BEARING FAULT DIAGNOSIS METHOD BASED ON MULTI-BRANCH CONVOLUTIONAL NEURAL NETWORK

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Abstract

Traditional rolling bearing intelligent fault diagnosis methods using a single signal input often face challenges such as low diagnostic accuracy and poor robustness to noise in practical applications. This paper proposes a multi-branch convolutional neural network (CNN) model based on multi-scale and multi-modal input data. The model realizes multimodal multiscale inputs by means of variational modal decomposition (VMD) and STFT transforms while combining the original signals. Compared with a single signal input, richer and complementary fault features can be extracted, fully reflecting the multidimensional information of the fault. By designing multiple parallel CNN branches, the model is able to extract key features from the signal at different scales and modalities and perform feature fusion through the attention mechanism, which further improves the diagnostic accuracy and robustness to noise.

1 Introduction

Rolling bearings, as key components in rotating machinery, are widely used in avionics, wind energy, construction machinery, and other fields[1]. Its health state has a crucial impact on the normal operation and service life of mechanical equipment[2]. Therefore, bearing fault diagnosis is of great significance.

Traditional bearing fault diagnosis methods rely on time-frequency analysis of vibration signals and machine learning[4], in which the two are executed independently, failing to optimize the joint performance and relying on experts' experience to select features, which is time-consuming and laborious.

Bearings are susceptible to dynamic loads in complex operating environments, resulting in vibration signals with nonlinear and non-smooth characteristics[7], which makes fault feature extraction more difficult. In the diagnostic methods of deep learning for bearing faults, the vibration signals are usually pre-processed first, aiming at fully extracting the fault features. Existing frequency and time-frequency domain analysis methods, such as the Fast Fourier Transform (FFT)[8], Wavelet Transform9, and Short-Time Fourier Transform (STFT)[10]. Among them, the FFT cannot capture the time-varying characteristics of the signal, the wavelet transform suffers from selection difficulties and redundancy problems, while the STFT is able to provide both time-domain and frequency-domain information[11]. In recent years, a lightweight convolutional neural network (CNN) combined with an attention mechanism (SAM) has demonstrated superior performance in fault diagnosis, especially in fault feature extraction of vibration signals, which can effectively improve diagnostic accuracy[12].

Although the above methods have achieved certain results, with the increased complexity of modern industrial equipment, the vibration signals are often accompanied by a large amount of noise, which affects the fault feature extraction. VMD effectively isolates the useful signals from the noise by decomposing the signals into modal functions (IMFs) with different center frequencies, which improves diagnostic accuracy and robustness[15]. Yang[17] proposed a rolling bearing state feature extraction method combining VMD and Improved Envelope Spectral Entropy (IESE) to further improve the fault diagnosis performance.

However, all of the above methods perform feature extraction through a single branch, which can easily lead to insufficient extraction of fault features and affect the results. In this paper, a three-branch convolutional neural network (CNN) model combining STFT transform and VMD is proposed. The model takes the original signal, the features extracted by the STFT transform, and the features extracted by the VMD as inputs and performs feature fusion through the multi-branch CNN structure and the attention mechanism, finally realizing efficient rolling bearing fault classification. The model assigns different weights to each branch through the attention mechanism for feature fusion, and the value of the weights is determined according to the contribution of each branch to the classification result. The model can extract the features of the fault more comprehensively, which in turn improves the accuracy and robustness of fault diagnosis.

1.1 STFT transformation

STFT, also known as plus window Fourier transform, transforms a one-dimensional signal into a two-dimensional matrix containing time-frequency information by multiplying the signal with a window function and then performing a

Fourier transform on each short-time window. STFT obtains the frequency spectrum of different time periods through the sliding-window function and generates time-frequency maps, which can be used as inputs to 2D CNNs to improve the fault diagnosis effect of mechanical vibration signals. Calculation formula below:

$$S_{TFT_x}x(t,\omega) = \int_{-\infty}^{\infty} x(t)h(t-\omega)e^{-j\omega t}dt \tag{1}$$

where: x(t) is the time domain signal; h(t-ω) is the window function.

