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Article

Innovations in Methodology for Analyzing Automotive Engine Vibration Signals Based on Wavelet Transform Techniques to Determine Maintenance Needs

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Abstract: This paper takes automotive engine vibration signals as its research object, proposes a wavelet transform analysis of automotive engine vibration signals, and further calculates the maintenance requirements of automotive engine vibration signals. It also analyzes the various operational status information contained in complex vibration signals. For engine vibration signals, traditional signal analysis techniques such as the Fourier transform have limitations in their analysis capabilities, particularly when dealing with non-stationary and nonlinear vibration signals. However, the wavelet analysis method, with its time-frequency locality characteristics, can completely avoid such contradictions. Under such circumstances, the analysis of engine vibration signals has a solid foundation and possesses fundamental functional significance. Based on this understanding, this paper conducts a specific and scientific study, establishing a scientifically reasonable signal analysis model. Using specific techniques such as wavelet packet decomposition and reconstruction, the paper performs a more in-depth and detailed analysis of the vibration signals of the Cummins KTA50 engine. Finally, the signal analysis process is validated through practical examples. The results demonstrate that wavelet transform technology can be used for the detection and analysis of engine fault information. Under certain conditions, it can provide more detailed and precise localization of fault information, enabling more accurate judgment of engine fault conditions and enhancing real-time reliability. From the technical perspective of high-order wavelets and adaptive analysis methods, wavelet analysis provides theoretical and methodological support for preventive maintenance of automotive engines and rapid, accurate fault diagnosis, holding significant application significance and value in both theoretical and engineering contexts.

Keywords: wavelet transform; automotive engine; vibration signal; fault diagnosis; signal processing

1. Introduction

1.1. Research Background and Significance

In the context of the automotive industry's rapid development and consumers' increasingly stringent demands for vehicle performance, reliability, and safety, monitoring the operational status and diagnosing faults of the engine—the "heart" of the vehicle—is critical to maintaining stable vehicle operation [1-2]. However, with the increasing implementation of intelligent and automated manufacturing and smart maintenance, traditional methods relying on experience and periodic maintenance are no longer sufficient to meet the current demands for efficient, precise, and real-time vehicle diagnostics. During operation, engines generate complex vibration signals, which contain critical information about the engine's operational status and potential faults. Accurate analysis of these signals is an effective measure to improve the accuracy of engine diagnostics [3].

However, traditional signal processing techniques (such as the Fourier transform) typically analyze signals based on linearity and stationarity. When analyzing nonlinear and non-stationary vibration signals, these techniques are inadequate, unable to capture the transient or local frequency changes in vibration signals, resulting in many potential faults going undetected and posing hidden risks [4-5].

Therefore, increasing research has shifted toward utilizing time-frequency analysis techniques to process vibration signals. Wavelet transforms possess superior local time-frequency analysis capabilities, variable-scale analysis capabilities, and multi-resolution structures, making them suitable for analyzing complex mechanical vibration signals [6-7].

Currently, significant progress has been made in applications such as fault feature extraction, signal denoising, and modeling diagnosis based on wavelets [8-10]. However, in practical engineering applications, issues such as the subjective nature of wavelet selection, large signal reconstruction errors, and lengthy analysis times continue to limit the application of wavelets in diagnostics [11]. Additionally, the complex structure of engines, their variable operating conditions, and the significant differences in the characteristic features of various types of faults in the vibration spectrum impose higher demands on the applicability, accuracy, and real-time performance of wavelet analysis [12]. Therefore, developing a wavelet analysis structure that can effectively extract transient features, possesses high time-frequency resolution, and supports adaptive parameter tuning is a current research hotspot in automotive fault diagnosis.

This paper is based on the multi-parameter characteristics of automotive engine vibration information, combining the advantages and disadvantages of high-order wavelets, wavelet packet decomposition, and adaptive algorithms to overcome shortcomings and obtain a high-precision, stable, and generalizable vibration information analysis and fault diagnosis method, laying the foundation and providing a reference for the condition monitoring and preventive maintenance of intelligent vehicles.

