Observation of time-frequency characteristics of the acoustic emission from defects in rolling element bearings

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Parameter analysis is a traditional and widely used method for the analysis of acoustic emission (AE) signals due to its simplicity and ease realisation. However, this approach has limitations and is not suitable for detailed analysis of the signals, and waveform-based methods are becoming attractive for the analysis of AE signals. This paper uses waveform-based analysis methods to investigate the time-frequency characteristics of AE signals arising from defects in rolling element bearings. This includes the composition of the signals, the generation mechanism of the defects and the influence of the operational condition of the bearing on these characteristics. The wavelet scalogram of the continuous wavelet transform is used to perform the qualitative analysis and the discrete wavelet transform is used for the quantitative analysis. The results demonstrate that the operational condition of the bearing will influence the time domain, the frequency domain and the time-frequency domain characteristics of the AE signals in various ways. The results also prove that the wavelet transform, and especially the wavelet scalogram, has great potential for the waveform-based analysis of AE signals from defects.

Keywords: acoustic emission, rolling element bearing, condition monitoring, wavelet transform.

1. Introduction

Rolling element bearings are very important components in rotating machinery. Any failures in such bearings (such as fatigue cracks, pitting, spalling, etc) will lead to malfunctions of the machine or even a catastrophic accident. As a consequence, condition monitoring and defect diagnosis of rolling element bearings is very important to guarantee the safe running of rotating machinery. For rolling element bearings, besides the traditional vibration signal-based method[5-9], the acoustic emission-based method has been developed as a complementary method for the condition monitoring and defect diagnosis of bearings[10]. Acoustic emission (AE) is defined as the resulting transient elastic wave generated when strain energy is released suddenly due to the relative motion among the particles within a material. When rollers roll over the defect on the race of bearings, elastic impulses and strain on the contact surface will be generated and lead to a release of the transient stress wave energy, ie AE. Such AE generally has a frequency range over 20 kHz and is relatively immune from disturbances by mechanical noise and other faults. Therefore, AE is receiving increasing attention. Much significant research has been performed on the application of the AE technique to detect defects in rolling element bearings[6-9]. Traditionally and generally, narrowband and resonant piezoelectric AE transducers are mainly used to acquire the AE signal. The traditional parameter analysis method is then commonly adopted to analyse the AE signal. Parameter analysis methods are popular due to their simplicity and easy realisation in applications, but they have limitations. For example, the AE count rate relies on the frequency of the AE signal[10] and the threshold set for the AE signal relies on the operator’s experience[11]. Parameter analysis methods give a gross evaluation and description of the AE signal, but not in detail and thus cannot be used to investigate the time-frequency characteristics, wave propagation characteristics and the composition of the AE wave. Therefore, waveform-based analysis methods are attractive to analyse the AE characteristics.

The Fast Fourier Transform (FFT) has been used extensively for the waveform analysis of AE signals. The AE signals from rolling element bearings are non-stationary and arise from non-linear dynamics, and the traditional FFT method is not appropriate for such signals. Time-frequency analysis methods, such as the Gabor transform[12] (windowed Fourier transform) and the bilinear time-frequency representation[13], are becoming popular for the analysis of non-stationary and non-linear signals, which simultaneously yield the time and frequency information in a signal. One particular time-frequency analysis method, the wavelet transform (WT)[14], has become an attractive and popular analysis method due to a number of benefits. Compared with other time-frequency analysis methods, the WT can be used for multi-scale analysis of a signal through dilation and translation and has better time-frequency characteristics. Thus the WT has been applied widely in various areas, including in the AE area[15-17]. Corresponding to the spectrums of the Gabor transform, the WT scalogram provides another alternative time-frequency analysis method for the non-stationary signal of AE, which can extract more effective time-frequency information of a signal and can display periodic, quasi-periodic, and even randomly occurring signals. Therefore, it seems that the WT scalogram should provide a strong tool for investigating the fundamental issues of AE. He et al.[17] first use the WT scalogram to investigate the time-frequency and propagation characteristics of the rubbing AE from a rotor-bearing system and demonstrate its advantage.

