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# Clustering of frequency spectrums from different bearing fault using principle component analysis

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**Abstract.** In studies associated with the defect in rolling element bearing, signal clustering are one of the popular approach taken in attempt to identify the type of defect. However, the noise interruption are one of the major issues which affect the degree of effectiveness of the applied clustering method. In this paper, the application of principle component analysis (PCA) as a pre-processing method for hierarchical clustering analysis on the frequency spectrum of the vibration signal was proposed. To achieve the aim, the vibration signal was acquired from the operating bearings with different condition and speed. In the next stage, the principle component analysis was applied to the frequency spectrums of the acquired signals for pattern recognition purpose. Meanwhile the mahalanobis distance model was used to cluster the result from PCA. According to the results, it was found that the change in amplitude at the respective fundamental frequencies can be detected as a result from the application of PCA. Meanwhile, the application of mahalanobis distance was found to be suitable for clustering the results from principle component analysis. Uniquely, it was discovered that the spectrums from healthy and inner race defect bearing can be clearly distinguished from each other even though the change in amplitude pattern for inner race defect frequency spectrum was too small compared to the healthy one. In this work, it was demonstrated that the use of principle component analysis could sensitively detect the change in the pattern of the frequency spectrums. Likewise, the implementation of mahalanobis distance model for clustering purpose was found to be significant for bearing defect identification.

## 1 Introduction

In any rotating machineries, rolling element bearing is important in which it is functioning as both thrust and radial load bearer. Without bearing, the rotating shaft will be exposed to an excessive vibration which later on led to the fatigue damage. Basically, an abrupt bearing failure will precipitate massive impact to the maintenance and operational cost. Therefore, it is greatly essential to make sure that the bearing is consistently in pristine

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condition while it is operating. Besides, early bearing fault detection is vital in order to prevent the failure as well as reduced the loss.

In industries, various technique can be applied for the purpose of bearing condition monitoring, and one of the common technique is vibration analysis [1, 2]. In simple cases, the vibration behavior of rolling element bearing can be analytically predicted. However, in more compounded system, vibration produced by rolling element bearing can be complex as a result from geometrical imperfection during manufacturing process, component instability as well as defect itself [3]. Apart from that, the other excitation frequency from other component or other unidentified sources might also affecting the vibration behavior. Consequently, the vibration signal produced are random and it is difficult to detect the damage-related component. Since the past several decades, the feature extraction analysis and classification technique was widely used as an approach in attempt to address on this issue. In general, the major aims of feature extraction analysis is to extract the hidden signal features among the complex signal that could lead to the detection of damage occurrence in the system that was monitored. Basically, on one hand, the feature was extracted directly from the acquired signal by determining its statistical parameter [4-7] and fundamental frequencies [3, 8] parameters. Meanwhile, on the other hand, the decomposition method such as wavelet analysis [9-12], and empirical mode decomposition [13-15] was applied before the feature is determined. The idea of decomposing the signal is to filter out all the non-related signal component which was initiated from both unidentified and unrelated sources during bearing operation.

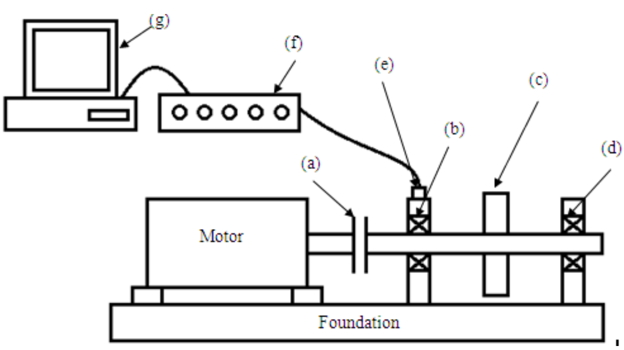
In industrial application, it is important to identify the damage in order to assess it's fitness for service. This is vital for the purpose of maintenance planning and that is the main reason why online monitoring system is needed at the first place. Basically, for damage identification purpose, several classification technique have been applied to the extracted features. This includes, Discriminative Subspace Learning [16], Hierarchical Diagnosis Network [17], Support Vector Machine [18, 19], Extreme Learning Machine [20], and artifial neural network [21]. Despite the wide exploration on the feature extraction and classification techniques, the unavoidable problems such as low signal-to-noise ratio due to the nonlinearity of the signal still becomes a major challenge even though wide variation of feature extraction approach was taken to overcome these problems.

