Lubrication starved bearings detection in electrical motors vibration signals by means of wavelet bispectral analysis

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Electrical motor condition monitoring for electrical and mechanical faults has become almost indispensable. A major portion of the mechanical failures in rotational machines are caused by bearing failures. Premature bearing failures can be caused by a large number of factors were one of the most common causes is an inadequate lubrication which can lead to a catastrophic failure. Improperly lubricated bearings detection of from vibration patterns is yet a difficult task especially when records from short operating periods are available. This problem has been addressed to by applying recently introduced wavelet bispectral analysis, a technique for revealing time-phase relationships. The method is firstly demonstrated and evaluated by use of generic signals where the phase coupling information is emphased and than applied to vibration signals of electrical motors. Test-set comprised of electrical motors with fault-free and with improperly lubricated bearings. The results reveal that improper lubrication is expressed as phase coupling increase in the high bifrequency region in the bispectrum domain.

1 Introduction

It is estimated that major portion of the electrical motor failures, about 40 % percent, are caused by bearing failures [1].. Inadequate lubrication is one of the common causes of premature bearing failure. Excessive wear of the bearing elements can be followed by a catastrophic failure [2]. The detection of bearings with inadequate lubrication in rotation machinery has received substantional research. Many methods based on vibration signal analysis have been developed in the past decades for this purpose [3, 4]. These methods include power spectrum estimation, envelope spectrum analysis, cepstrum analysis, wavelet transform, Hilbert-Huang transform, Teager-Huang transform, Wigner-Ville distribution high order statistics and others. A brief review of vibration monitoring techniques in both time and frequency domains can be found in [5]. However, the vibration signals are almost always interfered by random noises from near mechanical components. These noises reduce the signal to noise ratio and affect the fault diagnosis result. For the lubricant starving case it is necessary to distinguish the small variations in the vibrations between improperly and properly lubricated bearings which make this type of fault analysis very demanding. There have been several attemps to approach this issue, recently by using the cyclostationary analysis, spectral curtosis, minimum entropy deconvolution, singular spectrum snalysis, pocket wavelet analysis and others [5-10]. The efectivnes of the approach usualy depends on the frequency band selection where the bearings faults are the most expressed. This introduces limitations to the usage/sensitivity of the existing methods.

Higher order statistics can effectively suppress additive Gaussian noise of unknown power spectrum and extract the fault feature [11]. Previously, characteristic defect frequencies and their harmonics have been used to direct a bispectral analysis of the vibration signal to detect localized bearing defects [12-14]. All of the existing bispectral methods are based on treating the bispectral amplitude. When a certain defect is present on a bearing element, an increase in the vibration levels at this frequency can be noticed. In natural systems, properties of interacting oscillatory systems are not constant, but evolve or fluctuate in time. The assumption of stationarity for systems under study can no longer be presumed, making the system analysis complex. An enormous amount of effort has been made in recent years to develop time-series analysis for studying such systems. In our earlier work [15,16] we extended bispectral analysis to wavelets incorporating instantaneous frequency (phase) to cope with couplings among interacting nonlinear oscillators.

In this work, we apply the wavelet bispectral approach for the extraction of useful features from the electrical motor vibration signal for the purpose of bearing lubricant starving fault diagnosis.

2 Method

Details of time-bispectral analysis and wavelet-bispectral analysis can be found elsewhere [15, 16], while here we summarize the salient properties of the approach.

Bispectral analysis belongs to a group of techniques based on high order statistics that may be used to analyze non-Gaussian signals, to obtain phase information, to suppress Gaussian noise of unknown spectral form, and to detect and characterize signal nonlinearities [11].

