24th INTERNATIONAL CONGRESS ON SOUND AND VIBRATION
23–27 July 2017, London

SOUND PULSE SIGNAL PROCESSING METHOD FOR FAULT DETECTION

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The sound pulse signals recognition for industrial condition monitoring is studied in this paper. The fault feature extraction from signals is the key of condition monitoring, while the general features used for description of pulse signals, such as the slope of rise time curve and power spectral centroid, are incompetent in practice. Aiming at a kind of common pulse signals in industrial production, a new feature parameters – bispectrum weighted value is proposed, in which the frequency components of the signal are given proper weights according to the difference between normal samples and faulty samples. In the experiment of acoustic detection of cracks in the anvil of a large-volume cubic, the feature vector with the proposed parameters results in higher recognition accuracy comparing with the reference feature vector through the diagnosis of BP Neural Network. It has better noise immunity with the help of capability of restraining noise high-order cumulants, and also works well for sound pulse signals disturbed by Gaussian noise in other applications.

Keywords: sound pulse signal, feature parameter, bispectrum weighted value, BP neural network

1. Introduction

Fatigue fracture of metal is a common form of structure collapse, accounts for over 90% of the total. The specific process of the fatigue fracture of metal is as follows: a microcrack initiate in metal structure and due to the cyclic loading the crack grows after each cycle and results in sudden failure. Acoustic emission (AE) is a kind of transient elastic wave which is caused by the rapid release of energy when plastic deformation or crack is formed. Because the AE signal comes from the material itself, it is not easy to be influenced by the external conditions, so it is used to monitor the crack state of the metal structure.

The core of acoustic emission monitoring technology is the feature extraction. Because of the complexity of the components of the acoustic emission signals from the metal structures being in service in complex and noisy environments, the selection of appropriate feature parameters is of great significance to the monitoring results. In this paper, a feature parameter, bispectrum weighted value, is proposed for the acoustic emission signal of the anvil of a large-volume cubic. Finally, the experimental results show that the proposed method can effectively improve the accuracy of monitoring results.

2. Feature parameters

2.1 Existing Parameters

In the early application of acoustic emission technology, the selection of feature parameters of acoustic emission signals, which is constrained by the signal processing technology of the time, is mainly based on the profile of the acoustic emission signal waveform. For instance: ringing count, amplitude, rising time, duration, energy count, average energy, peak count, etc. Later, with the development of signal processing technology and the improvement of the demand of accuracy, the study on the intrinsic features of AE signals is carried out. New feature parameter which is responsive to different circumstances is put forward continuously, like: wavelet coefficients, node energy based on wavelet transform algorithm, IMF energy, energy entropy based on EMD decomposition, etc. Good results are achieved with their help. Yan et al. proposed two feature parameters--nested power spectrum centroid (NPSC) and mean-varying variance (MVV) and got the classification accuracy of 95% with them by using the sliding time window (STW) and support vector machine (SVM) methods in addition [1]; In Li's work, the feature vector consists of Recurrent rate, Determinism, Maximum length, Entropy, Trend, Percent Laminarity, Trapping time was proposed based on the recurrence plot method and with the use of wavelet threshold filtering, EMD, SVM methods the accuracy on recognizing the AE signals of metal pressure pipes improved to 93% [2]; Shan Guan, Zhenxing Kang, Chang Peng had the signals pre-processed with the wavelet packet analysis method and characterized the signals with 3 feature parameters (expectation, entropy, hyper-entropy) extracted from the cloud-model of the signals [3]

2.2 The bispectrum weighted value

In traditional signal processing methods, the pending signals are assumed to be linear and Gaussian, but the AE signal collected by sensors is from the stress relaxation of metals and influenced by environment and transfer paths. So the pulse signal obtained in practical applications is often non-linear, non-Gaussian. Meanwhile as a kind of sudden signal, the AE signal contains a lot of phase information in high frequency domain. Therefore, the introduction of higher order statistics (HOS) is particularly important for dealing with these problems. High order spectral analysis theory which is developed on the second order spectral analysis overcomes the defects of the power spectrum (the first order spectrum) in phase information and describes the nonlinear phase coupling which is closely related to faults. Among all the higher order spectrums, the order of bispectrum is the lowest and the calculation method is the simplest. As it contains all the information of higher order spectrums, the bispectrum can not only recover and extract the phase information of the signal, but also represent the nonlinear characteristics of the system. So the application of bispectrum is more extensive.

