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Wavelet Based Signal Demodulation Technique for Bearing Fault Detection

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Diagnostics of rolling elements under varying operational conditions, where disturbances and other rotating elements have strong influence on correctness of analysis, requires engagement of advanced signal processing techniques. Extraction of signal components generated by bearing faults has been proven to be an exceptionally promising method for rolling element bearing fault detection. In this paper, wavelet signal demodulation diagnostic techniques is presented.

The method is based on the wavelet transform as a method of signal demodulation. Properties of time–frequency representation of the signal enables extraction of typical damage signatures from the signal. First step of this method is a wavelet filtration, which uses Continuous Wavelet Transform (CWT). For this transformation, the Morlet wavelet function has been used. Next, the envelope function of a decoupled frequency component is estimated from wavelet coefficients. Finally, the Discrete Wavelet Transform (DWT) has been used as a post–processing method.

Keywords: Continuous wavelet transform, bearing diagnostics, signal processing, discrete wavelet transform

1. Introduction

Detection of local damages in a power transmission system is one of the most essential problems in diagnostics. Amplitudes of the signal connected with damage are usually low and propagation of the damage can be very fast. Bearing diagnostics based on the analysis of the vibration signals is extensively used in rotating machinery industry. Interaction between failed elements of bearing produced characteristic vibrations allow to determine which part of the bearing is damaged or exhibit sign of wear. When the damaged surface of bearing hit the another surface, an impulse is generated. This impulse can excite the bearing and machine. As a results of rotation, the amplitude modulated series of impulse responses arise. Amplitude modulation occur by reason of passage of the damage through the load zone or transmission path between measurement and impact point[5]. Spectral analysis of this kind of a signal is challenging because characteristic frequencies of bearing elements are masked by the harmonic series frequency components. Additionally, fluctuation be-tween successive impulse distance (changes of load angle for each rolling element) are frequently present. Differences in the levels of amplitudes of signals generated by bearings and different elements of power transmission system (meshing, shafts, etc.) often make the detection of damage symptoms based on non – processed vibration data impossible. Solution of this problem is the separation of the signal generated by bearings from signals derived from other elements. It gives also possibility of use this kind of methods in cases when many elements can be defected.

The basic idea of the methods for detection of local damages is instantaneous disturbance of kinematic pair dynamics caused by damage of race or rolling elements. For the sake of rotation, this disturbance is periodic. Additionally, diagnostic signal is very often masked by noise and other signals with finite band (meshing frequencies and their harmonics).

Nowadays, a number of methods exist for bearing diagnostic. Methods based on time domain in the majority of cases define statistical parameters of the signal (maximal values, kurtosis, skew–ness)[1 – 6]. For these methods, a preprocessing (filtration, averaging, etc.) is required. Procedures based on analysis in frequency domain detect changes in frequency components of the diagnostic signal. This approach is ineffective because of small energy of informing signal, high level of noise, and complex frequency structure of the signal. Wide used methods for local damage detection are methods in time-frequency domain. In this approach, the nonstationary data can be analyzed locally (wavelet transform, STFT, Wigner – Ville distribution, etc.). Unfortunately, the main disadvantage of this method is the computational complexity. The next useful tool for bearing diagnostics is the cepstral analysis based on analysis of sidebands amplitude. Another group of methods worth mentioning are such, which utilize the cyclostationarity approach[7] that gives the possibility to identify the type of modulation and its character.

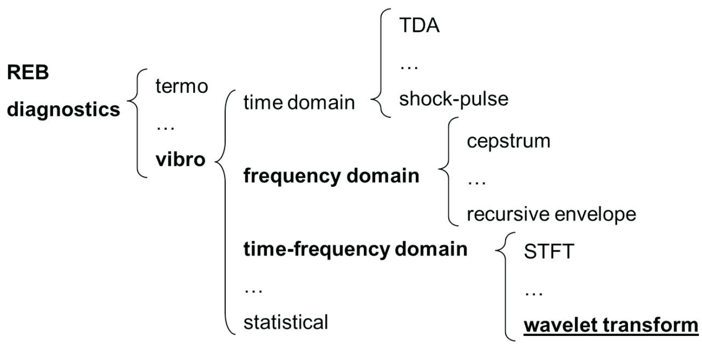

Figure 1 Selected REB diagnostics methods

Additionally, the extraction (the separation) of signal components is possible using blind source separation technique[8]. Finally, methods based on signal amplitude demodulation are widely used. This analysis makes possible to determine envelope function of a signal. Frequency representation of envelope function gives information about local defects. Selected methods of Rolling–Elements Bearings (REB) fault detection presents Fig. 1.

