JJMIE

Volume 3, Number 4, December 2009
ISSN 1995-6665
Pages 260 - 267

Jordan Journal of Mechanical and Industrial Engineering

Wavelet Decomposition for the Detection and Diagnosis of Faults in Rolling Element Bearings

J. Chebil [a,*], G. Noel [b], M. Mesbah [c], M. Deriche [d]

[a] *ECE Dep., Faculty of Engineering, International Islamic Univ. Malaysia, Jln Gombak, KL, Malaysia.*

[b] *Ecole Nationale Supérieur des Télécommunications. Paris, France.*

[c] *Signal Processing and Consultancy Group, University of Queensland, Brisbane, Queensland, Australia.*

[d] *Dep. of Electrical Eng., King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia.*

Abstract

Condition monitoring and fault diagnosis of equipment and processes are of great concern in industries. Early fault detection in machineries can save millions of dollars in emergency maintenance costs. This paper presents a wavelet-based analysis technique for the diagnosis of faults in rotating machinery from its mechanical vibrations. The choice between the discrete wavelet transform and the discrete wavelet packet transform is discussed, along with the choice of the mother wavelet and some of the common extracted features. It was found that the peak locations in spectrum of the vibration signal could also be efficiently used in the detection of a fault in ball bearings. For the identification of fault location and its size, best results were obtained with the root mean square extracted from the terminal nodes of a wavelet tree of Symlet basis fed to Bayesian classier.

Keywords: Discrete Wavelets Transform; Discrete Wavelet Packet Transform; Ball Bearing Fault Detection.

1. Introduction

Development of real-time fault detection and identification technologies will allow a migration from expensive scheduled based maintenance to the more efficient, less costly alternative of condition-based maintenance. One of the principal tools for diagnosing early faults has been vibration analysis [1-2]. Considerable research has been carried out previously for the development of various algorithms for bearing fault detection and diagnosis. These algorithms can be classified into time domain, frequency domain, time-frequency domain, higher order spectral analysis, neural-network and model based techniques [3-7].

Various time domain statistical parameters have been used as trend parameters to detect the presence of incipient bearing damage. Kurtosis and skew values of vibration signals are used in [8] for detection of bearing faults at early stages in their development. The paper in [9] presents a study on the application of sound pressure and vibration signals to detect the presence of defects in a rolling element bearing using a statistical analysis method. The most important shortcoming of the statistical analysis approach is its inability to detect bearing defects at later stages. In the frequency domain approach the major frequency components of vibration signals and their amplitudes are used for trending purposes. The frequency characteristics of the vibration for a defective bearing subject to various load conditions are investigated in [10]. Envelope analysis, originally known as the high frequency resonance technique, is the most commonly used frequency analysis technique for the detection and diagnosis of bearing faults. The technique is studied in detail in [11]. One of the problems with envelope analysis and the other frequency domain approaches is that, they require the bearing defect frequencies be known or pre-estimated. The other shortcoming is the increasing difficulty in analyzing the vibration spectrum when the signal to noise ratio is low and the vibration spectrum has a large number of frequency components due to the complexity of the system [3]. Bi-coherence spectra are used in [12] to derive features that relate to the condition of a bearing. Neural networks are also applied to bearing fault detection and diagnosis [13-14]. Time-frequency domain techniques use both time and frequency domain information allowing for the investigation of transient features. A number of time-frequency domain techniques have been proposed including Short Time Fourier Transform (STFT), the Wigner- Ville Distribution (WVD), and the Wavelet Transform (WT) [1], [4-6], [14-15]. This paper presents results of wavelet analysis in the detection and diagnosis of ball bearing faults. A brief description of the typical bearing faults is given along with an overview of wavelet analysis in the next subsections.

The structure of this paper is as follows. In Section 2, a description of the typical faults of the bearing is presented while the basic concepts in wavelet analysis are explained

* Corresponding author. jalel@iiu.edu.my.

in Section 3. The data used for monitoring and diagnosis is described in Section 4, whereas the detailed fault diagnosis procedure based on wavelet analysis is discussed in Section 5. The last section concludes the paper.

2. Bearing Condition Monitoring

Bearing condition monitoring has received considerable attention for many years due to the fact that the majority of the problems in rotating machines are caused by faulty bearings. A schematic diagram of rolling element bearing is shown in Figure 1a. The typical failure mode of rolling element bearings is a localized defect, which occurs when a piece of material on the contact surface is dislodged during operation. The dislodgement is mostly caused by fatigue cracking under cyclic contact stressing. In general, a ball bearing has three main components that can typically experience damage: the rolling elements, the inner race and the outer race [16].

