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Case Study Analysis of Rotating Machinery Fault Diagnosis for Course on Vibration Testing and Signal Analysis Techniques

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Abstract: With the development of modern educational technology, the teaching of vibration testing and signal analysis techniques faces new challenges. To enhance teaching effectiveness and improve students' understanding of complex theories, this paper proposes a teaching case for bearing fault diagnosis based on continuous wavelet transform and CNN-BiLSTM. First, by utilizing wavelet transform for time-frequency analysis of vibration signals, students can gain a deeper understanding of the core principles of signal processing. Second, the introduction of the CNN-BiLSTM model in deep learning enables students to not only grasp the fundamental concepts of deep learning but also enhance their problem-solving abilities in practical engineering scenarios. Experimental results indicate that this approach can effectively improve students' mastery of signal analysis and fault diagnosis techniques, showing significant advantages in fostering innovative thinking and practical skills. This study provides new ideas and practical cases for the reform of teaching vibration testing and signal analysis techniques.

1. Introduction

The course on vibration testing and signal analysis techniques is an important subject in fields such as mechanical engineering, automation, and electrical engineering. It primarily aims to cultivate students' ability to utilize modern testing and analysis methods for fault diagnosis and performance evaluation of mechanical equipment in engineering practice. The course content covers the collection, processing and analysis of vibration signals, and fault diagnosis methods, making it an essential pathway for developing students' engineering practical abilities, innovative capacities, and data processing skills. With the rapid development of industrial automation and intelligent manufacturing, equipment fault diagnosis technology plays a significant role in ensuring the normal operation of equipment, improving production efficiency, and extending the service life of equipment. As an important part of the mechanical system, bearing failures are often one of the fundamental causes of mechanical equipment failures. Therefore, timely and accurate diagnosis of bearing failures can not only ensure the normal operation of the equipment, but also effectively improve the production efficiency and reduce the maintenance cost, which is of great practical significance [1]. Traditional bearing fault diagnosis methods rely on expert experience and manual feature extraction. Although effective in certain situations, they have limitations when dealing with complex signals and addressing nonlinear problems. As the complexity of mechanical equipment and systems increases, the accuracy and operability of traditional diagnostic methods are increasingly challenged in practical applications. Vibration testing and signal analysis have been widely used as important tools for fault diagnosis in modern industry [2]. However, with the increasing complexity of equipment, traditional fault diagnosis methods and teaching methods are facing new challenges.

In recent years, the rapid development of deep learning technology has provided innovative solutions for fault diagnosis. Methods based on convolutional neural networks (CNN) and bidirectional long short-term memory networks (BiLSTM) have achieved remarkable success in various fields, particularly in handling complex signals and time-series data. The combination of CNN for local feature extraction and BiLSTM for capturing long-term dependencies offers significant potential for bearing fault diagnosis [3]. Additionally, continuous wavelet transform (CWT), as an effective signal processing method, can decompose vibration signals into multiscale time-frequency information, which helps provide richer feature information for subsequent deep learning models [4]. However, under the traditional teaching mode, effectively integrating these advanced technologies into the educational system remains a challenge. Current courses on vibration testing and signal analysis techniques mainly focus on fundamental theories and traditional methods, lacking systematic application and exploration of modern deep learning technologies. How to implement innovative teaching methods that not only enable students to master the foundational theories of bearing fault diagnosis but also cultivate their ability to apply deep learning techniques to solve practical engineering problems is a crucial issue that needs to be addressed in current higher education.

In this paper, the practical application of the CWT and CNN-BiLSTM model is introduced into the course on vibration testing and signal analysis techniques through innovative teaching methods. This approach helps students develop their ability to solve practical engineering problems through experimental operations and case analyses, building upon their theoretical learning. This teaching method, which combines modern signal processing technology with deep learning, aims to enhance students' technical proficiency and lay a solid foundation for their future involvement in the fields of intelligent manufacturing and automation. Through case-driven learning and technological integration, students not only master modern fault diagnosis methods but also enhance their innovative thinking and practical skills, enabling them to better tackle future challenges in the industrial field. The research in this paper provides new ideas and practical experience for the teaching reform of the course on vibration testing and signal analysis techniques, promoting the updating and improvement of teaching content and methods.

2. Fault diagnosis process and theoretical foundation

2.1. General process of fault diagnosis

In bearing fault diagnosis, this process generally includes key steps such as signal acquisition, preprocessing, feature extraction, feature selection, model training, and prediction.

