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Detecting mechanical failures inducing periodical shocks by wavelet multiresolution analysis. Application to rolling bearings faults diagnosis

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1. Introduction

Vibrations are the most effective tool in the conditional maintenance of rotating machines. Reduced to global measurements and in the absence of any specific analysis, the reliability of this technique is often limited.

In time domain, scalar indicators (kurtosis and crest factor) are a reliable parameters allowing the detection of defects inducing impulsive forces. Their efficiency for the diagnosis of bearings and gears failures is proven. Nevertheless, the kurtosis seems more sensitive than the crest factor, in particular to the rotation speed and the frequency bandwidth and finds its great efficiency of detection in narrow bandwidths at high frequencies, especially for incipient defects [1-3].

In normal conditions, the distribution of the amplitudes is as Gaussian type, if a defect appears, signal modification also appears in the form of impulses. In the case of damaged bearing, they are generated each time the rolling element meets a discontinuity caused by the defect. Fig. 1 represents a signal simulating impacts at 100 Hz with a sampling rate of 50000 Hz, natural frequency of 2800 Hz and relaxation time of 0.001 s, as modelled in [1].

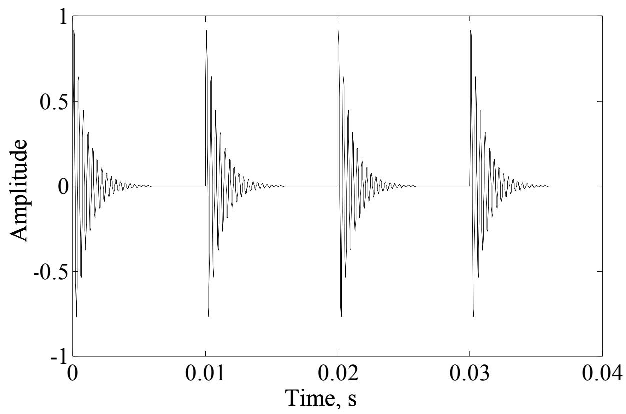


Fig. 1 Signal simulating impacts at 100 Hz: *Fs*= 50000 Hz, τ= 0.001 s

Due to mask effects, these impulses are often drowned in noise and other components of the machine. Fig. 2 represents the same signal of Fig. 1 to witch were added a significant level of with Gaussian noise and ten discrete components, arbitrarily chosen, to simulate low frequencies (20, 23, 24, 26, 29, 44, 45, 55, 60 and 130 Hz) so that the original signal represents 17% of the noisy signal. The impacts are masked and the scalar indicators being limited, several methods tend to solve this problem such as the high frequency resonance [4] and synchronous averaging technique [5]. De-noising techniques are also proposed for the improvement of their sensitivity; using wavelet analysis [6, 7], spectral subtraction [8, 9], adaptive noise-cancelling [10] and mixture de-noising [11].

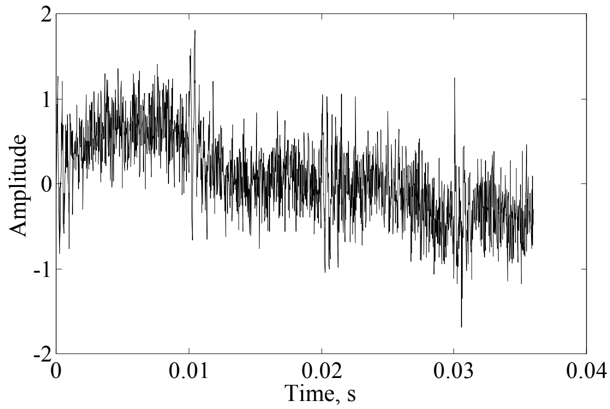


Fig. 2 Noisy signal

In frequency domain, spectral analysis is undoubtedly the oldest technique; it offers the hidden vision of the signal. Unsuited for transitory signals, its efficiency is limited. To solve this problem, the time-frequency distribution development allowed the installation of several reliable techniques such as the short-time Fourier transform, Wigner-ville distribution and wavelet transform. This last one, offering a compromise between time and frequency resolution, is the most recent. Several applications of wavelet transform for defect detection were proposed, using continues wavelet transform enriched with recent techniques [12-17], discrete (or recently called Wavelet Multiresolution Analysis) [18-20] and wavelet packet transform [21]. An interesting synthesis of these techniques is presented in [22].

The aim of this work is to propose a method based on the optimization of Wavelet Multiresolution Analysis. Adapted for the detection of defects inducing impulsive forces, it allows clear detection both for the low frequencies and for the high ones.