2.2.1 The definition of bispectrum

Assume that $\{x(n)\}$ is a three order zero-mean stationary random process, and the third order cumulant is defined as:

$$C_{3,x}(\tau_1,\tau_2) = cum\{x(n), x(n+\tau_1), x(n+\tau_2)\} \tag{1}$$

And the third order cumulant $C_{3x}(\tau_1,\tau_2)$ is absolutely summable:

$$\sum_{\tau_1=-\infty}^{\infty}\sum_{\tau_2=-\infty}^{\infty}\left|C_{3,x}(\tau_1,\tau_2)\right| < +\infty \tag{2}$$

Then the bispectrum (the third order spectrum) is defined as:

$$S_{3,x}(\omega_1,\omega_2) = \sum_{\tau_1}\sum_{\tau_2} C_{3,x}(\tau_1,\tau_2)\cdot\exp(-j\omega_1\tau_1)\cdot\exp(-j\omega_2\tau_2) \tag{3}$$

It can be concluded that the bispectrum can be regarded as the distribution of the signal skewness in the frequency domain, and the degree of deviation of the signal from the Gaussian distribution.

2.2.2 The bispectrum weighted value

The bispectrum weighted value is the feature parameter obtained by summating the value of bispectrum $S_{3,x}(\omega_1,\omega_2)$ which is assigned different weight $W_{3,x}(\omega_1,\omega_2)$ to at different frequency points. Different assignment methods for bispectrum reveal the different features of the signals. In this paper, a new assignment method is presented for a common kind of pulse AE signals in industrial production.

Taking the point $S_{3,x}(0,0)$ as the origin and ω_1, ω_2 as the coordinate axis, and the bispectrum values are divided into four quadrants, as shown in figure 1:

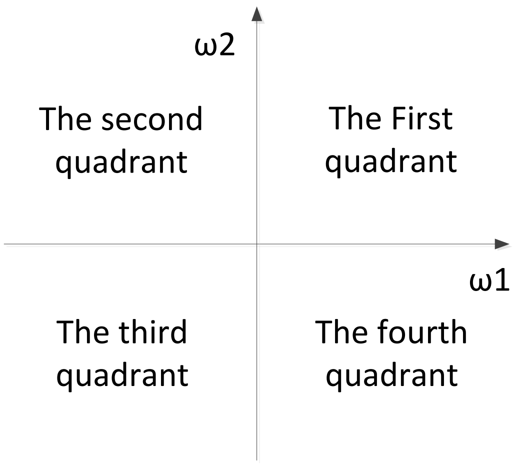

Figure 1

The first quadrant spread-weighted assignment method:

Extract the data of the first quadrant of bispectrum and give the weight 0.1 to the origin. And then take it as the center, the higher the weight is assigned to the points being farther away from the origin. Just like waves generated by a stone falling into a pool of water spread outward, the way of assigning weights is also spread. Specific method is shown in figure 2 (the weight expand from 0.2 to 0.8 with the different distance and points on the same line have the same weight):

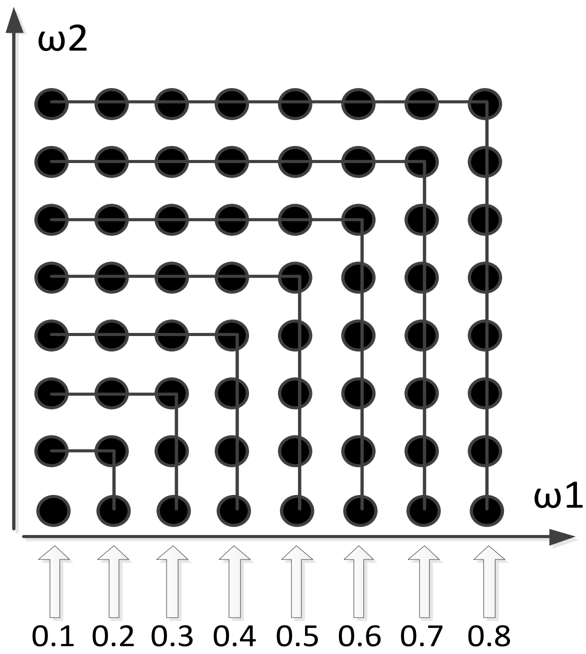

Figure 2

The forth quadrant zero-set spread-weighted assignment method:

