10th International Research/Expert Conference
"Trends in the Development of Machinery and Associated Technology"
TMT 2006, Barcelona-Lloret de Mar, Spain, 11-15 September, 2006

MOTOR BEARING FAULT DETECTION VIA WAVELET PACKET DECOMPOSITION OF VIBRATION DATA

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ABSTRACT
Condition Monitoring plays an important role in maintenance of electric machinery. Analysis of motor vibration data is one of the most widely used techniques for bearing fault detection. A special implementation of filter banks is utilized to provide bearing fault detection via wavelet packet decomposition (WPD) of motor vibration data in this paper.
Keywords: Bearing fault, motor condition monitoring, wavelet packet decomposition

1. INTRODUCTION
Fast Fourier transform (FFT) algorithms are used widely in frequency analysis of vibration data due to their low computational complexities. Fourier techniques are well suited for stationary signal analysis. However, bearing fault related vibration frequency components are often non-stationary waveforms due to varying load conditions and non-linear loads. The Fourier transform has a shortcoming in detecting the time locality of abrupt changes in the signal. Short time Fourier transform (STFT) provides one way to address this problem. This approach is useful when the transient signal energy is limited to a time window. However, the problem with this is that once the window size is selected, the time resolution becomes fixed.
The wavelet transform (WT) provides an alternative to STFT in non-stationary signal processing [1]. The wavelet based methods are used in power quality event detection and classification [2-4] in addition to the calculation electrical quantities such as power, voltage, and current [5,6]. In contrast to the fixed analysis window size in the STFT, the WT uses longer windows for low frequencies and shorter windows for higher frequencies. It results in better frequency and time resolutions for low and high frequencies respectively [7]. But, WT does not have the frequency resolution required for frequency analysis. Finer frequency resolution may be achieved via the wavelet packet transform (WPT) [8]. Wavelet decomposition is achieved via filter banks in signal processing. Therefore, the type of filters being employed plays an important part in the overall computational complexity. It is crucial to select filters with minimal number of coefficients. In this study, the use of specialized elliptic equiripple IIR half-band filters is suggested in wavelet packet decomposition [9,10].

2. WAVELET PACKET DECOMPOSITION
Wavelet theory today represents a collection of work done largely independently in various fields such as mathematics, physics, and engineering. Wavelets, filter banks, and multi-resolution signal analysis, which have been used independently in the fields of mathematics, signal processing, and computer vision respectively, have recently converged to form a single theory [7]. The wavelet transform (WT) provides an alternative to the short time Fourier transform (STFT) in non-stationary signal processing.
Wavelet analysis provides improved signal processing for transient signal analysis. It results in better time localization in higher frequencies in return for poorer frequency resolution. Coifman, Meyer, and Wickerhauser introduced wavelet packet analysis to improve the poor frequency resolution at high frequencies. They basically generalized the link between multi-resolution and wavelets. Wavelet

packets analysis offers a more efficient decomposition for signals containing both transient and stationary components. The frequency separation obtained by wavelet packet decomposition is depicted in figure 1. It is very similar to that of the STFT.

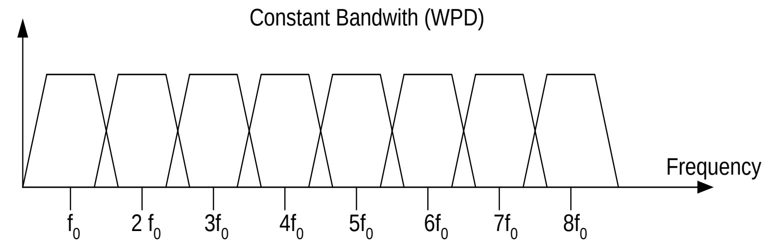

Figure 1. Frequency separation of signal by WPD

The wavelet filter bank structure to accomplish such decomposition is depicted in figure 2.

