Classification of Ball Bearing Faults using Entropic Measures

M. L. Dennis Wong[1], Chao Liu[2], and Asoke K. Nandi[2]

[1]FECS, Swinburne University of Technology Sarawak Campus
Jalan Simpang Tiga, 93350, Kuching, Sarawak, Malaysia.
[2]Department of Electronic and Computer Engineering
Uxbridge, UB8 3PH, United Kingdom
{dwong@swinburne.edu.my, [Asoke.Nandi, Chao.Liu]@brunel.ac.uk}

Abstract
The ability to detect faults in rotating elements is highly desired in machine condition monitoring applications (MCM). In this work, we present a novel method for discriminating faulty bearing under varying loads. The method utilizes a new feature set based on the sample entropy of the indexed time sequence acquired under operating conditions. Sample entropies of the raw and envelop vibration signals were investigated in this work. Empirical results demonstrate that a high 99% accuracy has been achieved with the proposed features in identifying the correct condition in roller element bearings.

1 Introduction

In the recent decades, the machine condition monitoring research [9,14] has undergone tremendous advances and progressed from a predominantly manually based monitoring approach to a highly automated approach where manual intervention is only required in the event of a fault being detected [4-5, 10-11]. This has created a need for techniques that are capable of automatically identifying when machine deviates from a normal condition. Many approaches have been advanced in this respect, from basic decision making by observation of the various characteristics of the vibration time series, through to various machine learning based approaches.

The ability of identifying a fault condition in roller element bearings enables one to prescribe appropriate solution when a fault is detected, e.g. applying lubrication, dusting, replacing the faulty ball bearing, etc. However, in many industries, scheduling downtime for corrective maintenance is often a complex task. Furthermore, for large scale machineries, waiting for a fault to occur could be catastrophic to the entire operation. Therefore, in such cases, periodically scheduled preventive maintenance measures are often sought. Nevertheless, these preventive maintenance measures, in many cases, are not so cost effective, as quite often the optimal lifetimes of specific parts are not known. This drawback led the industries and the research communities to search for measures that are able to estimate and predict when a fault is likely to occur, i.e. predictive maintenance.

To enable predictive maintenance, one needs to be able to monitor the running condition of the machine online. One commonly used approach is to install vibration transducers, e.g. displacement sensor, accelerometers, acoustic emission sensors, etc. The choice of transducers is largely dependent on the physical and running characteristics of the machine under monitoring. For ball bearings and roller element bearings, accelerometers are usually used for their wide dynamic range and bandwidth. The vibration time series acquired from the transducers are then monitored through dedicated computing workstations. For effective manual monitoring, time domain features (discriminating characteristics), including, but not limited to, the root mean squared (RMS) voltage, the peak voltage, the X-Y plot, the crest factor (the ratio of the peak voltage over the RMS voltage), etc., are often used. For more advanced monitoring mode, the vibration time series is then converted to frequency domain equivalent, i.e. the FFT or the Power Spectrum. In recent years, with the increase in computational power and digital storage, time-frequency representations are also used, including the waterfall diagram, discrete wavelet transform, etc.

One popular automation approach is to lend ourselves to the classical pattern classification framework. In this framework, one would map the raw vibration signals into features domain, and then employ one of the many learning machines available to decide automatically the decision planes for discriminating healthy and faulty patterns from the features. The same features mentioned are often used for this approach too. In this paper, we propose a new set of features developed using sample entropy (SampEn) (see [1] and Section 3 later). To our understanding the current contribution is the first work to propose SampEn as the discriminating feature, although there are some prior works that utilized closely related features, the Approximate Entropy (ApEn) [6, 7]. The motivation for using entropy based feature is reserved for further discussion in Section 3.

