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APPLICATION OF VIBRATION SIGNAL ANALYSIS METHOD IN THE FAULT DIAGNOSIS OF MECHANICAL GEARBOXES

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Abstract

The traditional mechanical gearbox diagnosis method is not enough to meet the operation requirements in terms of reliability and safety, so the purpose of this study is to collect and analyze the vibration signal of mechanical gearbox, and explore the application of vibration signal analysis method in fault diagnosis. A vibration sensor is installed in a gear box to collect real-time vibration data, and the data are denoised, filtered and aligned. The experimental results show that the waveform of the normal gear has obvious periodicity, while the high-frequency component of the faulty gear increases significantly. The diagnostic accuracy of fault types is wear, pitting, point wear, fracture wear and broken teeth. The envelope spectrum amplitude of normal bearings is maintained between 0.4-0.5. The innovation of the research lies in the development of a fault signal acquisition system based on advanced vibration sensing technology, which realizes real-time monitoring of gearbox status and accurate collection of vibration data, and optimizes the ability to extract fault characteristics from complex background noise by combining a variety of vibration signal processing technologies.

Keywords: gearboxes; vibration signals; fault diagnosis; time domain waveform.

1. INTRODUCTION

With the rapid development of industrial automation technology, mechanical gear box plays a vital role in all kinds of mechanical equipment. They are widely used in key industrial fields such as wind power generation, automotive transmission, and heavy machinery [1]. However, during long-term operation, the gearbox will inevitably suffer from wear, pitting, and other failures under complex load conditions [2]. Once these failures occur, they often lead to reduced performance of the entire system, and may cause downtime accidents or even personnel safety accidents. Therefore, accurate and rapid diagnosis of gearbox faults is the key to ensure the normal operation of the equipment [3]. In recent years, vibration signal analysis method, as an important non-destructive detection means, has been widely applied and researched in the fault diagnosis of mechanical gear boxes [4]. Vibration signals can reflect the internal vibration of the gearbox. By analyzing and processing vibration signals, fault prediction, classification and diagnosis can be realized [5]. In response to the difficulty in effectively identifying empty air states, Feng et al. tried to construct a comprehensive test system composed of high-speed cameras and vibration test systems on the basis of a high-precision universal hydraulic mechanical test bench. The experiment showed that the study finally obtained vibration signals under different cavitation states and cavitation images on runner blades [6]. Vibration signals play a crucial role in mechanical fault diagnosis. However, due to complex working environment, vibration signals are often covered by strong noise. For this reason, Miao et al. built a sparse representation layer to extract pulse components, suppressing the hidden noise in vibration signals. Experiments showed that this method had good feature learning and signal de-noising performance [7]. When pitting or cracking occurs in gears, the cavitation phenomenon is more severe due to stronger vibration, resulting in safety hazards. For this reason, Ouyang proposed a model combining computational fluid dynamics and fault gear dynamics. From the experiments, at 10000 rpm, the cavitation intensity first increased and then decreased with the deepening of pitting [8]. Machining process monitoring based on vibration sensing is the growing demand of intelligent manufacturing. For this reason, Wang collected data sets of small and large changes in cutting parameters and work-piece shapes for analysis. Experimental results showed that features obtained through manifold learning could distinguish vibration signals of different cutting parameters in low-dimensional space [9]. The structure, components, and faults of the rotor bearing system are of great significance for

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improving operational performance. Therefore, Ma et al. studied the operating conditions of cylindrical and elliptical lubrication bearing systems under normal working conditions and angular misalignment faults. Compared with normal operating conditions, the dislocation defect of the double-stage single-span rotor bearing system increased the displacement by 1.1-1.7 times [10].

With the improvement of industrial level, the fault diagnosis of mechanical gearbox has higher technical requirements. Vibration monitoring plays a key role in many applications, including predictive maintenance of machinery, shock detection, etc. Casamenti investigated the mechanical nonlinearity inherent in suspended glass waveguides as a means of optical retrieval of critical vibration mode information. The experimental results indicated that this information provided a means of detecting excessive vibration. It also provided a method for detecting excessive vibration. It also realized the identification of specific vibration patterns [11]. When cracks occur in a helical gear pair, the meshing stiffness and vibration response of the gear pair are affected. Therefore, Casamenti E et al. proposed an improved model to calculate the meshing stiffness of a helical gear system caused by gear cracks. Experimental analysis showed that gear cracks could greatly reduce meshing stiffness. The time domain vibration response of cracked gear during meshing changed [12]. To improve the accuracy of mechanical fault identification, Chu proposed a multi-scale convolution model based on multi-expansion rate and multi-concern mechanism. Through experimental analysis, the results showed that comprehensive experiments on two reference data sets of bearing and gearbox proved the effectiveness of this method [13]. The intelligent diagnosis of gearbox faults is of great significance to the safety assessment and risk analysis of rotating machinery. Therefore, Li et al. proposed a method based on feature fusion covariance matrix. Finally, the experimental results on two multi-sensor datasets verified that this method had good diagnostic performance [14]. Aiming at fault clearing in multi-terminal DC power grid based on modular multilevel converter, the Xiang et al. studied the synergistic characteristics of resistively superconducting fault restrictor and DC circuit breaker. It verified that the system would recover the main protection within 250ms after the fault occurred [15].

In conclusion, compared with traditional fault diagnosis methods, vibration signal analysis method has the advantages of no downtime, real-time monitoring and high sensitivity. It can provide more accurate and comprehensive fault information. Therefore, on the basis of vibration signal recognition, the research attempts to obtain quantitative information of vibration characteristics, including amplitude, peak value and kurtosis of gearbox vibration through technical means such as feature parameter extraction, spectrum analysis and pattern recognition. Then fault characteristics of different frequencies are identified through the spectral graph analysis. The research contribution is to develop a fault signal acquisition system based on advanced vibration sensing technology, which can monitor the gear box status in real time and accurately collect vibration data, thus providing high-quality input signals for fault diagnosis. The research innovation is to optimize the ability to extract fault characteristics from complex background noise by integrating multiple vibration signal processing techniques such as signal denoising, feature parameter extraction, and spectrum analysis. By using pattern recognition technology, the accuracy of judging different gearbox fault types is improved successfully.

