Acoustic Emission in Composite Materials under Fatigue Tests: Effect of Signal-Denoising Input Parameters on the Hits Detection and Data Clustering

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Abstract. In Acoustic Emission (AE) applications, the processing of continuous signals, which results from high AE rates or superimposition of transients emitted from different emission sources, is a major problem. In complex systems like Organic Matrix Composites (OMC) fatigue tests, a high AE activity is produced due to the emergence of several emission sources. Such a kind of tests involves often a lot of noise that corrupts the original signal. Conventional threshold-based techniques are highly influenced by the noise level leading to erroneous hits detection. A suitable denoising method is thus necessary to process the signal before performing the hits detection and separation. In this work, continuous AE signals obtained from experimental tests carried out on Carbon Fiber Reinforced Plastics specimens were processed. A numerical routine was implemented allowing the treatment of these signals. As the size of each acquisition is large due to the sampling rate (generally from 2 to 5 MS/s), the signal was divided into short segments. The Discrete Wavelet Transform (DWT) was then used for signal denoising. Adjustment of their input parameters is achieved in order to improve the denoising process. Hits determination was thereafter performed in order to localize potential hits contained in each signal segment. By comparing obtained results to a usual threshold-based technique, we remark that the problem of erroneous hits is overcome. The performance of the proposed approach as well as the sensitivity to the denoising parameters were evaluated by studying the impact of errors in hit detection on feature extraction and on damage assessment based on pattern recognition algorithms. The proposed approach leads to a better identification of natural clusters in AEs and improves the interpretation of damage mechanisms.

Introduction

During these recent decades, the use of Acoustic Emission (AE) technique has been increased for the inspection of Organic Matrix Composites (OMC) like Carbon Fiber Reinforced Plastics (CFRP) structures due to its efficiency to detect and localize damages [1]. During fatigue tests, a stress field is generated in the material by soliciting the structure using mechanical, thermal, pressure and chemical stressing. Fatigue failure is the consequence of the repetition of this solicitation, which is commonly encountered in-service. AE is dependent on some basic deformation and damage mechanisms. AE signals can be classified into three types of transients: bursts, continuous and mixed [2]. Bursts are generally short time-signals induced by the emergence of defects according to one or more of the damage modes. Continuous signals consist of multiple overlapping transients emitted from different emission sources among which noise could be found. Mixed transients include both bursts and continuous signals and are generated by both accrued damage (friction of crack surfaces) and damage growth and, in many cases, superimposed with ambient noise and rubbing [3]. This kind of transients is frequently encountered in CFRP composites under fatigue testing during which the specimen can be simultaneously submitted to various solicitations (tension, compression, torsion, and shear) [4]. In addition, the composite inhomogeneity resulting from the difference in material properties of the fibers and matrices will engender anisotropy in the velocity of the propagating waves [5].

In fatigue testing machines, a lot of noise is often generated by hydraulic systems. The temperature of the hydraulic fluid becomes high in fatigue tests because generally they last a long time. In such systems, *fluidborne noise* is created due to uneven flow characteristics and pressure waves that are transmitted through the fluid. Consequently, this results in a vibration also known as *structureborne noise*, which is transmitted through the structure [6]. AE signals received by the distributed sensors are affected by this noise. However, most of the commercial parameter-based AE systems employ the conventional technique based on both threshold and timing parameters for hit detection. A so-called ’Maximum Duration’ of each detected hit is defined in the system configuration in order to stop recording of long signals. When dealing with continuous emission, the threshold is permanently exceeded, so the AE signal is recorded entirely as the burst never drop below this threshold. Thus, the conventional AE technique is not suitable, as it is, when dealing with continuous signals in presence of noise.

One of the powerful methods of signal denoising is Wavelet Transform (WT) [7]. Among the applications of the WT theory is the Wavelet denoise method. The WT has been used in many studies [8] related to the Structural Health Monitoring field dealing with flaw-detection problems. The Wavelet denoise method has shown a good signal-to-noise ratio improvement much better than that obtained through some designed filters, and an important ability in processing signals for detecting multiple fault signatures [9,10]. Particularly, some studies have reported on the AE signal denoising based on the WT. Feng Y. *et al.* [11] have studied the denoising problem of AE signal to detect bearing defect on a rotating machine by using Discrete Wavelet Transform thresholding methods. Satour A. *et al.* [12] have developed a continuous wavelet denoising technique and applied it on AE signals obtained from cross-ply composite specimens.