1.2 VMD

The VMD algorithm is a method for decomposing a signal into multiple intrinsic modal components (IMFs) in a completely non-recursive manner. To obtain the bandwidths and marginal spectra of the IMFs, the Hilbert transform can be applied to the modal functions to obtain a one-sided spectrum, which is shifted to the baseband. The sub-bandwidth of the IMF is determined by calculating the squared parameter of the gradient, which is modeled as follows for the variational problem.

$$\min_{|u_k|,|\omega_k|} \left\{ \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta_{(t)} + \frac{j}{\pi t} \right) u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \tag{2}$$

$$s.t. \sum_{k=1}^{K} u_k = f(t) \tag{3}$$

where: f(t) is the input signal; δ (t) is the Dirac function; K denotes the number of modes decomposed; $\{u_k\}=\{u_1, u_2, u_3, \ldots, u_k\}$ denotes the kth modal component after decomposition; $\{\omega_k\}=\{\omega_1, \omega_2, \omega_3, \ldots, \omega_k\}$ denotes the center frequency of the kth modal component after decomposition.

2. Methodology

2.1 Model architecture

In this paper, we propose a bearing fault diagnosis method based on a multi-branch convolutional neural network. The model is a three-branch convolutional neural network (CNN) for the task of bearing fault diagnosis. Bearing fault diagnosis model of the multi-branch convolutional neural network is shown in Fig. 1. In its structure, the original signal, the modal signal obtained through variational modal decomposition (VMD), and the time-frequency spectrogram after STFT transformation are used as three input branches, respectively.

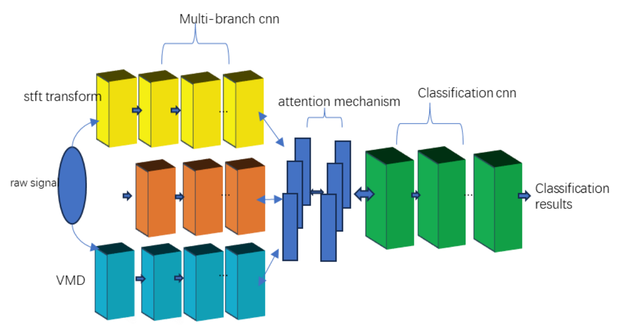

Fig. 1 Model of this paper

The outputs of the three branches are fused with features through the attention mechanism, which assigns learnable weights to different features so that the model can automatically assign important information to highlight effective features. This fusion process retains the global information of the original signal and, at the same time, combines the frequency band features from the VMD decomposition and the time-frequency information from the STFT transform to enhance the discriminative power of the model. Finally, the classification prediction of the input signal is completed by the classification layer. The overall structure gives full play to the advantages of VMD and STFT transform and improves the classification accuracy and robustness of bearing faults. The fault diagnosis process is shown in Figure 2.

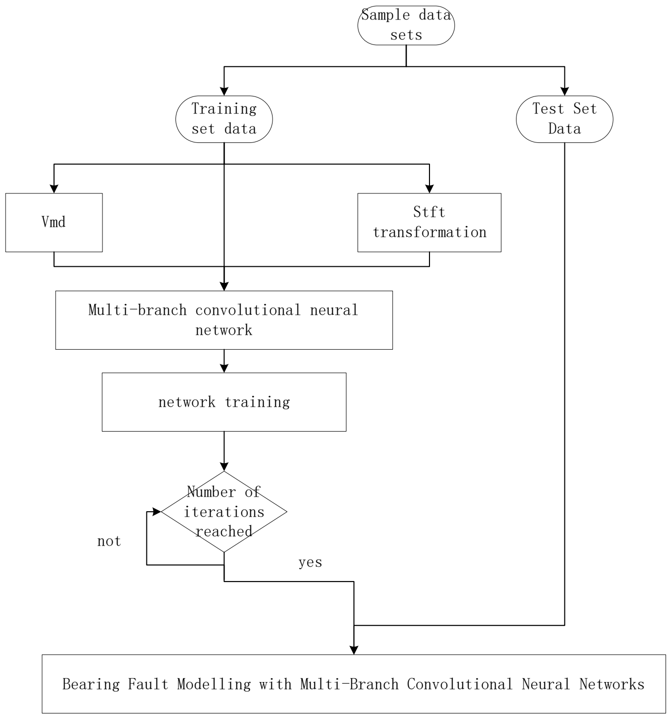

Fig. 2 Bearing fault diagnosis process of multi-branch convolutional neural network

3 Results

3.1 Experimental data

In order to verify the validity of the above model, this paper comes from the bearing dataset provided by Case Western Reserve University (CWRU) for specific experiments, and the data of the motor bearings used are collected from the bearings of model 6205-2RS JEM SKF with a rotational speed of 1772 r/min. The CWRU dataset used in this paper has a total of 10 classes of fault data, which categorize the bearing health status into normal, inner ring fault, outer ring fault, and rolling element fault, and each fault is divided into three fault levels according to the fault size (0.007 mm, 0.014 mm, and 0.021 mm). The dataset consists of 200 samples for each category, a total of 2000 samples, and each sample data comes from 1024 collection points, which are divided into training sets and test sets according to 8:2. As shown in Table 1.