The rest of this paper is organized as follows. In Section 2, we present the problem description and the two-class classification frameworks. Following this, we briefly discuss the ApEn and SampEn in Section 3. Section 4 presents the details of data pre-processing and feature extraction, while Section 5 gives an account of the empirical works and results obtained. Some discussions are also presented in the same section. Finally, concluding remarks are presented in Section 6

2 Problem Description

In this paper we attempt to distinguish faulty roller elements bearings from the healthy normal bearings. The vibration data used in the paper have been taken from experiments on a small test rig, which simulates an environment for running roller bearings. Six conditions have been recorded and tested. Two normal conditions -- a brand new condition (NO) and a worn but undamaged condition (NW); four fault conditions -- inner race (IR) fault, outer race (OR) fault, rolling element (RE) fault, and cage (CA) fault. Data was recorded over a range of 16 speeds. The variation of speeds adds the non-stationary characteristic to this problem. Figure 1 presents some typical time series plots for the six different conditions.

Depending on the fault conditions, the defects modulate the vibration signals with their respective patterns. The inner and outer race fault conditions have a fairly 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.

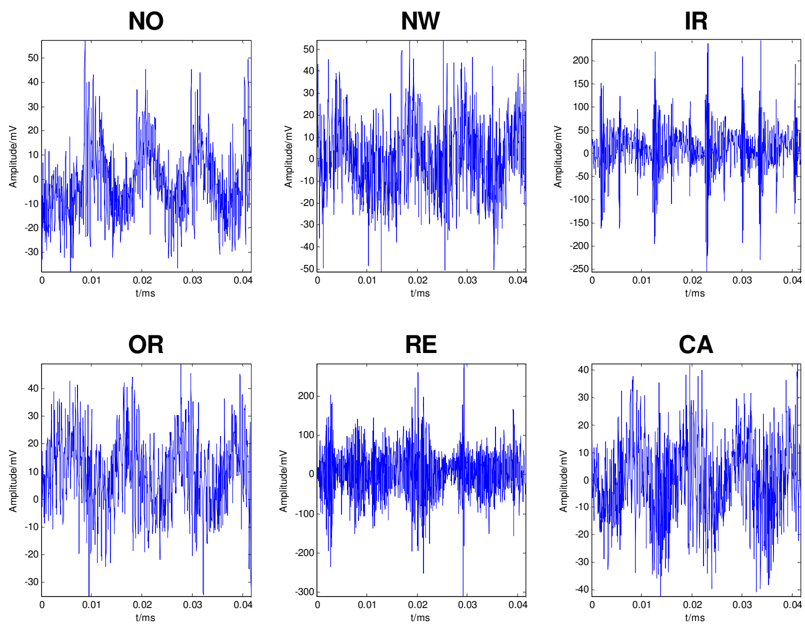

Figure 1: Exemplary instances of vibration signals for the six different conditions.

The experimental data used in this work was taken from a roller element bearing test rig. The test rig consists of a DC motor driving the shaft through a flexible coupling, with the shaft supported by two plummer bearing 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 lowpass 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.

3 Sample Entropy

The classical Shannon's entropy, $H_n = -\sum_{x_i \in X} p(x_i) \log p(x_i)$, has been long interpreted as a measure of system uncertainty. For a time indexed sequence of discrete random variables, such as the sampled and quantized vibration signals above, the joint entropy of each samples are defined as:

$$H_n = -\sum_{x_i \in X_0} \cdots \sum_{x_i \in X_{n-1}} p(x_0, \cdots, x_{n-1}) \log p(x_0, \cdots, x_{n-1}) \quad (1)$$

where $p(x_1, \cdots, x_n)$ is the joint probability of the n samples in the sequence. For characterizing the system dynamics, the Kolmogorov-Sinai (KS) entropy, which is defined as the average rate of new information generation, is usually used. However, it is difficult to estimate KS entropy within a satisfactory precision. However, for short, and noisy time series, Pincus [3] had proposed the approximate entropy (ApEn) to estimate the rate of generating new information. The notation ApEn(M,r,N) denotes the approximated negative natural logarithm of the conditional probability that a N-point sequence, having repeated itself for M points within a selected tolerance, r, will be repeating itself for (M+1) points. The tolerance parameter, r, by convention, is set to a fraction of the standard deviation of the sequence for convenience. A typical setting is 0.2 times the standard deviation. ApEn had been proposed as a discriminating feature for condition monitoring in this past decade [6-7].