In reference[18], using the traditional parameter analysis method, we presented an experimental study to validate the relationship between various AE parameters and the operational conditions of the rolling element bearings. In this paper, to further understand the detailed characteristics of the defect AE from rolling element bearings, the wavelet scalogram and discrete wavelet transform are used to perform the waveform analysis of the defect AE signal to investigate its time-frequency characteristics and its composition under various operational conditions of the rolling element bearing.
2. The wavelet transform (WT)[14]

Assume that \( x(t) \) is a finite-energy function, ie \( x(t) \in L^2(\mathbb{R}) \). Then the continuous wavelet transform (CWT) of \( x(t) \) is defined as:

\[
W_x(a, b, \psi) = \langle x(t), \psi_{a,b}(t) \rangle = a^{-1/2} \int x(t) \overline{\psi}_{a,b}(t) \, dt \quad (1)
\]

where \( a > 0 \), the superscript * denotes complex conjugation and \( \psi \) denotes the inner product. \( \psi_{a,b}(t) \) is generated by dilation and translation from the mother wavelet \( \psi(t) \), by:

\[
\psi_{a,b}(t) = a^{-1/2} \psi \left( \frac{t-b}{a} \right) \quad (2)
\]

where \( a \) is the scale parameter and \( b \) is the time shift parameter. The factor \( a^{-1/2} \) is used to ensure energy conservation for the transform. From this definition of the wavelet transform, the wavelet transform does not lose any information and energy is conserved by the transform. Thus:

\[
\langle x(t), x(t) \rangle = \int \int |W_x(a, b, \psi)|^2 \, da \, db \quad (3)
\]

for some constant \( C_x \). Thus \( W_x(a, b, \psi)^2/C_x a^2 \) can be considered as the energy density function of the time-scale plane \((a, b)\). \( W_x(a, b, \psi)^2 \Delta a \Delta b / C_x a^2 \) represents the total energy of a domain centered at \((a, b)\) with scale interval \( \Delta a \) and time interval \( \Delta b \). The wavelet scalogram is defined as the spectrum of the Gabor transform,

\[
SG_x(a, b, \psi) = W_x(a, b, \psi)^2 \quad (4)
\]

which can be seen as a spectrum with constant relative bandwidth \([8]\).

By discretising the parameters \( a \) and \( b \) in Equation (2) in the manner of a power series, ie setting \( a = 2^j \) and \( b = k \cdot 2^j \), then the wavelet function is written as:

\[
\psi_{j,k}(t) = 2^{j/2} \psi(2^j \cdot t - k) \quad (5)
\]

where \( j \) and \( k \) are integers. The corresponding wavelet transform is called the discrete wavelet transform (DWT) and is defined as:

\[
W_x(j, k) = \langle x(t), \psi_{j,k}(t) \rangle = \int x(t) \overline{\psi}_{j,k}(t) \, dt \quad (6)
\]

The DWT represents a signal without redundancy, given by the coefficients of the wavelet series, \( C_k \). The discrete signal, \( x(t) \), may be expressed by the wavelet functions and the wavelet coefficients as:

\[
x(t) = \sum_{j=0}^{\infty} \sum_{k=-N}^{N} C_k \psi_{j,k}(t) \quad (7)
\]

where \( t = 1, 2, \ldots, M \) and \( N = \log_2 M \)...

3. Experimental test-rig

The test-rig is shown in Figure 1 and consists of a motor, a rotor-bearing unit and a loading unit. A deep-groove ball bearing of type 6220 is employed as the test bearing and has the following parameters: roller diameter \( d = 22.8 \) mm; effective diameter \( D = 141 \) mm; and the number of rollers \( Z = 11 \). The radial load is applied to the test bearing by a lever system with a ratio of 1:200.