The bispectrum involves third-order statistics. Spectral estimation is based on the conventional Fourier type direct approach through computation of the 3rd order moments [11]. The classical bispectrum estimate is obtained as an average of estimated 3rd order moments (cumulants)

$$\hat{B}(k,l) = \frac{1}{K}\sum_{i=1}^{K}\hat{M}_3^i(k,l), \qquad (1)$$

where the 3rd order moment estimate $\hat{M}_3^i(k,l)$ is performed by a triple product of discrete Fourier transforms at discrete frequencies k, l and $k+l$

$$\hat{M}_3^i(k,l) = X_i(k)X_i(l)X_i^*(k+l), \qquad (2)$$

with $i = 1,\ldots K$ segments into which the signal is divided. The bispectrum $B(k, l)$ is a complex quantity, defined by magnitude $A = |B(k, l)|$ and phase $\phi = \angle B(k, l)$. Consequently, for each (k, l), its value can be represented as a point in a complex space, $\mathrm{Re}[B(k, l)]$ versus $\mathrm{Im}[B(k, l)]$, thus defining a vector. Its magnitude (length) is known as the biamplitude. The phase, which for the bispectrum is called the biphase, is determined by the angle between the vector and the positive real axis.

Generalization of bispectrum based on Fourier transform to wavelets can be seen as a generalization of the Fourier analysis [17] by adding time resolution - in a more fundamental way [18, 19]. Within this transform, the window length is adjusted to the frequency currently being analysed. It is a scale independent method. Window function is called a mother wavelet or basic wavelet. It can be any function that satisfies the wavelet admissibility condition [17]. This function introduces a scale s (its width) into the analyses. The mother wavelet is also translated along the signal to achieve time localization. Morlet mother wavelet was chosen to be the most suitable one and it gives a straightforward relationship between the scale and the frequency. The definitions are completely analogous to the definitions used in bispectral analysis based on Fourier transform [20]. The Wavelet Bispectrum (WB) is given by

$$WB(s_1, s_2) = \int_T W_g(s_1,\tau) W_g(s_2,\tau) W_g^*(s,\tau) d\tau, \qquad (3)$$

where $1/s = 1/s_1 + 1/s_2$. The WB measures the amount of phase coupling in the interval T that occurs between wavelet components of scale lengths s_1 and s_2 and s of signal $g(t)$, in such a way that the frequency sum-rule is satisfied. It is a complex quantity, defined by magnitude A and phase ϕ:

$$WB(s_1, s_2) = |WB(s_1, s_2)| e^{j\angle WB(s_1,s_2)} = Ae^{j\phi}. \qquad (4)$$

The instantaneous biphase and biamplitude are calculated from (3) and (4)

$$\phi(s_1, s_2, t) = \phi_{s_1}(t) + \phi_{s_2}(t) - \phi_s(t), \qquad (5)$$
$$A(s_1, s_2, t) = |WB(s_1, s_2, t)|.$$

The WB as defined in (3) can be seen as a special case of the cross-bispectrum when the three signals are the same. If two scale components s_1 and s_2 are scale and phase coupled, $1/s = 1/s_1 + 1/s_2$, it holds that the biphase is 0 (2π) radians. For our purposes, the phase coupling is less strict because dependent scale components can be phase-delayed. We consider phase coupling to exist if the biphase is constant (but not necessarily = 0 radians) for at least several periods of the highest scale component. Simultaneously, we observe the instantaneous biamplitude from which it is possible to infer the relative strength of the interaction. For ease of interpretation, the WB is plotted in the (f_1, f_2)-plane, rather than in the (s_1, s_2)-plane. The non-redundant region is the principal domain of the WB. Similarly, the principal domain can be divided into two triangular regions in which the WB has different properties: the inner triangle (IT), and the outer one. The IT is of our interest defined in [11].

2.1 Numerical example

For the purpose of understanding the basic principle of the later on applied wavelet bispectral method to the real measured signal we first demonstrate its phase coupling information extraction possibilities.

Let us consider a numerically generated time-series that mimic the general possible situation that occurs in electrical motor rotating system. We mimic the natural frequency of electrical motor system and possible bearings fault with a periodic signal with a characteristic frequency f_1 and f_2. To be as simple and presentative we use harmonic signals. Let us define a generic signal

$$x(t) = A_1\cos(2\pi f_1 t + \varphi_1) + A_2\cos(2\pi f_2 t + \varphi_2) +, \qquad (6)$$
$$+ A_3\cos(2\pi f_3 t + \varphi_3) + D\xi(t),$$

where $A_{1\text{-}3}$ are constanst amplitudes, $\phi_{1\text{-}3}$ initial phases, $f_{1\text{-}3}$ characteristic frequencies and $\xi(t)$ is

