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Diagnosing Localized and Distributed Bearing Faults by Bearing Noise Signal Using Machine Learning and Kurstogram

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Abstract

Bearings are a common component and crucial to most rotating machinery. Their failures are the causes for more than half of the total machine failures, each with the potential to cause extreme damage, injury, and downtime. Therefore, fault detection through condition monitoring has significant importance. Since the initial cost of standard condition monitoring techniques such as vibration signature analysis is high and has a long payback period, condition monitoring via audio signal processing is proposed for both localized faults and distributed/ generalized roughness faults in the rolling bearing. It is not appropriate to analyze bearing faults using Fast Fourier Transform (FFT) of the noise signal of bearing since localized faults are Amplitude Modulated (AM) and mixed up with background noises. Localized faults are processed using the Kurstogram technique for finding the appropriate filtering band because localized faulty bearings produce impulsive signals. The filtered signal in the band derived by the Kurstogram technique is then transformed into the analytical signal of Hilbert transform to demodulate the AM faulty signal. Since carrier frequencies of the AM bearing noise signal are eliminated by Hilbert transform, FFT of the analytical signal of Hilbert transform gives the fault frequencies like misalignment frequency, Ball Pass Frequency Inner race (BPFI) and Ball Pass Frequency Outer race (BPFO) to find out the location of localized faults. Misalignment experiments for different types of bearings at different speeds and related fault frequencies are identified. Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) are trained using the Mel Frequency Cepstral Coefficient (MFCC) feature of bearing noise signals with various background noises to distinguish between healthy bearing and bearing having distributed /generalized roughness faults. The ANN and CNN models can classify healthy or distributed/generalized roughness faulty bearing with validation accuracy of more than 90%.

Keywords: Audio processing, fault diagnosis, Hilbert transform, machine learning, Kurstogram

Introduction

Bearings play an important key role that may affect the operation, reliability, and efficiency of rotating machinery. As it has been reported in the literature, bearings have finite life that is limited by their resistance to fatigue, thus, the occurrence of faults is inherent to its operation, even under ideal operating conditions [1][2]. In this sense, most of the common faults in bearing may be attributed to the following causes such as overload which may be generated by static load and/or unbalances or misalignments, excessive or insufficient lubrication, external contamination, inappropriate installation and/or design, and electrical discharges passing through the bearing [3][4]. Bearing is the most used and frequently failing component in the industry. Since bearing failure may lead to a fatal accident and costly downtime, condition monitoring and fault diagnosis of the bearing are significantly important [5]. In the past several

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decades, many techniques have been investigated to diagnose bearing faults. Several of the commonly used methods include motor current signature analysis [6], vibration monitoring [7], [8], temperature measurement [9], and acoustic emission measurement [10]. Even though most of the abovementioned methods promise accurate results it costs a lot so intermediate industries cannot afford them for non-critical and less expensive applications as the cost of installing that standard diagnostic system might be greater than the cost of the monitored element itself.

Recently, acoustic analysis has attracted more and more attention and it has been applied in many fields, for example, speech recognition, nevertheless still very rarely it is applied in the industrial environment for condition monitoring purposes [11][12]. Therefore, audio signal analysis via a low-cost microphone and smartphone is to be analyzed for condition monitoring of the bearing. In the literature, analysis of condition monitoring done by audio is negligible compared to the standard method based on vibration signature, acoustic emission, and voltage measurement.

Even though there are many challenges with audio for fault diagnosis [13], some studies have proven that audio signal has the potential to diagnose faults in mechanical components. In [14-17], faults in moving mechanical components like drill and coffee grinder, three-phase induction motor, railway point machines, and spindle were diagnosed using audio signal processing with the help of machine learning techniques, which gave reasonable accurate results. In [18], it was found that sound signal has the potential to differentiate types of faults in DC motor using statistical quantitative measures of time and frequency domain signal.