(1) Firstly, signal acquisition is the fundamental basis for fault diagnosis, primarily relying on sensors (such as accelerometers and velocity sensors) to monitor the vibration signals of the equipment in real time. These signals reflect the operating status of the equipment and potential fault characteristics; therefore, the quality of signal acquisition is crucial for the accuracy of the diagnostic results.

(2) After obtaining the raw signal, the subsequent preprocessing stage involves denoising, filtering, and normalizing the signal. This step is aimed at removing high-frequency noise, low-frequency interference, and unnecessary vibration components to ensure the purity and stability of the signal required for subsequent analysis.

(3) Next, the feature extraction utilizes time-domain, frequency-domain, and time-frequency domain analysis methods (such as wavelet transform and Fourier transform) to extract key fault characteristic information from the vibration signals. CWT can decompose the signal at multiple scales, capturing instantaneous changes in non-stationary signals, which is why it is widely used in fault diagnosis.

(4) Feature selection then filters the extracted features to retain the most diagnostic value while removing redundant and irrelevant features, thereby simplifying the computation and improving the diagnostic accuracy.

(5) Finally, model training and prediction are the core components of fault diagnosis, often employing deep learning techniques such as CNN and BiLSTM. By training on a large set of labelled fault data, a classification model is constructed to automatically identify various fault types and perform fault prediction and classification on unknown data.

2.2. Continuous wavelet transform (CWT)

Continuous wavelet transform is a form of wavelet transform, the core of which is to generate a set of wavelet basis functions by scaling and time-domain shifting of the wavelet mother function, and then perform convolution operations with the original signal, so as to characterise the local details of the signal in the time-frequency domain at different scales (corresponding to different frequency ranges). Unlike the Fourier transform, the wavelet transform is able to provide both time and frequency local information, which makes it particularly suitable for analysing non-stationary signals. For bearing fault diagnosis, the vibration signals of bearings usually contain non-stationary characteristics (e.g., transient shocks, impulse signals, etc.), and the advantage of CWT lies in its ability to effectively capture these transient and non-stationary features [5].

The process of transforming the signal $x(t)$ by continuous wavelet transform can be expressed by the following equation:

$$CWT_x(a,b) = \int_{-\infty}^{+\infty} x(t)\varphi(\frac{t-b}{a})dt \tag{1}$$

where $x(t)$ represents the original signal, $\varphi(\bullet)$ denotes the wavelet basis function, a is the scale parameter (indicating the degree of expansion or compression of the signal), and b is the translation parameter (indicating the time-domain location of the signal). By adjusting the scale and translation parameters, the wavelet transform can effectively extract the characteristics of the signal across various time and frequency scales.

The choice of a wavelet basis function has a significant impact on the effectiveness of CWT. In bearing fault diagnosis, different wavelet basis functions are suitable for different signal characteristics and analysis needs. Among the current wavelet functions, there are many types, with commonly used ones including Haar wavelet, Morlet wavelet, Daubechies wavelet, and Mexican Hat wavelet. We will select one of these four wavelets as the appropriate wavelet basis function for this experiment.

(1) Haar wavelet

The Haar wavelet function is the most commonly used wavelet function in wavelet analysis. It is also the simplest of the four and a tightly supported orthogonal wavelet function. It has the advantage of quick computation; however, the disadvantage of the Haar wavelet is also quite apparent: it is discrete in the time domain. Therefore, compared to other wavelets, its feature expression is not superior. The expression of the Haar wavelet is:

$$y(t)=\begin{cases}1 & 0\le t\le \frac{1}{2}\\ -1 & \frac{1}{2}\le t\le 1\\ 0 & \text{otherwise}\end{cases} \tag{2}$$

(2) Morlet wavelet

Morlet wavelets are complex wavelets widely used in time-frequency analysis, composed essentially of the product of a complex exponential carrier and a Gaussian envelope function. Since these wavelets typically do not satisfy the strict admissibility condition for wavelets (i.e., zero mean), there is no corresponding scale function. Their mathematical expression is:

$$\varphi(t)=\pi^{-1/4}e^{j\omega_0 t}e^{-t^2/2} \tag{3}$$

where ω_0 represents the frequency of the wavelet, $e^{j\omega_0 t}$ denotes a high-frequency sine carrier signal, and $e^{-t^2/2}$ is a Gaussian window function that ensures the localization of the wavelets in the time domain, allowing Morlet wavelets to achieve good time-frequency localization capabilities. From the above expression, it can be seen that the Morlet wavelets are composite wavelets, whose time-frequency characteristics are determined by the product of a sine wave and a Gaussian window. The sine wave provides frequency information in the frequency domain, while the Gaussian window limits the duration of the signal in the time domain, thus enabling effective time-frequency analysis.

