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Improvement of the sensitivity of the scalar indicators (crest factor, kurtosis) using a de-noising method by spectral subtraction: application to the detection of defects in ball bearings

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Abstract

The aim of this article is to show the interest of spectral subtraction for the improvement of the sensitivity of scalar indicators (crest factor, kurtosis) within the application of conditional maintenance by vibratory analysis on ball bearings. The case of a bearing in good conditions of use is considered; the distribution of amplitudes in the signal is of Gaussian kind. When the bearing is damaged, the appearance of spallings comes to disturb this signal, thus modifying this distribution. This modification is due to the presence of periodical impulses produced each time a rolling element meets a discontinuity on its way. Nevertheless, the presence of background noise induced by random impulse excitations can have an influence on the values of these temporal indicators. The de-noising of these signals by spectral subtraction in different frequency bands allows to improve the sensitivity of these indicators and to increase the reliability of the diagnosis.

1. Introduction

There are different supervision indicators of the vibratory level of a machine allowing the detection or the follow-up of a defect evolution or of a set of defects. Among these indicators, one can find: the scalar indicators combined with the follow-up of a magnitude stemming from the power and from the peak amplitude of the vibratory signal (efficient value, peak value, peak factor, kurtosis,…); the spectral indicators allowing the follow-up of the evolution of the signal

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shape, of the component amplitudes making up this signal as well as its power (constant resolution spectrum, spectrum with constant band percentages, zoom, cepstrum, envelope analysis); the specific indicators combined with the advanced detection of a special defect [1].

Some potential defects (gears and bearings spalling) induce on the rotating machines periodical impulse forces which can stimulate the structure resonances and the sensor resonance. The characterization of the signals generated by this kind of defects within the temporal field may be achieved by the use of indicators such as the crest factor and the kurtosis [2]. Although these indicators are easy to set up, it is important to take into account the kinematics and the complexity of the mechanisms which can cause serious errors of interpretation. Some studies have been made on the impact of certain parameters on the value of the crest factor and of the kurtosis. Actually, these two indicators are more or less sensitive to parameters such as: variations of the rotation speed of the shafts, band-pass filtering, resonance of the sensor or background noise.

In the case of the monitoring of bearings by vibratory analysis, there are several methods of follow-up in time and frequency domains and their results on rolling element bearings have been presented [3–5]. The use of crest factor and kurtosis seems to be well adapted to the impulse nature of the stimulating forces which are generated by the damage likely to affect this kind of mechanical component. Measured within a wide band of frequencies (wide band scalar indicators), these two magnitudes nevertheless have a reliability which can be limited by causes such as the mask effects induced by the excitation of numerous resonances or by the functioning of other components of a same machine, by the non-relaxation of the resonances between two successive excitations or by the background noises generated by random impulse excitations (wear of surfaces in contact, bad lubrication, cavitation,…). The interest of the study lies in one of these causes and more particularly in the background noise contained in the time domain signal. The aim is thus to reduce the background noise by applying a method of de-noising by spectral subtraction and to determine the influence of this reduction on the value of the global indicators of detection.

2. De-noising of the time domain signal using spectral subtraction

From a taken time domain signal, the signal engendered by the shock (useful signal) is at first tried to be isolated from the noise signal. Among the methods allowing to suppress the noises within the signal, one can find the method of spectral subtraction done with analysis and synthesis using the Short Time Fourier Transform [6,7].

This method applies under certain conditions:

- The useful signal must be slightly present within the measured signal.
- The noise must be time-invariant.
- The noise and signal spectrum must be different.

2.1. Signal analysis by short-time Fourier transform

The short time Fourier transform is calculated using a small number of samples (e.g. $M=256$) and is repeated with a temporal sliding. The discretized signal using n samples is broken down into k blocks of M samples; these blocks being shifted forward with a superimposing ratio of one-half.

If the measured signal said to be corrupted by the presence of noise is represented by $x(n)$, the spectrum obtained by the short time Fourier transform can be denoted by $X(m)$. Here a weighting window of Hanning is used (the recorded signal is directly filtered by the measuring device using the window of Hanning). For number k block, one will have

$$X_k(m) = \frac{1}{M} \sum_{n=0}^{M-1} x\left(n + \frac{kM}{2}\right) e^{-j(2\pi/M)nm}, \tag{1}$$

$n \in [0, M-1]$; $m \in [0, L-1]$ with $L = \frac{M}{sha}$; sha the Shanon factor; $k = 2^i$ (i integer) and L the number of spectral lines.

