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A Fault Diagnosis Method Based on Temperature and Vibration Characteristics for High-speed Train Axle Box Bearing

Zixing Huang
School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan, China. E-mail: zxhuang@std.uestc.edu.cn

Yanfeng Li
School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan, China. E-mail: yanfengli@uestc.edu.cn

Wubin Cai
School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan, China. E-mail: wubin0410@hotmail.com

Hongzhong Huang
School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan, China. E-mail: hzhuang@uestc.edu.cn

High-speed train running speed unceasing enhancement, the vehicle running status monitoring and security put forward higher request, so the temperature characteristic of axle box bearing and axle box bearing fault diagnosis method is crucial to provide certain reference and reference for the engineering practice. For the fault diagnosis of high-speed train axle box bearings, a deep learning network-based method, considering the features of both temperature and vibration, is proposed in this paper. A two-channel CNN is constructed based on 2D-CNN and 1D-CNN, in which 2D-CNN takes infrared image as input, and 1D-CNN takes vibration signal as input. Convolution and pooling are carried out respectively, and stretching is taken as feature vector. Then, splicing is carried out in the aggregation layer, and classification is carried out through the fully connected network layer. This method can realize the effective fusion of one-dimensional vibration features and two-dimensional temperature field features, and improve the classification accuracy. The performance of the proposed model is analyzed by high-speed train bearing test. The results show that in this paper, deep learning network is used for bearing fault diagnosis without artificial feature extraction, and the average accuracy of training set is 100%, and that of verification set is 98.02%; Based on infrared thermal imaging system for lubrication of high sensitivity compared with vibration system, but the infrared thermal imaging system for mechanical fault vibration system, due to the interaction characteristics of machine learning algorithms.

Keywords: Bearing fault diagnosis, infrared image, temperature vibration fusion, deep learning, temperature characteristic.

1. Introduction

The axle bearing is a critical component to ensure the safe operation of high-speed trainsets and is one of the most vulnerable parts. It has a complex mechanical structure and operates in harsh environments. Its failure signals often exhibit characteristics such as weak intensity, nonlinearity, and coupling, and they are often obscured by strong background noise and interference signals. Existing literature has demonstrated the accuracy of various techniques used for mechanical fault diagnosis, such as acoustic emission [1], motor current signature analysis (MCSA) [2], and vibration analysis [3], especially in the field of rolling bearing fault diagnosis. Among these techniques, vibration analysis is a mature and widely used method [4]. In recent years, an increasing number of machine learning-based methods have been applied to bearing fault diagnosis. Liu et al. [5] proposed a rotor platform fault diagnosis method based on infrared images and convolutional neural networks (CNN), which automatically selects image features and identifies fault patterns. Ma Xianmin et al. [6] improved the accuracy of motor equipment fault diagnosis by using a genetic algorithm to optimize a backpropagation neural network at the feature level. Yuan [7] proposed a new diagnostic method based on convolutional neural networks. Janssens et al. [8] presented a multi-sensor system that uses both infrared thermography and vibration measurements to automatically detect the state and faults of rotating machinery. Duan Lixiang et al. [9] proposed a diagnostic method for multi-source heterogeneous information fusion based on an improved convolutional neural network, which processes vibration signals into time-frequency images using variational mode decomposition and Hilbert transform methods.

In the field of information fusion fault diagnosis for mechanical equipment, existing methods such as the D-S evidence theory and neural networks have limitations in dealing with high-dimensional and heterogeneous data. These methods rely heavily on parameter settings and the expertise of diagnostic personnel. To address these challenges, this paper proposes a multi-modal deep learning network that combines temperature and vibration signals at the data level. Unlike traditional methods, the proposed approach utilizes a dual-channel CNN to integrate three-dimensional image information with one-dimensional vibration data. This fusion of multi-modal information enhances recognition accuracy, reduces information loss, and improves the efficiency of fault diagnosis. By leveraging deep learning techniques, this method provides a more intelligent and effective solution for diagnosing faults in mechanical equipment.

2. Proposed Method Based on Temperature and Vibration

The basic process of the proposed temperature-vibration fusion-based axle bearing fault diagnosis method in this paper is illustrated in Figure 1. and consists of four main parts: data acquisition, data processing and dataset creation, data fusion, and fault diagnosis.