The research is divided into four parts. The first part is to analyze the research status of vibration signal analysis in gear box. The second part describes the design process of mechanical gear box fault diagnosis system based on vibration signal analysis. The third part verifies the diagnostic accuracy and reliability analysis of vibration signal in gear fault and bearing fault, respectively. The last part is the summary of the full text.

2 MECHANICAL GEARBOX FAULT DIAGNOSIS SYSTEM BASED ON VIBRATION SIGNAL ANALYSIS

The research will design a mechanical gearbox fault diagnosis system based on vibration signals, and finally complete the mechanical gearbox fault diagnosis instrument, which is used to determine the working state and fault type of the gearbox.

2.1. Application of vibration signal analysis in mechanical gearbox fault diagnosis

Vibration signal analysis is a method of processing and analyzing vibration signals to extract useful information from them [16]. In the field of machinery, vibration signal analysis is widely used in fault diagnosis, performance evaluation and structural monitoring, reflecting faults or abnormalities in mechanical systems [17]. By analyzing vibration signals, problems such as bearing failures, gear wear, and unbalance can be detected. Fault diagnosis and fault classification can be performed [18]. Vibration signal analysis usually includes time domain analysis and frequency domain analysis. The peak-to-peak value in the analysis index is shown in Equation (1).

$$X_{p-p} = Maxx_i - Minx_i, i = 0,1...n \tag{1}$$

In Equation (1), $Maxx_i$ is the value of the highest point in the vibration waveform. $Minx_i$ is the value of the lowest point in the vibration waveform. n represents the number of vibration waveform data points. Therefore, the peak-to-peak value is the difference between the highest point and the lowest point in the vibration waveform. In vibration measurement, the size of the signal energy is usually reflected by the RMS value, as shown in Equation (2).

$$X_{rms} = \left(\frac{1}{N} \sum_{i=0}^{N-1} x_i^2 \right)^{\frac{1}{2}} \tag{2}$$

In Equation (2), N is the number of waveforms. x_i is the waveform value. From this, the mean value in vibration measurement can be introduced, as shown in Equation (3).

$$\bar{x} = \frac{1}{N} \sum_{i=0}^{N-1} x_i \tag{3}$$

In Equation (3), $\bar{x}$ is the mean value of the vibration signal. The mean value can describe the average change of the signal, further showing the fluctuation and change of the mean value in the vibration signal. Therefore, the variance is used, as shown in Equation (4).

$$\sigma^2 = \frac{1}{N} \sum_{i=0}^{N-1} (x_i - \bar{x})^2 \tag{4}$$

In Equation (4), The variance can be used to reflect the dynamic component of the vibration signal. When a mechanical gearbox malfunctions, the fault can be visually observed from the time domain waveform. Fig. 1 shows the time domain waveform and frequency domain waveform of the gear meshing frequency.

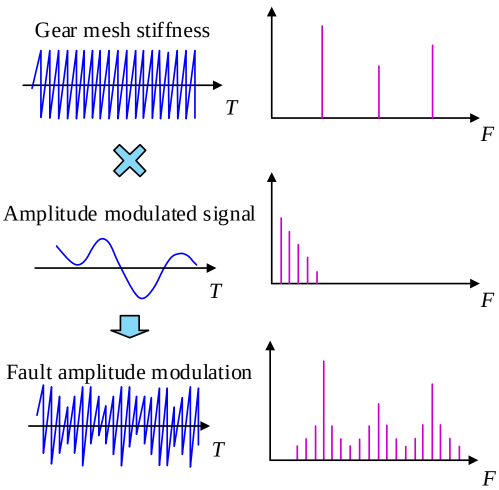


Fig. 1. The formation process of sidebands

Fig. 1(a) shows the amplitude modulation due to gear failure. When the gears operate normally, the gears are contacted uniformly. The power is transmitted without amplitude modulation. When a gear failure occurs, it leads to irregular contact of the gears. This leads to the instability of the transmitted power, resulting in changes in the operating speed and vibration frequency of the gear. It occurs at a certain frequency, forming the amplitude modulation phenomenon. Fig. 1(b) shows the frequency domain waveform formed by the Fourier transform of the amplitude modulation. After the Fourier transform, the frequency domain waveform of amplitude modulation usually presents the main frequency component, sub-frequency component and sideband frequency. The sideband frequency is the frequency distance between the main frequency component and the sub-frequency component. They are presented as symmetrical peaks on both sides of the main frequency. The vibration signal analysis can intuitively reflect the amplitude changes and impact phenomena, which can be used for fault diagnosis of mechanical gearboxes. To further refine the analysis of vibration waveforms, the craggy indicator is introduced to indicate the probability of mechanical gearbox faults forming large pulse values, as shown in Equation (5).

$$x_q = \frac{1}{N} \sum_{i=0}^{N-1} x_i^4 / x_a^3 - 3 \tag{5}$$

In Equation (5), x_a is the large magnitude pulse, as shown in Equation (6).

$$x_a = \frac{1}{N} \sum_{i=0}^{N-1} x_i^2 \tag{6}$$

Similarly, the peak value can be derived, as shown in Equation (7).

$$x_p = Max|x_i| \tag{7}$$

In Equation (7), x_p is the peak value. In addition, when a mechanical gearbox malfunctions, the failure frequency of different parts varies. To further decompose the different faults, an analysis is conducted from two aspects: gear faults and bearing faults. Fig. 2 shows the gearbox structure and common types of faults.