The measured signal is considered as being the sum of useful signal $s(n)$ (signal characterizing the shock) and noise signal $b(n)$:

$$x(n) = s(n) + b(n). \tag{2}$$

As the Fourier transform keeps the additive relation:

$$X(m) = S(m) + B(m), \tag{3}$$

$$X_k(m) = S_k(m) + B_k(m). \tag{4}$$

The $X_k(m)-B_k(m)$ subtraction then constitutes an estimation of useful signal $S_k(m)$.

2.2. Spectral subtraction

In order to estimate $B_k(m)$, the modulus is estimated and the $\varphi_k(m)$ phase of $X_k(m)$ is taken on again, given that $|B_k(m)|$ modulus is almost time-invariant and that the phase undergoes quick variations [8]:

$$\hat{S}_k(m) = (|X_k(m)| - |B_k(m)|)e^{\,j\varphi_k(m)}. \tag{5}$$

Given that the useful signal is slightly present within the measured signal, the noise signal can be estimated by averaging out the modulus of the $X_k(m)$ primary signal. In order to take into account the evolution of the noise, it can be estimated using the close past of the signal, with a forgetting factor, λ with $\lambda \in]0,1[$ (λ is generally taken between 0.95 and 0.99):

$$\begin{aligned} |B_k(m)| &= \frac{1-\lambda}{1-\lambda^{k-1}} A_{k-1}(m), \\ A_k(m) &= \lambda A_{k-1}(m) + |X_k(m)|, \\ A_0(m) &= 0, \quad B_1(m) = 0. \end{aligned} \tag{6}$$

2.3. Synthesis by inverse Fourier transform

During the synthesis all the $\hat{S}_k(m)$ are at first transformed into $\hat{s}_k(n)$ segments by the inverse Fourier transform. The time domain signal is then reconstituted by the sum of the segments respecting the superimposing used in analysis:

$$\hat{s}_k(n) = \sum_{m=0}^{L-1} \hat{S}_k(m)\mathrm{e}^{\mathrm{i}(2\pi/M)nm} \tag{7}$$

$$\hat{s}(n + kM/2) = \hat{s}_{k-1}(n + M/2). \tag{8}$$

3. Application to spalled ball bearings

3.1. Checking of the conditions of spectral subtraction

Consider the signal generated by a spalled bearing. This signal comes from vibratory measures made on a defective ball bearing tested in laboratory on a bench (see Fig. 1). On the outer ring of this bearing a defect is made using an electric pen. The width of this defect is of 3 mm, the repetition frequency of this defect is of 47.72 Hz. A static charge of 100 N is applied on the bearing, and the accelerometer is set on the outer ring as close as possible to the defect. The objective is to regain a maximum of energy generated by the shock, given that high frequencies are rapidly absorbed by the structure between the defect and the sensor.

The time domain signal (see Fig. 2) is characterized by the presence of a periodic shock occurring as soon as one of the balls of the bearing is in contact with the defect and by the presence of a high-level noise. It can be noticed that the useful signal is slightly present within the signal.

The spectral analysis (see Fig. 3) shows us that the noise and the shock spectrums are different in amplitude while they are occupying the same spectral band. It can be concluded that the conditions defined in the second paragraph are satisfied so we can apply the de-noising by spectral subtraction can be applied to this kind of time domain signal.

3.2. Scalar indicators of detection of spalling defect

Here the interest lies in scalar indicators such as the crest factor and the kurtosis which are well adapted to the detection of impulses in a time domain signal, therefore to spallings within the ball bearings.

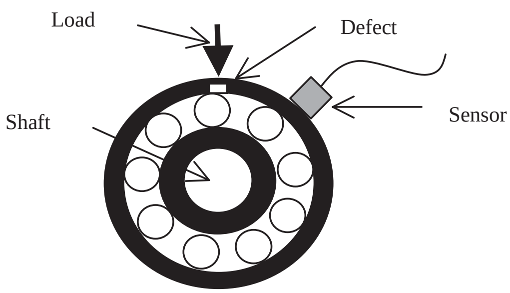

Fig. 1. Experimental device.

