Bearing Fault Diagnosis Using Shifted Wavelet Filters

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Abstract: - Vibration signals resulting from rolling element bearing defects, present a rich content of physical information, the appropriate analysis of which can lead to the clear identification of the nature of the fault. This paper proposes a method for processing of signals resulting from rolling element bearing defects, based on the use of a shifted wavelet filter family. Using a time-frequency representation of the signal, the method is designed in a way that can exploit the underlying physical concepts of the modulation mechanism, present in the vibration response of bearings with localized defects. Systematic selection criteria for the choice of the critical parameters that characterize the wavelet family are used. Experimental results and industrial measurements for different types of bearing faults confirm the validity of the overall approach.

Key-Words: - Wavelet, Wavelet packet, Vibration, Bearing, Fault Diagnosis

1 Introduction

Bearings are of great importance to almost all kinds of rotating machinery, and are among the most frequently encountered components in the vast majority of rotating machines. As a consequence of their importance and widespread use, bearing failure is one of the main causes of breakdown of rotating machinery. Therefore, quite naturally, fault identification of rolling element bearings has been the subject of extensive research [1].

Vibration analysis has been established as the most common and reliable analysis method. Defects or wear cause impacts at frequencies governed by the operating speed of the unit and the geometry of the bearings, which in turn are modulated by machine natural frequencies. The signature of a damaged bearing consists of exponentially decaying ringing that occurs periodically at the characteristic defect frequency. A corresponding well-established physical model has been proposed in [2]. The location dependent characteristic defect frequencies make it possible to detect the presence of a defect and to diagnose on what part of the bearing the defect is. The difficulty of defect detection lies in the fact that the signature of a defective bearing is spread across a wide frequency band and hence can be easily masked by noise. Its spectrum consists of of a series of harmonics of the characteristic defect frequency, with the highest amplitude around the resonance frequency. Typically the amplitude at the characteristic defect frequency is small and not easily noticed. For the solution of this problem several methods have been proposed, based either directly on the shape of the time domain form of the signal, or on its spectral content. Of all those methods, the most widely accepted is the envelope analysis [3-4]. This method includes band-pass filtering in a region where there is a high signal-to-noise ratio, typically around a resonance, and demodulation of the filtered signal.

The ringing modes of a bearing and its supporting structure cannot easily be predicted, because they depend on factors such as operating condition and development of the defect. Thus, in frequency domain methods, an intelligent selection of the frequency band is required.

In order to overcome this problem a number of time-frequency domain methods have been proposed, such as the Short Time Fourier Transform, the Wigner-Ville Distribution and the Wavelet Transform. Wavelets have been established as the most widespread tool in many areas of signal processing, due to their flexibility and to their efficient computational implementation [5]. They have been introduced in vibrations [6] and there are specific case studies for bearing fault detection [7-8] and for other machine components [9]. In many cases the application of wavelets has been combined and enriched by using additional features, such as Gaussian/exponential-enveloped functions [10], or de-noising methods [11].

In this paper a method is proposed, which uses a shifted wavelet filter for rolling element bearing fault diagnosis. Prediction of the resonant frequencies is not required, minimizing the interventions by the end user. In chapter 2 a brief review of the basics of the wavelet theory with emphasis on the wavelet filter design is presented. In section 3 the implementation of the proposed method is described. The major parameters affecting its performance are analyzed in section 4. Results of the implementation on a simulated signal, as well as on experimental and industrial measurements for two different types of bearing faults are provided in section 5, verifying the effectiveness of the method.

