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Spectral negentropy and kurtogram performance comparison for bearing fault diagnosis

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***Abstract*—While investigating rotating faults in vibration signals, one of the typical symptoms is the presence of repetitive transients, which are characterized by impulsive and cyclostationarity signature. The approach quite popular nowadays in the industry for their detection is time-frequency techniques. Those techniques are mainly analysis tools as opposed to processing tools, and in any case, are unable to offer a versatile methodology that applies to all mechanical signals in all circumstances. The paper is motivated by ideas borrowed from thermodynamics, where transients are seen as departures from a state of equilibrium; it is proposed to measure the negentropy of the squared envelope (SE) and the squared envelope spectrum (SES) of the signal. The main objective of the work is to investigate connections in both negentropy and kurtogram approaches to capture the signature of this repetitive behavior. The methodology used in this paper proposes to display spectral negentropy as images. The impulsive events are then detected and localized in frequency by high values of the squared envelope spectrum (SES) infogram in some frequency bands. In order to analyze the signal in the frequency domain, the Short-Time Fourier Transform (STFT) can then be used. The STFT is suggested in this study due to its simplicity and high flexibility. On the other hand, STFT is used for the analysis of kurtosis of temporal signals; this is well known as Kurtogram. For fault, such as bearings, Kurtogram was demonstrated to be efficient.**

***Keywords*—Vibrations; Measurement; Kurtogram; Negentropy; Fault Detection.**

I. Introduction

The concept of mechanical signature analysis makes possible to establish the evidence of vibration-based condition monitoring in identification of industrial machines from symptomatic state to critical health condition. Often machinery under faulty working condition generates vibration signals with signature likely resemble to repetitive transients. Simon Braun [1] presented in depth in his book some typical examples such as bearings or gears. An outstanding work which spawn the way for the analysis of spectral kurtosis is known in the literature as Antoni’s [2] contribution. STFT was therefore demonstrated to be one of the powerful tool in spectral investigation on rotating machines faults. During 15th Australian International Aerospace Congress, Sawalhi et al [3] proposed a method that combined minimum entropy deconvolution with spectral kurtosis. The outcome of their work establish that deconvolution approach can sharp the impulses and allow kurtosis values to rise. Based on considerable survey in the literature, the contribution in this paper will be firstly to display the frequency as frequency and frequency resolution which is known as Kurtogram. Technically, the kurtogram indicates high impulsiveness in corresponding frequency band. From wavelets to duel-tree wavelets, tremendous research works [4] dig into approaches allowing reliable implementation of the kurtogram for improving its efficiency. It is also reported in the literature that kurtogram has inability to recognize whether a series of transients is repetitive or not [5] despite its performance, because kurtosis value decrease when the repetition rate of the transients increases. On the other hand, the paper crystallize the analysis on spectral negentropy. The negentropy presented in this paper analysed the quantities when displayed as functions of frequency and frequency resolution, this is well known as Infogram.

II. Related Results in the literature

Since Antoni [6] introduced the spectral kurtosis(SK) concept, the scientific and industrial community become more interested in applying and improving the approach. The kurtogram, which is the more developed SK analysis for optimum selection of the bandwidth, is accepted and used in fault diagnosis, particularly for bearing case. In the process, the first technique involves the STFT for finding the optimal filter. The second is based on one over third (1/3) binary banks; this is known as fast kurtogram [8]. The work presented by Yaguo Lei et al [9] discussed the effectiveness of STFT and wavelet packet transform (WPT) to point out the fault characteristic; they came up with a conclusion showing that filters-based spectral kurtosis was not precise as WPT. In most of the literature reports, researchers realized that when the signal-to-noise ratio is low, using kurtosis to detect hidden impulses in the signal is quite hard. Moreover, kurtosis has a high probability of carrying high value for non-Gaussian noises. Barszcz et al [10] proposed one of the solutions to overcome this obstacle. Their approach suggested to measure kurtosis in the frequency domain; this is known as Protrugram. The outcome of their work demonstrates that in a case of low signal-to-noise scenario, Protrugram is effective. Nevertheless, in the frequency domain, whether the signal is the envelope or its counterpart, it contains much information on the fault compared to the original signal. The interest in SK led scientists to investigate a different solution for making the approach better, whether for fault detection, diagnosis, or classification presented by Sandeep s. and Kumar Singh [11] who used the generalized SK as a feature set to Extreme Leaning Machine. Since most mechanical degradation presents a series of repetitive transients, the Kurtogram or SK often hardly or almost cannot recognize them; therefore, spectral negentropy was demonstrated to be one of the alternatives to overcome this. Li, C et al [12] reported that Spectral Negentropy could characterize the periodicity and the cyclostationarity of a signal. Another interesting outcome of their work is that spectral negentropy can be used to extract fault features accurately.