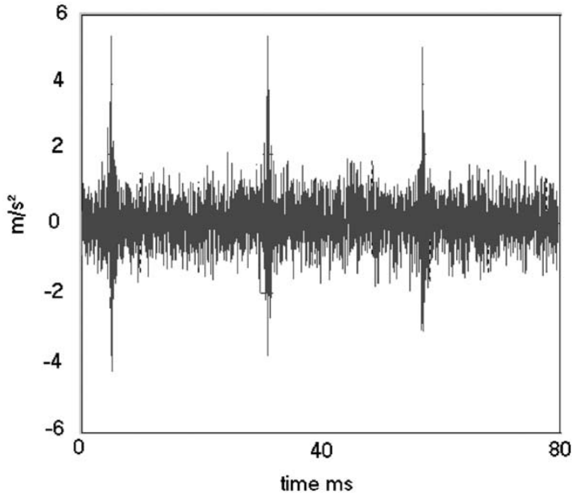

Fig. 2. Vibratory signal generated by a spalled ball bearing.

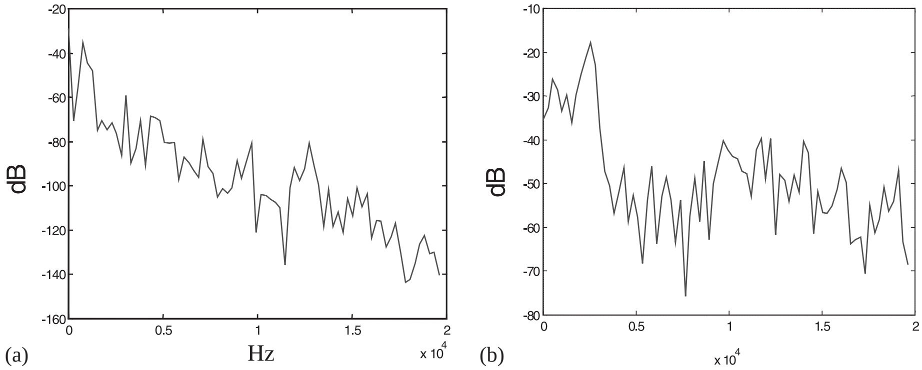

Fig. 3. Spectral analysis of the noise and the shock signal: (a) noise spectrum; (b) shock spectrum.

The crest factor corresponds to the ratio between the crest value (maximum absolute value reached by the function representative of the signal during the considered period of time) and the r.m.s. value (efficient value) of the signal:

$$Crest\ factor = \frac{Crest\ value}{r.m.s.\ value} = \frac{\sup|x(n)|}{\sqrt{(1/N)\ \sum_{n=1}^{N}\ [x(n)]^2}} \tag{9}$$

with N the number of samples taken within the signal, and $x(n)$ the time domain signal.

As the value of the crest factor of a signal whose amplitude distribution is Gaussian is between 3 and 6, this indicator can detect that kind of defects only if its value is at least equal to 6 [9].

The kurtosis is a statistical parameter allowing to analyze the distribution of the vibratory amplitudes contained in a time domain signal. It corresponds to the moment of fourth order norm and it has been shown that for a Gaussian distribution, its value is of 3 [9]:

$$Kurtosis = \frac{M_4}{M_2^2} = \frac{(1/N)\sum_{n=1}^{N}(x(n)-\bar{x})^4}{[(1/N)\sum_{n=1}^{N}(x(n)-\bar{x})^2]^2} \tag{10}$$

with M_4 the fourth order statistic moment, M_2 the second order statistic moment, $x(n)$ the amplitude of the signal for the n sample, $\bar{x}$ the mean value of the amplitudes and N number of samples taken in the signal.

In order to take advantage of the power of detection of these two indicators, the frequency of the shock repetition must not be too short. For the kurtosis, it must lie between 2.5 and 3 times the relaxation time of the shock; for the crest factor, it must lie between 7 and 13 times [10].

The kurtosis and the crest factor are two indicators sensitive to the shape of the signal. The calculation of the mean value of the instantaneous amplitudes of the signal, raised to the power of four gives a considerable weight to high amplitudes of the kurtosis. The crest factor attenuates the impact of an isolated event with high crest amplitude that only takes into account the crest amplitude of this event. The kurtosis therefore appears as a better indicator than the crest factor, given that the dispersion of the results coming from successive measures is weaker.