2. Scalar indicators of detection

The scalar indicators associated to a vibratory signal, generally observed in its temporal form on determined duration in relation with the installation kinematics, a number or scalar [2] various indicators are used for rotating machines, such us the efficient value (RMS), the peak value or a combination of these two parameters represented by the kurtosis and the crest factor. The kurtosis is a statistical parameter allowing to analyse the vibratory amplitudes distribution contained in a time domain signal. It corresponds to the moment of fourth order norm [4]. Its expression is

$$K = \frac{M_4}{M_2^2} = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(s(i)-\bar{s}\right)^4}{\left[\frac{1}{N}\sum_{i=1}^{N}\left(s(i)-\bar{s}\right)^2\right]^2} \tag{1}$$

with M_4 and M_2 the statistical moments of order 4 and 2, N the number of samples of the signal and $\bar{s}$ its mean value given by

$$\bar{s} = \frac{1}{N}\sum_{i=1}^{N} s(i) \tag{2}$$

The crest factor corresponds to the ratio between the absolute crest value of a signal and its efficient value. Its expression is

$$Cf = \frac{sup|s(i)|}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}[s(i)]^2}} \tag{3}$$

It was shown that the kurtosis is an indicator of degradation state of bearings if its value exceeds three, while it is six for the crest factor [1, 2, 4]. Moreover It was proven that the kurtosis is very sensitive, as detection factor, than the other scalar indicators [1, 2]. Its use as an optimization, selection and evaluation criterion is then justified.

3. Parameters setting of WMRA of shock signals

3.1. WMRA theory

The wavelet transform is a mathematical transformation which represents a signal $s(t)$ in term of shifted and dilated version of singular function called wavelet mother $\psi(t)$. The family of wavelets has the form

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{4}$$

With a and b the scale and the translation parameters, respectively. Noting by $\psi^*(t)$ the conjugate of $\psi(t)$, the continuous wavelet transform (CWT) of the signal $s(t)$ is defined by

$$CWT(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} s(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{5}$$

The discrete wavelet transform (DWT) is a discretization of the continuous wavelet transform (CWT). By replacing a and b by 2^m and $n2^m$, respectively, the above expression becomes

$$DWT(m,n) = 2^{\frac{-m}{2}}\int_{-\infty}^{+\infty} s(t)\psi^*\left(2^{-m}t-n\right)dt \tag{6}$$

with m and n integers.

A practical version of this transform, called wavelet multiresolution analysis (WMRA), was introduced for the first time by Mallat in 1989. It introduces the signal $s(t)$ in low-pass (L) and high-pass (H) filters. In this level, two vectors will be obtained, cA_1 and cD_1. The elements of the vector cA_1 are called approximation coefficients. They correspond to the low frequencies of the signal, while the elements of the vector cD_1 are called detail coefficients and they correspond to the highest of them. The procedure can be repeated with the elements of the vector cA_1 and successively with each new vector cA_j obtained. The process of decomposition can be repeated n times, with n the number of levels. Fig. 3 represents an example of waterfall decomposition for n=3.

During the decomposition, the signal $s(t)$ and vectors cA_j undergo a downsampling, this is why the approximation cA_j and detail cD_j coefficients pass through two new reconstruction filters (LR) and (HR). Two vectors result; A_j called approximations and D_j called details, satisfying the relation

$$\left.\begin{aligned} A_{j-1} &= A_j + D_j \\ s &= A_j + \sum_{i\le j}^{n} D_i \end{aligned}\right\} \tag{7}$$

where i and j are integers.

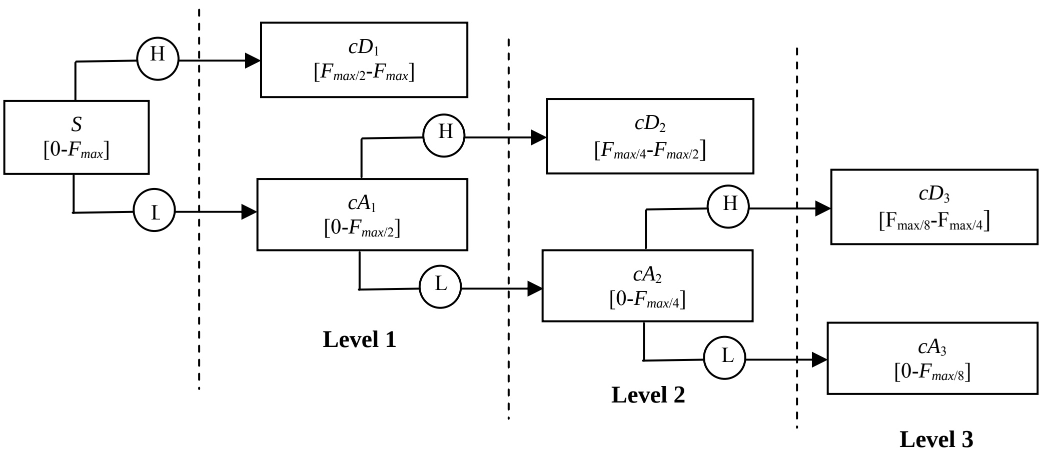


Fig. 3: Waterfall decomposition at three levels

3.2. Optimization of the WMRA parameters

The WMRA is a transform used for various purposes, to adapt it for the detection of defects inducing shocks. Some of its analysis parameters must be chosen, even optimized. The analysis parameters which one considered to be interesting are the number of decomposition levels, the optimal vector, the sampling rate of the input (or measured) signal and the wavelet family.