To reduce the bias caused by pattern self-matching, Richman and Moorman [4] proposed the Sample Entropy (SampEn) for sampled time series data from a continuous process which give the precise negative logarithm intended for ApEn above. For the actual process of computation, the readers are referred to [1] for an in-depth analysis and discussion. The parameters for SampEn are identical to the ApEn's. To the best of our knowledge the current contribution is the first work that investigates SampEn as a discriminating feature for condition monitoring applications. Prior to this, SampEn was used for biomedical monitoring applications [2].

The initial motivations for selecting SampEn as the features for this work are that: 1) entropies are a natural intuitive measure of information rate, and that 2) SampEn seems to be a natural extension of ApEn for finite time indexed sequence (vibration data).

4 Envelope Detection and Feature Extraction

As mentioned above, the defects in the roller element bearing led to distinguishing amplitude modulation on the vibration signals. Therefore, in this work we extracted the sample entropies of 1) the raw vibration data, and 2) the envelope signal of vibration data. The envelope detection is performed digitally through detection and interpolation of the peak values of the vibration signals. Procedurally, we performed a second order differentiation to localize the amplitude peaks in the vibration signal. Next, spline interpolation was used to construct the envelope of the vibration signals using the peak points detected. A sample illustration to demonstrate the envelope detection process is shown in Figure 2. For real world deployment, further processing stages such as trend removal and noise removal may be needed to ensure data consistency.

To construct the dataset, we repeatedly compute the sample entropy of the raw and envelope signals for the following values of M: 0, 1, and 2. Empirical data showed that for larger M values (> 2), the sample entropy computed may not be finite. Therefore, we have chosen to compute only the sample entropies with the above three values of M. The tolerance parameter has been fixed to the de facto 0.2 times the standard deviation.

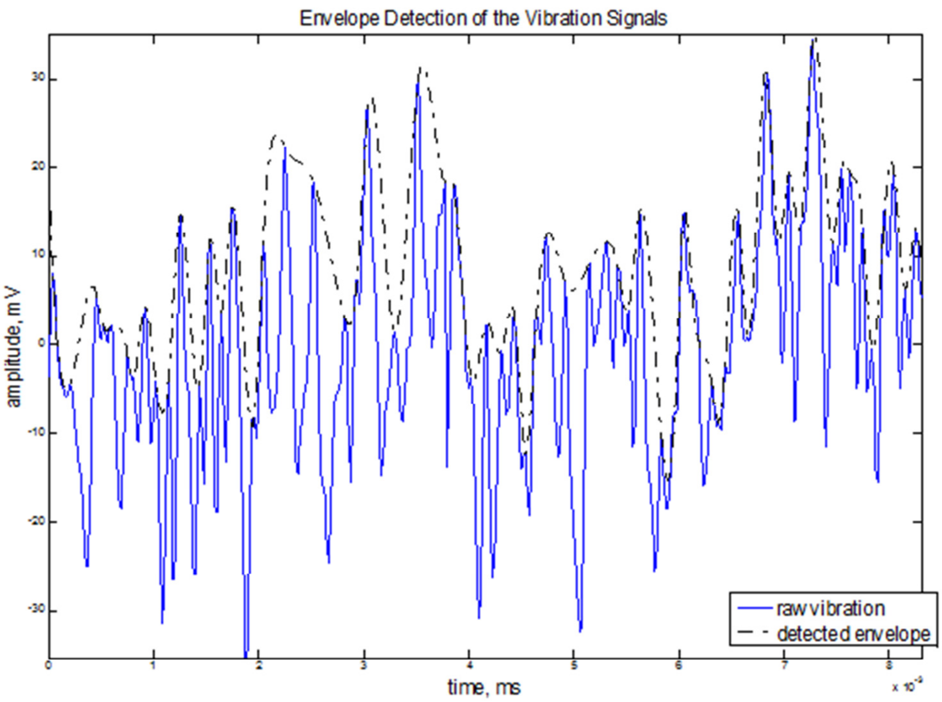

Figure 2: This figure demonstrates the raw vibration signal and its estimated envelope using the algorithm described in Section 3.