During bearing operation, wide band impulses are generated when rollers pass over the defect at a frequency determined by shaft speed, bearing geometry, and defect location. Some of the vibrational modes of the bearing and its supporting structure will be excited by the periodic impulses, and a distinct bearing signature will be generated. The leading edge of each impulse typically comprises a very sharp rise that corresponds to the impact between a roller and the defect. The ringing then decays with an approximately exponential envelope as the energy is dissipated by internal damping [7, 17] as shown in Figure 1b.

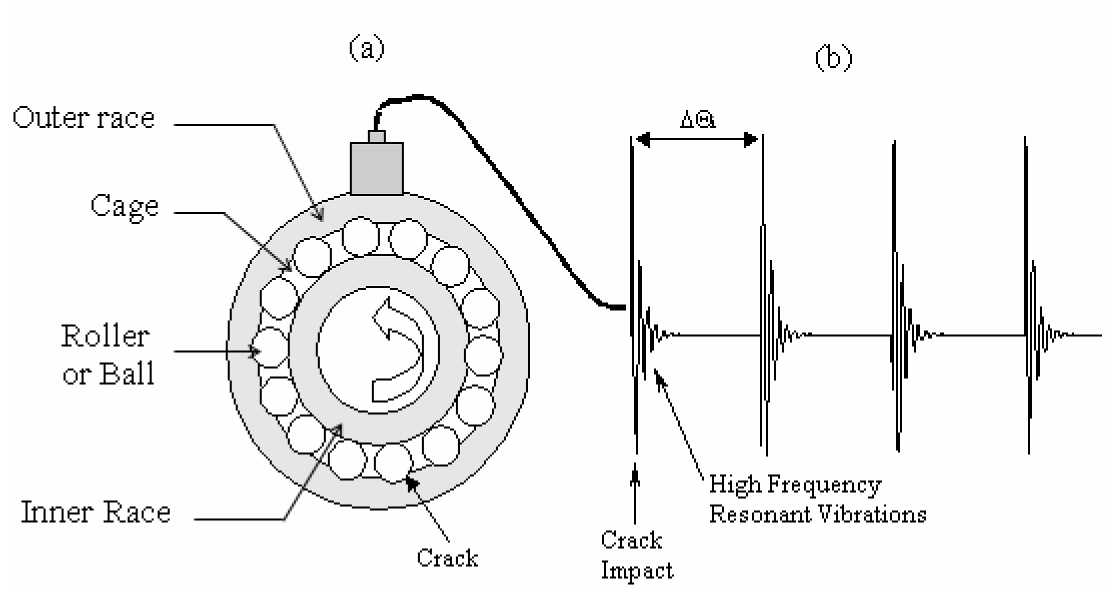


Figure 1. (a) Schematic diagram of rolling element bearings, and (b) the typical time waveform due to a crack on the outer race of a rolling element bearing. [17]

Applying Fourier transform to this type of signals results in a peak at the impact frequency along with harmonics due to the spike-resonance nature of the signal. However, the bearing fault component is often difficult to be distinguished due to the high levels of noise and other fault sources in the vicinity of the bearing fault frequencies. In addition, the frequency domain approaches are incapable of detecting nonstationary signals [18]. These problems can be overcome by using the wavelet analysis, which provides multi-resolution in time-frequency distribution for easier detection of abnormal vibration signals. Next section presents a brief summary about wavelet technique.

3. Wavelet Analysis

The wavelet transform has emerged as an efficient tool to deal with non-stationary signals such as vibrational signal waveforms [19-20]. It offers simultaneous interpretation of the signal in both time and frequency domain which allows local, transient or intermittent components to be exposed. Such components are often obscured due to averaging inherent within spectral only methods such as the Fourier transform. Wavelet transform can be continuous or discrete. The continuous wavelet transform reveals more details about a signal but its computational time is enormous. For most applications, however, the goal of signal processing is to represent the signal efficiently with fewer parameters and less computation time. The discrete wavelet transform (DWT) can satisfy these requirements.