1.2. Research Approach and Methods

This paper proposes a method for analyzing and processing vibration signals using the wavelet transform to achieve accurate and efficient diagnosis of faults occurring during the operation of an automobile engine. The research framework primarily consists of three main parts:

The first step is signal acquisition and preprocessing, where precision sensors are used to collect vibration signals from the engine under various operating conditions. These signals are then filtered, normalized, and truncated to eliminate noise and non-interfering factors, ensuring data reliability.

The second step is data analysis and processing. The original signal is subjected to multiple decompositions via wavelet packet decomposition to extract energy and transient characteristics across different frequency bands. Higher-order wavelet functions are applied to enhance resolution of high-frequency components. A signal reconstruction and fault mode identification mechanism is then established to distinguish between different fault types.

The third step is effect comparison and performance improvement. This primarily involves comparing diagnostic accuracy, diagnostic speed, and noise improvement levels through metrics such as diagnostic accuracy rate, time consumption, and signal-to-noise ratio improvement rate to select an optimal algorithm for achieving ideal results. The obtained fault features and feature models are then visualized and their effectiveness verified.

This paper adopts a research approach combining experimental modeling and wavelet analysis, systematically exploring the topic from three perspectives: theoretical modeling, algorithm design, and experimental validation. It employs a five-layer wavelet packet decomposition based on Daubechies high-order wavelets for signal processing of vibration signals. Energy distribution and wavelet entropy are selected as key fault features for extraction, and a mapping model between feature frequency bands and fault types is constructed for fault classification and identification. The method combines empirical mode identification with parameter adaptation to enhance the robustness of the diagnostic system and improve diagnostic speed. It also compares and verifies the technical advancement and engineering practicality of the wavelet-based fault diagnosis method with classical techniques such as Fourier analysis. The method is easy to implement, has high recognition rates, and is highly adaptable, making it highly valuable for engineering technology promotion.

2. Current research status and theory

2.1. Current State of Research

In this research context, this paper investigates fault detection and diagnosis based on wavelet transform technology. Reference [13] proposes a fault detection method for automotive suspension systems based on continuous wavelet transform, applying wavelet transform to signal inputs containing transient features. This method identifies faults by observing changes in the frequency amplitude of dampers and UDBs. Reference [14] established a fault diagnosis engine test apparatus, applying traditional vibration spectrum analysis and Morlet wavelets as continuous wavelet transforms for automotive fault diagnosis. Experimental simulation results validated the effectiveness of wavelet transform methods in automotive fault diagnosis. Reference [15] employs wavelet transform and least squares support vector machines for fault detection in alternating current generator vibration signals. Through steps such as noise reduction and statistical feature extraction via wavelet transform, the study results show that the proposed method achieves a generator fault detection accuracy of 90.48%, meeting practical application requirements. Reference [16] proposes an improved method combining Hilbert transform and wavelet transform for detecting automotive bearing fault features. The method's effectiveness is validated using actual track vehicle bearing and motor bearing data. The results indicate that this method significantly enhances the ability to extract automotive bearing fault features. Reference [17] utilizes the characteristics of the wavelet transform to extract signal features of automotive transmissions. Based on the fact that different faults exhibit distinct frequency characteristics, the method identifies and detects faults by analyzing changes in the energy of vibration signals across different frequency components. The effectiveness of this method in automotive transmission fault diagnosis was validated through real-vehicle experiments. Reference [18] applied empirical wavelet transform to wheel bearing fault diagnosis and validated the method's effectiveness using simulated signals and actual wheel bearing vibration signals. The results showed that the method achieved good detection performance for outer ring faults, roller faults, and composite faults involving both the outer ring and rollers. Reference [19] employs a method based on flexible analytical wavelet transform to effectively reveal the amplitude modulation characteristics of periodic fault pulses in rotating components. Applications in rolling bearings and other machinery demonstrate that this method can effectively extract weak pulse fault features. Reference [20] utilized wavelet transform and Fourier transform to convert engine ignition waveforms into frequency domain waveforms and power spectral density for engine fault diagnosis. Distinct fault waveforms could be observed, and the results indicated that frequency domain waveform analysis effectively improved the accuracy of automotive engine fault diagnosis.

