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Foreword

Alhamdulillah. First of all a big thank you and congratulations to the Editorial Board of *Esteem Academic Journal* of Universiti Teknologi MARA (UiTM), Pulau Pinang for their diligent work in producing this issue. I also would like to thank the academicians for their contributions and the reviewers for their meticulous vetting of the manuscripts. A special thanks to University Publication Centre (UPENA) of UiTM for giving us this precious opportunity to publish this first issue of volume 5. In this engineering issue we have upgraded the standard of the manuscript reviewing process by inviting more reviewers from our university as well as other universities in Malaysia. We have embarked from previous volume to establish a firm benchmark and create a journal of quality and this current issue remarks a new height of the journal quality. Instead of publishing once in every two years, now *Esteem* publishes two issues annually.

In this issue, we have compiled an array of 13 interesting engineering research and technical based articles for your reading. The first article is entitled "The Response of Tube Splitting on Circular Tubes by Using Various Types of Semi-angles Dies and Slits". The authors, Mohd Rozaiman Aziz and Roslan Ahmad investigated the axial splitting and curling behavior of aluminum circular metal tubes which was compressed axially under static loading using three types of dies with different semi-angles. The authors concluded that the introduction of slit to the specimen is necessary to initiate slitting rather than inversion.

Salina Budin, Aznifa Mahyam Zaharudin, and Sugeng Priyanto presents a model of energy conversion and impact energy generation during collision based on free falling experiment, which is closely resembles direct collision between ball and inner wall of the vial. Simulation results from the proposed impact energy model demonstrated that the impact energy generated during the collision is strongly influenced by the thickness of the work materials and reaches zero at certain value of the work materials thickness, which increases with an increase of falling height.

Salina Alias, Caroline Marajan and Mohamad Azrul Jemain wrote an article that looks at adsorption of zinc from waste water using bladderwort (*Utricularia vulgaris*). In batch adsorption studies, data show that dried bladderwort has considerable potential in the removal of metal ions from aqueous solution. The fourth article written by

Muhammad Khusairi Osman et al. looked at 3D object recognition using affine moment invariants and Multiple Adaptive Network Based Fuzzy Inference System (MANFIS). The experimental results show that Affine Moment Invariants combined with MANFIS network attain the best performance in both recognitions, polyhedral and free-form objects.

The article entitled "Construction Waste Management Methods Used by Contractors in the Northern Region" authored by Siti Hafizan Hassan, Nadira Ahzahar and Mohd Nasrul Nizam Nasri reports an ongoing study on the use of construction waste management methods by contractors and its impact on waste reduction in the Northern Region. In conclusion, the sizing and amount of materials to be ordered to reduce wastage is significant in reducing construction waste generation waste, alleviating the burden associated with its management and disposal. The sixth article by Muhammad Sofian Abdullah et al. examined on the performance of Performance of Palm Oil Fuel Ash (POFA) with lime as stabilizing agent for soil improvement. The authors concluded that POFA can be used to treat the silty soil as well as to reduce the environmental problem.

The seventh article penned by Soffian Noor Mat Saliah, Noorsuhada Md. Nor and Megat Azmi Megat Johari presents the results of an experimental study on the interfacial bond strength (IBS) of polypropylene fiber concrete (PFC). It was found that the interfacial bond strength between concrete and reinforcement bar was not affected by the inclusion of polypropylene fibers. However, concrete containing fibers exhibited no breaking of concrete and no debonding of reinforcement. The article by Juliana Zaabar and Rusnani measures, evaluates and analyzes the network link performance of fiber optic cable using OTDR. The authors suggested that the major loss for these measurements is connector loss. Preventive maintenance will increase the life time of fiber optic. From some of the findings, the PVC dust cap has been identified as a main source of contamination for the SC connector.

The article entitled "Symbolic Programming of Finite Element Equation Solving for Plane Truss Problem" by Syahrul Fithry Senin proposed a plane truss problem to be solved by finite element method using MAPLE 12 software. The numerical solution computed by the author was almost matched with the commercial finite element software solution, LUSAS. The tenth article by Nor Azlan Othman, Nor Salwa Damanhuri and Visakan Kadirkamanathan presents a detail review of fault diagnosis in rotating machinery using pattern recognition technique. The authors proposed a solution based on artificial neural network (ANNs) which is Multi-Layer Perceptron (MLP). The authors concluded that the proposed methods are suitable for rotating machinery on fault detection and diagnosis.