This work deals with continuous AE in an in-service-like environment. A signal processing method is developed for the purpose of conditioning continuous signals caused mainly by ambient noise encountered in fatigue test machines. The first section gives an overview of the adopted methodology and the used processing techniques. In the second section, the experimental study is addressed, where the proposed method is applied on signals obtained from the tensile test.

1. AE data processing

The proposed method is schematized in Figure 1. It consists in several steps in which the continuous emission signal is post-treated after being recorded continuously. The entire signal is either processed one shot, or it is partitioned into equal time segments. The two possibilities are compared in this work. The second way is adopted when dealing with massive data signals due to a high sampling rate and a long acquisition time. The signal is then denoised using the Wavelet Transform. The choice of appropriate denoising parameters is crucial in order to obtain a high signal-to-noise ratio.

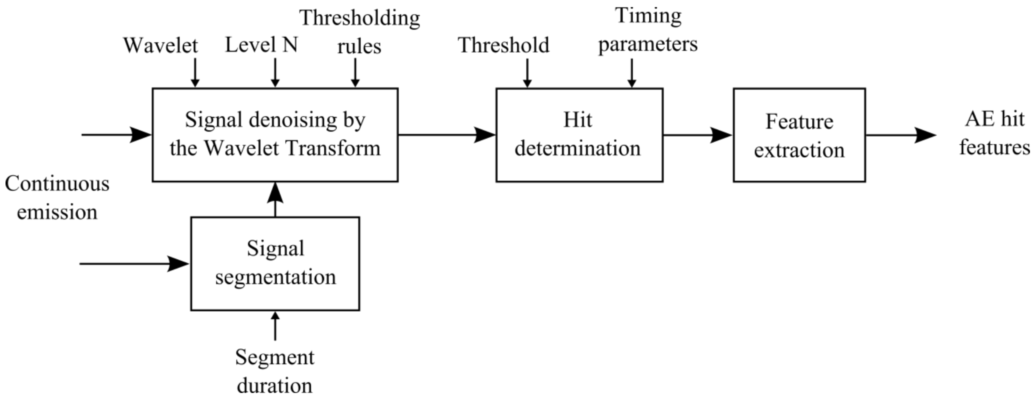


Figure 1. Principle of the AE signal processing method.

The typical procedure of signal denoising using the wavelet theory involves three steps. Firstly, after selecting a wavelet, the signal is decomposed by the wavelet transform at a chosen decomposition level N. Besides, after obtaining the detail coefficients, a thresholding is applied to these signal details for each level from 1 to N. Various threshold selection rules exist (fixed form, Stein's Unbiased Risk Estimate principle...) and either a soft or hard thresholding can be applied to the signal [13]. A basic model of the noise has to be taken into account for the thresholding strategy. Finally, the reconstructed signal is computed using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

Afterwards, the signal or segment is swept in order to determine potential hits. Using the separated hits, AE features are thereafter computed and stored. The hits detection technique used by several parameter-based AE systems involves comparing the signal to a defined threshold. This latter is typically set just above the noise and is maintained fixed during the test, or sometimes floating within a defined interval under conditions of high and varying background noise [14]. If the signal surpasses the threshold, a hit is detected and this instant is retained. After detecting the hit, three timing parameters (PDT, HDT and HLT) are usually used in the conventional method in order to determine the hit, i.e. isolate and separate it from the acquired waveform. Once the hit has been determined, AE hit based features can be calculated. Conventional features include Amplitude, Duration, Energy, Counts, Counts-to-peak and Rise time. Some frequency features exist such as Average Frequency, Frequency Centroid and Peak Frequency [15].

2. Experimental validation

2.1 Test Procedure

In this section, a tensile test with a high loading rate is carried out on an intact CFRP specimen until its total failure under a high ambient noise created by the hydraulic system of the tensile machine. The high loading rate engenders a high AE rate. This configuration simulates in-service-like cyclic loading under severe working conditions and results in complex experimental signals where continuous signals and possible transients could be superimposed.