The DWT employs a dyadic grid and orthonormal wavelet basis functions and exhibits zero redundancy. The DWT computes the wavelet coefficients at discrete intervals (integer power of two) of time and scales [20]. The computed DWT coefficients can be used to form a set of features that unambiguously characterize different types of signals. The dilation function of the DWT can be represented as a tree of low and high pass filters, with each step transforming the low pass filter into further lower and higher frequency components as shown in Figure 2. The original signal is successively decomposed into components of lower resolution, while the high frequency components are not analysed any further. The low-frequency components of the signal are called approximations, while the high-frequency components are called details. For example, if F_s is the sampling frequency, then the approximation of an N level DWT decomposition corresponds to the frequency band

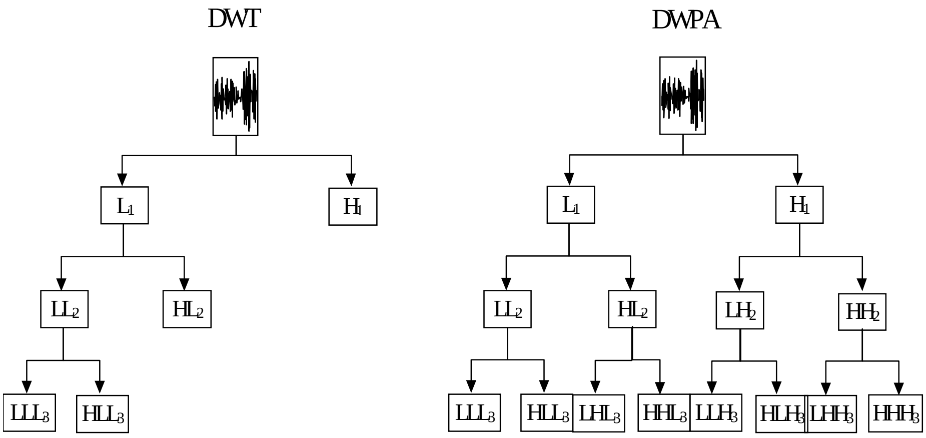


Figure 2. Filter bank representation of the DWT and DWPA decompositions [17].

[0, $\frac{F_s}{2^{N+1}}$], whereas the detail covers the frequency range [$\frac{F_s}{2^{N+1}}$; $\frac{F_s}{2^{N}}$].

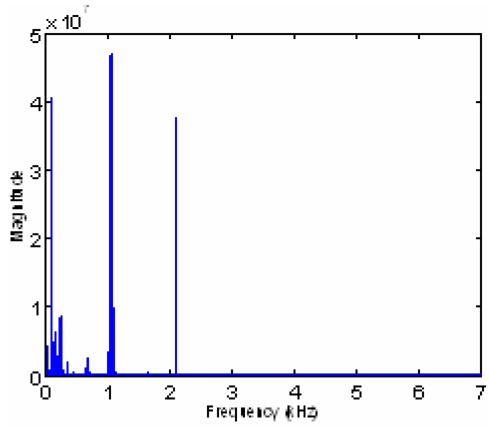
The power and the flexibility of the DWT can be enhanced by using the discrete wavelet packet transform, (DWPT). Unlike the DWT, which only decomposes the low frequency components (approximations), DWPT utilises both the low frequency components (approximations), and the high frequency components (details) [20-21]. From this family of bases, a method for choosing the optimum scheme for a particular signal can be developed. This process requires a lot of a-priori information such as the choice of a mother-wavelet, the level of decomposition, and the features to be extracted. In addition, an algorithm has to be found for the selection of the best basis.

4. Vibration Data Acquisition

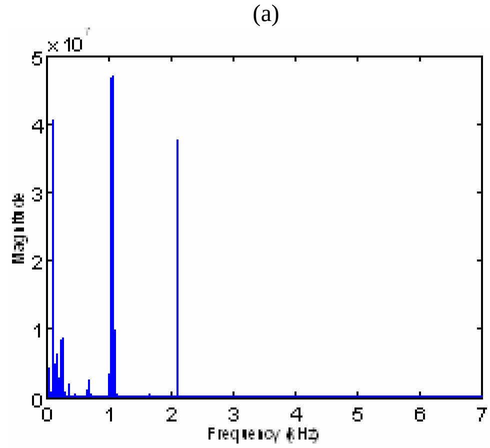
The experiments presented in this paper used the vibration data obtained from the Case Western Reserve University Bearing Data Centre [22]. The data were collected from an accelerometer mounted on the housing of an induction motor system coupled to a load that can be varied within the operating range of the motor. The data collection was done at two locations, one at the drive-end bearing and the other at the fan-end bearing. Data was gathered for four different conditions: (i) normal (N); (ii) inner race fault (IRF); (iii) outer race fault (ORF); (iv) ball fault (BF). Faults were introduced into the drive end bearing by using electro-discharge machining. For inner race and ball fault cases, the size of the fault is 0.007, 0.014 or 0.021 inches. For outer race fault case, the size of the fault is either 0.007 or 0.021 inches. The data is sampled at a rate of 12 kHz and the duration of each vibration signal was 10 seconds. All the experiments were repeated for four different load conditions: 0, 1, 2 and 3 horse power (HP). Therefore, experimental data consisted of 8 vibration signals for normal condition and 24 vibration signals for the inner race and ball fault conditions. For the outer race faulty case there were 23 vibration signals.

