Spectral kurtosis applied to acoustic emission in bearings

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Abstract: The application of Acoustic Emission (AE) in condition monitoring of rotating machines has been well documented. The majority of research works in this field has involved the use of conventional time domain analysis for processing the AE signals from the machines and there has been little attention given to application of more advanced signal processing methods. This research presents a study in which some advanced signal processing techniques such as Wavelet and Spectral Kurtosis (SK) has been applied to offer improved diagnosis for bearing defect detection.

1. Introduction

Today’s competitive market together with the revolution in consumer expectations and technology has made companies become more concerned about their productivity and performance [1]. For industries to survive in such a complex and competitive environment it is vital to improve their product reliability whilst cutting down on production cost. Product reliability is an important factor for the manufacturer in the mining, aviation, nuclear and chemical industries where operational failure can lead to a devastating disaster. According to the report issued by Mine Safety and Health Administration (MSHA) [2], 20% of the total fatal mining casualties in the US between 2005 and 2009 were caused by machinery failure. On the other hand, maintenance expenses can directly contribute to the final cost of product. Given the demand for product reliability, as well as the reduction in production cost, it is essential to employ condition monitoring (CM) techniques for firstly predicting the failure prior to the event and secondly preventing unexpected shutdowns of machinery. The former is particularly important in the oil and gas sector where unexpected plant shutdown can result in a major economic loss, while an unexpected failure can result in fatalities in civil aviation. There have been continuous challenges in designing robust CM systems capable of diagnosing damage in its early stages of development and predicting the remaining life of the machine.

Over the past decades, multi-resolution analysis using wavelet transform has gained ground as an effective signal-processing tool. The fundamental idea is to decompose the signal into several frequency ranges with finer resolutions, thereby achieving a better understanding of the time-frequency content of the signal [3]. In signal processing, two types, the continuous (CWT) and discrete (DWT) wavelet transforms are employed. The function of CWT is to break up the signals into scaled and shifted versions of a transient type of signal known as the mother wavelet, $\psi$. The scale, $a$, and frequency of each wavelet are inversely correlated with each other so that the higher scale corresponds to the low frequency version of same wavelet. The coefficient, $C$, for each segment of the signals is de-
termined based on the difference in energy of scaled and shifted versions of the mother wavelet and that of a particular segment, see equation (1) [3].

$$C(a, \tau) = \frac{1}{a} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-\tau}{a}\right)dt$$

Spectral Kurtosis (SK) is gaining ground as an effective signal processing method in vibration analysis. To determine SK, the signal is firstly decomposed into the time-frequency domain after which the Kurtosis values are determined for each frequency band [4]. The concept of SK analysis was first developed by Dwyer [5] as a tool which was able to trace non-Gaussian features in different frequency bands using the fourth order moment of the real part of the Short Time Fourier Transform (STFT). Dwyer investigated the application of SK on stationary processes but did not account for non-stationary vibration signatures typical of rotating machines. To date the most comprehensive calculations of the SK has been developed by Antoni [6] as the fourth order cumulant of the spectral moment (K).

$$K_Y(f) = \frac{S^4Y(f)}{S^2Y(f)} - 2$$

and

$$S_{XY}(f) = \left|Y_w(t, f)\right|^2$$

$Y_w(t, f)$ is estimated using the short time Fourier Transform:

$$Y_w(t, f) = \sum_{-\infty}^{\infty} Y(n) \cdot W(n-t) e^{-j2\pi nf}$$

Where $Y(n)$ is the sampled version of the signal, $Y(t)$, and $W(n)$ is the window function having zero value outside a chosen interval.

For the above calculations to be valid, the size of window ($N_w$) should be smaller than the length between two repetitive impulses and longer than the length of each impulse. In other words, the analysed signal should be locally stationary. Using the definition offered by Antoni [6], Antoni and Randall [7] developed the concept of the Kurtogram to detect non-Gaussianity in a signal. A Kurtogram simply maps the STFT-based SK values as functions of frequency and window size. Antoni [6] and Antoni and Randall [7] suggested the use of the Kurtogram for designing a band-pass filter which can be applied to increase the signal-to-noise ratio, thereby preserving the impulse-like nature of the signal. Additional authors aimed to find ways to automatically determine the optimum frequency band for envelope analysis. For this research the frequency and window size (bandwidth) at which the Kurtogram is maximum was employed to build a band-pass filter that was subsequently employed for analysis of measured AE and vibration data. In a separate investigation, Antoni [8] proposed an algorithm for fast computation of the Kurtogram. In this method instead of using STFT at different window lengths, the signal is decomposed by the means of quasi-analytic low-pass and high-pass filters to generate a pyramidal filter-banks tree with $2^k$ bands in each level ($k$). The Kurtogram is computed via calculating the kurtosis of all frequency bands, see equation (5):
\[ S_{ni}^{i}(f) = \left| C_{i}^{n}(n) \right|^2 \]

Where \( C_{i}^{n}(n) \) is the sequence of the coefficient from the \( i \)th filter at \( k \)th level.

