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Conference Paper · March 2020

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COOLING FAN COMBINED FAULT VIBRATION ANALYSIS USING CONVOLUTIONAL NEURAL NETWORK CLASSIFIER

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ABSTRACT
In this paper, an application of Convolutional Neural Network (CNN) to detect a predefined fault in vibration signal without any feature extraction. The vibration signal, after being normalized, is converted into a 2-D data called vibration image, and these images are passed in the CNN as input to detect whether there is a fault or not. Experiments are carried out with bearing data from the cooling Fan of a cement oven in CILAS-Biskra. Tests are done using different image sizes, and different training/testing data sets.

CCS Concepts
CCS → Computing methodologies → Machine learning → Machine learning approaches → Neural networks

Keywords
Convolutional Neural Network; Deep learning; Bearing fault diagnosis.

1. INTRODUCTION
Vibration analysis is widely used in industrial applications [1], [2], [3], [6], [7], [8], [13], [14], [15], [16]. Regardless of the defect type, vibration signals generated by the interaction between a damaged area and a rolling surface occurs. Consequently, vibration analysis is a significant technique to detect all types of physical faults, either localized or distributed. Generally, signal-based classic diagnosis methods include three steps as follows, as described in [12]: signal acquisition; feature extraction; and fault recognition.

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NISS2020, March 31-April 2, 2020, Marrakech, Morocco
© 2020 Association for Computing Machinery.
ACM ISBN 978-1-4503-7634-1/20/03…$15.00
https://doi.org/10.1145/3386723.3387898

Advances in machine learning techniques have enabled many data-based techniques to overcome the downsides of traditional signal analysis techniques. In particular, Deep Learning methods have caught the attention of many researchers in recent years [6], [8] due to their automated process of learning and the ability to transform the learned model into powerful and highly accurate classification algorithms. Particularly, CNN is a neural network architecture that has shown immense possibilities in image and audio processing [9], [10], [11], [17].

Image and vibration analogy in diagnosis occurs in 1-D signal to 2D image conversion, where the temporal vibration signal is converted into a set of gray-level images. To extract texture information from vibration images, 2-D feature extraction methods can be used. However, by exploiting the texture information, the 2-D image-based fault diagnosis can be highly reliable, but performance still depends mainly on handcrafted feature extraction [6].

Inspired from the efficient performances of CNN in vibration image classification [6], [8], this paper proposes a bearing fault diagnosis using CNN to detect a combined fault in cooling Fan of cement oven in CLIAS-Biskra [5]. Experiments using different image sizes and sets are carried out to study the efficiency of CNN to detect fault without any signal preprocessing.

This paper is organized as follows. The used fault diagnosis method is explained in detail in Section 2, Section 3 describes the implementation and performances. Finally, the conclusion is done in Section 4.

2. BEARING FAULT DIAGNOSIS METHOD
To be able to use CNN in image classification, the raw vibration signal, after being normalized between -1 and1, is converted into a 2-D gray-level image set. Then vibration images are feed into CNN classification. A part of image sets is used for CNN training, the other part is used for test and validation. The block diagram of the used method is shown in figure 1.