5. Experimental Results

The first step in a diagnosis of a ball bearing condition is to detect the presence of a fault, then identify its location and its size. Each step is discussed separately in the next sub-sections.



(a)



(b)

Figure 3. Typical spectrum of vibration data for (a) normal bearing, and (b) faulty bearing (IRF).

5.1. Fault Detection

Fault detection is an important and critical step. Any method developed for this purpose should be highly accurate. In this section, two approaches are investigated.

The first approach is based on the mechanical phenomenon of resonance. For a normal behaviour, the mechanical system is built to avoid resonance (Figure 3.a). But when there is a fault in the bearing, the resonant frequencies are likely to appear in the spectrum as peaks in high frequencies (Figure 3.b). The location of the frequencies peaks can be used to distinguish between normal and abnormal behaviours. In the first approach, the locations of the three first dominant frequency peaks obtained from the signal spectrums are used as features to discriminate between healthy and faulty behaviours.

Table 1. Frequency sub-bands for third level DWT decomposition.

Frequency Bands	1	2	3	4
Frequency range (Hz)	[0, 750]	[750,1500]	[1500, 3000]	[3000,6000]
	A3	D3	D2	D1

The second approach is based on the fact that cracks are translated into transient and high frequency phenomena in the vibration signal. Consequently, the abnormal behaviour can be detected by analysing the percentage of energy contained in high frequencies. In this study, DWT decomposition is applied to the vibration data for normal and abnormal bearing using mother wavelet Daubechies (Db1). Extensive experiments have showed that third level decomposition is sufficient for the problem of fault detection. The original signal is decomposed into four components: third level approximation A3, third level detail D3, second and first level details D2 and D1. The frequency sub-bands corresponding to each component of the signal are shown in Table1. It was found that when this approach is applied to the available data, the percentage of energy contained in the higher frequencies is large if the bearing is faulty and small if the bearing is healthy. Figure 4 shows sample results of the average energy contained in the frequency sub-bands 1, 2, 3 and 4 for vibration data of normal and abnormal bearing. The results demonstrate that the average energy in the first band is always the highest if the bearing is normal while it will be highest in other frequency bands if the bearing has defects. From these experiments, we could efficiently distinguish between normal and abnormal ball bearing behaviours by comparing the average energy of each sub-band.

In order to simulate noisy environments and compare the efficiency of the two methods, a white Gaussian noise with various power levels is added to the data. The detection results were perfect as long as the SNR is greater than -5 dB for the first method and greater than -20 dB for the second one. Therefore, for a noisy environment, the detection of a fault in a ball bearing is far more efficient with a system based on frequency peaks location obtained from the Fourier analysis rather than based on energy per band obtained from the DWT decomposition.

5.2. Fault Localisation

For many applications, the detection of the fault might not be sufficient; it is also essential to determine its location. For the ball bearing, the fault can generally be located at three places: the inner race, the ball and the outer race. Thus, the identification of the fault location can be looked at as a classification problem where each class represent one fault location. To have high classification accuracy, adequate and reliable features should be extracted from the data. In this section, two wavelets based techniques are explored and applied to the vibration data. The signals are decomposed using third level DWPT or DWT decomposition, and features such as root mean square (RMS), variance and norm are extracted from the terminal nodes. A Bayesian classifier is used to segregate between different classes where each class represents one type of fault location. A Bayesian classifier is dealing with a simple probabilistic classifier based on applying Bayes' theorem with strong independence assumptions combined with a decision rule. One common rule is to pick the hypothesis that is most probable using the well-known maximum a posteriori or MAP decision rule [23]. Using this method, a number of experiments were carried out with the aim of comparing the performance of the DWPT and the DWT and finding the best mother wavelet that produces the best extracted features. Noise with three power levels was added to the data with SNR equal to 120, 20 and 0 dB. The noisy data is added to test the strength of the proposed methods.

