Study on Acoustic Emission Damage Signal Denoising of 2D-C/SiC Composites

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Abstract. In the process of damage test of carbon fiber composites, the acoustic emission signal is affected by the measurement conditions and external environment, which contains a lot of noise problems. A denoising method based on wavelet threshold is proposed. Based on the analysis of the burst signal and continuous signal of carbon fiber composite, the wavelet analysis method is theoretically studied firstly. The selection criterion of wavelet base and the selection of wavelet decomposition layer are discussed theoretically, in order to solve the threshold of wavelet threshold denoising. A high-order non-conductible problem, a soft threshold function is proposed. Finally, the denoising experiments are carried out on the burst signal and the continuous signal respectively. The effects of different basis functions and different decomposition layers on the signal-to-noise ratio are compared. Finally, the optimal wavelet basis functions and the number of decomposition layers are obtained, which makes the denoising effect optimal.

1. Introduction

The carbon fiber composite material will generate acoustic emission signals during the process of stress damage [1]. The analysis and processing of these materials can grasp the evolution law of the damage of the material under external force and provide a judgment index for the damage of the object. Acoustic emission signals can be classified into burst type, continuous type (continuous type) and intermittent type according to the occurrence. Acoustic emission signals are susceptible to various noises in all aspects of measurement and transmission, which directly affects the accuracy of the system and the test results, which also restricts the development of acoustic emission detection technology. Therefore, the acoustic emission signal is denoised, the signal-to-noise ratio of the signal is increased, and the mean square error is reduced, which is necessary for the pre-processing of the acoustic emission signal.

The Fourier transform can be used to process stationary signals with fixed frequencies, so non-stationary random signals cannot be processed; short-time Fourier transforms use windows to process random signals, but they cannot enlarge or reduce the local features of the signals [2]; France, 1974 Engineer J. Morlet proposed wavelet transform. Compared with the short-time Fourier transform, the window function of the wavelet transform is scalable, so the wavelet transform has good time-frequency localization characteristics and adaptive ability. When the spectrum is analyzed by Fourier transform, the sine wave with different frequencies is used to fit the signal, so the fitting ability is poor,
and the wavelet transform uses different basis functions, so the choice is flexible. In this paper, the acquired acoustic emission signal is denoised by wavelet transform.

2. Acoustic emission signal denoising based on wavelet analysis

2.1. Research on Wavelet Denoising Method

The wavelet denoising algorithm can be divided into three types: modulus maxima denoising, threshold denoising and scale correlation denoising. Modulus maxima denoising uses signals and noise to have different propagation characteristics when performing different scale decomposition. When scale decomposition is performed, the corresponding modulus maxima and modulus maxima point average density are increased with the scale. The trend is reduced, and when the signal is decomposed by wavelet scale, the modulus maximum and the average density of the modulus maximum point increase with the increase of the scale. In this way, by multi-scale decomposition of the signal, the information of the modulus maxima at each scale is analyzed, the noise and the signal are distinguished, the modulus maxima corresponding to the noise is removed, and finally the signal is reconstructed to obtain the signal after the noise interference is removed[3].

The noise signal sumsin is taken to denoise using modulus maxima denoising, (soft and hard) threshold denoising and related denoising respectively. The wavelet function uses db4, the number of decomposition layers is 5 layers, and the number of iterations of the reconstructed signal at the modulus maximum is determined to be 20, and the peak signal-to-noise ratio (PSNR), mean square error (MSE), and normalization are selected. The de-noising effect is evaluated by correlation (referred to as NC) and running time (TIME). The effect evaluation parameters of the three denoising methods are shown in Table 1.

Table 1 Comparison table of three wavelet denoising methods

| Wavelet denoising method | PSNR | MSE  | NC  | TIME |
|-------------------------|------|------|-----|------|
| Modulus maxima         | 113.5795 | 0.7592 | 0.6657 | 0.8333 |
| Threshold method (soft) | 116.2908 | 0.5789 | 0.7792 | 0.0499 |
| Threshold method (hard) | 116.4196 | 0.5715 | 0.7814 | 0.0076 |
| Relevance method       | 113.5795 | 0.7592 | 0.6957 | 0.1486 |

In summary, the modulus maxima denoising requires reconstruction of the wavelet coefficients by the modulus maxima, which is computationally intensive and slow, and takes a lot of time, making it difficult to meet real-time requirements. Correlation denoising has a denoising effect and is advantageous for signal edge feature analysis, but there are problems such as large computational complexity and estimation of noise variance. Threshold denoising has wide adaptability. Compared with correlation denoising and modulus maximal denoising, it has small computational complexity and short running time. In this thesis, the wavelet threshold denoising method is used to denoise the acoustic emission signal.

