TOWARDS A BETTER LIFETIME PREDICTION OF COMPOSITE STRUCTURES UNDER IN-SERVICE CONDITIONS: ROBUST AND REAL-TIME PROCESSING OF ACOUSTIC EMISSION TIME-SERIES IN PRESENCE OF DAMAGE ACCUMULATION

Mohamed KHARRAT [1], Emmanuel RAMASSO [2], Dinh Dong DOAN [1,2], Vincent PLACET [1], Lamine BOUBAKAR [1]
[1]Department of Applied Mechanics
[2]Department of Automatic Control and Micro-Mechatronic Systems
FEMTO-ST Institute–UMR CNRS 6174–UFC/ENSMM/UTBM, 25000, Besançon, France
vincent.placet@univ-fcomte.fr

Abstract. Due to the difficulties encountered to predict the long-term behaviour of composite structures in operating conditions, a real-time monitoring of their integrity is required in order to anticipate catastrophic failures. Although the early detection of crack initiation and propagation is beyond the potential of most non-destructive techniques (NDT), acoustic emission (AE) is one of a limited number of methods that possess the capacity for continuously detecting the occurrence of damage in large composite components or structures. Even if promising and successfully exploited in several industrial fields using commercial systems, AE has not provided at this time an effective NDT tool for composite industry, in particular for mobile structures and in-service applications.

For such applications, the main difficulties are related to the real-time processing of a huge amount of complex AE time-series originating from multiple sensors. One major problem is the discrimination of AE signals generated by different damage modes from other external AE sources such as electromagnetic and mechanical noises which are mainly generated by the surrounding environment. Another important problem is the processing of continuous and complex AE signals resulting from high AE rates, from the superimposition of transients emitted by different sources, and from the distortion induced by damage accumulation.

We have developed a method able to objectively discriminate with robustness AE signals generated by a specific damage mode from other AE sources in carbon fibre reinforced composites submitted to complex loading. This method includes wavelet transform-based signal processing and unsupervised multivariate pattern recognition. This latter relies on a new approach based on the fusion of multiple clusterings, also called consensus clustering, leading to a robust assessment of damages together with a quantification of uncertainties. We have demonstrated on real cases that the proposed method is able to efficiently process massive AE data, as encountered in operating conditions, and take into account the distortion of the AE signals as well as the evolution of the clusters shape induced by the wave attenuation and damage accumulation in composite materials submitted to cyclic loading.

Introduction

A widespread application of composite materials in lightweight structures can be noted during these recent decades thanks to their superior fatigue resistance compared to traditional engineering materials (steel, aluminium alloys…). In the aerospace industry, a large variety of components that must withstand extreme cyclic loads for long times (aircraft propellers, wings, helicopter rotor blades, rotating machinery…) are increasingly made of composites. When these components are exposed to fatigue load conditions like stress or thermal cycling, damages such as matrix cracking, fibre tow breakage, debonding or delamination can be initiated and propagate until failure [1].

Structural Health Management (SHM) aims at anticipating failures on mechanical structures and performing maintenance at the right time and place. For that, three important problems are generally faced: 1) instrumentation, 2) data processing and 3) decision-making. Instrumentation is focused on the selection, or development, and location of the appropriate sensors in order to get relevant information about both critical damages, which could occur at various scales within the structure, and about loading and operational conditions, which may have an impact on the material properties. Interactions with the designers and experts in material science are generally necessary to obtain subtle priori knowledge about the behaviour of the structure. The measurements and priori knowledge obtained by instrumenting the structures are then used in a data processing unit. Data processing is the second important problem which allows one to eventually get high level information about the current and future level of damage. For that, specific data mining, pattern recognition or machine learning techniques have to be developed and validated. Those algorithms can also give a hand in the identification of the damage families and their location within the structure. Such information is indeed important for decision-making, in order to select the correct action to perform among a set of alternatives and in presence of many sources of uncertainty, before the occurrence of critical damages or total failure.