2. Theoretical background of wavelet transform

Wavelet transform is a kind of signal decomposition technique. From mathematical point of view, the complex continuous wavelet transform can be expressed as[9]:

$$(W_g x)(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\, g^*\left(\frac{t-b}{a}\right) dt \tag{1}$$

where

b – is translation (displacement) representing a region,

a – is dilatation (expansion) or scale parameter,

$g(t)$ – is basic wavelet function, $g^*(\cdot)$ – complex function, adjoin to $g(.)$.

Each value $(W_g x)(a,b)$ is normalized by the $a^{-\frac{1}{2}}$ coefficient Due to this normalization, the condition of internal energy given by each wavelet $g_{a,b}(t)$ independence is fulfilled. As it stems from the equation (1), the wavelet transform can be treated as a linear decomposition of a signal $x(t)$ into elementary functions, which can be obtained from the analyzed wavelet $g(t)$ as a result of dilatation and translation. It is a translation b that is responsible for time decomposition while decomposition scale (frequency segmentation) is obtained as a result of dilatation a.

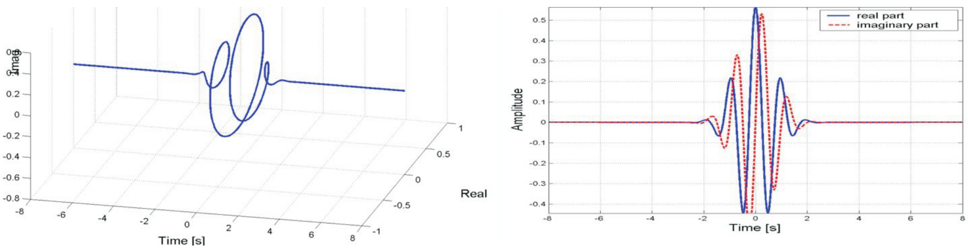

Figure 2 Morlet wavelet function

The Morlet wavelet (Fig.2) is one of the most widespread and most often used functions in the wavelet analysis and is defined as [10,11]:

$$g(t) = e^{j2\pi f_0 |t|} e^{-\frac{|t|^2}{2}} \tag{2}$$

It has been analytically proved [12] that Morlet wavelet function and complex continuous wavelet transform can be used for frequency components decoupling procedure. Schematically this process has been shown in Fig. 3.

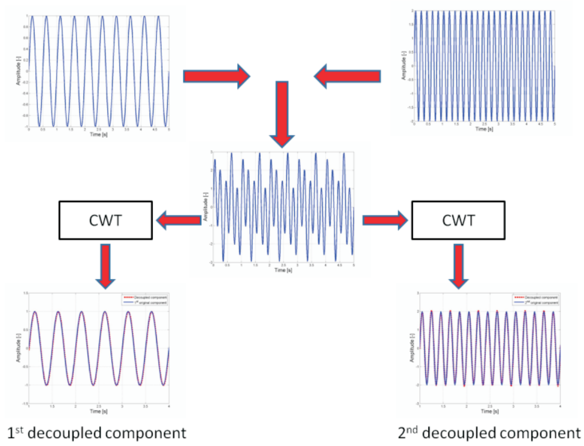

Figure 3 Wavelet based signal components decoupling

This features allow to analyze every component of the signal separately. Determination of wavelet functions which allows filtration of the given frequency component requires definition of a scale parameter associated with the frequency by the formula [13]:

$$f_i = \frac{T_s}{a_i} \tag{3}$$

where T_s is sampling time and f_i is frequency corresponding to scale parameters ai. Change of scale parameter a_i allows to change the wavelet filter frequency.