The eleventh article is entitled "RAS Index as a Tool to Predict Sinkhole Failures in Limestone Formation Areas in Malaysia". Damanhuri Jamalludin et al. found that, using the RAS classification method, the prediction of sinkhole occurrences can be easily be made by simply knowing the weekly rainfall especially in areas having limestone as the bedrock. The twelfth by Muhammad Hafeez Osman et al. explores cases regarding the histories of rock slope repair and stabilization of unstable boulder along the road from Bukit Cincin to Genting Highland and along the road from Gap to Fraser Hill. The last article is "Soil Nail and Guniting Works in Pahang". The authors, Damanhuri Jamalludin et al. concluded that if the stability of the embankment needs to be improved, soil nails can be installed and embankment surface can be covered with gunite to prevent erosion.

We do hope that you not only have an enjoyable time reading the articles but would also find them useful. Thank you.

Mohd Aminudin Murad
Chief Editor
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Fault Diagnosis in Rotating Machinery Using Pattern Recognition Technique

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ABSTRACT

This paper presents a detail review of fault diagnosis in rotating machinery. Pattern recognition technique which needs three main steps of fault diagnosis – feature extraction, dimensionality reduction and fault classification – was used. This paper focuses on the faulty bearing which is mainly caused by mass imbalance and axis misalignment. By analyzing the vibration signal obtained from the test rigs (rigs that are built to demonstrate the effect of faults in rotating machinery), it gives solid information concerning any faults within the rotating machinery.

Keywords: *Bearing fault, mass imbalance, misalignment, fault diagnosis, pattern recognition technique*

Introduction

Rotating machinery is widely used in many industries and power plant. Due to the progress made in the engineering and material science field, this rotating machinery has become faster and lighter than before as

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well as its ability to run for longer periods of time. With such a good and well developed product, this rotating machinery is still vulnerable to varieties of problems which come from rotating shafts, gears, pumps and others. All of these factors imply that the early detection of faults play a vital role in the field of rotating machinery.

Rotating machines are prone to number of faults, especially from bearing fault. With the development of new technology and material used, bearing plays a major part in making the rotating machine functioning well. A little defect such as a crack or chip at the inner or outer surface of the bearing could lead to a major disaster to the rotating machine. Mass imbalance, shaft misalignment and the improper surface of the bearing itself could be the major factors in the faulty bearing that need to be specially treated. Every inch and angle of each bearing that is used is closely monitored to prevent such disaster which presumably can affect the safety as well as the cost of the machine.

Pattern recognition techniques have been explored more intensively in the past few years. Here, the pattern recognition is used to develop a fault detection and diagnosis system in order to discriminate between the normal state of the system and some faulty state, in the absence of a dynamic model being available.

Literature Review

Several studies had been conducted by using various techniques of fault detection and diagnosis throughout many years. To date, various methods had been introduced to monitor as well as to detect fault at early stage. Since the rotating machinery plays a vital role in today's industries and power plant, such damage or the occurrence of unexpected problem could lead to economic loss and also safety matters. Huge impact of development in engineering and material science could produce tougher and more reliable rotating machinery, but prevention is always better than cure.

In rotating machinery, the root cause of faults is often due to faulty bearing. Faulty bearings are usually caused by shaft rotation, mass imbalance, stiffness variation and others. Yang, Mathew and Lin Ma (2004) came up with a method to detect and diagnose the fault of rolling element bearing by using a basis pursuit. This technique, which was recently developed, differed from others but the procedures or steps of detecting fault and diagnosis are just the same. This basis pursuit is basically the new time-frequency technique. This technique extract features from faulty rolling bearing signal with inner and outer race faults. And then by using the Discrete Wavelet Packet Analysis (DWPA), the result obtained is compared with the matching pursuit technique. This method gave features with finer resolution in time-frequency as well as improved signal-to-noise-ratio (SNR) so that the fault detection and diagnosis can be done with full of confidence.

Al-Ghamd and Mba (2004) had come up with different technique in order to do the fault detection and diagnosis on the bearing of rotating machinery. They applied an Acoustic Emission (AE) to diagnose the bearing faults. However, the succession of this AE technique was not impressive since this technique has a limitation in processing, interpreting and classifying the acquired data. The researchers also indicated that even though this AE technique has some limitation, still the AE technique offers earlier fault detection and improved identification capabilities than vibration analysis. Furthermore, they claimed that this technique gave an indication on defect size which allows user to closely monitor the rate of degradation on the bearing.

Other studies mainly focus on the fault detection and diagnosis of gear fault of rotating machinery. Baydar and Ball (1999) introduced a different method of detecting the gear fault via vibration and acoustic signals. They proposed a wavelet transform method to examine whether the acoustic and vibration signal can detect the various local faults in gearbox. Based on the result obtained, comparison had been made and result from acoustic signal was very affective for early detection compared to vibration signal.