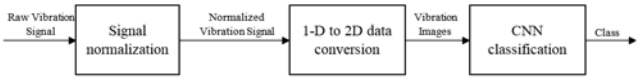


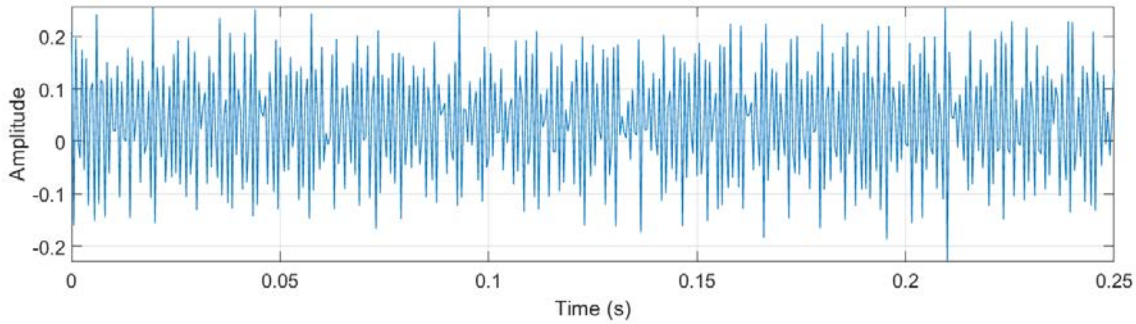
Figure 1. Fault Diagnosis with CNN

2.1 Signal Normalization

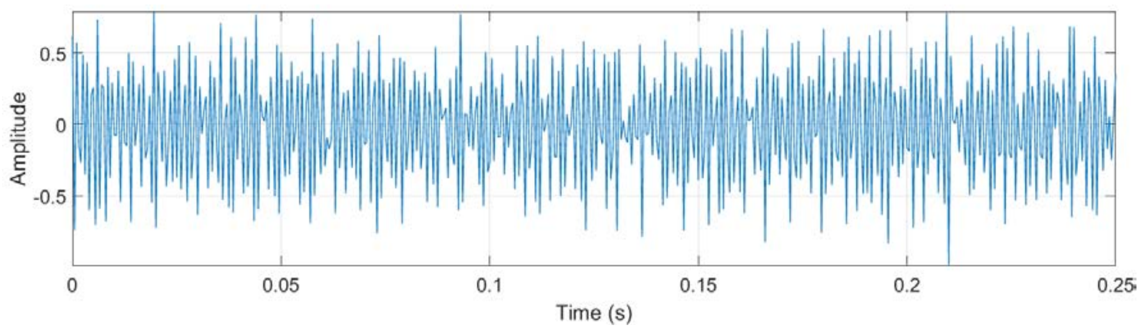
The first step is to normalize data since vibration signal has variable intervals ([-0.1;0.1], [-2;2], etc.). Normalized vibration signal is between -1 and 1, this is done using the following equation [4]:

$$X_n = \frac{2(X - X_{min})}{X_{max} - X_{min}} - 1 \tag{1}$$

Figure 3 shows raw signal (Figure 2(a)) and its normalized form (Figure 2(b)). It can be seen that the signal keeps its characteristics after normalization, only its amplitude that changes.



(a) Raw signal



(b) Normalized signal

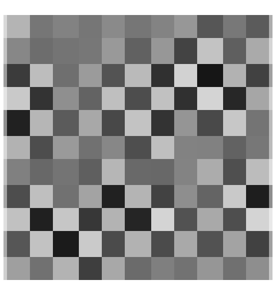
Figure 2. Signal normalization

2.2 Vibration 2-D Gray Image Construction

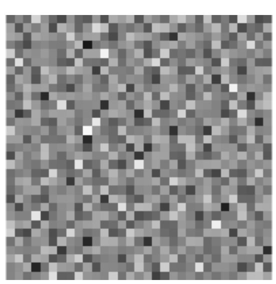
The normalized amplitude of each sample becomes the intensity of the corresponding pixel of the corresponding image. The conversion between the normalized amplitude of the sample and the corresponding pixel can be described as the following equation [6]:

$$P[i, j] = A[(i - 1)M + j] \tag{2}$$

Where $i = 1 \cdots N$, $j = 1 \cdots M$, and $P[i, j]$ is the amplitude of the corresponding pixel (i, j) in the $M \times N$ vibration gray-level image. The array A is the normalized vibration signal in function of time.



(a) $m = 11$



(b) $m = 31$

Figure 3. Samples of vibration images for different values of m.

2.3 Image Classification with CNN

The used architecture is shown in Figure 4, inspired by [8], and consists of two main components: filtering layer(s) followed by a classification layer. The input is normalized between -1 and 1. The hidden neurons at each layer are ReLU units.

