Enhancing Rolling Bearing Fault Diagnosis: A VMD-BILSTM Approach

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Abstract: Bearings are essential components in the machinery industry, and maintaining their stable operation is critically important. However, bearings frequently operate in challenging environments, which renders them prone to damage and various malfunctions. Existing methods for diagnosing bearing faults are plagued by inadequate anti-interference capabilities, limited robustness, and low accuracy. To improve fault recognition precision and enhance the model's resistance to interference, this paper presents a fault diagnosis method that employs Variational Mode Decomposition-Bidirectional Long Short-Term Memory (VMD-BiLSTM) for rolling bearing fault analysis. The VMD processes the extracted signal, decomposing it into several Intrinsic Mode Functions (IMFs). These components act as input signals for the LSTM's training, aiding in the processing and recognition of fault signals. Comparative experiments show that the VMD-BiLSTM model surpasses the CNN-Transformer and AlexNet models. The proposed model demonstrates significant advantages in fault recognition accuracy and stability, achieving an average recognition accuracy of 99.8%.

Index Terms: Bearing Fault Diagnosis; Variational Mode Decomposition; Bidirectional Long Short-Term Memory; Signal Processing; Fault Recognition

1. INTRODUCTION

Bearings as a crucial component in mechanical equipment, with their stability being directly linked to the reliability and safety of the entire system[1-3]. Bearings are susceptible to wear and degradation under conditions of prolonged high-load, strong impact, and high velocity, potentially leading to failures that can result in substantial property damage and human casualties. The occurrence of bearing failures not only diminishes mechanical efficiency but also risks causing production halts, equipment damage, and significant economic losses[4, 5]. Consequently, effective fault diagnosis of bearings, which enables real-time monitoring and early warning of operational status, holds paramount importance for ensuring the continuity and safety of industrialproduction.

Nevertheless, current bearing fault diagnosis methods encounter numerous challenges in practical applications[6-9]. On one hand, the collected signals are contaminated by various noises and interferences, complicating the accurate extraction of fault characteristics. On the other hand, the robustness and precision of existing methods require enhancement to fulfill the demands of bearing fault diagnosis in complex conditions. To address these challenges, researchers are investigating more sophisticated fault diagnosis techniques.

In recent years, the swift advancement of deep learning technology has revealed the considerable promise of data-driven intelligent diagnosis methods in the realm of bearing fault diagnosis[10, 11]. These methods are capable of autonomously learning intricate fault features from extensive datasets, thus enhancing the accuracy and robustness of fault detection. Among the array of deep learning models, Long Short-Term Memory (LSTM) excel in processing time-series data, owing to their distinctive gating mechanism[12, 13]. Nevertheless, LSTM models frequently overlook both local and global information when analyzing bearing vibration signals, which hampers the efficacy of fault diagnosis[14]. This paper introduces a bearing fault diagnosis method that integrates Variational Mode Decomposition (VMD) with a Bidirectional LSTM (VMD-BiLSTM). Initially, this method employs variational mode decomposition technology to disassemble the original vibration signal into modal components rich in fault information. Subsequently, these components serve as inputs to the BiLSTM, facilitating the learning and identification of fault features. By merging bidirectional information, the model is adept at capturing the signal's local nuances as well as its overarching trends, thereby attaining precise identification of bearing faults.

2 METHODOLOGY

2.1 VMD model

The VMD algorithm operates as an adaptive, fully non-recursive approach for mode variation and signal processing, effectively isolating individual modal components within complex signals[15]. Rooted in the variational principle, VMD aims to identify an optimal modulation function that decomposes the input signal into multiple Intrinsic Mode Functions (IMFs). These IMFs possess distinct frequencies and bandwidths, capturing the intrinsic structure and characteristics of the signal accurately. In contrast to Empirical Mode Decomposition (EMD), VMD offers a non-recursive signal processing alternative, enhancing stability and efficiency. Its adaptiveness stems from the capability to autonomously determine the requisite number of modes for signal decomposition, obviating the need for prior specification and thereby facilitating signal analysis.

The procedural steps of VMD include:

(1) Initializing parameters: This involves setting the number of modes, bandwidth constraints, lagrange multipliers, center frequencies, and frequency domain expressions.

(2) Updating modal components and center frequencies.