5 Experimental Results and Discussion

To validate the performance of the proposed feature set, we have run a number of classification experiments. Section 5.1 gives the details of the experiment setup and tools used. The performance analyses are summarized in Section 5.2 and Section 5.3. The primary aim of this work is to separate the machine conditions into two general states, normal and faulty, and the secondary aim is to distinguish further the different fault types, i.e. a multi-class classification problem.

5.1 Experimental Setup and Platform

For the roller element bearing dataset described in Section 2, we first construct the feature set as described in Section 4. The SampEn was extracted by utilizing the MATLAB scripts provided by PhysioNet (available online at http://www.physionet.org/physiotools/sampen/matlab/).

The computing platform for the experiment reported in this paper is a desktop, with an Intel i7 quad core processor, 8GB RAM, professional graphic card with 1GB VRAM, running on 64-bit Windows 7. MATLAB 2013a is used as the main testing platform, with necessary classifier toolboxes.

The classification accuracy rates are obtained by averaging the results of ten experiments for each classifier and for each experiment, ten-fold validation was employed. The averaged accuracy rate is used to indicate the performance.

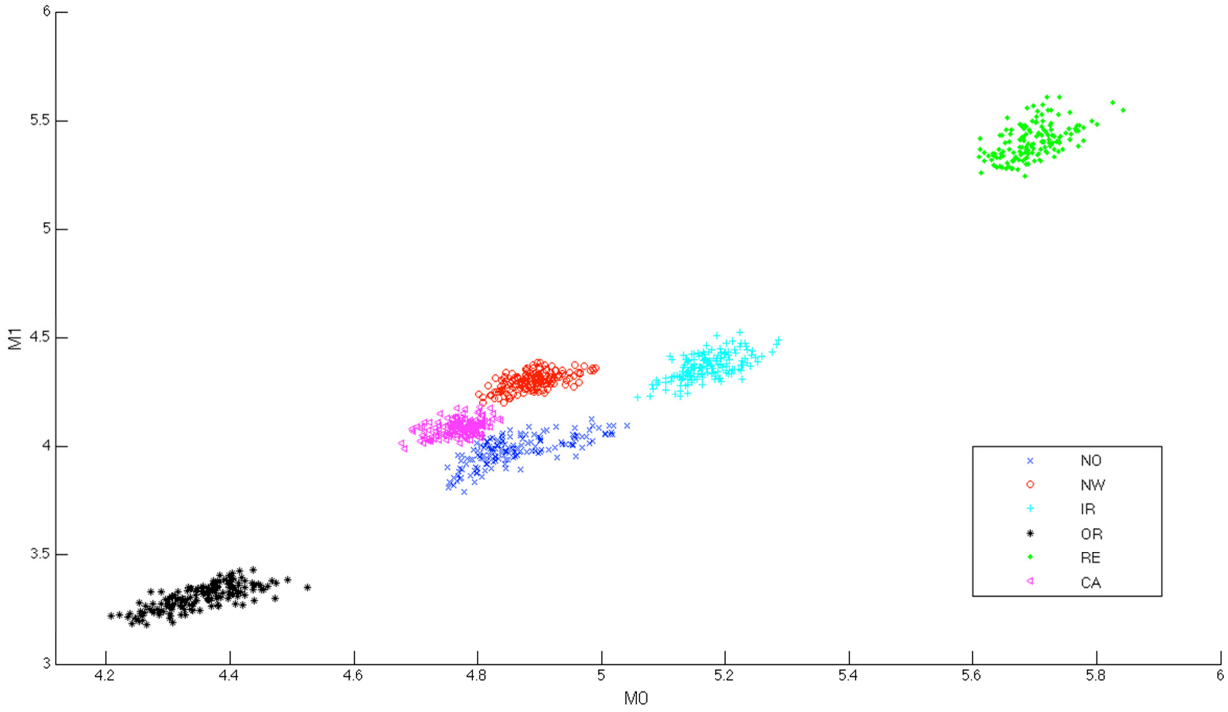

Figure 3: Scatter Plot of Raw Vibration Signal's Sample Entropy (M0 and M1)

Each class in Figure 3 is well separated from each other and almost no member of one class overlap with members of other classes, which is crucial for getting a high accuracy rate.