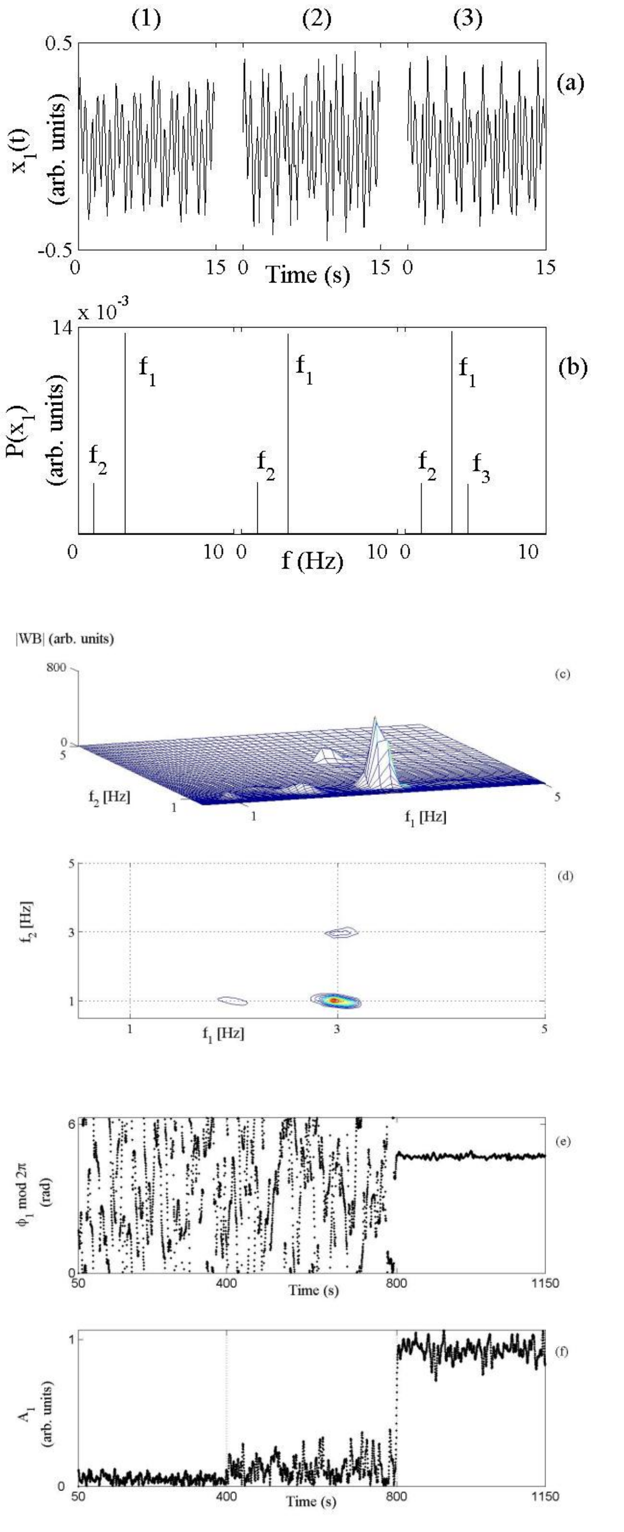

Figure 1: Generic signal x1(t). (a Time evolution, (b) its power spectrum, (c) and (d) is absolute walue of wavelet bispectrum and ist contour plot in bifrequency domain. (e) Time evolution of biphase and (f) biamplitude.