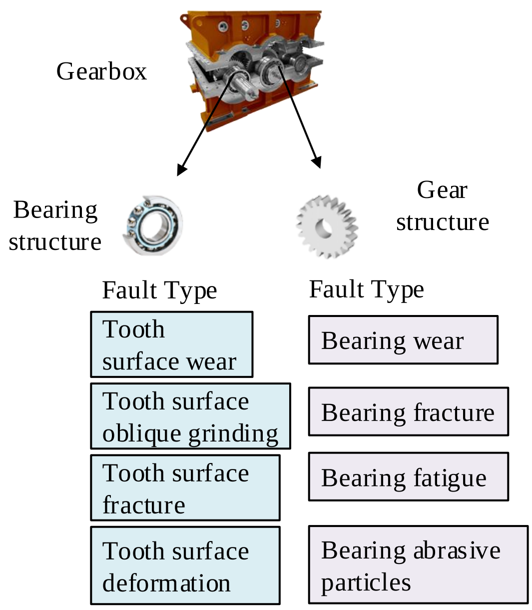


Fig. 2. Gearbox structure and common faults

Fig. 2 shows the gearbox structure and common types of failure. As a transmission device, a gearbox consists of multiple gears, bearings, oil seals and other components. Bearing failure and gear failure are two major failures in gearbox. Gear failure mainly includes tooth wear, tooth surface oblique grinding, tooth surface fracture, tooth surface deformation. This is due to poor tooth contact, poor quality of the tooth surface, poor lubrication and other reasons for the gear failure. Bearing failure types mainly include bearing wear, bearing fracture, bearing fatigue, bearing abrasive particles, etc., which is due to long-term high-speed operation of the gear box or improper use of the bearings, wear, fatigue fracture and other reasons. Therefore, in response to the diverse types of gearbox faults, there is an urgent need to find a solution that can accurately identify the type of failure.

After discussing the research status of vibration signal analysis applied to mechanical gear box fault diagnosis, the research will further analyze how to construct vibration signal model, and introduce the design and implementation of mechanical gear box fault diagnosis system based on this model in detail. The construction of this system aims to apply the above analysis method to the actual fault diagnosis, so as to improve the monitoring ability and fault identification accuracy of mechanical equipment.

2.2. Vibration signal model construction and system composition

A mechanical gearbox is a device used to transmit power and torque, which is commonly used in mechanical equipment, automobiles, ships, etc. [19]. It consists of several gears, shafts, etc., which can convert the speed and torque of the input shaft to the speed and torque of the output shaft. Mechanical gearbox consists of input shaft, gear set, bearings, conveyor system and other structures. When mechanical gear fails, the common faults are axis asymmetry, axis bending, axis imbalance, and axial shifting [20]. Fig. 3 shows the dynamic model of the mechanical gearbox.

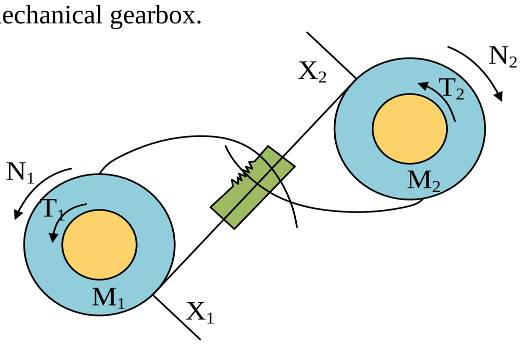


Fig. 3. Gear meshing physical model

A mechanical gearbox realizes power transmission and speed change by gear meshing. Its physical dynamic principle mainly involves the action of forces and moments. From Fig. 3, T_2 and T_1 are the torques acting on the gears. M_1 and M_2 represent the equivalent mass of the two gears, respectively. the gears in a gearbox receive externally applied forces during meshing. The magnitude of the forces depends on the load and speed of the transmission, which causes the gears to rotate. In a gearbox, the torque is determined by the radial force and force arm of the gears. During meshing, the torque transmission between gears causes gear rotation. Due to the difference in the size and teeth quantity of the gears, the moments are transferred and transformed between different gears. The kinetic equation for gear meshing is shown in Equation (8).

$$MX + CX + k(t)\left[x - E(t)\right] = (T_2 - iT_1)/R \tag{8}$$

In Equation (8), x is the relative displacement of the gears along the meshing line. $k(t)$ is the fitted stiffness. M is equivalent mass. $E(t)$ is the relative displacement of the two gears in the direction of the action line caused by gear deformation, errors and failures. C is damping coefficient. R is the gear ratio of the gear pair. The $E(t)$ can be decomposed into expression (9).

$$E(t) = E_1 + E_2(t) \tag{9}$$

In Equation (9), E_1 is the average static elastic deformation of the gear. E_2 is the fault function of the gear. $E_2(t)$ is the relative displacement between two gear teeth due to gear failure at time t. The expression of $k(t)$ is shown in Equation (10).

$$k(t) = k_0 + \sum_{m=1}^{M} k_m \cos(2\pi m f_z + \phi_m) \tag{10}$$

In Equation (10), k_0 is the average value of mesh stiffness. k_m is the amplitude of the m-th harmonic. ϕ_m is the phase of the m-th harmonic. f_z is the engagement frequency. The engagement frequency is shown in Equation (11).

$$f_z = f_1 Z_1 = f_2 Z_2 = \frac{n_1 Z_1}{60} = \frac{n_2 Z_2}{60} \tag{11}$$

In Equation (11), n_1 is the rotational speed of the master wheel. Z_1 is the number of teeth. n_2 is the rotational speed of the driven wheel. f_1 is the rotational frequency of the master wheel. f_2 is the rotational frequency of the driven wheel. Then, to realize the fault diagnosis of mechanical gearbox, the study starts from hardware and software to develop the mechanical gearbox fault diagnosis system. The development flow chart is shown in Fig. 4.

Fig. 4 shows the system development process of the fault diagnostic instrument for mechanical gearboxes. From Fig. 4, the system process is divided into three major parts. The first part is the hardware development, including the multi-parameter sensor selection, signal conditioner selection, and multi-channel collector selection. The second part is the software development part, including function formulation, function module development, and instrument assembly. The third part is the application part, which mainly includes the self-checking after instrument assembly, and the application in the experimental base and factory. The vibration sensor collects the vibration waveform of the mechanical gearbox. The vibration waveform is shown in Equation (12).

$$x(t) = \sum_{m=0}^{\sigma} A_m \cos(2\pi m f_z + \phi_m) \tag{12}$$

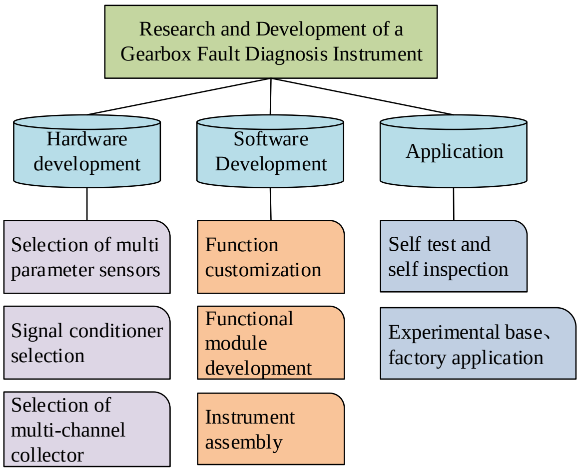


Fig. 4. Development flowchart of a echanical gearbox fault diagnosis instrument

In Equation (12), A_m is the harmonic amplitude. σ is the maximum harmonic number. However, when the vibration signal of the gear is affected by faults, modulation phenomenon will occur. The vibration waveform is shown in Equation (13).

