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Multi-condition Rolling Bearing Fault Diagnosis Method based on DRJDAN

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Abstract

In recent years, a large number of deep learning algorithms have been proposed for rolling bearing fault diagnosis, but there are certain drawbacks in the practical application. Most of these algorithms target a specific working condition, i.e. a situation where the training data and test data are identically distributed, and cannot accurately diagnose rolling bearing faults in other working conditions where the data distribution is inconsistent in real situations. At this time, the above deep learning algorithms are used for fault diagnosis, and the diagnosis effect will decrease. In this paper, we propose a deep residual joint distribution adaptation network (DRJDAN) for fault diagnosis of rolling bearings under different operating conditions by combining deep residual networks (ResNet) and joint distribution adaptation (JDA). Experimental analysis using two rolling bearing data sets affected by different variables resulted in an average fault diagnosis accuracy of 99.63%.

Keywords

Rolling Bearing; Fault Diagnosis; Transfer Learning; Deep Residual Networks; Joint Distribution Adaptation.

1. Introduction

Rolling bearings as a key component of mechanical equipment, its health status has an extremely important impact on the operational efficiency and production level of mechanical equipment. Therefore, an efficient and accurate method of diagnosing rolling bearing faults is essential[1][2]. In practical situations, accurate and efficient fault diagnosis of rolling bearings is extremely difficult. With the rapid development of society, more and more fields have been combined with internet technology, achieving unprecedented technological achievements[3-6]. Automation and intelligence have become the new direction of development for the machinery manufacturing industry. In the era of "big data", the combination with Internet technology has become a natural choice[7-10]. More and more experts and scholars are combining deep learning with transfer learning, using deep neural networks for transfer learning and applying it in various fields such as rolling bearing fault diagnosis. Inspired by the Wasserstein distance of optimal transmission, Cheng C et al. explored deep transfer learning methods based on the Wasserstein distance[11]. Li X and other researchers have published a new method for cross-domain fault diagnosis based on deep generative adversarial networks[12]. Related scholars propose a deep learning-based domain adaptation algorithm for mechanical fault detection, introducing adversarial training for edge domain coordination, while exploring unsupervised parallel data information to complete the alignment of conditional distributions about different mechanical health states[13]. Wen L et al. proposed a convolutional neural network-based transfer learning fault diagnosis measure for the rolling bearing fault diagnosis problem [14]. In practice, the operating conditions of rolling bearings are influenced by a number of variables, forming a variety of different operating conditions with non-constant load and speed. The inconsistent distribution of data between the different operating conditions creates certain difficulties for the diagnosis of rolling bearing faults. In order to take into account the fact that rolling bearings are affected by several non-constant variables during actual operation, the authors propose new methods for the diagnosis of rolling bearing faults under different operating conditions as a means of solving the practical problems of rolling bearing fault diagnosis.

2. Theoretical Basis

2.1 Deep Residual Network (ResNet)

ResNet has many advantages, the most obvious feature of which is the use of identity mapping to alleviate the difficulty of parameter optimization. In ResNet, gradients are not only backpropagated layer by layer, but also flow directly to the starting layer via identity mapping. ResNet consists of the convolutional layer, Rectified Linear Unit (ReLU) activation function, Batch Normalization (BN), Global Average Pooling (GAP) and cross-entropy loss function, and is a representative variant of the convolutional neural network. The concepts of the basic components of ResNet are described below.

Extracting the different features of the input is the purpose of the convolutional operation. The first three convolutional layers usually only recognise low-level features, such as corners, lines and edges, and the deeper network is able to obtain more complex feature information from the low-level features. The convolutional layer reduces the number of parameters required to optimise the network. This is achieved by using convolution rather than matrix multiplication because the parameters of the convolution kernel in the convolution layer are much less than those required for the transformation matrix in the fully connected layer (FC).