In this paper, the application of principle component analysis (PCA) as a pre-processing method for hierarchical clustering analysis on the frequency spectrum of the vibration signal was proposed. In common approach, PCA was implies to reduce the dimension of the complex signal before the features associated with the presence of defect was detected [22]. However, in this work, PCA was applied to identify the change in frequency spectrum pattern due to the basis that the amplitude of fundamental frequency will changed with the existence of defect. In this study, the vibration signal was acquired from the operating bearings with different condition and speed. In the beginning part, the response of vibration amplitude at the respective fundamental frequencies with the occurrence of damage will be discussed. On the next stage, the application of principle component analysis as feature extraction method and hierarchical clustering as damage identification analysis will be demonstrated.

# 2 Methodology

## 2.1 Experimental setup

The test rig for this experiment was designed to investigate failure and vibration characteristic of ball bearings. As illustrated in Figure 1, in this experiment, the shaft was driven by a variable-speed 0.37kW, 50Hz electric motor equipped with a controller in order to control the speed of the motor. A flywheel is installed at the middle of the spindle in order to apply load to the shaft and at the same time minimizing the speed oscillations of the shaft. A spring coupling was used to connect the motor and shaft to minimize shaft alignment error. The front side of the shaft (near to the motor) is fitted with tested bearing and the vibration response will be measured here while on the other side, a good bearing was fitted. In this study, a set of good bearings and another three bearings with different type of defect such as corroded, point defect and outer race defect were tested. The angular speed is set to 10%, 50% and 90% of the maximum motor speed, and shortly after the test commenced, the time response of vibration were acquired by using the Bruel & Kjær (B&K) 4506B accelerometer. The time series of vibration (acceleration) response was acquired with the sampling frequency of 20 kHz ($\Delta t = 0.039$ ms).




| No | Part/Component |
|---|---|
| a | Spring coupling |
| b | Tested bearing |
| c | Flywheel |
| d | Supporting bearing |
| e | Accelerometer |
| f | DAQ |
| g | Analyzer |

**Fig. 1**. Experiment setup.

## 2.2 Frequency spectrum clustering

In this work, 16 signals from healthy, corroded and outer race defect was selected for clustering analysis together with 12 signals from point defect bearing. Before starts the clustering process, the acquired time domain response from different types of bearings was converted into frequency spectrum through the Fast Fourier Transform (FFT) analysis. Direct observation on peak pattern at the respective fundamental frequency were made to identify the damage. Basically the fundamental frequencies were calculated based on the equation from [3]. Even though the fundamental frequency could be observed, it is important to reveal the different in structure of all the collected frequency spectrums from different bearing conditions because in some cases, the change in pattern is too small to be observed. To achieve the aims, the principle component analysis was applied. Basically, the principle component analysis implies the eigenvalue decomposition on the covariance matrix of the multiple dataset. In this work, one frequency spectrum was considered as one dataset contained $n$ number of samples. Moreover, all the dataset was normalized by its mean value before the covariance matrix was attained. In general, the PCA process could be represent in matrix operation as shown by [23] in equation 1 to 3 whereas in equation 3, $\gamma$ and $\vec{v}$ are the eigenvalue and eigenvector (principle component) respectively

$$[X] = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

$$[C_X] = [X].[X]^T \tag{2}$$

$$[C_X].\vec{v} = \gamma.\vec{v} \tag{3}$$

Basically, the result from PCA will be represented in scatter plot to show how the numerous dataset scattered based on its pattern. To classify this numerous dataset, the hierarchical clustering approach was taken in which the distance between dataset will be measured prior to clustering process. In this work, the mahalanobis model as shown in equation 4 [24] was selected for a distance measurement due to the nature of principle components which will scattered in oval shapes when the datasets is strongly related [25].