The original point is taken as a center, then the weight of points nearby are set to be zero. The residual weights are assigned higher values with the increasement of distances from center. Specific method is shown in figure 3(the points locates near the origin have the weight 0 and the weight of the other points expand from 0.5 to 0.8 with the distance farther away; points on the same line have the same weight):

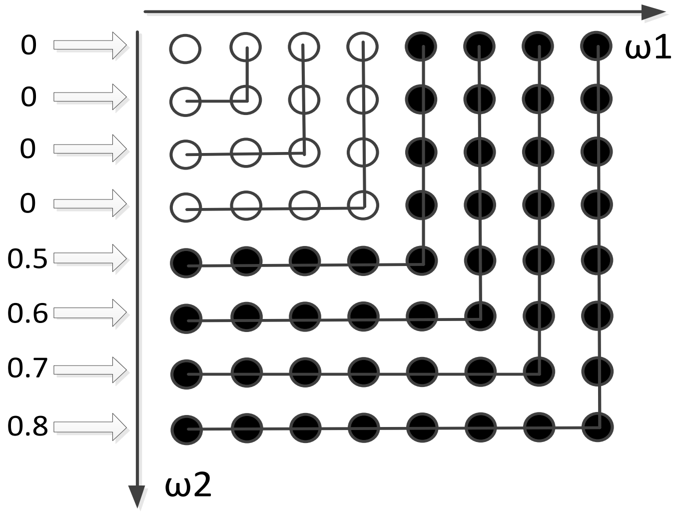

Figure 3

At last, sum the product of each bispectrum value and its corresponding weight. The summation is the new feature parameter—the first quadrant spread-weighted value (1st -SWV) or the forth quadrant zero-set spread-weighted value (4th-ZSSWV). That is:

$$K = \sum_{\omega_1=-\infty}^{+\infty} \sum_{\omega_2=-\infty}^{+\infty} W_{3,x}(\omega_1,\omega_2) \cdot S_{3,x}(\omega_1,\omega_2) \tag{4}$$

2.2.3 Analysis of the new parameters

1. Figures 4 and 5 show the spectrum of a normal signal and crack signal respectively. It can be learned from the figures that the distribution of bispectrum of crack signals is not as concentrated as normal signals. The difference in high frequency region is revealed between the two kinds of signals. Therefore, it is feasible to use the difference to distinguish normal and crack signals. (The black rectangle in the diagram is used to demonstrate the degree of concentration of the information in bispectrum.)

