Intelligent Vibration Signal Processing for Condition Monitoring

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Abstract

Recent advances in pattern analysis techniques together with the advent of miniature vibration sensors and high speed data acquisition technologies provide a unique opportunity to develop and implement in-situ, beneficent, and non-intrusive condition monitoring and quality assessment methods for a broad range of rotating machineries. This invited paper provides an overview of such a framework. It provides a review of classical methods used in vibration signal processing in both time and frequency domain. Subsequently, a collection of recent computational intelligence based methods in this problem domain with case studies using both single and multi-dimensional signals is presented. The datasets used in these case studies have been acquired from a variety of real-life problems

1 Vibration and Condition Monitoring

Vibration signals provide useful information that leads to insights on the operating condition of the equipment under test [1, 2]. By inspecting the physical characteristics of the vibration signals, one is able to detect the presence of a fault in an operating machine, to localise the position of a crack in gear, to diagnose the health state of a ball bearing, etc. For decades, researchers are looking at means to diagnose automatically the health state of rotating machines, from the smaller bearings and gears to the larger combustion engines and turbines. With the advent of wireless technologies and miniature transducers, we are now able to monitor machine operating condition in real time and, with the aid of computational intelligence and pattern recognition technique, in an automated fashion. This paper draws from a collection of past and recent works in the area of automatic machine condition monitoring using vibration signals.

Typically, vibration signals are acquired through vibration sensors. The three main classes of vibration sensors are displacement sensors, velocity sensors, and accelerometers. Displacement sensors can be non-contact sensors as in the case of optical sensors and they are more sensitive in the lower frequency range, typically less than 1 kHz. Velocity sensors, on the other hand, operate more effectively with flat amplitude response in the 10 Hz to 2 kHz range. Among these sensors, accelerometers have the best amplitude response in the high frequency range up to tens of kHz. Usually, accelerometers are built using capacitive sensing, or more commonly, a piezoelectric mechanism. Accelerometers are usually light weight ranging from 0.4 gram to 50 gram.

1.1 Advantages of vibration signal monitoring

Vibration signal processing has some obvious advantages. First, vibration sensors are non-intrusive, and at times non-contact. As such, we can perform diagnostic in a non-destructive manner. Second, vibration signals can be obtained online and in-situ. This is a desired feature for production lines. The trending capability also provides means to predictive maintenance of the machineries. As such, unnecessary downtime for preventive maintenance can be minimized. Third, the vibration sensors are inexpensive and widely available. Modern mobile smart devices are equipped with one tri-axial accelerometer typically. Moreover, the technologies to acquire and convert the analogue outputs from the sensors are affordable nowadays. Last but not least, techniques for diagnosing a wide range of problems exists in the literature, crack [3], worn or faulty bearings [4, 5] , shaft unbalance [6, 7] , faulty gearbox [8-11], etc.

1.2 Limitations of vibration signals

Although techniques based on vibration signals are generally versatile, their usefulness is limited by several factors. As mentioned above, different vibration sensors have different operating characteristic, and attention should be paid when selecting a suitable sensor. This would require the engineers to understand the physical characteristics of the vibration source. Also, useful characteristics of the vibration signal could be easily masked by inappropriate mounting of the sensors. The adhesion mechanism may also damp the high frequency component if it is not done correctly. Vibration sensors also come with a wide variety of dynamic ranges and sensitivities. Careful perusal of the datasheet is always recommended when choosing a suitable sensor.

2 Problem Framework

Machinery conditions monitoring is a crucial technique for guaranteeing the efficiency and quality of any production process. When certain machine failure happens, the correct monitoring data analysis helps the engineers to locate the problem and repair it quickly. The more ideal situation is that we could predict the machine failure in advance and carry out the maintenance before the failure happens, thus the machines will always run in a healthy condition and provide satisfactory work.

Most of the machines will vibrate when they are operating and with the miniature vibration sensors and high speed data collection technologies, those vibration signals can be acquired and used to analyse the machine conditions without physically opening the machine which is important for ensuring the continuous production process.

The vibration status has a close relationship with the condition of the component under monitoring. For example, the machines containing bearings often fail due to the wearing of the bearing rotating parts. Depending on the different faulty conditions, the defects modulate the vibration signals with their respective patterns. The inner and outer race fault conditions have a periodic signal; the rolling element fault may or may not be periodic, dependent upon several factors including the degree of damage to the rolling element, the loading of the bearing, and also the track that the ball describes within the raceway itself. The cage fault generates a random distortion, which also depends on the degree of damage and the bearing loading. Figure 1demonstrates the appearances of six different abnormal vibration signals.

The core objective is to categorize the acquired vibration signal into the corresponding machine condition correctly, which is generally a multi-class classification problem. A typical set-up of the overall framework for this problem is depicted in Figure 2.

3 Feature Extraction

The sampled vibration signal is a large collection of time indexed data point. To make sensible deduction automatically using a machine learning based classifier is not an easy task owing to the curse of dimensionality. Instead of processing the raw signals, the common approach is to compute certain attributes of the raw signal that can describe the signal in essence. In the machine learning community, these attributes are referred to as features. At times, multiple features are computed to form a feature sets. Depending on the number of features in the set, one may need to perform further filtering of the set using a feature selection algorithm. There are many algorithms proposed for this purpose, e.g. greedy algorithms, hill-climbing (forward selection), backward selection, forward-backward selection, etc. Evolutionary algorithms, e.g. Genetic Algorithms and Genetic Programming, were also proven effective in selecting the best features among the feature sets ([12] [13] [14]).

