyze the vibration signal.

2.2. Functions and Structural Features of Diesel Engine Cylinder Block in Diesel Engine

Diesel engine has the characteristics of large torque and good economic performance, because it is widely used in the engine. It has high thermal efficiency and economic value. Through compressed air, the air in the cylinder of the diesel engine is high temperature and high pressure, and its temperature will be higher than the auto ignition point of diesel. When diesel spray enters the cylinder, it will ignite. At the same time, the fuel supply system of the diesel engine is relatively simple, and the compression ratio of the diesel engine is high. At the same time, under the same power, the torque of the diesel engine is large, and the speed is low at the maximum power, which ensures its function in the engine to the greatest extent [11-12].

The cylinder block is the skeleton part of the diesel engine. Different mechanisms and systems are installed and configured on it. All parts of the diesel engine are installed inside and outside the cylinder block and bear all loads and impacts. Cylinder block is the basic part of diesel engine. When installing the cylinder block, the bottom and side are its reference planes. The flywheel rotates under the driving of the crank shaft, which is mainly used to ensure the stable rotation speed, so as to achieve effective starting and energy conversion.

2.3. Analysis of Diesel Engine Vibration Characteristics

It is necessary to know the characteristics of diesel engine cylinder head vibration signal itself to judge the fault location and fault degree of diesel engine by using diesel engine cylinder head vibration signal. The time domain characteristics of diesel engine cylinder head vibration signal refer to the vibration of diesel engine at different working hours. It can be seen from the structure of the diesel engine that the valve train is in the cylinder head, and the vibration of the valve train will be directly transmitted to the cylinder head surface [13-14].

The frequency domain characteristics of the cylinder head vibration signal refer to the reflection of the vibration signal in the frequency domain when the action time and magnitude of the excitation force change. Although there are many exciting sources of cylinder head vibration signals, they mainly include gas explosion pressure and impact force of intake and exhaust valve seating. When the intake and exhaust valve clearance of diesel engine changes, the energy value in the corresponding frequency band will change, and the valve clearance fault can be diagnosed according to this characteristic. The acceleration amplitude of cylinder head vibration signal increases obviously with the increase of inlet and exhaust valve clearance. The fluctuation of engine intake and exhaust valve status will lead to the obvious fluctuation of its corresponding time-frequency characteristics [15-16].

The vibration signal of the diesel engine cylinder head is an impact signal. When the inlet and exhaust valve clearance changes, the amplitude of the vibration signal will also change suddenly, and high frequency signals will appear at the changes. The vibration signal of diesel engine is unsteady and nonlinear. Because there are many vibration excitation sources of diesel engine, many noises are often mixed in the signal [17-18].

There are three main steps for the state detection of the cylinder. First, use oscilloscope to collect signals. The second is to obtain discrete post wavelet coefficients from the original data through A/D conversion. Third, the frequency domain analysis method is used to determine the parameters of each part. The specific process is shown in Figure 1:

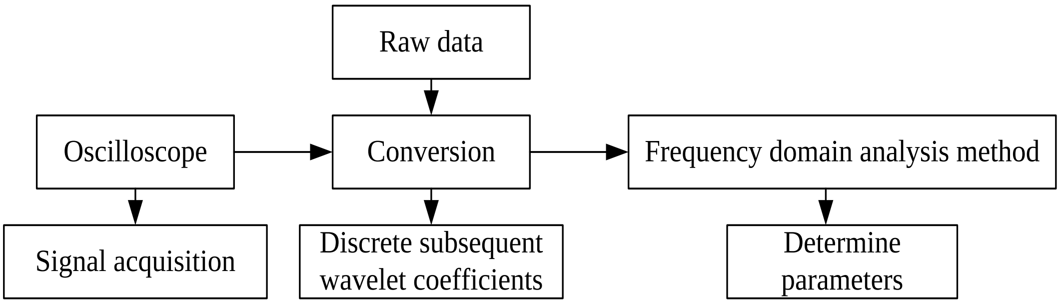

Figure 1. Status detection process of the air cylinder

In the actual detection process, due to factors such as measuring equipment, test environment and measured signal source itself, the results may be biased to some extent. In order to ensure the accuracy of sensor output data, and the amount of image information collected is large enough to obtain a relatively ideal SNR, the measurement method needs to be optimized and improved. In order to realize real-time monitoring and control of diesel engine, it is necessary to detect the temperature change curve in the cylinder during engine operation.