2.2. Wavelet Threshold Denoising

2.2.1. Selection of wavelet basis functions. The wavelet basis functions $\phi(t)$ used in wavelet analysis are not unique and have diversity. Commonly used wavelet bases include Haar wavelet, Daubechies (dbN) wavelet, Gaussian wavelet, Morlet wavelet, Meyer wavelet, and so on. In engineering applications, the selection of the optimal wavelet base is the key, and the same problem will produce different processing results with different wavelet base analysis.

To deal with the signal, first consider the characteristics of the signal. This paper focuses on the damage source location and tensile damage of carbon fiber composites. The acoustic emission signals have different characteristics in the two modes. The positioning experiment is to simulate the acoustic
emission source by breaking lead, and the sensor receives a transient signal. In the tensile test of carbon fiber composites, the carbon fiber undergoes deformation due to tensile stress, interfacial delamination, internal fiber breakage, etc., and its acoustic emission wave is a continuous signal and changes with time.

At present, the wavelet analysis is used to process the signal and the error of the theoretical result as the criterion for judging the quality of the wavelet base, so as to determine the wavelet basis. Therefore, the selection of the wavelet base should be divided into two cases, namely, the selection of the wavelet base in the lead-displacement and the selection of the wavelet base in the tensile test.

2.2.2. Selection of wavelet decomposition layer. In the process of decomposing the signal by wavelet transform, the selection of the number of decomposition layers is a key link. The noisy signal is processed by wavelet transform, and the signal is decomposed into wavelet coefficients at different scales. For a data signal of length N, the maximum number of decomposition layers can be taken to \( \log_2 N \). If the number of decomposition layers is increased by one layer, the data length will be reduced by half, and the corresponding calculation requires an additional calculation and storage space. In addition, when the number of decomposition layers is smaller than the optimal decomposition layer value, the signal-to-noise ratio of the signal increases as the number of decomposition layers increases, but the signal-to-noise ratio of the signal decreases after exceeding the optimal number of layers. Therefore, the number of decomposition layers is not as large as possible, which is not conducive to the amount of calculation and storage, and affects the noise reduction effect [4].

2.2.3. Selection of threshold. In wavelet threshold denoising, the selection of the threshold directly affects the denoising effect. The threshold selection has a general threshold, a grading threshold, a Sure threshold, a GCV threshold, and a Bayes Shrink threshold. The general threshold method is selected herein.

Let \( \omega_{j,k} \) be the wavelet coefficient of \( f(t) \), \( \bar{\omega}_{j,k} \) be the wavelet coefficient after threshold processing, and the modulus of \( \omega \) has different values according to the threshold \( \lambda \). The selection of the threshold includes the selection of the threshold function and the estimation of the threshold \( \lambda \). In the wavelet transform, the soft threshold and hard threshold denoising methods are widely used, and the denoising effect is better.

Hard threshold function:

\[
\bar{\omega}_{j,k} = \begin{cases} 
\omega_{j,k}, & |\omega_{j,k}| \geq \lambda \\
0, & |\omega_{j,k}| < \lambda
\end{cases}
\]  

(1)

Soft threshold function:

\[
\bar{\omega}_{j,k} = \begin{cases} 
\text{sign}(\omega_{j,k})(|\omega_{j,k}| - \lambda), & |\omega_{j,k}| \geq \lambda \\
0, & |\omega_{j,k}| < \lambda
\end{cases}
\]  

(2)

The hard threshold function is not steerable at \( \pm \lambda \), that is, there is a discontinuity point, but in practice, the threshold function needs to be derivation; the hard threshold denoising only processes the wavelet coefficients smaller than the threshold \( \lambda \), and the actual situation is greater than the threshold wavelet coefficient. There is also interference from noise signals. Therefore, only hard threshold denoising is used, and the signal is reconstructed with the wavelet coefficient \( \omega_{j,k} \), and the signal is oscillated.