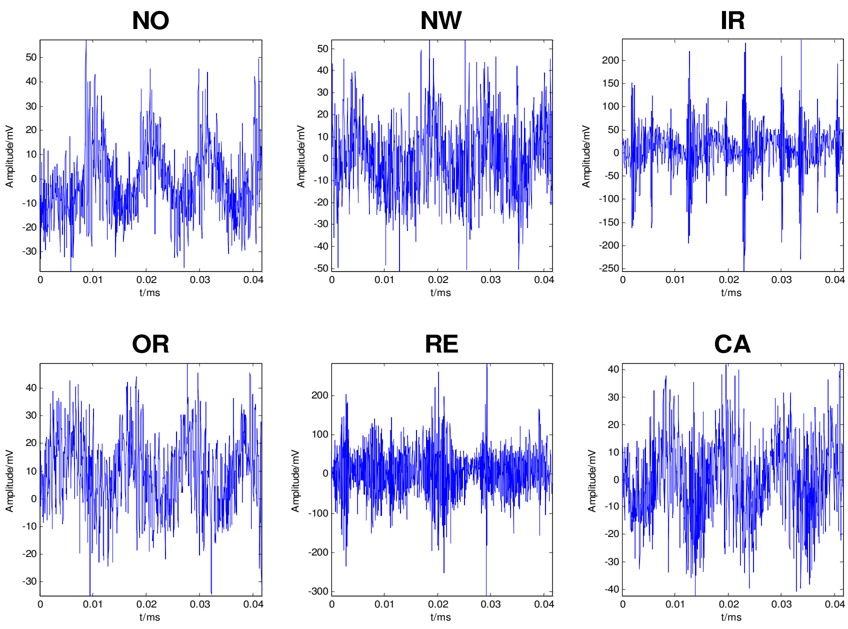

Figure 1: Vibration signals of the six different bearing operating condition.
NO: Normal NW: Normal Worn IR: Inner Race Fault OR: Outer Race Fault RE: Rolling Element Fault CA: Cage Fault

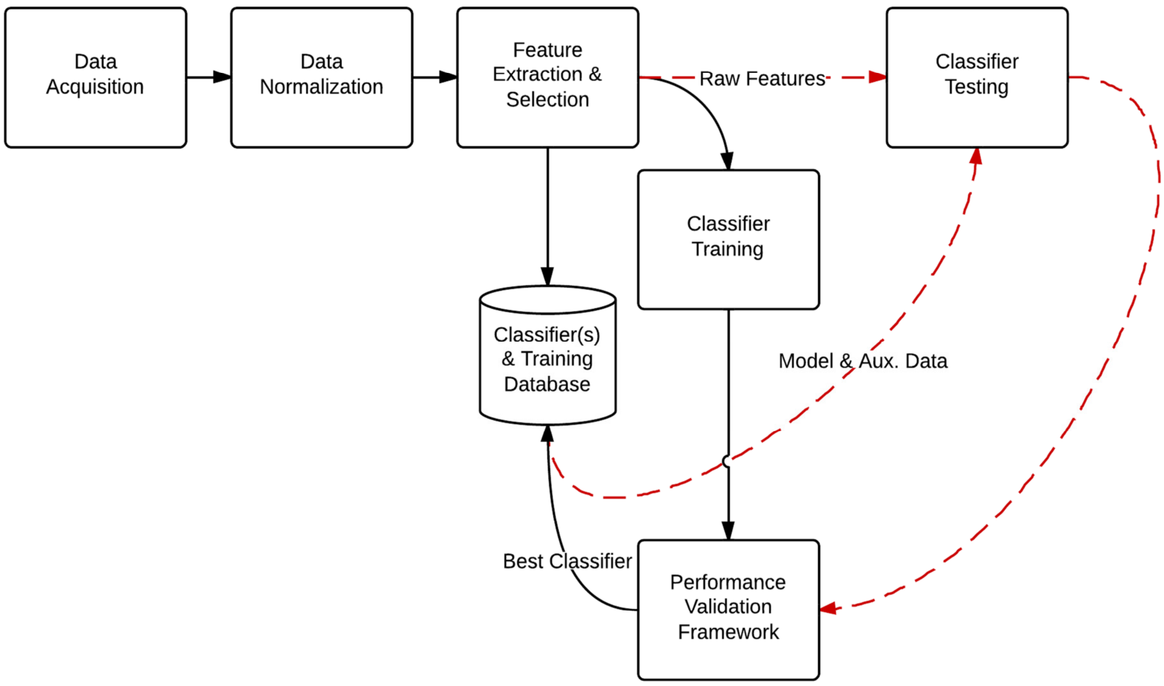

Figure 2: Overall Framework that involves training, testing and validation. The solid path denotes the training procedures and the dotted path denotes the testing procedures. The best classifier and auxiliary parameters are stored and deployed for real world application.

