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Bearing faults diagnosis using cepstral analysis and 1D Convolutional neural network

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The diagnosis of faults in the rotating machines has become necessary recently, in the order to ensure their safety and efficiency. the rolling bearing is one of the most components prone to failure in the rotating machines. In this work, we propose a novel approach to detecting and classifying the rolling bearing faults by using the cepstral analysis and 1D-CNN. First, the real, complex and power cepstrum are calculated, which are later used as input to the classifier. Second, a 1D-CNN is used as a classifier to diagnose the bearing faults. The proposed method is tested on the CWRU dataset from bearings under variable working conditions. Results of the proposed method gave a testing accuracy of 97.5 % for the complex cepstrum method and it also gave a testing accuracy of 99.88% for the real and the power cepstrum.

***Keywords**:* Rolling bearing, cepstral analysis, faults diagnosis, 1D convolutional neural network.

1. Introduction

Rotating machines are the most common type of machine used in industry, due to several causes faults can develop in these machines this is which can lead to a shutdown of the whole system and even a catastrophic failure. Therefore, it became necessary to develop a diagnostic system capable of detecting faults quickly [1]. Bearing fault diagnosis has recently become required due to the fact that it is the most prevalent fault in rotating machinery [2]. In this context, several preventive maintenance techniques have been used. However, vibration analysis remains the most widely used technique [3].

Several signal processing techniques have been used for the purpose of feature extraction, of which we mention the scalar indicators, Fast Fourier Transform (FFT), envelope analysis, cepstral analysis, wavelet transform and Hilbert Hang transform (HHT) [4]. many machine learning algorithms have been used in order to classify bearing defects such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Extreme Learning Machine (ELM) [5] and recently deep learning which has proved its superiority over previous techniques and its ability to classify bearing defects [6].

in this work, we proposed a method to detect and classify the bearing faults using cepstral analyses and a 1D CNN classifier.

2. Proposed Method

A. Cepstral analysis

The cepstral analysis, also known as the quefrency analysis, is a highly effective technique for diagnosing problems that cause periodic shocks, such as gear and bearing faults. The cepstrum is used to represent periodic phenomena that are concealed by spectra. The Fourier method assumes that the signals are stationary. However, in rotating machines, the signals emitted are non-stationary, so to perform the detection and resolve the limit of the Fourier method, cepstral analysis is used [7]. There are three types of cepstrum: the real, complex and power cepstrum, as represented in equations 1-3

$$R(\tau) = TF^{-1}[\log(abs(X(f))] \quad (1)$$

$$C(\tau) = TF^{-1}[\log(X(f)] \quad (2)$$

$$p(\tau) = abs(FFT(\log(abs(FFT(x))^2)))^2 \quad (3)$$

B. Convolution Neural Network

Convolutional neural networks (figure2) refer to a subcategory of neural networks. Their architecture is more specific: it is composed of two main blocks. The first block is the particularity of this type of neural network since it functions as a feature extractor. This block is divided into two parts, the first is the convolution part, where it filters the input with multiple convolution kernels and returns feature maps. From a more technical point of view, it involves dragging a matrix over an entry, and for each pixel, using the sum of the multiplication of this pixel by the value of the matrix. The extracted feature maps are then normalized with an activation function. The second part is the pooling, which is often placed between two convolution layers. The pooling operation consists in reducing the input size while preserving their important characteristics. For this, we divide the input into regular cells, then we keep within each cell the maximum or average value (max-pooling or average pooling). the second block is fully connected, in this block the values of the input vector are transformed (with several linear combinations and activation functions) to return a new output vector. The last layer of this block contains the different system classes.