(3) Applying $\lambda^{n+1}(w) = \lambda^n(w) + \tau\left[f(w) - \sum_{k}^{n+1} u_k(w)\right]$ to updates λ^{n+1}.

(4) Ceasing iteration: The process exits the loop, revisits step (2), and ultimately yields the final decomposed modes.

2.2 BiLSTM model

BiLSTM represents a recurrent neural network (RNN) architecture in deep learning that processes sequential data. As an enhancement of the LSTM, the BiLSTM integrates the memory function of LSTM and facilitates bidirectional information transmission and processing, thereby capturing dependencies within the data more effectively. At each time step, the BiLSTM merges the forward and backward LSTM outputs to establish the final hidden state. This integration enables the model to incorporate both antecedent and subsequent information of the sequence, enriching its comprehension of the data. In the BiLSTM, the forward and

backward LSTM layers may share identical weight parameters, simplifying the model's complexity. The training process typically involves back-propagation, updating the weights to minimize the discrepancy between the predicted output and the actual value. Practically, the BiLSTM architecture might include multiple stacked LSTM layers and additional fully connected layers succeeding the bidirectional layers. This configuration proves especially beneficial for tasks necessitating both contextual insights, and its deployment in bearing fault diagnosis markedly enhances diagnostic precision. Fig. 1 depicts the BiLSTM structure.
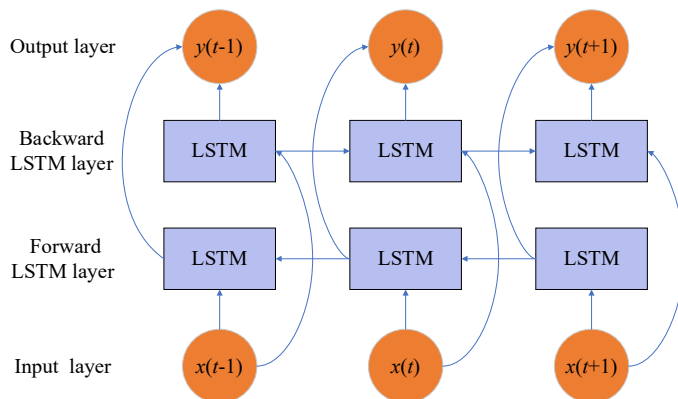

Fig. 1 BiLSTM structure diagram

2.3 VMD-BiLSTM algorithm

The VMD-BiLSTM model initially employs VMD preprocessing to decompose the original time series data, thereby simplifying the data's complexity and augmenting the model's generalization capability, yielding several distinct sub-modes. These sub-modes then serve as inputs to the BiLSTM, which discerns temporal dependencies within the time series via the BiLSTM network. Subsequently, the BiLSTM's output undergoes weighting to produce the ultimate prediction results. Upon acquiring these results, evaluative metrics such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) are typically utilized to assess the model's predictive efficacy.

The VMD-BiLSTM model's procedural steps are as follows: (1) Preprocess the original data by checking for initial missing values and duplicates; (2) Execute variational mode decomposition on the preprocessed data, selecting suitable parameters and penalty factors; (3) Employ IMFs derived from VMD as inputs to the BiLSTM model, where distinct sub-modes feed into varied network unit structures. The LSTM assimilates the sequence's correlation features in both directions, subsequently relaying the outcomes to the fully connected layer; (4) Post-processing through the fully connected layer, a summation occurs, culminating in the output of the sequence's predicted results. Fig. 2 illustrates the structure of VMD-BiLSTM model.
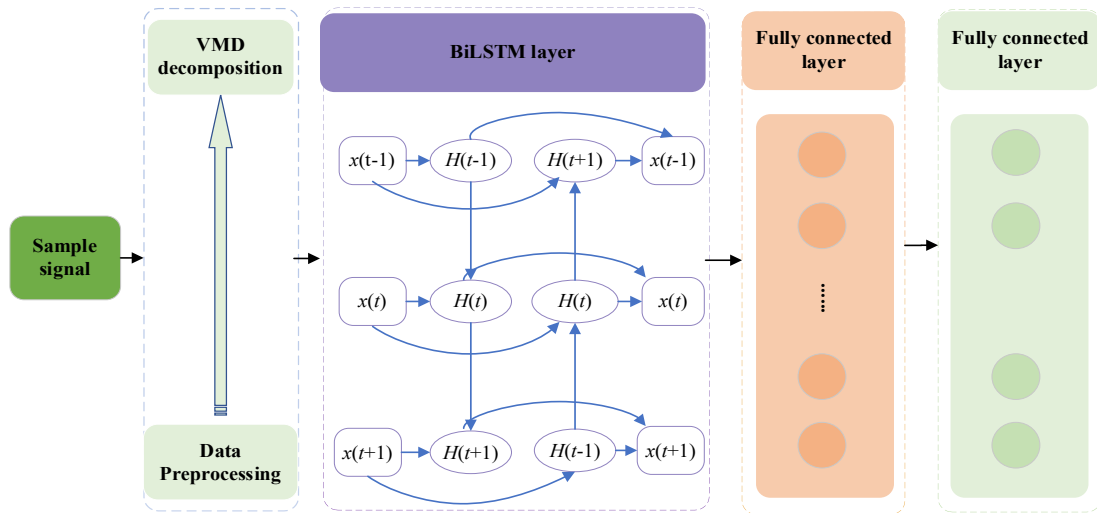
Fig. 2 VMD-BiLSTM model