III. Description of the method

A. Spectral negentropy

The spectral negentropy, a contraction for "negative entropy" was initially elaborated by Schrödinger in 1940 [13]. The approach developed in this paper is based on Infogram. From the thermodynamic perspective, entropy evaluates the level of the disorder in a system from the state of equilibrium; in parallel, negentropy measures the inclination of a system to increase its level of organization. In the science of information, entropy describes how much information contains a signal. For a discrete signal $y(k), k = 0, 1, 2, ..., N-1$, where N is the length of the signal. If one denotes its complex envelope as $y(k, f, \Delta f)$ in a defined frequency band, its squared envelope (SE) can be expressed as :

$$e(k, f, \Delta f) = |y(k, f, \Delta f)|^2 \tag{1}$$

In Fourier domain, the squared envelope spectrum (SES) can be express as :

$$E(\lambda, f, \Delta f) = \sum_{k=0}^{N-1} e(k, f, \Delta f) e^{-j2\pi k \frac{\lambda}{F_s}} \tag{2}$$

λ is the cyclic frequency and F_s is the sampling frequency.

From the SE expressed in the time domain, spectral negentropy can be defined as :

$$\Delta I_e(f, \Delta f) = \sum_{k=0}^{N-1} \left(\frac{e(k,f,\Delta f)^2}{\frac{1}{N}\sum_{k=0}^{N-1} e(k,f,\Delta f)^2} ln \left(\frac{e(k,f,\Delta f)^2}{\frac{1}{N}\sum_{k=0}^{N-1} e(k,f,\Delta f)^2} \right) \right) \tag{3}$$

Known as a weighted sum of the spectral kurtosis, the SE negentropy is hardly sensitive to the cyclostationarity of the repetitive transients even though it has a remarquable capability in measuring the impulsiveness of a signal. From observations made on SES, the spectral negentropy can be rewritten as

$$\Delta I_E(f, \Delta f) = \sum_{k=0}^{N-1} \left(\frac{E(k,f,\Delta f)^2}{\frac{1}{N}\sum_{k=0}^{N-1} E(k,f,\Delta f)^2} ln \left(\frac{E(k,f,\Delta f)^2}{\frac{1}{N}\sum_{k=0}^{N-1} E(k,f,\Delta f)^2} \right) \right) \tag{4}$$

The spectral negentropy is essentially a function of frequency-bandwidth/frequency resolution [14], [16], [17]. One can consider to calculate spectral negentropy for frequency-frequency resolution plan by partitioning finely and continuously, the infogram can then be obtain by cascading and displaying all the spectral negentropy in a single diagram. Eq.4 allows the generation of SE infogram, the peak location in the infograms links to the frequency band where the repetitive transients are found. The Fig.1 presents the flowchart of the proposed negentropy approach.