3.2.1. Optimal choice of the WMRA levels number

The principle of this choice is to preserve only the levels which include information. The maximum frequency of the final level approximation $F_{max}(A_n)$ must imperatively contain the shock frequency and at least some of its harmonics in order to confirm that it is indeed the defect frequency. Practically, one considers that three are rather sufficient, knowing that

$$F_{max}(A_j) = \frac{F_{max}(s)}{2^j} \quad (8)$$

The maximum frequency of the final level n must thus satisfy

$$F_{max}(A_n) = \frac{F_{max}(s)}{2^n} \geq 3F_c \quad (9)$$

Therefore, the number of levels must in its turn satisfy

$$n \leq 1.44\, log\left(\frac{F_{max}(s)}{F_c}\right) \quad (10)$$

3.2.2. Choice of the decomposition optimal vector

The WMRA allows to have a certain number of vectors constituted of details corresponding to the high frequencies and approximations corresponding to the lowest of them. The decomposition optimal vector is the one which allows the defect detection with the best possible resolution, which leads to select the best de-noised one. The optimal vector will be the one has having the most significant kurtosis, therefore

$$V_{opt} = cD_j \text{ or } cA_j \text{ (max. kurtosis)} \quad (11)$$

From the wavelet coefficients of this vector, a signal $s'(t)$ will be reconstructed having more significant kurtosis than that of the original signal $s(t)$.

3.2.3. Optimal choice of the sampling rate

Fig. 4 shows that the kurtosis of the reconstructed signal is significant in the highest sampling rate (50000 Hz) and especially associated to the smallest shock frequency (50 Hz), or rotation speed in practice. Indeed, if the shock frequency is weak the impacts repetition period is large and the kurtosis is then more significant. Studies showed that its optimal capacities are reached if this repetition is ranging between 2.5 and 3 times the relaxation time [1, 2]. On the other hand if the shock frequency is great, so that the condition below is not satisfied or the relaxation time exceeds the impact repetition period, the kurtosis loses all its reliability and its values are almost the same and not significant even for highest sampling rates (from F_c= 350 Hz in our case). In practice, then it is optimal to take the rotation speed as low as possible. If this is not always obvious, the maximal sampling rate is then recommended.

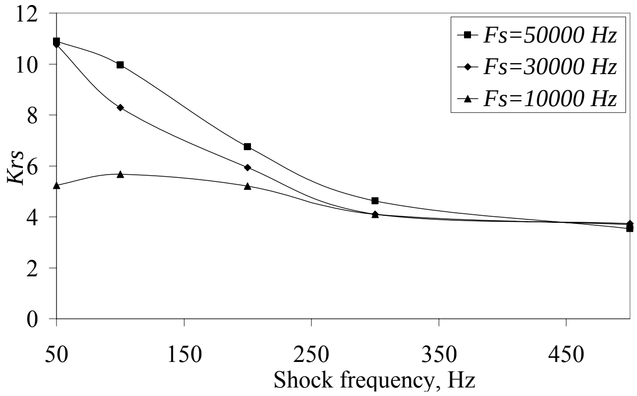


Fig. 4 Kurtosis of the reconstructed signal for different shock frequencies and for three sampling rates

3.2.4. Optimal choice of the analysis wavelet

In literature there are several families of wavelets whose qualities vary according to several criteria. After the elimination of the unsuited families for the fast algorithm of WMRA (such as Morlet, Mexican hat and Meyer), Daubechies family *(dbN)* is chosen as the wavelet mother, which seems the best adapted for such analysis [18, 19, 21]. The problem remains in the choice of the wavelet itself.

In the present case, the selected wavelet will be that which allows better filtering of the original signal thus having a maximum kurtosis of the reconstructed signal. After computing the kurtosis of the reconstructed signal with various Daubechies wavelets, maximal values are taken and Table gives the wavelets adapted for each sampling rate and shock frequency (or the ratio F_s/F_c).