2 Wavelets and Shifted Wavelet Filter

The continuous wavelet transform (CWT) of a finite energy signal *x(t)* with the analyzing wavelet $\psi(t)$ is the convolution of *x(t)* with a scaled and conjugated wavelet:

$$W(\alpha,b) = \alpha^{-1/2} \int_{-\infty}^{\infty} x(t)\psi^*(\frac{t-b}{\alpha})dt \quad (1)$$

The wavelet coefficient $W(\alpha,b)$ measures the similarity between the signal *x(t)* and the analyzing wavelet $\psi(t)$ at different scales as defined by the parameter *a*, and different time positions as defined by the parameter *b*. The factor $\alpha^{-1/2}$ is used for energy preservation. Equation (1) indicates that the wavelet analysis is a time-frequency analysis. Alternatively the wavelet transform can be also considered as a special filtering operation as it is implied by the following equation

$$W(\alpha,\tau) = \alpha^{\frac{1}{2}} F^{-1}\left\{X(f)\Psi^*(\alpha f)\right\} \quad (2)$$

where *X(f)* and $\Psi(f)$ are the Fourier transforms of *x(t)* and $\psi(t)$ respectively, and F^{-1} denotes the Inverse Fourier Transform.

Gauss enveloped oscillations are among the most widely used wavelet functions:

$$\psi(t) = ce^{-\sigma^2 t^2} e^{i2\pi f_0 t} \quad (3)$$

where *c* is a constant typically chosen as $c=\sigma/\pi^{1/2}$. The Fourier Transform of the analyzing function of Eq.(3) is a real valued Gaussian shaped window:

$$\Psi(f) = \Psi^*(f) = e^{-\frac{\pi^2}{\sigma^2}(f-f_0)^2} \quad (4)$$

where f_0 is the center frequency of the window and σ determines its width. Thus, the corresponding frequency band covered by the window is practically limited in the range $[f_0-\sigma/2, \quad f_0+\sigma/2]$. The parameter σ balances the width of the wavelet window in the time and in the frequency domain.

The shifted wavelet family in this paper, uses wavelets, whose shape in the frequency domain is defined by Eq. (4). The center frequency f_i of the the wavelets can be varied, but their frequency bandwidth remains unchanged, as indicated by the subsequent Equations (5) and (6)

$$W_s(f_i,\tau) = F^{-1}\left\{X(f)\Psi_i^*(f)\right\} \quad (5)$$

$$\Psi_i(f) = \Psi_i^*(f) = e^{-\frac{\pi^2}{\sigma^2}(f-f_i)^2} \quad (6)$$

$$f_i = f_0 - (i-1)f_h \qquad i = 1,\ldots,N \quad (7)$$

For a specific center frequency f_i, a complex signal $W_s(f_i,\tau)$ results in the time domain, which, in view of Equation (7) is considered to be analytic, since the function Ψ_i is real and well localized for appropriate values of σ. Figure 1 shows an example of shifted wavelets in the frequency domain. The similarity between the shape of the used wavelet and the typical impact generated transients, renders it an effective tool in magnifying and identifying impact components hidden in signals.

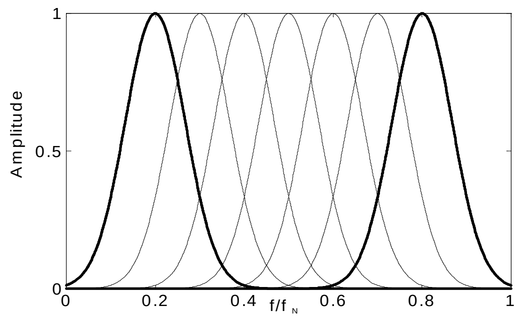

Figure 1. An example of shifted Gauss enveloped wavelet windows.

3 The Diagnosis Procedure

As previously mentioned, whenever a defect present in one surface of a bearing strikes another surface, an impact results, exciting the resonances of the bearing and of the overall mechanical system. Thus, the pulsation generated by rolling bearing defects, excites vibration at characteristic defect frequencies as well as a high-frequency response in the overall machine structure. In rolling element bearings, the interesting diagnostic information is contained in the repetition frequency of the impacts, rather than in their overall frequency content. The objective of the proposed approach is to isolate the low-frequency information of the measured signal, that contains the percussive frequencies caused by the bearing defect.

The wavelet of Eq.3 can provide a quite suitable and effective tool towards this direction.