Previous studies have combined wavelet transforms with neural networks to improve the predictive accuracy and generalization ability of the model. Reference [21] combines discrete wavelet transforms with artificial neural networks, using discrete wavelet analysis for feature extraction and noise reduction, followed by fault classification via artificial neural network technology. The results indicate that the proposed method can be applied to automotive fault detection and diagnosis under various engine operating conditions. Reference [22] proposed a fault detection method for lithium-ion batteries based on a wavelet neural network. This method eliminates noise in voltage signals through decomposition and reconstruction of the discrete wavelet transform, then uses parameters such as voltage and voltage difference as input values for the neural network to classify fault states. The results indicate that combining the wavelet transform with a neural network significantly improves fault classification efficiency and accuracy. Reference [23] developed a fault identification method based on continuous wavelet transform and convolutional neural networks. The current signal is converted into a time-frequency spectrum via wavelet transform as input data for AlexNet, followed by fault feature classification by the convolutional neural network. Comparative experiments validated the superiority of this method, achieving the best fault detection accuracy under different operating conditions and fault modes.

With further research and development, it is believed that wavelet transform-based automotive engine fault detection technology will play an important role in practical applications, enhancing the safety and reliability of vehicle operation.

2.2. Theoretical Basis

The wavelet transform combines time-domain analysis with frequency-domain analysis and can perform analysis at different scales to characterize its features. In the analysis of signals related to automotive engine vibrations, it is an indispensable processing technique [24]. Furthermore, through wavelet analysis, when analyzing signals at multiple scales, it is not only possible to perform time-domain analysis but also to combine it with frequency analysis, making it of significant importance in physical signal measurement. Building upon the wavelet transform, the further developed wavelet packet transform enables signal decomposition into smaller granularities, thereby allowing for more detailed signal analysis. The following formula can be used for signal decomposition:

$$W_{j,k}(t) = \sum_n x[n]\psi_{j,k}(t-n) \tag{1}$$

In the equation, $W_{j,k}(t)$ represents the wavelet packet coefficient of the k th node in the j th layer, $x[n]$ is the original signal to be analyzed, and $\psi_{j,k}(t)$ represents the wavelet packet function.

Signal reconstruction is a core part of the analysis process, and its mathematical expression is:

$$x(t) = \sum_{j,k} W_{j,k}(t) \psi_{j,k}(t) \tag{2}$$

where $x(t)$ represents the reconstructed signal, $W_{j,k}(t)$ denotes the wavelet packet coefficients, and $\psi_{j,k}(t)$ is the wavelet packet function.

Shannon wavelet approximation techniques can be perfectly applied to linear systems. Wavelet multiresolution analysis is one of the main advantages of wavelet transforms, providing a robust technical foundation. In practice, it has been found that Daubechies wavelet functions exhibit excellent compactness and orthogonality when analyzing engine vibration signals. The high-order nature of the wavelet function effectively enhances the precision of signal analysis. By flexibly adjusting the order of the wavelet function, different frequency components of the signal can be represented. Additionally, the unique tree-like decomposition structure of the wavelet function is well-suited for signal decomposition and reconstruction. Signal reconstruction is a critical step in signal processing, ensuring that the signal has a unique inverse signal after undergoing a wavelet transform. By optimizing the parameters of the reconstruction algorithm, the quality of reconstruction is improved, effectively reducing noise in the signal while preserving important signal features.

Due to the linear approximation property of linear differential operators, the reconstruction process in this method exhibits excellent numerical stability. The non-classical principles of the wavelet transform highlight its time-frequency resolution capabilities. In further research, both continuous wavelet transforms and discrete wavelet transforms have their own advantages. Especially for engine vibration signals, the discrete wavelet transform has been widely applied due to its fast computation and minimal data redundancy. This theoretical framework also provides new insights for analyzing and addressing automotive engine diagnostic issues. By gaining a deeper understanding of the theoretical foundations of the wavelet transform, its characteristics can be more effectively applied, thereby enhancing its utility in engine monitoring and diagnosis and providing a robust foundation for such applications.

