A Data-driven fault diagnosis and pattern classification approach of rotational machinery

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Abstract

The major concerns of a rotating machinery in industry are the reliability, safety, efficiency, and performance. The goal of health monitoring and fault diagnosis of rotating machinery is important. However, it is often labour intensive and cumbersome. For reliably diagnosing rotating machinery faults, effective and powerful feature extraction techniques are crucial. There are various vibration feature extraction methods and several pattern classification approaches for different types of rotating machinery. The main contribution of this paper is to accurately extract a fault feature from a set of vibration signals for the reason of fault diagnosis of rotating machinery. Then, fault features which represents a machine condition are then classified based on both a simple classifier called K-Nearest Neighbour. Finally, an improved approach known as K-mean clustering classifier is proposed to better classify the fault feature. To verify the effectiveness of the proposed method, a vibration datasets from an experimental benchmark rotational machine are tested and utilized.

KEYWORDS
Fault diagnosis, feature extraction, rotational machinery, pattern recognition, health monitoring, improved signal processing, nearest neighbor, K-mean clustering.

1. Introduction

Because of the increasing demand for higher performance as well as for increased safety and reliability of dynamic systems, fault diagnosis has been becoming more important for machine monitoring. Early diagnosis of machine faults while the machine is still operating in a controllable region can help to avoid abnormal event progression, which in turn can help to avoid major system breakdowns and catastrophes.

One of the most common applications of condition monitoring is fault diagnosis of electrical machines [5]. Even though motor current analysis has been widely utilised for electric machines, vibration monitoring is also accepted for diagnosis of faults in these machines [6]. Vibration monitoring of electrical machines has become an attractive field for many researchers and has also gained industrial acceptance, since it is related to almost all machinery failures and it does not require modification of the machine or access to the supply lines [8]. There are several fault types, mechanical and electrical, which can induce undesired vibration levels in electrical machines, such as misalignment, broken rotor bar, gear tooth wear, imbalance, resonance, stator winding faults and bearing failures [6].

Vibration signals collected from sensors and then processed are often contaminated by some noise and can thus be unusable for directly diagnosing machine faults. Features (also called characteristics and signatures) can go undetected without the assistance of certain techniques. Feature extraction techniques can either increase signal to noise ratio or locate certain components in signals to assist detection of machine faults. Numerous vibration techniques have been applied to the fault diagnosis of rotating machinery. Generally vibration techniques range from statistical to model based techniques, and comprise various signal processing algorithms to extract useful diagnostic information from measured vibration signals. In the past twenty years, some research has been conducted into reviewing vibration techniques from different points of view. In the1980's, Mathew and Alfredson presented a review of vibration monitoring techniques in the time and frequency domains for rolling element bearings [5]. McFadden, Smith [7] and Kim [8] included classical non-parametric spectral analysis, principal component analysis, joint time-frequency analysis, the discrete wavelet transform, and a change detection algorithm based on residual generation. Chow [7] provided a brief review of model-based approaches and signal processing approaches on motor fault detection and diagnosis. In this report, initially a graphic simulation is used to produce the signals. Signal processing techniques, like frequency filters, spectral analysis are then used to extract features that will later be used as a base to classify the states of the studied process.

2. Proposed approach for fault diagnosis

In this paper, vibration signals are utilised for detecting the faults of a rotating vibration machinery. The proposed approach consists mainly of four steps, as shown in Figure 1: data acquisition, signal processing, feature extraction and fault classification. These are specifically explained in the next sections. In this section, the summary role of each step is described as follows:

- Data acquisition: this step is used to collect the vibration Data.
- Signal processing: this includes transfer of data from time into frequency domain.
- Feature extraction: the most significant features, in this step, are calculated using feature parameters from both time and frequency domains.
- Fault classification: the data obtained from feature extraction step is fed into one of the classification methods to diagnose the faults in the rotational machines. The results obtained from the data test set indicate the total classification accuracy of the method which are utilised.