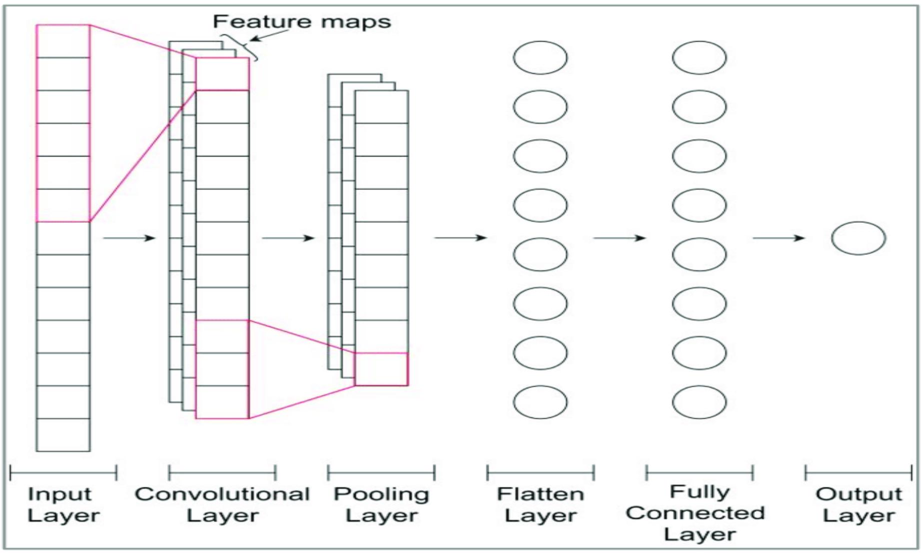

***Figure 1**: 1D convolutional neural network (CNN) architecture.*

3. CWRU Data Description

The dataset [8] consists of four groups and each group consisted of data collected from the bearing positioned on the drive end and also from the bearing positioned on the fan end. The first group contains the normal data with a sampling rate of 48 kHz. The second group includes the data of the drive end bearing faults with a sampling rate of 12 kHz, which was collected from three different positions of sensors. The third group comprises the fan end bearing data with a sampling rate of 12 kHz, which was collected from three different positions of sensors. The last group contains the data of the drive end bearing faults with a sampling rate of 48 kHz, which was collected from only two different positions of sensors.

The fault categories include rolling element fault, inner race fault, and outer race fault, with damage widths of 0.007, 0.014, and 0.021 inches, respectively, and a damage width of 0.028 inches custom for the second group of the dataset only. The entire dataset was collected under varied loads (0 to 3 hp), corresponding to shaft speeds from 1797 to 1730 rpm.

In this work, we use only the first and the second group of the dataset, which results in 12 bearing faults classes. Each signal from the dataset was divided into 58 sub-signals with 2048 points in each one, in order to augment the dataset. 70% of the data was selected for the training process and the rest was chosen for the test process, which produced a1944 sub-signals for the training and 820 sub-signals for the test.

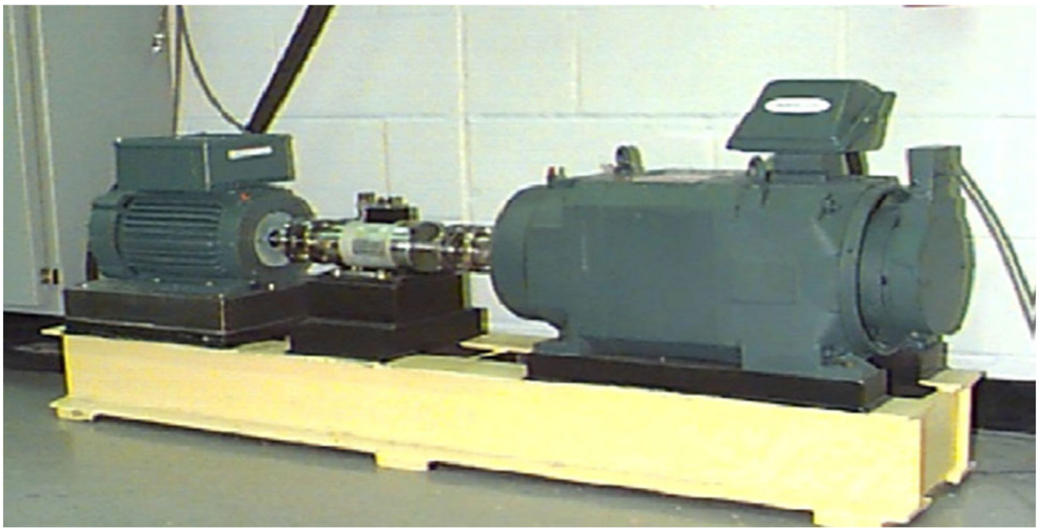

Figure 2: *CWRU bearing test rig*

Table 1. *Bearing fault descriptions for the CWRU dataset.*

Fault ID	Fault cause	Severity (inch)
1	Normal	-
2	Ball Fault	0.007
3	Ball Fault	0.014
4	Ball Fault	0.021
5	Ball Fault	0.028
6	Inner Fault	0.007
7	Inner Fault	0.014
8	Inner Fault	0.021
9	Inner Fault	0.028
10	Outer Fault	0.007
11	Outer Fault	0.014
12	Outer Fault	0.021

4. Proposed Architecture of the CNN

In the proposed 1D-CNN algorithm, the cepstrum data is directly imported into the 1D-CNN. The proposed CNN comprises three convolution layers, three pooling layers, two fully connected layers and a softmax layer. Therefore, for the first convolution layer, the kernel size is 32×1 and the stride are 16. Concerning the other convolution layers, the kernel size is 3×1 and the stride is two. For the pooling layers, the kernel size is 2 × 1 in the pooling layers, and the convolution stride is two. Then two fully-connected layers are adopted in the CNN model and the number of neurons is 64 in the first layer and 32 in the second one. In the end, the softmax layer has used to obtain the result of the classification corresponding to the 12 states of bearing faults. The parameters of the used model are presented in the table 2.