1. As a first step for the implementation of the proposed method Eq. (7) is applied, using a discrete signal *x(j) j=1,…,M,* where *M* is the number of

samples of the signal. A complex matrix W is thus formed

$$W(i,j) = F^{-1}\left\{X(f)\Psi_i^*(f)\right\} \tag{8}$$

Each row i of this matrix corresponds to a specific center frequency f_i, while each column j corresponds to a different time instant. The real part of each row i of the matrix W is in principle the bandpass filtered signal around a specific frequency f_i, and contains more interesting diagnostic information, when f_i is close to a resonant frequency.

2. A matrix C_w is formed, based on the real parts of the elements of the matrix W.

$$C_w(i,j) = real(W(i,j)) \tag{9}$$

3. A matrix R_w is formed by squaring the elements of the matrix C_w as follows:

$$R_w(i,j) = C_w(i,j)^2 \tag{10}$$

Each row of the matrix of the matrix R_w represents the squared bandpass filtered signal around one center frequency f_i.

4. A matrix P_w is formed. Each row $P_{w,i}$ of the matrix P_w is the power spectrum of each row $R_{w,i}$ of the matrix R_w.

$$P_{w,i} = \hat{R}_{w,i}(f) \tag{11}$$

where $\hat{R}_{w,i}$ denotes the power spectrum of a row $R_{w,i}$.The length of each row $P_{w,i}$ of the matrix P_w is $M/2$, where M is the length of the discrete signal $x(j)$, but actually a much smaller number $K(<M)$ of elements of each row is necessary to be kept, since the interesting diagnostic information has been moved to the low frequency region.

5. An average power spectrum P_{av} is formed by adding the elements of each column of the matrix P_w

$$P_{av}(k) = \sum_{i=1}^{N} P_w(i,k) \tag{12}$$

where $k=1,\dots,K$

Alternatively the autocorrelation functions of the rows of the matrix R_w may be used instead of the power spectra.

6. The spectrum P_{av} is inspected. The presence of a characteristic defect frequency indicates the presence of the corresponding fault.

The method is summarized in Fig.2. The basic idea is that the rectification generates sum and difference frequencies as well as double frequencies. The difference frequencies appear in the low frequency

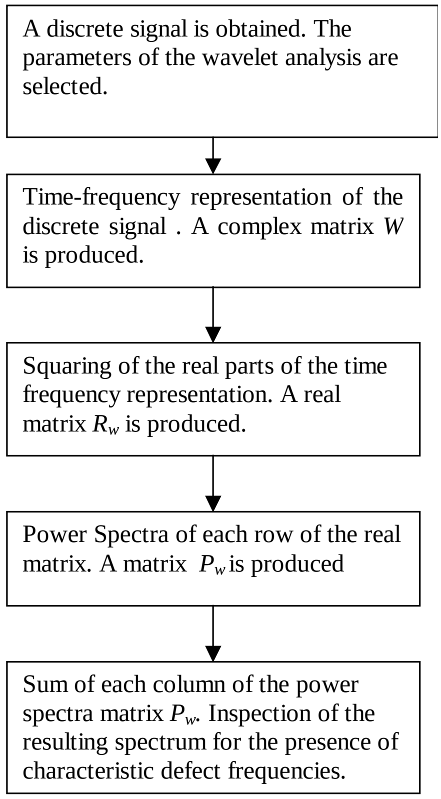

Figure 2. The diagnostic procedure using shifted wavelet filter

region of the spectrum of the rectified signal. If modulation exists, the modulating frequencies will dominate the low frequency region. In the case of a rolling element bearing with a defect, the successive impacts produce a series of impulse responses which may be amplitude modulated as a result of the passage of the fault through the load zone or of the varying transmission path between the impact point and the vibration measurement point. The spectrum of such a signal would consist of a harmonic series of frequency components spaced at the bearing defect frequency with the highest amplitude around the resonance frequency. Thus, the same modulation effect exists in all the frequency bands, being more evident in the resonance bands. The squaring process in Eq.10 causes a frequency shift to the low frequency region. The addition of the elements of each column of matrix P_w in Eq. (12) magnifies the modulating frequencies, while other frequency components fade. This happens because the modulating frequencies are concentrated on specific columns of the matrix P_w.