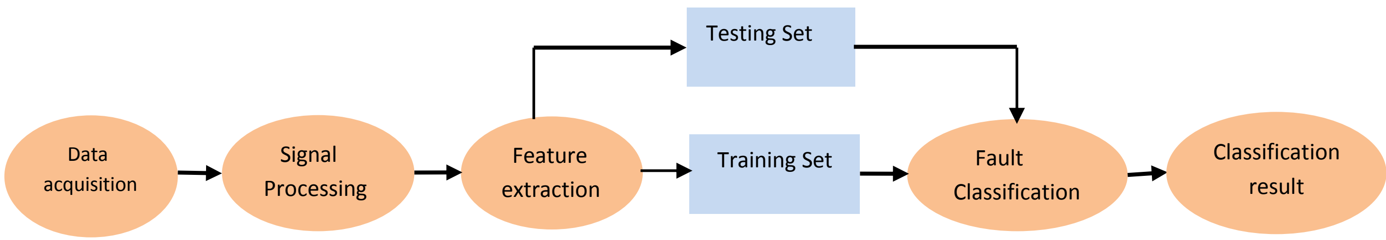

FIGURE 1 Proposed approach procedures for fault diagnosis

FIGURE 2 Stator motor faults (http//:www.wikipedia.org/wiki/File:vibration_machine.svg)

3. Experimental case study

Data acquisition

A data acquisition card (PCI 1711) and PC for the purpose of data collection are used as shown in Figure 3. The vibration data acquired from 1-axis accelerometer is captured by a PC based data acquisition system (DAQ) via PCI 1711. The Real-Time Window Target (RTWT) of MATLAB is utilized to provide the communication between PC and A/D Card [1].

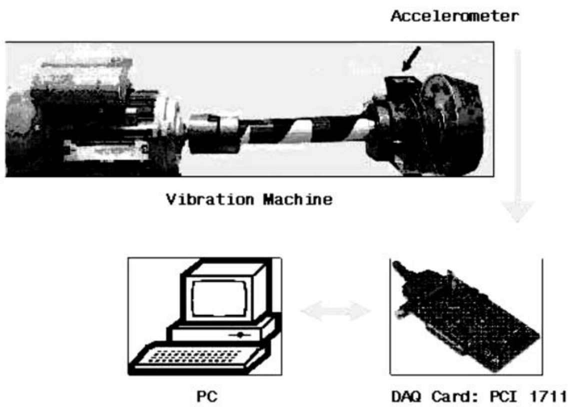

FIGURE 3 Vibration benchmark for fault diagnosis [9]

Vibration Signal Analysis

After loading data files of all fault types, which have been acquired from the sensors, various fault types are firstly represented in the time-domain in order to decide on their features as shown in Figure 4. As illustrated in Figure 4, it is not possible to distinguish the different types of faults and decide on their features. Therefore, it is required to apply a signal processing technique to convert the time domain in to frequency domain will be explained in the next sections.

Signal processing

One of the common procedures to generate useful features is signal transition from the time domain into the frequency domain.