The test specimen is a 1.5 mm thick composite ring with an outer diameter of 124 mm and a width of about 16 mm. It is mounted on a tensile testing machine using two clamping jaws (two half-cylinders) as illustrated in Figure 2. These two jaws are not in contact during the test, so the wave propagation is guided only by the composite ring. Four wide-band AE sensors (*'Micro80' - Mistras Group Ltd.*) with an operating frequency range of [200–900 kHz] and a resonant frequency of 325 kHz are employed. They are equidistributed and fixed directly on the jaws in this manner: Sensors 1 and 4 are on the upper half-cylinder, whereas sensors 2 and 3 are on the lower half-cylinder. It should be mentioned that the hydraulic system is located at the bottom of the machine and is in direct contact with the lower half-cylinder. Consequently, sensors 2 and 3 are intended to be more affected by the generated noise. Table 1 regroups the major AE system settings.

Table 1. AE system setup parameters

Threshold	Pre-Ampli.	Analog Filter	S. Rate	PDT	HDT	HLT	Max. Dur.
40 dB	20 dB	20 kHz – 1 MHz	2 MS/s	60 µs	120 µs	300 µs	200 µs

Practically, the test consists in applying an increasing tensile force (a ramp function) on the composite ring through the clamping jaws from 0 N to 60 kN with a speed of 15 kN/s until the total failure. Figure 2 illustrates the principle of the test.

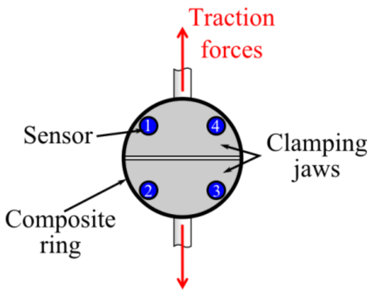
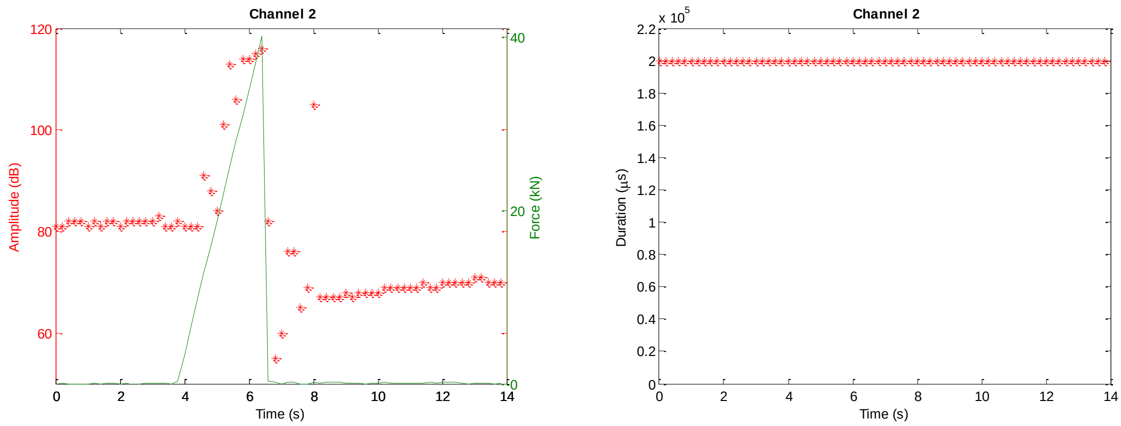


Figure 2. The test configuration.

Signals acquisition is launched just before the beginning of the loading and is stopped just after. The AE software records all the detected events produced and propagated at the surface of the material and determines all eventual hits. Some features of the AE events detected on channel 2 are retrieved from the data acquisition file of the AE system and presented in Figure 3.