The rolling bearing faults can be divided into two groups, localized faults and distributed and/or generalized roughness faults. Localized faults produce simple patterns in any domain of measure. Conversely, patterns excited by distributed and generalized roughness faults tend to be more complex [19]. Even though there is more work that diagnosis bearing using vibration measurement with the use of machine learning models to classify the type of localized faults [20-22], there are some works where localized faults such as inner race faults, outer race faults, and ball faults were classified by machine learning technique using features extracted from the audio signal. In [23], localized faults were classified using both audio and vibration signals. It is interesting to note that the classification accuracy of roller element bearing is higher when using the microphone of the smartphone than using a low-cost accelerometer since different speeds were used to train the machine learning model. In [24], bearing fault was diagnosed using combined audio and current measurement to diagnose localized faults at a different speed.

Some works measure the single pitting localized faults quantitatively using vibration analysis [25-28]. No study was found for the audio signal to quantitatively measure the single pitting localized faults since the audio signal has a low signal-to-noise ratio. As all the above-mentioned works were done based on the data acquired at the laboratory, the accuracy of the results is acceptable. Coming into reality, the industry is a noisy environment and noise is changing over time. Since there was no filtering before classification, it is doubtful when using it in the industry because the useful signal may be mixed up with various background noises, which may lead to misclassification.

Conventionally, distributed, and generalized roughness bearing faults could be identified by comparing statistical measurements or energy at a specific band of vibration, current, or voltage measurement with a predefined threshold [19, 29-30]. But these methods do not help with audio signal because of the low signal-to-noise ratio of audio. But some works classifies distributed and generalized roughness bearing faults using audio signal recorded in a less noisy environment. In [31], fault diagnosis of bearing using a descriptive statistical feature of sound and classification using Bayes classifier has been done with reasonable accuracy. In [32], the Support Vector Machine (SVM) classifier was trained using features extracted from the Fast Fourier Transform (FFT) of the sound signal, and the remaining useful life could be found. In [33], database-based fault diagnosis using spectral features have been done for the wheel bearing of an automobile. All those methods are not reliable when distributed fault diagnosing using audio because the noise varying in the industry is the hurdle. Therefore, the model which considers background noises should be there to be robust to handle varying noises. Although several works have been proposed to perform bearing fault detection and diagnosis, some gaps still exist that have not been addressed in the field of bearing fault assessment. Fault diagnosis of bearing using noise signal of that bearing is to be analyzed to detect both localized and distributed/generalized roughness faults. Considering localized faults, the noise of bearing is to be analyzed by a systematic method that is used for vibration analysis for the detection of localized faults such as inner race, outer race, ball, and misalignment faults. Coming into distributed/generalized roughness faults, conventional machine learning methods are not suitable when using audio as feature selection is hard and questionable. Therefore, deep learning techniques such as Artificial Neural Network (ANN), and Convolutional Neural Network (CNN) are to be evaluated to classify as healthy or faulty bearings using the noise signal of the rolling bearing.

Since localized faults are usually single pitting crake in the outer race, inner race, rolling elements, and cage or as well as the misalignment, the occurrence of any of these faults produce a characteristic pattern that can be associated with a specific frequency component. Hence, to assess the localized faults in the bearings, it is mandatory to know fault-related frequency components that are produced by the sudden occurrence of bearing faults [34]. And so, the mathematical equations to identify defects in the outer race and inner race of bearings are related to the fault-related frequency given by Equations (1) and (2), respectively and the frequency related to misalignment is stated as Equation (3). With the calculation of the BPFO (Ball Pass Frequency of the Outer race), BPFI (Ball Pass Frequency of the Inner race), and misalignment components, it is possible to locate the fault-related frequency components in the frequency spectrum and determine the presence of bearing faults on the outer race and inner race as well as the misalignment. It should be noted that these fault-related frequency components are computed in terms of the number of rolling elements (balls), N; the ball diameter, BD; the pitch diameter, PD; the contact angle, θ; and the rotational frequency, f, [35].

