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Investigation of damage mechanisms of composite materials : multivariable analysis based on temporal and wavelet features extracted from acoustic emission signals

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The aim of this work is the analysis of damage development and time-to-failure mechanisms within fibre-matrix composite materials using in situ ultrasonic sensors. Thus Acoustic Emission (AE), which represents the generation of transient ultrasonic waves in a material under load, is used to discriminate the different damage mechanisms in composite materials. In this work, unsupervised pattern recognition analyses (fuzzy c-means) associated with a principal component analysis are used for classifying the AE events. A cluster analysis of AE data is achieved and the resulting clusters are correlated to the damage mechanisms of the material under investigation. This method gives accurate results on complex composite materials such as glass fibre/polyester cross-ply composites, sheet molding compound (SMC), concretes... Furthermore, AE signals of heterogeneous materials are not stationary. Thus, time-scale or time-frequency methods (continuous and discrete wavelet transforms) are used to determine new relevant descriptors from AE signals. These new descriptors are introduced in the clustering process to provide a better characterization and discrimination of the different damage mechanisms.

1 Introduction

Glass fiber reinforced polymer composite materials are extensively used in industry. However, their damage and time-to-failure mechanisms still require a better understanding. Acoustic Emission (AE), which represents the generation of transient ultrasonic waves in a material under load, is a useful tool for non destructive testing [1]. It is used in this paper to identify the most critical damage mechanisms occurring in these materials in order to estimate their remaining lifetime in a non-destructive way. One of the main issues is to discriminate the different types of source mechanisms from the detected AE signals which are characterized by multiple relevant descriptors.

Most studies so far have used AE descriptors such as the amplitude and the energy of the signal to characterize the development of damage [2,3]. In order to improve these analyses, it is possible to consider all descriptors with multivariable data analyses [4]. Thus, each AE signal are associated to a pattern composed of multiple descriptors. In the feature space, the patterns can be divided into clusters representative of damage mechanisms according to their similarity by the use of pattern recognition algorithms.

In order to improve the classification for complex composite materials, fuzzy C-means clustering [5] associated with a principal component analysis (PCA) [6] are proposed in this paper. The fuzzy C-means clustering method is an effective unsupervised algorithm for automatic clustering and separation of AE events based on multiple features extracted from the random AE waveforms. The PCA is first used to give an idea of the relevance of the descriptors. If the representation in the projection space shows several clusters with a minimum overlap between them, the features could lead to classify the damage mechanisms. The clustering data obtained with the fuzzy C-means are also visualized in the projection space given by the PCA.

The proposed method, applied on different composite materials such as SMC and cross-ply composites, leads to the identification of the damage mechanisms and their evolution with time till the sample failure.

However AE signals in composite materials mainly result from the energy release of failure modes and are usually not stationary. Thus, waveform processing of AE signals based on time-scale [7] or time-frequency analysis appears as a very promising signal processing technique to discriminate fracture mechanisms. Some previous works have shown that the continuous and discrete wavelet transforms can provide relevant information from AE signals to discriminate the damage types [8,9].

In this paper, we investigate this point and we use two wavelet transforms in order to define new relevant time-scale descriptors to improve the characterization of damage mechanisms. Classification results obtained with time features and then with time-scale descriptors are compared and confirm the improvement of the discrimination.

2 Multivariable data clustering

Multivariable analyses provide a data classification. Similarities are found between data clusters in a multidimensional space with the use of several features. Applied to AE, these methods permit to identify, within multiple parameters, signal clusters with similar features and thus characterizing the same source damages in a material.

