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Blade fault diagnosis using empirical mode decomposition based feature extraction method

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Abstract. Blade fault diagnosis had become more significant and impactful for rotating machinery operators in the industry. Many works had been carried out using different signal processing techniques and artificial intelligence approaches for blade fault diagnosis. Frequency and wavelet based features are usually used as the input to the artificial neural network for blade fault diagnosis. However, the application of others time-frequency based feature extraction technique and artificial intelligence approach for blade fault diagnosis is still lacking. In this study, a novel blade fault diagnosis method based on ensemble empirical mode decomposition and extreme learning machine was developed. Bandpass filtering was applied to the raw vibration signals and integrated with the high pass filter to obtain the velocity signal. Synchronous time averaging was then applied to the velocity signals. Three ensemble empirical mode decomposition based feature extraction methods were proposed: direct statistical parameters extraction, intrinsic mode functions averaging statistical parameters extraction and features averaging statistical parameters extraction. The effectiveness of different feature vector sets for blade fault diagnosis was examined. Feature vector set of intrinsic mode functions averaging statistical parameters extraction was found to be more effective for blade fault diagnosis. With the novel proposed method, blade fault diagnosis could be more accurate and precise.

1 Introduction

Blades are now widely used in the mechanism of varies type of turbines such as steam turbine, and wind turbine to extract energy from fluid flow and convert into useful usage on daily work in the industries. Catastrophic failures of blades in the turbine commonly induced by varies causes such as fatigue, impact or overload, can provoke the entire machine to broke down, and on the same time, bringing risk to the surrounding. This demand the operations of the turbines forced to cease. Fault diagnosis is significant for rotating machinery in terms of maintenance cost and breakdown time. The challenging part of fault diagnosis is to detect the faults and its signature pattern within a signal for further analysis. Thus, various type of fault diagnosis method had been investigated in different field and area. Networked control systems (NCS) are a system using feedback through the data networks, where the performance of the feedback system might vary [1]. Other than that, gear as one of the most important parts of a power transmission machine where it might cause failure to the machine once breakdown. According to that, gear fault diagnosis based on Continuous Wavelet Transform (CWT) had been done [2-3]. In recent years, artificial intelligence (AI) was applied in fault diagnosis for automated fault detection, classification and localisation. There is an increasing trend in the demand for using AI technique in fault diagnosis. This implies the significance of AI in the fault diagnosis nowadays. Thus, a robust and effective AI model is required in the field of fault diagnosis to prevent and reduce the chances of breakdown time and thus, reduce the cost significantly. Before AI was introduced, fault diagnosis solely influenced by human intervention. Frequency and time-frequency plot will be the reference for the manual analysis [4-5]. AI can be briefly classified into three steps, which is collecting the data, extract the features from the data and follow by machine learning to detect or classify the faults.

Fault diagnosis technology and condition monitoring is an effective method to reduce turbine-blade failures and enact as a current trend in the industries. It is essential for the blade faults diagnosis method to detect the blade failures in the early phase to prevent break down of the entire machine. Selecting the suitable and applicable feature extracting method and pattern recognition method will greatly optimise the outcome of the fault diagnosis. Various research had been carried out using different method to perform blade faults diagnosis. Frequency domain such as Fourier transform and time-frequency domain such as wavelet analysis had been successfully applied in the blade faults diagnosis [6-9]. However, the application of other time-frequency technique and machine learning method is still lacking from the open literature for blade faults diagnosis. In this

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study, a novel blade fault diagnosis method based on ensemble empirical mode decomposition and extreme learning machine was developed.

2 Extreme learning machine & empirical mode decomposition

Empirical mode decomposition was proposed as a fundamental part of Hilbert-Huang transform (HHT), which is a method applicable to analyse natural signals, which most often are non-linear and non-stationary signals. It breaks down signal with the time domain remained, and form a completely thorough and nearly orthogonal basis from the original signal, by filtering out the functions. EMD is capable of decomposing any complicate signal data set into a finite and often small number of components, which also called as Intrinsic Mode Function (IMF). IMF was introduced as a result of the EMD, and it is an essential intermediate step toward computing instantaneous frequency through Hilbert Transform or other methods.

An IMF is a function that always satisfies two conditions:

1. The number of extrema and the number of zero crossings must either equal or differ at most by one in the whole dataset.
2. The means value of the envelope defined by the local maxima and the envelope defined by the local minima is zero at any point.