$$d_{mahalanobis}(x, y) = \sqrt{(x-y)C^{-1}(x-y)^T} \tag{4}$$

## 3 Results and discussion

### 3.1 Frequency spectrums

In this paper, due to the same result's pattern for all rotational speed, only the result from the test with rational speed of 287 rpm was presented. As explained earlier, the time series of the vibration signal acquired from the rolling element bearings with different condition is converted into frequency domain signal and these signal were illustrated in Figure 2. Meanwhile its theoretical fundamental frequency was shown in Table 1. Based from the Figure 2, it was clear that the ball spin frequency, BSF, and the ball passing frequency outer race, BPFO are obviously appear in frequency spectrum of healthy as well as defect bearings. In contrast, the ball pass frequency inner race, BPFI are barely unseen in the frequency spectrums of the corroded bearings in which the opposite trend had been shown in the frequency spectrums of other types of bearing.

From the deeper observation, it was found that high amplitude of acceleration occur at BPFO for outer race defect bearing. In conjunction with that, among all the frequency spectrums from healthy and defects bearings, the amplitude of acceleration was higher at BPFI for point defect bearing. Based from this results, it was confirmed that the presence of specific defect will increase the amplitude of vibration at the specific fundamental frequencies. Previous findings [8] also have proven these phenomena accordingly. In contrast, the spectrums of corroded bearings shows high amplitude values for all fundamental frequencies. This is probably due to the uniform behavior of the defect itself.

**Table 1.** Fundamental Frequency of Rolling Element Bearing which rotates at 287 rpm.

| Fundamental Frequency | Value (Hz) |
|---|---|
| Ball Passing Frequency Outer Race, BPFO | 13.65 |
| Ball Passing Frequency Inner Race, BPFI | 24.58 |
| Fundamental Train Frequency, FTF | 1.707 |
| Ball Spin Frequency, BSF | 1.67 |

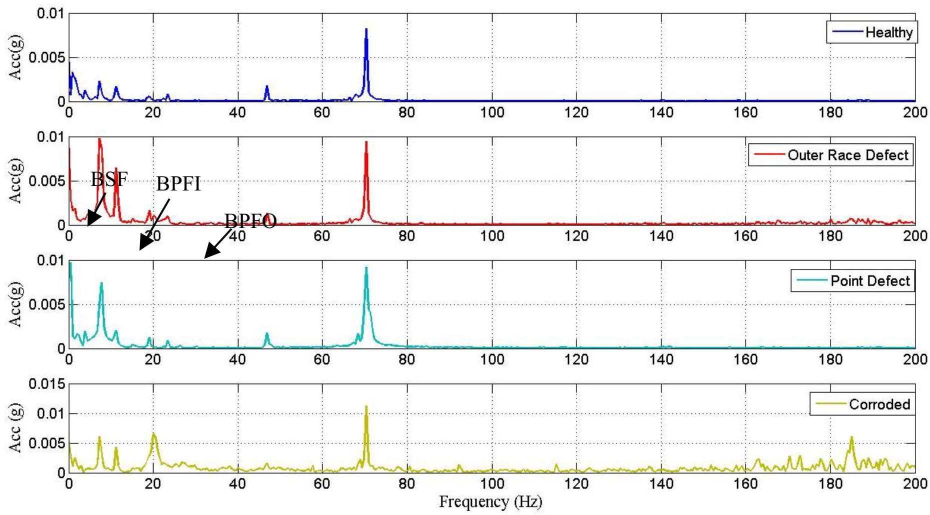
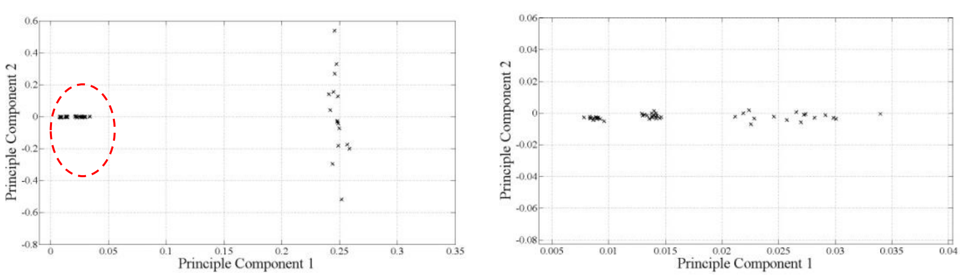