$$x(t) = \sum_{m=0}^{N} A_m \left[1 + a_m(t)\right] \cos(2\pi m f_z + \phi_m + b_m(t)) \tag{13}$$

In Equation (13), $a_m(t)$ is the amplitude modulation parameter. $b_m(t)$ is the phase modulation parameter. ϕ_m is the harmonic phase. N is the maximum harmonic number. The different amplitude modulation signal is shown in Equation (14).

$$y(t) = V(t) E_2(t) \tag{14}$$

In Equation (14), $V(t)$ is the carrier signal. When the amplitude modulation signal rotates a revolution in the gear, the tooth meshing frequency and octave components change once. According to the convolution theorem of the Fourier transform frequency domain, the amplitude modulation can be defined in the frequency domain, as shown in Equation (15).

$$S_y(f) = S_k(f) * S_E(f) \tag{15}$$

In Equation (15), $S_y(f)$ is the Fourier transform of the amplitude modulated signal $y(t)$. The overall design of the final gearbox fault diagnostic instrument is shown in Fig. 5.

Fig. 5 shows the final design of the mechanical gear fault diagnostic instrument system. From Fig. 5, the system includes signal conditioning, signal acquisition, GPIB interface instrument, interface card, serial interface instrument, VIX instrument, and field-bus device. The role of the sensor is to collect vibration signals from the gearbox. After signal conditioning, the measured signal is amplified and filtered. The collection equipment converts it

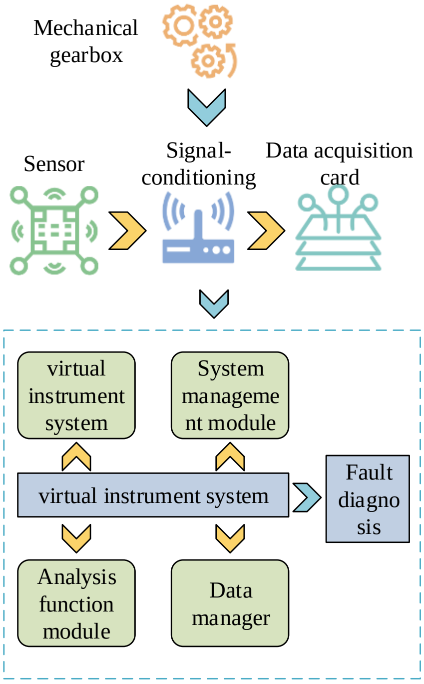


Fig. 5. Development flowchart of gearbox fault diagnosis instrument

into the standard signal. The data acquisition part of the conditioned analog signal is converted to digital signals to facilitate computer processing and analysis. The software part of the system contains data acquisition module, analysis function module, system management module and data management module. The data acquisition module utilizes various signal processing methods to extract useful information and diagnose mechanical transmission faults. Finally, in the fault diagnosis, according to the calculation results, the software is analyzed to determine whether the mechanical gearbox has malfunctioned. Since the bearing fault vibration signal can be received by the sensor on the bearing seat, the acceleration sensor is used to measure the bearing fault in the evaluation of the mechanical gear fault diagnosis instrument designed in this study. In the experiment, the sensor is installed through the magnetic base, and the orientation is horizontal and vertical. When sampling the signal, the bearing frequency needs to be calculated first, and the sampling frequency needs to be twice the highest frequency. The instruments used in the experiment include signal generator Tektronix, wire several, RBH8351 data acquisition card. The design scheme in Fig. 5 incorporates the latest sensing technology and intelligent data processing algorithms to improve the accuracy and efficiency of fault detection. The system uses high-precision vibration sensors to capture key performance indicators in real time, and through fine signal analysis, it is able to catch small anomalies in the gearbox, thereby achieving early fault warning and avoiding potential equipment damage and production disruption. A significant advantage of the system is its real-time monitoring capability, which not only facilitates continuous assessment of equipment status, but also helps reduce downtime caused by failures, thereby significantly improving the reliability and efficiency of industrial production. In addition, intelligent algorithms such as machine learning can process and analyze large amounts of collected data to identify complex failure patterns and potential maintenance needs. In terms of environmental adaptability, the system demonstrates a high degree of robustness and excellent anti-interference capability, ensuring reliable operation in a variety of industrial environments, which is critical to increasing industrial automation and enabling predictive maintenance. At the same time, the cost-benefit analysis revealed that the system is designed to optimize resource utilization and reduce maintenance costs, while ensuring the highest level of performance and diagnostic accuracy.

3 ANALYSIS OF MECHANICAL GEARBOX FAULT DIAGNOSIS RESULTS BASED ON THE VIBRATION SIGNAL METHOD

To verify the accuracy and accuracy of different fault vibration signal diagnosis for mechanical gearbox in practical application, sample database is established in the experiment. The superiority of the research system in gear fault diagnosis and bearing fault diagnosis of mechanical gearbox is verified by time-domain waveform and envelope spectrum analysis.