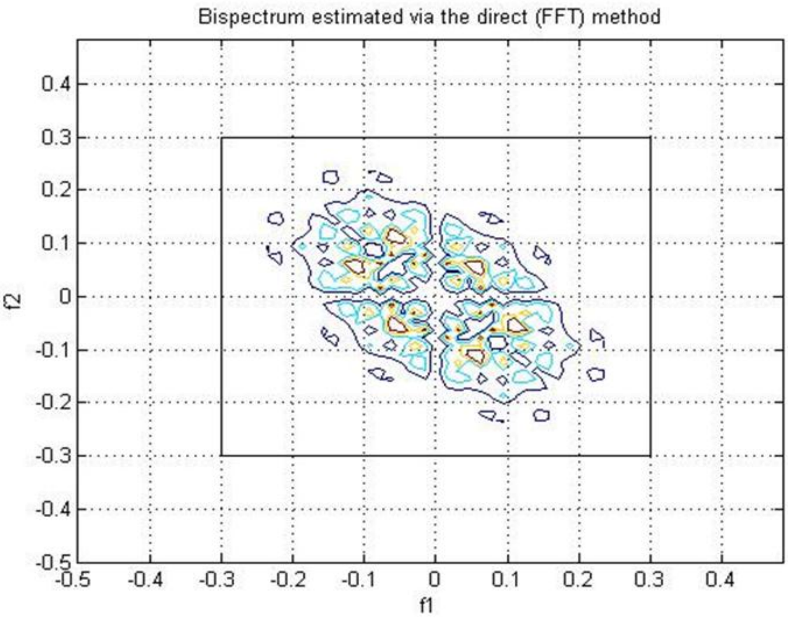

Figure 4

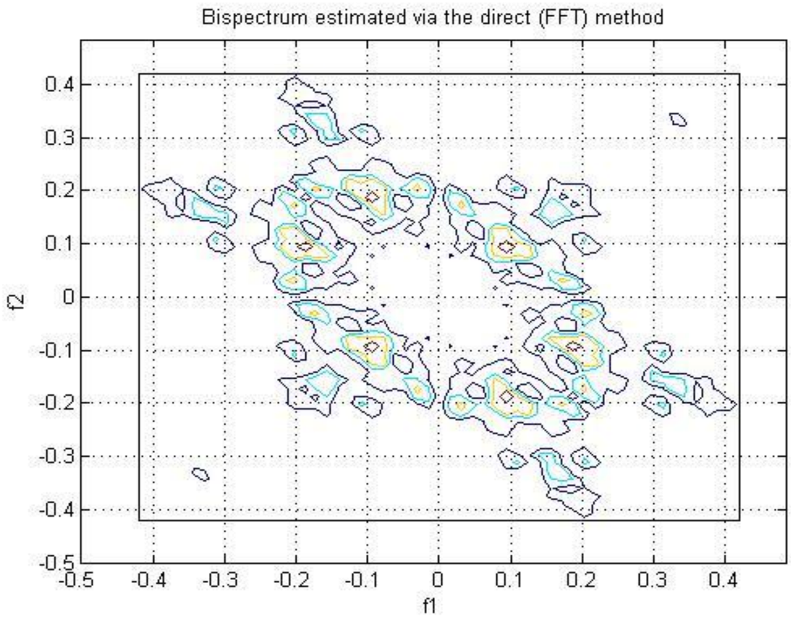

Figure 5

2. The noise of the collected signals in this experiment are mostly Gaussian white noise. The high order statistics of white noise is 0, so the method can effectively suppress white noise.

3. Experiments

The data contains 140 pulse AE signals collected from the anvil of a large-volume cubic, including 100 normal signals and 40 crack signals. Then 50 signals are selected from normal signals and 20 crack signals are chosen from crack signals as the teacher signal of the BP neural network. The rest remains to be recognized. The sampling frequency is 131072Hz and the hidden layer of BP neural network consist of 16 nodes.

3.1 Recognition accuracy of the new feature parameters--experiment 1

In experiment 1, 5 existing feature parameters (amplitude, average energy, spectral centroid, spectral peak, IMF energy entropy) and 2 new feature parameters presented in this paper are calculated. A BP neural network is trained with the teacher samples selected previously, and utilized to classify the test samples. The recognition accuracy with different parameters is shown in Table 1:

Table 1

Feature parameter	accuracy		Feature parameter	accuracy
Amplitude	51.43%		IMF energy entropy	65.71%
Average energy	35.71%		1st-SWV	76%
Spectral centroid	37.14%		4^{th}-ZSSWV	77.86%
Spectral peak	60%			

3.2 The noise immunity of the new parameter--experiment 2

According to experiment 1, the top three parameters, two new parameters and IMF energy entropy, are chosen in this experiment. There are 3 groups of signals, namely the original signal, the addition of the original signal and the 15dB Gaussian white noise and the addition of the original signal and the 20dB Gaussian white noise. The experiment processes are same as experiment 1. The performance of each parameter is displayed in Table 2:

