The improved Autogram via Gini index: Real application to the vibratory surveillance and diagnostic of wind turbine generator

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Abstract— Envelope analysis is one of the most useful approaches for bearing diagnostics, but obtaining an appropriate frequency band for demodulation has been a major challenge for a long time. Spectral Kurtosis and Kurtogram are commonly used to address this issue, but they can fall short in situations where the Signal to Noise Ratio is too low or in the presence of non-Gaussian noise, thereby reducing their performance.
To solve this issue, this work investigates two versions of the Autogram: one (close to the original) using kurtosis and the other using the Gini Index, with the aim of comparing their ability to detect impulsive content. Both methods take advantage of the high levels of second-order cyclostationarity present in vibration data from bearings, particularly in the presence of mechanical faults.
The comparison was made on real experimental vibration data from a Suzlon S88 wind turbine generator with a 2 MW power generation capacity.
Keywords— Wind turbine generator, bearing faults diagnosis, Kurtosis, Kurtogram, Autogram, Gini Index

1 Introduction

Bearings are one of the most used components in a rotating system, and their failure is the most significant source of machinery breakdowns [1]. Wind Turbine Generators (WTGs) present many failure modes due to the high mechanical charge and the fluctuating of wind speed. As believed by National Renewable Energy laboratory statistics [2], the High-Speed Shaft Bearing (HSSB) is the most components, which have an important percentage of failure compared to other components inside the gearbox. Thus, correctly identifying and diagnosing bearing failure at prior stages of their total failure is very important. It avoids catastrophic damage, which leads to electricity production cessation.

As a localized fault generates, either on the outer race, the inner race, the cage or the balls, a shock is created each time the fault rolls through the defect. Consequently, the system structure and the bearing are flurried, especially at their resonance frequencies [3]. The vibration signal will include all the harmonics of this, which repeats periodically at a rate depending on bearing geometry. Investigation of the vibration data is crucial to identify the defects and many approaches in the literature have been established to extract the bearing specific frequencies of the vibration signals. Among them, envelope analysis [3, 4], also named high frequency resonance approach, has been used for a long period: the signal is first band-pass filter in the excited structural resonance frequency band, and the analysis is carried on the spectrum of the envelope signal.
Spectral kurtosis (SK) has been a good tool to solve this difficulty. This approach efficiently identifies the series of impulses in a signal and can be used to detect the suitable demodulation frequency band in which a signal has the maximum impulsivity.
Kramti applied in [5] the approach of Antoni [6] which is based on filter banks. In the Short-Time Fourier Transform (STFT) based SK, the goal is to detect the window length N_w and the central frequency f which maximize the value of the SK over all probable choices. The Kurtogram is shown in 2D coloured maps present the values of SK for every pair N_w and f. Additionally, Antoni [6] evolved the Fast Kurtogram (FK), which is essentially based on the multirate filter-bank structure (MFB) to overcome the rigorous but long computation of full Kurtogram. The approach is very useful and robust for industrial process.
The remainder of this work is divided as follow: Proposed Approaches in the second section. Section third established the diagnostic results and the conclusion is drawn in the fourth section.

2 Proposed Approaches

2.1 Spectral Kurtosis and Kurtogram

The kurtosis is a statistical feature which calculates the peakedness of a signal, therefore it can be used to identify mechanical faults in vibration signal related the rotary process. Kurtosis is defined as

$$K = \frac{\sum_{i=1}^{N}(x(t_i) - \mu_x)^4}{[\sum_{i=1}^{N}(x(t_i) - \mu_x)^2]^2}$$

Where $x(t_i)$ is the sample at time $t_i = \frac{i}{f_s}$, f_s is the sampling frequency, N and μ_x are the length of data set and the mean value respectively. The SK is the derived from kurtosis equation to frequency domain where a band is created to modulate the signal in order to remove its impulsive and non-stationary part. The SK can be represented by the fourth order normalization cumulant [6] it is defined as

$$K_x(f) = \frac{\langle |Y(t_i, f)|^4 \rangle}{\langle |Y(t_i, f)|^2 \rangle^2}$$

Where $\langle \blacksquare \rangle$ is the time averaging operator. $Y(t_i, f)$ is the STFT of signal $x(t_k)$ achieved at time t_i by changing a constant length window *(N_w)* along the signal, therefore SK is a function of frequency and STFT window length.

As mentioned in [7], N_w really involve the STFT based SK. So its value should be perfectly selected in real application, the window length N_w and the frequency f could be found in maximizing the STFT based SK over all probable choices. The map created by the STFT based SK as a function of N_w and f is known as kurtogram [9,10,11]. An optimal band-pass filter for the envelope analysis was obtained from the maximum of the SK with optimal N_w. So, the bandwidth of the band-pass filter B_f and the optimal central frequency f_c can be defined by which both maximize the kurtogram.