$$BPFO = \frac{N}{2} f \left(1 - \frac{BD}{PD} \cos\theta\right) \qquad \textit{(Equation 1)}$$

$$BPFI = \frac{N}{2} f \left(1 + \frac{BD}{PD} \cos\theta\right) \qquad \textit{(Equation 2)}$$

$$f = \frac{RPM}{60} \qquad \textit{(Equation 3)}$$

Since localized faults produce amplitude modulated signal at any measurement like vibration motor current or noise of bearing as shown in Figure 1, it would not produce an accurate result when extracting frequency components from draw signal.

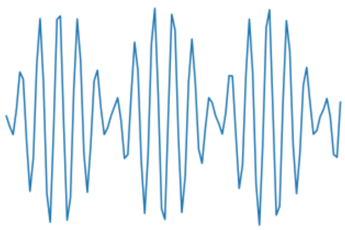

Figure 1. Amplitude modulated signal of localized fault

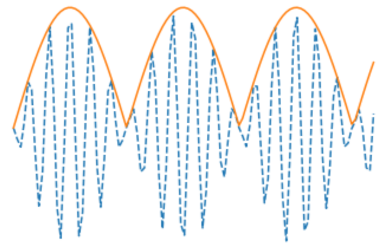

Figure 2. Demodulated signal of localized fault

Therefore, the draw signal is to be demodulated before extracting fault frequencies as shown in Figure 2. There are noises everywhere. But the noises associated with the audio is higher compared to the other measurement such as vibration and motor current. Therefore, the audio signal should be filtered at the appropriate band before demodulating the signal.

Distributed faults are regarded as bearing surface defects spread over a large area that occur due to imperfect manufacturing, faulty mounting, and misuse [36–39]. As the bearing ages, localized faults evolve and spread over a wider area, thus becoming distributed. Generalized Roughness is a type of fault when the condition of a bearing surface over a large area has considerably degraded and become rough, irregular, or deformed. Pollutant contaminated oil, shortage of oil, shaft currents, and system misalignment are major causes of Generalized Roughness failure. Generalized Roughness and distributed faults are more common failure types than Single points [40]. Since distributed / generalized roughness faults produce a complex and arbitrary signal at any measure it increases the challenge of diagnosing distributed / generalized roughness faults in a rolling bearing using the noise signal of the bearing since audio usually has a low signal-to-noise ratio because of its ease of mixing exposure to other external background noises. MFCC features are widely used in many auditory applications such as voice recognition, speech emotion recognition, acoustic event monitoring since MFCC features represent approximated human auditory system [41]. The MFCC feature extraction technique includes windowing the signal, applying the Discrete Fourier Transform (DFT), taking the log of the magnitude, and then warping the frequencies on a Mel scale, followed by applying the inverse Discrete Cosine Transform (DCT). Therefore, deep learning techniques such as ANN and CNN trained using the MFCC feature are evaluated to distinguish between healthy bearing and bearing having distributed/ generalized roughness faults.

Methods for Diagnosing Localized and Distributed/ Generalized Roughness Faults

In this study, the potential of bearing noise signals to diagnose both localized and distributed/generalized roughness faults have been analyzed. Since each fault must be analyzed using different methods, the methods for each fault type have been described under subheadings.

Localized Faults

Figure 3 shows the proposed method for diagnosing localized faults in rolling bearing using the noise signal of the bearing. The audio is filtered through the filtering band derived by the Kurstogram because spectral kurtosis is higher for impulsive signals and zero for white noises since localized faults are impulsive.