(3) Daubechies wavelet

Daubechies wavelets are characterized by compact support and orthogonality, with both the scaling and wavelet functions having finite support. This enables time-domain localization while preserving good spectral properties. By using finite impulse response (FIR) filters, Daubechies wavelets fulfil multi-resolution analysis requirements, allowing for effective signal decomposition and reconstruction. This wavelet family is categorized by order (e.g., db1, db2, db4), with higher orders providing increased smoothness for various signal analysis tasks. Their orthogonality allows the Daubechies wavelet transform to represent signals without redundancy, making it highly effective for data compression and noise reduction applications.

(4) Mexican Hat wavelet

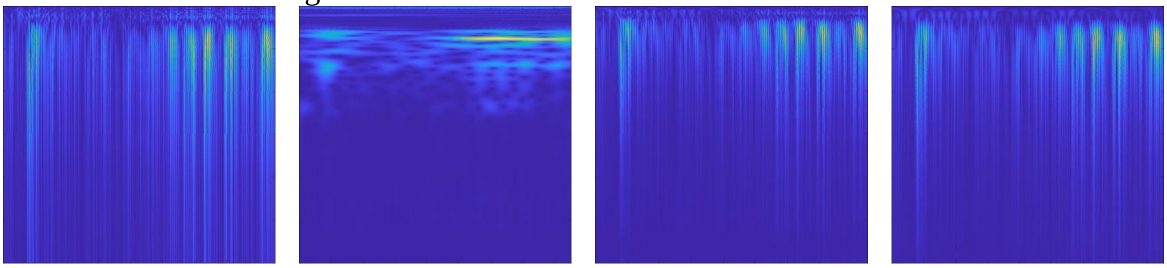
The Mexican Hat wavelet function is mathematically defined as the second derivative of a Gaussian function, as shown in Equation 2.

$$\varphi(t)=(1-t^2)e^{-t^2/2} \tag{4}$$

Its expression in the time domain has compact support, allowing for localization in the time domain, which effectively captures the features of short-duration signals. Because it is related to the Gaussian function, it has a relatively narrow bandwidth in the frequency domain, making it well-suited for analysing specific frequency components of a signal.

From the above wavelet analysis, it can be seen that most wavelets possess excellent capabilities for representing local features and can effectively display characteristic information as needed. Therefore, wavelet analysis has been widely applied in nonlinear and non-stationary signals. Based on an in-depth study and analysis of gear vibration signals, this experiment will utilize wavelet transform for time-frequency analysis, taking into account the characteristics of the vibration signals.

The time-frequency maps obtained from four different wavelet transforms of the bearing data in normal state are shown in Figure 1.



(a) (b) (c) (d)

Figure 1: Time-frequency diagram of (a) Haar wavelet, (b) Morlet wavelet, (c) Daubechies wavelet and (d) Mexican Hat wavelet

From Figure 1, it can be seen that the Morlet wavelet, with its optimal time-frequency localization capability, exhibits significantly better energy concentration than other wavelet basis functions. This wavelet presents clear frequency focusing characteristics in the time-frequency plane, allowing for precise capture of periodic impulse signals (such as the characteristic frequency components of bearing faults). It strikes a balance between time and frequency resolution, making it particularly suitable for extracting transient features in non-stationary vibration signals. Therefore, it has been chosen as the basis function for this study.

2.3. CNN-BILSTM model

In bearing fault diagnosis, with the advancement of deep learning technology, traditional feature extraction methods have gradually been replaced by deep learning models such as CNN and Long Short-Term Memory networks (LSTM). In particular, the neural network model that combines CNN and BiLSTM, referred to as CNN-BiLSTM, has shown significant advantages in signal feature extraction and fault pattern recognition. The details of CNN-BiLSTM are illustrated in Figure 2.