3.1 Classical Methods

As vibration signals typically exhibit in the form of a high frequency sinusoidal signal modulated by multiple lower frequencies, sometimes aperiodic, signals (see [15] for a mathematical model), it is not surprising to find earlier works in this area focus on time domain amplitude based features. The following is a list of common features used either for manual inspection or automatic monitoring:

1. Peak amplitude, x_p, refers to the maximum positive amplitude of the vibration signal.
2. Mean amplitude, $\bar{x}$, refers to the average of the vibration signal over a sampled interval.
$$\bar{x} = \frac{1}{T}\int x(t)dt$$
3. RMS amplitude or the root mean square amplitude is defined as the variance of the signal magnitude, i.e.
$$x_{RMS} = \sqrt{\frac{1}{T}\int |x(t)|^2 dt}$$
where T is the sampled signal duration, and x(t) is the vibration signal. RMS amplitude is resilient to spurious peaks in the steady state operating condition.
4. Peak to Peak amplitude, x_{pp}, is the range of the vibration signal, $x_{max}(t) - x_{min}(t)$, which denotes difference between the maximum positive peak amplitude and the maximum negative peak amplitude.
5. The crest factor is obtained from computing the ratio of x_P and x_{RMS}, that is
$$CF = \frac{x_p}{x_{RMS}}$$
The crest factor is useful in detecting early stages of fault condition and is used in on-line monitoring. The crest factor of a pure sine wave is 1.414.

The above time domain features are sensitive to components of the vibration signals induced by faults. However, they only work with signals which are no zero mean and unit variance.

With the invention of fast Fourier transformation and digital computers, the efficient computation of the signal's power spectrum became feasible. Analogous to the mathematical duals, frequency domain features are popularly used in condition monitoring.

1. Arithmetic Mean of a frequency spectrum (in dBm) is defined as
$$20\log\{(\frac{1}{N}\sum_{N} A_n)/10^{-5}\}$$
with A_n denotes the amplitude of the nth component in a total of *N* components. The feature gives the average amplitude value within a frequency range.
2. An alternative to the arithmetic mean is the Geometric Mean. It is defined (in dBm) as
$$\frac{1}{N}\{\sum_{N} 20\log(\frac{\frac{A_n}{\sqrt{2}}}{10^{-5}})\}$$
when a reference spectrum is available, one can compute the followings:
3. Matched Filter RMS provides the RMS amplitude of the frequency component with reference to the reference spectrum. Note that the operation is in logarithm.
$$M_{frms} = 10\log\{\frac{1}{N}\sum_{N}\left(\frac{A_i}{A_n^{ref}}\right)^2\}$$
where A_n^{ref} denotes the nth component is N components of the reference spectrum.
4. The RMS of Spectral Difference on the other hand computes
$$R_d = \sqrt{\{\frac{1}{N}\sum_{N}\left(P_n - P_n^{ref}\right)^2}$$
where P_n and P_n^{ref} denote the amplitude (in dB) of the incident and reference spectrum.

5. The Sum of Squares of Spectral Difference gives greater weight on the high amplitude components

$$S_o = \{\frac{1}{N}\sum_{N}\sqrt{[(P_n + P_n^{ref}) \times |P_n - P_n^{ref}|]}$$

Similar to the amplitude features, the above frequency domain features will provide a quick overview of the machine condition without specific diagnostic capability. Nevertheless, one can apply these features in sub-divided frequency bands to provide more diagnostic ability.

Another classical method dealing specifically with imbalance is by placing two sets of orthogonal probes and displaying them in the X-Y mode of an oscilloscope, which then display the orbital representation of the vibration signal.

As in other signal processing domains, statistical tools are also proven useful for vibration signal processing. In particular, higher order statistics [16] and its associated high order spectra can provide great insights in vibration signal processing. Some useful features are listed below:

1. Higher order moments are in essence higher order expectation of a mathematical variable. The first and second order moments, mean and variance, are used widely in all statistical applications. The n^{th} order moment is then computed through rising the exponent is the expectation expression to n. In general, the n^{th} central moments for a signal f(x) of x are computed using $\mu_n' = \int_{-\infty}^{\infty}(x-c)^n f(x)dx$ where c denotes the DC component.

2. Higher order cumulants is closely related to the higher order moment through the logarithms of moment generating function. The first four cumulants can be written in terms of moments as:

$$\kappa_1 = \mu_1'$$
$$\kappa_2 = \mu_2' - \mu_1'$$
$$\kappa_3 = \mu_3' - 3\mu_2'\mu_1' + 2{\mu_1'}^3$$
$$\kappa_4 = \mu_4' - 4\mu_3'\mu_1' - 3{\mu_2'}^2 + 12\mu_2'{\mu_1'}^2 - 6{\mu_1'}^4$$

If the vibration signal is normalized to zero mean and unit variance, then the computation simplify leaving only the non-μ_1 terms. For this reason, among others, it is customary to normalize the vibration signal to zero mean and unit variance. The third and fourth order cumulants are commonly referred to as skewness and kurtosis. Kurtosis is often compared with the crest factor as they both good at discriminating emerging faults.

Where there are more than one signals, it is also possible to compute the cross cumulants.

3. As with second order statistics, it is possible to define higher order correlation functions at different lags and their associated spectra. Bi-spectrum and Tri-spectrum [17] are examples of the higher order spectra which are useful for identifying the non-linearity among multiple vibration signals.

The above methods assume steady state signal with fixed speed. In the cases where the rotating frequency is varying, then order tracking algorithms can be used to convert the signal into steady state equivalent.

3.2 Novel Methods

In recent years, there have been many extensions of features building on the features presented in Section 3.1. Liang et al. proposed a new method of generating meta-features, features derived from main features, and the idea had led to impressive performance reported in [18]. In his scheme he tried two different approaches, one with a single GP and another with a bundle of GPs.