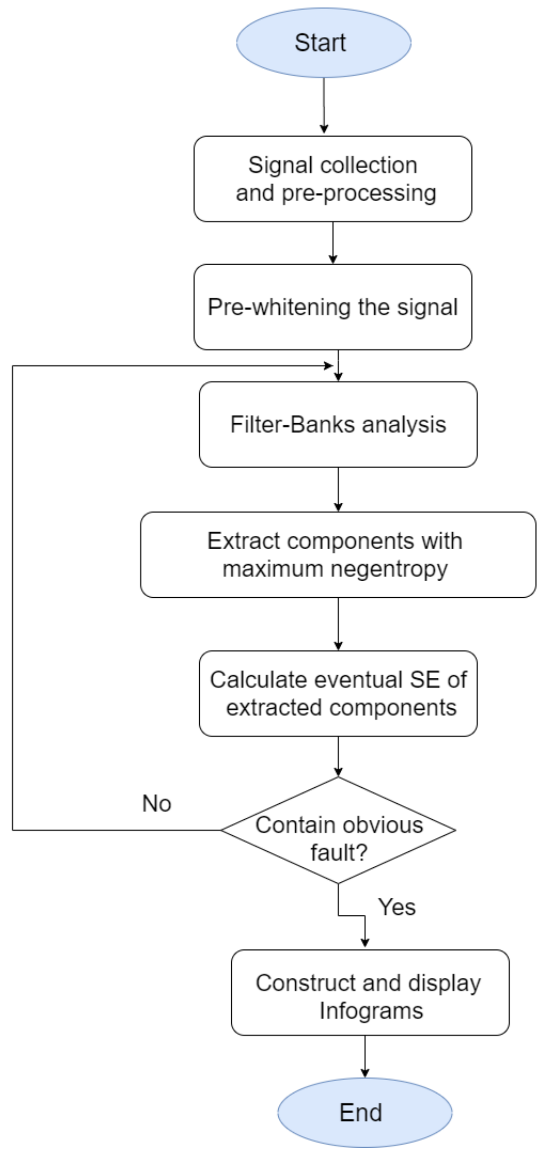

Fig. 1. The flowchart of the proposed negentropy approach.

In the case of bearing fault, the vibration generate often features repetitive impulses. The more impulses the fault induces, the larger is the spectral negentropy.

B. Kurtogram

In the literature, most of the authors including Antoni [14] have agreed on the fact that kurtogram has been drawn from spectral kurtosis. Technically, the use of SK for transients detection in a signal, focuses on measurement of distance between random and Gaussian process. Following the calculation for each frequency component of the signal, one can obtain the SK value. More than indicate transient components, SK can also track the locations of those components in the frequency domain. The Fig.1 presents the flowchart of the algorithm used in this paper.

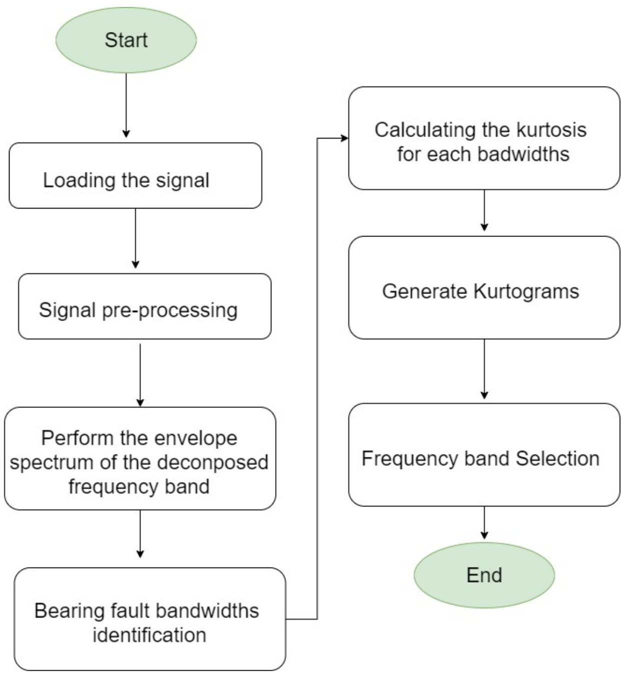

Fig. 2. The proposed kurtogram approach

From the Wold-Gramer [15] decomposition of a given non-stationary signal, one can define $y(t)$ as the response of system with time varying impulse response $h(t,s)$ exited by signal $x(t)$. The signal $y(t)$ can be written as :

$$y(t) = \int_{-\infty}^{+\infty} e^{j2\pi f t} H(t,f)\, dX(f) \tag{5}$$

$H(t,f)$ is the complex envelope of the considered signal, and $dX(f)$ is the spectral process in $x(t)$ investigation. For a given frequency, the calculation of the SK values is implemented using STFT of the analyzed signal. It can be expressed by :

$$F_y(\tau,f) = \int_{-\infty}^{+\infty} y(t)\, w^*(t-\tau)\, e^{j2\pi f t}\, dt \tag{6}$$

Even if kurtogram outcomes are satisfactory, the kurtosis-based estimator tends to point out misleading frequency [15]. One of the solution to overcome this is the synchronous averaging, but this as well may cause loss of information.