3.1. Analysis of mechanical gearbox gear fault diagnosis results

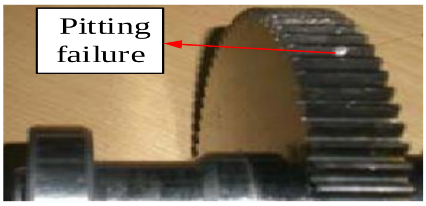
Gear failure is one of the main failures in mechanical gearboxes. The causes of its failure mainly include excessive load or frequent load changes in mechanical gearboxes, as well as poor meshing between gears, resulting in reduced transmission efficiency, increased noise, and other problems. Ultimately, gear failures such as wear, breakage, tooth breakage, pitting, wear marks, and spot grinding occur. In the experiment, LC01 series piezoelectric acceleration sensor is selected to collect vibration signals, with a sensitivity of 500mv/g. The measuring range is 10g, with a frequency range of 0.35-3500Hz. The resolution is 0.00004g. The constant current is 2-20mA. The configuration of the mechanical gearbox in the experimental diagnostic analysis is as follows. The number of teeth of the master gear is 55, the slave gear is 75, and the modulus is 2. The experiment simulates six different types of gear failures, including normal, wear and tear, broken grinding, broken teeth, pitting, and grinding, etc. The experimental samples were selected from the open data set of MFPT fault diagnosis test platform of Case Western Reserve University in the United States for the mechanical fault diagnosis research in the experiment. The rationale for using open datasets is to compare data from multiple types of faults and normal operating conditions with other existing techniques, and to improve the reproducibility of studies, allowing other researchers to test and validate proposed methods with the same dataset, thus ensuring transparency and credibility of the methods. The sample data of gears are shown in Table 1.

Table 1. Gear fault sample data

State	RMS	Crest Factor	Kurtosis	Peak indicator	RSMF	Frequency variance
Normal	0.126	0.2713	0.0271	0.1332	0.3341	0.0214
Wear and tear	0.7231	0.4321	0.5322	0.4212	0.0324	0.6342
Broken grinding	0.6721	0.3452	0.6231	0.4231	0.0321	0.7823
Broken teeth	0.3616	0.4139	0.5797	0.3613	0.1832	0.4264
Pitting	0.1681	0.7197	0.7687	0.4827	0.7935	0.2558
Point grinding	0.5431	0.4261	0.4421	0.4202	0.2057	0.674

The root mean square, margin indicator, cliff indicator, peak indicator, root mean square frequency, and frequency variance are the parameters of vibration signals in Table 1. The root mean square of the gear wear type is the largest, indicating that the vibration signal energy of wear is the largest. In the margin indicator, the pitting corrosion is the largest, indicating that the difference between the peak of its vibration signal and the root mean square value indicator is the largest. In the crest factor indicator, the indicator of pitting is the largest, which shows that there are shocks and nonlinear phenomena in the vibration signal. In the frequency variance, the index value of the broken grinding is the highest, which shows that its vibration signal spectrum has the highest dispersion degree. The energy distribution is not concentrated.

According to the sample data in Table 1, the specific relationship between different fault types and parameters can be obtained. From the RMS analysis, the RMS value is usually higher during wear, indicating that the energy of vibration signal increases, reflecting the irregular contact caused by gear surface wear. The root-mean-square value of pitting faults increases significantly, indicating that the impact in the vibration signal increases, which is usually associated with small pits on the gear surface. The root-mean-square value may fluctuate somewhat, exhibiting distinct pulse characteristics, reflecting the instantaneous energy release due to the fracture. From the analysis of the amplitude, the normal gear amplitude is relatively stable, reflecting the stable running state of the gear. The point wear amplitude increases obviously, due to the poor contact between gears and irregular relative motion, resulting in increased transmitted power and vibration frequency. From the analysis of peak values, the peak values of pitting corrosion and fracture are usually significantly higher than the normal state. Compared with normal conditions, the peak value of wear faults shows an increasing trend. From the analysis of kurtosis, the value of pitting fault kurtosis will increase obviously. The fault also shows high kurtosis. The frequency component is not stable. The data set gear fault picture is shown in Fig. 6.

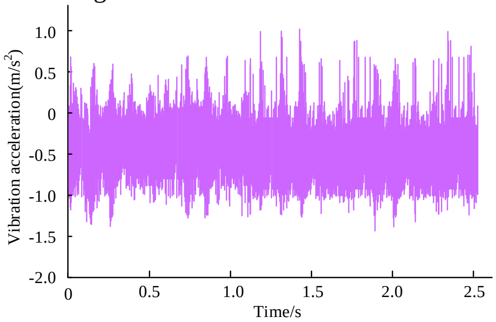


(a) Pitting failure

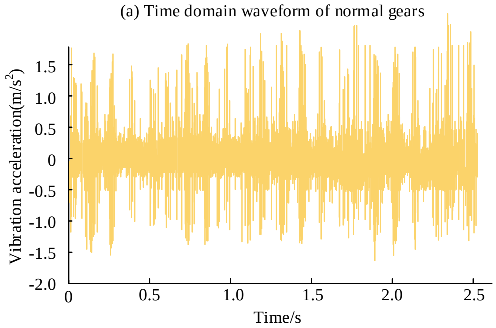
(b) Outer ring failure

Fig. 6. Gear fault picture

Then in the experimental data preprocessing, time-domain waveform comparison is conducted for pitting faults in gear faults, analyzing the effectiveness of vibration signals in diagnosing mechanical gearbox faults. The analysis results are shown in Fig. 7.



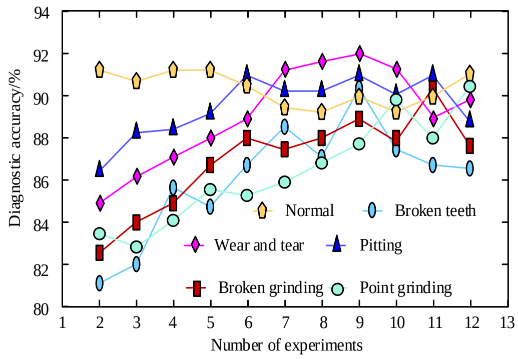
(a) Time domain waveform of normal gears



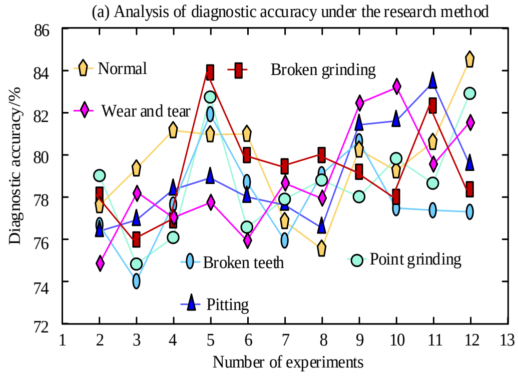
(b) Time domain waveform of pitting fault gears