For the AE data acquisition, SR15 broadband AE transducers are employed, with an operating frequency range of 20 Hz - 300 kHz. The AE transducers are mounted on the outside surface of the outer race. The sampling rate is set to 500 kHz and the sample time is 0.5 s. Electric spark erosion is used to seed a simulated corrosive pitting defect onto the outer race of the bearing artificially, and defect sizes of diameters 3 and 5 mm are prepared (denoted D1 and D2, respectively). Two load cases are considered, namely 3 and 7 kN (denoted L1 and L2, respectively), and two rotating speeds of the test-rig are chosen as 222 and 444 r/min (denoted S1 and S2, respectively).

4. Experimental analysis and results

4.1 Parameter optimisation of the Morlet wavelet transform

The performance of the CWT time-frequency transform depends greatly upon the selection of the mother wavelet. The mother wavelet is selected so that its wave shape is as close as possible to the analysed signal, and the wavelet entropy can be used to determine this similarity; the smaller the wavelet entropy, the greater the similarity\([17,19]\). He et al\([20]\) discussed the transform performance, using the wavelet entropy, of various wavelets with respect to typical AE signals and concluded that the Morlet wavelet is the most suitable for the analysis of AE signals.

The Morlet wavelet is defined, for real signals, as:

\[
\psi(t) = \exp \left(-\frac{\beta^2}{2} \right) \cos(\omega_0 t), \quad \beta > 0 \quad (8)
\]

with Fourier transform:

\[
\hat{\psi}(\omega) = \frac{\sqrt{\pi / 2}}{\beta} \exp \left(-\frac{\omega^2}{2\beta^2} \right) \quad (9)
\]

Strictly speaking, the Morlet wavelet does not satisfy the admissibility condition, since:

\[
\hat{\psi}(\omega = 0) = \left(\sqrt{\pi / 2} / \beta \right) \exp(-\omega_0^2 / 2\beta^2) = 0 \quad (10)
\]

However, for \( \omega_0 / \beta \approx 5 \), the condition is approximately satisfied\([20]\).

As we know, the parameters \( \beta \) and \( \omega_0 \) control the shape of the basic Morlet wavelet: when \( \omega_0 \) is fixed, increasing \( \beta \) will accelerate the attenuation of the basic wavelet and decrease the support domain of the wave shape. As \( \beta \) tends to infinity, the basic wavelet becomes a Dirac function, which has the finest time resolution possible, but no frequency resolution. As \( \beta \) tends to 0, the basic wavelet becomes a cosine function, which has the finest frequency resolution possible but no time resolution. When \( \beta \) is fixed, \( \omega_0 \) controls the oscillating frequency on the time support domain; increasing \( \omega_0 \) will accelerate the oscillation of the basic wavelet. When used to analyse the same frequency component, increasing (decreasing) the Morlet wavelet central frequency \( \omega_0 \) will make the frequency resolution higher (lower), while time resolution lower (higher).

From the above discussion, it can be seen that \( \beta \) and \( \omega_0 \) balance the time-frequency resolution. For different signals, different parameters should be selected for better performance. The half-power bandwidth of the Morlet wavelet is \( \beta \sqrt{\ln 2}/\pi \) Hz, and the central frequency in Hz is \( f_s = \omega_0 / 2\pi \). The quality factor \( Q \) (central frequency/bandwidth) may be calculated as \( \omega_0 / 2\sqrt{\ln 2} \beta \), and hence \( \beta \) and \( \omega_0 \) determine the quality factor of the Morlet wavelet. Thus, the wavelet analysis performance is optimised simultaneously when these two parameters are optimised when the wavelet entropy is close to its minimum. The wavelet entropy may be used as the fitness function and genetic algorithm (GA) used to optimise these two parameters to improve the performance of the Morlet wavelet\([20]\).
Figure 3 presents a performance comparison of the wavelet scalogram analysis. The analysed signal is a simulated AE which is composed of three exponential decaying components, as shown in Figure 2. Comparing Figure 3(a) with Figure 3(b) shows that parameter optimisation improves the differentiation of the three components in the scalogram. Thus parameter optimisation of the Morlet wavelet greatly improves the time-frequency performance of the scalogram analysis. Hence the lower frequency component has higher frequency resolution and lower time resolution, while the higher frequency component has higher time resolution and lower frequency resolution, which is an ideal time-frequency performance.