3 EXPERIMENTS

3.1 Experimental Settings

This experiment relies on experimental motors, sensors, and data acquisition equipment for completion. The experimental data is obtained under constant load and speed conditions. In the experiment, the motor speed is set to 2100 r/min. The experimental platform for motor bearing fault diagnosis is depicted in Fig. 3.
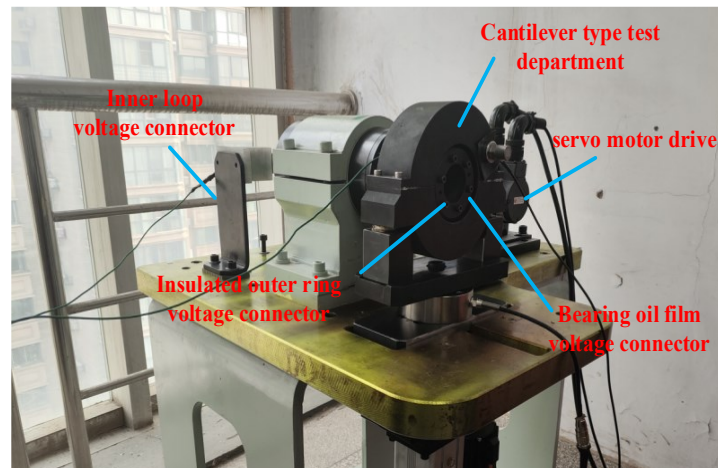

Fig. 3 The experimental platform for motor bearing fault diagnosis

In the experiment, the vibration signals of 1000 sample points are intercepted for analysis, and the time-domain diagram is presented in Fig. 4.
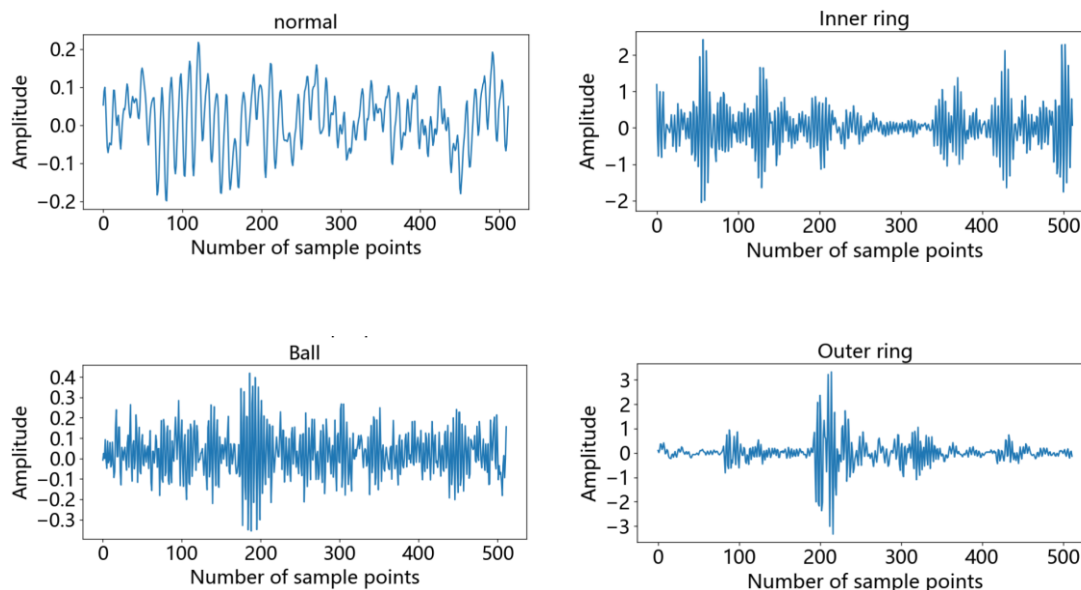
Fig. 4 Time domain diagram of signal