The parameters collected from AE waveforms are the components of an input pattern vector. Each component provides information from the AE signals such as the amplitude of the signal, its energy... To make this study as general as possible we used an unsupervised pattern recognition analysis: the fuzzy C-means clustering method (FCM) [4,5]. It uses fuzzy partitioning so that each pattern vector can belong to all clusters with different membership grades between 0 and 1. The input parameter of the algorithm is the number of clusters. Each cluster resulting from the classification corresponds to a different damage mechanism identified in the material. In order to associate each output cluster of the algorithm to the corresponding damage mechanism, the distribution of the amplitude is computed. Indeed, the amplitude of each signal is one of the most relevant time-based descriptor. The distribution of the amplitude of each obtained cluster is compared to other results found in the bibliography relative to characteristics of damage types of composite materials [2,3,8,10]. Thus, we can associate each resulting cluster to the corresponding damage type.

A principal component analysis is applied on the matrix composed of the time-based parameters collected from AE waveforms. The PCA projection shows the distribution of the data. If the data do not overlap, an automatic classification should be possible. Thus, we can deduce the most relevant temporal descriptors to be used in the clustering. The PCA shows that the temporal descriptors can separate the damage mechanisms. In addition, once the automatic classification is realized with the fuzzy C-means clustering method, we use the PCA to visualize the clusters of data into a two-dimension subspace.

The fuzzy C-means clustering method requires the knowledge of damage mechanisms in the materials as each cluster corresponds to a different damage mechanism. This method has been validated on well-known unidirectional fibre composite materials and provides fair results even for more complex materials such as cross-ply composites or SMC [9]. This method enables to identify and monitor in real time several damage mechanisms at the microscopic scale.

3 Wavelet analysis

AE source identification of composite materials is usually based on temporal features of AE waveforms. However, AE signals generated within local displacements inside materials (microcracks, etc) are generally not stationary. That is why wavelet transforms are applied in order to identify the different damage mechanisms as, in addition, the temporal descriptors are not always relevant. The two types of wavelet transforms: continuous and discrete are well adapted to our problem [8,9] and are used to extract quantitative descriptors in order to improve the discrimination of damage mechanisms within composite materials.

The continuous wavelet transform (CWT) of a signal f(t) is defined as follows [7]:

$$CW_f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\psi^*(\frac{t-b}{a})dt, \quad (1)$$

with the scale parameter a, the time translation factor b, the analyzing wavelet ψ and * represents the complex conjugation. The first feature extracted from the CWT is the sum of the square moduli of CWT coefficients defined as [9]:

$$f_1(a, I_b) = \sum_b |CW_f(a,b)|^2, b \in I_b. \quad (2)$$

The second feature is the maximum of the square moduli of CWT coefficients [9]:

$$f_2(a, I_b) = \max|CW_f(a,b)|^2, b \in I_b. \quad (3)$$

f_1 and f_2 are calculated for each scale on a limited time duration I_b. This duration is set from an adaptive threshold which corresponds to a percentage (10%) of the maximum amplitude of the wavelet coefficients. The duration of the AE signal I_b corresponds to the time during which the amplitude of the wavelet coefficients goes beyond the threshold. Then the features corresponding to the most energetic scale are selected as new descriptors.

The discrete wavelet transform (DWT), which enables to decompose each signal on a wavelet basis, is defined as [7]:

$$DWT_f(j,k) = \int_{-\infty}^{+\infty} f(t)\psi^*_{j,k}(t)dt, \psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t-k), \quad (4)$$

with the scale parameter j, the time translation factor k, the analyzing wavelet ψ and the analyzed signal f(t). The DWT decomposes f(t) on a wavelet basis referring to different continuous frequency bands, called wavelet levels [7]. The original signal passes through two complementary filters and two signals are obtained, corresponding to the approximation and detail coefficients. The approximations are the high scale, low frequency components of the signal $\left[0 \;\; \frac{f_e}{2^{j+1}}\right]$. The details are the low scale, high frequency components $\left[\frac{f_e}{2^{j+1}} \;\; \frac{f_e}{2^j}\right]$. f_e denotes the sampling frequency and j is the level of decomposition.