The SHM literature is rich. In this paper, we consider Non-Destructive Evaluation (NDE) technologies, in particular Acoustic Emission (AE). AE is an effective NDE technique able to ensure an *in-situ* monitoring of the structure and has been used to detect damages at a very early stage well before the structure fails [2]. Among the pros of the AE technique is the ability to monitor damage initiation and accumulation in real-time, which is not possible with most other NDE techniques [3]. However, the prediction of the remaining lifetime of composite structures is still a challenging issue. A reliable lifetime assessment needs a well understanding of the damage mechanisms and kinetics, as well as an efficient real-time signal processing and data analysis able to discriminate the damage-related AE events from other external sources (electromagnetic and mechanical noises such as rubbing and friction) which are mainly generated by the surrounding environment. Among the major issues for lifetime prediction of composite structures is the processing of continuous and complex AE signals. The complexity induced by high AE rates, various sources with unknown properties and damage accumulation.

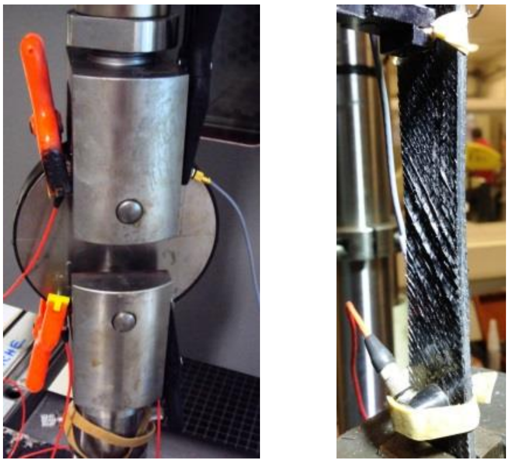
This paper presents a methodology covering the three aforementioned problems and that has been implemented for SHM of various composite materials at FEMTO-ST Institute. Illustrations used subsequently are focused on particular ring-shaped Carbon Fibre Reinforced Polymers (CFRP) optimized to reproduce, at the scale of laboratory specimens, complex stress fields that can be measured in high performance tubular-shaped composite structures submitted to complex solicitations in extreme environmental conditions. The main advantage of the proposed methodology is the possibility to extract with high robustness useful patterns from AE streaming, originating from multiple sensors distributed on the structure. A preliminary screening process based on the discrete wavelet transform allows one to perform efficient wave picking despite high and complex noise level due to the environmental conditions and to the geometry of the structure [4]. The patterns obtained from the sequence of AE waves contain information about the accumulated damages and emphasize avalanches of micro/macro structural changes [5]. Those patterns are accompanied by a quantification of the uncertainty inherent to the parameterization of the algorithms which is useful for decision-making. The second advantage is also the possibility to "learn" the behaviour of the material from AE data obtained during quasi-static tests and to refine and adapt these statistical models during fatigue tests [6].

1. Mechanical Testing and Instrumentation

Several experimental configurations have been used with various specimen geometries, materials, and modes of solicitation. For tubular structures, the ASTM D2290 standard test procedure has been developed for apparent hoop tensile strength of plastic or reinforced plastic pipe by split disk method. We have performed several tests according to this standard on CFRP rings, as shown in Figure 1(a). Specimens were 1.5mm-thick with an outer diameter of 124mm and a width of 16mm, mounted on a tensile testing machine using two clamping jaws. The test consisted in a monotonic tensile loading up to failure on the composite ring starting from 0N to 60kN with a speed of 15kN/s. The test was performed under a relatively high noise level (55dB) created by the hydraulic system of the tensile machine. The high loading rate engendered a high AE rate in order to simulate in-service-like cyclic loading under severe working conditions, and yielding complex AE signals made of continuous emissions and damage-related transients superimposed.

A PCI2-based AE system provided by Mistras Group was used. It is based on the conventional threshold technique for extracting the AE hits. Four wide-band AE sensors of Micro80-type were fixed on the jaws. Each sensor is equipped with a 20dB pre-amplifier. Sampling rates usually encountered ranged from 2 to 5 MS/s. A band-pass filter with a frequency range of [20 kHz - 1 MHz] was configured.