Baydar and Ball (1999) proved another method in detecting the gear deterioration under varying load conditions. They introduced a time-frequency distribution called Instantaneous Power Spectrum (IPS) in detecting of local faults in helical gear. This technique is capable in extracting condition which have information from gear vibration signals and assessing the fault severity. In addition to this gear fault detection, Loutridis (2004) introduced an instantaneous energy density as a feature that can be used to detect faulty gear.

This paper will discuss a different method in fault detection and diagnosis to rotating machinery. Like other methods mentioned above, the method used in this paper applied the same principal in detecting the fault. Vibration signal obtained from the rotating machinery is extracted by using non-parametric or parametric method to get the power spectrum density (PSD). Principal Component Analysis (PCA) is then introduced to reduce the complexity as well as smoothen the classification process.

Methodology

Overview of the Pattern Recognition Technique (PRT)

This paper present a general framework of the pattern recognition technique as illustrated in Figure 1. The main target is to be able to analyze all the vibration signals obtained from the test rigs and classify it into known fault classes or categories by using all of the techniques of fault detection including feature extraction, dimensionality and fault classification.

Welch methods is used to extract vibration signals and transform into a set of multi-dimensional features without losing any of the information. For some applications, one or two key features can help to reach diagnostic conclusion directly without requiring further processing.

In most situations, however, sensitive features are not straightforwardly obtained and for further analysis dimensionality

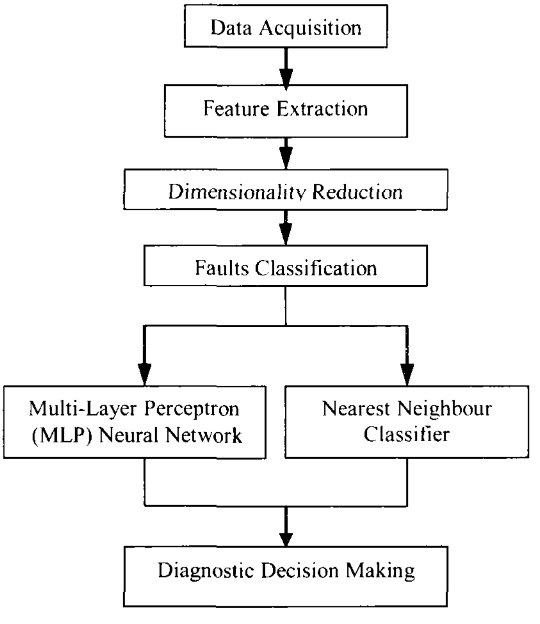

Figure 1: Pattern Recognition Method for Machinery Fault Diagnosis

reduction is necessary. Dimensionality reduction is used to visualize the data by reducing the high dimensional data to 2 dimensional feature vectors. One of the dimensionality reduction techniques is Principle Component Analysis (PCA).

This project proposes a solution based on artificial neural network (ANNs) which is Multi-Layer Perceptron (MLP). This is a powerful technique for pattern recognition and can be applied to the classification type of faults. Besides, Nearest Neighbour Classifier is used as another technique of classification to compare their performances in term of diagnosis results.

Data Acquisition

The vibration signals are captured by the accelerometer and transferred to the PC through Data Acquisition Card for further analysis (see Figure 2). Due to time constraint and the availability of some of the test rigs, only two rigs are of interest in this project: the imbalance and misalignment rigs, since most of the bearing problems come mainly from this two common faults.

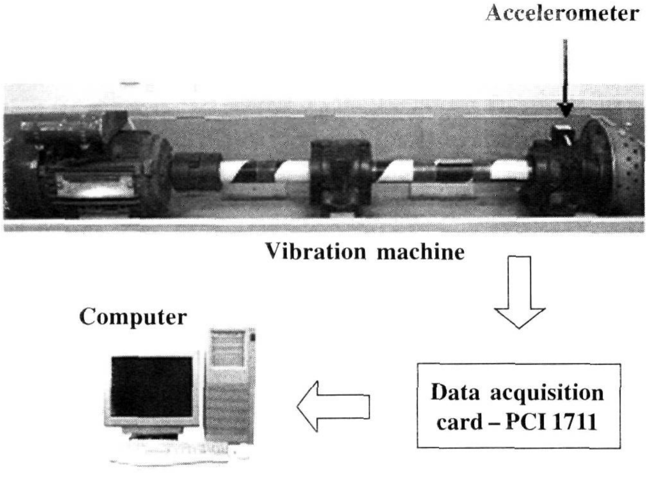

Figure 2: Test Set-Up

Feature Extraction

Nowadays, feature extraction is needed in most processes since a fault pattern vector is being extracted from the measured signal; some of the measured data might be lost, redundant or highly correlated. Amongst them, there might be useful or important data that will give information corresponding to application of interest.