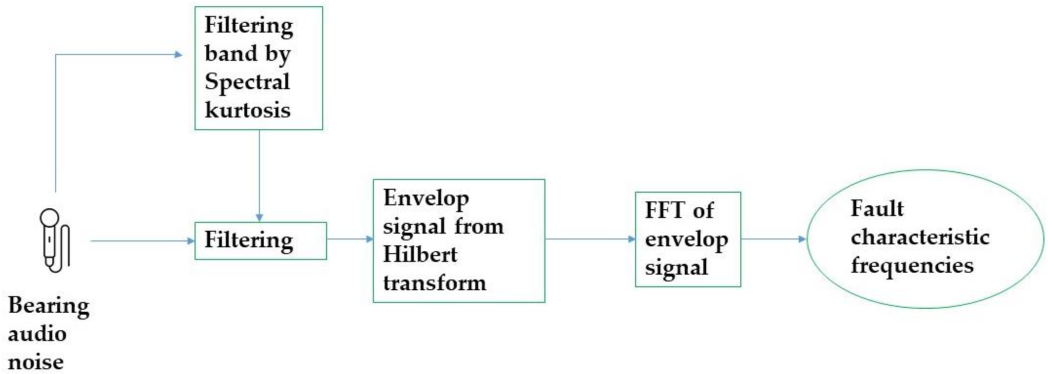

Figure 3. Method for localized faults

Since the localized faults are amplitude modulated, Kurstogram is used to find out the carrier frequency band of AM fault signal. Then, the analytical signal of Hilbert transform of the filtered signal is derived to get envelop of fault signal. Since localized faults are AM the FFT of the envelope signal gives the fault frequencies of the rolling bearing. The filtering process expects not only the isolation of the impulsive bearing noise signal but also the elimination of other background noises. Moreover, the effect of enveloping the filtered signal also aids to eliminate background noises with high frequency and low amplitude.

Distributed / Generalized Roughness Faults

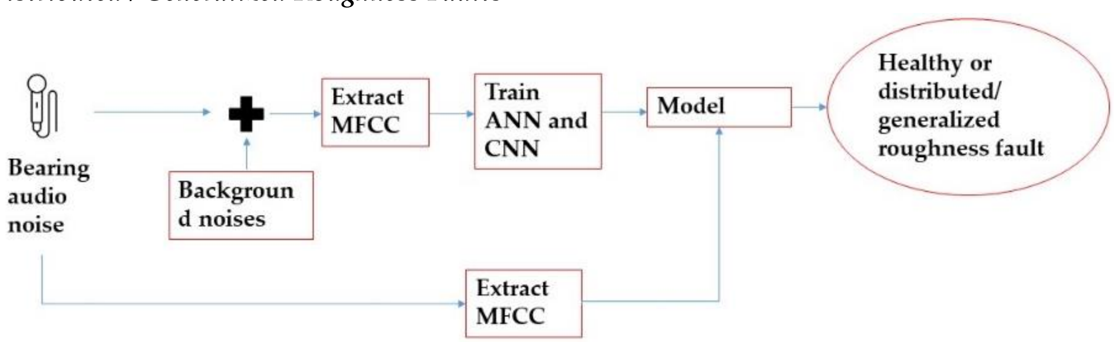

Figure 4. Method for distributed/ generalized roughness faults

Figure 4 shows the proposed method to diagnose distributed / generalized roughness faults. Mel Frequency Cepstral Coefficient (MFCC) feature of bearing noise of distributed/ generalized roughness faulty bearing and healthy bearing are used to train the ANN and CNN. Audio samples with and without industrial background noises are used to train the model to generalize the model to be robust for unseen background noises.

Experimental Setup

Figure 5. Experimental setup of frequency monitoring

The dataset of bearing noises was obtained by a custom-made experimental setup as shown in Figure 5. There, a 0.5Hp motor was used to turn the bearing at different speeds. The experimental setup allowed to take readings from different types of bearings. Deep groove ball bearing (6205E) and needle roller bearing (25 38 15 CS) were turned at 1420 RPM and 1445 RPM and the bearing noise signals were recorded by "Ipad-7th gen" at about 10cm distance from bearing for a duration of each of the 60s at 22050 Hz sampling frequency. Here microphone of the iPad is selected rather than a commercial one to be a low-cost solution. However, characteristics of the iPad's microphone such as the omnidirectional, short range of frequency response, unflatten frequency response, and sensitivity would be the limitation [42]. The speed of the motor was measured by a DM6236 digital tachometer.