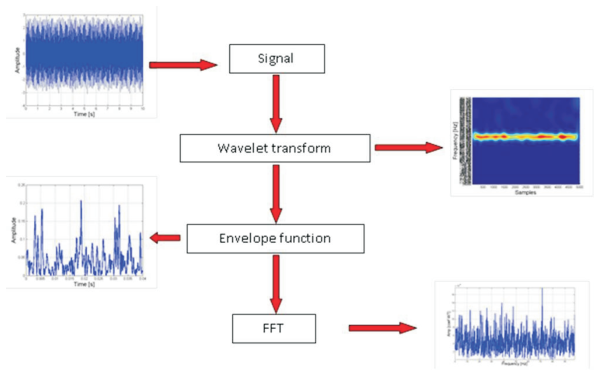

Figure 4 Procedure of wavelet demodulation

3. Amplitude demodulation procedure

Based on the properties of wavelet transform described above, the procedure of wavelet demodulation is illustrated in Fig 4. First, the signal is filtered using Morlet wavelet function. For given scale parameter (frequency), the signal component are represented by series of complex values – wavelet coefficients. Next, the envelope function given by [14]:

$$env = |W_g x\,(a, b)| \tag{4}$$

is assigned for set of signal components. The real values of wavelet coefficient represents the time history of signal component with frequency corresponding to wavelet frequency. In the next step of algorithm, Fourier transform of envelopes are estimated and characteristic frequencies of bearing damage are searched.

4. Simulated signal

The performance of the two methods is demonstrated using a computer–generated simulated signal [15, 16]. The signal was built with a sampling frequency of 25 [kHz], and a length of 10seconds. The major components include a 25 [Hz] fast shaft (relative amplitude 1.0), 12 [Hz] slow shaft (relative amplitude 0.8), 420 [Hz] gear meshing frequency (relative amplitude 0.3), and a 124 [Hz] characteristic frequency, carried on a modulated 4.0 [kHz] wave, with a random jitter (max. 3%), simulating for instance a rolling–element–bearing outer race fault; the signal has initial amplitude of 0.1, decaying with a time constant of 2 [ms].

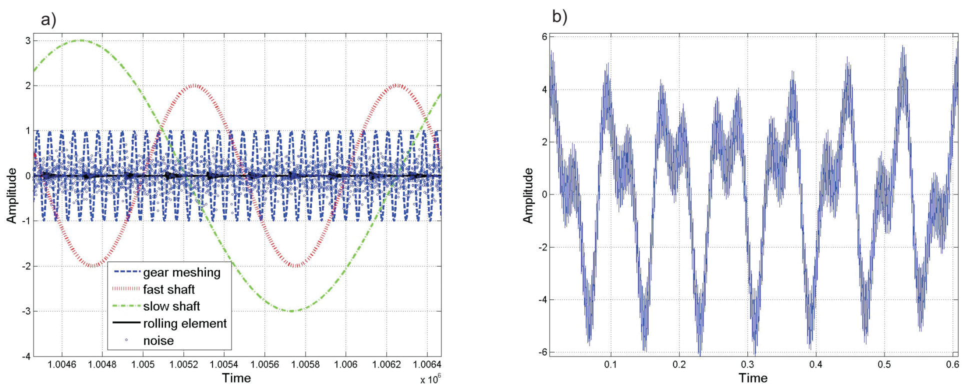

Figure 5 The simulated signal: a) separate components time plot, b) time history of the signal

The signal also contains a Gaussian random noise with the standard deviation equal to 0.25. The time view of the total signal, time view of separate components, as well as a spectrum illustrated in Fig. 5. Fig. 6b shows, that for the noise amplitude 0.25, the dB spectrum does not identify the frequency band, where the fault–induced signal is clearly observable. Additionally the different time shift between subsequent impact excitations caused by rolling elements and damage introduce spectral line

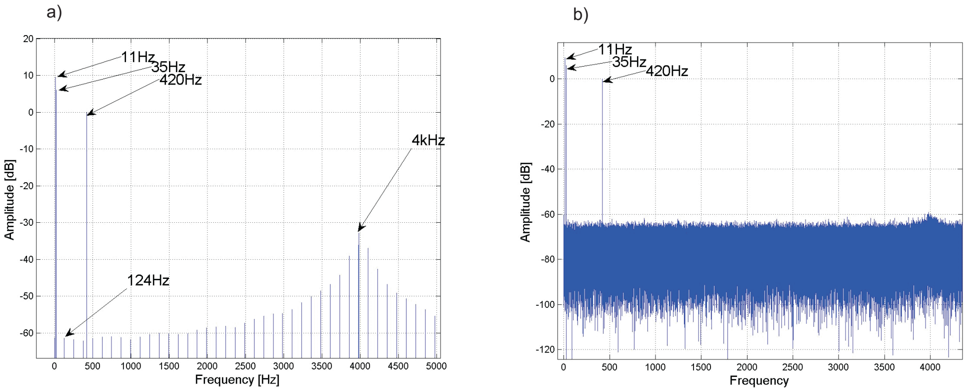

Figure 6 The dB-spectrum of the signal: a) without noise and jitter, b) with disturbances

broadening. Comparison of signal dB spectra for cases with and without above mentioned disturbances shows Fig. 6a.