Another configuration has been also used on rectangular specimens, as illustrated in Figure 1(b), to monitor the effect of the damage evolution on the AE waveforms and features. The tested material is a ±45◦ biaxial carbon fibre reinforced epoxy resin. The specimens are 250×25×3.5mm and composed of eight plies stitched with textured polyester yarn. In order to determine the composite material properties, several quasi-static tensile tests were performed on healthy specimens. Other specimens were also subjected to tensile-tensile fatigue tests at different loading levels.



(a) Ring. (b) Beam.

Figure 1. Test configurations on different types of specimens.

2. Data Processing

2.1. Data Screening

Some AE features are retrieved from the data acquisition file of the AE system. Figure 2(a) ("raw") shows the amplitude of the detected hits obtained using the threshold-based technique of the commercial AE system. The loading has taken place approximately between 4th and 7th second before the complete failure of the ring. Durations are represented as a function of time in Figure 2(b) ("raw") and are all equal to the maximum duration predefined in the AE system (200ms) due to a saturation phenomenon explained by the aforementioned continuous emissions. These hits are thus poorly separated. Increasing the threshold would help to avoid saturations, but this might eliminate many damage-related hits. This issue shows the limitation of the threshold-based technique frequently used in the AE applications and the need of an efficient signal processing of the raw AE data.

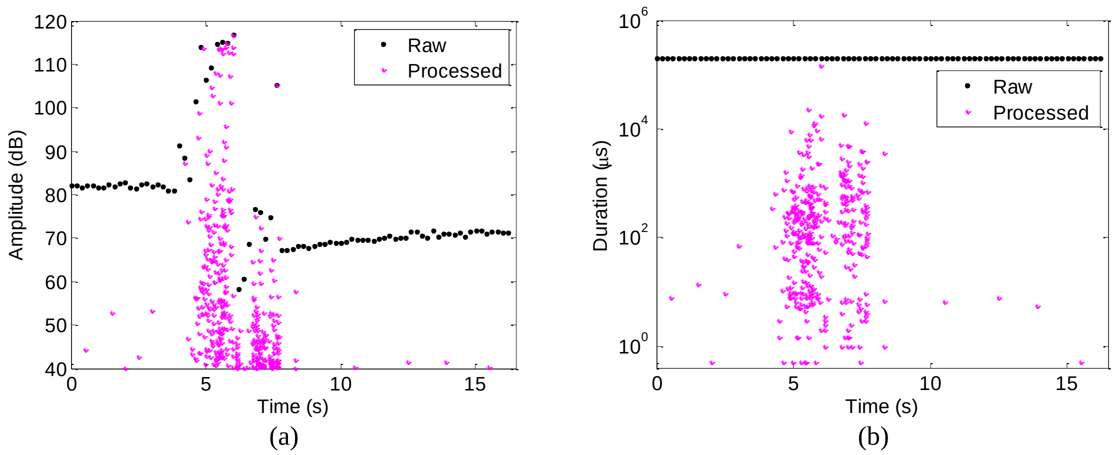
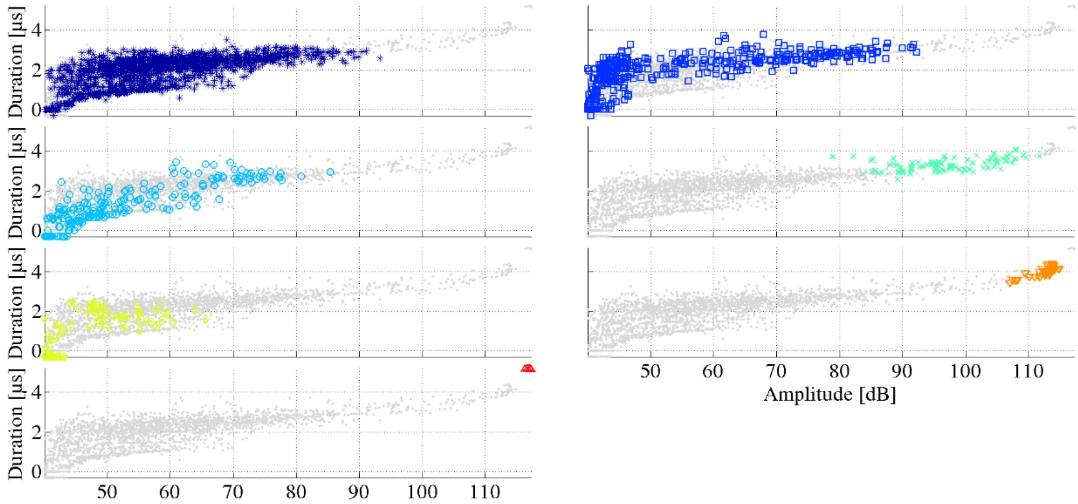