The DWT could also provide new relevant descriptors to add in the clustering analysis. Thus, an another feature is defined: the maximum of the square detail coefficients for each level of decomposition. This new descriptor is defined as follows [9]:

$$f_3(j) = \max_k(DWT_f(j,k)^2), \quad (5)$$

with $DWT_f(j,k)$ detail wavelet coefficients of each level of decomposition j. This descriptor f_3 is calculated for the levels of decomposition with the most significant amplitudes.

4 Results and discussion

4.1 Materials, testing procedure and acoustic emission

The experimental work is carried out on glass fiber reinforced polymer composite materials. Complex composite materials are studied: cross-ply composites. Cross-ply laminates noted $[\pm 90°]_8$ consist of 8 layers of unidirectional reinforcement at ±0° and ±90° to the loading direction. The composite materials samples are in parallelepiped form and have dimensions 21×280×2 mm^3.

An external load applied to the composite materials results in several damage mechanisms occurring at a microscopic scale. Some damage mechanisms are predominant depending on the composite materials and the fibre orientation in comparison with the loading direction. In this study, cross-ply composite materials are damaged with static three-point bending tests. Experiments are performed at room temperature using a servo-hydraulic Instron universal testing machine with a 5 kN capacity. The crosshead speed of the machine is fixed at 0.05 mm/min.

Simultaneously, transient ultrasonic waves generated by damage creation and propagation within the materials were recorded using AE two channel data acquisition system of Euro Physical Acoustics company (EPA). AE is used to discriminate the different damage mechanisms and permits real-time monitoring of damage growth by the analysis of these generated ultrasonic waves. AE measurements are achieved by using two piezoelectric sensors with a frequency range 100kHz - 1MHz, coupled on the faces of the specimens with silicon grease. To eliminate background noise, we included an amplitude threshold of 42dB, where 0dB corresponds to 1µV. The data acquisition system is used to record AE data such as temporal descriptors and waveforms of each AE signal with a sampling rate of 5MHz and 40dB pre-amplification. Several time-based descriptors are calculated by the acquisition system for each AE event (Fig.1): maximum amplitude, energy, duration, rise time, number of peaks whose amplitudes is higher than the given amplitude threshold (called counts), etc. These collected features as well as the new time-scale descriptors are used as input parameters in the proposed classification method.

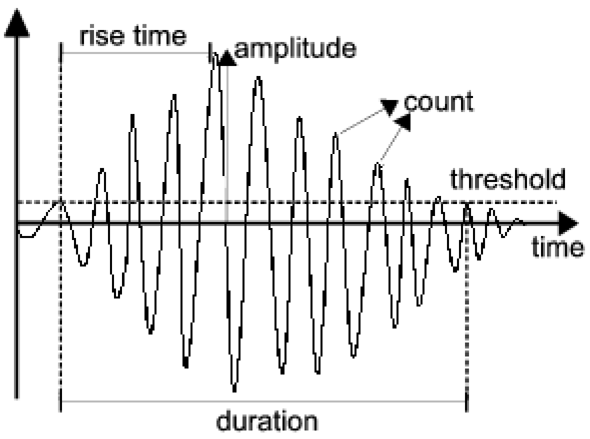

Fig.1 Common waveform descriptors calculated by the AE acquisition system for each AE event.

4.2 Classification results

In this section, we present a comparison between the PCA results for clustering represented in two feature spaces: first with the use of the traditional temporal AE features, then with the use of the new time-scale descriptors. The analysis is applied to random AE events collected from a static three-point bending test on an actual material as the cross-ply composite material. This method was first validated in a previous study on a sample of known AE signals [9].

Two damage mechanisms, matrix cracking (called A signals) and fiber-matrix debonding (B signals), are identified on 729 AE events from a static three-point bending test on a cross-ply composite material. In this experiment, because of the low thickness of the samples no delamination was generated. Figure 2 presents the force applied on the material during the test time and the AE hits collected. Two typical signals representative of matrix cracking and interfacial debonding are represented in figure 3.