Results and Discussion

Some analyzed bearings are named as follows for ease of explanation.

- Bearing-1: Healthy deep groove ball bearing
- Bearing-2: Generalized roughness faulty deep groove ball bearing
- Bearing-3: Generalized roughness faulty deep groove ball bearing
- Bearing-4: Generalized roughness faulty needle roller bearing

The noise signals from healthy and faulty deep groove ball bearings (25 38 15 CS) turned by the experimental setup discussed in section 3 were analyzed using FFT. As shown in Figure 6,7,8, healthy and faulty bearings could be distinguished when there is no external noise in the field. Coming into the point, when the bearing is diagnosed in the industry, there is always different kind of noises. It was not possible to observe any fault-specific frequency component because important information related to the state of the bearing noise signal is mixed up with background noises. Therefore, the proposed methods for both localized faults and distributed/ generalized roughness faults have been analyzed as follows.

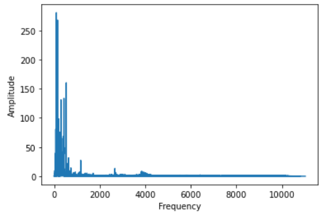

Figure 6. FFT of healthy bearing-1 noise signal

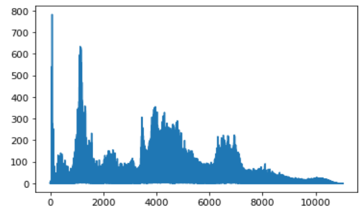

Figure 7. FFT of Faulty bearing-2 noise signal

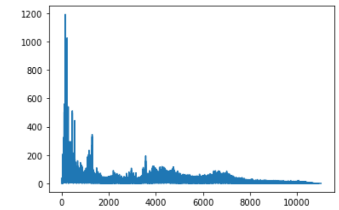

Figure 8. FFT of faulty bearing-2 noise signal with industrial background noise signal

Localized Fault

The noises of the bearing were recorded each for the 60s by the experimental setup as discussed in section 3 and its processing as stated in section 2.1 is carried out by MATLAB, which is a dedicated software used in many engineering applications.

The Same Type of Different Bearing

The misalignment was adjusted in the experimental setup to get the effect of misalignment in the deep groove ball bearing. The bearing noise signals were recorded when two same types of bearings were turned