Fig. 7. Comparison of time-domain waveforms for pitting faults

Fig. 7(a) shows the time domain waveform of the normal gear. From Fig. 7(a), the waveform of the normal gear shows obvious periodicity, producing a fluctuation cycle within 0.1s. The waveform is symmetrical in both vertical and horizontal directions, which shows that the amplitude and frequency of the waveform of the normal gear are relatively stable. There is no abnormality. The number of gear teeth and the tooth shape of the gear are also symmetrical in the normal state of the waveform. Fig. 7(b) shows the waveform of the pitting fault gear. From Fig. 7(b), the time domain waveform has a fluctuation period of about 0.09 s. Compared with the normal gear waveform, the high frequency component of the waveform increases significantly from 0.5 m/s^2 to 1.5 m/s^2. This is consistent with the phenomenon of irregular deformation of the gear tooth surface caused by pitting faults, resulting in high-frequency details and noise. The vibration signal can accurately determine whether there is a mechanical gearbox failure. To verify whether the vibration signal can judge different fault categories, the experiment analyzes the judgment accuracy of six different gear fault types under the vibration signal. In the experiment, the research method was compared with existing methods of oil analysis, a traditional method of mechanical equipment fault diagnosis commonly used to monitor and analyze the condition of equipment such as gearboxes, hydraulic systems and engines. By detecting trace metal particles, chemical composition, viscosity changes, contaminant levels, and more, oil analysis can reveal wear and other potential problems within equipment. The analysis results are shown in Fig. 8.



(a) Analysis of diagnostic accuracy under the research method



(b) Analysis of diagnostic accuracy under oil analysis method

Fig. 8. Analysis of fault type diagnosis accuracy

Fig. 8(a) shows the diagnostic accuracy analysis based on vibration signal analysis method under different gear fault types. From Fig. 8(a), the diagnostic accuracy based on vibration signals is above 80%. The diagnostic accuracy shows an upward trend with the increase of the number of experiments. When the number of experiments is 5, the diagnostic accuracy of pitting is 92.6%, which is 2.1%, 6.4%, 4.3% and 5.2% higher than the diagnostic accuracies of wear, tooth breakage, breakage and point grinding, respectively. When the number of tests exceeds 5, the diagnostic accuracy of different gear fault types exceeds 85%. When the number of tests is 10, the diagnostic accuracies of different fault types in descending order is wear, pitting, pitting grinding, broken grinding, broken teeth. Fig. 8(b) shows the diagnostic accuracy of different gear fault types under the oil analysis method. It can be seen from Fig. 8(b) that the diagnostic accuracy based on the oil analysis method is unstable in different experiment times, and the diagnostic accuracy of different gear faults is less than 83.7%, which is far less than that based on the vibration signal analysis method. In summary, the analysis method based on vibration signals can accurately determine whether the mechanical gear box failure and diagnose the types of faults in the gearbox. Based on the above experimental results, the quantitative indicators for diagnosis of each fault type are shown in Table 2.

Table 2. Quantitative indicators for diagnosis of each fault type

Fault type	Diagnostic accuracy (%)	RMS	Peak	Kurtosis	Variance
Normal	97	0.1260	0.2713	0.0271	0.0214
Wear	90.5	0.7231	0.4321	0.5322	0.6342
Pitting	92.6	0.1681	0.7197	0.7687	0.2558
Point wear	87.2	0.5431	0.4261	0.4421	0.6740
Fracture wear	85.3	0.3616	0.4139	0.5797	0.4264
Broken tooth	88	0.6721	0.3452	0.6231	0.7823

In Table 2, the diagnosis accuracy of normal state is the highest, reaching 97%; The diagnostic accuracy of pitting fault is 92.6%. The diagnostic accuracy of wear and damage fault was 90.5% and 85.3%, respectively. The accuracy of point wear and broken tooth faults is relatively low, 87.2% and 88% respectively. In terms of RMS, the RMS value of wear fault is 0.7231, and the RMS value of normal state is only 0.1260. In terms of Peak value, the peak value of pitting fault is 0.7197, and the peak value of wear fault (0.4321) is low, which is consistent with the root-mean square value and diagnostic accuracy, indicating that although the vibration generated by wear is strong, the instantaneous impact is small. In terms of Kurtosis, the kurtosis value of pitting fault is 0.7687, and the kurtosis value of wear and broken tooth is relatively high, which is 0.5322 and 0.6231, respectively, indicating that these two faults will also lead to the increase of signal non-stationary characteristics. In terms of Variance, the frequency variance of the broken tooth fault is 0.7823, which indicates that the vibration frequency distribution caused by the fault is not concentrated and has greater uncertainty and complexity. The frequency variance of point wear fault is also relatively high, its value is 0.6740, which may indicate that its vibration characteristics are close to the broken tooth fault, making it more complicated in the accurate diagnosis.

3.2. Analysis of mechanical gearbox bearing fault diagnosis results

Bearings are important components in gearboxes that bear loads and provide support. When bearings fail, it will lead to unstable operation of the gearbox, generate noise, increase vibration and other problems, which may lead to equipment downtime and damage in serious cases. Therefore, to verify whether the vibration signal can diagnose the mechanical gearbox bearing failure, the experimental data is selected to perform time-domain waveform envelope analysis on the envelope trajectory. The analysis results are shown in Fig. 9.

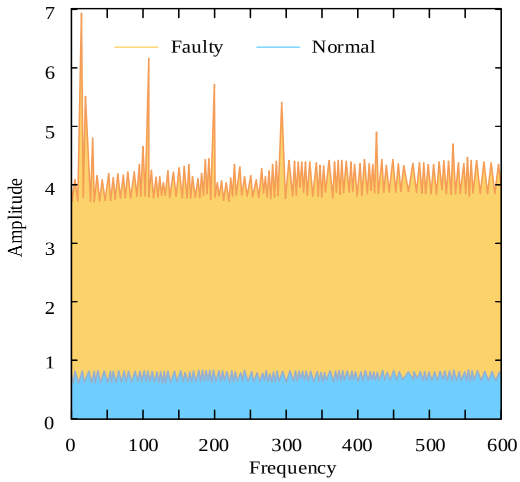


Fig. 9. Envelope Analysis of Normal and Faulty Bearings

Fig. 9 shows the vibration signal analysis of the normal bearing and the faulty bearing in the mechanical gearbox. In Fig. 9, the fundamental frequency of the normal bearing is consistent with the rotational speeds of the inner and outer rings of the bearing. The amplitude of the envelope spectrum for the normal bearing is more stable, remaining between 0.4 - 0.5. Compared with the envelope spectra of normal bearings, the envelope spectra of faulty bearings show obvious fundamental frequency peaks. Some low-frequency peaks and multiple harmonic frequency peaks appear in the figure, which reflects the unevenness and asymmetry inside the bearings. Unlike the normal bearing, the amplitude of the faulty bearing changes significantly. The amplitude varies within 0.8. To further verify this conclusion, the fast Fourier variation is used to compare the normal and faulty bearings. The comparison results are shown in Fig. 10.