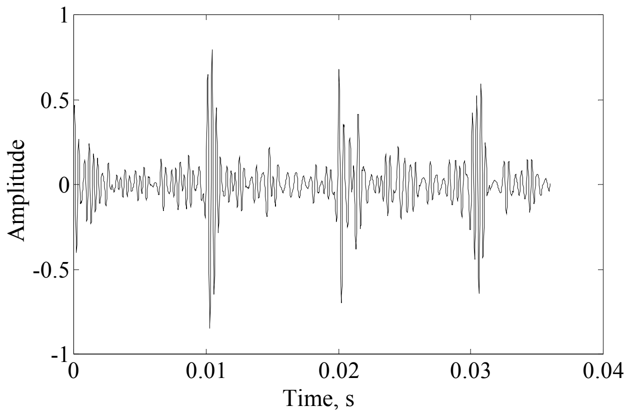
Table

Type of the wavelets adapted for each sampling rate and shock frequency

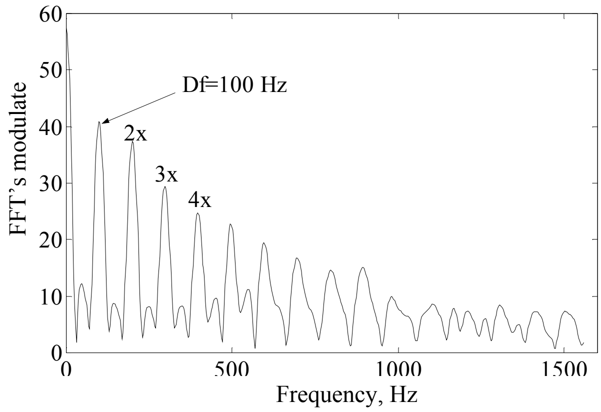
	F_s/F_c				
F_s, Hz	50	100	200	500	1000
10000	**db5**	**db5**	**db5**	**db5**	**db6**
30000	**db5**	**db12**	**db5**	**db6**	**db5**
50000	**db6**	**db12**	**db10**	**db5**	**db10**

4. Theoretical simulation

The analysis parameters being optimised, the proposed method is applied to the noisy signal of Fig. 2; note that in this case the shock frequency is equal to 100 Hz. The signal is broken up into four levels, the kurtosis values of the various details and approximations resulting from the wavelet multiresolution analysis were calculated, indicating that detail 4 (D4) is the optimal. The signal is thus reconstruct from this level (Fig. 5, a). The reconstructed signal is more filtered than the noisy one; its frequency bandwidth is from 1562.5 Hz to 3125 Hz, which indicate that the simulated natural frequency (2800 Hz) is included into this interval. The envelope spectrum of the wavelet coefficients allows detecting the shock frequency (100 Hz) as well as a certain number of its harmonics (Fig. 5, b). The noise and the ten added frequencies are completely filtered.



a



b

Fig. 5 Reconstructed signal (a), its envelope spectrum of wavelet coefficients (b)

5. Application for the rolling bearings defects detection

In order to validate the proposed method, several experiments were carried out on a laboratory test rig. Fig. 6 represents a global scheme of the experiment set up. Three types of defects were simulated on the outer, inner races and ball of a 6200 ball bearing. The defects were artificially localized in a rectangular shape by a diamante tool turning with 50000 rpm. Measurements were taken by a B&K 4384 type accelerometer and a B&K 2035 type analyzer with anti-aliasing filter. Signals were measured with 2048 samples at several rotation speeds and different sampling rates. The post processing is carried out on Matlab.

The first case is examined when a 6200 ball bearing on witch a defect was simulated on its outer race, is rotating at 50 Hz. The defect characteristic frequency (BPFO) is consequently equal to 131 Hz. Fig. 7, a represents the measured signal. Its corresponding spectrum (Fig. 7, b) does not give any information about the nature and the defect frequency except modulations due to the natural frequencies of the bearing and the test rig on which it is assembled.