IV. Result and Discussion

The measurement campaign is perform on a test bench described in the Fig.3. The used motor frequency is 48.7 Hz with a speed of 2855 rpm and a sampling frequency of 50 000 Hz. The accelorometer is connected to the outer ring of the motor end bearing of type $NU206$.

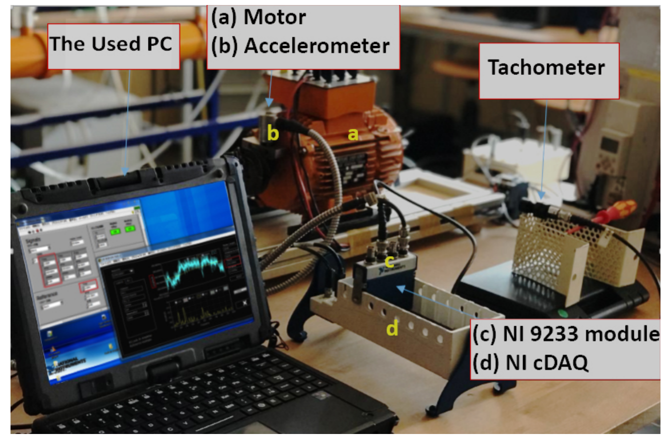

Fig. 3. Test Bench

The load and the speed of the motor were alternatively modified. The speed used for the test is 2000 rpm, and three loads (200, 500, and 700 N) were combined during the experimentation. Four main situations were analyzed, the first when the bearing is flawless (fault size = 0.00mm^2), three cases with faulty bearing (fault size = 0.192mm^2, 1.50mm^2 and 3.00mm^2). Faults size were created using an electric pen. The Fig.4 and Fig.5 display different analyzed cases.

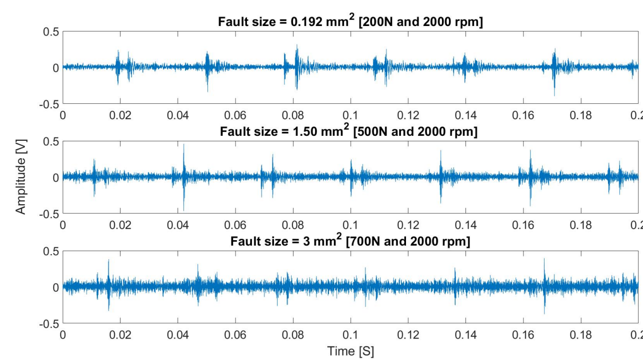

Fig. 4. Raw signal for the case where faults size and laod change.

One can see in the Fig. 6 (a) how the signal carries the series of transients and the impulsive noise.

The Fig. 6 (b) and (c), present the corresponding kurtogram and SES infogram for the case where the fault size is around 0.192mm^2. It's obvious to see that both kurtogram and infogram shows some interesting information. The bearing faults under investigation are display in the table I. The case analyzed here is an inner race fault (BPFI)estimated around 2000 rpm.

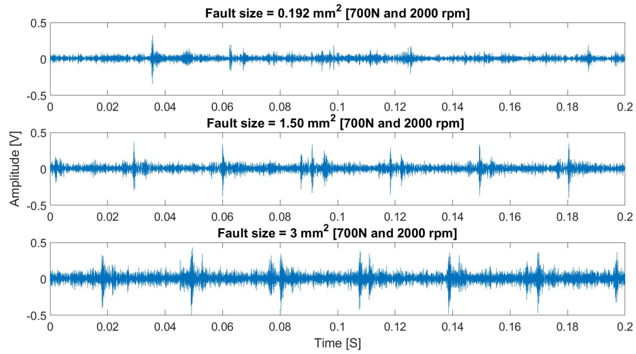

Fig. 5. Vibrations for the same speed and three load configuration.