Therefore, the feature extraction is used to transform the vibration signal obtained from the test rig into a set of multi-dimensional features without losing any of the information. Feature extraction can also be defined as a method to create new features based on transformation or combinations of the original features in the set. In other words, it is used to map from an N-dimensional pattern space extracted from the measured signal to an n-dimensional feature with $n > N$ such that much of the information contained in the pattern space is retained in feature space.

Welch method or modified periodogram allows a non-rectangular window such as Hamming window or Hanning window to be used. These windows are applied in order to get smooth edges of the signal. The Welch method is an average periodogram which is used to decrease the variance of the estimate of overlapped and windowed data sections.

Theoretically, in the Welch's method, data is divided into K overlapping segments, and then a window such as Hamming window is applied to each segment to get the periodogram of each segment as well as the average periodogram of overlapped and windowed data section.

Hence, if the segments of a set data sequence $x(n)$, $n = 0, 1, K, N-1$ are offset by D point, it can be expressed as

$$x_k(n) = x(n + kD) \tag{1}$$

$$k = \frac{N-L}{D} + 1 \tag{2}$$

Where:

K = k[th] segment of set data sequence
L = segment length

Then, the power spectrum can be estimated by

$$\hat{P}_w(\omega) = \frac{1}{KLU} \sum_{k=0}^{K=1} \left| \sum_{n=0}^{L=1} w_x(n) x(n + kD) e^{-jn\omega} \right|^2 \tag{3}$$

Where:

$$U = \frac{1}{2\pi N}\int_{-\pi}^{\pi}|W_x(\omega)|^2 d\omega$$

$|W_x(\omega)|$ is the Fourier transform of the data window $W_x(n)$.

Dimensionality Reduction

Features extracted from the sensory signals are usually not direct indicators ready for reaching diagnostic conclusions. Further analysis and dimensionality reduction of the extracted features are necessary so that a combined effect can be obtained to indicate machinery health condition. Such a process is usually nonlinear due to the complex relations among a large number of extracted features. Dimensionality reduction is used to visualize the data by reducing the high dimensional data to 2 or 3 dimensional feature vectors.

The need to perform dimensionality reduction and map the feature space onto a two-dimensional classification space is required before the classification process. Principal Component Analysis is used to perform a nonlinear mapping with predetermined two-dimensional targeted outputs. The reason for choosing two-dimensional output is partly due to the convenience of visual assistance in the development stage hence easy to classify. A good mapping should generate non-overlapping clusters of the data points in the classification space.

PCA is only interested in features with maximum variation in data. The purpose of PCA is to reduce the dimensionality of the data set as well as to retain most of the original variability in the data. PCA also transforms a number of correlated variables into a smaller number of uncorrelated variables.

Classifications

Theoretically, the fault classification is a decision making device that is trained to classify an incoming patterns or samples as belonging to one of the learned classes. In other words, this fault classification is simply used to classify the features extracted from the vibration signal into a known fault categories. By doing so, it will provide information to which categories that the new fault falls into.

MLP Neural Network and Nearest Neighbour Classifier are being discussed. For the purpose of machinery fault diagnosis, supervised learning is most relevant where samples with known classes of machinery condition from the past are available. Such a learning process takes place each time new sample data with known type of fault becomes available. As such, the quality of mapping should improve as more experience is learnt.

Nearest-Neighbour Classifier

One of the simplest methods in the fault classification is the Nearest-Neighbour Classifier. It focuses more on the distance measurement between the trained data and the tested data. This method will find the closest object in the n-dimensional feature space from the training set to an object being classified. Since the neighbour is nearby, thus it is likely to be similar to the object being classified and can be assigned it into the same class as that object. In simple words, if the new tested fault data is near to the class 1 or learned class, thus the new tested data is classified as learned class. This decision rule is called the 1 nearest-neighbour classifier.

When a sample n with m features is represented by a feature vector, $[x_1(n), x_2(n), K, x_N(n)]$ the distance between the two samples n_1 and n_2 $D(n_1,n_2)$ is given by Euclidean distance;

$$D(n_1,n_2)=\sqrt{\sum_{i=1}^{N}(x_i(n_1)-x_i(n_2))^2} \tag{4}$$

Where:

$x_i(n)$ = value of the i^{th} feature of sample n

Multi-layer Perceptron (MLP) Neural Network

The most widely used neural classifier today is Multilayer Perceptron (MLP) network which has also been extensively analyzed and for which many learning algorithms have been developed. The MLP belongs to the class of supervised neural networks.

