Fault Detection and Diagnosis of Rolling Element Bearing based on Neural Network

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ABSTRACT

In this paper, a neural network based diagnosis technique is developed to detect fault and estimate the severity of the spalls at the inner race, outer race, roller and cage. To this end, a bearing test rig is developed, in which the normal and faulted bearings with differing spall size at different locations are operated under accelerated loading conditions. Features are extracted from the bearings, which include the time-based indicators such as RMS, peak, crest and kurtosis, frequency based indicators obtained by envelope analysis, and time-frequency based ones like wavelet decomposition. Neural network model is constructed using the features for the classification. The model is then applied to diagnose the fault in the new bearings, which includes the identification of the fault and severity. Particular attention is made to the study of statistical significance to check the validity of the model.

1. INTRODUCTION

Bearing is one of the most important components in rotating machineries. Its failure leads to catastrophic accidents and industrial down-time. de Azevedo (2016) reported that about 50% of faults on gearboxes was because of bearing defects. To overcome this problems, prognostics and health management (PHM) technologies which diagnosis the health condition of machine system and predict its remaining useful life gets a lot of attention. PHM consists of three stages; Data acquisition, diagnostics, and prognostics. In the first stage, data is acquired through the sensor which is attached to the machine system. Then a feature which reflects the current health condition is extracted via signal processing. In the stage of diagnostics, fault isolation, fault identification, and classification is carried out. Final stage is the prognostics which predicts the remaining useful life of the system. To accomplish the accurate prognostics, diagnostics should be made properly. Many studies have been performed in the field of bearing diagnostics. Randall (2011) introduced the tutorial for bearing diagnostics with various signal processing method with envelope analysis representatively. Siew (2015) established a correlation between the vibration signal and the actual extent of bearing fault propagation. Samanta (2003) proposed procedure which requires only a few features extracted from the measured vibration data either directly or with simple preprocessing. Then the bearing fault is diagnosed through the trained artificial neural network. In the field of bearing diagnostics, both early fault detection and accurate fault diagnostics are crucial. In this study, a bearing test rig is prepared, faults are imbedded to the inner and outer race of the roller bearing, the vibrations are measured from the sensor, and the types and the severities of the fault are identified via the proper features extraction and applying the artificial neural network.

2. BEARING TEST RIG

The bearing test rig used for this paper is shown in Figure 1. The bearing is roller bearing with model NJ 2306 and its specification is listed in Table 1. Data is acquired through accelerometer attached to the test bearing housing.

Figure 1. Bearing test rig

Bearing typically has four failure modes; outer race fault, inner race fault, cage fault and rolling element fault. Lessmeier (2016) suggested that the inner race damages are more likely to occur because of the higher Hertzian stress but is not as easy to detect as the outer race damage. Based on

Table 1. NJ2306 bearing specification

Roller Bearing (NJ2306)	
Inner Diameter	30 mm
Outer Diameter	72 mm
Width	27 mm
Dynamic load rating	51.5 kN
Static load rating	51 kN

this suggestion this paper has focused on the inner race defect. The basic bearing diagnostics procedure is shown in Figure 2. The inner race fault is induced artificially using the electric discharge machining. Bearings with artificially imbedded fault with different severity are prepared, which are normal, 0.3mm, 0.5mm, 0.6mm and 1.0mm of spall width as shown in Figure 3.

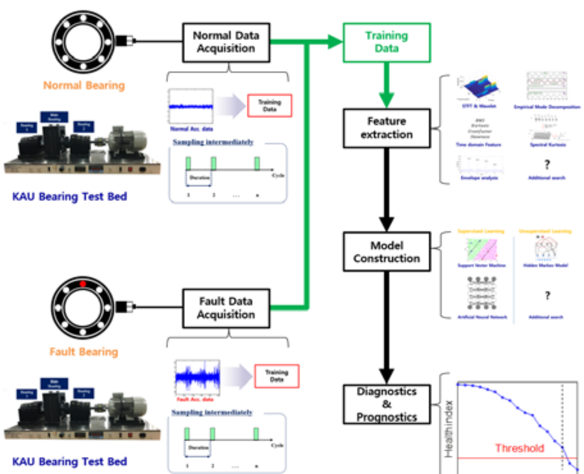


Figure 2. Bearing diagnostics flow chart

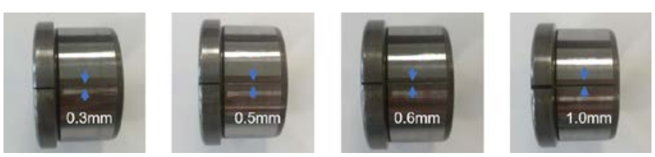
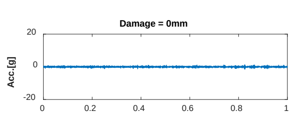


Figure 3. Bearings with imbedded fault

3. DATA ACQUISITION

Test was conducted with 400kgf vertical load and 1200 rpm. Vibration data was sampled with 51.2kHz. 50 data for each bearing was obtained, and 250 data set are made in total. Figure 4 shows one of the data sets of the vibration signal for bearings with 5 severities.