CNN is a type of deep learning model that excels at automatically extracting features from images or time-series data. In fault diagnosis, the CNN is typically used to extract efficient spatial features from bearing vibration signals. Through multiple layers of convolutional and pooling layers, CNN can identify local and important frequency features within the signals, which are crucial for diagnosing different types of faults. The convolutional layer performs convolution operations on the input signal using convolutional kernels to extract local features. Assuming the input signal is $x(t)$, the convolution operation can be represented as:

$$z(t) = (x * \omega)(t) = \sum_{k=0}^{N} x(t-k)w(k) \tag{5}$$

where $z(t)$ is the output signal after the convolution, $w(k)$ is the convolution kernel, and $*$ represents the convolution operation.

The role of the pooling layer is to reduce computational load and extract more representative features through downsampling. The formula for the max pooling operation is:

$$y(t) = \max_{k \in Kernel\ Size} (z(t+k)) \tag{6}$$

where the Kernel Size refers to the size of the pooling window, and $y(t)$ is the output from the convolutional layer. Through these operations, CNN can automatically extract representative frequency features from vibration signals, providing a foundation for subsequent fault diagnosis.

LSTM is a special type of recurrent neural network (RNN) that can effectively handle long-term dependencies in sequential data. Compared to traditional RNNs, LSTM successfully avoids the vanishing gradient problem by introducing gating mechanisms. In fault diagnosis, LSTMs can learn time-dependent features in vibration signals, such as long-term trends and periodic variations. BiLSTM is an extension of LSTM that further improves the accuracy and robustness of the model by simultaneously considering information flow in both forward and backward directions. By combining CNN with BiLSTM, the neural network model can not only extract effective spatial features from vibration signals but also capture long-term and short-term dependencies in the time domain, thereby achieving more precise fault diagnosis. This combination fully leverages the advantages of both approaches, reduces manual intervention, and enhances robustness against complex fault patterns and signal noise.

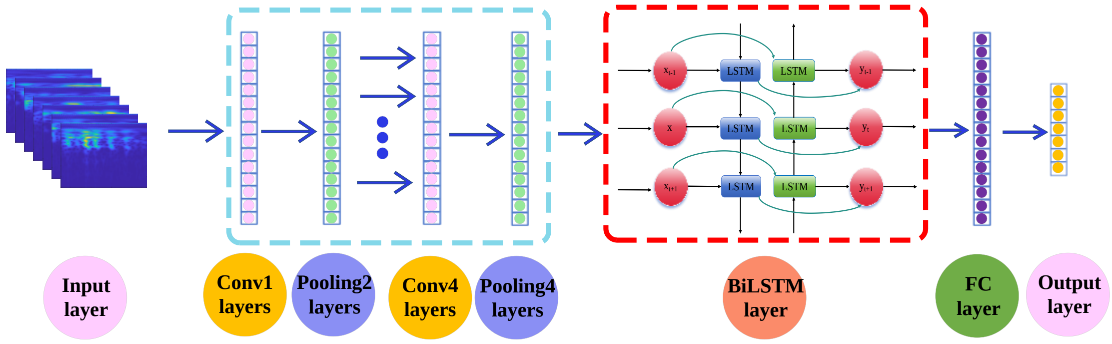


Figure 2: Details of CNN-BiLSTM neural network

3. Case study

3.1. Experimental platform setup

To conduct bearing fault diagnosis experiments, we established a dedicated experimental platform, shown in Figure 3, to collect high-quality bearing vibration signals and build a corresponding fault dataset. This platform consists of components such as a motor, gearbox, and eddy current brake, where the motor drives the bearing, and the eddy current brake simulates the load under actual operating conditions of the bearing. We installed high-precision accelerometers at different locations on the test bench to collect vibration signals in real-time, which are generated by bearings under various fault conditions. To simulate real fault scenarios, we set up multiple types of faults, including inner race, outer race, and rolling element faults. Data collection was conducted at different rotational speeds and loading conditions to obtain vibration signals from various operating scenarios. This data will be used to build the bearing fault dataset, providing realistic and diverse sample support for the training of subsequent deep learning models and fault diagnosis.