Wong et al. [19] on the other hand proposed statistical descriptors on the sub-bands on the vibration power spectra where 8 different statistical moments were calculated by treating the power spectrum as a time series and as a histogram. The individual power spectrum was divided into sections of equal bandwidth.

Wavelets are also popular choices in signal processing where the vibration signals are decomposed into components of brief oscillation. In contrast to Fourier's assumption, wavelet transform analyses the signal by projecting it onto the wavelet subspaces. This approach had been well investigated. For instance, Prünte et al. [20] proposed a matched wavelet approach for condition monitoring of linear guideways while Ece and Başaran [21] proposed a coupling wavelets packets for condition monitoring of induction motors.

More recently, empirical mode decomposition (EMD) based on an extension of the Hilbert Transform proposed by Huang [22] received increasing popularity. Similar to wavelets, the EMD decomposed the signal into a collection intrinsic mode functions (IMF). The IMFs are obtained in an iterative manner using the Hilbert-Huang Transform. In essence, the transform extract the signal envelope and subtract it from the signal and the process is repeated until the terminating criterion is met. Yang et al. proposed a bivariate EMD for turbine condition monitoring in 2011 [23]. He and Li also approached a two-step data-mining approach for Plastic Bearing using EMD [24].

In order to address non-stationary operations of certain type of machines and components, researchers also lend themselves to entropic features such as the Renyi Entropy [25], Approximate Entropy [26], Fuzzy Entropy etc. In a recent work, Wong et al. propose the use of fuzzy entropy to detect bearing fault with good preliminary results [27].

4 Classification Methods

Many classification techniques can be used to classify different vibration type based on the features provided. If the vibration signals' features are carefully devised and the parameters of the classifiers are carefully tuned, it is possible that to achieve a high accuracy in classification performance. The following section introduces some widely used state of the art classifiers that have been already used in classify vibration signal status.

4.1 Decision Tree/Forest

Decision tree/forest [28] is the name of a series of algorithms that approximate the discrete classification function by using the tree based representation. In each decision tree, the instance is passed down from the root node to a leaf which includes a final decision (classification result). Each node in the tree carries out a test for certain attribute of the instance and each branch of this node corresponds to one possible value of the attribute. If we describe the decision tree classification process in a more understandable way, it is a set of if-then rules.

To deal with multiclass classification, one can use one tree and assign each leaf node a class (more than one leaf node may represent one class). Thus if an instance passes down the tree, it will finally fall into one class. However, using one tree easily causes over fitting and thus a random forest is often used to do the classification. Random forest is an ensemble learning method that constructs multiple decision trees during the training process and the final output is the mode of the classes output by each individual decision trees.

Decision tree is well suited for those situations where the instances (input) are represented by attribute pair values, i.e. data vectors. It even can tolerate that there are some missing feature values which happens when it comes to the real-time data collection and feature extraction process. A more enhanced version is to have the decision tree to evolve using a genetic programming paradigm [14].

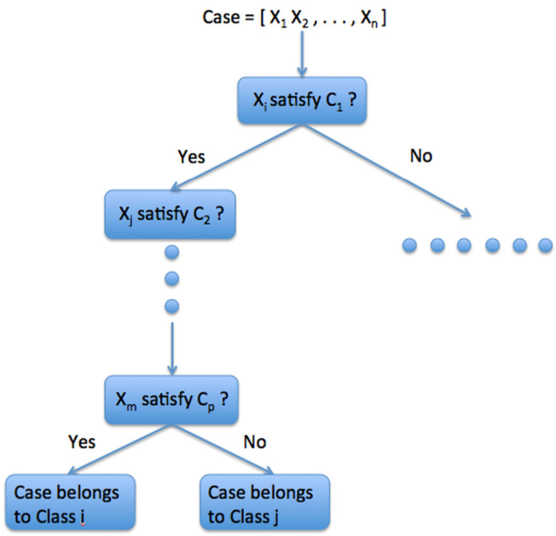

Figure 3: A typical Decision Tree classifier

4.2 Artificial Neural Network (ANN)

The Artificial Neural Network [29] is a learning method that can learn real-valued, discrete valued and vector valued target function. It is inspired by the biological learning system which is constructed by huge amount of interconnected neuron cells. In general, ANN consists 3 parts, the input layer, hidden layer and output layer. Each layer has several to large amount of artificial neurons which accept an input and generate an output according to the pre-defined rules. Artificial neurons in one layer are densely connected to the neurons in adjacent layer and each connection are assigned a weight, which is updated during the training process according to the errors in the output layer, to fit for the correct classification results. Figure 4 shows the structure for an ANN.

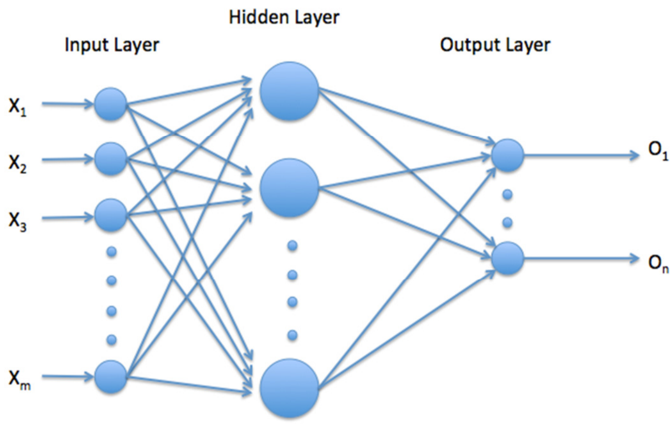

Figure 4: A Multilayer Perceptron Model for ANN

There is a special case that if the ANN is trained using the unsupervised learning to generate a normally two dimensional representation of the input space, it is called Self Organizing Map (SOM). There is exiting works that use SOM to process vibration signals, e.g. [19] and [30].

