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

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Due to the importance of rolling bearings as one of the most widely used industrial machinery elements. Therefore, the development of a method to monitor the condition of bearing is very important. This work presents a novel method to classify the bearing faults by using an envelope analysis and 1D-CNN. Firstly, envelope analysis is used as a method for pre-processing by calculating the envelope spectrum of the raw vibration data. Secondly, 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 different rotating speeds. Results of the case study show that the proposed method can achieve a testing accuracy of 99.85 %.

Keywords: Rolling bearing, Hilbert transform, envelope analysis, 1D convolutional neural network.

1. Introduction

In the modern era, Rotating machinery is the most commonly used type of machine in modern industry and civil applications. Diagnosing defects as early as feasible is thus critical because a breakdown in any element of this equipment can trigger a shutdown of the entire system and possibly catastrophic failure. which leads to very significant economic and human losses [1].

Bearings are the mechanical components that are commonly used in most rotating devices and are the primary cause of defects in such equipment; bearing faults can account for up to 44% of all faults in certain devices [2]. Vibration data is a common technique of preventive monitoring used to identify and classify bearing faults.

Usually, the process of bearing faults identification is divided into three steps, the first one is feature extraction, after that, a feature selection is coming and the last one is faults classification. To extract the defect features in the bearings, many signal processing approaches were applied. Time-domain statistical analysis, Fast Fourier Transform, envelope analysis, wavelet transformation, and empirical mode decomposition are all included [3]. in order to classify the bearings faults, many algorithms of machine learning have been used, such as artificial neural network (ANN), support vector machine (SVM) and k-nearest neighbour (KNN). Deep learning techniques have recently been demonstrated to regularly outperform previous techniques in a variety of disciplines, owing to the fact that their inputs might be 2D or 1D data.

The aim of this work is to classify bearing faults using envelope spectrum analysis and an 1D_CNN classifier.

2. Proposed Method

The essential components of the bearing are four: a rolling element, outer race, inner race and the cage. In most cases, the degradation of one of the raceways or a rolling element of the bearing produces a shock on each pass. Defective bearings generate vibration frequencies depending on the rotational speed and the geometric dimension of each part of the bearing. The flowchart in figure 1 illustrates the suggested method. The first step is to segment the raw vibration signal into sub-signals. The envelope spectrum of each sub-signals is calculated as a second step. Finally, the bearing defects are classified using the 1D-CNN classifier.

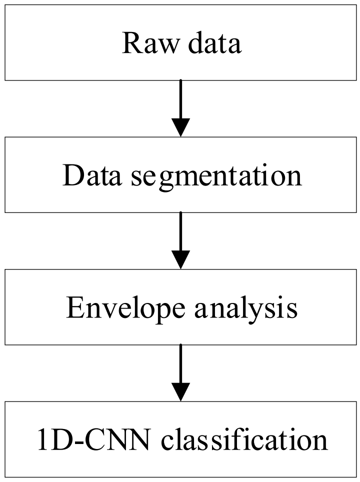

Figure 1: *Flowchart of the suggested fault diagnosis method*

3. Envelope Analysis

Envelope analysis is a technique that has been used for bearing fault diagnosis [4]. In practice, the envelope analysis method requires a series of processing of the raw temporal signal before obtaining the result, there are three essential steps which can be summarized as bandpass filtering, extraction of the envelope and the envelope spectrum calculation. In the first step, a bandpass filter centered on the resonant frequency of the machine is applied to eliminate the undesirable components outside the passband [5]. The second step is the calculation of the signal envelope, which is obtained by the application of the Hilbert transform. This method is used to calculate a complex signal from the raw real signal where the imaginary component is a phase-shifted copy of the real signal, which can be obtained by the following equations.

$$X = fft\,(x_{in}) \tag{1}$$

$$X_a(k) = \begin{cases} X(k)\,, & if\ k = 0, \frac{N}{2} \\ 2X(k), & if\ 0 < k < \frac{N}{2} \\ 0 \quad , & if\ \frac{N}{2} < k < N \end{cases} \tag{2}$$

$$x_a = ifft(X_a) \tag{3}$$

Where X is the Fast Fourier Transfer of x_{in}, X_a is the Invers Fast Fourier Transfer of X, and k is the index of data sequence with the length of N [6].

Then, the envelope of the calculated signal can be computed using (4).

$$x_{env} = \sqrt{z_a \times conj(z_a)} \tag{4}$$

And to finish, the Fourier transform is applied to calculate the spectrum of the envelope which allows us to detect the defect if it exists. (Equation 5)

$$X_{env} = |fft(x_{env})| \tag{5}$$

4. Convolution Neural Network

Convolutional neural networks (Figure 2) are simple artificial neural networks, in addition to the presence of additional layers represented by convolution and pooling layers. The convolutional layer convolves the input local regions with filter kernels, then followed by the activation function to generate the output features. The pooling layer reduces data dimensions by combining the outputs of groups of neurons in one layer into a single neuron in the next layer. Pooling can be done for a maximum or an average. Maximum pooling uses the maximum value of each group of neurons from the previous layer. Average pooling uses the average value of each group of neurons from the previous layer. After that, the fully connected layer is used. This layer is a traditional multi-layer Perceptron. The objective of this layer is to use these characteristics to classify network inputs into different classes based on the training database.