Extreme Learning Machine (ELM) is a learning algorithm for single-hidden-layer feed-forward neural network (SLFN) [10]. Input weights and the biases of ELM are randomly assigned while tuning is not needed. However, the number of hidden nodes requires manual configuration. The simple generalised inverse operation was used to determine the output weights analytically. An architecture of an SLFN is shown in **Figure 1**. An extremely faster learning speed, better generalisation performance is offered by ELM, comparing to conventional learning algorithm of SLFN.

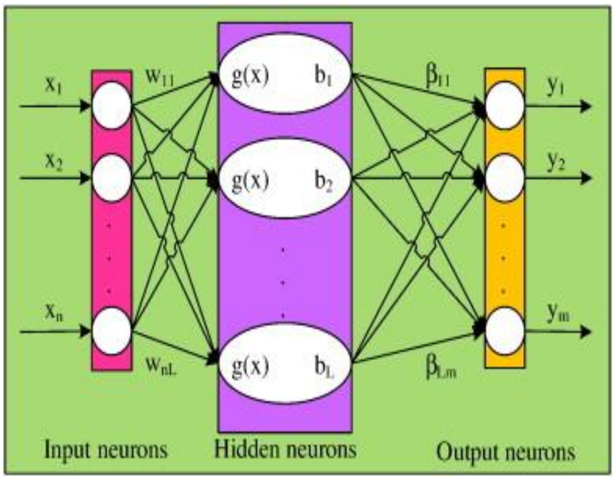

Figure 1: SLFN structure [10]

3 Experimental study

In this study, raw vibration signals and tachometer signals were simulated through a blade fault test rig as shown in **Figure 2**. The components of the test rig include the motor, coupling, bearings, accelerometer and the rotor casing. The blade fault test rig is to simulate different type and configuration of blade faults.

The blade fault test rig consists of three rows of rotor, where the first row, second row and the third row consists of eight, eleven and thirteen pieces rotor blades respectively. Loss of blade part, twisted blade and blade rubbing were simulated using this test rig in this research as shown in **Figure 3**. This gave a result of twelve conditions from each row of the rotor blade and each fault, including the healthy baseline. The accelerometer was used to capture the vibration signals, in the vertical and horizontal direction. For the tacho signal, an optical laser probe was installed perpendicularly to the rotating shaft. The vibration signals of each condition were collected under a sampling rate of 5 kHz and a rotating speed of 20 Hz, which is also equivalent to 1200 rpm. The condition and the type of blade fault were illustrated in **Table 1**.

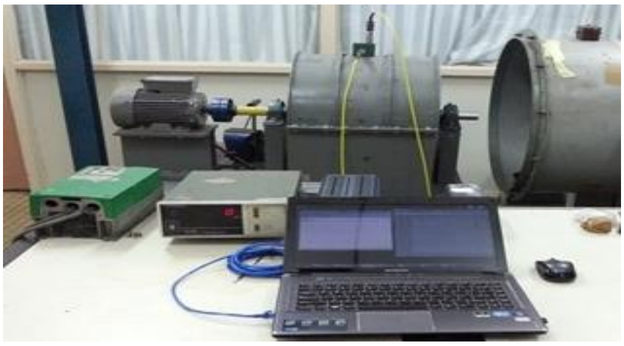

Figure 2: Blade fault test rig [9]

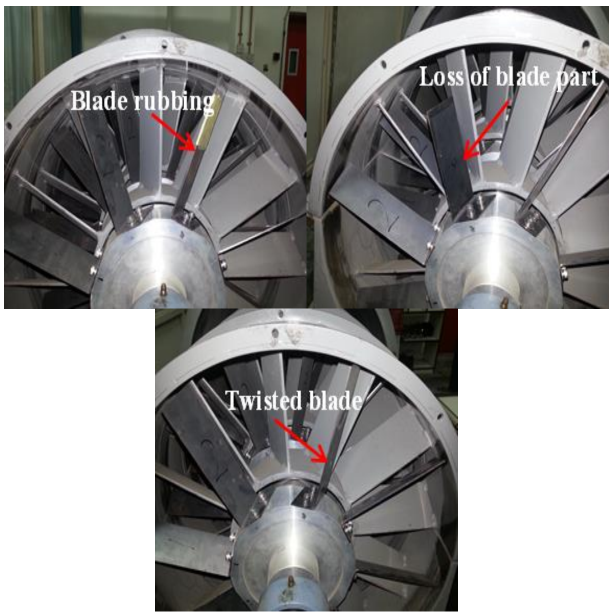

Figure 3: Types of blade fault [9]