Table 2

accuracy	IMF energy entropy	1^{st}-SWV	4^{th}-ZSSWV
Original signal	65.71%	76%	77.86%
the addition of the original signal and the 15dB Gaussian white noise	60%	74.29%	72.86%
the addition of the original signal and the 20dB Gaussian white noise	37.14%	70%	68.57%

3.3 The accuracy of feature vector consists of the new parameters--experiment 3

At first the feature vector consisting of amplitude, spectral peak, IMF energy entropy is inputted to the BP neural network and do the training and classification. After that, one or several elements in the feature vector are replaced with the new feature parameters, and the same processes are executed. The results of the different feature vectors are presented in Table 3:

Table 3

Elements of vector	accuracy		Elements of vector	accuracy
Spectral peak +amplitude +IMF energy entropy	79.86%		1st-SWV +amplitude +IMF energy entropy	87.14%
Spectral peak +amplitude +1st -SWV	92.86%		4th-ZSSWV +amplitude +IMF energy entropy	85.71%
Spectral peak +amplitude +4th-ZSSWV	90%		1st-SWV +4th-ZSSWV +IMF energy entropy	84.28%
Spectral peak +1st-SWV +IMF energy entropy	85.71%		1st-SWV +4th-ZSSWV +amplitude	82.85%
Spectral peak +4th-ZSSWV +IMF energy entropy	84.28%		1st-SWV +4th-ZSSWV +spectral peak	82.85%

4. Analysis of experimental results

The experiment 1 shows that the new feature parameters proposed in this paper perform better than the existing feature parameters on the accuracy of classification. The first quadrant spread-weight value has a superior result because of the use of the information in the low-frequency range which the forth quadrant zero-setting spread-weight value ignored. And in experiment 2, all of the chosen feature parameters exhibit a decrease of the accuracy of classification when the noise signal is applied. But the decreasing amount of the new feature parameters is much smaller for the reason that the algorithm of bispectrum has the ability to restrain the interferes of white noise. And the excellent anti-white noise property makes it possible that the new feature parameters can be used in recognition of AE signals with white noise interference under different work backgrounds. In experiment 3 , all of the feature vectors that include new parameters outperform the feature vector that exclude the new parameters on accuracy, in which the feature vector with amplitude, frequency peak value and the 1st-SWV value has the best result. But the result becomes poor when the feature vector consists of both of the 1st-SWV value and the 4th-ZSSWV value. The reason is that amplitude, frequency peak value and the 1st-SWV value describe the information of time domain, frequency domain and bispectrum domain respectively and it is the most comprehensive. While 1st-SWV and 4th-ZSSWV both reflect the information of bispectum domain, part of the information is repetitive, which could worsen the result as the experiment shows. This indicates the good compatibility of the new feature parameters with the existing feature parameters as the new ones provide extra information. The feature vector composed of new parameters and proper existing parameters works well on recognizing the AE signals with a high level accuracy.

But shortcomings are also found in our study. 1, The new parameters cannot work with the signals in colored noise due to the deficiency of the algorithm of bispectrum. 2, The experiment results are affected by the performance of BP Neural Network. Although efforts to reduce the impact of BP Neural Network are made through repeated experiments, the influence cannot be fully eliminated. 3, The data processed in the experiments are raw data and according to the conclusion from experiment 2, a proper pre-processing may put up accurately ratio (In our relevant work, the accuracy can increase to 97% with the data pre-processed by spectral subtraction, but this method was not adopted in this paper for the purpose of removing the impact of pre-processing operations.). So these works still need further studies.

5. Conclusion

In this paper, two new feature parameters are put forward aiming at a common kind of sound pulse signals with white noise interference and proved to own great accuracy, anti-noise ability and compatibility. According to the results of experiments, in the situation where the requirement of the accuracy of recognition is not high (the accuracy is blow 75%), the recognition could be achieved with one new parameter proposed in this paper. And compared with the previous work, such as: Yan's research in this field, the accuracy can be greatly improved (The accuracy of recognition is 99.14 % by using the new parameters with the sliding time window method presented by Yan which is much higher than the 95% accuracy.) [1]. The new parameters also reflect advantages in compatibility with existing parameters as the feature vector consists of both shows a better performance.

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