3.3. Influence of the number of k blocks and of the λ forgetting factor on a simulated signal

The influence of the two parameters (k and λ) is studied using a noised simulated signal. The vibratory signals generated by a bearing defect can be modelled by the response of a model to a freedom degree, to a series of impulses [11].

The response signal to the system can be defined as being the product of convolution between a structure resonance and a sequence of Dirac impulsion of T_d step. This function can be represented by the following figure (see Fig. 4).

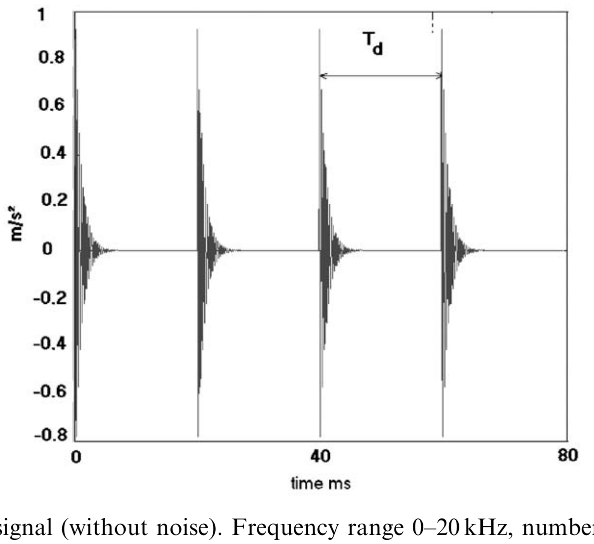

Fig. 4. Simulated signal (without noise). Frequency range 0–20 kHz, number of samples 4096.

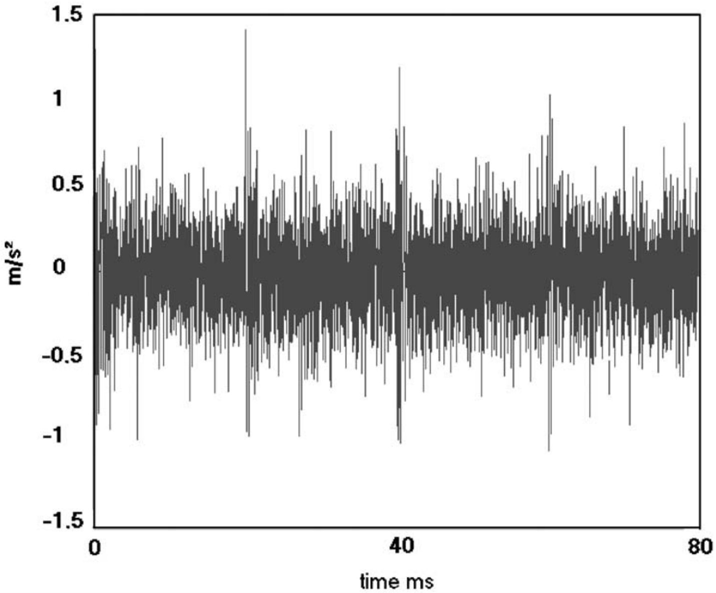

Fig. 5. Noised simulated signal $x(t) = s(t) + b(t)$. Frequency range 0–20 kHz, number of samples 4096.

Table 1
Evolution of the crest factor and of the kurtosis according to the number of block

Number of blocks (k)	4	8	16	32	64	128	512
Number of values/block (M)	2048	1024	512	256	128	64	32
Crest factor	6.6	6.66	6.79	6.8	7.05	7.13	7.12
Kurtosis	6.8	6.5	6.9	7.2	8	8.04	6.6

The noised simulated signal $x(t)$ is equal to the sum of the non-noised signal $s(t)$ and a Gaussian white noise $b(t)$ (see Fig. 5).

The de-noising by spectral subtraction depends on two parameters k and λ. The aim is to determine the best compromise, by studying the values of the crest factor and of the kurtosis according to the variation of k and λ with the use of the simulated noised signal $x(t)$.

Table 1 first shows that the two indicators reach their maximum values when k varies between 64 and 128 ($\lambda = 0.99$). By varying the λ parameter between 0 (value corresponding to the non-denoised signal) and 0.99 with $k = 128$ blocks of 64 values, it can be noticed (see Figs. 6 and 7) that the crest factor and the kurtosis remain time-invariant when λ is superior to 0.75. The best compromise can be achieved with $k = 128$ and $0.8 \leqslant \lambda < 1$. Fig. 8 shows the $x(t)$ simulated signal de-noised by spectral subtraction ($k = 128$, $M = 64$, $\lambda = 0.99$).