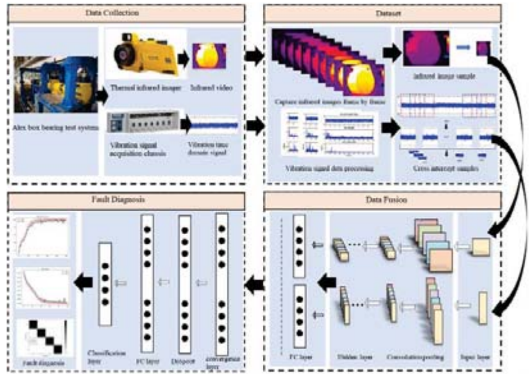

Figure 1. Fault diagnosis method of axle box bearing based on temperature vibration fusion

(1) Data Collection

In this part, based on the constructed axle bearing test bench, infrared videos of different bearings are captured using an infrared thermal imaging system. Simultaneously, vibration signals in the time domain are collected through vibration sensors. Data is collected by simulating the operating conditions of axle bearings under different working conditions.

(2) Dataset

This part involves data processing based on the collected data. The infrared videos are frame by frame extracted into images, which are then subjected to image processing and normalization. The vibration signals in the time domain are sampled by segmenting the data, and the dataset is created after applying the minimum entropy deconvolution (MED) method. Two types of signals are prepared as training and testing datasets, and one-hot encoding is used for encoding.

(3) Data Fusion

In this part, a multi-modal CNN deep learning network is constructed to train, validate, and test the datasets of infrared images and vibration signals. Based on 2D-CNN and 1D-CNN, the infrared images are input into the 2D-CNN, and the vibration signals are input into the 1D-CNN. Convolutions and pooling are performed separately, followed by stretching into feature vectors and concatenation at the pooling layer. This enables the effective fusion of one-dimensional vibration features and two-dimensional temperature field features.

(4) Fault Diagnosis

In this part, the fused fully connected layer is randomly dropped out, and a classifier is used for the classification of axle bearing faults, achieving the diagnosis of mechanical faults and lubrication faults in the axle bearing.

2.2 Data Acquisition and Preprocessing

In this section, the collected infrared images and vibration signals are preprocessed separately. Then, the infrared images and vibration signals are divided into datasets. Finally, the divided datasets are used to train the temperature-vibration fusion fault diagnosis model.

2.2.1 *Infrared image*

Using the os.listdir function, the collected infrared images are randomly shuffled, and then they are sequentially divided into a training set and a testing set in a 3:1 ratio. Each condition has 800 samples, including 600 training samples and 200 validation samples. During this process, the collected infrared images with dimensions of 640×480×3 are compressed into 100×100×3 pixels, and the pixel values of the images are normalized to the range of [0, 255]. To reduce the influence of environmental factors, shooting angles, and image vibration, this study conducted two sets of repeated experiments for each condition, and two different speeds were set.

2.2.2 *vibration signal*

For the collected axle bearing vibration signals, this paper adopts a cross-segment sampling approach to obtain samples from the time-domain signals. The sampling method is illustrated in Figure 2. Starting from the first point of the signal, n points are sampled as the first sample. Then, starting from the (n-m)th point, another n points are sampled as the second sample, and so on. Each type of fault signal has 800 samples, out of which 600 samples are used as training samples and 200 samples are used as validation samples.

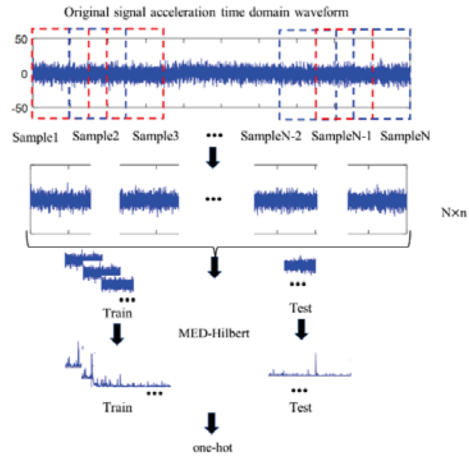

Figure 2. Cross intercept samples

The vibration dataset is divided, and each sample consists of 1999 time-domain data points. Therefore, the sample space for each signal category is 800 × 1999, and the total sample space for the eight categories is 8 × 800 × 1999.