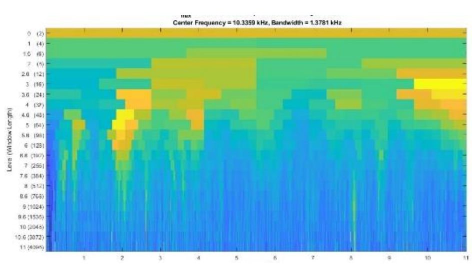

Figure 9. Kurstogram of noise of bearing-2 @ 1400RPM

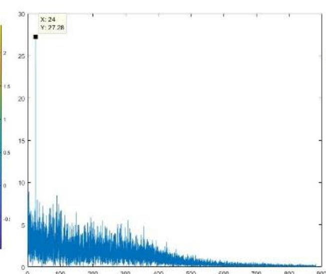

Figure 10. FFT of envelop of bearing-2 @ 1400RPM

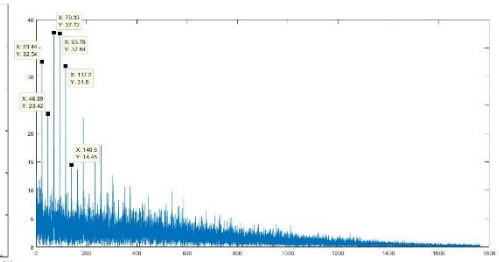

Figure 11. FFT of envelop of bearing-3 @1420

at 1400 RPM and 1420 RPM with misalignment. Figure 9 shows the Kurstogram of bearing-2 turning at 1400 RPM and the filtering band is derived by the Kurstogram of that bearing-2 as the center frequency of 10.34 kHz and bandwidth of 1.38 kHz. The bearing noise signals of bearing-2 and bearing-3 were filtered by the same filtering band derived from the Kurstogram of the noise signal of bearing-2. Even though the filtering band is defined by the Kurstogram of the noise signal of bearing-2, it was possible to get the expected frequency hike representing misalignment not only for the noise signal of bearing-2 (1400 RPM /60 = 23.33 Hz) but also for noise signal of bearing-3 (1420 RPM /60 = 23.66 Hz) using filtering band defined by Kurstogram of noise signal of bearing-2 since bearing-2 and bearing-3 are the same types. Therefore, if a filtering band is known for a specific type of bearing it can be used to diagnose any same type of bearing using this proposed method.

Bearing at Different Speeds

The misalignment was adjusted in the experimental setup to get the effect of misalignment in the needle bearing. Figure 12 shows the Kurstogram of the noise of needle bearing turning at 1445 RPM and the filtering band is derived by the Kurstogram of that needle bearing as the center frequency of 16.14 kHz and bandwidth of 114.84 Hz. The bearing noise signals of bearing turning at 1445 RPM and 1420 RPM were filtered by the same filtering band derived from the Kurstogram of noise signal of bearing turning at 1445 RPM. Even though the filtering band is defined by the Kurstogram of the noise signal of bearing turning at 1445 RPM it was possible to get the expected frequency hike representing misalignment not only for the noise signal of bearing turning at 1445 RPM (1445 RPM /60 = 24 Hz) but also for noise signal of bearing turning at 1420 RPM (1420 RPM /60 = 23.66 Hz) using filtering band defined by Kurstogram of noise signal of bearing turning at 1445 RPM. Therefore, if the filtering band is known for a bearing at any RPM it can be used to diagnose bearing turning at any speed using this proposed method.

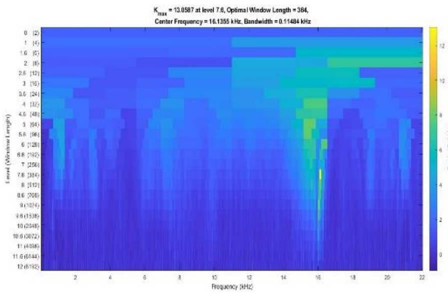

Figure 12. Kurstogram of bearing-4 @ 1445RPM

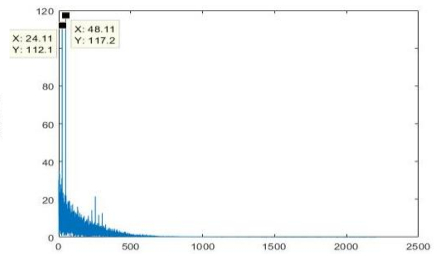

Figure 13. FFT of envelop of bearing-4 @ 1445RPM

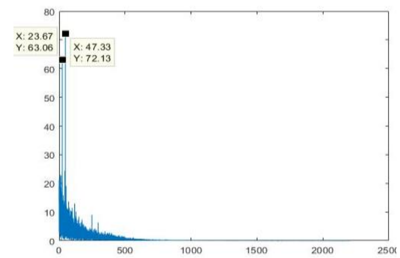

Figure 14. FFT of envelop of bearing-4 @ 1420RPM

Distributed / Generalized Roughness Fault

The MFCC feature of faulty bearing noises with and without different industrial background noises was extracted and the extracted MFCC are shown in figures 15, 16, 17. Thirteen coefficients were extracted using the window length of 2048 and hop length of 512.