Figure 2. Problem illustration of AE processing using the standard ("raw") and the proposed approach ("processed") for a quasi-static tensile test on a CFRP ring. (a) Amplitude and (b) duration over the acquisition time.

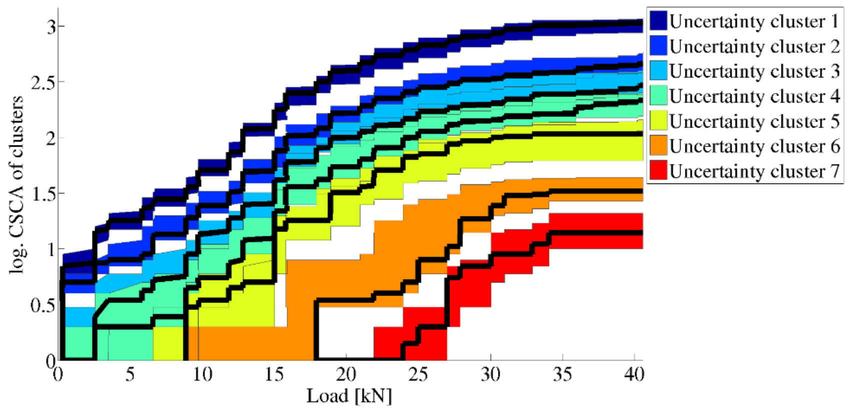
An AE signal processing approach has been proposed where the Discrete Wavelet Transform (DWT) is employed for an efficient denoising [4, 7]. As the choice of appropriate denoising parameters is crucial for obtaining a high signal-to-noise ratio, we have developed a simple and efficient procedure based on pencil lead breaks. Figure 2 ("processed") shows the results obtained by the proposed approach. The most important ascertainment is that the saturation phenomenon is now eliminated (Figure 2(b)). All the separated hits have durations less than the pre-defined maximum duration (200ms). The number of detected hits before the start of the loading is greatly reduced. This method has demonstrated that an appropriate hit detection leads to a reliable identification of natural clusters in AEs and improves the interpretation of damage mechanisms [4].

2.2. Feature Extraction and Selection

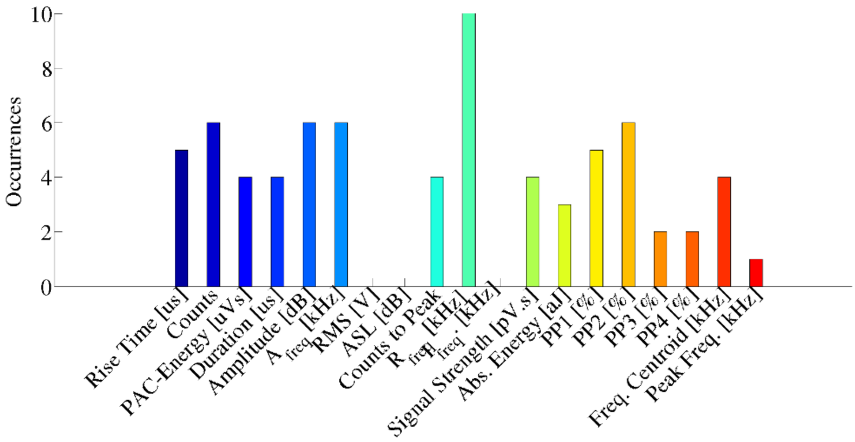
The features aim at representing an AE signal by a finite set of relevant values describing and characterizing the signal in a compact form. Generally, many features are extracted from AE signals and can be regrouped into two main categories: time-based features (such as various forms of the energy like absolute energy, MARSE energy or RMS, amplitude, zero-crossing, duration and so on), and frequency-based features (peak frequency, partial powers, wavelet coefficients and so on). The problem is then to automatically select the most relevant features from this list made of potentially relevant or irrelevant features.