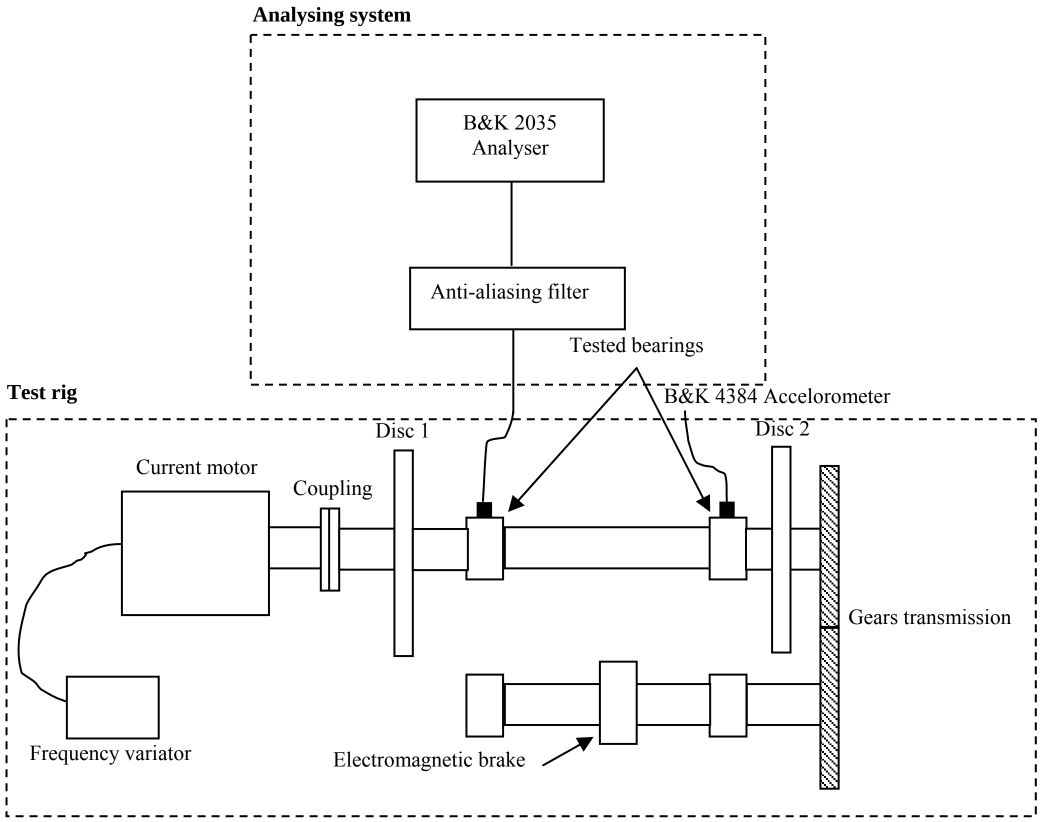


Fig. 6 Experiment set up

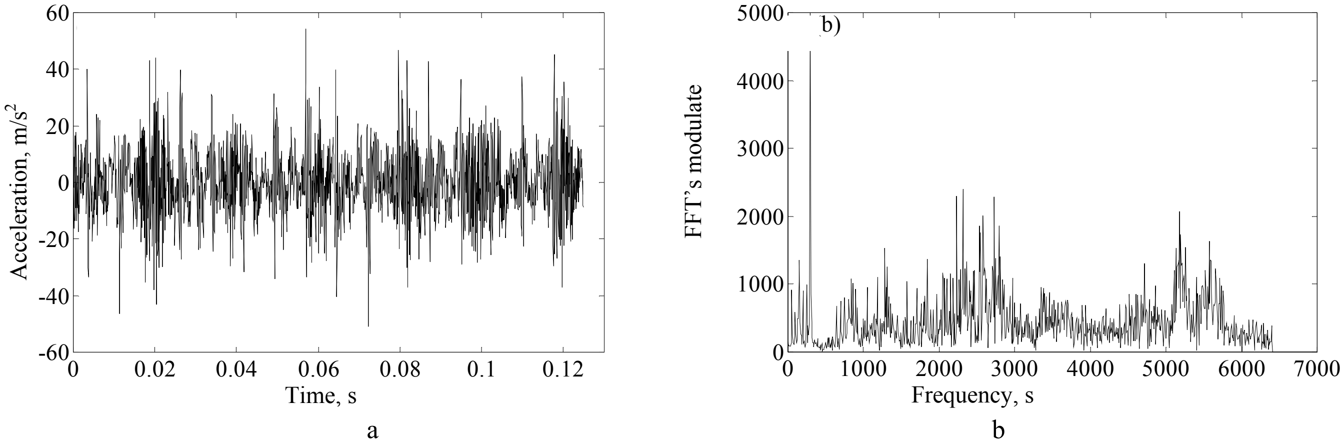


Fig. 7 Measured signal (a), its spectrum (b). Bearing with outer race defect

The proposed method is applied. The measured signal is broken up by the wavelet multiresolution analysis into four levels. The reconstructed signal from the optimal level is represented by Fig. 8, a. Impacts due to the defect are clearly shown what highlights the de-noising capacity of the proposed method. Its envelope spectrum of wavelet coefficients clearly shows the defect characteristic frequency (131 Hz) as well as a certain number of its harmonics (Fig. 8, b).

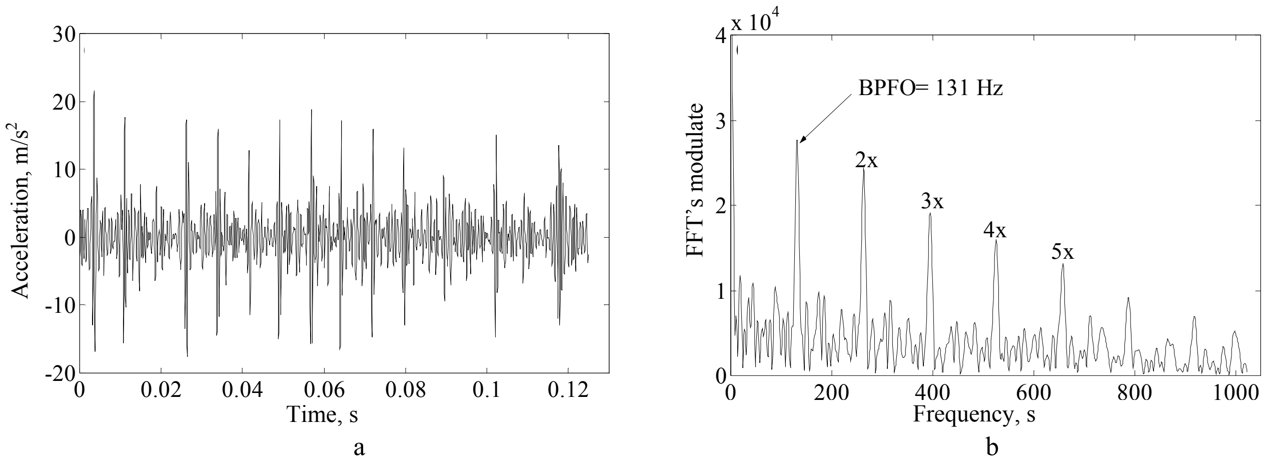


Fig. 8 Reconstructed signal (a), its envelope spectrum of wavelet coefficients (b). Bearing with outer race defect

In the second case a small defect is caused on the ball. The bearing rotates at 30 Hz. The defect characteristic frequency is then equal to 56 Hz. Fig. 9, a and b show the measured signal and its spectrum, respectively. The reconstructed signal highlights impulses due to the defect but the period remains difficult to determine (Fig. 10, a). Indeed, considering the chaotic rolling of the ball, this periodicity is not always obvious.