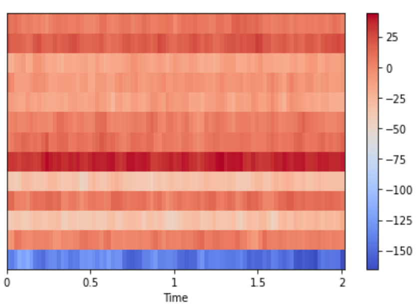

Figure 15. MFCC of noise of faulty bearing-2

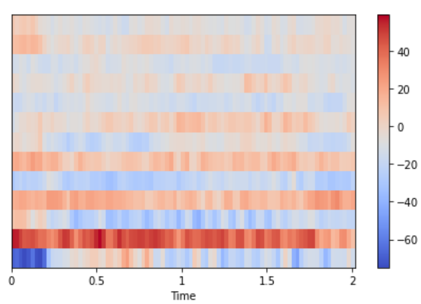

Figure 16. MFCC of noise of bearing-2 with industrial background noise type-1

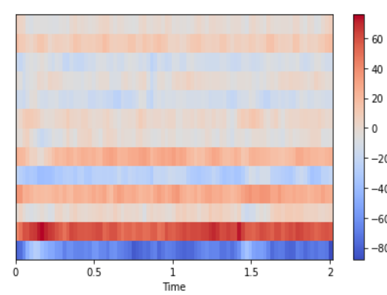

Figure 17. MFCC of noise of bearing-2 with industrial background noise type-2

These results show that it is not possible to observe and grab the information on whether the bearing has distributed /generalized roughness fault because of the background noises. Therefore, ANN and CNN are trained using the MFCCs extracted from the bearing having distributed /generalized roughness fault and healthy bearing. ANN and CNN were trained using both pure bearing noise signals and bearing noise signals mixed up with various industrial background noises such as tire manufacturing, lathe machine operation, arc welding, and milling machine operation. Table 1 shows the dataset used to train the ANN and CNN.

Table 1. Dataset for distributed/ generalized roughness fault

Bearing type	Number of bearing	Duration (s)	Number of segments
Healthy deep groove ball bearing	2	60	30
Faulty deep groove ball bearing	2	60	30
Healthy needle bearing	2	60	30
Faulty needle bearing	2	60	30

The bearing noise signals recorded for 60 s were segmented into 30 segments to increase the number of samples. The ANN was implemented as in table 2 and ANN was trained using Adam optimizers with a 0.2 learning rate.

Table 2. Parameters of ANN

Layer	Number of neurons	Activation function
Flatten layer (input)	1118 (86 x 13)	Relu
Dense layer (hidden)	512	Relu
Dense layer (hidden)	256	Relu
Dense layer (hidden)	64	Relu
Dense layer (output)	2	Softmax

The dataset was divided into training and validation at the ratio of 6:4. Figure 18 shows the training and validation accuracy of the ANN with epochs. More than 90 % of validation accuracy was got after ten epochs when using ANN.

Table 3. Parameters of CNN

Layer type	Number of kernel / neurons	Pooling	Activation function
Conv2D	32 kernel	Maxpooling2D	Relu
Conv2D	32 kernel	Maxpooling2D	Relu
Conv2D	32 kernel	Maxpooling2D	Relu
Flatten and Dense	64 neurons	-	Relu
Dense	2 neurons	-	Softmax

Table 3 shows the implemented model's parameters of the CNN. The CNN also trained using the same dataset divided into training and validation as the ratio of 6:4. Figure 19 shows the training and validation error and accuracy of trained CNN and more than 90 % of validation accuracy was got after ten epochs.

