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A Novel Fault Diagnosis Method Based on MADCNN for Rolling Bearings

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Abstract. Rolling bearings are treated as important machinery power components, faults of rolling bearings affect machinery operation, so an intelligent fault diagnosis method is very useful of safety operation in rolling bearings. This paper proposes a novel fault diagnosis method based on improved Adaptive Deep Convolution Neural Networks algorithm to realize fault recognition for rolling bearings. First, the Continuous Wavelet Transform (CWT) method is applied to the time-frequency decomposition of vibration signals and extract feature information images for training and testing. Second, to further improve self-learning ability of the Adaptive Deep Convolution Neural Network (ADCNN) in feature images, the Multiple Channels ADCNN method is proposed to classify different fault image types for the rolling bearing. Finally, fault images corresponding to different health states of the rolling bearing are applied to the proposed method, the experiment proves that the proposed method has a better performance for fault recognition in rolling bearings.

Keywords: Fault diagnosis, Multiple Channels Adaptive Deep Convolution Neural Network, rolling bearings

1. Introduction

Rolling bearings play an essential component in mechanical system such as engines, power systems, etc. The failure caused damage to operation machinery that increase the economic loss [1-3]. Therefore, it is of crucial significance that an intelligent fault diagnosis method is required to monitor health condition and achieve the safety operation for rolling bearings.

Currently, machine learning methods are widely used for classification and identification. Such as a Support Vector Machine method was applied to identify fault states through statistical feature analyses [4]. machine learning methods primarily extract features from signals and use some feature information to train mode for fault diagnosis. However, these machine learning methods require massive datasets to train on and lack the self-learning ability for feature analysis, meanwhile, training process needs presetting parameters and long time to overcome the overfitting drawback.

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As Deep learning approaches have the characteristics of autonomous feature learning, therefore, some intelligence methods using deep learning technologies showed great potential in classification and identification [5, 6].

Traditional Convolutional Neural Networks (CNN) method had a widely application in fault classification, however, these studies used noise data and decreased self-learning ability for feature information [7-10]. Therefore, Deep Convolutional Neural Network (DCNN) method was developed to stronger the extraction feature ability from noise data and improve deep learning quality [11-13]. And then, the Adaptive Deep Convolution Neuron Networks (ADCNN) developed to classify the health states of vibration signals and show a good performance [14]. Meanwhile Multitask convolutional Neural Network (CNN) made use of obtaining useful features from branch tasks data to change the quality of classification, these ideas were very useful for this paper [15,16]. According to above good methods and further improving the self-learning ability and classification accuracy, a novel Multiple Channels Adaptive Deep Convolution Neuron Networks (MADCNN) is proposed for fault classification in rolling bearings.

The rest of this paper is mainly organized as follows: Section 2 provides some basic information of ADCNN method. The proposed novel framework is described in Section 3 and experimental results are concluded in Section 4, finally some conclusions are shown in Section 5.

2. The adaptive deep learning neural network

The frame of Adaptive Deep learning neural network is developed from CNN basic theory, which mainly contains some convolution layers, pooling layers, several fully connected layers and one final output layer [11,14]. The feature extraction process is achieved through the inter-layer self-learning ability.

2.1. Convolution layer

Basically, the Convolution Layer has a series of Kernels with filtering ability, which can achieve convolution process and each filter used the same kernel size to extract feature information from input data [5]. this whole convolution process is described as following activation:

$$x_n^m = f\left(\sum_{i\in K_n} x_i^{m-1} * w_{in}^m + b_n^m\right) \tag{1}$$

Where x_n^m is the output of m^{th} kernel in convolutional layer n, and K_n is the n^{th} convolution region, $f(*)$ is a nonlinear activation function, w_{in}^m denotes the weight matrix in convolutional layer in and b_n^m is the bias vector.

2.2. Pooling layer

Max pooling layer often follows the convolutional layer, which decreases the redundancy and avoids over-fitting from extracted features [9]. In this architecture, max pooling is used to detect maximum values from previous output:

$$x_n^m = f(w_n^m * \max(x_n^{m-1}) + b_n^m) \quad (2)$$

Where, x_n^m is the output, w_n^m is the weight, b_n^m is the bias and $\max(*)$ is the max pooling function.

2.3. Full connected layer

A full connected layer is applied to the feature information extraction and form a final output, such as follow:

$$y^z = f(w^z x^{z-1} + b^z) \quad (3)$$

Where y^z denotes the output for the final connected layer and z represents the network.

2.4. Backward propagation

The cross-entropy loss formula is developed to compute loss function error, which can acquire the target data in accordance with the dataset [14]. These weights and biases parameters can be updated, the cross-entropy loss formula is described as follows:

$$E(w) = \frac{1}{n}\sum_{z=1}^{n}[y_z \, ln\bar{y}_z + (1 - y_z)\ln(1 - \bar{y}_z)] \quad (4)$$

Where y_z is the actual target and $\bar{y}_z$ represents the predicted value.