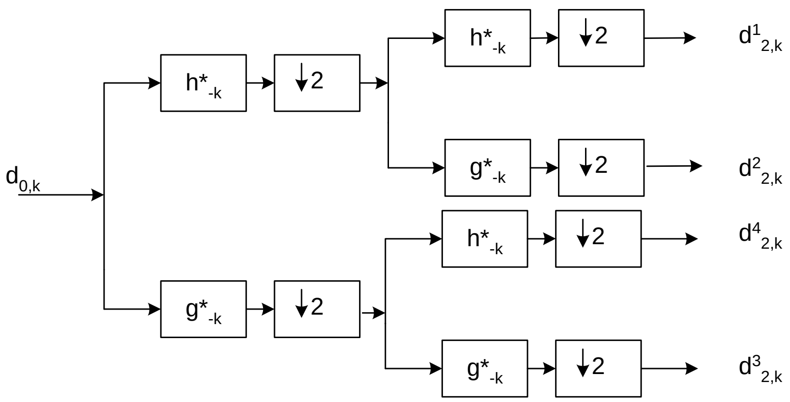

Figure 2. Wavelet packet decomposition via two-channel filter banks

It should be noted that, d^4_{2k} and d^3_{2k} are in reversed order in the previous figure. This is due to the natural, or Paley, order produced by the algorithm. The algorithm may be easily modified to produce a sequence ordered wavelet packet analysis [8].

3. CALCULATION OF WAVELET PACKET COEFFICIENTS

Daubechies showed that the following equations can be used to numerically obtain wavelet and scaling coefficients.

$$\psi_{j,k}(x) = 2^{-j/2}\psi(2^{-j}x - k) \tag{1}$$

The wavelet coefficients for level j can be obtained from scaling coefficients from level j-1 using

$$\psi_{j,k}(x) = \sum_n g_{n-2k}\phi_{j-1,n}(x) \tag{2}$$

$$\langle f, \psi_{j,k} \rangle = \sum_n \overline{g_{n-2k}} \langle f, \phi_{j-1,n} \rangle \tag{3}$$

The scaling coefficients for level j can be obtained from the scaling coefficients for level j-1 using

$$\phi_{j,k}(x) = \sum_n h_{n-2k}\phi_{j-1,n}(x) \tag{4}$$

$$\langle f, \phi_{j,k} \rangle = \sum_n \overline{h_{n-2k}} \langle f, \phi_{j-1,n} \rangle \tag{5}$$

Where *g* and *h* are high-pass and low-pass filters respectively. The procedure can start by calculating $\langle f, \psi_{1,k} \rangle$ and $\langle f, \phi_{1,k} \rangle$ from $\langle f, \phi_{0,n} \rangle$ using equations 3 and 5 respectively. Then, the same procedure is used until the level j is reached. In the case of wavelet packet decomposition, the wavelet bases, W_j, are decomposed into approximation spaces W^0_{j+1} and W^1_{j+1}. The wavelet filter bank structure to accomplish such decomposition is depicted in figure 2. The wavelet packet coefficients, $d^p_{j,k}$, can be used to calculate the rms value of any node (*j*,*p*).

The wavelet packet coefficients, $d^p_{j,k}$, can be used to calculate the rms value of any node (j,p).

$$x_{rms}(j,p) = \sqrt{\sum_k (d^p_{j,k})^2} \tag{6}$$

where

$$d^{2p}_{j+1}[k] = d^p_j[k] * \bar{h}_0[2k] \tag{7}$$

and

$$d^{2p+1}_{j+1}[k] = d^p_j[k] * \bar{h}_1[2k] \tag{8}$$

can be used repeatedly to obtain all the wavelet packet coefficients.

4. TESTING

The test motor is a 1 hp, 240 V, 50 Hz, 3000 rpm, two-pole induction motor. The test data is taken at no load condition. Cage defect is simulated by adding associated fault frequency components to the vibration data. The bearing cage defect characteristic vibration frequency at no load speed (3000 rpm) has the fundamental component at 20 Hz and the second harmonic at 40 Hz. Since the bearing related frequencies are modulated by the rotational frequency of 50 Hz, cage defect related frequencies would appear at 10, 30, 70, and 90 Hz in the frequency spectrum. In this case, the nodes 2, 5, 12, and 15 are selected for the analysis. These four nodes contain the 6.25-12.5 Hz and 31.25-37.5 Hz, 68.75-75 Hz, and 87.5-93.75 Hz frequency bands respectively. The wavelet packet coefficients for tests with a healthy and a faulty bearing are plotted in figures 3 and 4 respectively.