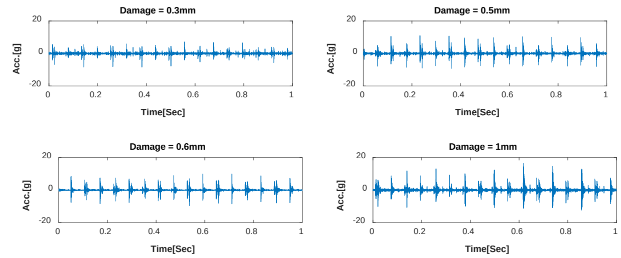


Figure 4. Vibration signal of bearings with different fault size

4. FEATURE EXTRACTION

Feature extraction is the most important stage for PHM. To accomplish the accurate diagnostics and prognostics performance, high quality features should be extracted. In this study, various time-domain features and frequency-domain features are used. In the time-domain, statistical measure such as RMS, Peak, Kurtosis, Crest factor are taken. In the frequency-domain, envelope analysis which is widely used for bearing diagnostics is used and amplitudes at the bearing defect frequencies are employed. In the time-frequency features, the energy values of coefficients at each nodes after going through the wavelet transform are introduced. After all, the number of features employed in this study is 21.

Table 2. Table of features

Index	Time	Frequency	Time-frequency
1	RMS	BPFO	WPD1
2	Kurtosis	BPFI	WPD2
3	Variance	BFF	WPD3
4	Crest factor	FTF	WPD4
5	Max		WPD5
6	Entropy		WPD6
7	Residual energy		WPD7
8	Residual RMS		WPD8
9	Residual kurtosis		

5. ARTIFICIAL NEURAL NETWORK

To accomplish accurate bearing diagnostic and classification, it is necessary to construct classification models and validate its accuracy. In this study, artificial neural network is employed to construct two classification model. Artificial neural network is widely used machine learning algorithms in the field of speech recognition, classification etc. The architecture of neural network is illustrated in Figure 5. The model is then applied to diagnose the fault in the new bearings, which includes the identification of the fault and its severity.

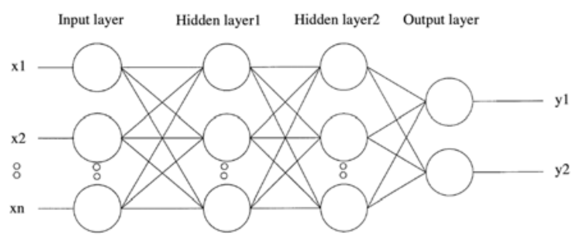
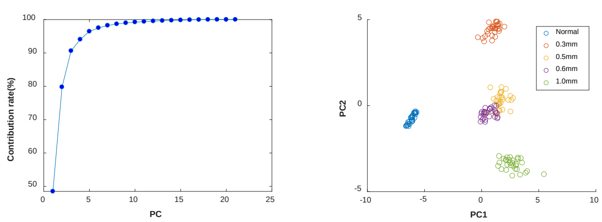


Figure 5. Architecture of neural network

6. DIAGNOSTICS BASED ON NEURAL NETWORK

In the feature extraction stage, principal components analysis (PCA) is applied to the 21 features for the dimension reduction. As shown in the Figure 6, which is the contribution plot, 8 principal components account for more than 95% of the data variability. These 8 components are used for the input data of neural network. The figure 6(b) shows the scattered data plot of the two biggest components PC1 and PC2 for the five fault classes.



(a) (b)

Figure 6. PCA result

To evaluate the model accuracy, among 250 data set, 200 data are considered as training set and rest of them are used for test data set. As a result, constructed neural network model shows 94% accuracy for test data as shown in Figure 7.

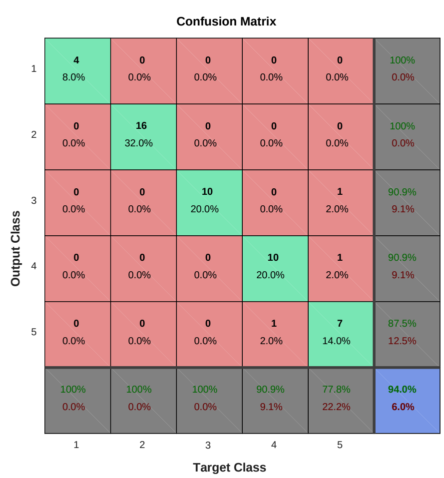


Figure 7. Confusion matrix

7. CONCLUSION

This paper has proposed a method for bearing diagnostics based on the fault severity. For this purpose, various classification models and machine learning algorithms are employed. However, the study did not consider two main things: First, the analysis was made on the artificially induced fault. Naturally induced damage will show different behavior from the ones by artificially damage. Second, only the inner race fault was considered. As mentioned above, bearing has four failure modes. For accurate diagnostics, health index that can identify these failure modes should be developed. These two main subjects will be explored in future and presented in the conference.

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