PATTERN RECOGNITION STUDY OF ACOUSTIC EMISSION SIGNALS OF AIRCRAFT FATIGUE CRACKING BASED ON WAVEFORM ANALYSIS AND ARTIFICIAL NEURAL NETWORKS

ZHEN-LONG HU\textsuperscript{1,2}, GONG-TIAN SHEN\textsuperscript{1}, GUAN-HUA WU\textsuperscript{2}, SHI-FENG LIU\textsuperscript{3}, and ZHAN-WEN WU\textsuperscript{1}

\textsuperscript{1} China Special Equipment Inspection and Research Institute, Beijing 100013, China, \textsuperscript{2} Key Lab of Nondestructive Testing, Ministry of Education, Nanchang Hangkong University, Nanchang 330063, China, \textsuperscript{3} Beijing Soundwel Technology Co. Ltd., Beijing 100029, China

Abstract

In this paper, SOM neural network was used to identify the AE signal waveforms of aircraft fatigue test, which produced a group of suspected crack signals. Three peaks of relatively large energy appear simultaneously in frequency spectra. The frequency of peak 3 (168.5 kHz) was consistent with previous result (175.8 kHz), showing characteristics of crack AE signal.

Keywords: Waveform analysis; fatigue crack; WPD; SOM neural network; spectrum analysis

1. Introduction

Use of acoustic emission (AE) technology for the monitoring of aircraft fatigue crack initiation and growth has important practical significance [1-4]. In the past, due to the limited ability of waveform recording and storage of AE instrument, people made the judgment of crack generation dependent on AE parameters analysis [5-7]. However, AE waveforms contain more information than parameters [8-9]. Therefore, a full waveform AE system was used to monitor the aircraft fatigue-crack initiation and propagation with waveform analysis.

Some references point out that the automatic processing of AE signals can be achieved by methods of artificial neural network pattern recognition [10-11]. However, the traditional neural network methods (supervised neural network) need to determine the input vector and output vector. It means that the typical crack signal should be obtained first as an input vector, but this is difficult to achieve due to the interference of noise, which comes from the fatigue test itself. Therefore, in this paper, SOM neural network (Self-Organizing Feature Map, unsupervised neural network) was used to identify the AE waveforms of aircraft fatigue test. A group of suspected crack signals and their characteristics were obtained. Due to the serious interference of noise, which comes from both the aircraft structure itself and the surrounding environment in the process of fatigue test, the filtering process of collected signal is necessary.

2. Test Equipment and the Acquisition of AE Signals

In this study, SEAU2S full waveform AE system, which was provided by Beijing Soundwel Technology Co Ltd., was used to monitor the airfoil AE signals. The sampling frequency is 10 Ms/s. The sensor model is SR150, with 150-kHz resonant frequency, and the arrangement is shown in Fig. 1. Before the start of the fatigue test, the airfoil was inspected by normal NDT methods and no defect was found. Therefore, the collected AE signals in the early stages of test can be defined as noise signal (pure noise). By the same token, in the middle and late stages of the fatigue test, it can be considered that the collected AE signals containing both crack and noise signals, since the crack was found at this time and eventually broken. The extraction of...
these two types of signal has important implications to the accuracy of the SOM algorithm classification results.

Fig. 1 Fatigue test device and sensor arrangement.

3. Wavelet Packet Noise Reduction Processing Method

Due to the existence of large amplitude and broad frequency band noise, individually detecting the weak crack AE signal is difficult. The interference of noise was mainly reflected in the following two aspects:

(1) More noise, low percentage of the useful crack signal, which accounted for the total signal;

(2) In the useful crack AE signals, noise component occupied a very high percentage of the total waveform energy.

Therefore, the selection of the useful crack AE signal from the noise faces the following two problems:

(1) Since the useful crack AE signals appear at low percentage, an approach to consider signals to be crack signals over an entire period is not likely to be realistic.

(2) Even in the useful crack signal, noise occupied greater proportion of energy, which leads to the serious distortion of the original crack signal, and it is difficult to distinguish a crack AE signal from noise subjectively.

Based on previous experiences that although the frequency distribution of noise is broad, but its energy is mainly concentrated at low frequency; although the frequency of crack AE signal is high, but affected by the signal attenuation and the frequency response of the sensor. The high frequency always means serious signal attenuation and waveform distortion. Therefore, the selection the appropriate filter range can reduce the interference of noise on crack AE signals, while increasing the classification accuracy of SOM.

Fig. 2 Wavelet packet noise reduction processing.
According to Wang et al. [12], the center frequency of cracking in a similar test on an aircraft component was around 175 kHz. Therefore, the filtering program of 7-layer wavelet packet decomposition was selected and 117-234 kHz band-pass filtering effect was achieved by the reconstruction of its 4, 5 and 6 layers. As shown in Fig. 2, the use of wavelet packet decomposition and reconstruction reduced the low-frequency part of the original signal (usually large amplitude), making the filtered signal “simpler”.