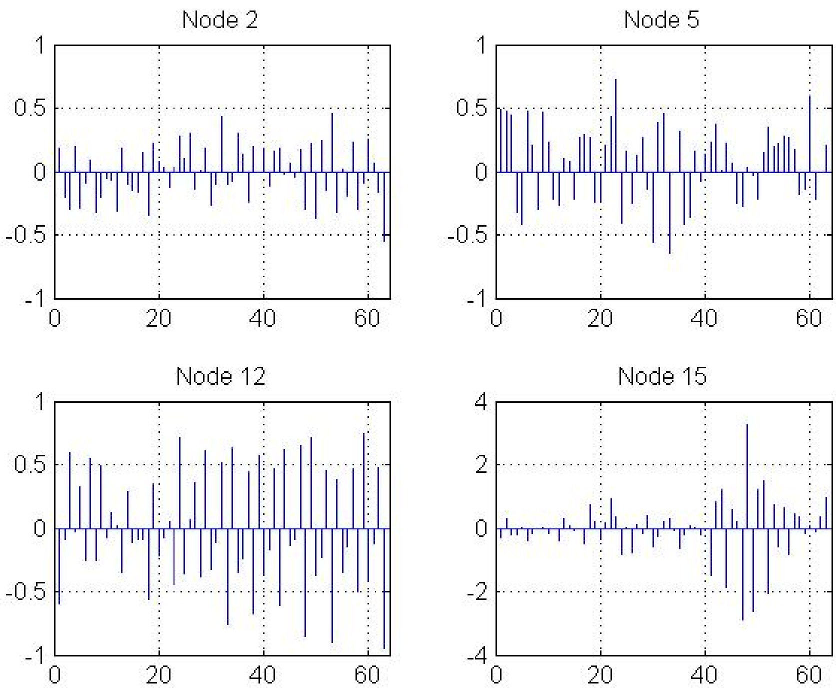

Figure 3. Wavelet packet coefficients for a bearing with cage defect

Comparing RMS values for wavelet packet coefficients depicted in figures 3 and 4, there is significant increase in the energy levels of bearing fault related frequency bands in the case of faulty bearing.

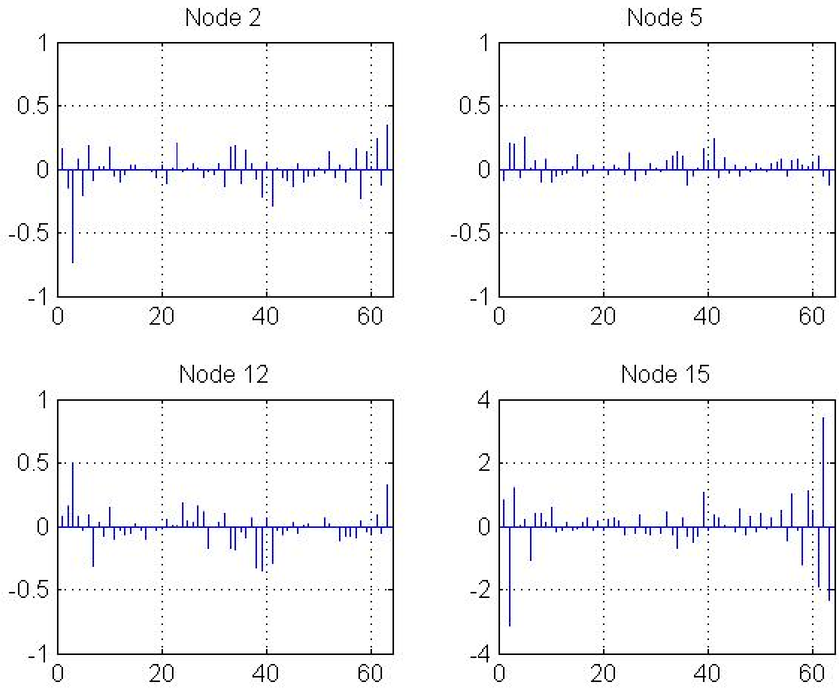

Figure 4. Wavelet packet coefficients for a healthy bearing

5. CONCLUSION

Motor bearing fault detection via wavelet packet decomposition of vibration data is studied in this paper. Since the bearing related vibration is non-stationary in nature, wavelet packet decomposition results in better analysis than commonly used Fourier methods.

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