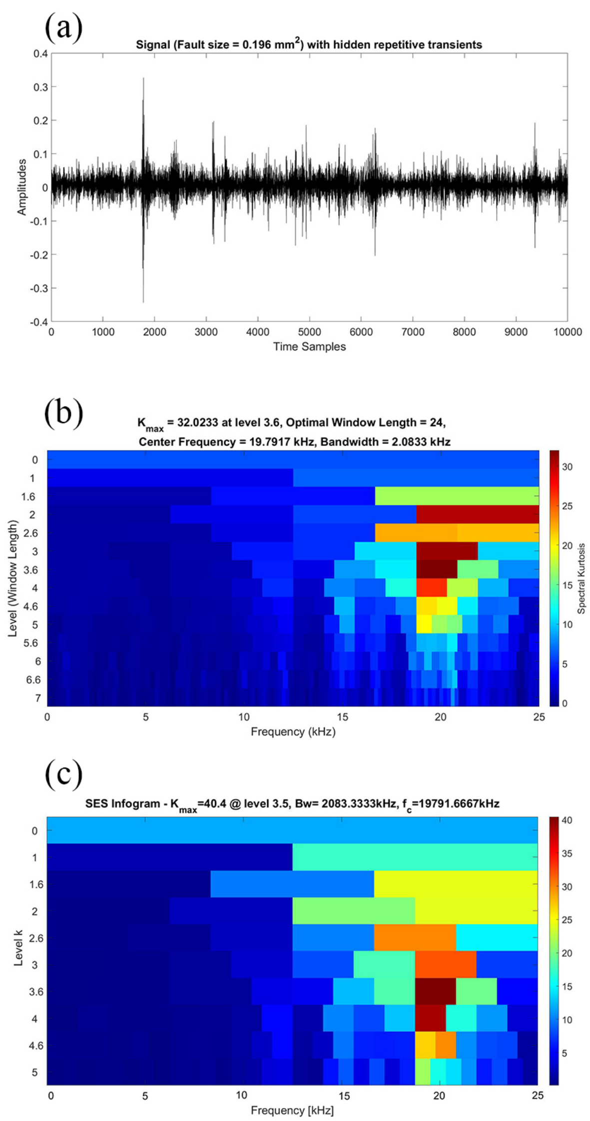

Fig. 6. First case

TABLE I
CHARACTERISTIC FREQUENCIES ESTIMATED IN Hz

Motor Speed (rpm)	2000	1500	1000
BSF	13.4	10.1	6.7
BDF	164.8	124.3	82.4
BPFO	174.7	131.0	84.7
BPFI	258.6	194.0	129.3

The kurtograms and the infograms in case where fault increases from $1.50mm^2$ to $3mm^2$ are displayed on the Fig.7

One can see clear high values of the kurtogram and infograms in several regions on the figure. It can be said that the kurtogram displays an obvious presence of impulsive behavior in the signal. On the other hand, the SES infogram confirms the corresponding events cyclostastionarity extension in several bands. One can then look at different regions that are likely to contain repetitive transients. Different bands to likely to contain useful information on the fault are $[15.66 - 16.18]$ kHz, $[15.66 - 16.64]$ kHz, $[3.16 - 6.22]$ kHz, $[3.94 - 4.66]$ kHz, $[4.19 - 5.18]$ kHz and $[15.76 - 16.54]$ kHz.

All those bands reveal the signature of an inner race fault. The SES infograms on Fig. 7 (c) show that cyclostationary events are below 4 kHz, which do not necessarily point out the equivalence in the kurtogram and SES infogram; this might probably due to surrounding noise or some other machine components which is not specifically analyzed in this work. It can be confirmed here that, the kurtogram and infogram may be complementary rather than being redundant.