The envelope spectrum of the wavelet coefficients clearly shows the frequency component of these impulses which correspond to the ball defect and some of its harmonics (Fig. 10, b).

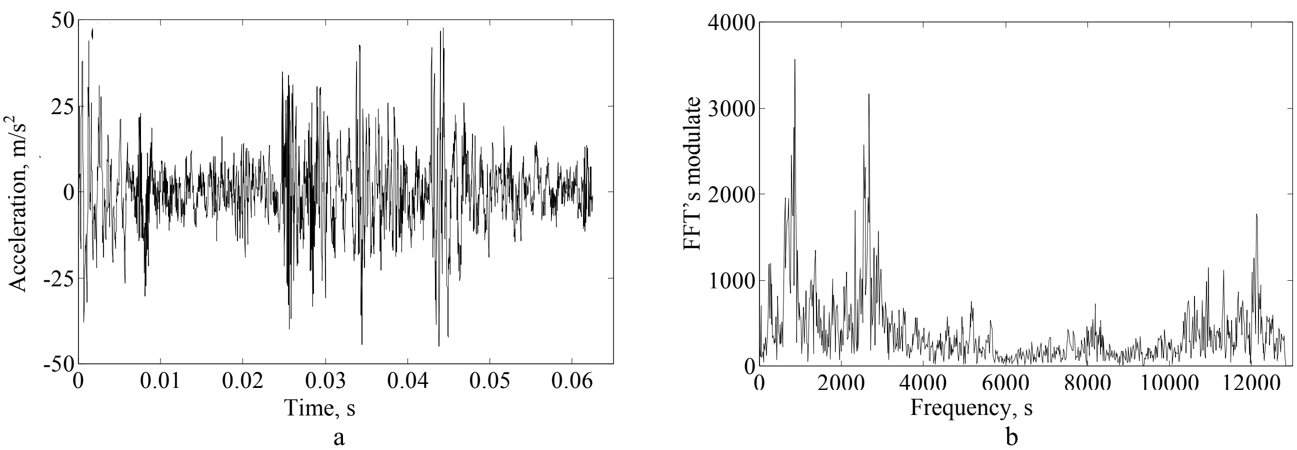
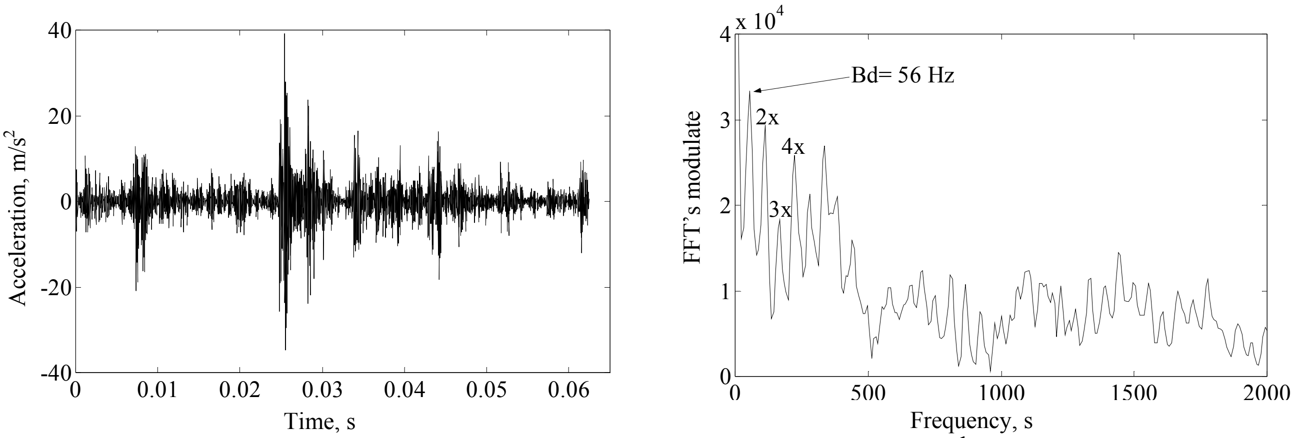