3. The architecture of MADCNN

The proposed method consists of two ADCNN branches' structure illustrated in Figure 1. Each ADCNN branch mainly has two convolutional layers and two pooling layers, two dense layers and fully connected layers, and finally combined with each branch into one fully connected layer, meanwhile one output layer is used for training and testing. The input size is $32 \times 32 \times 1$, Convolution 1 layer is 3*3, Convolution 2 layer is 3*3, and final full connected layer is used to classify different health states from input fault images, some network parameters are shown in Table 1.

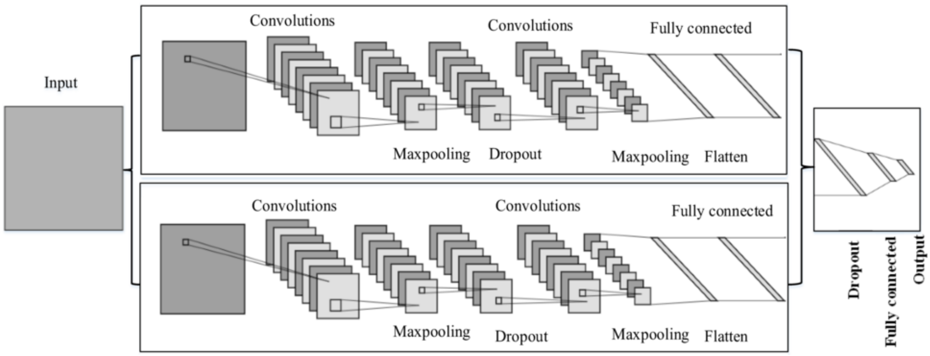

Figure 1. The architecture of proposed method.

Table 1. Detail information of the proposed method used in this experiment.

No.	Branch 1-layers type	kernel size/stride
1	Convolution1.1	3*3
2	Pooling1.1	2*1
3	Dropout1.1	0.02
4	Convolution2.1	3*3
5	Pooling2.1	3*1
6	Dropout1.1	0.02
7	Flatten1.1	16
8	Full-connectedlayer1.1	10
No.	**Branch 2-layers type**	**kernel size/stride**
1	Convolution1.2	3*3
2	Pooling1.2	2*1
3	Dropout1.2	0.02
4	Convolution2.2	3*3
5	Pooling2.2	3*1
6	Dropout1.2	0.02
7	Flatten1.2	16
8	Full-connectedlayer1.2	10
No.	**Combined layers type**	**kernel size/stride**
17	Dropout	0.02
18	Flatten	16
19	Full-connected layer	10

4. Experiment

To validate the performance of proposed method, bearing datasets from Case Western Reserve University were applied to fault classification [2, 9]. As shown in Figure 2, this experiment platform consisted of a transducer, a dynamometer and an induction motor. The experimental sampling frequency was 12 kHz under 2 hp electric motor, the testing bearing was 6205-2RS JEM, and there were mainly four state types: Inner Race Fault (IF), Ball Fault (BF), Normal Condition (NC) and Out Race Fault (OF). These state types had three levels of severity with diameters of 0.007inch, 0.014 inch and 0.021 inch respectively, ten styles data were used to prove this proposed method, where Google TensorFlow and Python3.7 were applied for experimental simulation.

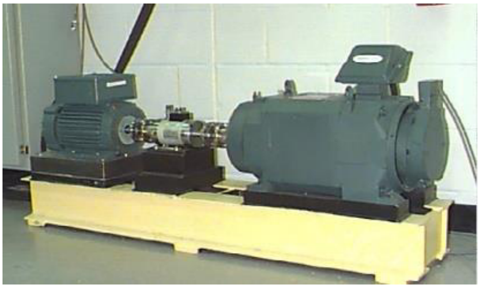

Figure 2. Motor driving mechanical system used by CWRU.

The whole fault classification using the proposed method is described in Figure 3, the CWT method is used to process 1-D vibration signals and get 2-D image data for training and testing, the same process from [15]. Some 2-D images for datasets are shown in Figure 4, and then the MADCNN method classifies fault images for training and testing, which achieves good performance for classification accuracy.

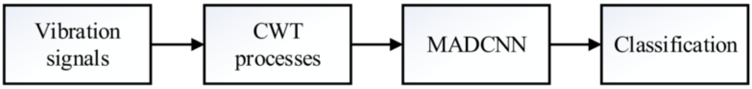

Figure 3. The process of the MADCNN method for fault classification.