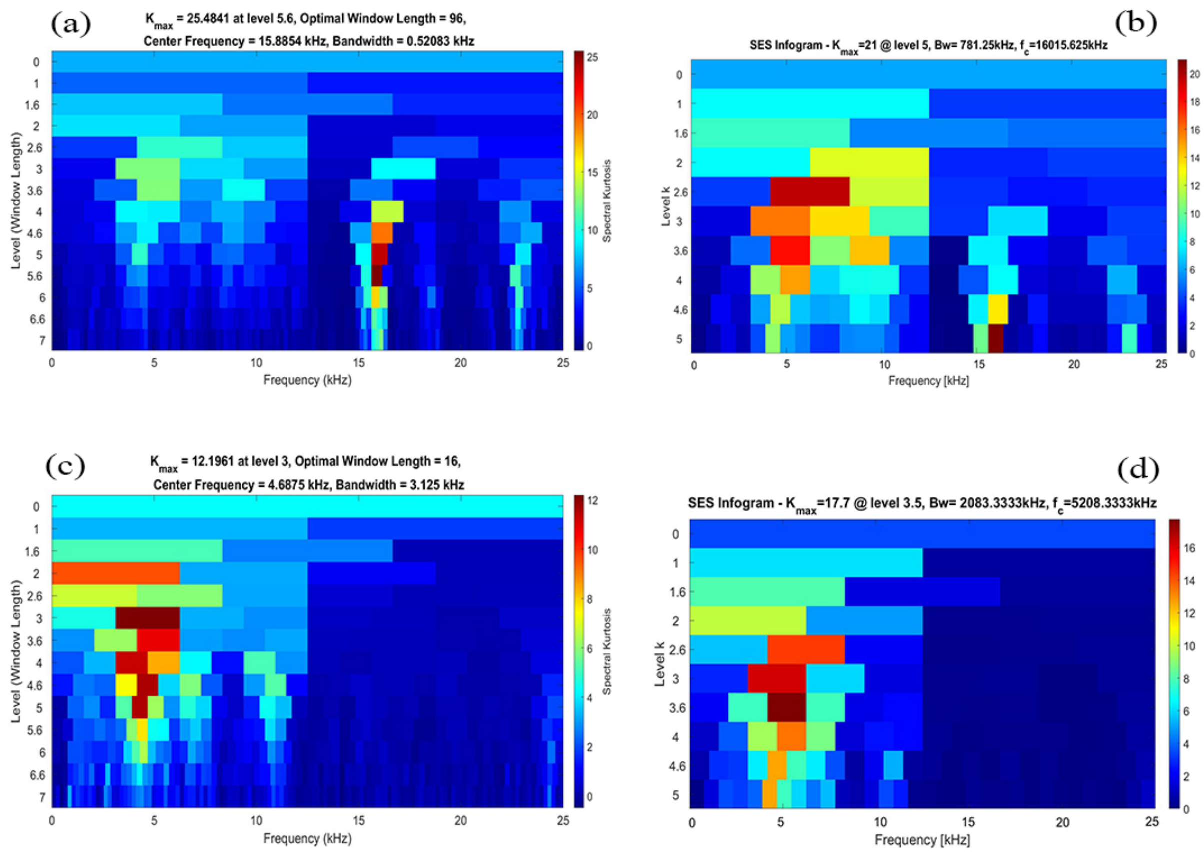

Fig. 7. First case

V. Conclusions

This paper aimed to spawn way for fault detection using kurtogram and spectral negentropy, a concept borrow from the thermodynamic field. The case investigated was the Ball Passing Frequency Inner Race (BPFI), of an electric motor, where bearings are housed in a casing allowing the shaft to rotate while driven by a variable speed electric motor. The study outcomes demonstrate the capacity of kurtogram and spectral negentropy to identify nonstationary events of different nature by locate more precisely and specifically demodulation frequencies, which might be of considerable use for several fault detection and diagnosis scenarios. It was found that high values appear in a set of frequency bands. The processing effort grows then proportionally with the number of frequency bands where the signal has to be demodulated; easily, one can use them to compute the envelope spectrum. For fault like BPFI, it was shown that the negentropy gives more information even for a shallow size of fault and allows the localization of meaningful frequency bands. The paper demonstrated that results obtained from negentropy by means of infograms could significantly extend the domain of the applicability of the Kurtogram.

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