The soft threshold function overcomes the problem of discontinuous points in the hard threshold denoising process, which is continuous in the wavelet domain, but the derivative of the soft threshold
function is discontinuous, so there are also discontinuous points in the high-order derivative. The soft threshold function is to compress the wavelet coefficients larger than the threshold, and the non-conforming noise components gradually decrease as the wavelet coefficients increase [5].

This paper proposes a multi-section derivable threshold function to overcome the problem that the soft and hard threshold functions are discontinuous and multi-section is not. The threshold function is as shown in equation (3)

\[
\omega_{j,k} = \begin{cases} 
\omega_{j,k} - \frac{\lambda}{1 + e^{-\frac{\lambda}{2}}} & \omega_{j,k} \geq \lambda \\
0 & |\omega_{j,k}| < \lambda \\
\omega_{j,k} + \frac{\lambda}{1 + e^{-\frac{\lambda}{2}}} & \omega_{j,k} \leq -\lambda 
\end{cases} \tag{3}
\]

Where \(a\) is an adjustment factor and its value is any normal number. When \(a \rightarrow +\infty\), then:

\[
\overline{\omega}_{j,k} = \lim_{a \rightarrow +\infty} \left( \omega_{j,k} - \frac{\lambda}{1 + e^{-\frac{\lambda}{2}}} \right) = \omega_{j,k} - \lambda \tag{4}
\]

When \(a \rightarrow 0\), then:

\[
\overline{\omega}_{j,k} = \lim_{a \rightarrow 0} \left( \omega_{j,k} - \frac{\lambda}{1 + e^{-\frac{\lambda}{2}}} \right) = \omega_{j,k} \tag{5}
\]

\[
\lambda = \sigma \sqrt{2 \ln N} \tag{6}
\]

It is known from equations (4) and (5) that by adjusting the value of \(a\), the threshold function of equation (3) has both the characteristics of a hard threshold function and the smoothing characteristic of a soft threshold function. The threshold \(\lambda\) is as in equation (6), where \(\sigma\) is the noise variance and \(N\) is the signal length.

3. Denoising experiment of acoustic emission signal of carbon fiber composite board

3.1. Acoustic emission signal denoising in carbon fiber composite board positioning experiment

Take a 500mm × 500mm × 3mm carbon fiber composite board and arrange the sensor. In the Ø0.5mm HB refill, the lead-breaking experiment was performed at a distance of 30cm from the sensor on the experimental board. The angle between the pencil and the carbon fiber board was 30 degrees. The sampling frequency of the acoustic emission detection system is set to 2 MHz, and the time domain waveform of the detected signal is as shown in Fig. 1.
Wavelet denoising is performed on the acoustic emission signal shown in FIG. 2. The wavelet base selects dbN, where the N values are taken from 1 to 8 respectively; the number of decomposition layers is selected from 3 to 7 layers, and the multi-section threshold function proposed in this paper is selected to compare the normalized correlation (NC) and peak signal ratio of the wavelet base. (PSNR) was used as an evaluation index, and the results are shown in Table 2 and Table 3. The analysis results show that for the acoustic emission signal detected in the carbon fiber composite board positioning experiment, the db5 wavelet base is used to decompose the signal in three layers, which can achieve the ideal noise removal effect.

### Table 2 NC values of db wavelet basis functions under different decomposition layers

| Layer | db1  | db2  | db3  | db4  | db5  | db6  | db7  | db8  |
|-------|------|------|------|------|------|------|------|------|
| 3     | 0.798034 | 0.818247 | 0.830378 | 0.836562 | 0.837546 | 0.83575 | 0.833983 | 0.833902 |
| 4     | 0.457043 | 0.467714 | 0.476406 | 0.4701 | 0.468071 | 0.471871 | 0.46883 | 0.467089 |
| 5     | 0.277099 | 0.26227 | 0.261678 | 0.256852 | 0.256585 | 0.252117 | 0.255104 | 0.250985 |
| 6     | 0.174974 | 0.158482 | 0.151169 | 0.15667 | 0.149728 | 0.151678 | 0.154626 | 0.150081 |
| 7     | 0.11047 | 0.098655 | 0.096274 | 0.097963 | 0.096544 | 0.09564 | 0.096433 | 0.096658 |