A simulation was made using vibratory signals from new and damaged bearings. The results confirmed those made by simulation and more particularly for $\lambda > 0.9$ value.

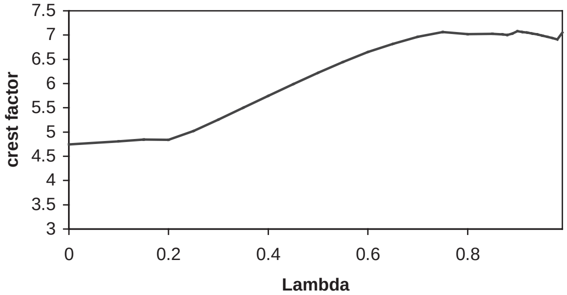

Fig. 6. Evolution of the crest factor according to the λ parameter ($k=128$, $M=64$).

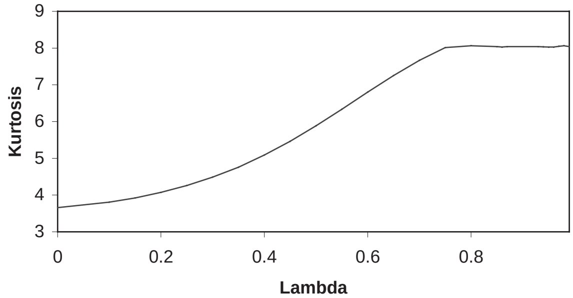

Fig. 7. Evolution of the kurtosis according to the λ parameter ($k=128$, $M=64$).

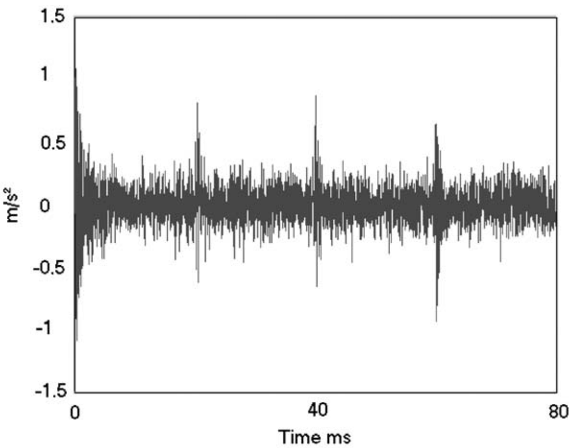

Fig. 8. De-noised simulated signal.

4. Application to the early detection of ball bearing defect

Different tests are achieved on 10 rolling bearings whose geometrical characteristics are: inner diameter = 20 mm, outer diameter = 42 mm, ball diameter = 6.34 mm, ball number = 9. The first rolling bearing is kept in good state while on the others, a circular defect, varying between 0.5 and

4.5 mm is made on the outer ring with the help of an electric pen. These defects can be used to simulate spalling. For each tests, a static charge of 100 N is applied on the outer ring in front of the defect. Different measures are made in wide frequency band and in narrow frequency bands. Treatment by spectral substraction made on each rolling bearings is applied to one single signal, our objective being firstly the validation of the method.

4.1. Wide band measures

The vibratory signals from each rolling bearings are measured using a piezoelectric sensor. The rolling bearings are placed on a test bench and they function in the same conditions. The functioning and measured conditions are as follows: rotation speed of the inner ring 800 r.p.m. (outer ring does not run); frequency range: 20 kHz; number of samples; 4096 points, defect frequency of the outer ring f_{def} = 47.72 Hz.

The crest factor and the kurtosis, are calculated from each ball bearing vibratory signals before and after the application of the spectral subtraction.

Fig. 9 shows that the defect detection on the outer ring is achieved when the spectral subtraction is applied to the signal with an impulse sufficiently important. If the spectral subtraction is not applied, the crest factor value never exceeds 6, which is necessary to the detection of impulsive defect.

Fig. 10 shows that the kurtosis value is always equal to 3 for a good state rolling bearing. If there is a defect, the kurtosis value increases at the same time as the size of the defect. This increase is better when using spectral subtraction.