This research presents several experimental investigations where the advanced signals processing methods were applied on recorded AE signals from a bearing that was run to failure with the purpose of improving the signal-to-noise ratio so as to enhance features of bearing damage.

2. Experimental tests

The test rig used in this experiment is displayed in figure 1. The bearing test rig has been designed to simulate varying operating conditions and accelerate natural degradation. The chosen bearing for this study was an SKF single thrust ball bearing, model number SKF51210. To ensure accelerated failure of the race the standard grooved race was replaced with a flat race, model number SKF 81210TN. This caused a point contact between the ball elements and the race resulting in faster degradation of the race and early initiation of sub-surface fatigue cracks. The load on the test bearing was applied by a hand operated hydraulic pump (Hi-Force No: HP110-Hand pump-Single speed-Working Pressure: 700 BAR). The flat race was fitted onto the loading shaft in a specifically designed housing. This housing was constructed to allow for placement of AE sensors directly onto the race. Modifications were made to the support of the flat bearing race so as to allow positioning of the AE sensors, see figure 2. The motor on the rig operated at 1500rpm and the number of rolling elements in the test bearing was 14 and the ball pass frequency (BPF) was 175Hz.

Figure 1. Test rig assembly.

Figure 2. Sensor arrangement on the flat race showing the circumferential distance between sensors.
The AE acquisition system employed commercially available piezoelectric sensors (Physical Acoustic Corporation type ‘PICO’) with an operating range of 200–750 kHz at temperatures ranging from 265 to 1770°C. The AE sensors were connected to a data acquisition system through a preamplifier (40dB gain). The system was set to continuously acquire AE absolute energy (atto-Joules) over a time constant of 10 ms at a sampling rate of 100 Hz. However, AE waveforms were sampled at 2MHz.

The test rig was allowed to operate until vibration levels far exceeded typical operating levels at which point the test was terminated. An axial load of approximately 50000N was applied on the bearing throughout the test and a total of three tests were performed.

Two tests are presented in this paper with quite distinct signal-to-noise ratios; Test 2 was significantly nosier for both vibration and AE measurements. This was attributed to the variation in test rig assembly, such as adjustments and sensor attachments therefore it offered a good opportunity to asses methods for diagnosis. Such challenges with AE sensor attachment and noise interference have been discussed recently [9]. Figure 3 presents the defect observed on termination of Test-1 clearly displaying a spall on the flat race.

![Figure 3. Defect on the outer race of test-1, (naturally developed over 4hrs of operation).](image)

The AE signals for different intervals, as set in table 1, were chosen for further analysis, see figure 4. Interestingly, for Test-1 at time period ‘F’, the AE waveform showed large transient bursts spaced at one of the bearing defect frequencies. This is a classical AE bearing defect phenomenon as noted by several investigators [10-12]. However, for the second test, the underlying noise level obscures any apparent high transient events in the waveform.

| Test   | Interval |
|--------|----------|
| Test 1 |          |
| A      | 35 min   |
| B      | 70 min   |
| C      | 105 min  |
| D      | 140 min  |
| E      | 175 min  |
| F      | 210 min  |

| Test 2 |          |
|--------|----------|
| A      | 42 min   |
| B      | 87 min   |
| C      | 132 min  |
| D      | 174 min  |
| E      | 219 min  |
| F      | 267 min  |

The frequency spectrum of recorded AE signals show the AE activity is concentrated between 50-450 kHz, see figure 5. In order to identify any modulating features, the envelop spectrum of the signals
were generated using the Hilbert transform. The plots of envelop spectrums for both tests are presented in figure 6. Results from the first test show the presence of the BPF and its harmonics. Surprisingly the presence of the defect frequency 175 Hz, was noted for all the timing intervals (A-F) although the magnitude of the peak increased with time reaching a maximum at the termination of the test. For the second test, the presence of the harmonics noted in the first test were not evident though the second and forth harmonics were noted at the end of the test, time interval ‘F’. The reason for inadequate clarity in discriminating of the harmonics and fault frequency is attributed to the presence of noise and therefore a lower signal-to-noise ratio than Test-1.