In order to compare the performance of the two types of decompositions when used with the Bayesian classifier, the classification accuracy has been evaluated for various extracted features and for different wavelet bases. Tables 2 and 3 present the results for the fan–end bearing and for the drive-end bearing respectively. The tables show that DWPT is more efficient than DWT in identifying the fault location for the two above-mentioned cases. However, DWT-based technique can still be used if a lower level of computation is required.

Table 2. Classification accuracy (%) using the extracted features from the DWPT and DWT on the fan-end bearing data.

Feature	Wavelet	IRF*		BF*		ORF*	
		DWPT	DWT	DWPT	DWT	DWPT	DWT
RMS	Db4	100	88	100	82	100	100
RMS	Db6	100	85	100	91	100	100
RMS	Sym4	100	79	100	88	100	100
RMS	Sym6	100	85	100	94	100	100
Norm	Db4	73	61	100	94	100	97
Norm	Db6	85	55	100	100	100	91
Norm	Sym4	64	67	100	97	100	88

*IRF: inner race fault, BF: ball fault, ORF: outer race fault

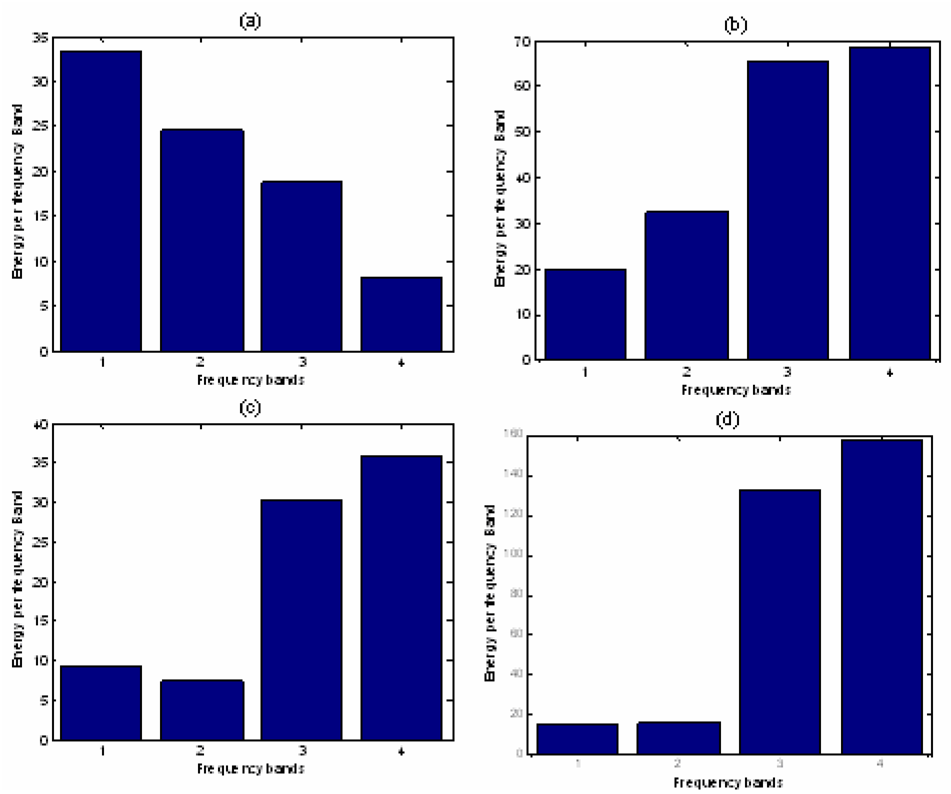


Figure 4. Average energy contained in the frequency sub-bands 1, 2, 3 and 4 for vibration data for rolling element bearing with (a) no fault, (b) IRF , (c) BF, and (d) ORFz

Table 3. Classification accuracy (%) using the extracted features from the DWPT and DWT on the drive-end bearing data.