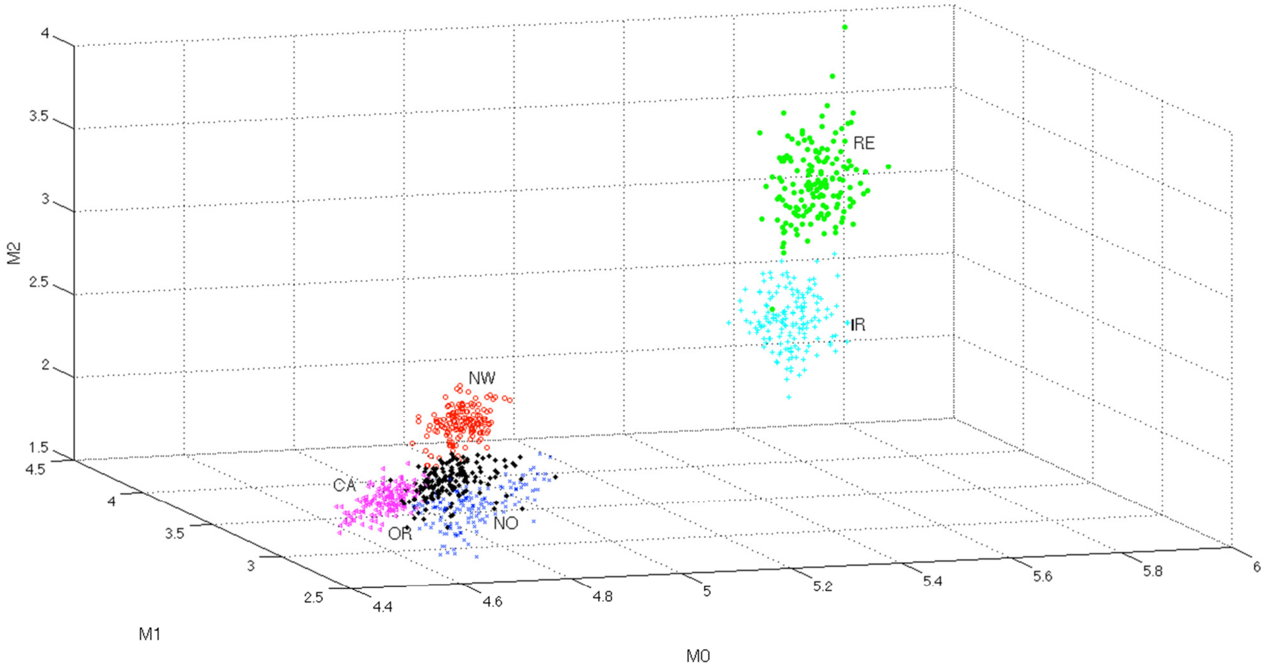

Figure 4: 3D Scatter Plot of Envelop Signal's Sample Entropy (M0, M1 and M2)

Although the classes in Figure 4 do not separate as well as they do in Figure 3 (especially for the area where classes CA, OR, and NO meet each other), most of the members in each class do not overlap with members in other class.

5.2 Classification Results

We have run a series of classification experiments on the feature set extracted according to the method mentioned in section 3 and 4, using different off-the-shelves classifiers. The ten-fold cross validation method was used to get the training and test datasets and the final result of one experiment is the average of the accuracy rate of each fold. In order to show the stability of the classification, the standard deviation of the accuracy rate among the ten-fold results and among different experiments are also given. The details of the classifiers used in this experiment are as the following.

1) Support Vector Machine (SVM): The kernel is radial basis function (RBF) with gamma = 16, c = 32, and the tolerance of termination criterion epsilon = 0.001. Other parameters are set to "libsvm" [12] defaults.

2) Multi-Layer Perceptron (MLP): The size of the hidden layer is 20 and the training function is Levenberg Marquardt back propagation algorithm. Mean squared error is used to compute the error. During the training process, a small portion of data was used to validate (5%) and test (5%), to try to prevent the over-fitting towards the training data.