(a) Diagram of the AE hits duration (log scale) [μs] against amplitude [dB].



(b) Diagram of the cumulated damages (clusters) with uncertainty envelops (log scale, called CSCA) against loading [kN]. Solid line: results of the clustering fusion [5].



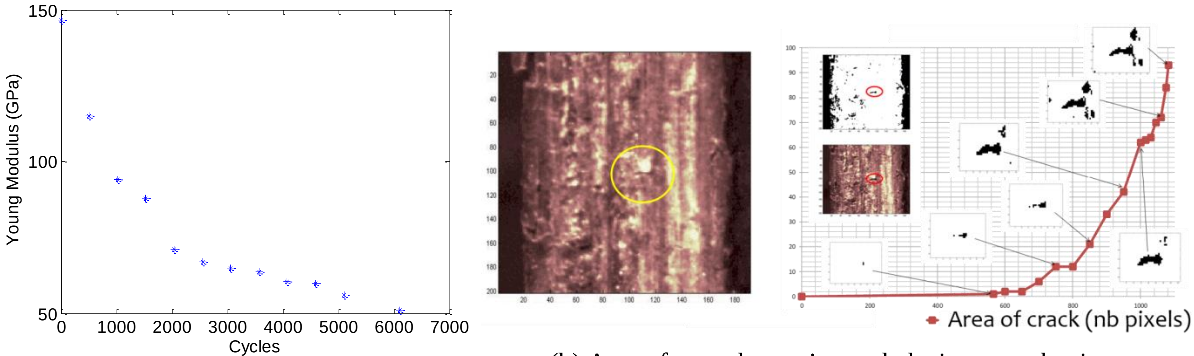
(c) Representativeness of features used in the fusion process (automatically selected using an information-theoretic formulation)

Figure 3. Results of the fusion process proposed in [5] on a CFRP ring.

Standard approaches consist in applying the *principal component analysis* [8] or to apply *wrapping*-based selection [9] or *filtering*-based selection [6]. A new *fusion*-based approach, specifically dedicated to AE signals, has been developed in [5]. It automatically selects multiple subsets of multifarious features which are eventually exploited by an information fusion unit to get a robust decision about the damage families. The number of clusters is also optimized by an information-theoretic criterion. The results of this method on the previously studied ring are shown in Figure 3, which depicts the clusters in the duration-amplitude space (Figure 3(a)) with complex clusters shape, the evolution of the cumulated damages during the test (Figure 3(b)) and the occurrence of features used in the fusion process (Figure 3(c)). The fusion (Figure 3(b)) can allow a designer to quantify the loading thresholds required to activate some damages (onsets) and for their propagation.

2.3. Health Indicator Estimation

A health indicator (HI) aims at quantifying the level of degradation [10] based on observed variables. Practically, several HIs can be computed and combined according to the amount of uncertainty about the health status. For composites, several factors may have an influence on the fatigue endurance and those factors make it difficult the reliable estimation of HIs [11]: Residual stress and initial defects (e.g. due to manufacturing), stress state during cycling (stress amplitude, load sequence), modification of the geometry that may yield stress concentrations (e.g. due to impact or replacement, initiation and propagation of macro-cracks, delamination level) or the variation of the surrounding environment (humidity, temperature). For CFRP, we have considered the remaining stiffness (Figure 4(a)), the S-N curves, the evolving area of cracks over the time computed from optical apparatus (Figure 4(b)) and the temperature released at the surface [12]. The combination of those NDE methods allows getting some information about the fatigue endurance. Using AE signals, the cumulated absolute energy is a common approach to monitor crack onset and growth in composites [13-15].



(a) Stiffness degradation with cycling loading.

(b) Area of a crack opening and closing over the time.

Figure 4. Health indicators built during fatigue tests on CFRP.