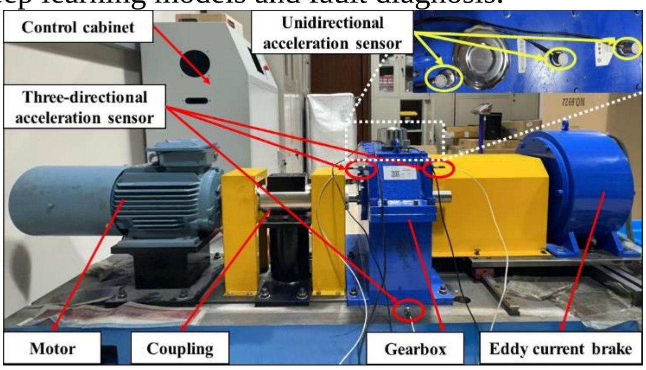


Figure 3: Experimental setup and signal acquisition

Based on the experimental setup, the bearing dataset includes four types of conditions: normal condition, inner race fault, outer race fault, and rolling element fault, with each condition containing 300 samples. To ensure the generalization capability of the model, the dataset is divided into training and testing sets in an 80:20 ratio, where 80% of the data is used for training and 20% for testing.

3.2. Fault diagnosis and analysis

To comprehensively evaluate the diagnostic capability of the model, we adopted four evaluation metrics: Accuracy, Precision, Recall, and F1 score.

(1) Accuracy measures the proportion of correctly classified samples relative to the total number of samples, and is specifically defined as follows:

$$Accuracy = \frac{\sum TP_i}{Total} \tag{7}$$

where TP_i is the number of samples correctly predicted for the i^{th} class, and $Total$ is the total number of samples.

(2) Precision, also known as positive predictive value, is a key performance metric used to assess the accuracy of a classification model. It focuses on the quality of the positive predictions made by the model. It represents the ratio of true positive predictions to the total number of positive predictions made by the model, defined as follows:

$$Precision_i = \frac{TP_i}{TP_i + FP_i} \tag{8}$$

where FP_i is the number of samples incorrectly predicted for the i^{th} class.

(3) **Recall**, also known as sensitivity or true positive rate, is a performance metric used to evaluate the effectiveness of a classification model, particularly in scenarios where identifying positive instances is crucial. Recall measures the proportion of actual positive class samples that are successfully identified by the model, defined as:

$$Recall_i = \frac{TP_i}{TP_i + FN_i} \tag{9}$$

where FN_i is the number of samples in the i^{th} class but incorrectly predicted as other classes.

(4) **F1 score** is a crucial metric for evaluating the performance of classification models, especially in scenarios where class imbalance is present. It combines both Precision and Recall into a single score, defined as follows:

$$F1_i = \frac{2Precision_i \times Recall_i}{Precision_i + Recall_i} \tag{10}$$

Using the evaluation metrics shown in Table 1, the bearing fault diagnosis method based on wavelet transform and CNN-BiLSTM demonstrates exceptional performance. At a load current of 0A, the method achieves an accuracy of at least 99.76%, with precision, recall, and F1-score all at 100%. For load currents of 0.3A and 0.5A, it maintains 100% across all metrics. These results confirm the robustness and generalization ability of the fault diagnosis model, allowing it to identify faults under different load conditions. This innovative method offers a reliable solution for the industry, ensuring high accuracy and effective identification of different fault types, thereby enhancing bearing condition monitoring and maintenance.

Table 1 Results of the proposed method after five executions.

Load current (A)	Accuracy (%)	Precision (%)	Recall (%)	F1 score
0	99.76	100	100	1
	100	100	100	1
	99.76	100	100	1
	99.76	100	100	1
	100	100	100	1
0.3	100	100	100	1
	100	100	100	1
	100	100	100	1
	100	100	100	1
	100	100	100	1
0.5	100	100	100	1
	100	100	100	1
	100	100	100	1
	100	100	100	1
	100	100	100	1

4. Conclusions

In this study, we provide an in-depth exploration of a bearing fault diagnosis method utilizing wavelet transform and CNN-BiLSTM. Experimental results show that wavelet transform can effectively extract the time-frequency features of bearing vibration signals, while the CNN-BiLSTM model exhibits high accuracy, recall, and F1 scores in fault classification tasks, demonstrating its superiority in bearing fault diagnosis. Additionally, regarding the teaching reform in the course on vibration testing and signal analysis techniques, we have integrated this advanced fault diagnosis method into the course curriculum. Through practical case analysis and experimental operations, we have enhanced students' understanding and application of modern signal processing technologies. The innovative design of the course allows students to gain practical experience while mastering theoretical knowledge, thereby increasing their engineering practice and problem-solving abilities. Through this reform in teaching methodology, students not only learn advanced fault diagnosis techniques but also cultivate their innovative thinking and interdisciplinary application skills.

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