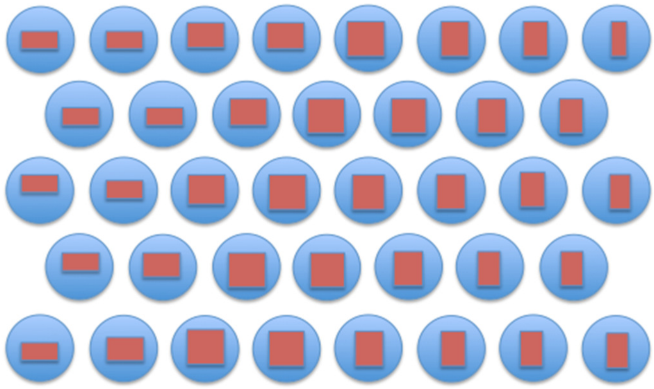

Figure 5: A SOM illustrations for grouping shapes.

Compared with decision tree algorithms, the training time for ANN is often much longer, especially the network has huge amount of neurons and thus updating the weights need a lot of computations. But given a trained network model, computing the output given an input vector is fast.

4.3 Support Vector Machine (SVM)

SVM is a supervised learning model which constructs one or a set of high or infinite dimensional hyper plane(s) to separate the data into different classes [31]. By using different kernels, SVM can make linear or non-linear classifications according to the features of the data. Although SVM is initially for the binary classification problem but through building a set of SVMs based on one class versus all or one class versus one rules, the multiclass problems can be solved.

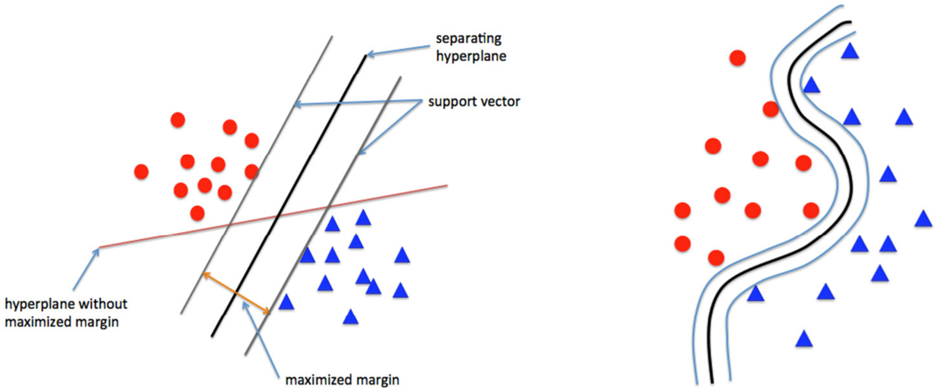

Figure 6 a) Linear SVM and b) Non-linear SVM

SVM has high accuracy and nice theoretical guarantees regarding over fitting. It can perform well even if the data is not well separable in the original feature space with appropriate kernel and carefully tuned parameters. However, it is hard to interpret the model and tune the parameters. If the users do not have a lot of experience, it might be difficult to work efficiently with SVM.

4.4 Summary

There is no obvious best classifier for any given task. Each classifier has its own specific drawbacks such as over fitting and bias. One should bear in mind that good training data or well separated feature space is much more desired than good classifiers or classification algorithms. When the data is highly separable, the choice of the classifier does not matter much. When the data is not sufficiently separable, validation and model selection procedures play an important part to help choose the most generalised classifier. In practice, features extracted are corrupted with noise and measurement errors. So obtaining separable data that are well generalised can be a practical challenge.

In summary, the data collection and feature extraction processes play the most vital part in vibration signals classification as if these processes are dealt with properly; good classification performance is then warranted.

5 Case Studies

5.1 Unbalance Detection on Rotating Shaft

Unbalance is a condition where unevenly distributed mass are present on the rotating shaft, causing undesired deviation from the rotating path. Using two vibration sensors mounted in an orthogonal set-up, we can observe the orbit plot of the rotating shaft. In Figure 7, a test bed set up for unbalance detection is presented. A DC motor is used to drive the flywheel on a shaft connected to a computerised sensing block with two accelerators. To simulate unbalance, weight can be added to flywheel and rub can be applied to the shaft. The data were acquired for a range of varying motor speed from 77 rev/s to 100 rev/s. The sample orbit plots and the corresponding Fast Fourier Transform (FFT) plots for the four possible combinations are shown respectively in Figure 8 and Figure 9.