4. SOM Neural Network Pattern Recognition Methods

SOM neural network is a competitive neural network, proposed by Finnish scholar Kohonen in 1981, and a network structure is shown in Fig. 3. SOM neural network, also known as “Unsupervised” neural network, has obvious differences from commonly used methods, can classify input patterns automatically according to learning rules. It means that, in the case of no expected output vector, SOM can capture the mode characteristics of each input vector through repeated learning, and finally show the classification results in the competition layer. Based on the characteristics that SOM can classify automatically, two AE signals from different periods, one from the initial signal (pure noise, called Set A) and the other from a certain period after a crack was discovered (a mixture of crack and noise, called Set B), are fed to the SOM. Set A and Set B have the following characteristics.

Set A
a) Set A contains noise only;
b) Because of the diversity and uncertainty of noise, the noise signal in Set A may contain signals similar to the crack AE.

Set B
a) Set B certainly contains crack AE signals;
b) Set B also contains noise.

Fig. 3 SOM neural network structure.

Fig. 4 SOM ideal classifications (two categories).
Ideally, SOM algorithm is capable of classifying the signal with similar characteristics automatically when Set A and Set B are randomly mixed and combined. The classification may result in two categories, for example, as shown in Fig. 4. However, due to the lack of such capability, SOM can only classify but not distinguish the crack AE signal. Therefore, additional “criteria” are needed to enhance the classification results and identify the possible crack AE signals:

Criterion 1: If all the signals in a set come from set B, then define it as Set C, which represents a potential set of crack AE signals;
Criterion 2: When all the signals come from Set A, then define it as Set D, which represents a set of noise samples;
Criterion 3: If a large percentage (80%, for example) of the signals in a set come from set B, also regard it as Set C.

5. AE Signals Classification and Characterization

(1) SOM network training and classification
The construction of SOM network was achieved by the function called “newsom”. Among the parameters provided are the numbers of neurons in competitive layer set to \(6 \times 8 = 40\), with the remaining parameters using the default values. 2454 waveform signals were selected randomly as noise (set A) in the initial test, and 4416 waveform signals were selected continuously as the collection of crack and noise (Set B) taken after the detection of a crack. After randomly mixing Set A and B, the mixture was used as the input vector of the network, which was trained for 100 cycles and the classification results are shown in Table 1.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Total amount</th>
<th>From Set A (pure noise)</th>
<th>From Set B (crack + noise)</th>
<th>(B / (A + B))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1*</td>
<td>1344</td>
<td>1</td>
<td>1343</td>
<td>99.92%</td>
</tr>
<tr>
<td>2</td>
<td>581</td>
<td>492</td>
<td>89</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>269</td>
<td>174</td>
<td>95</td>
<td></td>
</tr>
<tr>
<td>4*</td>
<td>1237</td>
<td>9</td>
<td>1228</td>
<td>99.27%</td>
</tr>
<tr>
<td>5*</td>
<td>373</td>
<td>73</td>
<td>300</td>
<td>80.42%</td>
</tr>
<tr>
<td>6</td>
<td>198</td>
<td>44</td>
<td>154</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1086</td>
<td>812</td>
<td>274</td>
<td></td>
</tr>
<tr>
<td>8*</td>
<td>109</td>
<td>1</td>
<td>108</td>
<td>99.08%</td>
</tr>
<tr>
<td>9</td>
<td>227</td>
<td>219</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1181</td>
<td>568</td>
<td>613</td>
<td></td>
</tr>
<tr>
<td>11*</td>
<td>10</td>
<td>0</td>
<td>10</td>
<td>100%</td>
</tr>
<tr>
<td>12</td>
<td>245</td>
<td>51</td>
<td>194</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>10</td>
<td>10</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

From Table 1, it can be found that the categories of 1, 4, 5, 8 and 11 have a high percentage of signals coming from Set B. These could be respectively considered as potential crack AE sets. Subsequently, all the waveforms in categories, especially c1, c4, c5, c8 and c11, were analyzed for their spectra.
(2) Spectrum analysis of the potential crack AE signals
From the spectrum analysis, most of the waveforms do not have obviously features, and their energy is not high and is concentrated in the low-frequency parts (<60kHz), as shown in Fig. 5.