The Kurtogram is a fourth-order spectral analysis approach used for identifying the non-stationarity in a signal. The model based on the affirmation that each type of transient is related to a suitable (frequency/frequency resolution) dyad $\{f, \Delta f\}$ which maximises the kurtosis values, and hence its detection.

To generate the exact bandwidth and center frequency, all probable window widths should be mentioned, which is costly and may be unrealistic in true applications. According quasi-analytic filters and multirate filter bank (MFB) structure, the fast kurtogram was more evolved to fast compute and determine the SK results [12]. The fast kurtogram results are really close to those of kurtogram, and can be calculated more rapidly than the kurtogram, thus it has been largely applied and almost considered as a benchmark tool for bearing failure diagnosis. The fundamental algorithm of the kurtogram is built in an arborescent MFB configuration. The ½-binary tree kurtogram estimator where the bandwidth and the center frequency can be automatically computed. Those colours presented in many squares in Fig.1 easily show the values of SK. Therefore, the maximum value can be clearly found by some easy searching tool.

2.2 Autogram

This work introduces a recent approach based on unbiased Autocorrelation (AC) to surmount the restrictions established by grave Gaussian and non-Gaussian background noise. The unbiased AC is calculated on the squared envelope of the signal as follows

$$\widehat{R_{XX}(\tau)} = \frac{1}{N-q}\sum_{i=1}^{N-q} X(t_i)X(t_i+\tau)$$

Where X is the squared envelope of the filtered signal, the delay factor is $\tau = \frac{q}{f_s}$, and $q=0...,N-1$.

The proposed approach is thought to be sufficiently typical for mechanical failure detection impulsive signal, e.g. Bearings and gears. Analogous to FK, the Autogram is blind and no prior knowledge of signals is needed. The proposed method composed of 4 steps and the details of every step are explained as follows.

Step 1: In this step, time domain signal is divided into frequency bands using the Maximal Overlap Discrete Wavelet Packet Transform (MODWPT). More details can be found in Ref [13].

Fundamentally, the MODWT is used as a filter for the considered time history and a series of data is consequently created at every level of decomposition. The filtered data, each corresponding to a frequency band and central frequency (node), are the inputs for step 2.

MODWT has been applied because it preserves full-time resolution, which is necessary for the proposed approach.

Step 2: The essential idea which leads to this paper is to take advantage of periodicity of the autocovariance function, which represent the second order cyclostationarity of bearing vibration data. Therefore, the unbiased AC of the periodic instantaneous of the signal is calculated where the signal is filtered by MODWPT at the previous step. AC has the advantage of eliminating the uncorrelated elements of the signal, i.e. noise and random impulsive contents, both detached to any specific bearing defects. In addition, the periodic portion of the signal, which is associated to faults is enhanced.

The output is the AC, which moves in an extra diagnosis process than possible with the original outputs of MODWPT. In fact, impulsive noise, which ineffectively assigns a high kurtosis value to a signal, can generally be eliminated.

Step 3: the main goal of this step is to obtain the appropriate frequency band for demodulation. This is important to have an efficient bearing diagnosis. So here the kurtosis is calculated from the signal resulting from the previous step, i.e. the unbiased AC of the squared envelope, for each level and frequency band (nodes). Consequently, the kurtosis values of all nodes like FK are plotted in a colormap, whose colour degree is linked to kurtosis value, and the horizontal and vertical axis correspond to the frequency and level of the MODWPT decomposition respectively. The concept is similar to Kurtogram and this process is based on autocorrelation for this reason the authors in [14] propose the name “Autogram”

Step 4: The Fourier Transform is eventually applied to the squared envelope of the signal involved to the node chosen in the previous step. The mechanical failure frequencies are extracted, and the diagnosis is achieved.