4 Parameter Selection

The sampling rate determines the total frequency bandwidth. This bandwidth should be selected as high as necessary, in order to include a necessary number of structural natural frequencies, excited by the characteristic impulses of the bearing defect. Thus, the measured signal includes all the relevant information necessary for allowing the fault features to be properly exposed.

The parameters N, f_0,, f_h in Equations (5-7) are chosen in such a way, that the center frequencies of the first and last wavelet correspondingly comply to the typical values of $0.8f_{Nyq}$ and $0.2f_{Nyq}$, where f_{Nyq} is the Nyquist rate. Thus, a frequency range $[0.2f_{Nyq}, 0.8f_{Nyq}]$ is scanned in intervals determined by the choice of N. The lower limit of this range must be high enough to suppress low frequency components due to misalignment, unbalance etc. Besides, the upper limit of this range, namely the center frequency of the first wavelet window, must be sufficiently lower than the Nyquist rate, in order to avoid frequency folding when applying squaring in Eq.(10).

The weighting parameter σ in Eq.(6) determines the width of the Gaussian window of the shifted filter. The width of the Gaussian window determines the number of harmonics of the characteristic ball pass frequency that will be observed in the final spectrum. The characteristic defect frequencies of a bearing depend on the rotor frequency F_R. For example the BPFI (Ball Pass Frequency Outer Race) of a bearing is rF_R, where r is a constant, which depends on the geometrical characteristics of the bearing. The values of r are known for each type of bearing and in a general case r=10 is proposed as an approximation. Usually two or three harmonics of the characteristic defect frequency are expected for bearing fault diagnosis. So the value of σ should satisfy:

$$\sigma \approx \frac{n_h r F_R}{F_{Nyq}} \tag{13}$$

where n_h determines the number of the expected harmonics of the characteristic defect frequency. The value of N can be estimated if an overlap coefficient n_{ov} is assumed, according to $N= 0.6n_{ov} /\sigma$ (the nearest integer). Large values of the number N result in smaller frequency intervals and thus in a greater possibility that the center frequency of a wavelet exactly coincides with a resonant frequency. A value of n_{ov} =1.3 is proposed as a compromise between accuracy and computational effort.

5 Experiments

The method is first tested on a simulated impulse train. Each impulse is assumed to be modulated by a single harmonic frequency with an exponential decay. This signal can be considered as a simulation of a signal resulting from a rolling element bearing with a fault on the outer race. The impact repetition frequency (BPFO) is assumed to be 120 Hz and the natural frequency excited is assumed to be 3 kHz The sampling rate is assumed 16384 Hz. The

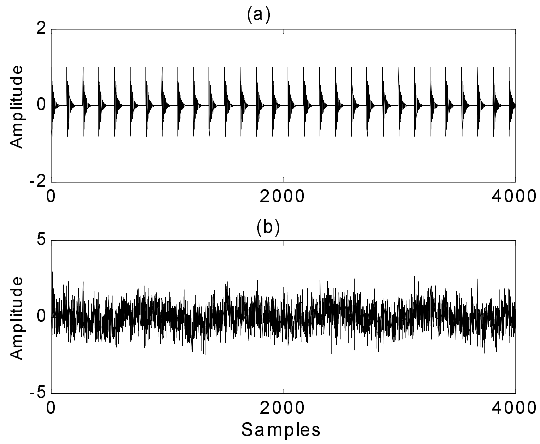

Figure 3. a) A simulated pulse train b) The simulated pulse train with additive noise and discrete low frequencies.