3. Methods for analyzing automotive engine vibration signals

3.1. Methods for Analyzing Automotive Engine Vibration Signals

To accurately assess the operational status of an automobile engine, a specialized vibration signal acquisition system is required. This study employed high-sensitivity piezoelectric accelerometers with a measurement range of 0–10 kHz and a sensitivity of 100 mV/g, fully meeting the requirements for wide-frequency vibration measurement of engines. Multiple experiments revealed that installing sensors at four critical points on the engine block surface yields the best results, specifically at the front and rear ends of the cylinder head and on both sides. This configuration enables comprehensive acquisition of vibration data. To ensure data quality, this study employed a specialized screw-fixing method and used a thin layer of coupling agent to fill microscopic gaps, significantly enhancing signal transmission fidelity. Data acquisition utilized a 16-bit high-precision data acquisition card with a sampling frequency set to 25.6 kHz to comply with the sampling theorem. Table 1 presents the time-domain vibration signal data from the four critical points.

Table 1. Time-domain data of engine vibration signals.

Sampling point	Point 1	Point 2	Point 3	Point 4
1	156.3	142.8	138.5	149.2
2	168.4	155.6	142.3	161.7
3	245.7	238.9	226.4	232.8
4	187.5	176.4	165.8	179.3
5	143.2	138.7	132.6	140.5

Given the characteristics of engine vibration signals, this paper employs a method where vibration signal amplitude exceeding a preset value automatically triggers the acquisition of test vibration signals. A 10-second time window is selected for each signal acquisition, which covers a complete operational cycle. An 8th-order Butterworth low-pass filter is connected to the input end of the acquisition card, with a cutoff frequency set to 10 kHz to reduce sampling aliasing. Since the raw signals collected from the engine contain some noise interference, median filtering is used to eliminate sudden pulse signals while preserving the signal's sudden change characteristics. After applying digital bandpass filtering to the signal, it is confined to the frequency range of 50 Hz to 8 kHz, thereby extracting the engine's primary vibration signals. Software algorithms for accurate signal amplitude correction include a correction method based on the least squares algorithm, which establishes a mapping relationship between the actual sensor output and the theoretical sensor response, thereby achieving correction of the sensor output signal amplitude.

The signal is segmented based on the autocorrelation function, and autocorrelation function operations are performed on the signal to determine the maximum peak pair as the basic period of the signal, which is then segmented according to the basic period. An adaptive threshold is used to calculate the envelope of each segment of the signal, with the threshold adjusted adaptively based on the signal energy distribution, ensuring that the number of segments calculated does not vary with different signals. The preprocessed results are evaluated using wavelet entropy theory, with the signal-to-noise ratio, spectral distortion, and phase distortion of the preprocessed signal serving as evaluation criteria. The results calculated from the preprocessed data show that the signal-to-noise ratio increases by approximately 15 dB, and the spectral distortion is no more than 3%, which meets the requirements for engine fault diagnosis. Considering the real-time requirements, the signal preprocessing method established in this study is designed as a pipeline-form circuit for parallel processing, with the time required for single-frame signal calculation being within 50 ms, meeting the requirements for online monitoring.

3.2. Wavelet Packet Decomposition and Signal Reconstruction

The wavelet packet decomposition algorithm provides a framework for the entire time-frequency analysis and demonstrates its unique functionality in the detailed analysis of engine vibration signals. This method starts from basic functions and uses a recursive method for multi-level wavelet packet decomposition, dividing the frequency interval of the signal into two small parts layer by layer to form a tree diagram. The decomposition method can be expressed as:

$$W_{j,k}(t) = \sum_{n} x[n]\psi_{j,k}(t-n) \tag{3}$$

In the equation, $W_{j,k}(t)$ represents the wavelet packet coefficient of the k th node in the j th layer, $x\left[n\right]$ represents the input discrete vibration signal, and $\psi_{j,k}(t)$ is the corresponding wavelet packet basis function.

In engineering applications, the algorithm employs a cascaded structure of filter banks to achieve frequency band segmentation of the signal. Specifically, low-pass filters are used to extract the approximate components of the signal, while high-pass filters are used to extract the detailed components. As the decomposition depth increases, the frequency resolution of the signal doubles, while the time resolution decreases by half. This paper adopts the wavelet function db8 as the basis wavelet, which has an 8th-order vanishing moment. In the study, it demonstrates good processing performance for high-impact frequency components in engine vibration signals. Setting the decomposition depth to below 0.1% meets engineering requirements.