MLP networks are general-purpose, flexible, nonlinear models consisting of a number of units organized into multiple layers. The complexity of the MLP network can be changed by varying the number of layers and the number of units in each layer. Given enough hidden units and enough data, it has been shown that MLPs can approximate virtually any function to any desired accuracy. In other words, MLPs are universal approximators. MLPs are valuable tools in solving problems when one has little or no knowledge about the form of the relationship between input vectors and their corresponding outputs.

In this project, the number of neurons is 2 for the input layer, 10 neuron for hidden layer and 2 for the output layer. Two input layer are imbalance and misalignment. Therefore, the connection of three layer neural network is shown in Figure 3. To train the neural network, adoption the supervised learning algorithm is proposed. The training and testing samples are obtained after PCA calculation made with known faults types. The standard back propagation training algorithm is used to update weights at every neuron.

The multi-layer feed-forward neural network is trained by supervised learning using the iterative back-propagation algorithm. In the learning phase a set of input patterns, called the training set, are presented at the input layer as feature vectors, together with their corresponding desired output pattern which usually represents the classification for the input pattern.

The back-propagation algorithm is a gradient descent optimizations procedure which minimizes the mean square error between the network's output and the desired output for all input patterns P

$$E = \frac{1}{2P}\sum_{P}\sum_{k}(d_k - out_k)^2 \qquad (5)$$

The training set is presented iteratively to the network until a stable set of weights is achieved and the error function is reduced to an

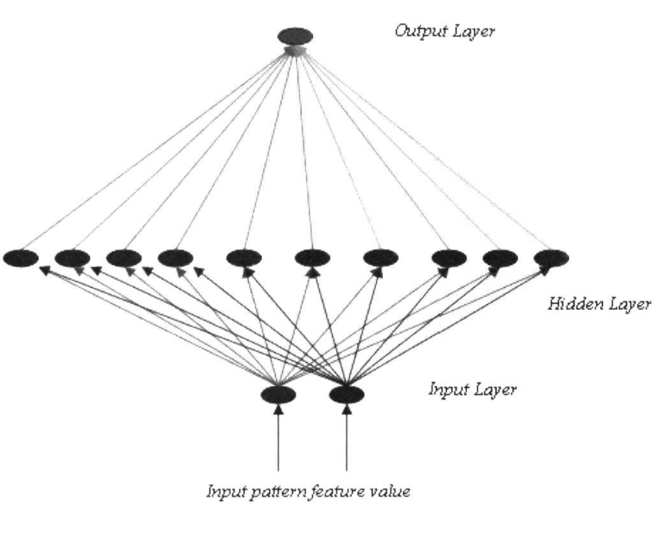

Figure 3: Architecture of Multi-Layer Perceptron

acceptable level. In this project, weight is selected at random and target error is equal to 10^{-5} and final weight is achieved when final error is equal to target error. To measure the generalization ability of the multi-layer feed-forward neural network it is common to have a set of data to train the network and a separate set to assess the performance of the network during or after the training is complete.

Diagnostic Decision-Making

Conclusions for fault diagnosis are straightforward after all the train input is recognized with their train target output, whereby the testing input of features will be sorted into it desired target output. By using MATLAB software, the count number of faults classes will appear on Command Window.

To apply the proposed pattern recognition technique to rotating machinery fault diagnosis, one needs to build the diagnostic system as depicted in Figure 1. An online monitoring process is the best solution in monitoring the condition.

At any time when a certain class of fault is detected, a recommendation for scheduled maintenance or a shut-down should be issued. After the scheduled maintenance and the assessment of the type of fault, the diagnostic system should be updated with the confirmed case, meaning that classification is trained again with the newly acquired sample case added to the database. Such training will result in a new mapping function and boundaries for classification. Subsequently, the monitoring cycle continues with the updated training results.

Results

This paper presents more on the imbalance and misalignment since these two defects are the most common faults that can be monitored in the bearing problems. In the data given for the imbalance and misalignment rigs, both consist of 150000 vibration data.

By using feature extraction method, 150000 vibration data is transformed into a multi-dimensional feature. Figures 4 and 5 show the vibration data signal from the imbalance and misalignment respectively. Both samples have been formatted into a 500×300 matrix. Different colors represent 300 columns in the matrix.