Feature	Wavelet	IRF		BF		ORF	
		DWPT	DWT	DWPT	DWT	DWPT	DWT
RMS	Db4	100	97	67	6	100	100
RMS	Sym4	100	97	78	30	100	100
RMS	Sym6	100	100	70	6	100	100
Norm	Db4	100	100	100	89	100	94
Norm	Sym6	100	95	100	91	97	100

The next step is to determine the best mother wavelet that produces the best DWPT-based features. Table 4 shows the classification accuracy results obtained using the extracted features from the DWPT of the data for various mother wavelets: Daubechies family (Db) and Symlets family (Sym). The root mean square (RMS) and the norm are found to be the best features extracted from the DWPT. The choice of the mother wavelet is not as critical as its size and could be selected from Db4, Db5, Db6, Sym4, Sym5, and Sym6. When the combined RMS and Sym6 were applied to the database, a perfect classification was achieved.

5.3. Fault Size

The results of the previous experiments do not solve the issue of the fault size. The problem is now to determine the best information that can help in the classification of the size of the faults. First, we assume that the diagnosis is going to adopt a multi-level classification as shown in Figure 5. The Bayesian method, as explained in the previous section, is used here on signals belonging to a specific type of fault location. The signals are decomposed by a third level DWT decomposition to obtain four terminal nodes for the drive-end bearing and to second level decomposition for the fan-end bearing. The study of the results for the two bearings shows that RMS with a mother wavelet among Db4, Db5, Db6, Sym4, Sym5, and Sym6 is a suitable choice.

Table 4. Classification accuracy (%) after a DWPT for the drive-end bearing (DE) and a fan-end bearing (FE) data.

Feature	Wavelet	IRF		BF		ORF	
		DE	FE	DE	FE	DE	FE
Variance	Db4	100	88	0	91	100	100
Variance	Sym6	100	97	0	94	100	100
RMS	Db4	100	100	69	100	100	100
RMS	Db6	100	100	69	100	100	100
RMS	Sym6	100	100	75	100	100	100
Norm	Db4	100	73	100	100	100	100
Norm	Sym6	100	67	100	100	97	100

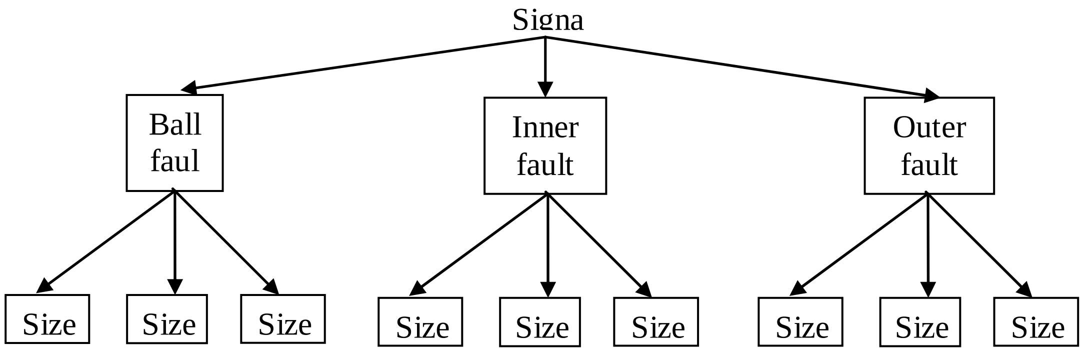


Figure 5. Multilevel classification where Size 1= 0.007 inch, Size 2= 0.014 inch and Size 3= 0.021 inch.

6. Conclusion

This paper shows that wavelet-based analysis techniques can be efficiently used in condition monitoring and fault diagnosis of bearings. In the first part of the paper, it was found that the peak locations in spectrum of the vibration signal could be efficiently used in the detection of a fault in ball bearings. For the identification of fault location and its size, the RMS extracted from the terminal nodes of a wavelet tree can be reliably used as discriminating feature. It was found that the choice of the mother wavelet Sym6 combined with the use of the RMS feature produce excellent classification results.

References

[1] S. Wadhwani, S. P. Gupta and V. Kumar, “Wavelet based vibration monitoring for detection of faults in ball bearings of rotating machines”. Journal Inst. Eng. (India) –EL, Vol. 86, 2005, 77-81.

[2] S. Pati, J. Mathew, P.K. RajendraKumar. “Bearing signature analysis as a medium for fault detection: A Review”. Transactions of ASME, Journal of Tribology, Vol. 130, No. 1, 2008, 014001-1 to 7.