zero-mean white Gaussian noise $\langle \xi(t) \rangle = 0$, $\langle \xi(t), \xi(0) \rangle = D\delta(t)$ and D=1 is the noise intensity. We assume that when a bearing fault is present it results a new frequency component f_2 that interacts with a mechanic system natural frequency f_1 and typicaly produces new frequency components, t.i. f_3, at side bands of f_1 as a result of nonlinear interaction/mudulation. Signal x_1 is composed of three time sections (1)-(3) each lasting for 400 s, Fig 1 (a). In the first 400 s there is no interaction between f_1 and f_2 signal frequency components. In the second epoch f3 is present however its phase φ_3 is not related (it is randomized) to φ_1 and φ_2 and in the last 400 s epoch the signal frequency component f_3 is a result of frequency and phase coupling of f_1,, f_2 and φ_1, φ_2. Fig. 1 (b). Fig. 1. (c) and (d) shows absolute value of WB for the bifrequency domain. A peak at bifrequency (3 Hz, 1 Hz) is obvious. It represents interaction between signal frequency components f_1 and f_2. Their interaction might produce f_3. This can examined by observing time evolution of biphase $\phi_{1.}$ For the first 800 second it is randomized and for the last 400 s it is constant, Fig 1 (e) and (f). This phase information is not possible to extract from the signal x_1 by using the 2nd order spectrum, t.i. the power spectrum.

3 El. motor vibration signal analysis

To test the bispectral method for the purpose of lubrication starved bearing detection we used vibration signals measured from electronically commutated motors (ECM). Test rig is shown on Fig. 2.

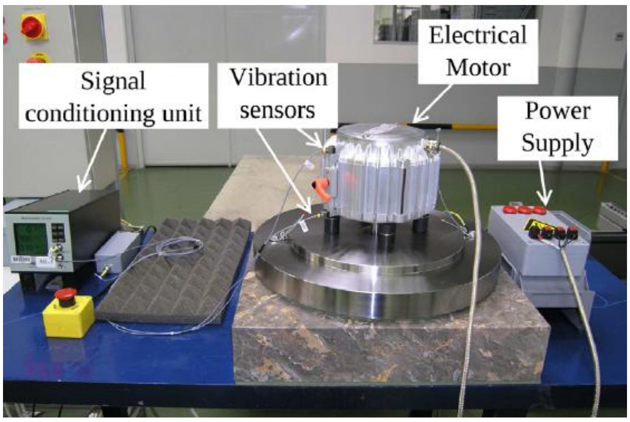

Figure 2: The prototype assessment point.

3.1 Data

The data acquisition techniques have already been described [6, 7] but, in summary, were as follows. Two groups of motors were utilized. One group contained 28 ECM with properly lubricated bearings. The second group contained 32 ECM with lubrication starved bearings. The lubrication starved bearings were prepared by cleaning the grease with tetrachloroethylene. A special care was taken to prevent entry of any foreign debris within the bearing raceways. All the vibration signals were obtained during the nominal rotational speed (38 Hz) of the ECM. Firstly, vibration signals were low-pass filtered with cut-off frequency at 22 kHz and sampled at 60 kHz. Further signal's envelope were calculated by using a Hilber transform and further resampled to 40 kHz, normalized between 0 and 1 and zero meaned. Only vibration signals from the lower accelerometers are the case in this paper.

3.2 Results

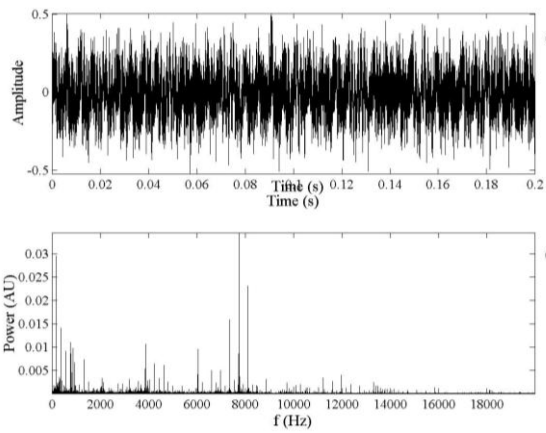

Figure 3: Envelope vibration signal for the case of fault free electrical motor. (a) Time evolution and (b) its power spectrum.