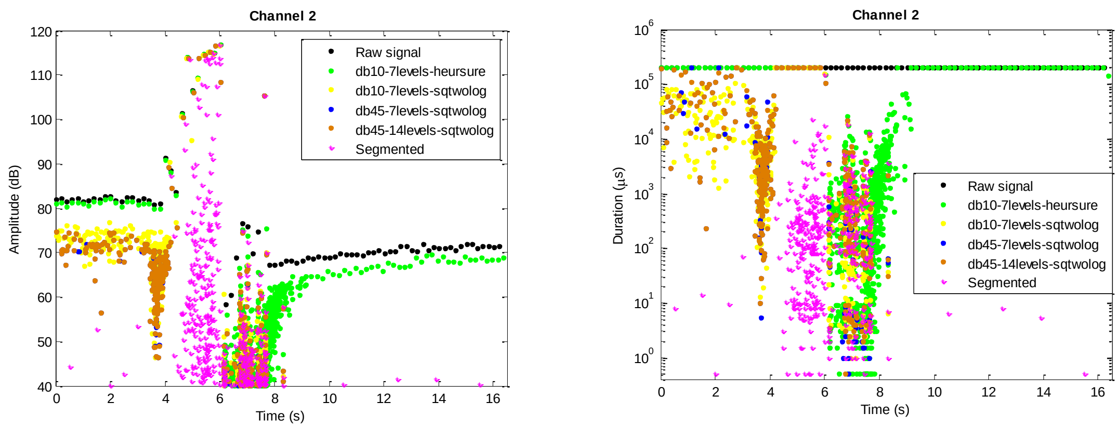
(a) (b)

Figure 3. A selection of features retrieved from the AE data acquisition file of the tensile test for channel 2 over the acquisition time: (a) Amplitude and force; (b) Duration.

Figure 3(a) shows the amplitude of the detected hits and the applied force exerted by the machine on the specimen over time. As we can note, the amplitude increases with force that begins to rise a little before the 4^{th} second; then it falls again when the force tumbles down shortly before the 7^{th} second with the complete failure of the ring. Hits' durations, obtained using the AE software, are also represented as a function of time in Figure 3(b). Durations of all detected hits are equal to the maximum duration. This is a total saturation of the AE system throughout the time. The AE software has considered a number of signal segments with a duration of 200ms as detected hits because the amplitude is stagnated above the threshold during a certain period within the test. These hits can be thus poorly separated. This potentially erroneous hit separation may be caused either by noise or by damage growth and accumulation in the material leading to a high AE activity. This phenomenon is quite significant in channels 2 and 3 as they are more impacted by the generated noise. Increasing the threshold would help to avoid saturations but this might eliminate low amplitude hits.

2.2 Signal Denoising

Using the recorded time signals, AE features are calculated after post-processing by the implemented method and compared to those determined by the AE system. Initially, the implemented method is applied on the entire recorded signals of each channel. The denoising as well as the hit determination and separation are carried out on each signal after loading it one shot. This strategy has the drawback of requiring a lot of computer memory when treating massive data files as the size of each acquisition is large due to the sampling rate, which is generally from 2 to 5 MS/s in this kind of tests. Time signals of the four channels are subjected to denoising using different wavelets and noise estimation rules [13] implemented in Matlab, in order to find a suitable method efficiently applicable to this kind of tests. By using different Daubechies wavelets, decomposition levels and noise estimation rules, the raw signals are denoised and associated hits are determined. After applying the implemented method to the entire raw signals, some features are extracted and compared to those determined by the method of the AE system. A comparison of the denoising results is presented in Figure 4.



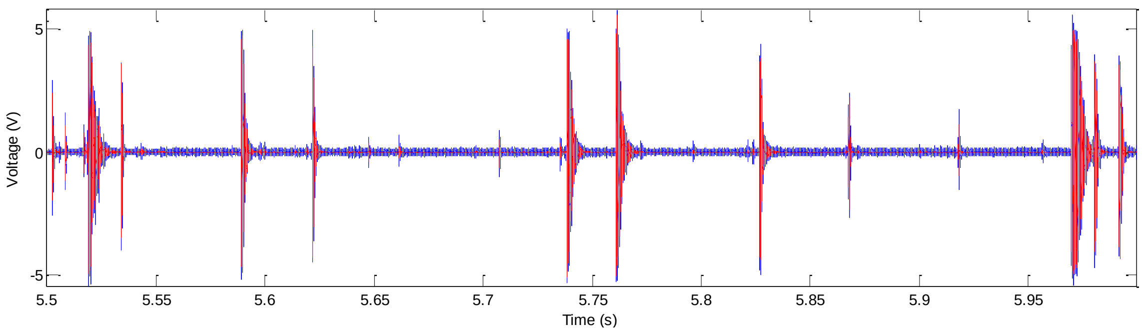
(a) (b)

Figure 4. Hits detected using different denoising input parameters applied on the entire signal of channel 2 compared to hits (∗) detected after segmenting the signal and denoising using 'db45-7levels-sqtwolog'.