2.3 Gini Index

Recently, the Gini Index (GI) is introduced for the feature extraction of mechanical fault diagnosis, Miao et al in [15] applied GI to replace kurtosis feature to improve the traditional Kurtogram. A numerical example introduced in [16,17] proved that GI has a raising direction when the impulses in the signal increases, yet the maximum value of other features (Hoyer measure, L1/L2 norm and kurtosis) appears when the signal has a single impulse. So, GI might have a better ability to distinguish impulsiveness and repetitive transients in the signal compared to other features. GI of signal x is defined as follows

$$GI = 1 - 2\sum_{n=1}^{N} \frac{x_{(n)}}{\|\vec{x}\|_1}\left(\frac{N-n+0.5}{N}\right)$$

Where the data x with length N. The vector $\vec{x} = [x_{(1)}x_{(2)}x_{(3)}\ldots]$ and the elements are arranged from smallest to largest values (ascending order), i.e. $x_{(1)} \leq x_{(2)} \leq x_{(3)} \leq \cdots \leq x_{(n)}$. And $\|\vec{x}\|_1$ is the l_1 norm of $\vec{x}$

3. Diagnosis results

The vibration data are measured from high-speed shaft bearing installed in real wind turbine generator (S88, Suzlon) given by the Green Power Monitoring System (GPMS) in the USA more details can be found in ref [8].

The data set includes run-to-failure investigation where the recording time of vibration data was 6s each day during 50 days with a high sample rate. In this paper, the authors investigate only the last vibration measurements (the 50th day) as shown in Fig.2 (a). The shaft speed is 1888 rpm and the theoretical failure frequencies referenced to the shaft frequency (1888/60=31.4 Hz) are as follows: Ball pass Frequency, Inner race "BPFI=9.25", Ball pass Frequency Outer race "BPFO= 6.72", Fundamental train frequency (cage speed) "FTF=0.42" and Ball (roller) Spin Frequency "BSF=2.87".

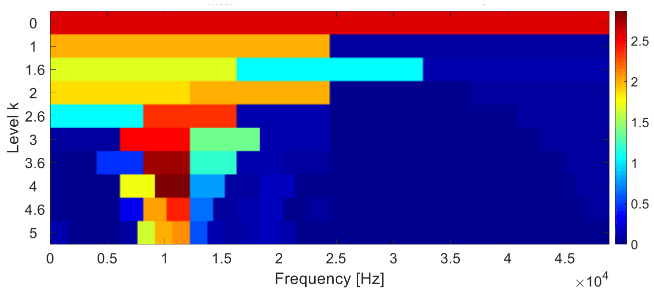

Figure 1: Fast Kurtogram (B_w=3051.75 Hz, f_c=10681.125Hz) at level 4.

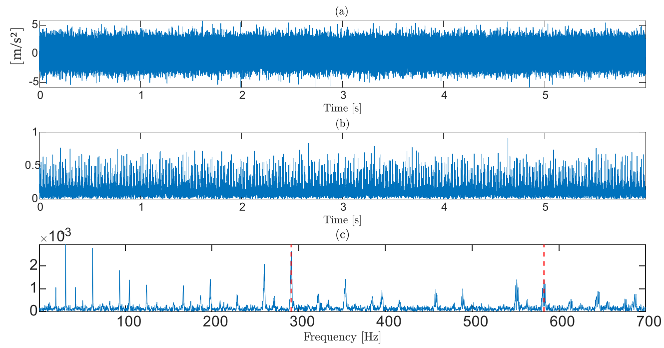

Figure 2: (a) original signal, (b) envelope of the filtered signal and (c) Fourier transform of the squared envelope (Fast kurtogram)

The proposed approaches (Fast kurtogram, Autogram and the Improved Autogram) are applied to the mentioned vibration signal in Fig.2 (a). The Fast Kurtogram is shown in Fig.1 the maximum value is obtained with center frequency 10681.125 Hz and bandwidth 3051.75 Hz at level 4. The Fourier transform of the squared envelope of the signal associated with a node with highest kurtosis is presented in Fig.2 (c) where the red dashed lines are first two harmonics of the BPFI (290Hz and 580 Hz), this approach is unable to limit the influence of non-periodic impulses and noise from raw vibration data, which are not linked to any actual mechanical faults, so Fast kurtogram isn't robust for bearing diagnosis in this application.

The Autogram is shown in Fig.3 the maximum value is obtained with center frequency 8392.3 Hz and bandwidth 1525.8 Hz at level 5. The Squared Envelope Spectrum (SES) of the signal associated with a node with highest kurtosis is presented in Fig.4, where the green dash-dot line is the shaft frequency, red dashed lines are first two harmonics of the BPFI (290Hz and 580 Hz), and red dotted lines are first order modulation sidebands at a shaft speed around the BPFI and its harmonics.

The Improved Autogram has the same algorithm than the Autogram but the Gini index is used instead of the kurtosis in step 3, as shown in Fig.5 the maximum value is obtained with center frequency 10681.125 Hz and bandwidth 3051.75 Hz at level 4. The Squared Envelope Spectrum (SES) of the signal associated to node with highest Gini Index is presented in Fig.6, where the green dash-dot line is the shaft frequency, red dashed lines are first two harmonics of the BPFI (290Hz and 580 Hz), and red dotted lines are first order modulation sidebands at a shaft speed around the BPFI and its harmonics. The best diagnosis result is achieved using the Improved Autogram where the non-periodic impulses and noise are reduced and the periodic impulses related to bearing defects are improved compared to the previous approaches.