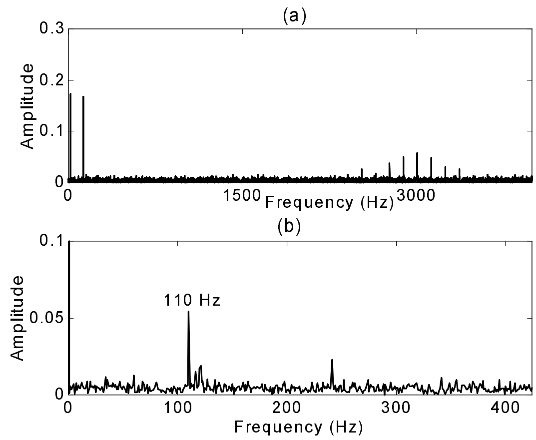

Figure 4. a) Spectrum of the simulated signal of Fig.3 (b). b) Spectrum of the envelope of the simulated signal

resulting simulated waveform, is shown in Fig. 3(a). Figure 3(b) presents the signal after adding a significant level of white Gaussian noise, and two discrete frequencies 20 Hz and 130 Hz in order to simulate low frequency effects. In Fig.4, a) the spectrum of the simulated noisy signal and b) the spectrum of its envelope are illustrated. The information regarding the impulse sequence can not be detected, because it is masked by the additive noise and the low frequencies. In Fig.5 the spectrum obtained by the proposed procedure is dominated by the assumed repetition frequency of the impacts

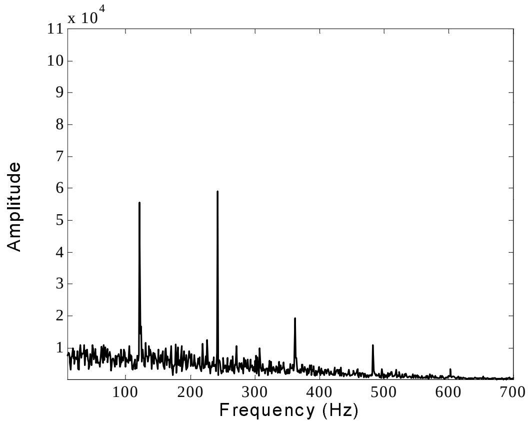

Figure 5. Spectrum of the simulated signal of Fig.3(b) using the shifted wavelet filter

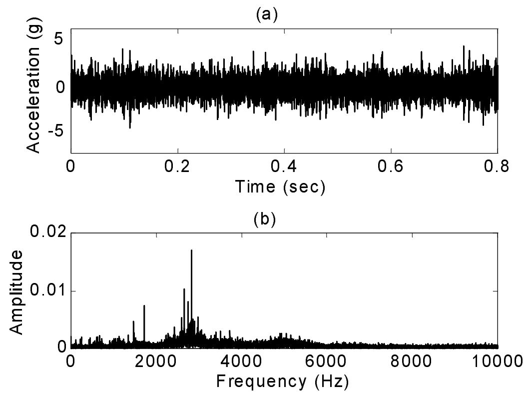

Figure 6. a) Time waveform and b)spectrum of the vibration response of a outer race fault signal.

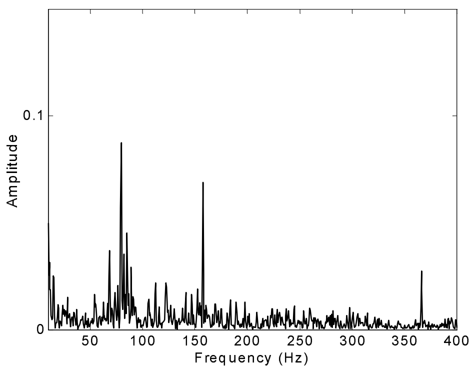

Figure 7. Spectrum of the outer race fault signal using shifted wavelet filter

(=120 Hz) and its harmonics. The interesting diagnostic information has been detected.