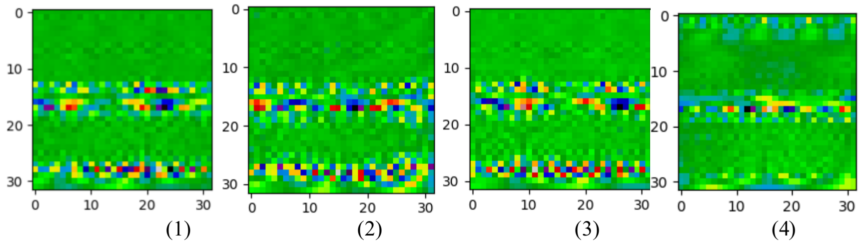

Figure 4. Some 2-D images for datasets.

In this experiment, ten state types of datasets: 3000 training samples and 1600 testing samples, to show the feature extraction classification in the experiment, t-distributed Stochastic Neighbor Embedding (t-SNE) is applied to self-learning feature capacity from the input data, Raw data information in Figure 5, and the final classification result of the MADCNN method in Figure 6, which shows the best clustering result.

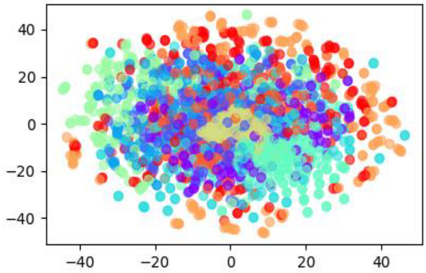

Figure 5. The t-SNE for raw data.

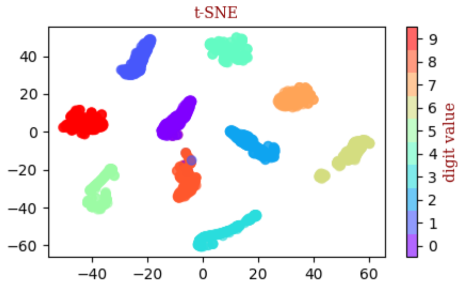

Figure 6. The t-SNE for final classification of the proposed method.

To validate the performance of different methods, as shown in Figure 7, for 3000 training samples and 1600 testing samples, DCNN approach can achieve 97.8% for prediction accuracy, ADCNN method is 98.1% and the proposed method has 99.0%. For 3400 training samples and 1200 testing samples, DCNN method can achieve 97.7% for classification accuracy, ADCNN method is 98.2%, and the proposed method has 99.1%. For 3800 training samples and 800 testing samples, DCNN method can achieve 97.9% for classification accuracy, ADCNN method is 98.0% and the proposed method is 99.0%. For 4200 training samples and 400 testing samples, DCNN method can achieve 97.7%, ADCNN method is 98.3% and the proposed method is 99.1%, and the detail information is show in Table 2.

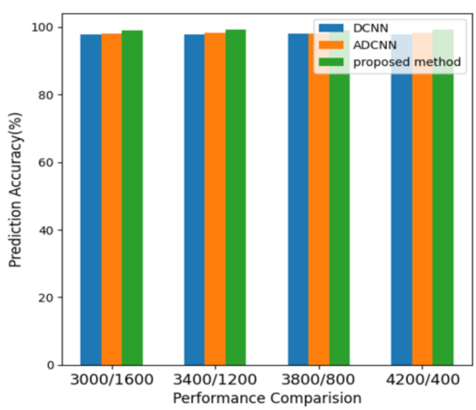

Figure 7. The performance comparison of different methods.

Table 2. Prediction precision for different methods.

Data set	Training/testing	DCNN	ADCNN	Proposed Method
	3000/1600	97.8%	98.1%	99.0%
A	3400/1200	97.7%	98.2%	99.1%
	3800/800	97.9%	98.0%	99.0%
	4200/400	97.7%	98.3%	99.1%

5. Conclusion

In this paper, a novel fault diagnosis method based on MADCNN is introduced to rolling bearings in complex environment, the DWT method is used to extract the features and input them into the novel MADCNN method for fault classification, in addition, the proposed method can optimize the extracting feature ability than ADCNN method and improve the prediction accuracy.

The t-SNE can shows the self-learning ability from input data. To further analyze the prediction accuracy of different methods, ten health states data are used to achieve fault classifications, compared with the DCNN method and the ADCNN method, the proposed method can show a higher accuracy and performance for fault classification.

Combined the obtaining complementary information advantage from multiple channels learning with the self-learning ability of ADCNN method, the MADCNN method can overcome ADCNN method cannot extract complementary feature information from a single channel learning, so the proposed MADCNN method has a better performance for fault classification in rolling bearings. Meanwhile, rolling bearings work in complex environments, MADCNN is expected to be more suitable for complex data, this architecture needs more flexibly applications for mass data.

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