3. Diesel Engine Cylinder Working Fault Detection Experiment

3.1. Condition Monitoring Method

The multi-scale method of diesel engine cylinder condition monitoring is mainly embodied in two aspects: first, the boundary value method, trend chart analysis method, performance parameter analysis method and image wavelet analysis method are comprehensively used to reflect the cylinder condition of diesel engine from multiple scales. The second is to use different wavelets when decomposing the image with wavelet transform, and select the wavelet that is most suitable for image processing. It is also necessary to use a certain mathematical method to establish a data model and conduct qualitative and quantitative analysis of the data to achieve the purpose of monitoring the condition of the cylinder of the equipment.

3.2. Experimental Equipment

The experimental equipment for oil and noise analysis mainly includes atomic emission spectrometer, analytical ferrograph, direct reading ferrograph and ferrograph microscope. Only when we have a full understanding of the structure principle and working process of the equipment can we use the equipment correctly and ensure the reliability of the experimental results.

3.3. Experimental Methods

Fixed point collection: place the collection microphone near the operating test bench, and set the test bench at several different values of the final speed of 10Hz~30Hz respectively through the control of the motor controller. Among them, several different schemes are selected for acceleration and deceleration time, respectively, to collect signals of the cylinder's rolling bearing, rotor, shaft, and gearbox under normal and fault operating conditions. As an effective technology for analyzing the state of diesel engine cylinder, noise analysis has high technical requirements, and there are many factors that affect the analysis results. Therefore, mastering the correct noise sampling method and analysis technology plays a great role in the final cylinder state monitoring results.

4. Fault Diagnosis Results

4.1. SVM Distance Classification Accuracy from Far to Near

Because this experiment involves two kinds of simulation experiments: mobile acquisition and fixed point acquisition, first consider whether the mobile acquisition process has a great impact on the classification accuracy of SVM. The mobile collected signal is considered to be divided, and the distance between each segment of the signal and the experimental platform is different. The classification accuracy of SVM is shown in Table 1:

Table 1. The SVM distance was ranged from far to near for classification accuracy

	Internal circle failure	Outer ring fault	Rolling body failure	Mixed fault
1	92.53	94.62	96.73	97.62
2	92.56	98.23	99.41	99.41
3	96.47	99.41	99.11	100
4	94.12	98.82	98.82	98.23
5	96.17	99.41	99.71	97.35
6	98.23	96.71	97.94	98.23