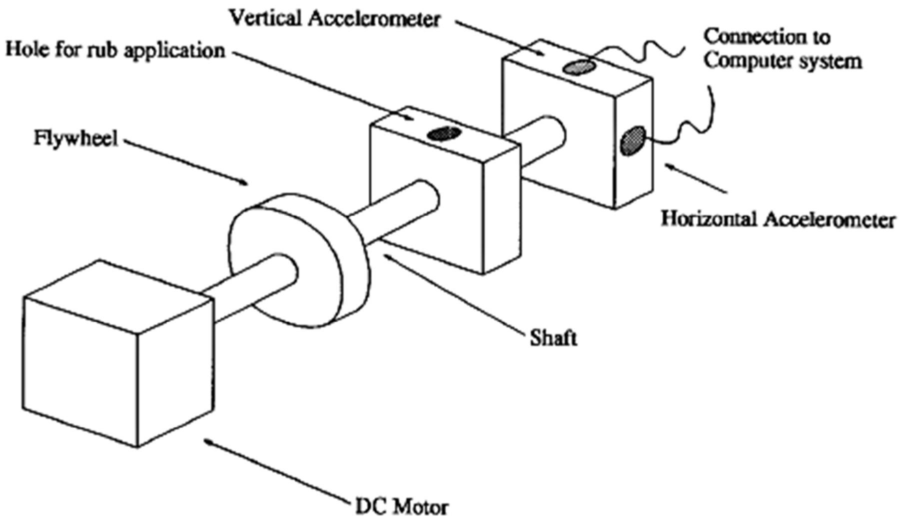

Figure 7: Experimental Setup for Unbalance Classification [Image taken from [6]].

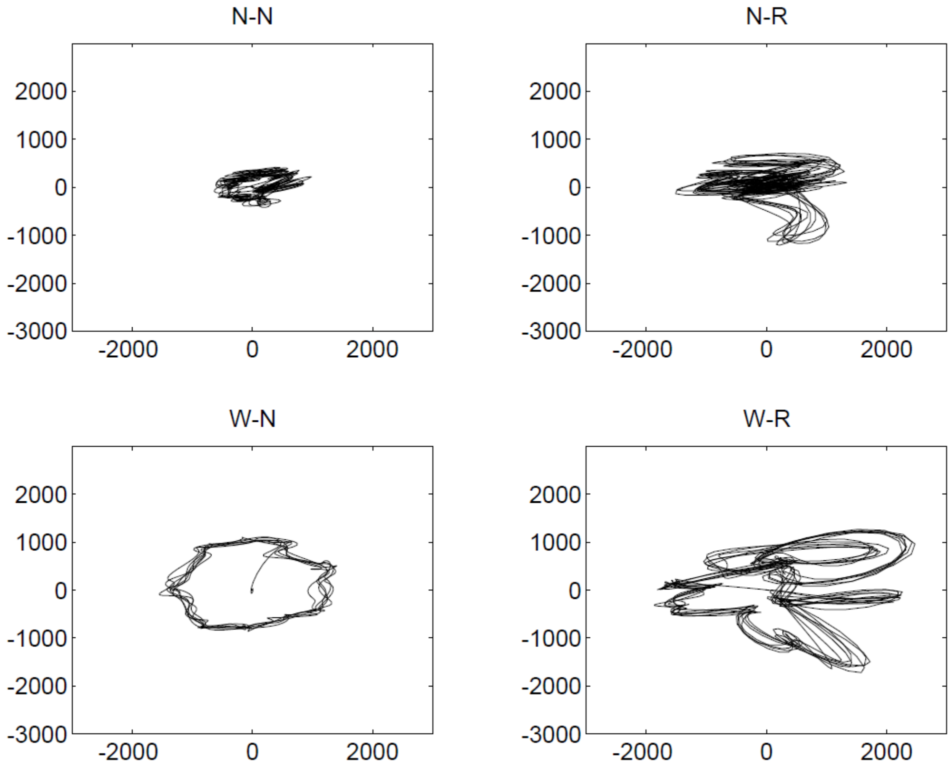

Figure 8: Sample Orbit Plots of the four conditions. N-N: Normal Condition (No rub and No weight); N-R: Rub-only; W-N: Weight-only; W-R: Both Weight and Rub Applied [Image taken from [6]]

McCormick and Nandi [6, 32] investigated this problem with a variety of processing methods and attempted to classify the condition with classical statistical methods and a set of ANNs. The best performance reported in this work was around 92% classification accuracy in the test set. Both moment based features and FFT based features were investigated for the problem. The best performance was achieved with the FFT based feature set.