In this paper, to investigate and observe the time-frequency characteristics of the defect AE more accurately, the Morlet wavelet is selected and the GA-based optimisation method is used to optimise the parameters of this wavelet in the time-frequency analysis.

4.2 Time-frequency analysis based on wavelet scalogram

In this section, the wavelet scalogram is used to analyse the time-frequency characteristics and the composition of the AE signal with a defect on the outer race of the rolling element bearing under various operational conditions. Figure 4 shows a typical AE signal under the condition (L1, S1, D1), together with its FFT spectrum and wavelet scalogram. Figures 4(a) and (b) show that the AE signal produced when the roller rolls over the defect includes multiple AE bursts and covers a wide frequency range. The energy is mainly concentrated in the range from 40 to 100 kHz, accompanied by higher frequency components over 100 kHz with much smaller amplitude. However, the FFT spectrum provides only frequency information and is a gross description in the frequency domain but has no time domain information relating to the transient information in the signal. Thus we cannot know if a frequency component exists during the whole signal time span, or whether it is localised, because the FFT used transforms the signal globally. In contrast to the FFT spectrum, the wavelet scalogram, shown in Figure 4(c) and (d), reveals the time and frequency information in the AE signal simultaneously. The time-frequency distribution of the AE signal

Figure 4. Analysis of the AE under condition (L1, S1, D1): (a) original AE; (b) FFT spectrum; (c) scalogram without optimisation; (d) scalogram with optimisation
is clearly revealed and the duration of each frequency component shown. However, comparing Figure 4(c) with Figure 4(d) shows that heavy interference occurs between the components which are close to each other, especially between the components with large value, in the wavelet scalogram without parameter optimisation. Such interference blurs the time-frequency distribution of AE in the scalogram. It is not easy to observe and identify detailed and fine time-frequency characteristics of AE from such blurred time-frequency distribution accurately. However, parameter optimisation greatly improves the time-frequency performance of the scalogram and the interference is suppressed efficiently. In addition, the ideal time-frequency performance improves the centrality of the energy and can provide better concentration to the impact signal. Therefore, some components with small energy can be observed in the optimised scalogram, which do not appear in the scalogram without optimisation. It means that parameter optimisation can make it easier to identify the weak or fine time-frequency characteristics in the scalogram. In the following sections, parameter optimisation is performed for all scalogram analysis.

From Figure 4(d), it can be seen that the AE signal from the defect has an obvious impact characteristic, i.e., the AE signal is mainly composed of a series of impulse signals. The strongest burst happens at around 3 ms, but every AE burst at different times has very similar frequency distribution characteristics, i.e., the main frequency components of the AE distribute in the range from 40 kHz to 100 kHz with some small amplitude and higher frequency components. The results demonstrate that an AE event when the roller rolls over the defect should be composed of a series of elastic impulses and relative dislocation among the particles within the material, with different energy levels. Such an observation and results cannot be obtained from the FFT spectrum.

Figure 5 shows the corresponding results (AE signal, FFT spectrum and wavelet scalogram) when the load is increased (case L1 to case L2). Comparing Figures 4 and 5 shows that the AE signal from conditions (L1, S1, D1) and (L2, S1, D1) have almost identical time-frequency characteristics in terms of the frequency distribution and composition; only the amplitude or energy of the AE signal is larger for the higher load over all of the frequency range. This indicates that the constant radial load has little obvious influence on the strain mechanism or the dislocation mechanism of the particles within the material (i.e, the AE generation mechanism), but does increase the impact energy when the roller rolls over the defect.