All of the hyper-parameters for the above classifiers are optimised through grid based parameter selection. Table 1 below shows the summary of results obtained from our experiments. Table 2 shows the confusion matrix for the RBF SVM with the raw data SampEn features. From Table 2, the precision value for classifying normal and faulty bearings was deduced to be 99.7% and 99.8% respectively, and an overall accuracy of 99.8%

	Features	Classifiers	
		RBF SVM	MLP
Raw Data	M0, M1	99.9% (0.11)	99.8% (0.14)
Envelop Data	M0, M1, M2	93.5% (0.5)	93.7% (0.21)

Table 1: The mean accuracy and its respective standard deviation of the ten-fold validation for each of the two classifiers.

Predicted Conditions	True Conditions						class precision
	NO	NW	IR	OR	RE	CA	
NO	160	0	0	0	0	0	100.0%
NW	0	159	0	0	0	1	99.4%
IR	0	0	160	0	0	0	100.0%
OR	0	0	0	160	0	0	100.0%
RE	0	0	0	0	160	0	100.0%
CA	0	1	0	0	0	159	99.4%
class recall	100.0%	99.4%	100.0%	100.0%	100.0%	99.4%	

Table 2: A sample confusion matrix for RBF SVM classifier using the raw data SampEn features.

5.3 Comparison with Related Works

In this section, we have summarized a few related works where the same data set has been used. A summary is presented in Table 3. Zhang et al. [4] proposed a genetic programing (GP) based method and worked with 156 raw features to achieve one particular solution with 10 input features. The training time for their method was reported to be in the order of hours. The best performance reported for the GP detector was 100% in classifying all six classes. On the other hand, Wong et al. [5] 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, similar to our dual class classification result deduced in

Section 5.2. In another work, Guo et al. [13] also used GP to generate four features that had reported a classification accuracy of 97.1% for classifying the six bearing conditions.

From the feature design perspective, Yan and Gao [6] and Tian et al. [7] both investigated the feasibility of identifying machine fault using Approximate Entropy. Unfortunately, both works did not attempt to perform any classification experiment. Incidentally, both works have chosen M = 2 and r = 0.2 times standard deviation as the single discriminating feature. On a separate note, a fuzzy entropy based method is also reported in [8] and a detection accuracy of 83% was achieved. A summary of the comparisons is tabulated in Table 4.

Using the identical feature set, our proposed method can achieve 99.9% accuracy rate. It is important to note that the time of training and classification is negligible if a state of the art classifier is used. In this paper, the SVM classifier is programmed using C and the execution time is within one second. Even for the MATLAB built-in ANN tool, the time for training and classification is within 2 minutes. This is very crucial for the online monitoring. It shows the sample entropy feature is robust and fast enough to be used to monitor conditions of machines.

Research Works	Features	Classifier(s)	Best Performance
Zhang et al. [4]	156 Statistical, Spectral Feature	GP/ANN, GP/SVM, GP	100%
Wong et al. [5]	96 Moment Estimates of Frequency Spectra	Modified SOM	99.8% in detection only
Guo et al. [13]	GP extracted feature sets	ANN, SVM	97.3%
This Paper	two Sample Entropy Features	ANN, SVM	99.9% with 99.8% in detection only

Table 3: A summary of related fault detection work

	Method	Application Field
Yan and Gao [6]	Approximate Entropy	Ball Bearings Condition Monitoring
Tian et al. [7]	Wavelet Filtering Approximate Entropy	Rotating Fan Motors Monitoring
Wong et al. [8]	Fuzzy Entropy	Roller Bearings Condition Monitoring

Table 4: A summary of related entropic features works

6 Conclusions

In this paper, we proposed a new feature set based on sample entropy to detect faulty roller element ball bearings. The motivation for choosing such a feature set arose from the intuition of KS entropy as the measure of new information generation. As the bearings age with time, faults may emerge accordingly. By monitoring these entropy values, one may be able to predict a fault developing. This is the main direction of our future work, i.e. to establish the trending capability of this entropy based features in the goal of achieving true preventive maintenance. The discriminating strength of this new feature set was validated through a number of empirical studies. Also, in our future work, we intend to investigate the application of SampEn features in cyclostationary signal problems as reported in [15, 16].