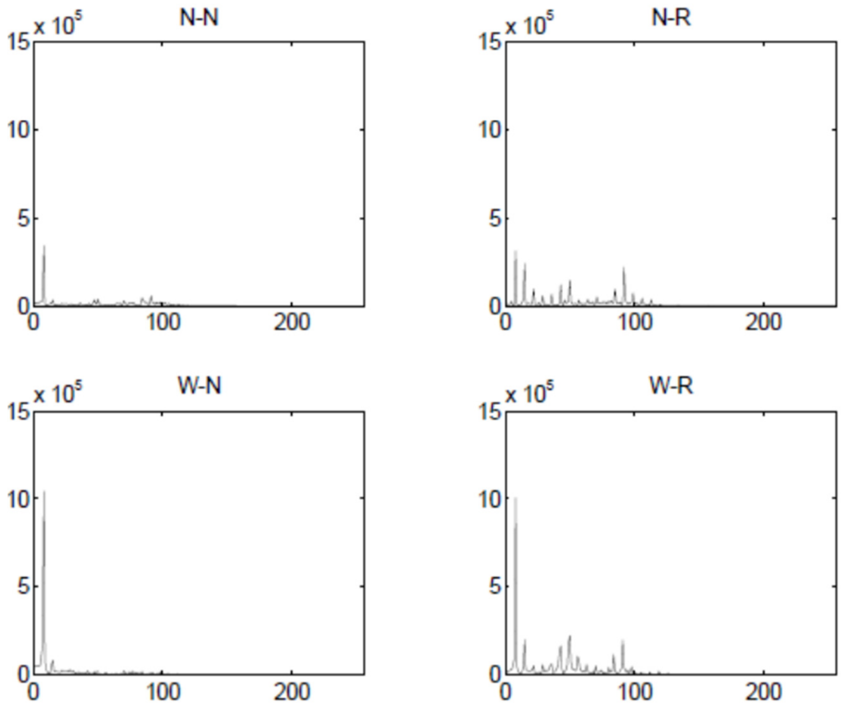

Figure 9: Sample FFT plot of Figure 8 [Image taken from [6]].

5.2 Ball Bearing Fault Classification

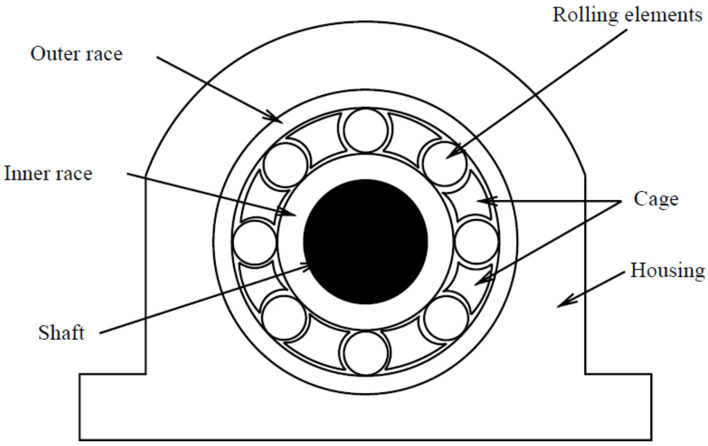

Figure 10: A cross section of a Ball Bearing

Ball bearings are commonly found in mechanical machines and they attribute to a large percentage of the machine failures [12, 31]. The basic composition of a ball bearing is as depicted in Figure 10. The experimental data used in this work was taken from a roller element bearing test rig ([31]). The test rig consists of a DC motor driving the shaft through a flexible coupling, with the shaft supported by two plummer blocks. A series of damaged bearing were inserted in one of the plummer blocks, and the resultant vibrations in the horizontal and vertical planes were measured using two accelerometers. The output from the accelerometers was fed back through a charge amplifier to a Loughborough Sound Images DSP32 ADC card (using a low-pass filter with a cut-off 18 kHz), and sampled at 48 kHz, giving a slight oversampling. The machine was run at a series of different speeds ranging between 25 and 75 rev/s, and ten time series were taken at each speed. This gave a total of 160 examples of each condition, and a total of 960 raw data files to work with.

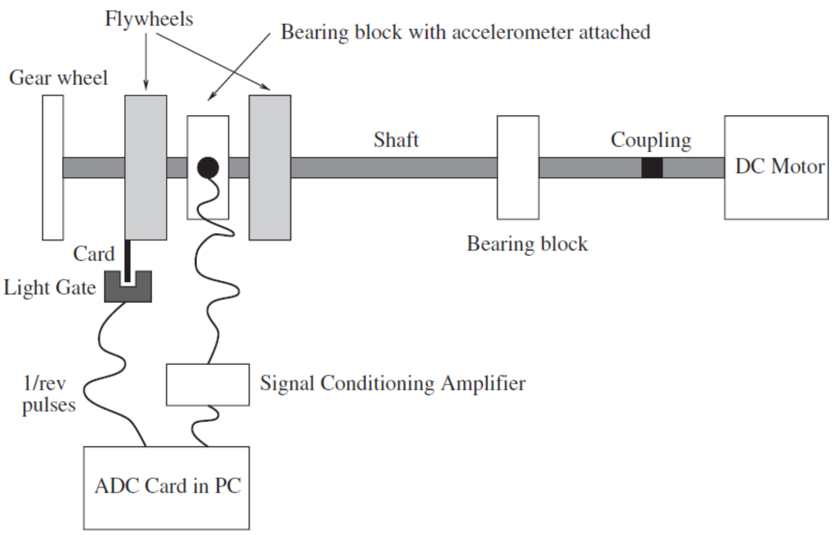

Figure 11: The Ball Bearing Test Rig

A few works had been reported for this problem. Jack and Nandi [31] investigated the problem extensively by interrogating the effectives of 90 statistical features with a range of different pre-processing methods (e.g. difference and sum signals, low pass and high pass filtering) as well as the Spectral (66 FFT point) feature set. With the raw statistical feature set, Jack and Nandi report 97.6% of test accuracy using a support vector machine and the figure was further improved to 100% with a Genetic Algorithm (GA) based feature selection procedure. Twelve features were selected by the

GA. Subsequently, Zhang and Nandi [13] proposed a genetic programing (GP) based method and worked with 156 raw statistical and FFT features to achieve one particular solution with ten selected features. The best performance reported for the GP classifier was again 100% in classifying all six classes. This was the first GP based classifier for Machine Condition Monitoring. In another work, Wong et al. [19] proposed a novelty detection based method that learn from only the healthy data without knowledge of the faulty data distribution. A modified self-organizing map (SOM) was utilized with 96 spectral and statistical feature sets and the best performance reported was 99.8% for fault detection. More recently, Guo et al. [14] also used GP to extract four features that had reported a classification accuracy of 97.1% for classifying the six bearing conditions. Others who attempted the same problem include Rojas and Nandi[4], as well as Mu and Nandi [33].