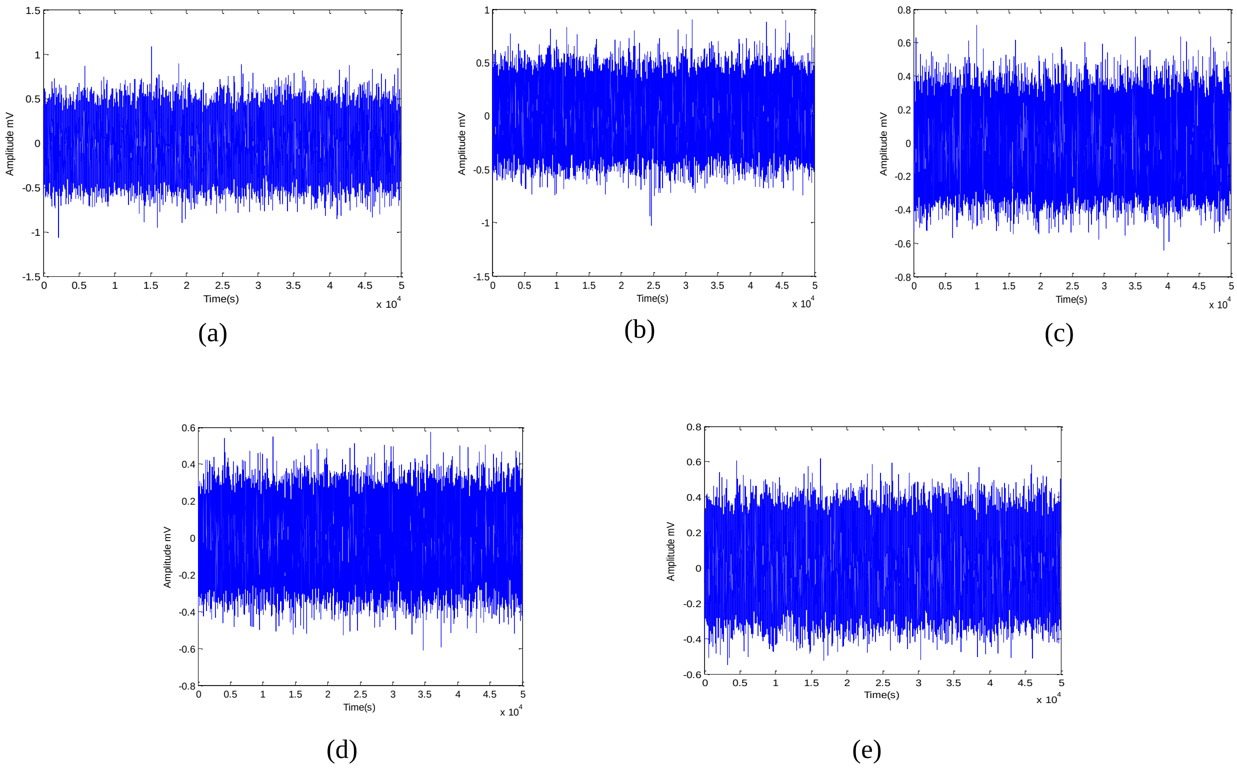

FIGURE 4 Different fault types of rotational machines, (a) bearing, (b) gearmesh, (c) misalignment, (d) imbalance, (e) resonance.

A 1000-point Fast Fourier Transform (FFT) is computed from each discrete time signal. In addition, Power Spectral Density (PSD) and FFT of vibration signals were computed using Matlab R2018a. Figure 5 illustrates a computed FFT amplitude, PSD, for different faults of a machine. The FFT analysis produced 1000 sample data for each fault. The amplitudes of the harmonic components for the rotating machinery being tested have been plotted with Matlab. Harmonic spectra are generated from collected data by the accelerometer using FFT. Bearing and gear mesh are quite noisy signals. The harmonic spectrum from Figure 6 is generated from data acquired by the accelerometer which is mounted on the electrical machine frame. The vibration signals transmitted to the analyser are very relevant and can be used to fault diagnosis. The rotational frequency of the machine can be computed as $f = f_r = 220\ Hz$. The vibration amplitude for this frequency with f_2 and f_3 are important and the amplitudes for other frequencies are small. Because of difficulty of deciding on features and separate them, feature extraction will be used in the next section.

Feature Extraction

Feature extraction is the process of transforming the measurements to invariant characteristics form of the system [1]. Feature extraction are powerful and effective under these conditions:

1. It should remove the redundancy and high correlation in the measurement data.
2. It should produce distinct data with sufficient discriminatory information.
3. It should allow data visualisation.

If these conditions are not satisfied, the original set of measurements would be better to construct the health condition monitoring [1].