It can be noticed from the previous results that the kurtosis is a better indicator than the crest factor in the spalling detection and that the spectral subtraction allows to detect the defect earlier. These wide band measures show the interest of the spectral subtraction on the crest factor and on the kurtosis. Nevertheless, it can be noticed that the resonance of the structure or of the sensor can improve the detection of a defect, creating periodic impulsive forces. This method of detection has to be used in the case of simple kinematics systems and the analysis of the time domain signal has to be made in narrow band.

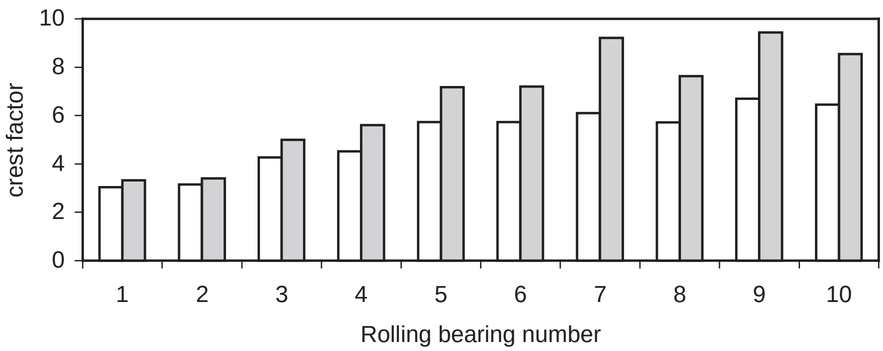

Fig. 9. Comparison between the crest factor before and after the spectral subtraction in the frequency range of 0–20 kHz: ☐ before s.s.; ▩ after s.s.

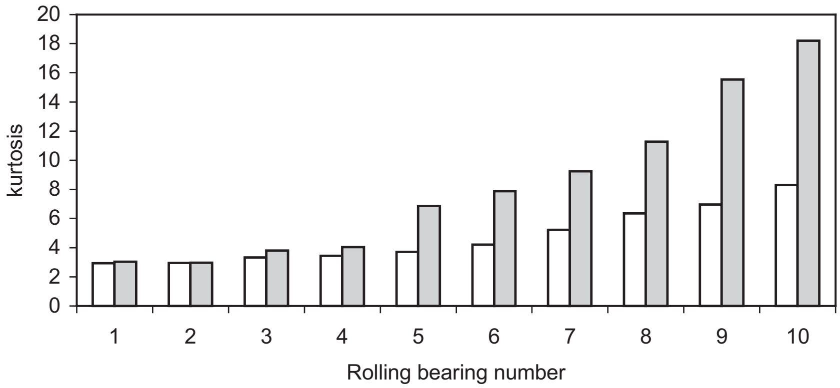

Fig. 10. Comparison between the kurtosis in the frequency range of 0–20 kHz before and after the spectral subtraction: ☐ before s.s.; ▨ after s.s.

4.2. *Measures with band-pass filter*

The vibratory response from a sensor is the response from many resonances of the structure distributed on a wide frequency range, thus the useful signal can be concealed by high amplitude sinusoids due to the operation of other mechanical components of the rotating machine. That is the reason why we often make a band-pass filtering of the signal around the resonant frequency in order to characterize it in different frequency bands. In the study, the frequency bands are 0–5 kHz; 5–10 kHz; 10–15 kHz; 15–20 kHz.

The band-pass filter is applied to the first and second bearings, for which the spectral subtraction in the case of wide band measures did not allow the detection of a potential defect.

A band-pass filter is then applied to the rolling bearings whose defects cannot be clearly detected with the kurtosis or the crest factor (rolling bearings 1–2).

4.3. *Measures on the rolling bearing number 1 and 2*

4.3.1. *Measures on the rolling bearing number 1*

Ball bearing number 1 is in a good state, which is confirmed by the results of Figs. 11 and 12. It can be noticed that the spectral subtraction does not affect a lot the kurtosis and the crest factor value which are under the significant value of a ball bearing with a defect.

4.3.2. *Measures on the rolling bearing number 2*

It can be noted from the previous results (see Figs. 13 and 14) that neither the kurtosis nor the crest factor can detect the defect in a wide frequency band (0–20 kHz) and in narrow frequency bands (0–5 kHz; 5–10 kHz; 10–15 kHz; 15–20 kHz) before the spectral subtraction of the signal. The application of the spectral subtraction allows to detect the defect in the narrow frequency band 10–15 kHz using the kurtosis and not the crest factor ($kurtosis = 4.175 > 3$; $crest\ factor = 3.99 < 6$). This detection in high frequencies proves that it is a short impact shock close to Dirac impulse which excites the ball bearing [12].