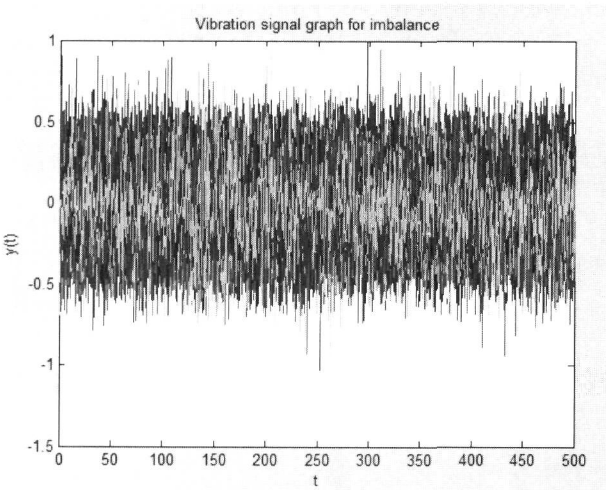

Figure 4: Vibration Signal for the Imbalance Samples

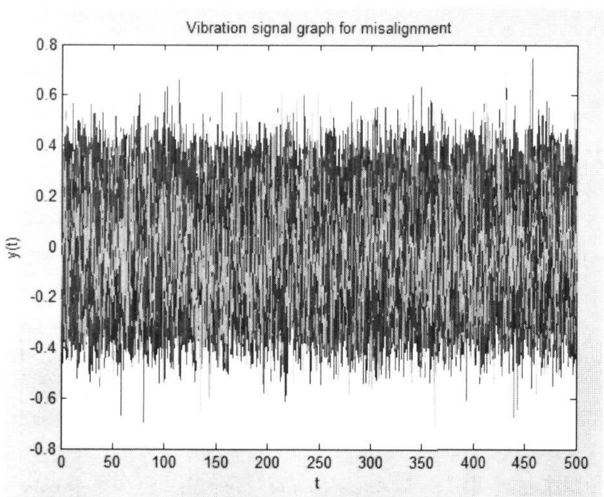

Figure 5: Vibration Signal for the Misalignment Samples

In many cases, especially on the oscillations of measured signals which are either of harmonic or stochastic nature or both, the power spectrum changes when faults occur. The simplest non parametric method was selected which is "modified periodogram" or "Welch method". 50 percent of overlapped is chosen and Hamming Window is applied to each segment which offset by 500 point. By using Equation (3), power spectrum for both faults is estimated. Figures 6 and 7 show power spectrum analysis for imbalance and misalignment respectively.

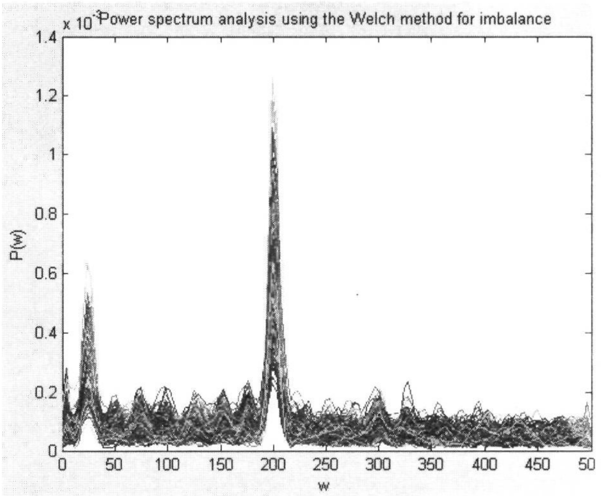

Figure 6: Power Spectrum Analysis by Using the Welch's Method for the Imbalance Samples

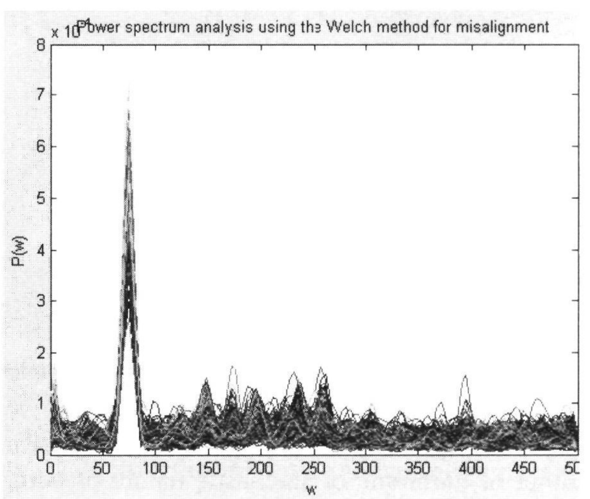

Figure 7: Power Spectrum Analysis by Using the Welch's Method for the Misalignment Samples

The matrix obtained for both power spectrum of imbalance and misalignment is [129 × 300]. The matrix obtained is then divided into two parts; training data consists of 129 × 150 (the first 150 column in the matrix) and testing data consists of 129 × 150 (the last 150's column in the matrix).