2.4. Health Assessment and Diagnostics

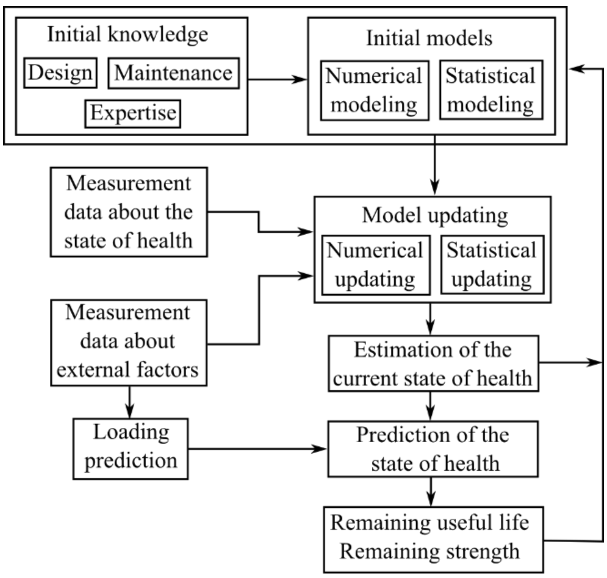
AE features and HIs are then used for health assessment, involving both the estimation of the degradation level and the quantification of the evolution of particular damage families, and diagnostics aiming at finding the cause of damages. When using the AE technique, one challenge is to perform the health assessment in real-time during fatigue testing. In [6] and [16], we have proposed new data-driven approaches able to distinguish between several AE sources (potentially damage families) based on massive AE streaming originating from highly emissive CFRP. To cope with the quantify and the quality of AE signals, the concept of evolving models has been exploited to build and refine two statistical models: one that discriminates between noise and non-noise AE signals, and another that assigns AE sources. Both models are refined with new measurements, meaning that their parameters are adapted along cycles.

3. Towards a Better Lifetime Prediction

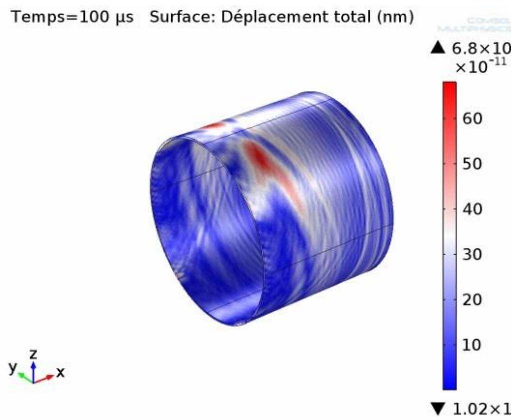
Several bottlenecks have to be unlocked in instrumentation, data processing and decision-making. Below are presented two important problems currently tackled.

3.1. Hybrid Models

Combining material and data sciences for enhanced on board monitoring of structures was underlined more than a decade ago as a key challenge [17] (Figure 5(a)). This is still an open problem called "hybrid" SHM that requires solving problems at both the material and the data mining levels. Our current developments on this area are focused on tubular structures for aerospace and transport applications. Promising results were obtained by combining multiphysics modelling and AE technique (Figure 5(b)). The integration of those algorithms for robust *in-situ* prognostics is under way.



(a) General methodology for SHM, adapted from [17].



(b) Numerical modelling of AE generation and propagation in tubular composite structures.

Figure 5. Hybrid prognostic approach based on numerical and statistical modelling.

3.2. Prognostics

A damaged structure can still ensure its mission, but the evolution of particular properties may lead a decision-maker to reconfigure the structure or perform mission replanning. When reliable health indicators are available on board, mathematical models can be fitted for predicting their future trend. However, due to many external factors and sources of uncertainty, it is practically difficult to apply those approaches in real cases. The AE technique together with efficient data processing would bring useful information about damages for design improvement and robust in-situ prognostics.

Acknowledgment

This work has been carried out in the framework of the Laboratory of Excellence ACTION (program "Investments for the future") managed by the National Agency for Research (references ANR-11-LABX-01-01), and the SMART COMPOSITES Project in the framework of FRI2 supported by "Région Franche-Comté" and "Bpifrance financement".

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