Fig. 9 Measured signal (a), its spectrum (b). Bearing with ball defect

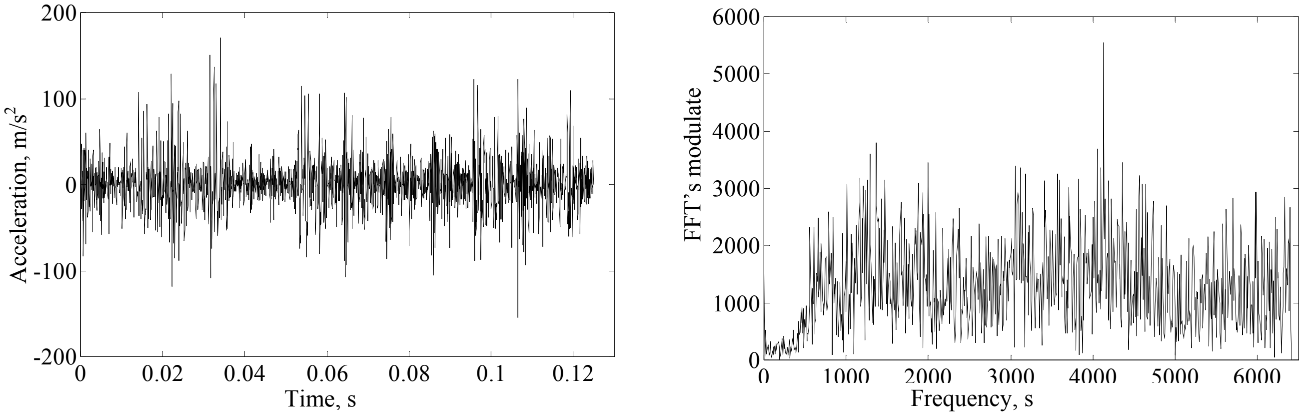


a b

Fig. 10 Reconstructed signal (a), its envelope spectrum of wavelet coefficients (b). Bearing with ball defect

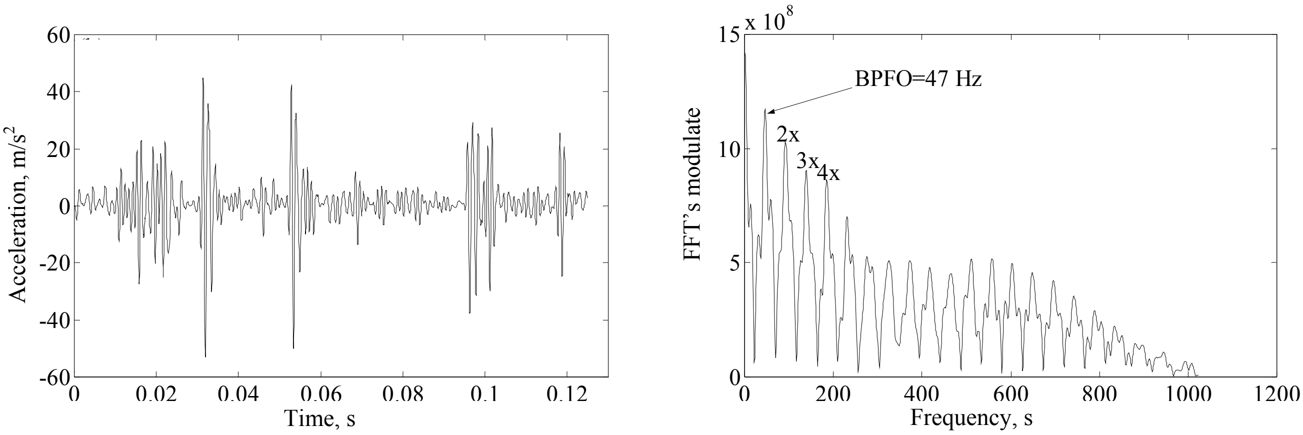
6. Application on rotating machine

In this case, measurements were performed on a parallel lathe turning at 710 rpm. Fig. 11, a represents the signal measured on a N205 cylindrical roller bearing, No information is announced except the modulations due to the natural frequencies of the bearing and other elements of the machine (Fig. 11, b). After the application of the proposed method, the reconstructed signal highlights impacts due to a periodical defect and which seems great (Fig. 12, a). Its envelope spectrum of wavelet coefficients energy shows the frequency of these shocks and witch correspond to an outer race defect (BPFO = 47 Hz) (Fig. 12, b). The diagnostics is also confirmed at another rotation speed (2000 rpm). In this case the reconstructed signal shows impacts spaced with 0.0076 s which correspond to a defect frequency of 130 Hz (Fig. 13).



a b

Fig. 11 Measured signal (a), its spectrum (b). Parallel lathe turning at $N_r = 710$ rpm



a b

Fig. 12 Reconstructed signal (a), its envelope spectrum of wavelet coefficients energy (b). Parallel lathe turning at $N_r = 710$ rpm