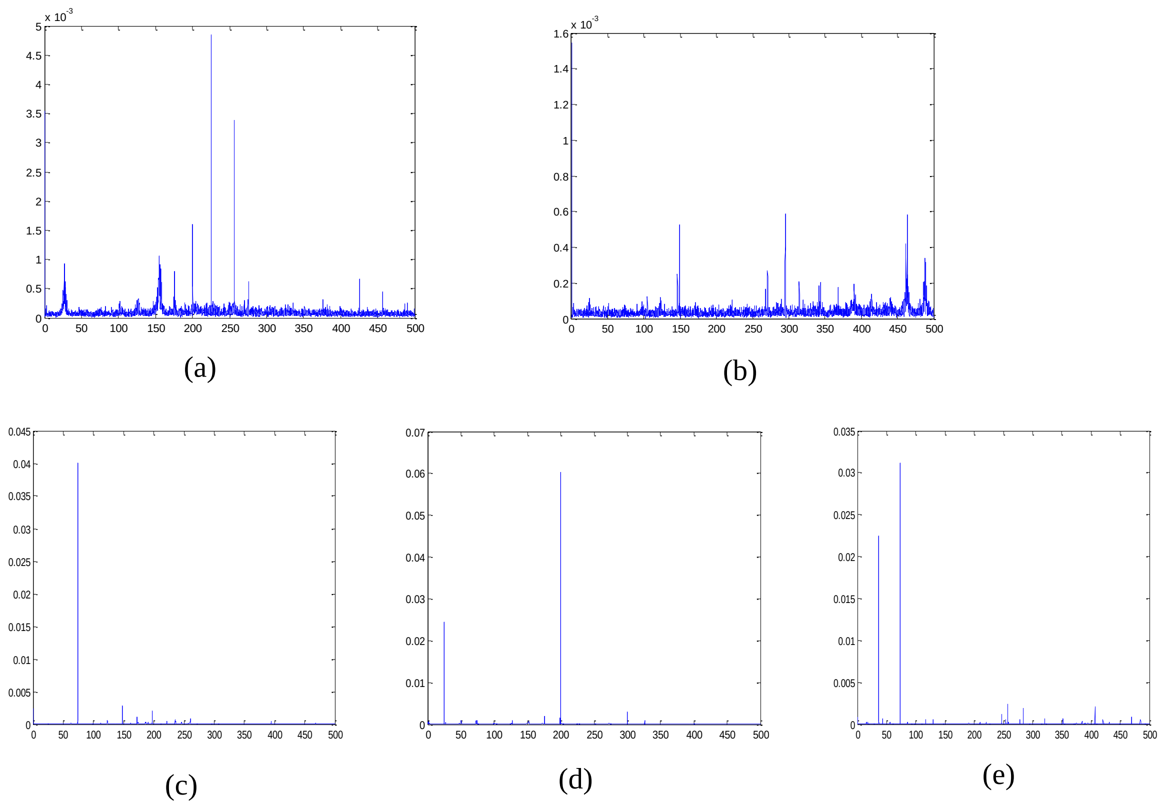

FIGURE 5 Spectral analysis based PSD of each fault, (a) bearing, (b) gearmesh, (c) misalignment, (d) imbalance, (e) resonance.