As the result,

Training data;	Imbalance	= 129 × 150
	Misalignment	= 129 × 150
Testing data;	Imbalance	= 129 × 150
	Misalignment	= 129 × 150

Before calculating the PCA for the training data, the matrix of imbalance and misalignment is combined and becomes a matrix of 129 × 300.

PCA is only interested in the feature with maximum variation in data shown in both Figures 6 and 7. Figure 8 below shows the distribution of the two samples, imbalance and misalignments results after the dimensionality reduction technique is applied. These samples are training samples that will be used for future fault classification. With these two training data are set as a learned data, hence whenever a new test data is analyzed, it can be classified into which group it belongs to.

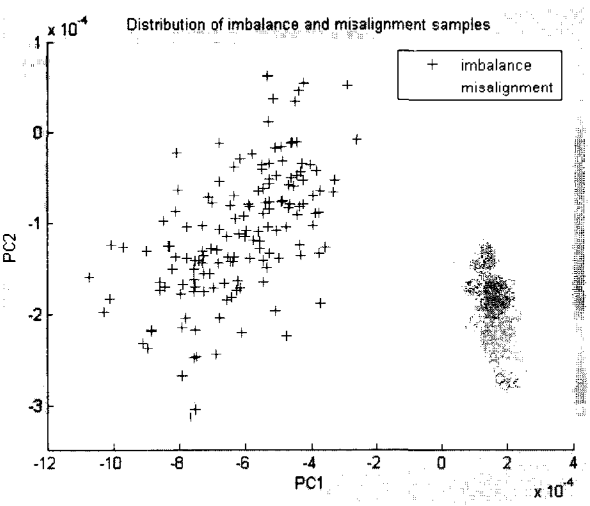

Figure 8: Distribution of Imbalance and Misalignment Samples for the Training Data

For diagnostic decision making, MLP Neural Network and Nearest Neighbor Classifier are used. MLP Neural Network is used to train back training data results from PCA and to recognize the training input to their target output. Figure 9 shows the performance of error achieve goal or target error at epochs 6. To prove that, the combination of testing data as results from PCA is used to test back as testing input and all the data is recognized to their classes or target output. The results are shown in Figure 10 and Table 1.

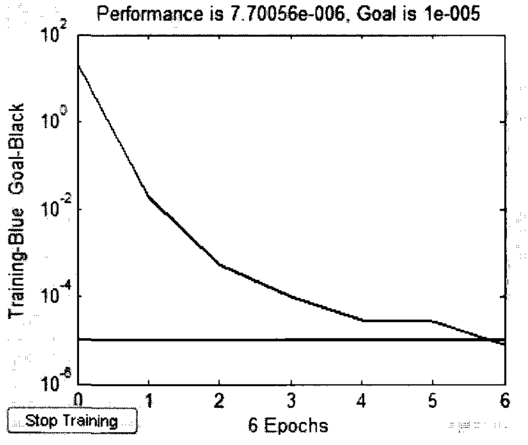

Figure 9: Performance of Error Using MLP Neural Network

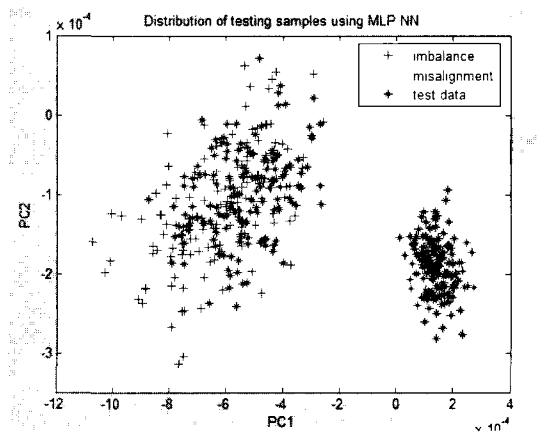

Figure 10: Distribution of Testing Data Projected to the Training Cluster Using MLP Neural Network

The distribution of testing sample using Nearest Neighbour Classifier is shown in Figure 11. After applying Nearest Neighbour Classifier the same results is achieved and summarized on the same Table 1.

Discussion

Figure 12 shows power spectrum analysis using periodogram, as the number of sample increases, the expected value of the periodogram approaches the true PSD. The problem with the periodogram estimate is, the variance is large and does not decrease variances as the number of samples increases.

An improved version of the periodogram is the "modified periodogram" or Welch method which allows a non rectangular window e.g, Hamming window, to be applied in order to smooth the edges of the vibration signal.