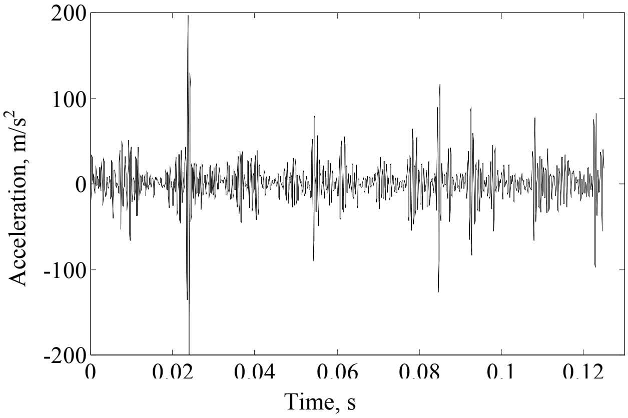


Fig. 13: Reconstructed signal. Parallel lathe turning at N_r = 2000 rpm

7. Conclusion

In this article, Wavelet Multiresolution Analysis was proposed for the identification of mechanical faults inducing periodical impulsive forces. The kurtosis was used as a selection and evaluation criterion. Some parameters were then optimised and chosen; the WMRA levels number, the decomposition optimal vector, the sampling rate and the wavelet family. Adapted for such objective, the method was proposed on theoretical signal simulating periodical impacts. The experimental validation was undertaken on damaged rolling bearings, on witch various defects were simulated.

The results show the efficiency of the proposed method in various configurations and for different simulated defects. In each application, the impacts were isolated and the defect characteristic frequency is clearly shown by the envelope spectrum of wavelet coefficients. Finally, an industrial application realized on a parallel lathe confirms the reliability of the proposed method which seems, at the same time, effective and easily usable and can be integrated on any system of conditional maintenance of rotating machines.

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MECHANINIŲ SUIRIMŲ, KURIUOS SUKELIA PERIODINIAI BANGINIAI SMŪGIAI, NUSTATYMO MULTISPRENDINIŲ ANALIZĖ. TAIKYMAS RIEDĖJIMO GUOLIŲ DEFEKTŲ DIAGNOSTIKAI

R e z i u m ė

Straipsnyje nagrinėjamas multisprendinių analizės taikymas nustatyti mechaniniams defektams, atsirandantiems dėl periodinių impulsinių jėgų sukeltų smūgių. Suderinimo analizei parinkta keletas netgi optimizuotų parametrų. Kaip atrankos vertinimo ir optimizavimo kriterijus panaudotas kurtosis. Esant normalioms sąlygoms, parametrų amplitudės pasiskirsto pagal Gauso dėsnį. Atsiradusio defekto sukelti pokyčiai pasireiškia kaip periodinio impulso formos signalas. Tuo atveju kurtosis, kuris yra labai jautrus šiems smūgiams, leidžia nustatyti defektą. Pradžioje pasiūlytas metodas taikytas signalams imituoti, o eksperimentų duomenims patvirtinti bandymų stende atlikta keletas 6200 guolių matavimų serijų. Tai leido imituoti daug defektų. Galutinai taikymas patikrintas gamybinėmis sąlygomis.

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DETECTING MECHANICAL FAILURES INDUCING PERIODICAL SHOCKS BY WAVELET MULTIRESOLUTION ANALYSIS. APPLICATION TO ROLLING BEARINGS FAULTS DIAGNOSIS

S u m m a r y

The aim of this article is to show the interest of the wavelet multiresolution analysis within the detection of mechanical faults inducing periodical impulsive forces. To adapt it for this purpose, several of its analysis parameters are chosen, even optimized. The kurtosis is used as an optimization, selection and evaluation criterion. Indeed, in normal conditions the distribution of the amplitudes is as Gaussian type, if a defect appears a modification is seen in the signal in form of periodical impulses, the kurtosis is very sensitive to these shocks and allows detecting the defect. First, the proposed method is applied on simulated signal, for the experimental validation several series of measurements were carried out on a 6200 ball bearings on test rig, for this purpose various defects were simulated. Finally, the industrial application is carried out on production machine.

А. Диебала, Н. Оуелаа, Н. Хамзаоуи, Л. Чааби

АНАЛИЗ МУЛЬТИРЕШЕНИЙ ДЛЯ ОПРЕДЕЛЕНИЯ МЕХАНИЧЕСКИХ РАЗРУШЕНИЙ, ВЫЗВАННЫХ ПЕРИОДИЧЕСКИМИ ВОЛНОВЫМИ УДАРАМИ. ПРИМЕНЕНИЕ ДЛЯ ДИАГНОСТИКИ ДЕФЕКТОВ РОЛИКОВЫХ ПОДШИПНИКОВ

Р е з ю м е

Цель настоящей статьи – показать значение использования анализа мультирешений по волналету для обнаружения механических дефектов, вызванных импульсными периодическими силами. Для анализа выбрано несколько параметров, даже оптимизированных. Как критерий оптимизации отбора и оценки использован куртосис. При нормальных условиях амплитуды параметров распределяются по закону Гаусса. Изменения, вызванные дефектом, появляются в сигнале в форме периодических импульсов, при этом куртосис, очень чувствительный к этим ударам, позволяет обнаружить дефект. Первоначально предложенный метод применялся для симулирования сигналов, а для экспериментального подтверждения данных на испытательном стенде было осуществлено несколько серий измерений 6200 подшипников. Таким образом было симулировано много дефектов. Промышленное применение реализовано на производственной машине.

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