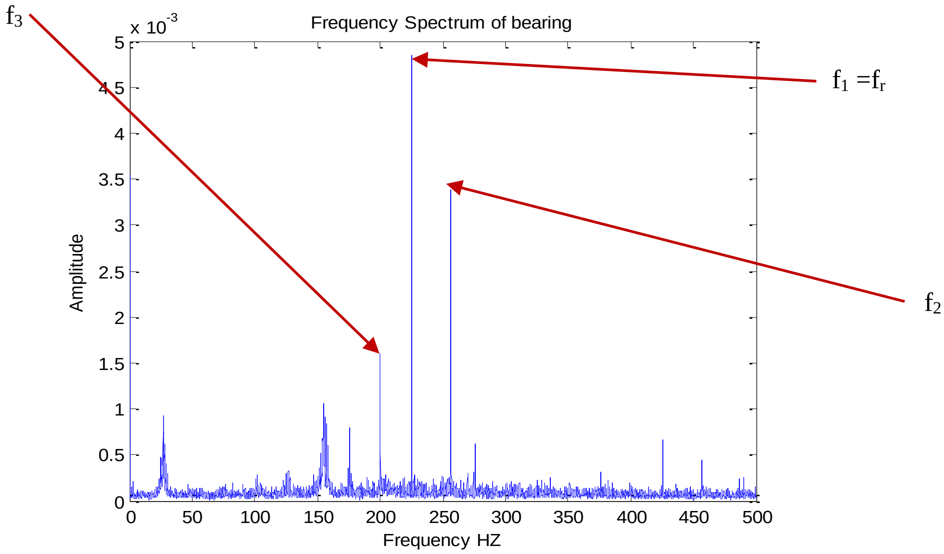

FIGURE 6 Harmonic vibration spectrum for induction motor with faulty bearing

There are two main feature extraction approaches, spectral feature extraction and AR model parameter estimation. A non-parametric approaches, Fast Fourier Transform (FFT) based periodogram and Welch approach, can significantly extract the spectral features. Due to the requirements for large amount of data, most of the times the spectral patterns have a huge back round of noise. Another approach which can be utilized as an alternative approach is parametric approach like Burg’s method but with limited data in order to produce smooth spectra with fewer resonance frequency features. These are related to the AR model parameters being used as feature s since Burg's method first requires AR model Identification. A model-based approach is to estimate the parameters from data using the AR model Identification procedure. The set of parameters can also be used as features that show variation to the different faults such as bearing failure and rotor imbalance [1].

In this paper, five types of faults have been used each with dimension 5000×1. The vector of each fault is divided in to 50 blocks (non-overlapping) each with length 1000[1]. Four features are extracted from these signals (f_1, f_2, f_3, f_4) with different frequencies. Figure 6 and Figure 7 show the bearing fault to provide feature extraction.

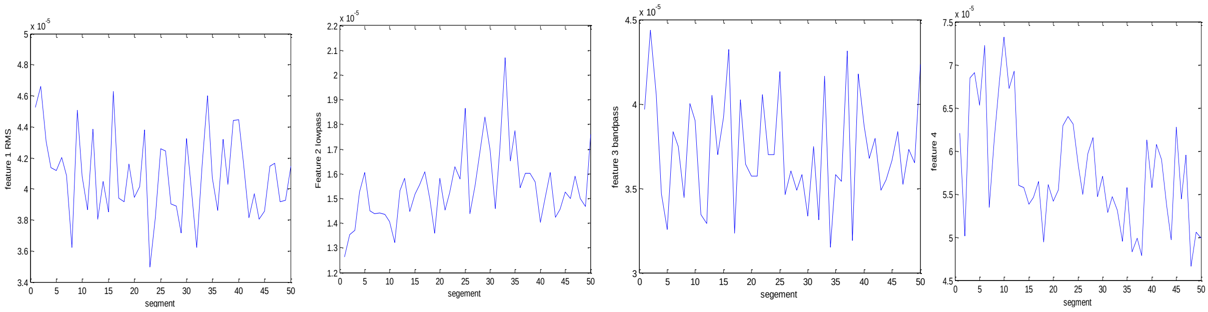

FIGURE 7 Time domain features of acquired vibration signals (bearing fault)

Data Visualisation

As it is mentioned before, one of the advantages of using feature extraction is to visualize the data. Here, the feature extraction, which has been carried out, allows visualisation of the data. The following matrix from the feature extraction step for all types of faults is achieved:

$$G = \begin{bmatrix} Fault1 \\ Fault2 \\ Fault3 \\ Fault4 \\ Fault5 \end{bmatrix} = \begin{bmatrix} f1 & f2 & f3 & f4 \\ f1 & f2 & f3 & f4 \\ f1 & f2 & f3 & f4 \\ f1 & f2 & f3 & f4 \\ f1 & f2 & f3 & f4 \end{bmatrix} \tag{1}$$

The dimension of all fault features which are (50×1) has been achieved. The dimension of the G matrix in eq.(1) is going to be (250×4). Hence, it is clear that the feature dimension is four. Therefore, it is not possible to visualize them in four dimensions as there is computationally not feasible. Thus, in order to reduce the dimension of the G matrix in to two dimensions which is convenient to plot, a technique called the Principle Component Analysis (PCA) is required. The dimensionality reduction has been carried out by using a software tools in order to make the G Matrix from (250×4) to (250×2) by using the PCA approach which takes the first 2 principle components of G matrix as shown in Figure 8.