Fig. 3 presents a typical signal of a free fault group of signals before the bispectral analysis. For the purpose of bispectral results normalization, first a bispectral normalization value was calculated for all the signals under the study for the whole IT bispectral domain. This enabled us to be able to compare signal results from different ECM and different states (fault-free, lubricant starving) and outer bearing

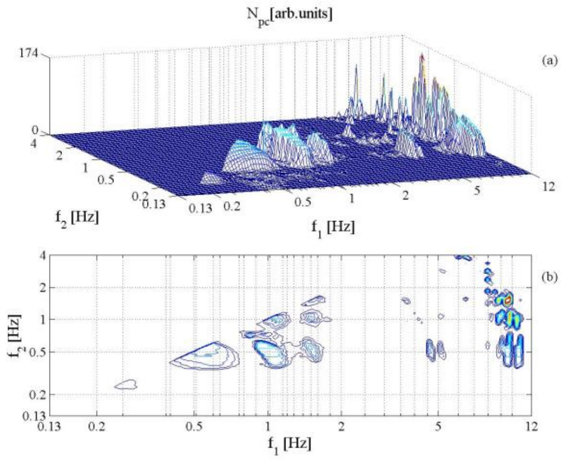

Figure 4: Number of phase couplings Npc for fault free envelope vibration signal.

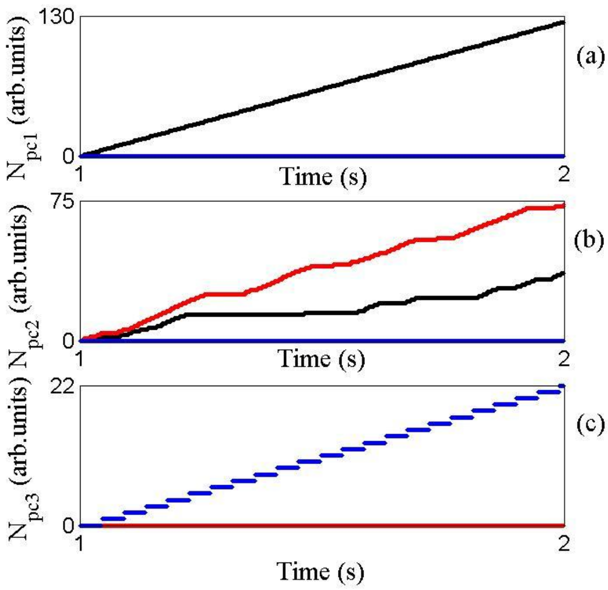

Figure 5: Number of phase coupling N_{pc} results for black - fault free, red - lubrication starving and blue line - outer bearing failure for selected fault characteristic bifrequencies (a)-(c).

ring fault for the purpose of comparison with the existing resulls). From the absolute value of WB results it is hardly possible to resolve the 2 different states (fault-free and lubricant starving). Areas, where the WB peaks, almost completely coincide. Nevertheless by extracting the biphase in the WB domain we are able to gain additional information as it was shown by a generic signal $x_1(t)$. We could not resolve relation among different frequency components in the signal fom the biamplitude. It is conditional that it is above certain level (noise, variance, rounding error...) but it is not sufficient. In this way we can distinguish between different bearings fault origin. Fig. 4 shows biphase information further treated to obtain number of phase coupling N_{pc} in the bifrequency domain for vibration signal of fault free ECM. Biphase for each bifrequency that is constant for a specific time epoch (here it is 8 periods of the lower (slower) coupling frequency to overcome noise diffrent than the gaussian one) adds 1 to the value of the N_{pc}. From all the WB results bifrequencies are extracted that represent a specific bearing fault state. An example is shown on Fig. 5. Bifrequency (a) represents fautl free, (b) lubricant starving and (c) outer bearings fault state. Vibration signal of fault free ECM state would result in a contant biphase epoch (sloped black line) for bifrequency (a), randomized biphase (no constant epoch) for (c) and partly constant biphase for (b). Vibration signal of outer bearings fault ECM state would result in sloped line for (c) and zero lines for (a) and (b). The lubricant starving case of el. motor failure woud have zero lines under (a) and (c) and predominant biphase constant epochs for (b). Moreover the height of the slope line can be used as a lubricant starving level indicator.

4 Conclusions

Paper presents application of wavelet bispectral method to the problem of detection of improperly lubricated ECM bearings through vibration analysis. The proposed technique is shown to be capable of detecting improperly lubricated bearings by extracting phase information from the vibration signals. WB method enables us to analyse the whole bifrquency domain at once and no frequency band selection is needed what makes this method particulary promising.

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