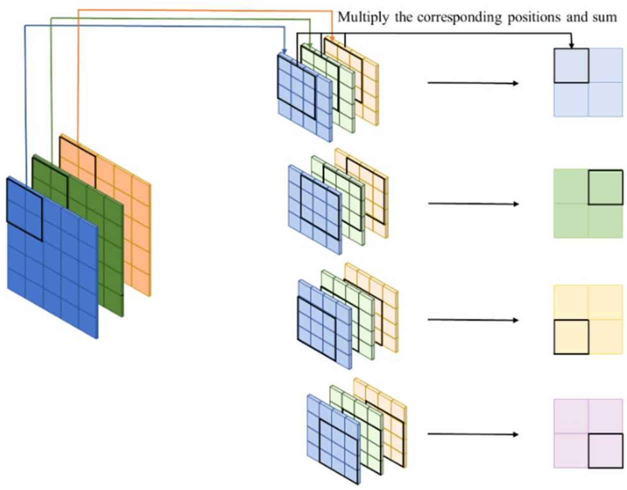

Figure 1. Convolution process

2.2 Joint Distribution Adaptation (JDA)

In the diagnosis of rolling bearing faults under different operating conditions, the source and target condition data usually follow different probability distributions. Therefore, the main reason for using transfer learning methods is the ability of JDA to calculate the distribution distance between different conditions, while minimising the difference in distribution between conditions and retaining the important attributes of the input data, and then learning the classifier on the re-weighted source condition data [17,18].In reality, rolling bearings are used in a wide range of working conditions, depending on the production requirements, and the marginal and conditional distributions of the data collected under different working conditions are different. Deep Residual Joint Distribution Adaptation Network (DRJDAN).

Firstly, the one-dimensional timing signal is converted into a two-dimensional image signal. As the rolling bearing fault diagnosis signal is mostly one-dimensional time-series vibration signal, and

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ResNet has outstanding performance in feature extraction of two-dimensional images, in order to enable ResNet to carry out effective feature extraction of the fault diagnosis signal, this study converts the one-dimensional time-series signal into a two-dimensional image signal. Figure 2 shows the conversion of a one-dimensional vibration signal into a two-dimensional image signal.

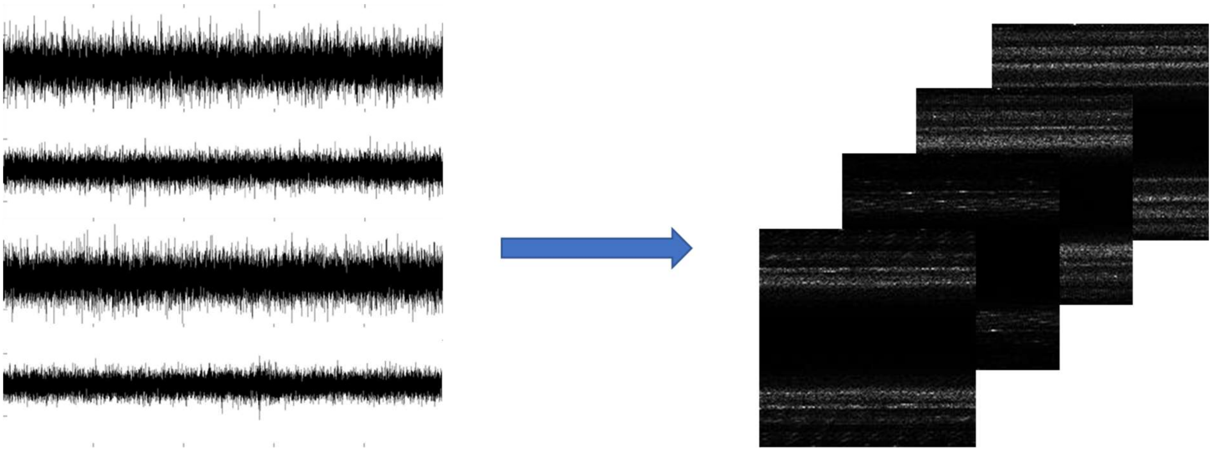

Figure 2. One-dimensional vibration signal is converted into two-dimensional image signal

3. Experimentation and Analysis

The load or speed of a rolling bearing during operation is variable, resulting in an inconsistent distribution of rolling bearing signals at different loads or speeds, making it difficult to train the network and perform accurate fault diagnosis using rolling bearing signals that obey different distributions. In this paper, a DRJDAN-based rolling bearing fault diagnosis method is proposed to address the problem of inconsistent data distribution under multiple operating conditions, using the Case Western Reserve University (CWRU) bearing dataset and the bearing dataset obtained through the Machinery Fault Simulator (MFS) to conduct experiments respectively. The two bearing datasets have similar experimental bench structures, but the CWRU bearing dataset includes rolling bearing vibration signals at different loads and the MFS bearing dataset collects rolling bearing vibration signals at different speeds.

3.1 CWRU Bearing Data Set and Analysis of Experimental Results

The CWRU bearing dataset is a well-known open source dataset for mechanical equipment fault diagnosis and is widely used for rolling bearing fault diagnosis experiments. The experimental platform is constructed from the motor, drive end bearing, torque sensor, dynamometer and other devices, as shown in Figure 3[19].