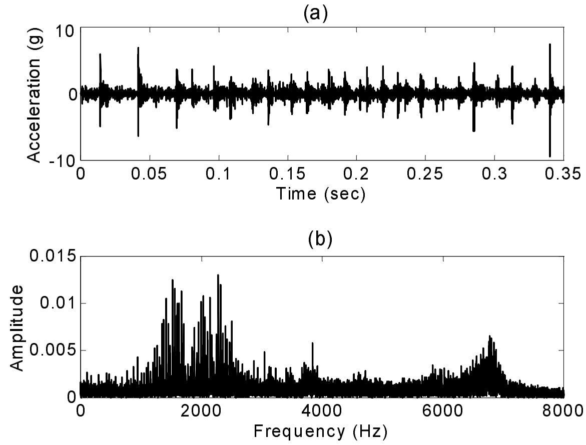

Figure 8. a) Time waveform and b) spectrum, of a vibration signal measured on a bearing with inner race fault.

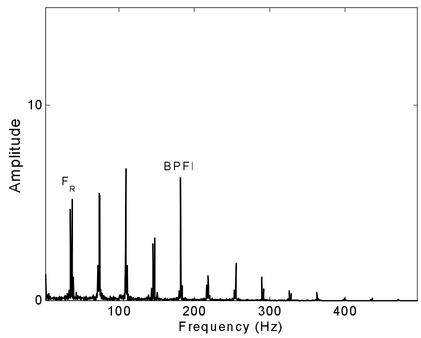

Figure 9. Spectrum of the inner race fault signal using shifted wavelet filter.

Two characteristic experimental cases are also presented, each one been typical of a vibration response, corresponding to a different type of bearing fault. In all cases, the measuring device was based on a Pentium II/266MHz portable computer, equipped with a PCMCIA DAQCard-1200 data acquisition card from National Instruments. This is an 8-channel software-configurable 12-bit data acquisition card, with a total sampling rate capacity of 100KHz. A B&K type 8325 accelerometer was used, with a sensitivity of 97.3 mV/g and a dynamic range of 1 Hz to 10 kHz. The code of the algorithm that was used in the data acquisition procedure has been developed under the LabVIEW programming environment of National Instruments. Case A presents an outer race fault and case B an inner race fault. The measurement in case A was conducted on an industrial motor bearing and in case B the measurement was conducted on a machinery fault simulator.

The bearing examined in Case A is of type 6324MC3 manufactured by SKF. The rotor speed is about 1,500 rpm and the characteristic Ball Passing Frequency Outer race (BPFO) is approximately 78 Hz. The sampling frequency of the measurment was 20 kHz. Figure 6 presents, (a) the measured acceleration signal and (b) the spectrum of the measured signal. The proposed procedure is applied and the spectrum obtained is illustrated in Fig.7. It is dominated by the characteristic defect frequency BPFO and a harmonic. The fault has been identified.

The bearing examined in Case B consists of 8 balls, has a ball diameter equal to 0.2813 inches, a pitch diameter equal to 1.1228 inches and a contact angle equal to 0 deg. A fault on the inner race was produced. The shaft rotation frequency was about 36 Hz. The sampling frequency of the measurement was 16394 Hz. Figure 8 presents, a) a part of the time waveform and b) the spectrum of the measured signal. Although a "spiky" behavior is observable in the signal, the nature of the fault cannot be identified without further processing. The proposed method is applied and the obtained spectrum is illustrated in Fig.9. The shaft rotation frequency its harmonics and the characteristic defect frequency (BPFI=181Hz) are dominating the spectrum. In this case, a strong modulation effect by the shaft rotation frequency is observed, indicating a severe inner race defect.

4 Conclusion

The exploitation of the underlying physical concepts of the modulation mechanism and of the time-frequency localization capabilities of the used wavelet, can lead to an effective method being able to effectively identify the nature of rolling element bearing faults. In all cases, the spectrum obtained, contained the corresponding necessary diagnostic information.

The implementation of the method can be conducted in an almost automatic way, with the minimal possible degree of user intervention. It can be easily implemented for on line applications.

The method provides a consistent algorithm for detection of localized defects in rolling element bearings and allows the diagnosis of the locations of the defects, but is still a qualitative approach. Further work is needed for a quantitative application.

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