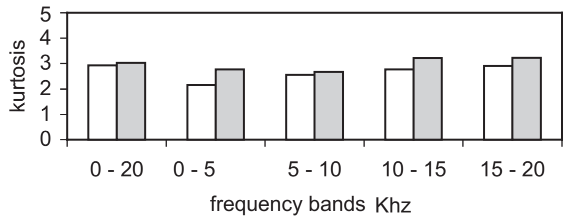

Fig. 11. Kurtosis in frequency band before and after the spectral subtraction on the rolling bearing number 1: □ before s.s.; ▨ after s.s.

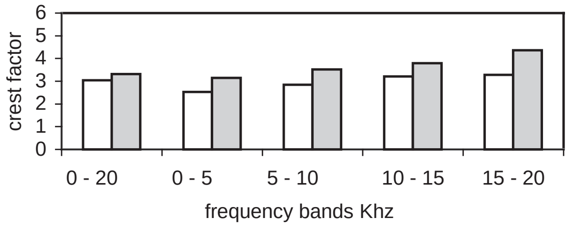

Fig. 12. Crest factor in frequency band before and after the spectral subtraction on the rolling bearing number 1: □ before s.s.; ▨ after s.s.

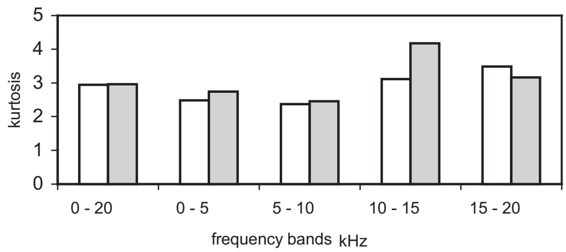

Fig. 13. Kurtosis factor in frequency bands before and after the spectral subtraction on the rolling bearing number 2: □ before s.s.; ▨ after s.s.

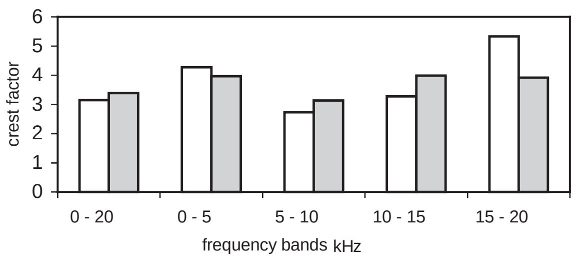

Fig. 14. Crest factor in frequency bands before and after the spectral subtraction on the rolling bearing number 2: □ before s.s.; ▨ after s.s.

Identical measures and treatment were made on other bearings. An improvement of the kurtosis and of the crest factor sensibility can be noticed, such as for the first and second bearings. It can also be noticed that those two indicators (crest factor and kurtosis) do not vary in a linear manner when the size of the defect is important [13]. Indeed, when the size of the defect is important, the time space between two successive shocks becomes inferior to the relaxation time and the hypotheses on which the application validity lies on are not any more confirmed [2]. The crest factor and the kurtosis value become inferior or equal to three and are not any more characteristic of an impulsive signal.

5. Conclusion

Spectral subtraction is a method based on the short time Fourier transform. It allows to remove the time invariant noise of a signal. This method improves the sensibility of temporal indicators such as the kurtosis and the crest factor which are often used in conditional maintenance by vibratory analysis. It allows to carry out better conditional maintenance based on vibratory analysis. Nevertheless, the use of those two indicators is restricted to simple kinematics machines. The use of experimental measurements on rolling bearings with different spalling sizes proves the interest of this method. Indeed the detection occurs earlier using spectral subtraction, either in large frequency bands or in narrow frequency bands.

This study also shows that the kurtosis is a better indicator than the crest factor for the detection of an impulsive defect.

This methodology is in the process of being used in the industrial field. Indeed, this study is subjected to a partnership with a company specialized in maintenance and anxious to develop its conditional maintenance pole in a more important way by vibratory analysis. Its aim is to minimize the times of measure recordings and the times of analyses in the different companies in which it is used.

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