**Fig. 2**. Frequency spectrum for bearings that rotates 287 rpm.

### 3.2 Frequency signal classification

As discussed in the previous section, it is clear that the frequency spectrum from each of the bearing condition showed a significant different in its structure. To represent cluster all of these spectrums, the principle component analysis was applied to a set of frequency spectrums which consists of healthy, point defect, outer race defect and corroded bearings and the results was shown in Fig. 3. Fig. 3(a) illustrates the overall scatter plot of principle component 1 and principle component 2 while Fig. 3(b) shows the zoomed part. According to the result in both sub-figures, it was found that the principle components (PC) of frequency spectrums was scattered into four different groups. However, the scattered data form a group or population in ellipsoidal shape. This scatter trend occurs due to the similarities in the patterns of the tested dataset [26]. In other words, it is strongly believed that each ellipsoidal-shape scattered dataset is belonging to the same group of bearing types.




(a) (b)

**Fig. 3.** Classification of frequency spectrum from different bearing condition using principle component analysis (a) Overall (b) Zoomed part

To confirm the claims, clustering process in needed in which for this process, the mahalanobis distance had been calculated in order to cluster the PCs from different type of bearings. The clustering result was shown in dendrogram plot in Fig 4. According to the figures, based on mahalanobis distance, it was clear that the data have been regrouped in four major cluster. Yet, the dataset 49 and 54 was identified to be outliers. Table 2 was shown to simplify the representation of the dendrogram. As referred to the table, those dataset which belongs to corroded, outer race defect, healthy and point defect was registered to be in cluster 1, 2, 3, and 4 respectively. Meanwhile, two dataset which belongs to corroded bearing was found to be as outliers.