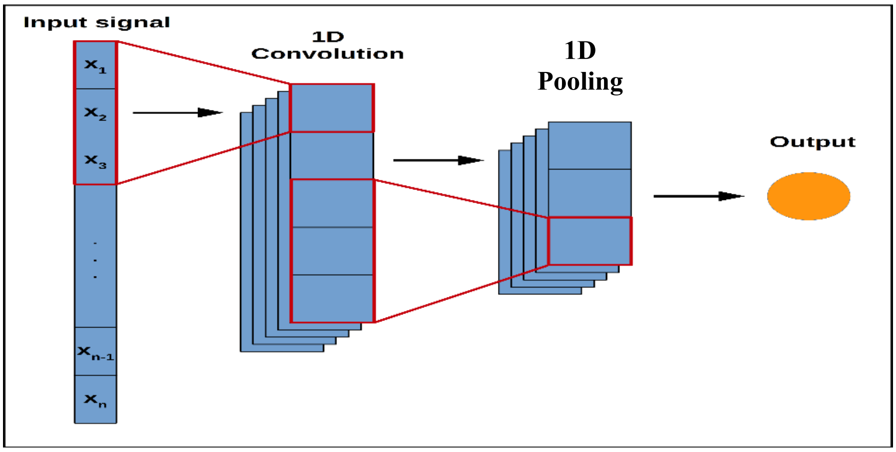

Figure 2: 1D convolutional neural network (CNN) architecture.

5. CWRU Data Description

The experiment rig contains a 2 hp motor, a torque transducer, dynamometer and control electronics, as shown in Figure 3. The dataset [7] consists of four parts: the first part includes the baseline or normal data collected from the bearing positioned on the drive end and also from the bearing positioned on the fan end of the system at a sampling rate of 48 kHz. The second part contains data collected from the drive end bearing with three different positions of sensors under three different fault types at a sampling rate of 12 kHz. The third part consists of data collected from the fan end bearing with three different positions of sensors under three different fault types, and the sampling rate is also 12 kHz. The last part comprises data collected from the drive end bearing with only two different positions of sensors under three different fault types at a sampling rate of 48 kHz.

The three different fault types are rolling element fault, inner race fault, and outer race fault, with damage widths of 0.007, 0.014, and 0.021 inches, and another damage width of 0.028 inches custom only for the second part of the dataset. The whole dataset was collected under various loads (0 to 3 hp), corresponding to the shaft speeds of (1797 to 1730 rpm), respectively.

In this work, we use all the drive end data with a sampling rate of 12 kHz except the data of 0.028 inches, thus we have 10 fault conditions in all (Table 2). Each sample in this experiment has 2048 data points, yielding a total of 58 data samples for each failure signal. 41 of the 58 samples are placed aside for training, while the reset is chosen for testing. Finally, a training set of 1640 samples and a testing set of 680 samples are formed.

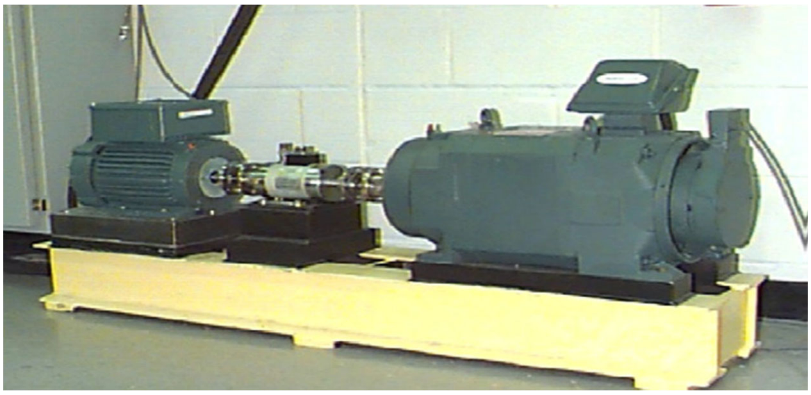

***Figure 3**: CWRU bearing test rig*

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	Inner Fault	0.007
6	Inner Fault	0.014
7	Inner Fault	0.021
8	Outer Fault	0.007
9	Outer Fault	0.014
10	Outer Fault	0.021

6. Proposed Architecture of the CNN

The proposed 1D-CNN architecture used in this experiment includes three convolution layers, where the first convolutional kernel has a size of 64×1, and the other kernels have a size of 3×1. The architecture also includes three pooling layers, where maximum pooling is used as the type of pooling and ReLU as an activation function. these layers are followed by fully connected hidden layers and, at the end, a softmax layer to classify the 10 bearing defect classes. After each convolutional layer and fully layer a batch normalization is performed, with the aim of increasing the performance of 1D-CNN. Table 2 summarizes the parameters of the proposed 1D-CNN.