[3] H. Ocak, K.A. Loparo, “A new bearing fault detection and diagnosis scheme based by on hidden Markov”. Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing ICASSP '2001, Salt Lake City-UT, USA, 2001.

[4] E. K. Lada, J. C. Lu, J. R. Wilson, “A wavelet-based procedure for process fault detection”. IEEE Transactions on Semiconductor Manufacturing, Vol. 15, No. 1, 2002, 79-90.

[5] M. H. Kahaei, M. Torbatian, J. Poshtan, “Detection of bearing faults using Haar wavelets”. IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences, E89-A(3), 2006, 757-763.

[6] X. Lou, K. A. Loparo, F. M. Discenzo, J. Yoo, A. Twarowski, “A wavelet-based technique for bearing diagnostics”. International Conference on Acoustics, Noise and Vibration, Montreal, Canada, August 2000.

[7] J. Altmann, J. Mathew, “High frequency transient analysis for the detection and diagnosis of faults in low speed rolling element bearings”. Proceedings of Asia Pacific Vibration Conference '97, Vol. 2, Kyungju, Korea, 1997.

[8] H. R. Martin, F. Honarvar, “Application of statistical moments to bearing failure detection”. Journal of Applied Acoustics, Vol. 44, 1995, 67-77.

[9] R. B. W. Heng, M. J. M. Nor, “Statistical analysis of sound and vibration signals for monitoring rolling element bearing condition”, Journal of Applied Acoustics, Vol. 53, No. 1-3, 1998, 211-226.

[10] Y. T. Su, S. J. Lin, “On initial fault detection of a tapered roller bearing: frequency domain analysis”. Journal of Sound and Vibration, Vol. 155, No. 1, 1992, 75-84.

[11] P. D. McFadden, J. D. Smith, “Vibration monitoring of rolling element bearings by high freq. resonance technique: A Review”. Tribology International, Vol. 77, 1984, 3-10.

[12] C. James Li, J. Ma, B. Hwang, “Bearing localized defect detection by bicoherence analysis of vibrations”. Journal of Engineering for Industry, Vol. 117, November 1995, 625-629.

[13] M. Subrahmanyam, C. Sujatha, “Using neural networks for the diagnosis of localized defects in ball bearings”. Tribology International, Vol. 30, No. 10, 1997, 739-752.

[14] C. James Li, Jun Ma, “Wavelet decomposition of vibrations for detection of bearing-localized defects”. Independent Nondestructive Testing and Evaluation (NDT&E) International, Vol. 30, No. 3, 1997, 143-149.

[15] Gary Y. Yen, Kuo-Chung Lin, “Wavelet packet feature extraction for vibration monitoring”. Proceedings of the IEEE International Conference on Control Applications, August 1999, 1573- 1578.

[16] S. H. Upadhyay, S. P. Harsha, S. C. Jain, “Nonlinear vibration signature analysis of high speed rotor due to defects of rolling element”. Advances in Theoretical and Applied Mechanics, Vol. 1, No. 7, 2008, 301-314.

[17] J. Altmann, J Mathew, “DWPA best basis demodulation for the detection and diagnosis of faults in rolling element bearings”. Proceedings of the 1st Australasian Conference on Systems Integrity and Maintenance, Surfers Paradise, Australia, October 3, 1997, 331-339.

[18] P.W. Tse, Y. H. Peng, Richard Yam, “Wavelet analysis and envelope detection for rolling element bearing fault diagnosis: Their effectiveness and flexibilities”. Journal of Vibration and Acoustics, Vol. 123, No. 3, July 2001, 303-310.

[19] V. Giurgiutiu, A. Cuc, P. Goodman, “Review of vibration-based helicopters health and usage monitoring methods”. 55th Meeting of the Society for Machinery Failure

Prevention Technology, Virginia Beach, VA, USA, April 2001.

[20] Mertins A. Signal analysis: wavelets, filter banks, time-frequency transforms and applications. John Wiley & Sons Ltd; 1999.

[21] J. Altmann, J. Mathew, "Multiple band-pass autoregressive demodulation for rolling-element bearing fault diagnosis. Mechanical Systems and Signal Processing, Vol. 15, No. 5, 2001, 963-977.

[22] Case Western Reserve University Bearing Data Center. http://www.eecs.case.edu/laboratory/bearing/download.htm, 2009.

[23] Wikipedia, The Free Encyclopedia, http://en.wikipedia.org/wiki/Naive_Bayes_classifier, 2009.