4 Feature extraction

In this section, the feature extraction method used is explained. The proposed feature extraction method can briefly classify into two-step, which is signal pre-processing and statistical features calculation as shown in **Figure 4**. The signal was first to undergo filtering and segmentation before inputted into EMD. Statistical parameters calculation was then performed on the IMFs obtained from EMD, which will provide the desired features. The features obtained will be inserted into ELM classifier. Both steps will be explained in details in the following subsection.

First of all, raw signals were first filtered using a bandpass filter to obtain the operating frequency, which is 20 Hz and the blade pass frequency of each row, which are 160 Hz, 220 Hz and 260 Hz to filter out others unused impurities signal that will affect the accuracy of blade fault diagnosis. The filtered vibration signal was then converted from the acceleration signal to the velocity signal through integration together with high pass filtering. The signals were then segmented into 790 cycles using the tachometer signals as the reference, with 250 data points for each cycle. Synchronous time averaging (STA) was then applied to the segmented signals. STA of 5 cycles resulting 158 cycles averaged from 790 cycles.

Table 1: Blade fault condition

Condition	Type of blade fault	Description
1		No blade fault, N1
2	Baseline	No blade fault, N2
3		No blade fault, N3
4		LBP in row 1
5	Loss of blade part (LBP)	LBP in row 2
6		LBP in row 3
7		BR in row 1
8	Blade rubbing (BR)	BR in row 2
9		BR in row 3
10		TB in row 1
11	Twisted blade (TB)	TB in row 2
12		TB in row 3

There are several sets of processed data will be used as input for EMD, which are the segmented velocity that with five cycles of STA. The processed signal was then inputted into the EMD algorithm and undergo the sifting process. Standard deviation will be calculated for the data and a sifting loop of ten had been set as the stopping criteria [11]. First IMF was obtained and the following IMFs were obtained by subtracting the previous IMF from the data residue. A total of eight IMFs were obtained from each analysed STA signal. The IMFs obtained from EMD was then processed using three different techniques to acquire the feature vectors.

First set of feature vectors were constructed by calculation of eleven statistical parameters on each of the IMFs, which will contribute feature vectors that contain 176 features. Second set of feature vectors will first execute averaging on the eight IMFs, to become one averaged IMF, then only used to calculate the eleven statistical parameters, which contribute feature vectors that contain 22 features. For the third set of the feature vector, an averaging of eight were performed on the feature vector set obtain from the first feature extraction method. The eleven statistical parameters used in this study consist of kurtosis, root mean square, mean, variance, standard deviation, skewness, energy, Shannon entropy, crest factor, central moment, and energy to Shannon entropy ratio. **Table 2** summarised the feature vectors considered in this study.

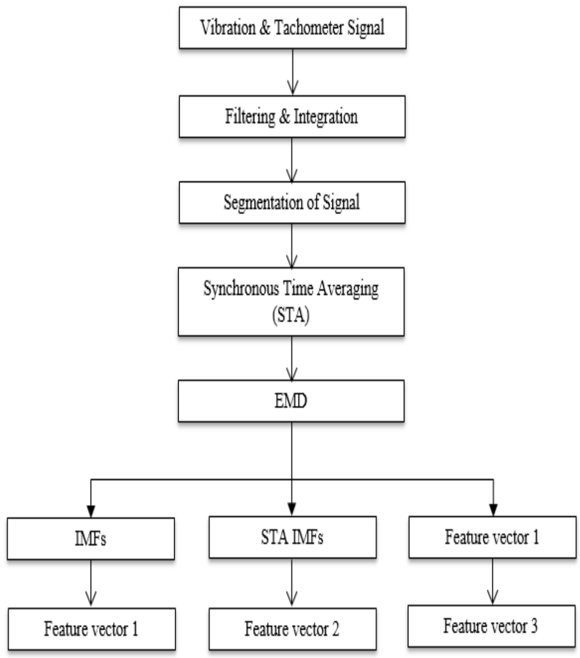

Figure 4: Feature extraction method

4 ELM modelling

In this study, the effectiveness of statistical features obtained from EMD for blade fault diagnosis is compared. Three different feature vectors were considered as the input for ELM. For each condition, two-third of the feature vector will be used for training and the remaining were used to test the network.