Table 2. *1D-CNN model details*

NO	Layer type	Kernel size	Stride	Number of Kernel
1	1D Convolution	64 × 1	16 × 1	16
2	Max Pooling 1D	2 × 1	2 × 1	16
3	1D Convolution	3 × 1	2 × 1	32
4	Max Pooling 1D	2 × 1	2 × 1	32
5	1D Convolution	3 × 1	2 × 1	64

6	Max Pooling 1D	2 × 1	2 × 1	64
7	Fully-connected	64	-	1
8	Softmax	10	-	1

7. Experiment results

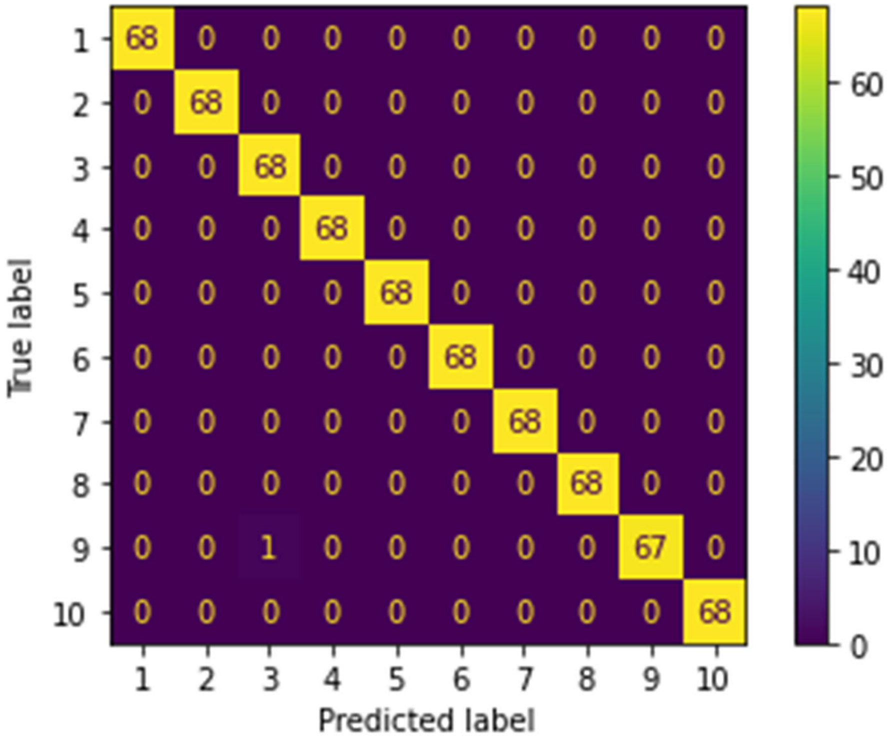

***Figure 4**: Confusion matrixes of the prediction results*

The proposed approach has a testing accuracy of 99.85%. To clearly demonstrate the diagnostic accuracy of the presented technique, the confusion matrix is used to analyse the diagnosis results in detail, as shown in Figure 4. Only one sample of label 9 is incorrectly categorised. The results show that the suggested approach is successful at classifying bearing defects.

8. Conclusion

This study proposes a new bearing faults classification method based on envelope analysis and 1D-CNN to classify the bearing faults. The envelope spectrum is used as input to the 1D-CNN rather than the raw vibration signals. The proposed architecture gave good results with testing accuracy equal to 99.85%.

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REFERENCES

[1] B. Bengherbia, R. Kara, A. Toubal, M. Ould Zmirli, S. Chadli, and P. Wira, “FPGA implementation of a wireless sensor node with a built-in ADALINE neural network coprocessor for vibration analysis and fault diagnosis in machine condition monitoring,” *Measurement*, vol. 163, p. 107960, 2020.

[2] G. Georgoulas, T. Loutas, C. D. Stylios, and V. Kostopoulos, “Bearing fault detection based on hybrid ensemble detector and empirical mode decomposition,” *Mech. Syst. Signal Process.*, vol. 41, no. 1–2, pp. 510–525, 2013.

[3] Y. Toumi, B. Bengherbia, S. Lachenani, and M. Ould Zmirli, “FPGA Implementation of a Bearing Fault Classification System Based on an Envelope Analysis and Artificial Neural Network,” *Arab. J. Sci. Eng.*, 2022.

[4] S. Tyagi and S. K. Panigrahi, “An improved envelope detection method using particle swarm optimisation for rolling element bearing fault diagnosis,” *J. Comput. Des. Eng.*, vol. 4, no. 4, pp. 305–317, 2017.

[5] S. A. McInerny and Y. Dai, “Basic vibration signal processing for bearing fault detection,” *IEEE Trans. Educ.*, vol. 46, no. 1, pp. 149–156, 2003.

[6] S. L. Marple, “Computing the Discrete-Time ‘Analytic’ Signal via FFT,” *IEEE Trans. SIGNAL Process.*, vol. 47, no. 9, pp. 2600–2603, 1999.

[7] “Bearing Data Center | Case School of Engineering | Case Western Reserve University.” [Online]. Available: https://engineering.case.edu/bearingdatacenter. [Accessed: 04-Apr-2022].