As with the vibration analysis, the SK analysis was undertaken for the AE waveforms. Table 2 shows the optimum frequency bands for time intervals ‘A’ to ‘F’. According to the table, the optimum centre frequencies associated with undamaged race (A-E) were outside the sensor measurement range. This is because for the undamaged bearing the higher frequencies within the sensor measurement range are predominately gaussian so the maximum Kurtosis value occurs at the lower frequency range, below 30 kHz to 40 kHz.

![Figure 4. The AE waveform at different time intervals [X-axis: Time (msec) / Y-axis units: Volts].](image)

![Figure 5. Frequency spectrum of the AE signal.](image)
Table 2. Optimum Bandwidth and Centre frequency for AE signal

|       | Test 1 |          | Test 2 |          |
|-------|--------|----------|--------|----------|
|       | Fc (Hz) | log2 (NW)| Fc (Hz) | log2 (NW)|
| A     | 39062  | 7.5      | 31250  | 7        |
| B     | 31250  | 7        | 31250  | 7.5      |
| C     | 31250  | 7        | 65185  | 12.5     |
| D     | 31250  | 7.5      | 31250  | 7.5      |
| E     | 31250  | 7.5      | 15625  | 8        |
| F     | 71484  | 8.5      | 61523  | 10.5     |

The filtered waveforms are presented in figure 7 showing a significant improvement in level of SNR compared with the unfiltered signals in figure 4. The AE spikes seen at operational interval ‘F’ are a direct consequence of the bearing defect. The improvement of SNR is also manifested in figure 8 in which an average of approximately 242% and 95% increase in Crest Factor (CF) values were noted for the filtered signals on Test-1 and Test-2 respectively. The Crest Factor is a peak-to-average ratio and offers an insight into the relative amplitude of bursts under varying noise levels. Furthermore, figure 9 illustrates the envelop spectrum of the filtered signals based on SK analysis. The BPF and its second harmonic were present across the frequency spectrum for both tests while such observations were not noted for the unfiltered envelope spectrum in figure 6.

Figure 6. The AE envelop spectrum for the first and second tests [Y-axis units: Volts].
Having noted the improvement in signal-to-noise ratio particularly for Test-2, the authors compared the SK to wavelet-based filter analysis. The AE signals were decomposed using Debauches wavelet of order 8 (db8). The reason for choosing db8 as a mother wavelet is firstly because of being orthogonal and secondly the shape of it is close to the mechanical impulse. The envelop spectrum at each level of decomposition (D1-9) were carefully studied and level D1 (500 kHz - 1000 kHz) was found to be the most sensitive for identifying the presence of the defect. The envelop spectrums of the signals at D1 are presented in figure 10 in which BPF and its harmonics are evident upon the termination of both test.

The CF values for the original filtered (SK) and decomposed (db8) signals are presented in figure 11. In comparison to the original values of CF, the SK filtered signals showed an increase in CF of approximately 242% and 95% for Test-1 and Test-2 respectively. Crest factor values noted for decomposed signals (D1) were in the order of 18% and 70% for Test-1 and Test-2 respectively; implying the SK offered the optimum filtered characteristics for identifying impulsive effects, which are typically associated with defective bearings. The waveforms together with CF values at interval ‘F’ for D1, the original unfiltered waveform and the filtered waveform (SK) are also presented in figure 12 in which the presence of impulsive AE events associated with the defective bearing are most evident for the SK filtered signals. There was only one instance where the wavelet based filter had a better CF than the SK filtered data (Test-1, interval ‘F’). Although the defect frequency and its harmonics are clearly marked in the envelop spectrum presented in figure 10, the level of signal to noise...
ratio for SK based filtering is relatively high. This observation reinforced the benefits of applying the SK for defect diagnosis for varying signal-to-noise ratio.

Figure 9. Envelope spectrum of the SK-based filtered signals [Y-axis units: Volts].

Figure 10. Envelope spectrum of the AE signals at D1 [Y-axis units: Volts].

Figure 11. CF value attribute to different diagnostic.
4. Conclusion
Condition monitoring of the bearings may demand the application of the advanced signal processing methods to effectively correlate the damage accumulation with AE signals. The spectral kurtosis has demonstrated added advantages, relative to wavelet analysis, in improving the signal-to-noise ratio for AE signatures from defective bearings.

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