2.3 Method Based on Temperature and Vibration Framework

This paper proposes a multi-modal deep learning network based on temperature-vibration fusion, and its framework is shown in Table 1. By utilizing 2D-CNN and 1D-CNN, a dual-channel CNN is constructed. The 2D-CNN takes infrared images as input, while the 1D-CNN takes vibration signals as input. Convolution and pooling are performed separately, followed by stretching into feature vectors. Then, the feature vectors are concatenated at the pooling layer, and classification is performed using a fully connected network layer. This approach effectively integrates one-dimensional vibration features and two-dimensional temperature field features, thereby improving classification accuracy. The temperature-vibration fusion-based multi-modal deep learning network is implemented using PyTorch.

Table 1. Method Based on Temperature and Vibration Framework

	Lay	output channels	Size	Step size	Output size
	Conv	32	3×3	1	608×608
	Conv	64	3×3	2	304×304
	CrossStagePartial				
1 ×	Conv	32	1×1	1	304×304
	Conv	64	3×3	1	304×304
	Residual	—	—	—	304×304
	Conv	128	3×3	2	152×152
	CrossStagePartial				
2 ×	Conv	64	1×1	1	152×152
	Conv	64	3×3	1	152×152
	Residual	—	—	—	152×152
	Conv	256	3×3	2	76×76
	CrossStagePartial				
8 ×	Conv	128	1×1	1	76×76
	Conv	128	3×3	1	76×76
	Residual	—	—	—	76×76
	Conv	512	3×3	2	38×38
	CrossStagePartial				
8 ×	Conv	256	1×1	1	38×38
	Conv	256	3×3	1	38×38
	Residual	—	—	—	38×38
	Conv	1024	3×3	2	19×19
	CrossStagePartial				
4 ×	Conv	512	1×1	1	19×19
	Conv	512	3×3	1	19×19
	Residual	—	—	—	19×19
	Maxpool	512	5×5	1	19×19
	Maxpool	512	9×9	1	19×19
	Maxpool	512	13×13	1	19×19

3. Experimental Study and Result Discussions

The experiments were conducted on a high-speed train axle bearing test bench. The test bench consists of several main components and adopts a horizontal structure. These components include a vibration table, bearing housing, supporting bearings, extension table, motor, support frame, test bearing, and main shaft system of the loading system. In this test bench, the actual operating conditions of high-speed trains on the track are simulated through coordinated loading of various components, while collecting infrared images and vibration information.

3.1. Analysis of the Temperature-Vibration Fusion-based Deep Learning Network Results

To analyze the results of the two single-sensor systems and the multi-sensor system, Figure 3. and Figure 4. presents the training results of the proposed temperature-vibration fusion-based deep learning network. It can be observed from the figure that the proposed network achieves high accuracy, with an average accuracy of 100% on the training set and 98.02% on the validation set. Figure 5. shows the confusion matrix of the validation set for the temperature-vibration fusion-based deep learning network. In the coordinates of this confusion matrix, the labels in Dataset are defined as follows: bearing with cage fault and normal lubrication (bcj), bearing with outer ring fault and normal lubrication (wq), bearing without fault but poor lubrication (zc1), and bearing without fault and sufficient lubrication (zc2). By observing the confusion matrix, it can be seen that the model achieves 100% diagnostic accuracy for lubrication conditions in the test set.

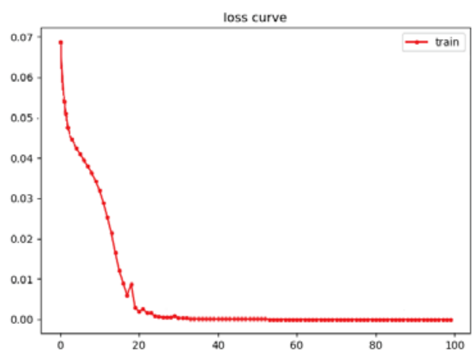

Figure3. Loss curve

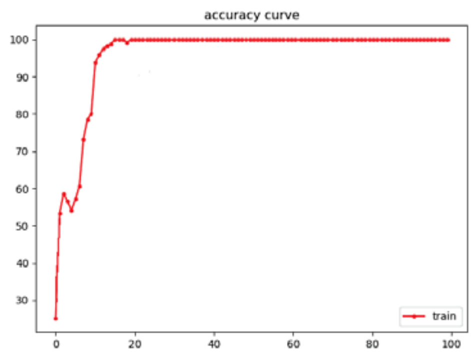

Figure 4. Accuracy curve

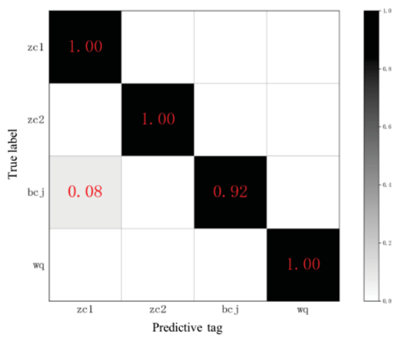

Figure 5. Deep learning network verification set confusion matrix for temperature vibration fusion

3.2. Analysis of the Fault Diagnosis Results of the Single-Sensor Systems

For comparison purposes, a CNN network is also applied to the single infrared thermal imaging system. The same dataset as the temperature-vibration fusion-based deep learning network is used for training which presents the training results using images captured by the single infrared thermal imaging system.