Table 1. Description of the CWRU rolling bearing data set

Bearing condition	Degree of failure/mm	numbered label
normalcy	0	0
Rolling body failure	0.007	1
	0.014	2
	0.021	3
Inner ring failure	0.007	4
	0.014	5
	0.021	6
Outer ring failure	0.007	7
	0.014	8
	0.021	9

3.2 Experimental results

The model proposed in this paper classifies faults through three branches. A dropout layer is added to the model to prevent overfitting. The learning rate is set to 0.001, with 64 training samples input at each step, and a total of 70 iterations. The accuracy and loss curves of the multi-branch convolutional neural network are shown in Figure 3.

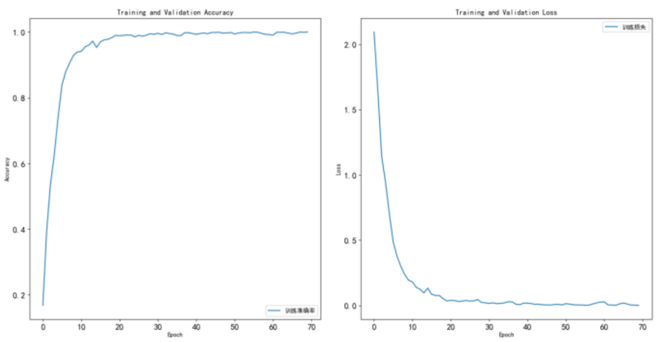

Fig. 3 Accuracy of the proposed methodology and losses

In Fig. 3, as the number of iterations increases, the accuracy curve gradually increases and tends to stabilize the trend, and after about 40 iterations, it starts to converge, and the diagnostic accuracy of the trained network reaches 99.75%. The confusion matrix of the test results is shown in Fig. 4

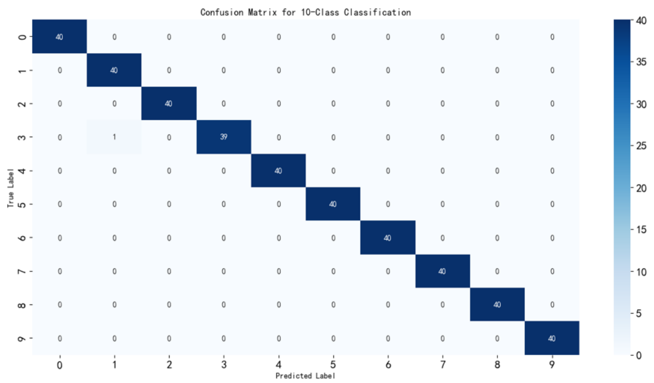

Fig. 4 Confusion matrix of test results

In order to verify the superiority of the method proposed in this paper. The accuracy is recorded after 10 repetitions of the experiment, and the average value is taken to get the accuracy the model is compared with several other common fault diagnosis models under the same dataset, and the accuracy of the proposed method under the same data samples is higher than that of the other comparative networks as can be seen in Table 2.

Table 2. Comparison of accuracy of different methods

methodologies	% accuracy
random forest	73.80
SVM	75.05
VMD+CNN	95.10
STFT+CNN	97.25
proposed methodology	99.55

In order to verify the superiority of the proposed method against noise, Gaussian white noise with a signal-to-noise ratio of 5 is added to the dataset used in the above experiments to simulate the situation where the industrial generation overshoots contain noise. The model proposed in this paper is compared with the above model because the random forest and SVM do not work well without adding noise, so only the remaining two are compared. The comparison results are shown in Table 3.

Table 3. Comparison of accuracy of different methods for SRN=5

methodologies	% accuracy
VMD+CNN	95.05
STFT+CNN	94.50
proposed methodology	99.35

4 Conclusion

To address the challenges faced by traditional single-channel signal-based bearing fault diagnosis methods, such as susceptibility to noise interference, insufficient feature extraction, and difficulty in adapting to complex working conditions, this paper proposes a multi-branch convolutional neural network-based bearing fault diagnosis method. The proposed approach is validated on the CWRU dataset, and experimental results demonstrate its superior performance in fault diagnosis tasks. The model incorporates three feature extraction branches, integrating Variational Mode Decomposition (VMD) and Short-Time Fourier Transform (STFT), while employing an attention mechanism for feature fusion to enhance multi-scale feature extraction capabilities. This method not only improves the recognition of complex fault patterns but also significantly enhances diagnostic accuracy and robustness.

5 References

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