Table 2. *1D-CNN model details*

NO	Layer type	Kernel size	Stride	Number of Kernel
1	1D Convolution	32 × 1	16 × 1	64
2	Max Pooling 1D	2 × 1	2 × 1	64
3	1D Convolution	3 × 1	2 × 1	32
4	Max Pooling 1D	2 × 1	2 × 1	32
5	1D Convolution	3 × 1	2 × 1	16
6	Max Pooling 1D	2 × 1	2 × 1	16
7	Fully-connected 1	64	-	1
7	Fully-connected 2	32	-	1
8	Softmax	13	-	1

5. Experiment results

Table 3. Average testing diagnosis accuracies for the proposed methods

Method	Testing accuracy
Real cepstrum	99.88 %
Complex cepstrum	97.5 %
Power cepstrum	99.88 %

Table 3 gives the testing accuracy of the three proposed methods; it can be seen from the table that a testing accuracy of 99.88% is recorded for the real and power cepstrum method and regarding the complex cepstrum the testing accuracy decreased to 97.76%. To clearly demonstrate the diagnostic accuracy of the proposed methods, the confusion matrix results are plotted in figure 5.

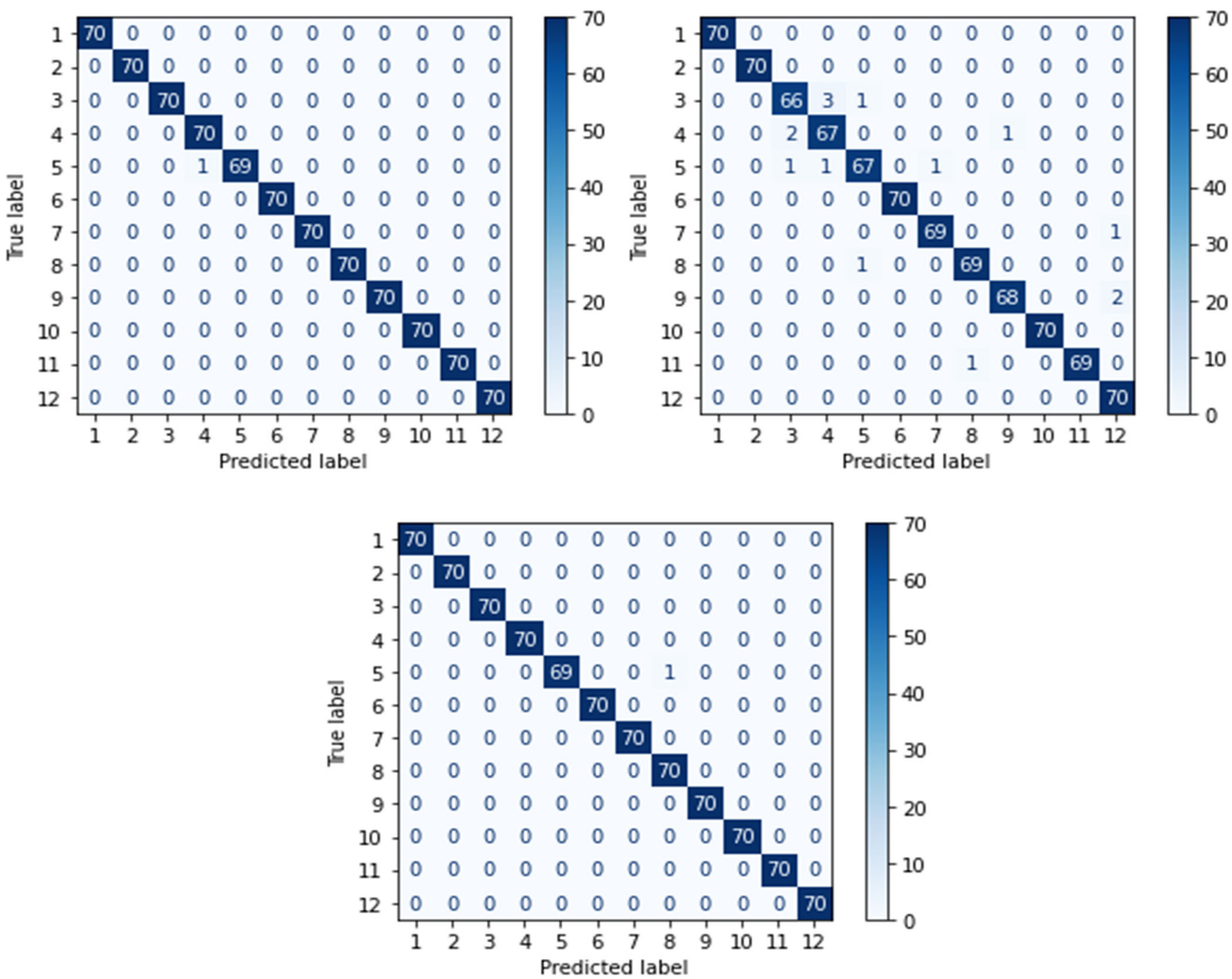

***Figure 3**: Confusion matrixes of the prediction results: (a)* real cepstrum; *(b) c*omplex cepstrum; *(c)* power cepstrum

6. Conclusion

In this paper, we proposed a novel approach combining 1D-CNN with three cepstral analysis methods to diagnose and classify the rolling bearing faults under variable working conditions. The three cepstrum methods (real, complex, power) are used as input to the 1D-CNN. The proposed architecture gave good results with the highest testing accuracy equal to 99.88%.

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