To further evaluate the optimization effect of each label under the network model, classification confusion matrices are constructed. Figure 6. and Figure 7. shows the confusion matrices for the two network test sets. In the coordinates of this confusion matrix, the labels are defined as follows: bearing with cage fault and normal lubrication (bcj_1200), bearing with outer ring fault and normal lubrication (wq_1200), bearing without fault but poor lubrication (zc1_1200), and bearing without fault and sufficient lubrication (zc2_1200). By observing the confusion matrix, it can be seen that the model achieves 100% diagnostic accuracy for lubrication conditions in the test set. Compared to the vibration-based approach, the proposed temperature-vibration fusion-based deep learning network improves the accuracy of outer ring fault diagnosis by 4%, the accuracy of diagnosing poor lubrication conditions in normal bearings by 16%, and the accuracy of diagnosing sufficient lubrication conditions in normal bearings by 4%. Compared to the infrared thermal imaging system, the accuracy of diagnosing cage faults improves by 17%, indicating a significant improvement in accuracy.

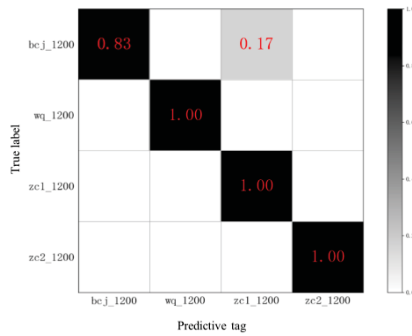

Figure 6. Infrared image test set confusion matrix

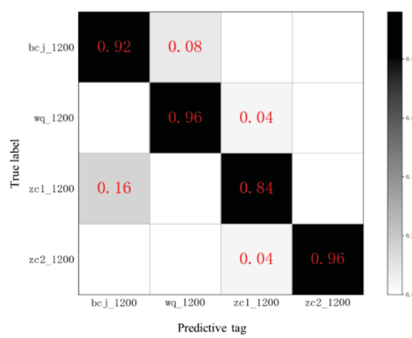

Figure 7. Vibration signal test set confusion matrix

When observing the confusion matrices of the single-sensor-based infrared thermal imaging system and vibration system, it can be concluded that the infrared thermal imaging system is more sensitive to lubrication conditions compared to the vibration system, but it is less sensitive to mechanical faults compared to the vibration system. Both single-sensor systems exhibit specific weaknesses that can be compensated for by the advantages of the other sensor. Therefore, combining them yields better results. Additionally, due to the feature interactions in machine learning algorithms, there are overall improvements in all categories on top of eliminating the weaknesses of the respective single-sensor solutions. In this way, through data-level fusion of information from the two sensors, the accuracy is improved by 2.27% compared to the infrared thermal imaging-based system and by 5.82% compared to the vibration-based system.

4. Conclusion

(1) The high-speed train axle bearing test bench is used to simulate the operating conditions of different fault types of axle bearings during high-speed train operation. Vibration and temperature signals of axle bearings with different fault types are collected. The collected signals are then used to identify the fault types using the constructed multi-modal deep learning network. The results show that the proposed temperature-vibration fusion-based deep learning network achieves high accuracy.

(2) By comparing the confusion matrices of the single-sensor-based infrared thermal imaging system and vibration system, it can be concluded that the infrared thermal imaging system is more sensitive to lubrication conditions compared to the vibration system, but it is less sensitive to mechanical faults compared to the vibration system. Both single-sensor systems exhibit specific weaknesses that can be compensated for by the advantages of the other sensor. Due to the feature interactions in machine learning algorithms, there are overall improvements in all categories on top of eliminating the weaknesses of the respective single-sensor solutions. The proposed network model not only has higher accuracy than other networks but also has the smallest difference in diagnostic accuracy between the training and testing sets, indicating model stability.

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