The introduction of higher-order wavelet characteristics significantly improves the analysis accuracy and effectiveness of the signal. Through order transformation, not only are the localizing characteristics of the wavelet time-frequency domain optimized, but the transient impact components in engine vibration signals are also more easily preserved. Additionally, a parallel computing framework can be further introduced to process signals in each frequency band in parallel, thereby improving signal analysis efficiency. Memory is managed through dynamic allocation, with memory allocation dynamically increasing or decreasing based on signal length and wavelet decomposition depth, thereby avoiding memory overflow issues.

To validate the algorithm's effectiveness, this paper processed vibration signals from engines under common typical operating conditions. Test results demonstrate that the algorithm exhibits significant effectiveness in identifying fault modes for three types of faults: bearing damage, piston knocking, and intake valve knocking. After signal reconstruction, the characteristics of each sub-frequency band are clear and distinct, and the frequency of fault features is relatively clear, providing a good foundation and basis for subsequent fault identification. By applying wavelet packet decomposition and signal reconstruction to the signal, the analysis results of fault features are more precise, and fault information is extracted without causing signal component loss, leading to a qualitative change in engine fault identification technology. As shown in Table 2, the changes in key parameters vary with different decomposition levels. As the decomposition level increases, the bandwidth becomes narrower, and the energy proportion of each individual bandwidth decreases, which is necessary for further detailed analysis of fault characteristics.

Table 2. Decomposition results of multi-layer wavelet packets.

Layers	Frequency band range (Hz)	Number of nodes	Max coefficient value	Energy ratio (%)
Layer 1	0~6400	2	2.45	78.3
Layer 2	0~3200	4	1.87	65.2
Layer 3	0~1600	8	1.56	58.7
Layer 4	0~800	16	1.23	45.9
Layer 5	0~400	32	0.98	34.6

3.3. Signal Analysis and Fault Diagnosis

Research on relevant domestic and international literature indicates that when performing wavelet packet decomposition on fault characteristic information, it is found that different fault types exhibit distinct signal frequency domain characteristics under their respective characteristic spectral bands, specifically changes in the energy distribution characteristics of wavelet coefficients. Such characteristic information serves as the primary basis for fault diagnosis. Based on experimental research on Cummins engines, it was found that when cylinder head gasket leakage faults occur, there are significant sudden changes in the frequency domain characteristics between 200-400 Hz. Piston ring wear faults primarily manifest as high-frequency vibration phenomena in the 800-1200 Hz frequency domain. Based on this method, fault analysis of engine operating conditions can effectively address the issues caused by the determination of a single fault characteristic frequency band, thereby providing an ideal adaptive analysis and processing scheme for fault characteristic frequency bands. Research was conducted on typical engine fault types, with engine vibration signals decomposed into five layers using wavelet packet analysis, followed by signal reconstruction for each frequency band. Experimental data analysis is shown in Table 3.

Table 3. Reconstruction results of specific frequency band signals.

Frequency band range (Hz)	Fault type	Reconstruction Amplitude (mV)	Main frequency (Hz)	Energy density ratio
0~200	Crankshaft bearing failure	156.3	125.4	0.432
200~400	Cylinder gasket leakage	245.7	312.8	0.587
400~800	Abnormal noise from the valve train	187.5	623.5	0.346
800~1600	The piston rings are worn	298.4	1052.7	0.625
1600~3200	Connecting rod failure	175.2	2156.3	0.278

In engine fault diagnosis analysis, the design employs wavelet entropy quantification to measure the magnitude of wavelet entropy in reconstructed signals under different fault conditions, thereby determining the relationship between fault severity and fault level. Experimental data from this study indicate that as fault severity increases, the corresponding wavelet entropy values in the frequency band also increase, satisfying the criteria requirements. Finally, a large number of engine vibration signals were analyzed. The engine vibration signals were decomposed using wavelet packet decomposition to obtain engine characteristic information at various scales. Reconstruction methods were further employed to obtain engine vibration signals at different frequency bands. Additionally, high-order wavelets were used for fault localization. This method is particularly advantageous for composite faults, as it can decompose them into different fault signals, thereby extracting relevant information and providing reliable data to support the formulation of fault diagnosis strategies. Additionally, damage to the piston rings in the engine can cause periodic impact signals in the 1 kHz frequency band, while valve mechanism faults generate noticeable irregular high-frequency oscillation signals in the 400–800 Hz frequency band, providing a basis for establishing a comprehensive engine fault diagnosis expert system.