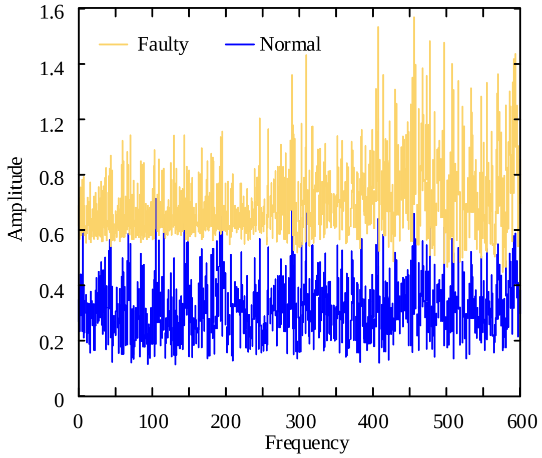


Fig. 10. Fast Fourier transform diagram

In Fig. 10, compared with the fast Fourier transform line of the normal bearing, the line spectrum amplitude transformation of the faulty bearing is larger. There are high harmonics, side frequencies and abnormal frequency peaks. Therefore, it can be deduced that there are faults in the bearing such as fatigue damage, poor lubrication, or the entry of impurities. The vibration signal can accurately determine whether the bearing of the mechanical gearbox is faulty. Then, in order to analyze the classification effect of vibration signal and oil analysis method on different bearing fault types, five experimental samples of bearing fault types, including shaft asymmetry, shaft bending, shaft imbalance, axial run-out and normal, are selected to test the diagnostic effect of vibration signals. The results are shown in Fig. 11.

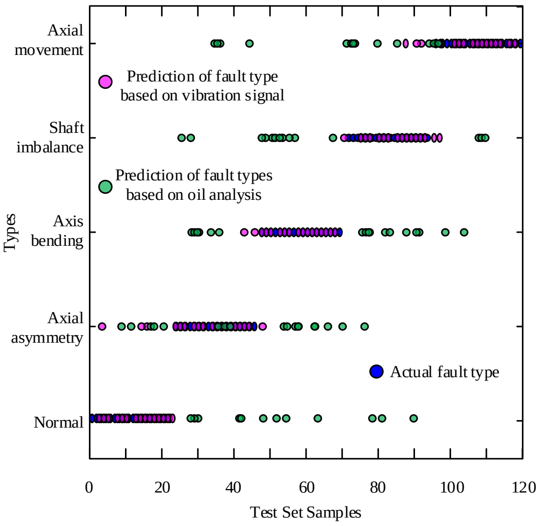


Fig. 11. Bearing fault experimental detection results

It can be seen from Fig. 11 that under the vibration signal analysis method the normal has the highest prediction accuracy, followed by the shaft imbalance type, whose predicted type matches the actual type by 97%. The shaft asymmetric predicted type matches the actual type by 91%. The axial tampering predicted type matches the actual type by 89%. The shaft bending predicted type matches the actual type by 96%. The prediction of different shaft fault types by vibration signals is basically consistent with the actual fault types, which indicates that vibration signals can determine the different shaft fault types. Under the oil analysis method, the prediction accuracy of axial movement is the highest 78%, the prediction accuracy of shaft imbalance is 72%, the prediction accuracy of axial bending, axial asymmetry and normal is 71%, 69% and 58%, respectively. Then, to further analyze the diagnostic accuracy of vibration signals on different shaft fault types, five different types of bearing faults are selected for diagnostic accuracy analysis. The results are shown in Fig. 12.

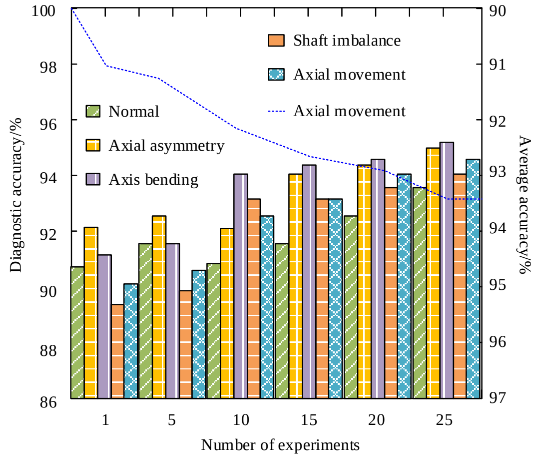
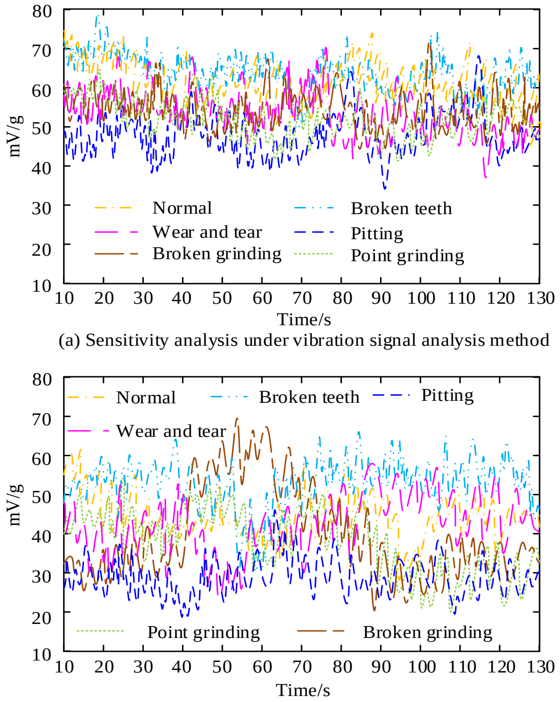