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Table 2: Feature vectors

Feature vector	Total features
Feature vector 1	176
Feature vector 2	22
Feature vector 3	22

In this study, ELM with 20 hidden neuron and 4 output neurons had been used to classify four-classes classification problem (healthy, twisted blade, loss of blade part, and blade rubbing) using the statistical parameters calculated from the IMFs. Three ELMs were trained by using the same ELM parameters with different statistical feature vectors. Each feature vector was inputted into the ELM algorithm and run for 15 times, and the accuracy was recorded. Parameters of ELM were summarised in **Table 3**.

Table 3: ELM Parameters

ELM Parameter	Parameter used
Training data file	2/3 of feature vector
Number of hidden neurons	20
Number of output neurons	4
Activation function	Sigmoid function

5 Results and discussion

In this section, the effectiveness of the three different feature vectors which is the direct statistical parameters extraction, IMF averaging statistical parameters extraction and features averaging statistical parameters extraction in identifying the types of blade faults is compared, and the results are shown in **Table 4**.

Table 4: Classification results

Feature Vector	Highest accuracy	Avg. accuracy	Variance
Feature vector 1	47.31 %	40.95 %	0.0010
Feature vector 2	98.73 %	83.01 %	0.0047
Feature vector 3	51.27 %	46.82 %	0.0008

The classification results shown that the feature vector 2 which is the IMF averaging statistical parameters extraction method achieved the best performance with average accuracy of 83.01%. Network developed using feature vector 2 also had the highest accuracy of 98.73%, follow by feature vector 3 with 51.27% and feature vector 1 with 47.31%. This indicate that feature vector 2 manage to identify the type of blade fault perfectly. The convincing result could be explained as the averaged IMFs are more correlated and representative to characterize the whole signal instead of just considering part of it.

Among the three proposed feature extraction method, feature vector 1 and 3 achieved lower variance as compared to feature vector 2. However, the classification accuracy for these two feature vector are far lower than feature vector 2. From all the above results, it can be concluded that feature vector 2 are more effective than feature vector 1 and feature vector 3 in identifying the types of blade fault.

6 Conclusion

Blade fault diagnosis is getting attention from time to time from industries, as it can assure the safety of machine operator and prolong the lifespan of a rotating machinery. Thus, an effective and robust blade fault diagnosis method is essential. In the current stage, there are much research had been conducted on the signal processing method in blade fault diagnosis using artificial intelligence approaches. In this study, a novel EDM based feature extraction method used for blade fault diagnosis with ELM was proposed. The classification results shown that the IMF averaging statistical parameters extraction method achieved the best performance with average accuracy of 83.01%. It was been found that quality of the features, is much more important than the quantity of features. The proposed EMD based feature extraction method can therefore use as an alternative method for blade fault diagnosis.

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References

1. H. Fang, H. Ye, & M. Zhong, *Annual Reviews in Control*, **31(1)**, 55–68, (2007)
2. Z. Zhang, Y. Wang, & K. Wang, J Intell Manuf, **24(6)**, 1213–1227, (2013)
3. H. Zheng, Z. Li, & X. Chen, Mech Syst Signal Process, **16(2–3)**, 447–457, (2002)
4. E. Cardenas Cabada, Q. Leclere, J. Antoni, & N. Hamzaoui, Mech Syst Signal Process, **97**, 33–43, (2017)
5. N. Saravanan, K. I. Ramachandran, Expert Syst Appl, **36(8)**, 10854–10862, (2009)

6. M. H. Lim, & M. S. Leong, *ASME Turbo Expo 2010: Power for Land, Sea, and Air*, 31–37, (2010)
7. M. H. Lim, M. S. Leong, &W. K. Ngui, Appl Mech Mater, **390**, 215–219, (2013)
8. M. H. Lim, W. K. Ngui, *22 International Congress on Sound and Vibration*, (2015)
9. W. K. Ngui, M. S. Leong, M. I. Shapiai, & M. H. Lim, IJAERD, **12(4)**, 519–526, (2017)
10. Y. Tian, J. Ma, C. Lu, & Z. Wang, Mech Mach Theory, **90**, 175–186, (2015)
11. Y. Lei, J. Lin, Z. He, & M. J. Zuo, Mech Syst Signal Process, **35**, (2013)