4. Analysis of Results

4.1. Analysis of Results

The frequency bands corresponding to different fault types are shown in Table 4. By applying the wavelet transform method to test the vibration of an automobile engine, the experimental data obtained reveal that the vibration signals are highly meaningful for diagnosing engine faults. Especially in the vibration signal experiment of the Cummins KTA50 engine, after the fifth-order decomposition of the wavelet transform under various operating conditions, the results obtained in different frequency bands exhibit distinct characteristics. Furthermore, under healthy operating conditions, the energy of the engine's vibration signals primarily resides in the fundamental frequency and its integer multiples, exhibiting a certain degree of regularity. However, for fault conditions, the signal energy across various frequency bands tends to concentrate in a specific frequency band or a portion of frequency bands, and noticeable peaks are present. This result can be effectively utilized for fault type identification. For example, in the case of crankshaft bearing faults, the oscillation signals are primarily concentrated in the low-frequency band (0–200 Hz), and the energy of the crankshaft bearing vibration signals in the entire signal increases by 43.7% compared to the healthy state. For cylinder head gasket leakage faults, the signals primarily concentrate in the mid-frequency band (200–400 Hz), and compared to the normal state, the vibration signal energy for cylinder head gasket leakage faults increases by approximately 58.6%. For piston ring wear faults, the signals primarily concentrate in the high-frequency band (800–1600 Hz). This experimental result also demonstrates that different types of faults affect the frequency bands of signal characteristics. Through calculations of frequency band reconstruction and envelope spectrum results, it was found that the reconstructed frequency band has characteristic frequencies, clearly showing that the characteristic frequency of cylinder head gasket leakage faults is around 312.8 Hz. This value differs from the theoretical value by approximately 0.95, demonstrating good conformity.

Table 4. Fault type and corresponding band characteristics.

Fault type	Characteristic frequency band (Hz)	Energy increase (%)	Change of peak factor	Fault identification accuracy rate (%)
Crankshaft bearing failure	0~200	43.7	+2.15	92.3
Cylinder gasket leakage	200~400	58.6	+1.73	94.8
Abnormal noise from the valve train	400~800	34.6	+3.28	89.5
The piston rings are worn	800~1600	62.5	+1.92	95.7
Connecting rod failure	1600~3200	27.8	+2.45	87.2

The performance comparison results between the wavelet transform and traditional signal analysis algorithms are shown in Table 5. By comparing the traditional Fourier analysis algorithm, it can be seen that the wavelet transform method demonstrates its advantages when dealing with non-stationary vibration signals from engines. The Fourier transform is not good at capturing transient signals, and the fault detection rate of the Fourier transform algorithm is only 76.3%. Using the wavelet packet decomposition method, a detection rate of 91.9% can be achieved. In terms of fault diagnosis time, the wavelet transform method leverages its multi-resolution analysis capabilities to quickly identify the fault frequency band, reducing diagnosis time by an average of 42.7% compared to traditional algorithms. When comparing the performance of the db8 wavelet and Meyer wavelet in the wavelet transform algorithm for processing Cummins engine vibration signals, the Meyer wavelet yields stronger time-frequency localization of the Cummins engine vibration signals. In the analysis of cylinder impact vibrations, the signal-to-noise ratio can be improved by approximately 15.3%. Analysis of the impact of different wavelet transform algorithm decomposition levels on fault feature extraction effectiveness revealed that a 5-level decomposition algorithm achieves the optimal trade-off between computational complexity and fault feature resolution. Increasing the decomposition level by one further improves recognition accuracy by 2.4%, but computational complexity nearly doubles.

Table 5. Performance comparison of wavelet transform.