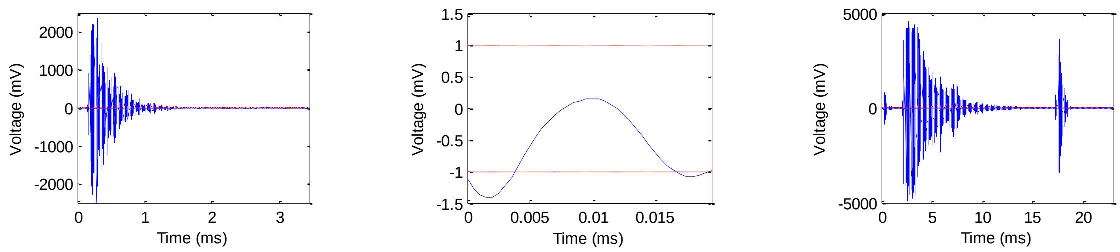
Results show that hits obtained using 'db10-7levels-heursure' (for channel 2) are not well denoised; whereas 'db45-7levels-sqtwolog' is better than 'db10-7levels-sqtwolog' since it eliminates more efficiently noise hits detected before starting the loading of the specimen. While increasing the decomposition level to 14, no better improvement in signal denoising is noticed. Since increasing the decomposition level is time consuming, there is no need to adopt 7 levels. Accordingly, the optimal adjustment of the denoising process is obtained using the Daubechies wavelet 'db45', 7 decomposition levels, a soft thresholding with a selection rule of the universal threshold 'sqtwolog', and considering a non-white noise model. Moreover, although the noise hits are eliminated after the total failure of the ring, the amplitude of those detected before the start of the loading is reduced by about 10dB. From Figure 4(a), the amplitudes of the hits detected during the loading which are associated to various AE evolving sources, are shown to be approximately conserved. That is to say the denoising process did not alter the effective AE information. Besides, in Figure 4(b) information hidden by the effect of noise is now considerably revealed. However, some continuous AE still persists: about twelve hits during the loading have durations equal to 200ms (Max Duration).

2.3 Signal Segmentation

In order to overcome the problem of loading heavy signal files and trying to eliminate completely the hits saturation, signal segmentation is adopted. The signal to be processed is thus divided into short segments with equal durations of 0.5s. This value is chosen so that the number of samples in each segment is easily loaded and handled by the computer routine. Then, each signal segment is successively denoised and eventual hits are determined. This strategy has the advantage of surmounting the limitation of computer memory since the entire signal is now loaded segment by segment and not a single shot. Nevertheless, the first strategy has the advantage of taking less processing time, once the signal is loaded, than partitioning the signal into segments. The obtained results are presented in Figure 4, where the amplitude and duration of the hits detected after segmenting signals are compared to those obtained previously by treating the entire signal. First of all, we can observe an increase in the number of hits during the loading (approximately between the 4th and the 7th seconds). Moreover, the most important ascertainment is that the saturation phenomenon is now eliminated. All the separated hits have durations less than the pre-defined Max Duration. For channel 2, the number of detected hits before the start of the loading is greatly reduced. In fact, by segmenting each signal the denoising procedure is improved. Noise estimation is performed for each signal segment independently of other segments, so that denoising parameters are updated and adjusted for each segment. Otherwise, by loading the entire signal, the wavelet denoising procedure constructs a noise model based on the full length of the signal. This blockwise wavelet denoising is more accurate to cope with highly non-stationary noise.



(a) Raw (-) and denoised (-) signals.