The results of this study are enough to be comparable with other studies based on the standard methods such as vibration, acoustic emission, given that the experimental conditions are different. In [20] [21] [22], localized faults are classified based on the vibration measurement using machine learning algorithms sequentially using CNN with 98.6 %, DS evidence theory-based fusion model with 94 %, and SVM with

81 %. There is a study that classifies the degree of distributed faults such as lightly damaged, heavily damaged, and healthy bearing based on acoustic emission, vibration, stator current signals, and high-frequency bearings pulses, and an average of 93.33 % accuracy could be obtained [43]. In this study, more than 90 % accuracy was obtained. Therefore, it is possible to classify healthy or faulty bearing based on the noise signal of the bearing with confidence comparability with standard techniques.

Even though the proposed method for fault diagnosis of rolling bearing using bearing's noise signal has many advantages such as non-contacts to the machine, easy to install, and low cost, this method has a major weakness in that they can be mixed up with background noise easily which has a significant effect on the accuracy. Some methods can lessen the effect of background noise, like noise dampening enclosures [13]. The low-cost microphone with low sensitivity is not able to detect minor acoustic signals from bearings due to the lubrication layer and the clearance between the rolling element and inner and outer races. It would be great if vibration measurement via a low-cost vibration sensor and the bearing's noise signal is fused to diagnose bearing faults in future work. It is recommended to experiment and analyze the feasibility of the bearing's noise signal to diagnose other localized fault types such as inner race fault, outer race fault, and rolling element fault.

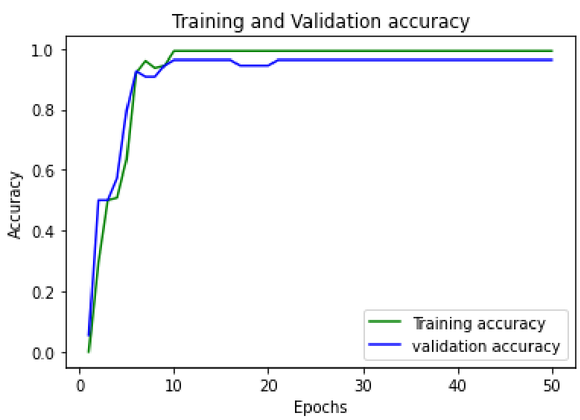

Figure 18 . Accuracy of ANN

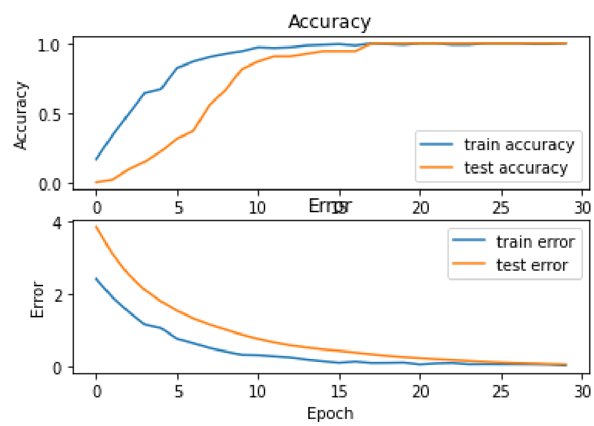

Figure 19. Accuracy and error of CNN

Conclusion

Fault diagnosis of the rolling bearing by noise signal of the bearing is evaluated. Localized faults especially misalignment was diagnosed using envelop spectral analysis and it yields expected frequency hikes representing misalignment. Kurstogram is used to find the appropriate filtering band and the Hilbert transform is used to extract envelop of the filtered noise signal. It could be observed that the MFFC feature of the bearing noise signal is not enough to distinguish between healthy bearing and faulty bearing by just observing the MFCC feature of the bearing noise signal. Bearing with distributed / generalized roughness faults and healthy bearing are distinguished by ANN and CNN using the MFCC features of noise signal of the bearing with and without various industrial background noises and the validation accuracy was obtained at more than 90% for both ANN and CNN.

Conflicts of Interest

The authors declare no conflict of interest

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