Figure 6 shows the results (AE signal, FFT spectrum and wavelet scalogram) when the speed is increased (case S1 to case S2). Comparing Figures 6(a) and (b) with Figures 4(a) and (b) shows that the amplitude and energy of the AE signal greatly increases over the whole frequency range with increasing rotating speed, but the frequency range and frequency distribution are almost the same from the FFT spectrum. However, the wavelet scalogram shows more detailed time-frequency information and highlights that the frequency distribution and composition of the AE signals are significantly different between conditions (L1, S1, D1) and (L1, S2, D1). The higher rotating speed makes the release of the strain energy more concentrated when the roller rolls over the defect and thus the energy distribution of the AE signal becomes more concentrated in the wavelet scalogram plane. In addition, the main AE bursts happen at different time points for the two speeds. These results demonstrate that the varying rotating speed makes the excitation manner (impact frequency and strength) of the material change and consequently influences the strain mechanism and the AE generation mechanism, which leads to changes in the energy strength but not in the time-frequency characteristics of the AE signal.

Figure 7 shows the results (AE signal, FFT spectrum and wavelet scalogram) when the defect size is increased (case D1 to case D2). Comparing Figures 7(a) and (b) with Figures 4(a) and (b), shows that the amplitude, the energy and the frequency distribution of the AE signal from condition (L1, S1, D2) are almost the same as that from condition (L1, S1, D1). However, the wavelet scalogram

![Figure 5. Analysis of the AE under condition (L2, S1, D1): (a) original AE; (b) FFT spectrum; (c) scalogram](image)

![Figure 6. Analysis of the AE under condition (L1, S2, D1): (a) original AE; (b) FFT spectrum; (c) scalogram](image)

![Figure 7. Analysis of the AE under condition (L1, S1, D2): (a) original AE; (b) FFT spectrum; (c) scalogram](image)
shows that the AE from condition (L1, S1, D2) includes more AE bursts within the time period from 7 ms to 10 ms. One possible explanation of this observation is that the bigger defect increases the time duration for the roller to roll over the defect and thus more AE bursts are generated. These results demonstrate that varying the defect size changes the environment and the mechanism of the AE generation, and therefore the time duration and distribution of the AE energy.

This time-frequency analysis shows the effect of various operational conditions on the time-frequency characteristics of the AE signal. The results indicate that the wavelet scalogram, especially that with parameter optimisation, has distinguishable advantages for the waveform analysis of the AE output. However, this analysis is mainly qualitative because the wavelet basis of the CWT is not orthogonal. Therefore, in the next section, the DWT is used to perform a quantitative analysis of the AE signals from defects under various operational conditions.

4.3 Energy distribution analysis of the defect AE based on DWT

He et al.\(^{[17]}\) concluded that the DB10 wavelet is most suitable for the DWT analysis of AE signals. Therefore, this wavelet is selected for the analysis in this section. From the frequency analysis in the previous section, the frequency range of the AE signal is from 40 kHz to 250 kHz. The decomposition level is set to 4 and Table 1 shows the frequency range of various decomposed components for the DWT. Here \(a_i\) denotes the approximation component and \(d_n\) denotes the detailed component of the \(n\)th level, respectively. Table 1 shows that the detailed components totally cover the frequency range of the AE signal from the defects, that is from 15.63 kHz to 250 kHz. These detailed components are used to analyse the energy distribution quantitatively, using the energy conservation law of the DWT.

<table>
<thead>
<tr>
<th>Approximation component</th>
<th>Frequency range</th>
<th>Detailed component</th>
<th>Frequency range</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_1)</td>
<td>0–125 kHz</td>
<td>(d_1)</td>
<td>125–250 kHz</td>
</tr>
<tr>
<td>(a_2)</td>
<td>0–62.5 kHz</td>
<td>(d_2)</td>
<td>62.5–125 kHz</td>
</tr>
<tr>
<td>(a_3)</td>
<td>0–31.25 kHz</td>
<td>(d_3)</td>
<td>31.25–62.5 kHz</td>
</tr>
<tr>
<td>(a_4)</td>
<td>0–15.63 kHz</td>
<td>(d_4)</td>
<td>15.63–31.25 kHz</td>
</tr>
</tbody>
</table>