5.3 Helicopter Gearbox Fault Detection

The Westland helicopter datasets was made available from Pennsylvania State University (http://www.wisdom.qvl.psv.edu/Westland/data unavailable). The vibration data were acquired from the aft main transmission of a US Navy Westland CH-46E helicopter. Eight channels of vibration data were digital acquired at a rate of 103,116 Hz. There are eight conditions available:

- Planetary bearing corrosion. (#2)
- Input pinion bearing corrosion. (#3)
- Spiral bevel input pinion spalling. (#4)
- Helical input pinion chipping. (#5)
- Helical idler gear crack propagation. (#6)
- Collector gear crack propagation. (#7)
- Quill shaft crack propagation. (#8)
- Normal operating condition. (#9)

Only one fault was placed within the transmission at any one time. Vibration data was sampled with eight different accelerometers placed in the Starboard engine input, Port engine input, Aft side of mix box, Starboard quill shaft, Starboard planetary, Port planetary, Port quill shaft, and Accessory drive.

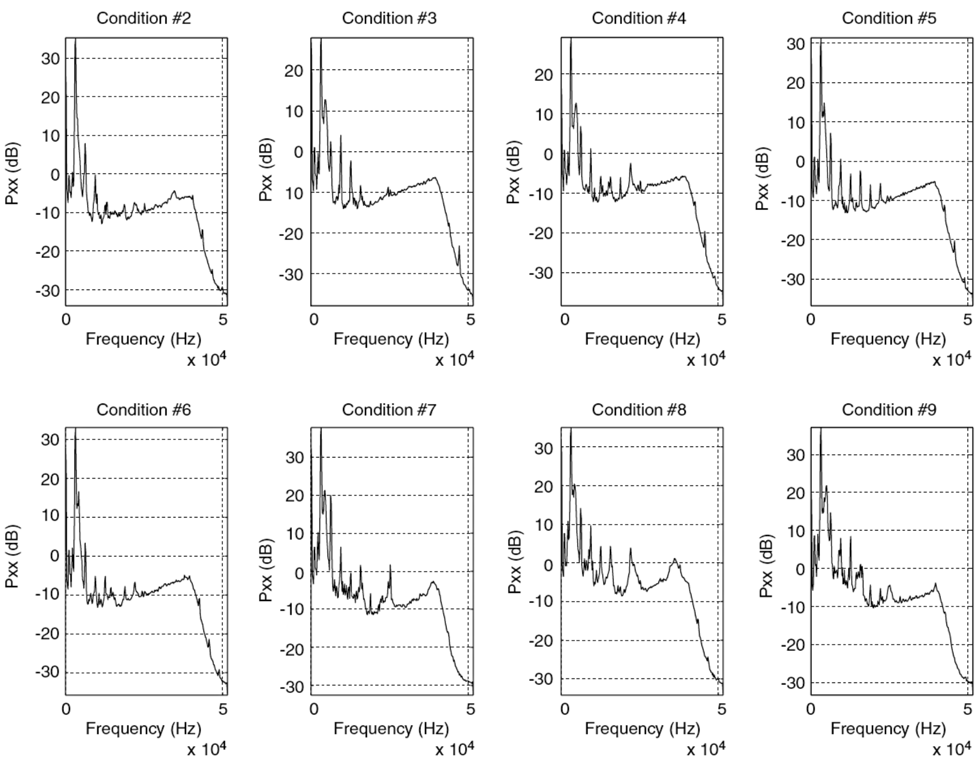

Figure 12: Power Spectra of the Westland Helicopter's Port Quill Shaft at zero load.

Fig. 12 shows typical power spectra for the eight different conditions mentioned above. This figure was generated using the accelerometer at the Port Quill Shaft at zero load level. Wong, Jack and Nandi [19] attempted to detect the faulty condition using a SOM based novelty detection based method. The motivation behind this is that it will be difficult and expensive to simulate faults in an expensive and safety critical machine such as a helicopter. Therefore, when there is a deviation from the normal operating condition, an alarm should be raised for preventive maintenance to take place. To tackle the problem, multiple SOM were deployed for each sensor dimension, a final decision is reached by setting appropriate threshold on the Mahalanobis distance metric. Statistical descriptors on the Power Spectral of the vibration data were used as the feature set. In the end, a detection accuracy of 99% was reached with 100 training epoch, with a 50 kHz bandwidth Westland data set. This is a good example of multi-dimensional vibration data set where simple data fusion is used for decision making. The classifier has no knowledge of the faulty conditions.

6 Conclusions

Vibration signals are useful for diagnosing rotating machines' health condition. This paper summarizes a collection of work from our research group. We have not dealt with non-stationary vibration signals in this paper. To address the non-stationary signals, we will need to lend ourselves to more signal processing tools that exploit cyclostationary properties in these signals, as well as perform additional pre-processing tasks, such as Autoregressive Filtering [9, 10, 32], Order Tracking[34-36], etc. Entropy based features was also recently demonstrated to provide good performance in non-stationary cases[37] .

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