### Table 3 PSNR values of db wavelet basis functions under different decomposition layers

| Layer | db1  | db2  | db3  | db4  | db5  | db6  | db7  | db8  |
|-------|------|------|------|------|------|------|------|------|
| 3     | 211.715 | 212.423 | 212.8817 | 213.1275 | 213.1668 | 213.0939 | 213.0237 | 213.0207 |
| 4     | 205.3235 | 205.433 | 205.525 | 205.4579 | 205.4366 | 205.4766 | 205.4464 | 205.4264 |
| 5     | 203.9232 | 203.8855 | 203.8825 | 203.8586 | 203.8573 | 203.8358 | 203.8501 | 203.8303 |
| 6     | 203.5271 | 203.4765 | 203.4556 | 203.4712 | 203.4517 | 203.4571 | 203.4654 | 203.4527 |
| 7     | 203.3586 | 203.3362 | 203.3318 | 203.3348 | 203.3323 | 203.3308 | 203.3322 | 203.3324 |

3.2. Acoustic emission signal denoising in tensile damage test of carbon fiber composite board

The form and size of the experimental test piece are prepared in the form of type II sample in GB/T 1447-2005 "Test method for tensile properties of fiber reinforced plastics". To prevent the sample from being crushed by the tester chuck, a hard aluminum reinforcement sheet was attached to both ends of the test sample. Apply a layer of silicone grease to the surface of the sensor to make it in close contact with the surface of the carbon fiber board to be tested, increasing the ability to receive elastic waves. The preamplifier gain of the acoustic emission detection system is set to 40dB, the signal threshold is 40dB, the sampling frequency is 4MBPS, the sensor frequency range is selected from 40 to 400kHz, and one channel is used to record the entire acoustic emission event. The time domain waveform during the stretching process of the carbon fiber composite panel is shown in Fig. 2.
Wavelet denoising analysis is performed on the tensile damage signal in Fig. 2. The wavelet base $dbN$ is also selected. The $N$ value is 1-8; the decomposition layer is 3-7 layers, and the multi-section guide threshold function is selected. The $dbN$ wavelet basis function is different. The NC value and PSNR value under the decomposition layer are shown in Tables 4 and 5. The analysis results show that for the acoustic emission signal detected in the tensile damage test of carbon fiber composite board, the $db8$ wavelet base is used to decompose the signal in three layers, which can achieve the ideal denoising effect.

| Layer | db1 | db2 | db3 | db4 | db5 | db6 | db7 | db8 |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|
| 3     | 0.893792 | 0.948653 | 0.966002 | 0.974968 | 0.978903 | 0.981839 | 0.984477 | 0.987147 |
| 4     | 0.893211 | 0.948252 | 0.965973 | 0.974541 | 0.978911 | 0.981882 | 0.984333 | 0.987065 |
| 5     | 0.890825 | 0.945771 | 0.962876 | 0.970885 | 0.975045 | 0.978587 | 0.981109 | 0.984362 |
| 6     | 0.885478 | 0.943688 | 0.961988 | 0.970474 | 0.974844 | 0.978474 | 0.981042 | 0.983418 |
| 7     | 0.883588 | 0.943206 | 0.961837 | 0.970422 | 0.974822 | 0.978465 | 0.981038 | 0.983415 |

| Layer | db1 | db2 | db3 | db4 | db5 | db6 | db7 | db8 |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|
| 3     | 123.06 | 129.90 | 133.78 | 136.65 | 138.15 | 139.47 | 140.90 | 142.68 |
| 4     | 122.66 | 129.22 | 132.96 | 135.35 | 136.83 | 137.93 | 138.98 | 140.65 |
| 5     | 122.19 | 128.40 | 131.69 | 133.59 | 134.75 | 135.87 | 136.74 | 137.95 |
| 6     | 121.76 | 128.07 | 131.49 | 133.47 | 134.69 | 135.83 | 136.71 | 137.93 |
| 7     | 121.62 | 127.99 | 131.46 | 133.46 | 134.69 | 135.82 | 136.71 | 137.93 |

4. Conclusion
In this paper, the characteristics of the respective signals are studied for the burst and continuous types of acoustic emission signals of carbon fiber composite plates. A wavelet denoising method based on soft-hard threshold equalization is proposed. For the burst-type acoustic emission signal in the carbon fiber composite material positioning process, the $db5$ wavelet base is used to decompose the signal in three layers, which can achieve the ideal denoising effect. For the continuous acoustic emission signal in the carbon fiber composite material stretching process, $db8$ is adopted. The wavelet base decomposes the signal in three layers, which can achieve the ideal denoising effect.
5. References

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