Table 1

Classes	Results
Imbalanced	150
Misalignment	150

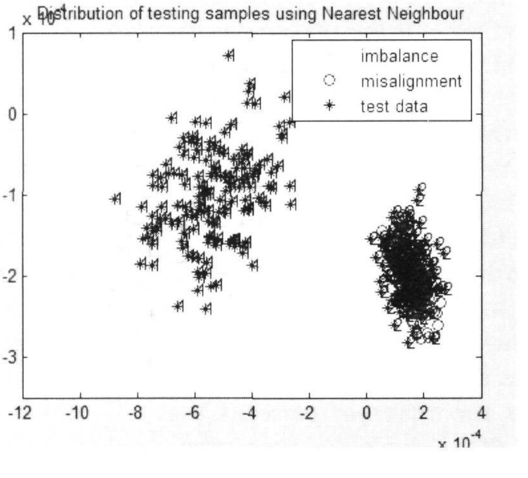

Figure 11: Distribution of Testing Data Projected to the Training Cluster Using Nearest Neighbour Classifier

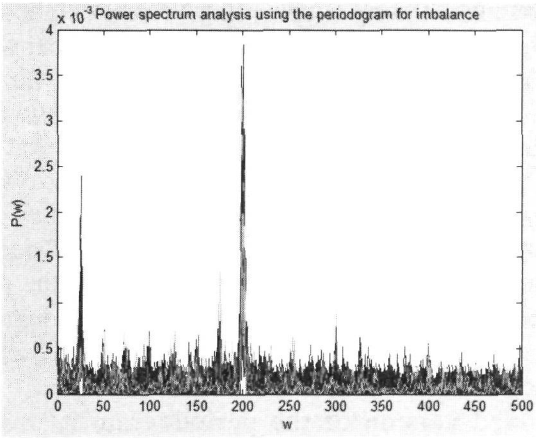

Figure 12: Power Spectrum Analysis Using Periodogram Method for Imbalance Samples

This reduces the effect of section dependence due to overlap, because the window is tapered to 0 on the edges. A non rectangular window diminishes the side lobe interference or spectral leakage while increasing the width of the spectral peak. With suitable window, overlap rates of about half the section length have been found to lower the variance of the estimate significantly.

Figures 5 and 6 show power spectrum analysis using Welch method reduces the variance of the power spectrum estimate by breaking the signal into non over-lapping sections. It also decreases window data section.

In the power spectrum it is not easy to identify the fault either misalignment or imbalance due to dynamic and large amount of feature with some being redundant and difficult to discriminate from each other. Classification method is proposed to make easy in classifying faults.

One of the difficulties with fault classification is high dimensionality in the rotating machinery. Many variables can affect the process of fault detection, including load, saturation, unpredictable operating conditions, electrical noise and temperature. These can result in dozens of possible combinations for different patterns that will mark the vibration measurement. PCA technique is successful to reduce the high dimension and results of non-overlapping in the classification will make classification task easier to diagnose.

By using MLP Neural Network, all the training inputs are trained to minimize error between target outputs and training outputs. After achieving the target error, testing inputs are applied on the same network to get the output of classes. As shown in Figure 10 all the testing input is recognized with their target outputs. The same result is captured by using Nearest Neighbour Classifier which 150 data for imbalance and 150 data for misalignment. Though these two methods can be applied to make faults diagnosis, there are advantages and disadvantages. For MLP classification, the run time is faster and the algorithm of MLP is complicated compared to Nearest Neighbour. MLP also need to achieve the target error which is 10^{-5} and if the target error is not achieved, the train will end at 1000 epochs.

Even though the nearest-neighbour is the easiest and simplest method to use, but there is still some advantage and disadvantage of this method. The advantage is it easy to implement since it only deals with the distance between the two samples. But the computing time will become slower when dealing with the larger samples of training set.

Both methods have their own style of classification, but based on this project MLP Neural Network works better compared to Nearest Neighbour Classifier due to its effectiveness and faster run time.

Conclusion

In this paper, a general methodology for machinery fault diagnosis through a pattern recognition technique is developed. This involves data collection, feature extraction, reduce the high dimension data and classified using MPL and nearest neighbor. Although bearing defect diagnoses was used as illustrative examples, the proposed method can be applied to other applications by only modifying the features extracted from the sensory signal. The proposed methods are suitable for rotating machinery in fault detection and diagnosis.

Future Developments

A Graphical User Interface (GUI) technique is suggested as future development to make this project user friendly. Further analysis can be done to improve the fault detection and diagnosis on rotating machinery. Practically, more vibration signal data can be obtained if the test rigs are available and hence, provide more information concerning any faults within the rotating machinery. This will increase the sensitivity and reliability of pattern recognition, whereby one is encouraged to include feature parameters as many as possible without concerning redundancy or numerical singularities. Future development of the technique will be directed towards the ability to estimate the remaining life of mechanical components.

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