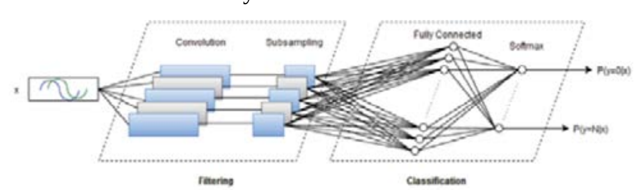


Figure 4. Implementation of CNN classifier [8]

3. EXPERIMENTAL WORK

3.1 System Description

At the CILAS-Biskra unit, the Cooling Fan is a key machine in the cement manufacturing process and requires continuous monitoring. It includes a fan, electric motor drive, motor, shaft, and other types of equipment. During a two-month internship, measurements were obtained from 4 bearings in the 3 directions, vertical, horizontal, and axial. The sampling tool used is the *SKF Microlog Analyzer GX* and its software installed on a desktop PC (*SKF @ptitude* *analyst*). The software facilitates the detection of characteristic frequencies of faults, harmonics and frequency modulations.

Figure 5. Cooling Fan [5]

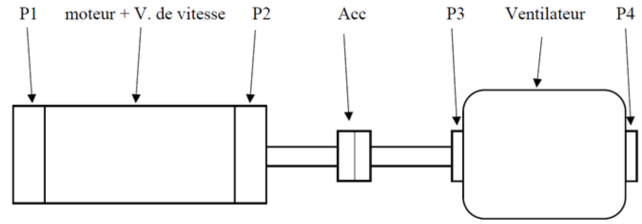
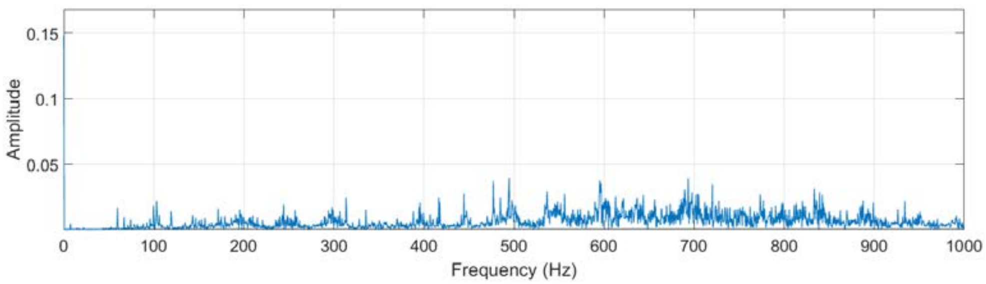
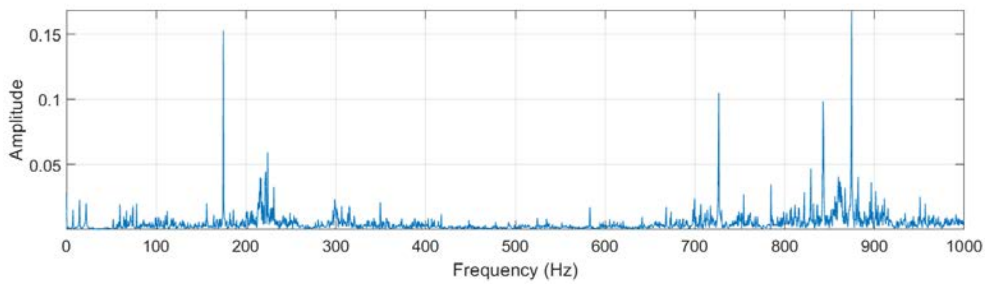


Figure 6. Measurment points [5]

The vibration signals were taken during the period from December 2017 to February 2019, [5] has done diagnosis using experience from company engineers to decide that a fault has appeared since June 2018. In this work, only Axial vibration from Bearing 3 is taken into account. The bearing fault diagnosed in [5] was metal-to-metal friction and rotating unbalance in the Fan axle.



(a) FFT of healthy signal



(b) FFT of faulty signal

Figure 7. Signal FFT for healthy and faulty cases.

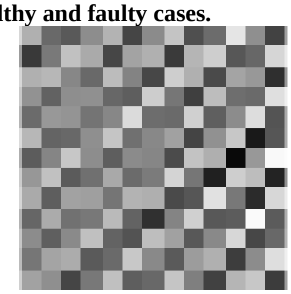
3.2 Fault Diagnosis with CNN

In the following section, the normalized vibration signal will be split into non-overlapping segments. Since image size will be $M = N = m$, each segment will be m^2. Temporally normalized signals from Bearing 3 (only axial) are considered, each signal used in this experiment has 4096 samples. Therefore, each signal will give ech samples as follows:

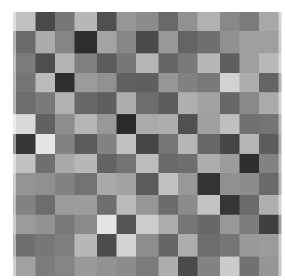
$$ech = fix\left(\frac{4096}{m^2}\right) \tag{3}$$

Where $fix(X)$ rounds the real number X to the nearest integers towards zero.