Thus, FCM is applied with two clusters corresponding to the two damage types. The traditional temporal AE features are first used to build patterns. Five descriptors are used: energy, amplitude, rise time, counts and duration of the

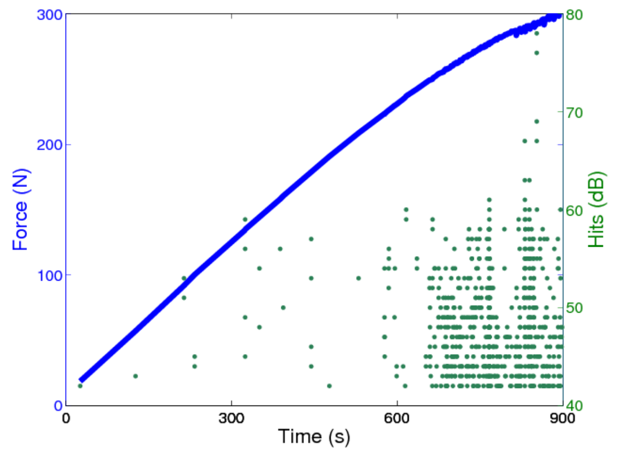

Fig.2 Force and number of AE hits of three-point bending test on a cross-ply composite material.

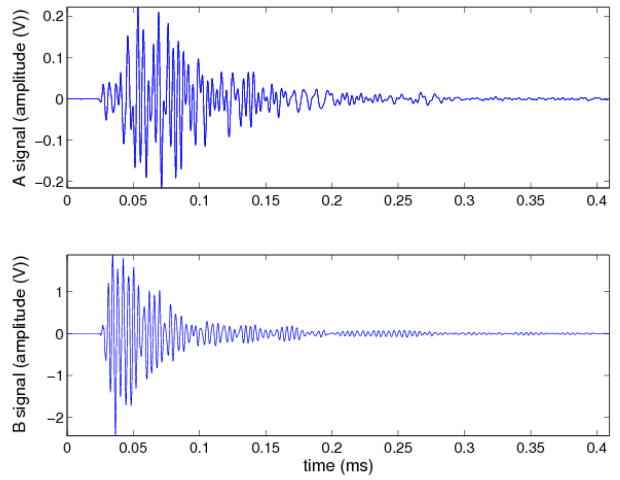

Fig.3 AE typical signals: matrix cracking (A signal) and fiber-matrix debonding (B signal).

signals (Fig.1). A PCA is achieved in order to visualize the results in a two-dimension subspace (Fig.4). The PCA projection shows that two clusters are well identified but some patterns are mixed with each other. Thus, with the temporal descriptors, the separation between the patterns is not effective in this area. In order to improve the clustering, new relevant descriptors defined from wavelet analyses are used to build patterns used for the automatic classification.

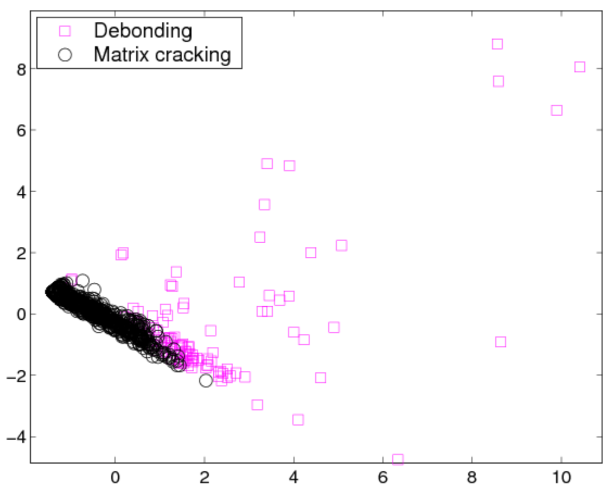

Fig.4 PCA visualization of the fuzzy C-means clustering with temporal descriptors of three-point bending test on a cross-ply composite material (90% information kept).