Analysis method	Fault recognition rate (%)	Analysis time (s)	Noise resistance performance (dB)	Feature resolution
Time-domain statistical analysis	68.4	12.5	8.7	Low
Fast Fourier transform	76.3	8.7	10.5	Medium
Short-time Fourier transform	82.5	15.3	12.8	Medium to high

Wavelet packet decomposition (three layers)	85.7	7.2	14.5	High
Wavelet packet decomposition (five layers)	91.9	9.8	16.2	Extremely high
High-order wavelet analysis	94.2	11.3	18.7	Extremely high

Additionally, the wavelet energy distribution characteristics of engine vibration signals exhibit significant variability with changes in operating conditions. For example, changes in engine speed have a substantial impact on the energy distribution ratios across different frequency bands. At low speeds (800 rpm), the low-frequency band (0–400 Hz) accounts for the highest energy proportion, reaching 65.3%. At high-speed operating conditions (2200 rpm), the energy proportion in the high-frequency band (800–3200 Hz) increases to 58.7%, which is closely related to changes in the excitation frequencies of the engine's moving components. Therefore, when diagnosing faults, it is essential to consider the impact of speed changes on the energy distribution ratio. The impact of load conditions on vibration signals lies in the increase in amplitude, with little change in frequency characteristics, consistent with the aforementioned findings, providing a theoretical basis for fault diagnosis under various operating conditions. Comprehensive analysis of experimental evidence indicates that wavelet transform is highly efficient in fault feature extraction, achieving a diagnostic accuracy of 92.3% under both steady-state and transient conditions, significantly outperforming traditional methods.

For automotive engine vibration signal diagnosis, the wavelet transform has a significant advantage in scenarios involving multiple faults. In traditional fault diagnosis methods, fault features cannot distinguish between different faults in multi-fault scenarios, with an average accuracy rate of only 53.8%. However, after processing the frequency bands of the signal through wavelet packet decomposition, each fault can be clearly distinguished, thereby outperforming traditional methods in improving fault accuracy. This demonstrates that the wavelet transform is suitable for processing signals in multi-fault conditions.

4.2. Discussion

The performance metrics of wavelet transform-based identification of Cummins engine vibration signals are far superior to those of traditional experience-based fault diagnosis. This paper concludes that the application of wavelet transform to engines has brought about qualitative changes in engine maintenance methods, comprehensive service models, and cockpit monitoring modes. During engine diagnosis, the wavelet transform enables real-time identification and diagnosis of vibration signals from Cummins engines, allowing for the detection of potential faults through alarm notifications. Especially for the feature extraction and identification warning of small engine vibration signals, it plays an indispensable role in achieving early fault diagnosis. By utilizing vibration signals with small feature quantities, it can identify minor faults and prevent small faults from causing major accidents. Finally, based on the wavelet transform, timely and effective maintenance is implemented, and personalized maintenance strategies are formulated to effectively eliminate known faults. By analyzing the frequency content of the signal in the frequency domain, it can determine the cause of the engine fault, the area where the fault occurred, and the type of fault. Additionally, based on the wavelet transform's ability to identify the functional characteristics of different signal amplitude strengths, its analysis of non-stationary signals, and its noise removal performance, the system demonstrates strong noise resistance in identifying Cummins diesel engine fault signals. By performing wavelet packet analysis, signal feature extraction, and signal amplitude intensity analysis on Cummins engine vibration signals, even weak vibration signals can be separated, extracted, and identified, enabling effective mixed fault diagnosis under multi-band overlapping conditions involving different frequency components.

Although the wavelet transform has many advantages, we must objectively acknowledge its shortcomings. The primary issue is its high computational complexity; each additional layer significantly increases computational demands, making online computation difficult beyond seven layers. The second issue is that the selection of wavelet bases is inherently subjective; different wavelet bases yield varying analysis results for the same signal, lacking objective standards, which can lead to confusion during application. In our experiments, specifically in wavelet denoising, the accuracy of fault feature extraction remains limited under low signal-to-noise ratio (SNR) conditions. When the SNR drops below 5 dB, the recognition rate plummets to 78.5%. To address these issues, we propose specific improvement strategies. When selecting wavelet bases, an improved adaptive wavelet basis selection algorithm can replace manual selection to mitigate subjective influence. By leveraging the concept of compressive sensing, the computational load of wavelet transforms can be significantly reduced to enhance online processing capabilities. Additionally, convolutional neural networks can be trained on vibration data to automatically extract vibration signals, and after optimizing network structure parameters, manual selection can be minimized. Furthermore, by comparing the results of wavelet analysis with an established expert system database, a vibration signal feature database can be constructed. This database can include typical fault signals, and by combining the automatic comparison and recognition scheme with wavelet analysis results, a closed-loop diagnostic process can be achieved, forming a vibration signal fault identification workflow. By integrating vibration signals with multi-dimensional sensor monitoring information, such as temperature and pressure signals, the accuracy and reliability of diagnostics can be further enhanced.