5. Fault detection

For a numerical verification, the signal described above has been used. Process of wavelet filtering has been carried out with Morlet wavelet and following parameters:

- Central frequency – 1 [Hz].
- Bandwidth parameter – 10 [Hz].
- Scale parameters – 2:0.25:20

The procedure has been implemented in MATLAB environment. First, the signal decomposition by wavelet transform has been performed. For every bandwidth (scale parameter) the time representation of wavelet coefficients has been reconstructed. Next the envelope function has been estimated using equation (4). Finally, the Fourier transform for set of envelopes has been estimated.

Characteristic frequency (124 [Hz]) and their harmonics are clearly observable for scale parameter equal 6.25. It correspond to frequency 4 [kHz] assumed for simulation. Figure 7 shows time representation of decoupled 4 [kHz] carrier and its envelope. Spectrum of envelope for 4 [kHz] component presents Fig. 8.

The method correctly detect the characteristic frequency (124Hz) and its harmonic. However, it is worth mentioning that application of the method affects the ultimate amplitude level of the harmonic components. Though the "true" amplitude may be considered as an issue for a discussion, it may be neglected in majority of industrial cases, since analyses of diagnostic systems frequently detect the relative deviations of amplitudes. The amplitude can be also used to assessment of damage. It can allows to predict and plan maintenance strategy.

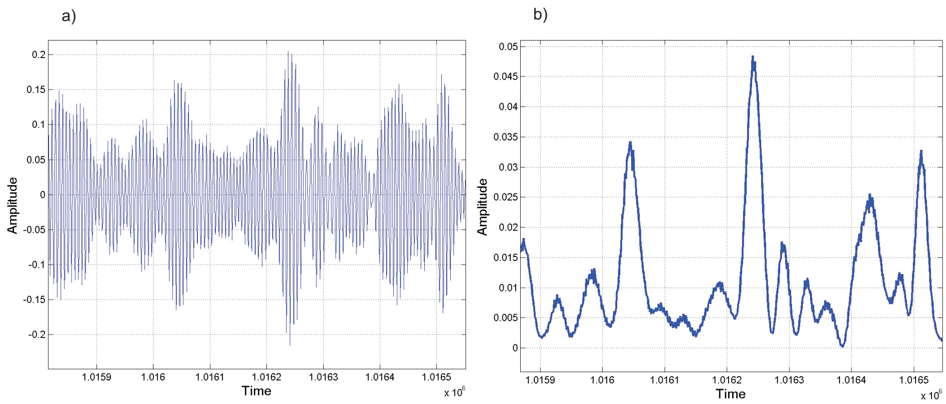

Figure 7 Results: a) decomposed component 4kHz, b) envelope of decomposed component

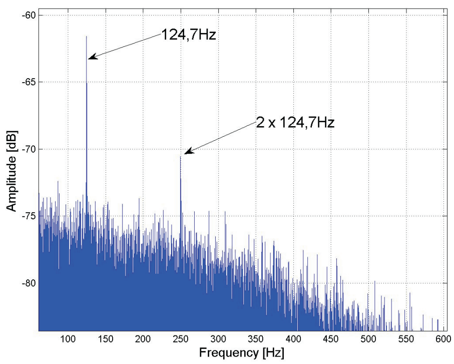

Figure 8 Resultant envelope spectra of the Wavelet analysis

6. Summary

Presented method for the detection of characteristic frequencies in a presence of a high–level Gaussian noise were presented in this paper. The method is based on the wevelet transform as a method of signal decomposition which allow separate components of the signal. This separation enable analysis of single component signal. The algorithm was presented in flow charts, and described step–by–step.

The results shows that the method correctly detect modulating characteristic frequencies in a vibration signal. The major merit of the presented methods is the ability of optimal frequency band detection (i.e. the center frequency and the bandwidth) for the amplitude demodulation without a priori knowledge and influence of signal sampling frequency on results. Preliminary information about carrier frequency significantly reduces signal bandwidth where the characteristic frequencies are searched. Too low sampling frequency reduces resolution in frequency domain for wavelet transform This can translate into the quality of the results. Above mentioned problems were not investigated in this paper. Finally, the methods shows superior characteristic component detection in a presence of a higher level noise. The next step of algorithm validation should be application to real data.

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