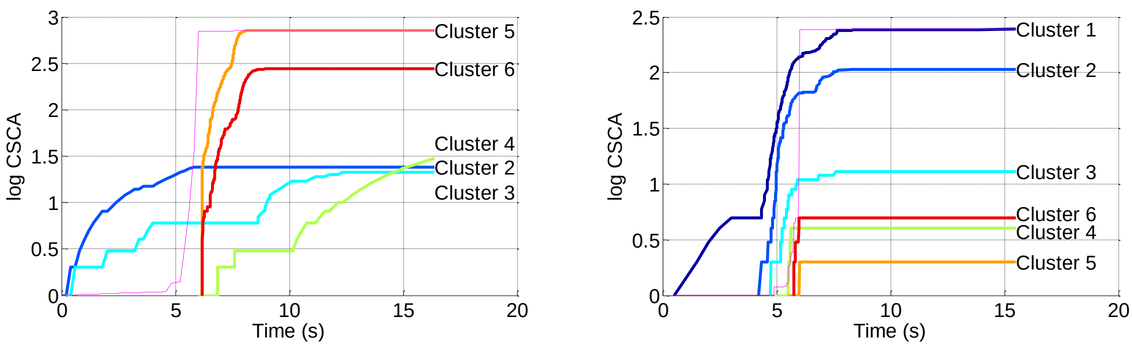
(b) (c) (d)

Figure 5. Example of a signal segment (a), and types of extracted hits (b-d).

Figure 5 shows an example of signal segment where the denoised response is compared to the raw one, as well as three types of hits that can be extracted by the algorithm. Fig. 5(b) represents a typical burst of a natural AE source. However, Fig. 5(c) shows a short transient, and in Fig. 5(d) the hit is relatively long exhibiting more than one waveform packet that may be engendered by the superimposition of multiple AE hits. The hit separation presented in these last figures is not properly performed and may be caused by non-appropriate timing parameters HDT and HLT.

2.4 Data Clustering

AE data obtained after the above-mentioned denoising procedures using the two processing methods, namely one-shot and segment-based, has been analyzed by pattern recognition tools. The Gustafson-Kessel algorithm [16] is used for AE hits clustering using the same parameterization as suggested in [17] by considering 6 natural clusters and the following input features: PAC-Energy, Amplitude, Average Frequency, Reverberation Frequency and Absolute Energy. Figure 6 presents the sequences of clusters based on the two processing methods, where the vertical axis corresponds to the decimal logarithm of the cumulative occurrence of AE hits in a given cluster. These graphs allow locating the time of occurrence of each of the clusters, and following the temporal evolution of their activity. In Fig. 6(a), two clusters (number 2 and 3) appear at the very beginning while the loading has not been applied yet (Fig. 3a). Furthermore, no cluster is correlated with the beginning of loading, but several clusters come later close to the specimen failure while the loading was already stopped. The damage scenario suggested by this sequence seems unlikely. The sequence obtained in Fig. 6(b) is different. A first cluster starts at the same time as the AE acquisition (without loading) which is coherent with the activation of an AE source related to structureborne and fluidborne noises. Cluster 2 starts at the same time as the loading, at low loading level, and is activated all along the test. This cluster is thus associated to the activation of an AE source related to friction between the specimen and the half-cylinders which has been observed after specimen failure. The remaining clusters are likely to be associated to material damage mechanisms as they appear within the specimen loading duration. In CFRP composites, major damage mechanisms are matrix cracking, delamination, debonding, fiber cracking and fiber pull-out [18].



(a) Entire signal denoised with 'db10-7levels-heursure'.
(b) Segmented signal denoised with 'db45-7levels-sqtwolog'

Figure 6. AE sources sequences for two post-processing method. (—) Cumulated Absolute Energy.

4. Conclusion

The problem of continuous acoustic emission in CFRP composites was addressed in this paper. Continuous signals generated by in-service-like environment are post-processed using a developed algorithm. This latter includes denoising of raw signals, hits detection and separation, and feature extraction. The implemented method was tested on AE signals derived from a tensile test on a composite ring under high noise level. A correct parameterization of the wavelet denoising method is shown to be of great interest for improving hit detection in continuous AE signals. Signal segmentation is able to improve results by eliminating hit saturations especially when dealing with non-stationary noise in long time signals recorded during fatigue tests. Also, this signal segmentation is found to be of interest for pattern recognition. An appropriate hit detection algorithm leads to a better identification of natural clusters in acoustic emissions and improves the interpretation of damage mechanisms.

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