After VMD decomposition, the initial signal decomposes into 8 IMF components. The correlation coefficients of each component of the experimental motor bearing fault signal are calculated. The IMF component with the highest correlation coefficient is identified as the optimal component, indicating that this component contains the most fault characteristic information. Using the optimal component as input, the data is trained with CNN-Transformer, AlexNet, and BiLSTM models, where the classification accuracy is validated and analyzed.

3.2 Result Analysis

The sample data are divided according to an 8:2 ratio and used as training and validation sets, respectively. The parameters of all types of samples are displayed in Tab. 1.

Tab. 1 Data description of the test bench

| Fault type	Size/mm	Number of training	Number of validations	Label
Normal bearing	0	1600	400	0
	0.1778	1600	400	1
Rolling fault	0.3556	1600	400	2
	0.5344	1600	400	3
Inner loop fault	0.1778	1600	400	4
	0.3556	1600	400	5
	0.5344	1600	400	6
Outer ring fault	0.1778	1600	400	7
	0.3556	1600	400	8
	0.5344	1600	400	9

We conduct comparative experiments among the CNN-Transformer, VMD-AlexNet, and VMD-BiLSTM models. The experimental results are repeated 10 times to obtain their respective averages. The test results are shown in Fig. 5, with the accuracy of the CNN-Transformer model being 99.1%, the accuracy of the VMD-AlexNet model being 99.4%, and the accuracy of the VMD-BiLSTM model being 99.8%.

The epoch is set to 1000. After 1000 training iterations, the accuracy curve of the data tends to stabilize, which holds significant reference value. As shown in Fig. 5, the VMD-