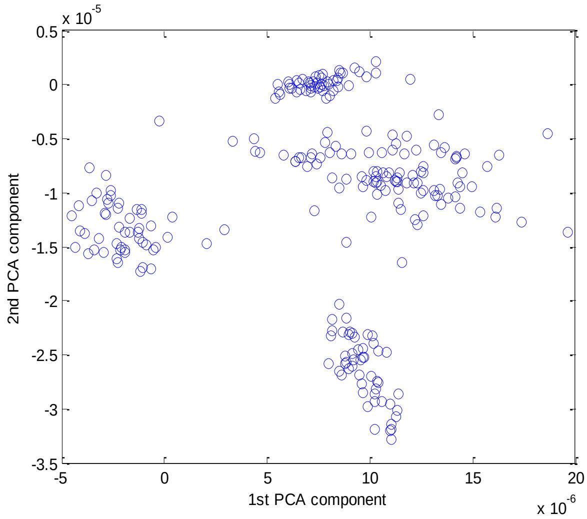

FIGURE 8 PCA based feature extractor

It is obvious in Figure 8 that each fault type cannot be completely separated because some of their features are mixing together, however, if more features are extracted, it would guarantee a better result.

Pattern Classification

The main purpose is to classify the condition of the machine and classify the fault feature types. In this case, five fault feature types is classified for the purpose of pattern recognition. Several approaches are available for pattern classification such as Naive Bayes classifier, Decision trees/ decision lists, support vector machines (SVM), Kernel estimation and K-nearest-neighbour algorithms, Perceptron, and Neural networks (multi-level perceptron). Among those approaches, Nearest Neighbour Method is one of the simplest and efficient classifier technique which can be applied based on distance measurement [1]. The K-Nearest Neighbour algorithm is a method to classify objects based on closest training examples in the feature space. K-Nearest Neighbour is a type of instance-based learning, or lazy learning where the function is only approximated locally and all computation is deferred until classification. The K-Nearest Neighbour algorithm can be classified as the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbours, with the object is assigned to the class most common amongst its K-Nearest Neighbours (K is a positive integer, typically small). If K = 1, then the object is simply assigned to the class of its nearest neighbour also if K=2, it takes two nearest neighbour from the operating point and for K=3, it takes three shortest neighbours and so on. To determine these distances, the Euclidean distance is utilized here based on the Euclidean distance equation [1]. In this method (K=1), after getting the 2-dimentional data from PCA technique, then the data is partitioned in to two groups as mentioned in Figure 1 called Training and Testing data. Training data as a rule should be greater than the testing data, this is the reason why we have taken for training test (1:35) and for testing (36:50(end)) which is (15 data). There are some advantages behind using Nearest Neighbour method in this paper, it can be easily implemented [1], the training of classifier is not necessary [1], If K is increased, the result would be more robust to the noisy data and outliers [1], Non-linear boundaries can be determined [1], "Additional labelled measurements could be readily incorporated"[1]. In addition, in 1-Nearest Neighbour method, it is not necessary to plot the data rather than the Accuracy of the classifier have to be computed and can be evaluated as:

$$A = \frac{N_c}{N_a} \times 100 \qquad (2)$$

where A is the accuracy in percentage, N_c is the number of all correctly classified samples and N_a is the Number of samples. The accuracy of the classification can decide how good the classifications are. In this case, the accuracy of the proposed classification method is high enough and is about % 98.6667. This indicates that the K-Nearest Neighbours approach can optimise the accuracy of the classification method. In order to verify whether the result in this work, Figure 9 shows that the fault 3 has not been well classified based on the proposed method this is why the %100 accuracy has not been achieved in this method.

Proposed improved approach

In order to optimise the accuracy of the classification method to optimise the fault feature classification, an alternative approach called K-Mean Clustering is used in this paper.