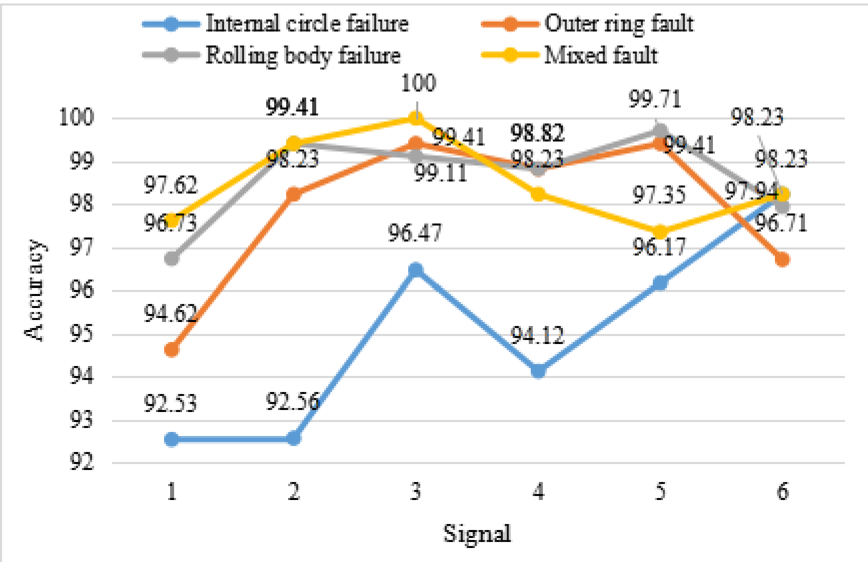

Figure 2. The SVM distance was ranged from far to near for classification accuracy

As shown in Figure 2, it is not difficult to see from the display of classification accuracy results that the relative position of the experimental platform has little impact on the SVM processing results. Even if the distance is far, the collected signal still contains fault information when the signal-to-noise ratio is low, which proves the feasibility of mobile collected noise signal for fault diagnosis from the side.

4.2. Classification Accuracy Results of Rolling Bearings

The signal processing will process the fixed point and moving acquisition signals of rolling bearing fault, rotor fault, shaft fault and gearbox gear meshing fault collected in this experiment. Taking the classification accuracy of rolling bearings as an example, the specific classification results are shown in Table 2:

Table 2. Rolling bearing classification accuracy results

	Fixed-point collection	Mobile collection
Internal circle failure	99.32%	94.12%
Outer ring fault	97.54%	98.57%
Rolling body failure	99.91%	98.32%
Mixed fault	96.16%	98.43%
Multi-state classification	85.28%	87.41%

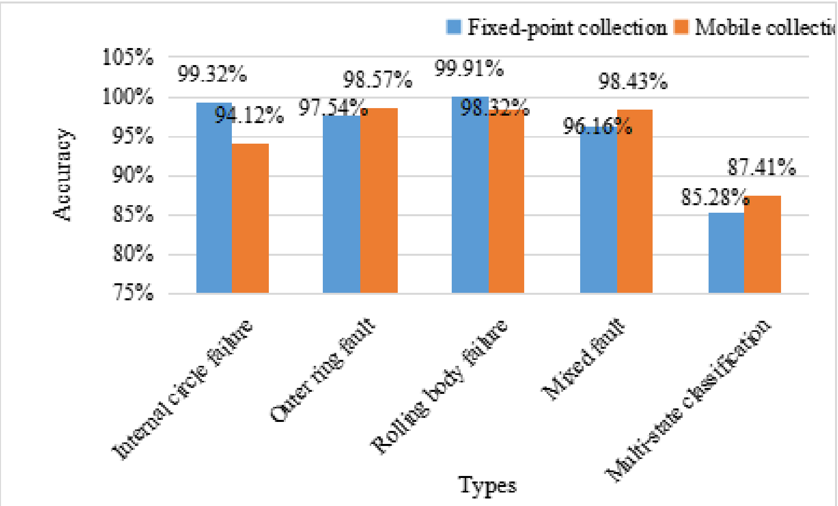

Figure 3. Rolling bearing classification accuracy results

As shown in Figure 3, we can find that the accuracy of single cylinder fault classification is higher than that of multi state classification. The test accuracy of classification between normal working state and single fault state is also ideal. But compared with vibration signal, its classification accuracy is lower. The classification accuracy of the spot acquisition signal is not much different from that of the mobile acquisition signal.

5. Conclusion

Diesel engine working state detection is mainly to measure the high frequency and high frequency signals of the cylinder, and use these data as the basic information to judge faults. To determine the working state of the cylinder, first analyze the object to be tested, and calculate its specific state according to the calculation formula. Then it is transformed into a mathematical model, and the results are obtained by solving. We need to process the continuous wavelet transform signal and transform it into a discrete time model. The experiment of this paper shows the effect of SVM on cylinder fault classification based on noise signal.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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