Acknowledgments

Chao Liu would like to thank Brunel University for his scholarship support.

References

[1] J. S. Richman, J. R. Moorman, *Physiological time-series analysis using approximate entropy and sample entropy*, American Journal of Physiology Heart and Circulatory Physiology, Vol. 278, No, 12, The American Physiological Society (2000), pp. H2039-H2049.

[2] D. E. Lake, J. S. Richman, M. P. Griffin, J. R. Moorman, *Sample entropy analysis of neonatal heart rate variability*. American Journal of Physiology Regulatory Integrative Comparative Physiology, Vol. 283, The American Physiological Society (2002), pp. R789—R797.

[3] S. M. Pincus, *Approximate entropy as a measure of system complexity*, Proceedings of the Natioal Academy of Sciences USA, Vol. 88, National Academic of Sciences (1992), pp. 2297—2301.

[4] L. Zhang, L. B. Jack, A. K. Nandi, *Fault classification using genetic programming,* Mechanical Systems and Signal Processing, Vol. 21 No. 3, Elsevier (2007), pp. 1273-1284.

[5] M. L. D. Wong, L. B. Jack, A. K. Nandi, *Modified self-organising map for automated novelty detection applied to vibration signal monitoring*, Mechanical Systems and Signal Processing, 20(3), 593–610 (2006).

[6] R. Yan, R. X. Gao, *Machine health diagnosis based on Approximate Entropy*. in: Proceedings of the 21st IEEE Conference of Instrumentation and Measurement Technology Conference 2004, Vol 3, Como, Italy (2004), pp. 2054—2059.

[7] J. Tian, J.-J. Gu, X.-Z Peng, Z.-M Qing, *A fault diagnosis method based on wavelet approximate entropy for fan*, in: Proceedings of 6th International Conference on Machine Learning and Cybernetics, Hong Kong, (2007) pp. 519—523.

[8] M. L. D. Wong, S.-H. Lee, A. K. Nandi, *Anomaly Detection of Rolling Elements using Fuzzy Entropy and Similarity Measures*, in: Proceedings 10th International Conference on Vibrations and Rotating Machine (ViRM 2012), London (2012), pp. 693-702.

[9] P. J. Tavner, *Review of condition monitoring of rotating electrical machines*. IET Electrical Power Applications, Vol. 2, IET (2008), pp. 215-247.

[10] W. Changting and R. X. Gao, *Wavelet transform with spectral post-processing for enhanced feature extraction [machine condition monitoring]*, IEEE Transactions on Instrumentation and Measurement, Vol. 52, No. 4, IEEE (2003), pp. 1296-1301.

[11] L. B. Jack, A. K. Nandi, *Genetic algorithms for feature selection in machine condition monitoring with vibration signals*. IEE Proceedings for Vision, Image and Signal Processing, Vol 147, No. 3, IEE (2000), pp. 205-212.

[12] Chang, Chih-Chung, Lin, Chih-Jen, *LIBSVM: a library for support vector machines*. ACM Transactions on Intelligent Systems and Technology, Vol. 2, No. 2, ACM (2011), pp. 27:1--27:27, 2011. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm

[13] H. Guo, L. B. Jack, A. K. Nandi, *Feature generation using genetic programming with application to fault classification*, IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, Vol 35, No. 1. IEEE (2005), pp. 89-99.

[14] A. C. McCormick, A. K. Nandi, *Classification of the rotating machine condition using artificial neural networks*. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science Vol 211, IMechE (1997), pp. 439-450.

[15] A. C. McCormick, A. K. Nandi, *Cyclostationarity in rotating machine vibrations*, Mechanical Systems and Signal Processing, Vol 12, No.2. Elsevier (1998), pp. 225-242.

[16] Antoni, Jérôme, *Cyclic spectral analysis in practice*, Mechanical Systems and Signal Processing, Vol. 21 No. 2, Elsevier, pp. 597-630.