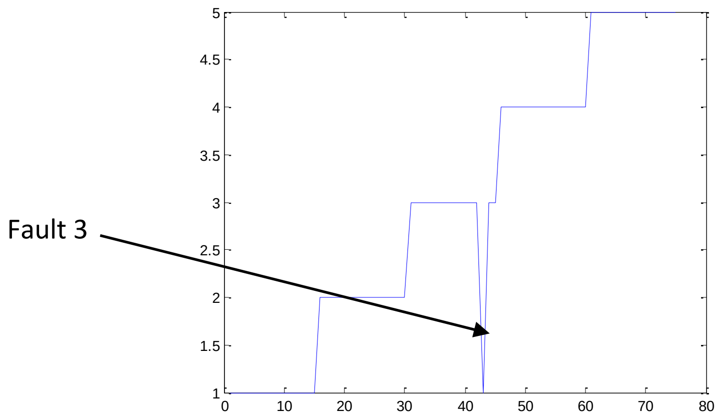

FIGURE 9 Classification performance

The main reason to use an alternative method of nearest neighbour is that K-Nearest Neighbours method needs to keep all historical data which is not quite good since a large amount of data need to be memorized and each time the historical data should be attained, therefore, more memory location for saving these data are required. In addition, it has a high computational cost for decision making. K-Mean clustering, unlike nearest neighbour, depends on the average of each cluster and utilizes a cluster centres as a reference point in subsequent partitioning and also it is very sensitive to noise. It is shown in Figure 10 that the proposed approach in this paper is superior in classifying all five different fault features

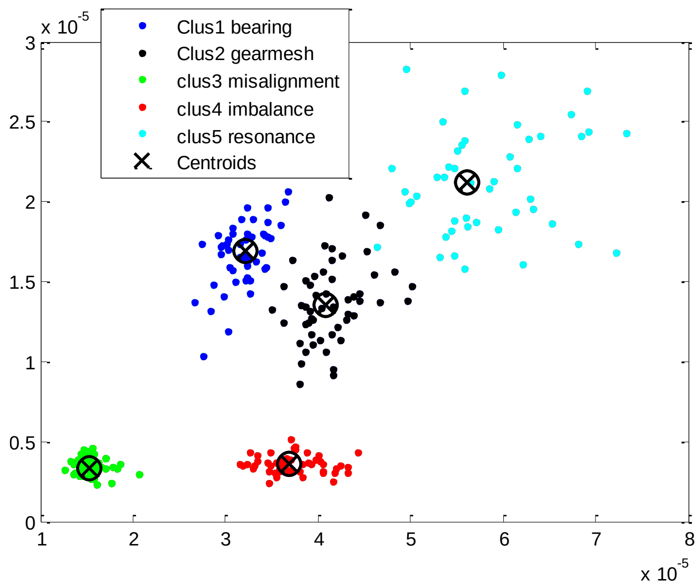

FIGURE 10 Classification of faults using K-clustering method

including bearing, gearmesh, misalignment, imbalance and resonance. Compared to the K-Nearest Neighbour method, the proposed method in this work, shows a better result and can classify various faults successfully.

4. Conclusion:

The fault diagnosis and pattern classification method include four different procedures including data collection, signal processing, feature extraction, and feature classification. In this paper, firstly, the vibration data sets has been acquired from the sensors in the Laboratory. Then, different fault features in bearing, gearmesh, misalignment, imbalance, and resonance are extracted using different signal processing techniques. Finally, the fault features are classified using a proposed pattern classification method. There are various pattern classification techniques for the fault diagnosis. If the patterns are linearly separable, then the classification system can be developed easily by applying the Linear Discriminant classifier. However, if it is nonlinearly separable nonlinear classifier such as nearest neighbour and neural network algorithm can be utilized. In this paper, as the nonlinear separable is available, K- Mean Clustering as an improved method is proposed. If the patterns are not separable then the neural network can be trained to produce minimum average classification error and for K-nearest neighbour you can increase the K value to make it robust. In this paper, firstly, the method called K- Nearest Neighbour is utilized to classify different fault features. As it is obvious in the proposed result, the accuracy of this method is not good enough due to the computational cost. In order to improve the result, an alternative method known as K- Mean Clustering approach is applied as an alternative technique to increase the accuracy of the classification method. The result of the proposed method in this paper shows the accuracy of the classification approach is significantly improved and the various faults in the rotational machinery can be successfully diagnosed and classified. In the future, an intelligent classification approaches such as Neural Networks, Case based Reasoning, Fuzzy Expert Systems, and Adaptive Neuro Fuzzy Inference System (ANFIS) can be studied.

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