![Fig. 5 A waveform from c1 set with its FFT spectrum.](image1)

![Fig. 6 A waveform from c5 set with its FFT spectrum with three distinct peaks.](image2)

In the potential set of crack AE signals (c1, c4, c5, c8 and c11), only 300 waveforms from c5 sample set showed 3 distinct peaks on the FFT spectrum. Such peaks were absent in the waveforms of the remaining four sample sets. The three peaks in the c5 set appear in the frequency range of 0 - 20 kHz, 20 - 120 kHz, 120 - 240 kHz, and called peak 1, 2 and 3, respectively, as shown in Fig. 6. Further statistical analysis found that these 3 peaks have the following rules.

The 300 waveforms in c5 set come from Set B were judged to have 3 distinct peaks in the spectrum, because the peak energy is much greater than the average band energy. The ratio of the peak energy to average band energy is shown in Fig. 7. The average values of the ratio for each peak are 4.5, 4.6 and 5.3, as indicated in the figure.

Frequency of the three peaks is plotted against sample number for 300 waveforms in c5 set in Fig. 8. The position of the three peaks is relatively fixed, and the mean frequency was, respectively: 13.4 kHz, 46.2 kHz and 168.5 kHz. The frequency of peak 3 (168.5 kHz) was consistent with the previous result (175.8 kHz), and reflects that of the sensor used. It was previously attributed to crack AE signal [12]. Relative peak energies of the three peaks are shown in Fig. 9.
Fig. 7 Ratio of peak energy to average band energy vs. sample number for 300 waveforms in c5 set.

Fig. 8 The distribution of peak frequency for 300 waveforms in c5 set.

Fig. 9 Ratio of peak energy among 3 peaks for 300 waveforms in c5 set.

Fig. 10 A waveform from category of 12 with its FFT spectrum.

These appear simultaneously in a frequency spectrum and it is the obvious difference between these 300 waveforms and others that show no peaks. Therefore, it can be assumed that
these ratios of peak energies are another important basis for the identification of these 300 waveforms. The mean values of the ratios (3/1, 3/2, and 2/1) are 0.26, 0.49 and 0.53 (Fig. 9).

Outside of these five sample sets, the existence of the peak of around 168.5 kHz also can be found on the FFT spectrum in the category of 12 (194 waveforms). All these waveforms are "overflowing" signals as their signal amplitude is greater than 100 dB, exceeding the instrument's maximum dynamic range, as indicated in the Fig. 10.

(3) Possible origins of these frequency peaks

AE signals generated under large cyclic load were often accompanied by noise due to collision and mechanical friction. Therefore, the crack AE signals collected were actually the combination of pure crack signals and noise. They have the characteristics of both crack AE signals and noise, which are likely to be reflected in the frequency spectrum. We can expect both frequency peaks due to cracking and noise.

According to Kaiser Effect, AE signals from the same crack cannot be obtained again until the stress exceeds its highest previous value. That is, the generation of crack AE signals is often accompanied by the larger load. However, larger load usually means larger low-frequency mechanical noise and this is the mainly cause of peak 1 and peak 2 in the spectrum in the two low frequency ranges. In the c5 sample set (300 waveforms), the appearance of peak 3 is always accompanied by peak 1 and peak 2 simultaneously. That may be interpreted as that the large load not only produces crack AE signals of specific frequency (168.5 kHz), but also generate noise, which may be caused by friction. These noise waveforms were easy to identify and concentrated in the low frequency part (13.4 kHz, 46.2 kHz). Thus, the ratio of 3 peaks energy can be considered as an important feature to identify crack AE signals.

Similar to the peak 3 in c5, the peak in the category of 12 may also be generated by cracks. As mentioned earlier, a larger load (large amplitude) usually means larger noise, and the crack signals may be annihilated in the noise, leading to the incorrectly classification results because of the relatively weak contribution of crack characteristics to the entire waveform. Due to the random distribution of large load, the overflow signals may appear at any period during the entire experiment, not only at the time of cracking. That is why the waveforms of category 12 are distributed both in Set A and Set B.

6. Conclusions

(1) Utilizing an SOM neural network with the use of reasonable choice of data sample, and the support of some selection “criteria”, the useful crack AE signals can be extracted from a large number of waveforms. These methods are feasible and confirmed by spectrum analysis.

(2) The classification results of SOM algorithm could be more reliable after applying wavelet packet noise reduction processing method.

(3) Currently, it is unable to meet the requirements of real-time monitoring of crack, since the calculation of SOM algorithm needs post-processing.

(4) The waveform characteristics of fatigue crack signals, such as the frequency, energy and ratios of three peaks, can become an important basis for the identification of crack.

(5) It is very possible that some of the crack signals in Set B (4416 waveforms) may appear outside c5, for example, the category of 12. The main reason is the noise. Therefore, the further study of denoising algorithm is very necessary.
With the progress of the test, if the crack depth analyses can become feasible using waveform characteristics of fatigue crack AE signals, a special AE system would be developed for AE real-time monitoring of aircraft fatigue.

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References