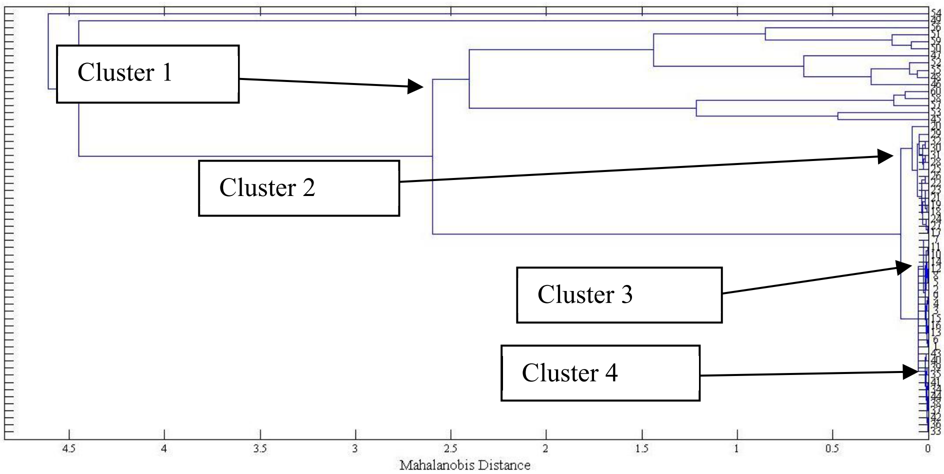



**Fig. 4**. Dendrogram plot of principle component 1 and 2.

**Table 2.** Clustering result.

| **Cluster 1** | | **Cluster 2** | | **Cluster 3** | | **Cluster 4** | | **Outliers** | |
|---|---|---|---|---|---|---|---|---|---|
| **Signal No** | **Bearing Type** | **Signal No** | **Bearing Type** | **Signal No** | **Bearing Type** | **Signal No** | **Bearing Type** | **Signal No** | **Bearing Type** |
| 56 | Corroded | 20 | Outer Race Defect | 7 | Healthy | 43 | Point Defect | 54 | Corroded |
| 51 | Corroded | 29 | Outer Race Defect | 11 | Healthy | 40 | Point Defect | 49 | Corroded |
| 59 | Corroded | 32 | Outer Race Defect | 10 | Healthy | 39 | Point Defect | | |
| 50 | Corroded | 30 | Outer Race Defect | 14 | Healthy | 35 | Point Defect | | |
| 47 | Corroded | 31 | Outer Race Defect | 12 | Healthy | 41 | Point Defect | | |
| 52 | Corroded | 28 | Outer Race Defect | 8 | Healthy | 34 | Point Defect | | |
| 55 | Corroded | 25 | Outer Race Defect | 5 | Healthy | 44 | Point Defect | | |
| 48 | Corroded | 26 | Outer Race Defect | 2 | Healthy | 38 | Point Defect | | |
| 46 | Corroded | 22 | Outer Race Defect | 9 | Healthy | 37 | Point Defect | | |
| 60 | Corroded | 23 | Outer Race Defect | 4 | Healthy | 42 | Point Defect | | |
| 58 | Corroded | 21 | Outer Race Defect | 3 | Healthy | 36 | Point Defect | | |
| 57 | Corroded | 19 | Outer Race Defect | 15 | Healthy | 33 | Point Defect | | |
| 53 | Corroded | 18 | Outer Race Defect | 16 | Healthy | | | | |
| 45 | Corroded | 24 | Outer Race Defect | 13 | Healthy | | | | |
| | | 27 | Outer Race Defect | 6 | Healthy | | | | |
| | | 17 | Outer Race Defect | 1 | Healthy | | | | |

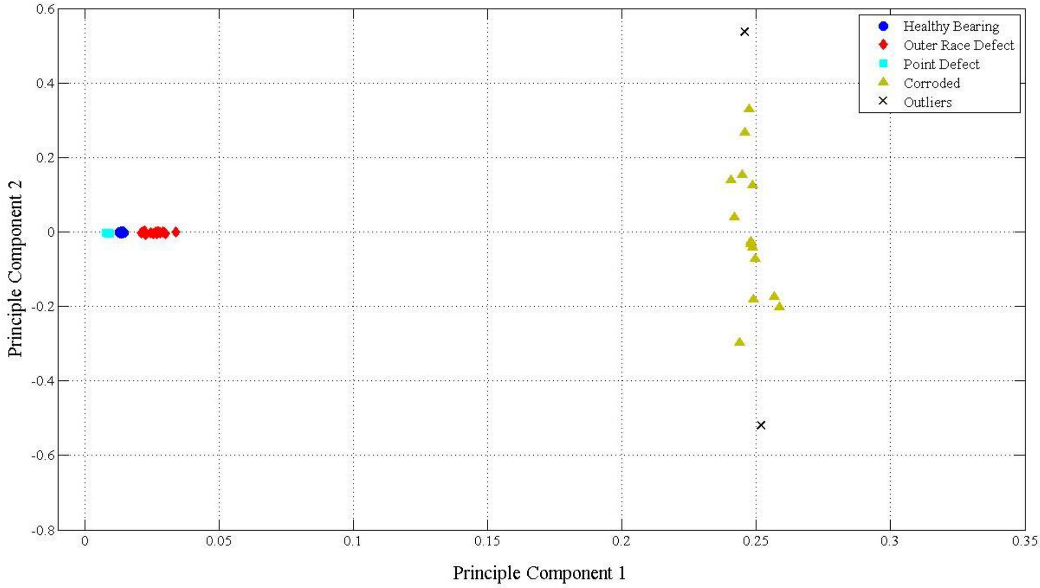



**Fig. 5.** Principle Components scatter plot with cluster group.

## 4 Conclusions

According to the results, it was found that the amplitude of vibration at Ball Passing Frequency Outer Race and Ball Passing Frequency Inner Race will increase in align with the presence of outer race defect and inner race defect respectively. Moreover, the overall amplitude of vibration spectrum was found to be uniformly increased for the case of corroded bearing due to the widespread uniform corrosion on the entire bearing. By applying principle component analysis, the change in amplitude at any of these fundamental frequencies can be detected. Meanwhile, the application of mahalanobis distance was found to be suitable for clustering the results from principle component analysis. Uniquely, it was discovered that the spectrums from healthy and inner race defect bearing can be clearly distinguished from each other even though the change in amplitude pattern for inner race defect frequency spectrum was too small compared to the healthy one. To draw the conclusion, it was demonstrated that the use of principle component analysis could sensitively detect the change in the pattern of the frequency spectrums. This was believe to give more option to detect the damage from the change in signal pattern apart from decomposing it. Likewise, the implementation of mahalanobis distance model for clustering purpose was found to be significant for bearing defect identification.

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