Figure 8 shows the decomposed detailed components and their FFT spectra for the AE signal given in Figure 4 under the condition (L1, S1, D1). All of the detailed components are composed of a series of AE bursts with different amplitudes, and the frequency ranges of the various components coincides with those given in Table 1. Since the wavelet basis is orthogonal, the transform conserves energy, and thus:

\[
\sum_{j=1}^{N} \| x(t), \psi_j, k \|^2 = \| x \|^2 \quad \text{(10)}
\]

The wavelet energy can be defined as the quadratic sum of the wavelet coefficients over a single scale as:

\[
E_j = \sum_k \| C_j(k) \|^2 \quad \text{for } j = 1, \ldots, N \quad \text{(11)}
\]

Using this definition, the energy of the four detailed components can be calculated and the total energy obtained as:

\[
E_{\text{tot}} = E_1 + E_2 + E_3 + E_4 \quad \text{(12)}
\]

![Figure 7. Analysis of the AE under condition (L1, S1, D2): (a) original AE; (b) FFT spectrum; (c) scalogram](image)

![Figure 8. Detailed components of the DWT of AE under condition (L1, S1, D1): (a) \(d_1\) component; (b) \(d_2\) component; (c) \(d_3\) component; (d) \(d_4\) component](image)
and the distribution of the energy is given by:

\[ P_n = \frac{E_n}{E_{total}} \quad \text{for} \quad n = 1, 2, 3, 4 \quad \ldots \ldots \ldots \ldots (13) \]

where \( E_n \) is the energy of the \( n \)th component and \( E_{total} \) is the total energy. Figure 9 shows the energy proportion and distribution of the AE signal of the system with the defect under condition (L1, S1, D1). The energy of the AE signal is concentrated mainly in the 2nd and 3rd components.

Figure 9. Energy proportion and distribution of the AE under condition (L1, S1, D1)

Figures 10, 11 and 12 show the change in the energy distribution due to changes in the load (L1 to L2), the rotating speed (S1 to S2) and the defect size (D1 to D2), respectively. From all of these Figures, it can be seen that the increase of the radial load, the rotating speed and the defect size respectively all will lead to the change of the energy proportion and distribution of the defect AE with almost the same change manner, that is, the energy will shift to the frequency range of the 2nd component. This means that the energy induced by the increasing load, rotating speed and defect size respectively is absorbed mainly by the 2nd component. The results also indicate that the defect AE is mainly composed of the components and modes with frequencies within the range [62.5 125] kHz; the increasing fault condition parameters mean such components are generated with higher energy. This quantitatively verifies the analysis and observation results in Section 4.2.

5. Conclusions

In this experimental study, wavelet transforms, in particular the wavelet scalogram and the discrete wavelet transform, are used to analyse the time-frequency characteristics, the composition and the generation mechanism of AE signals from defects in a rolling element bearing. The influence of varying operational conditions, namely the radial load, rotating speed and defect size, on the AE characteristics and mechanism has been investigated. The results demonstrate that, for all operational conditions, the AE signal from the defect is composed of a series of AE bursts, whose energy is concentrated mainly in the range from 40 kHz to 100 kHz. The signals also contain higher frequency components over 100 kHz with smaller amplitudes, and the AE signal has an obvious impact characteristic. The operational condition of the bearing influences the time domain, the frequency domain and the time-frequency domain characteristics of the AE signal differently. The constant radial load has little obvious influence on the AE generation mechanism but does change the impact energy, thus mainly increasing the amplitude of the AE signal. The rotating speed has a strong influence on the AE generation mechanism through changing the impact frequency and strength. Therefore varying the rotating speed will lead to obvious changes in the time-frequency characteristics of the AE. The defect size has no obvious influence on the generation mechanism of the AE but changes the generation environment of the AE and therefore the time duration of AE energy. In addition, the quantitative analysis results show that increasing the radial load, rotating speed or defect size all lead to energy migrating to the frequency range [62.5 125] kHz. This indicates that the AE signals arising from the defects are mainly composed of components and modes with frequencies within this range.

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References