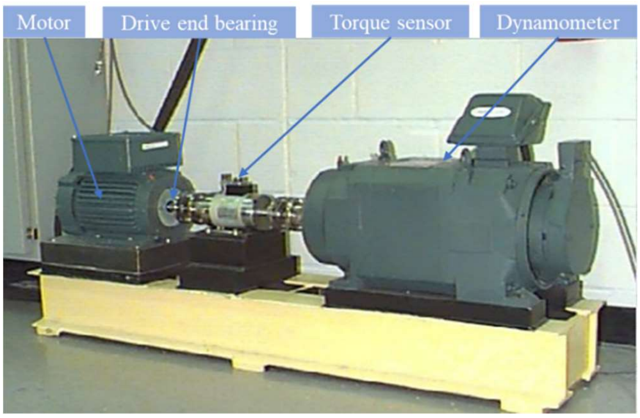

Figure 3. CWRU bearing data set experiment bench

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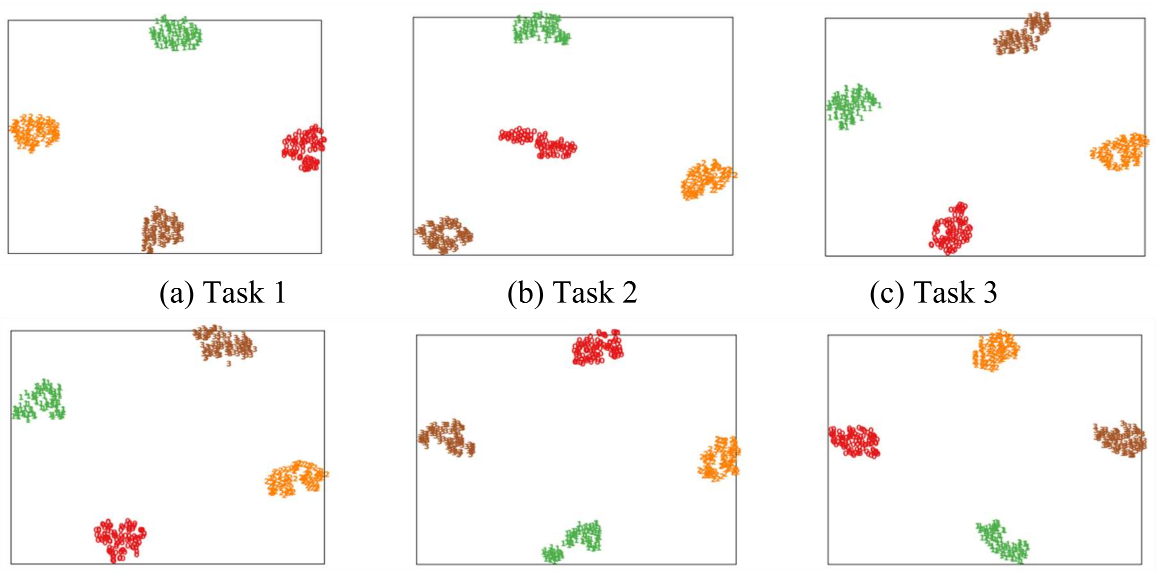
Depending on the load, the CWRU bearing dataset was divided into four subsets according to the different loads, each containing 100 images of each fault type and 400 images of the four fault types. Experiments were conducted using the CWRU dataset, and in order to fully consider the effects of different loads, each of the two different load conditions were set as the source and target conditions, and a total of six sets of tasks were constructed. The task settings and the accuracy of the corresponding tasks are shown in Table 1, and the visualisation results for each set of tasks are shown in Figure 4.

Table 1. Task setting and corresponding task accuracy

Task	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
Source conditions	0HP	0HP	0HP	1HP	1HP	2HP
Target conditions	3HP	2HP	1HP	3HP	2HP	3HP
Accuracy	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%



(a) Task 1 (b) Task 2 (c) Task 3

(d) Task 4 (e) Task 5 (f) Task 6

Figure 4. CWRU bearing data set fault diagnosis visualization results

The experimental results are visualised using t-SNE. Figure 4 shows the visualisation results of fault diagnosis for different tasks set by the proposed model in this paper for the CWRU bearing dataset due to different loads. It can be seen from Table 1 and Figure 4 that the fault diagnosis results of the DRJDAN algorithm are very satisfactory and can effectively overcome the problem of inconsistent data distribution between source and target conditions due to different loads, and the difficult problems in the fault diagnosis process are solved so that the fault diagnosis accuracy of rolling bearings for a variety of operating conditions is improved.

4. Conclusion

Considering that the load or speed of a rolling bearing is non-fixed in actual operation, there are differences in the distribution of the collected rolling bearing signals. In this paper, the advantages of deep learning and migration learning are fused and a DRJDAN rolling bearing fault diagnosis method for different operating conditions is proposed. The method requires a two-dimensional transformation of the one-dimensional vibration signal of the rolling bearing to obtain a two-dimensional image signal that ResNet is good at processing. The t-SNE visualisation results show that the DRJDAN model can effectively close the distribution distance of homogeneous fault features. The experimental results confirm the feasibility of the method proposed in this paper.

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