For this experiment, there are 80 signal sequences, divided into two equally classes: healthy and combined fault. In the next section, vibration data will be divided into two parts: training and testing data. Training and testing ratios will be studied later on.



(a) Vibration image example



(b) Vibration image example

Figure 8. Vibration image examples for $m = 13$.

The used configuration of CNN classification is as follow:

- One layer: convolution layer, 30 kernels, each kernel has size 6 × 6, stride step 1, ReLU activate function;
- full connection layer;

- output layer: two outputs (corresponding to the two classes need to be classified).

4. CLASSIFICATION RESULTS

CNN training and validation has been done using Matlab R2018b installed in a Windows 7 64bit computer equipped with an intel core i3-3210 CPU @ 3.20 GHz and 6 GB of RAM.

4.1 Image size comparison

In this case, the classification will be done for different values of m training/testing ratio will be 20 / 20 signals respectively, each ratio is for the two different classes. Which yields to:

$$\begin{cases} training = 2 \times 20 \times fix\left(\dfrac{4096}{m^2}\right) \; images \\ testing = 2 \times 20 \times fix\left(\dfrac{4096}{m^2}\right) \; images \end{cases} \quad (4)$$

Results are shown in table I:

Table 1. Validation performances for different values of *m*.

m	Training (images)	Testing (images)	Accuracy (%)
6	4550	4550	89.45
11	1354	1354	91.8
16	640	640	95.63
21	370	370	97.03
26	242	242	92.98
31	170	170	94.71
36	126	126	85.17

Figure 9 shows a comparative bar graph of accuracies for different values of m:

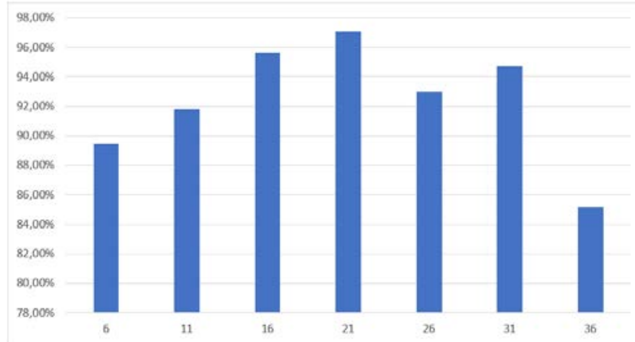
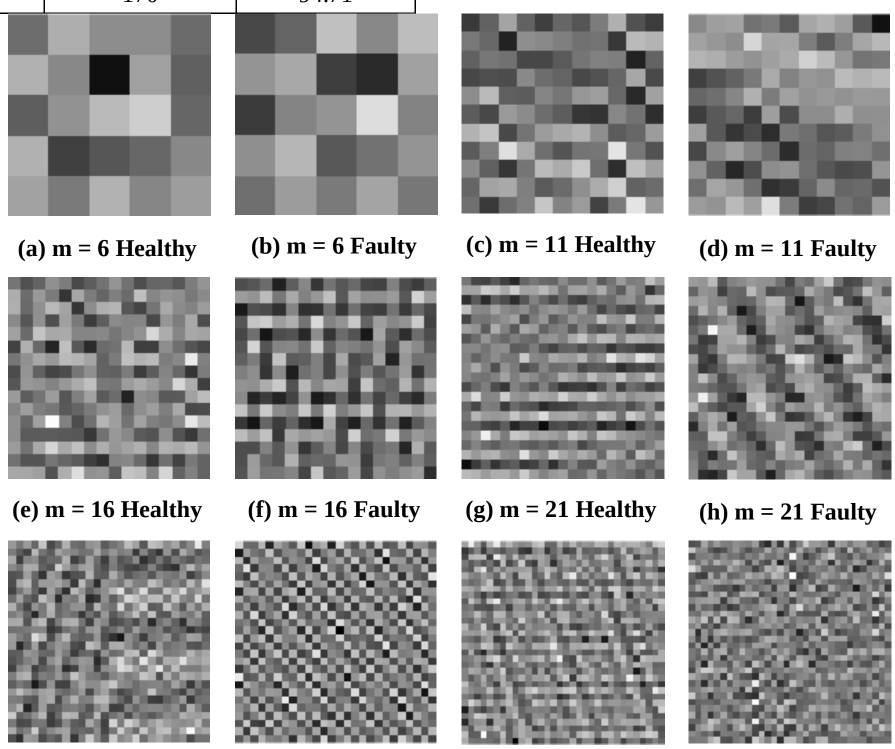