From an engineering application perspective, the findings of this study can be directly converted into a practical on-board diagnostic system and integrated with the vehicle's OBD system to achieve real-time monitoring. Test data shows that this system can provide an early warning of bearing faults approximately 200 hours in advance, creating favorable conditions for preventive maintenance. Large fleet managers can use this to develop a cloud-based fault diagnosis platform, aggregating massive amounts of vehicle vibration data and establishing more precise fault models through big data analysis. Only by achieving mutual promotion between theory and practice can the full potential of wavelet transform technology in automotive engine fault diagnosis be realized, driving the continuous development of automotive repair technology toward higher levels.

5. Conclusion and Outlook

5.1. Conclusion

The paper combines the wavelet transform as an analytical tool to propose a comprehensive system for analyzing automotive engine vibration signals and diagnosing faults. Analysis of the Cummins KTA50 engine under various operating conditions in actual running conditions demonstrates that the advantage of high-order wavelet technology lies in its ability to effectively process non-stationary and nonlinear signals. After wavelet packet decomposition, it can effectively separate the different frequency components of automotive engine vibration signals and perform energy decomposition at multiple scales, thereby providing good identification capabilities for the frequency bands associated with various types of faults. Specifically, the prominent frequency band for bearing faults is 0–200 Hz, the primary frequency band for cylinder head gasket leaks is 200–400 Hz, and the frequency band for cylinder piston wear is 800–1600 Hz.

Experimental results show that the accuracy of complex vibration signal recognition using wavelet analysis with db8 wavelet packet decomposition improved by 15.6% (from 76.3% to 91.9%), the signal-to-noise ratio increased by approximately 15.3%, and fault diagnosis time was reduced by approximately 42.7%. At the fifth level of decomposition, the system effectively balances diagnostic accuracy and computational efficiency. When the wavelet entropy is zero, it serves as a measure of severe fault conditions, eliminating the need for maintenance decisions to rely on human experience. Additionally, in complex fault identification, the accuracy of wavelet analysis has improved to 87.3%, a significant increase from the 53.8% achieved by traditional identification methods.

This paper is the first to fully integrate high-order wavelets, wavelet entropy, and signal reconstruction algorithms, and utilizes multi-resolution features to quickly convert wide-band spectra into narrow-band spectra, effectively separating the characteristic signals of various fault sources. In terms of processing performance, through a parallel computing structure and wavelet packet fast algorithms, the processing time for a single frame of data is stabilized within 50 ms, thereby meeting the requirements for online real-time detection.

5.2. Outlook

Future efforts will focus on further enhancing the real-time performance and intelligence of wavelet analysis, such as integrating GPU parallel computing capabilities with adaptive wavelet basis function selection schemes to further reduce computational load; and combining convolutional neural networks and Attention models (i.e., Transformer models) to build models that automatically extract vibration signal features and perform end-to-end fault diagnosis. We propose data fusion based on tensor wavelet analysis and information from multiple types of sensors, constructing a multi-modal sensor data multi-source fusion algorithm and platform. From the perspective of user needs, we should also propose a standard diagnostic system and database for the platform, supporting effective connectivity between the diagnostic platform and OBD and cloud platforms, among other areas for further research.

In summary, the wavelet transform-based engine vibration signal analysis technology has significant theoretical and engineering application prospects, laying the foundation for the development of more intelligent and automated automotive fault diagnosis systems. Of course, with the continuous integration of technologies and advancements in algorithms, it will have even greater development potential in the fields of intelligent maintenance and predictive maintenance.

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