Fig. 12. Comparison of diagnostic accuracy for different bearing types

Fig. 12 shows the diagnostic accuracy and average accuracy analysis results of different bearing types. With the increase of the number of experiments, the diagnostic accuracy of each fault type shows an increasing trend. When the number of experiments is 11, the diagnostic accuracy of shaft bending is the highest, 94.2%, which is higher than the diagnostic accuracies of shaft asymmetry, shaft imbalance, axial run-out and normal by 1.9%, 0.7%, 1.1% and 2.2% respectively. When the number of experiments is 25, the diagnostic accuracy of different bearing failures in mechanical gearboxes is 93% higher. This shows that the vibration signal can accurately determine different types of bearing faults. Finally, the fault sensitivity based on vibration signal and oil analysis is tested, and the test results are shown in Fig.13.

Fig. 13(a) and Fig. 13(b) show sensitivity tests of each fault type under vibration signal method and oil analysis method respectively. It can be seen that broken teeth has the highest sensitivity with an average sensitivity of 64.7 mV/g, while Pitting has the lowest sensitivity with an average sensitivity of 53.8 mV/g. In the sensitivity analysis of each fault based on the oil analysis method, the one with the highest average sensitivity is also broken teeth, reaching 58.3mV /g, while the one with the lowest average sensitivity is Pitting, reaching 32.4mV /g. It can be seen that compared with oil analysis, vibration signal based fault type judgment sensitivity is higher.



(a) Sensitivity analysis under vibration signal analysis method

(b) Sensitivity analysis under oil analysis method

Fig. 13. Sensitivity testing of different methods

4. DISCUSSION

The research of mechanical gear box fault diagnosis system based on vibration signal analysis provides an important theoretical basis and practical guidance for the health monitoring of industrial equipment, and analyzes the diagnostic accuracy and vibration characteristics of various faults by quantitative indicators. Through the combination of advanced vibration sensing technology and data analysis methods, this study has performed well in the diagnosis accuracy of various fault types. This highly accurate fault detection capability means that industrial enterprises can more effectively identify faults, so that appropriate maintenance measures can be taken at an early stage to reduce the risk of accidents caused by equipment failure. According to the experimental results, especially for common fault types such as pitting and wear, the accuracy rate has reached more than 90%. This provides equipment managers with a basis for data-based decision making, enabling them to monitor equipment status in real time and prevent potential failures in advance. The results of this study provide strong support for enterprises to promote predictive maintenance strategies. By continuously monitoring vibration signals, combined with historical fault data analysis, companies can achieve real-time assessment of the health of machinery and equipment. When the abnormal vibration characteristics are identified, the maintenance team can check and repair the equipment in a timely manner, without waiting for the fault to formally occur before intervening. This approach not only reduces the probability of unplanned downtime, but also helps to extend the service life of the equipment and reduce maintenance costs. A fault diagnosis system based on vibration analysis can provide identification of specific fault types, such as wear, broken teeth, etc., allowing maintenance teams to focus resources on the affected parts when a failure occurs. At the same time, quantitative metrics, such as peak and root mean square, can crystallize the health of equipment and help maintenance personnel prioritize equipment that is at high risk of failure. In the same type of study, Huang et al. proposed a kernel extreme learning machine method based on high order multi-scale recursive features, dynamic adaptive noise removal and dimensionality reduction algorithms, and Angle optimization to solve the gearbox fault diagnosis problem. The results show that. This method achieves maximum classification accuracy and minimum fluctuation, which indicates that this method effectively realizes gearbox fault diagnosis [21]. Touti et al. proposed a simple and fast diagnostic scheme based on time-domain analysis for wind turbine gear tooth wear detection. The experimental results show that the fault index generated by the method can effectively distinguish between health and fault states, and its efficiency is validated using 10 real data sets from the planetary gearbox of a wind turbine. This method has the advantages of low calculation time and easy interpretation, and is especially suitable for gear fault diagnosis [22]. By monitoring equipment operation in time before failure occurs, the proposed diagnostic method can effectively improve the implementation of predictive maintenance and reduce the downtime and maintenance costs caused by equipment failure. In contrast, the studies of Huang et al and Touti et al were less involved in maintenance efficiency and cost-benefit analysis, which failed to fully demonstrate the economy and feasibility of their schemes in actual industrial applications.

5. CONCLUSION

Due to the various types of mechanical gearbox faults, the traditional manual monitoring cannot accurately diagnose them. It also cannot realize the real-time monitoring of mechanical gearboxes. To solve this problem, based on the research of vibration signals, a fault diagnosis instrument for mechanical transmissions is designed. Compared with the normal gear waveform, the high-frequency component of the faulty gear waveform significantly increases from 0.5 m/s^2 to 1.5 m/s^2. For any type of faults, the diagnostic accuracy of its vibration signals is above 80%. With the increase in the number of experiments, the diagnostic accuracy increases as well. When the number of experiments is 5, the diagnostic accuracy of pitting corrosion is the highest, 92.6%, which is 2.1%, 6.4%, 4.3% and 5.2%

higher than the diagnostic accuracies of abrasion, tooth breakage, fracture grinding and point grinding, respectively. Compared with the envelope spectra of the normal bearings, the faulty bearings have obvious fundamental frequency peaks in the envelope spectra, with an amplitude of 0.8. When the number of experiments is 11, the diagnostic accuracy of the shaft bending is 94.2%, which is 1.9%, 0.7%, 1.1% and 2.2% higher than the diagnostic accuracy of shaft asymmetry, shaft imbalance, axial runout and normal respectively. In summary, the vibration signal can accurately determine the fault condition and fault type of mechanical gearbox. The shortcomings lie in the insufficient analysis of fault types, which can be further refined in the subsequent study of fault types.

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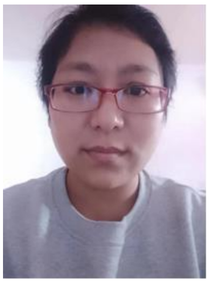

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