Figure 9. Accuracy for different values of *m*.

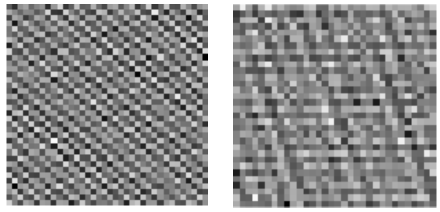
It can be seen that the minimal m value is 6, this is due to the choice of the first CNN layer, which has a 6 × 6 kernel size. It can be seen also that the best accuracy value is for m = 21, this can be explained by the lack of feature extraction. As can be seen in Figures 10(g) and 10(h), which are images for m = 21, there is a visible difference between the two studied classes. However, for m = 6, 11, 16, 26 and 31, images features are more or less visible, this can explain the small accuracy results. Moreover, for m = 36, accuracy is very low, this can be explained, from Figures 10(m) and 10(n), by the very small features that need a more complicated CNN model which is not studied in this work.



(a) m = 6 Healthy **(b) m = 6 Faulty** **(c) m = 11 Healthy** **(d) m = 11 Faulty**

(e) m = 16 Healthy **(f) m = 16 Faulty** **(g) m = 21 Healthy** **(h) m = 21 Faulty**

(i) m = 26 Healthy **(j) m = 26 Faulty** **(k) m = 31 Healthy** **(l) m = 31 Faulty**



(m) m = 36 Healthy **(n) m = 36 Faulty**

Figure 10. Vibration images for different values of *m*.

4.2 Training vs. Test comparison

In this part, the number of training/test samples will be varied, for a constant $m = 21$, to see the influence of sample ratios on accuracy. Table 2 shows a comparison between different sample values.

Table 2. Accuracy values for different sets of training/validation.

		Test images						
		92	**184**	**278**	**370**	**464**	**556**	**650**
Training images	**92**	90.22	66.30	77.34	78.11	84.05	81.83	78.00
	184	71.74	94.57	88.85	83.78	95.26	86.15	
	278	82.39	84.24	82.09	86.22	83.84		
	370	85.87	88.59	88.49	95.95			
	464	96.74	95.11	97.84				
	556	89.13	95.11					
	650	90.22						

It can be seen that the training/testing ratio makes a big difference in classification accuracy. Though, the best classification cases are given when training images are more than testing images, which makes sense since there are fewer testing samples to examine with. However, CNN showed good results even for testing images more than training (case for 184/464 images for training/testing respectively). This is due to CNN performances to classify complex time series with good accuracy.

5. CONCLUSION

In this study, the classification method was tested on real data set for vibration in the function of time of bearing in essential equipment, which is cooling Fan of cement oven. The classification has been done using a Convolutional Neural Network, the data set has been pre-cut to two different classes (healthy and combined fault).

This work gave good classification results with simple CNN configuration and low training samples, which gives promising outcomes that can be used in the real diagnosis process. The results were very interesting since the classical diagnosis methods used in this plant are completely based on human intervention [5].

However, this work allows further investigation on Deep Learning methods and can be listed, but not limited, as follows:

- Change CNN model to have more elaborate results for more complicated configurations;
- Try to test the trained Deep Learning in real-time to detect faults at a very short time-lapse.

6. ACKNOWLEDGMENTS

This work has been done using data extracted from diagnosis software "SKF @ptitude analyst" during a two-month internship in the CILAS – Biskra company, Biskra, Algeria.

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