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BiLSTM model achieves the highest accuracy in classification results, reaching 99.8%. Additionally, the VMD-BiLSTM model fits the training data well and exhibits better predictive performance at peaks and valleys compared to other models. This indicates that the model can capture most of the features in the data, especially in cases of significant data fluctuations. Both in terms of fitting effect and classification accuracy, this model outperforms the other two models significantly. The datasets in this study are collected from experimental sites. In situations with high noise levels, the VMD-BiLSTM model shows significant fluctuation trends in the early stages of iteration. However, as the number of iterations increases, its accuracy curve gradually flattens, thereby improving the fault tolerance of the experimental results and enhancing the accuracy and reliability of the experiments.
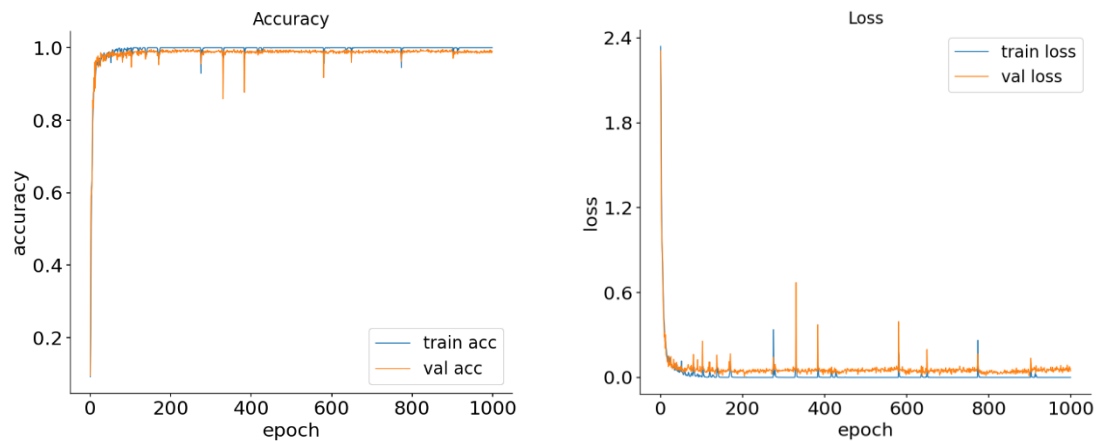
(a) CNN-Transfromer test result
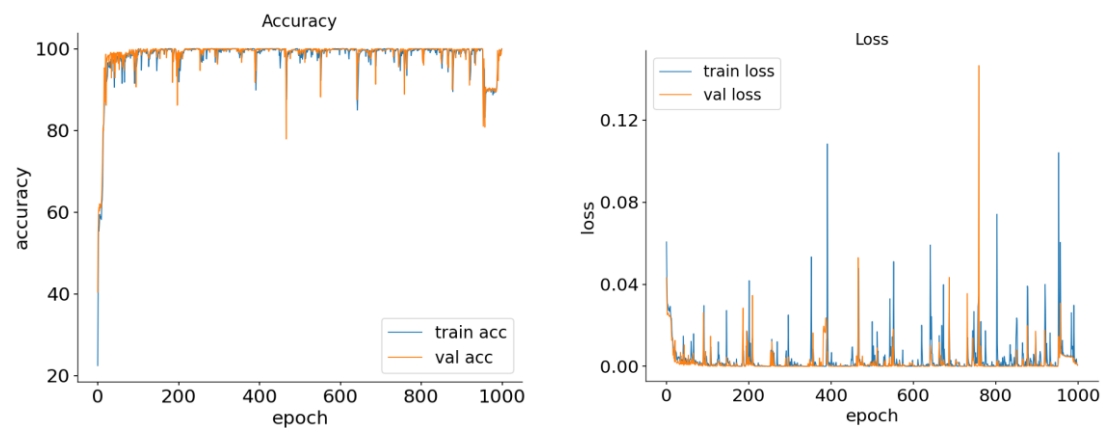
(b) VMD-AlexNet test result
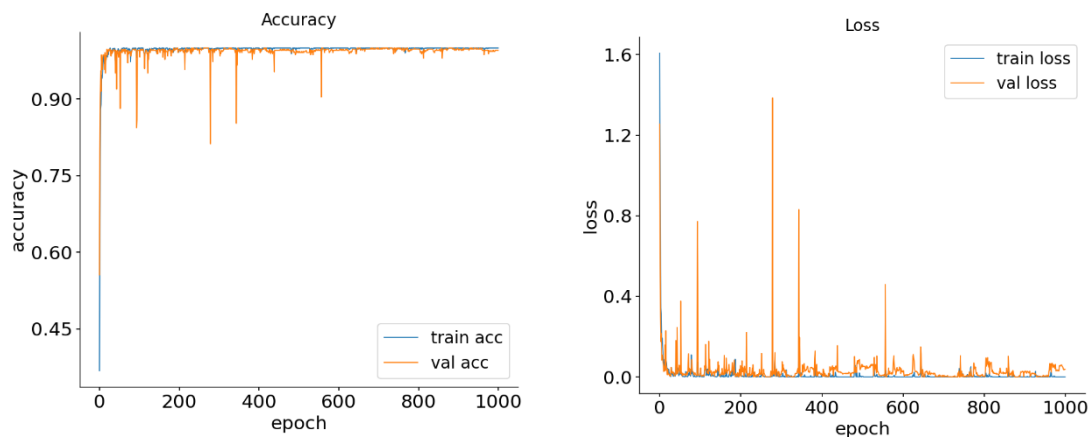
(b) VMD-BiLSTM test result

Fig. 5 Test results of different models

4 CONCLUSION

This paper proposes a deep learning algorithm based on the VMD-BiLSTM model for bearing fault diagnosis, which demonstrates high recognition accuracy and strong robustness in bearing fault diagnosis, with good generalization ability. The study focuses on motor bearings as the experimental subject, collecting vibration signals during motor bearing operation. Experimental validation of the proposed method shows its advanced nature, achieving an accuracy rate of 99.8%.

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