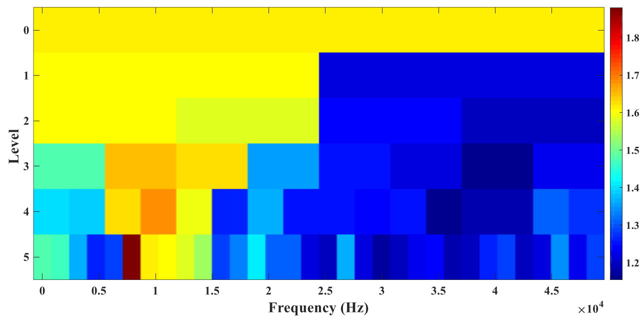

Figure 3: Autogram (B_w = 1525.8, f_c = 8392.3) at level 5

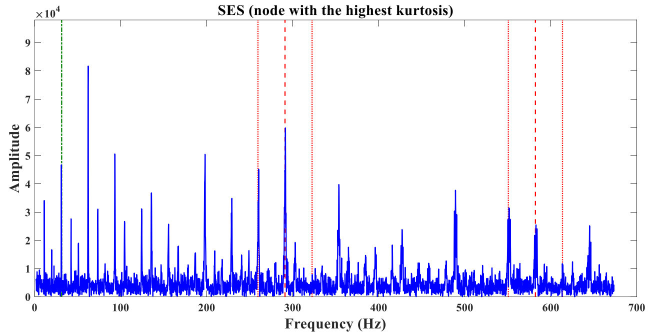

Figure 4: Squared Envelope Spectrum (Autogram)

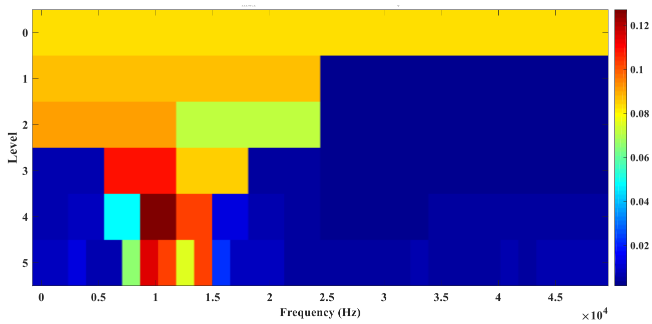

Figure 5: Improved Autogram (B_w=3051.75 Hz, f_c =10681.125 Hz) at level 4.

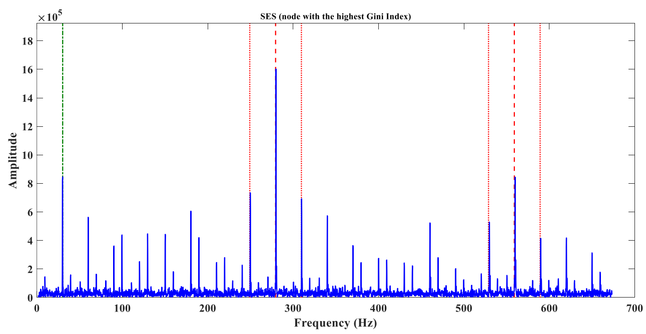

Figure 6: Squared envelope spectrum (Improved Autogram)

4. Conclusion

This work introduces a recent approach for finding the appropriate frequency band demodulation in bearing defect diagnosis. Initially, the Fast Kurtogram is applied, but the resulting spectral analysis includes many non-periodic impulses, leading to a difficult diagnosis task as relevant information is drowned out.

Two versions of the MODWPT are then compared to select the most informative frequency band. Both are based on the unbiased autocorrelation of the squared envelope of the signal, computed to take advantage of the second-order cyclostationarity of the failure signal, and reducing the level of uncorrelated random noise and enhancing the defects linked peaks.

The main advantage of the Autogram is its ability to reduce the impact of non-periodic impulses and noise from raw vibration data, which are not linked to any bearing faults. Despite the robustness of the Autogram, the improved Autogram appears to be more efficient than the mentioned approaches in this work due to the use of the Gini index, which The Gini index might be more powerful in detecting impulsiveness in a signal because it considers the entire distribution of the signal, whereas kurtosis only considers the tails of the distribution.

All three approaches have been tested on real vibration signals from a wind turbine generator provided by GPMS in the USA.

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