In what follows, the time-scale descriptors presented above (f_1, f_2, f_3 and I_b) are used for the classification. The PCA results for clustering on the same AE data set are also given in figure 5. The two damage mechanisms are well identified in the material. Indeed, the PCA projection highlights the similarities between the patterns. In addition, there is no overlap between the data with these time-scale descriptors. Thus, the data classificiation and the identification of the different damage mechanisms are improved. The two classifications provided by clustering are different: 2.5% less patterns are classified as B signals (debonding) with the use of temporal descriptors.

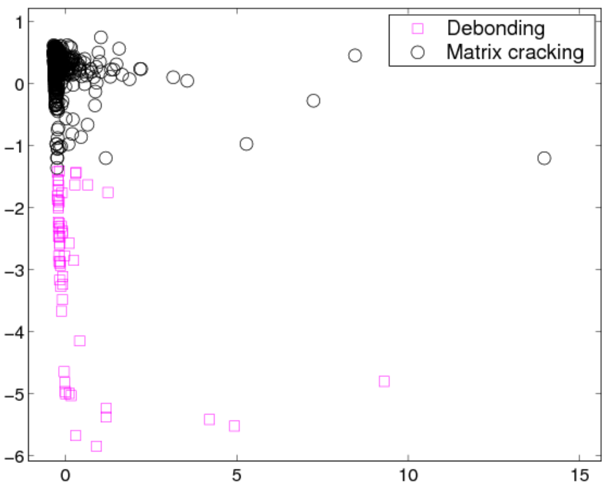

Fig.5 PCA visualization of the fuzzy C-means clustering with time-scale descriptors of three-point bending test on a cross-ply composite material (94% information kept).

The classification also allows us to follow the time dependency of the two damage types in the material (Fig. 6). This visualization shows that the matrix cracking is the most important damage mechanism as it begins from the start of the test and involves much more numerous events. The interfacial debonding appears in the middle of the experiments and their number increases till the final failure of the material.

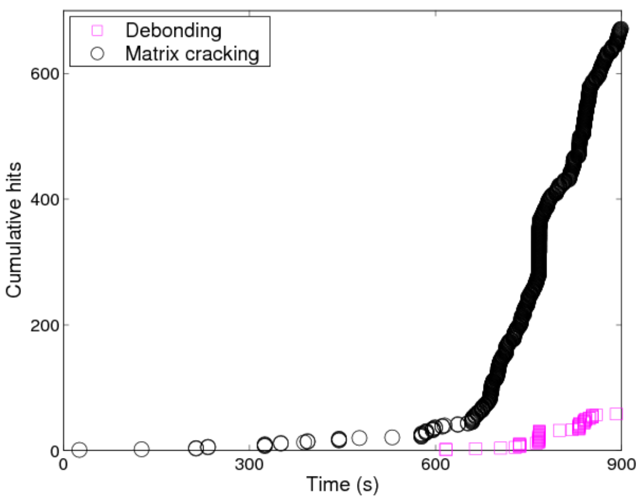

Fig.6 Time dependency of the identified damage of three-point bending test on a cross-ply composite material.

5 Conclusion

Fuzzy C-means clustering method has been coupled with a principal component analysis to discriminate the different damage mechanisms from the AE signals and to visualize the classification into classes. Clustering, applied with the typical temporal descriptors of AE waveforms, permits to identify the different damage mechanisms in complex composite materials such as cross-ply composites. Wavelet analyses applied to transient AE signals permits to define new relevant time-scale descriptors. The use of those new descriptors in the clustering method improves the identification of damage mechanisms of complex composite materials. This method also leads to the time evolution of damage types in these materials till the final failure. Thus, the most critical damage sources in a composite material can be identified. The perspectives of this work are to apply clustering to different complex composite materials in which different damage types can occur when damaged. The identification of damage sources with time could permit to estimate the remaining life time of materials.

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