Damage identification in composites through acoustic emission monitoring

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ABSTRACT

In this work, three carbon/glass hybrid composite tubes are instrumented with eight piezoelectric wafer active sensors (PWAS), used as passive receivers of acoustic emission (AE) signals. A three point bending quasi-static loading is conducted, either in a single cycle until failure or incrementally through multiple loading/unloading cycles. In the first instance, AE signal features such as maximum amplitude, peak frequency, signal duration, and energy are used to distinguish between different damage mechanisms such as matrix cracks, delamination, and fibre breakage. The group velocity of the longitudinal modes – L(0,1) and L(0,2) – is obtained experimentally in a pitch-catch configuration between the PWAS network using the time of flight (ToF). The time of arrival (ToA) method is then used to calculate damage source locations from the received AE signals. To involve more signal features for data classification, an unsupervised clustering algorithm is applied to the datasets. Optimisation of the number of clusters is completed by maximising the robustness and minimising the uncertainty of the final result. It is found that the temporal evolution of clusters indicate the ability to distinguish between the initiation and growth of damage, as well as identifying non-damage related signals caused by extraneous noise or related to the test set-up.

Keywords: Composites, normalised mutual information, pattern recognition, piezoelectric sensors, unsupervised clustering

1. INTRODUCTION

Composite materials have become attractive for use in structural applications over recent years, since their properties can be tailored according to needs, but assessment of damage remains a challenge. Periodic non-destructive inspections (NDI) of components can give an insight into their performance but the complexity of these techniques often results in significant down-time and increased labour costs. The cost of inspection in aerospace composites, for example, can represent up to a third of the lifecycle costs [1]. Since composite materials allow for the integration of sensors, with negligible effect on their mechanical properties, permanent structural health monitoring (SHM) systems have sparked a great deal of interest [1]. Piezoelectric transducers are particularly used for their low cost, small size, durability, and low power consumption [2].

In this work, quasi-static three point bending of carbon/glass hybrid composite tubes has been completed. By monitoring acoustic emission (AE) signals during loading, it is possible to estimate damage source locations and speculate about different damage modes [3], [4] via signal analysis. The effort is in distinguishing between matrix cracking, delamination, and fibre breakage. An unsupervised pattern recognition algorithm – an extension of [5] – has been applied to AE data to understand the initiation and progression of damage when the data is separated into clusters.

2. MATERIALS AND METHODS

2.1 Instrumentation of composite tubes

The composite tubes (60.3 mm internal diameter and 1.6 mm thick) presented in this work are a hybrid of unidirectional (UD) carbon fibres oriented in the axial (0°) direction and UD glass fibres in the hoop (90°) direction (supplied by Easy Composites Ltd.). The lay-up order of fibers is [0, 90, 0, 90, 0]. Each specimen was cut to a length of 1 meter prior to instrumentation with sensors.

Three specimens were tested, each instrumented with piezoelectric wafer active sensors (PWAS) [6] supplied by PI ceramic – PIC255 with 10 mm diameter and 0.5 mm thickness [7]. Eight PWAS were surface mounted on each specimen for AE monitoring during loading. On specimen 1, 32 PWAS were also bonded for pitch-catch excitation of guided waves. The arrangement of PWAS is shown in Figure 1.

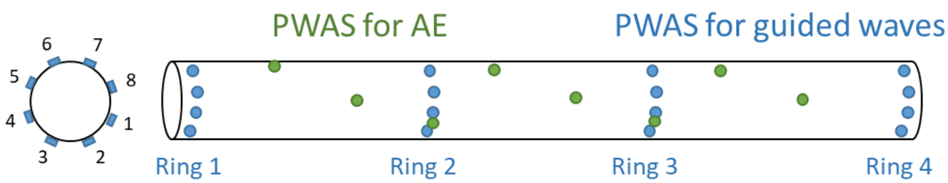

Figure 1. Schematic showing the approximate positions of PWAS used for AE (green) and guided waves (blue) on specimen 3.

2.2 Experimental set-up

The experimental set-up for flexural three point bending is shown in Figure 2. Three specimens were tested in total: specimen 1 was first subjected to a low velocity impact with approximately 5 J (resulting in an axial crack of approximately 7 cm length [8]), followed by three point bending over five cycles of loading/unloading; specimens 2 and 3 were subjected to bending until failure. The low frequency cycling of specimen 1 was introduced to encourage the progression of damage through repeated loading. The load vs. time curves are shown in Figure 3.

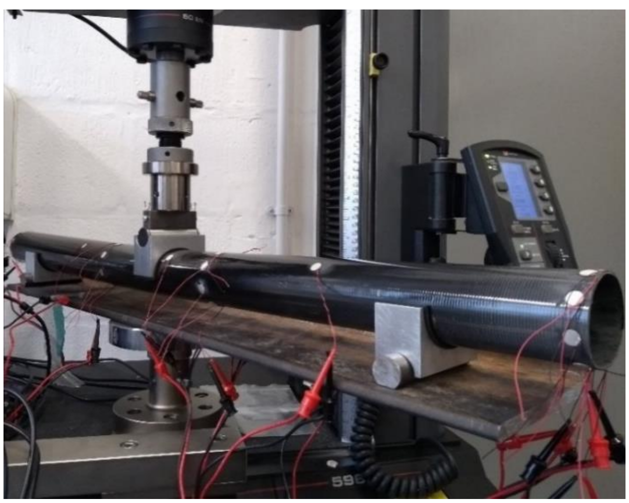

Figure 2. Experimental set-up for three point loading of specimen 1.

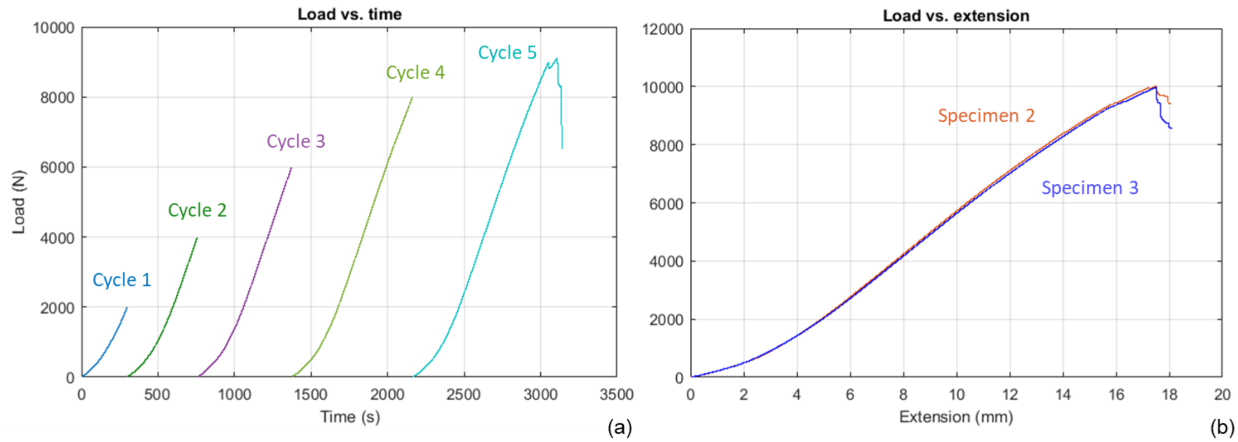

Figure 3. (a) Load vs. time for all cycles on specimen 3; (b) Load vs. extension for specimens 2 and 3.

2.3 AE data acquisition and processing

During loading, AE activity was recorded via eight channels on a PCI-2 based acquisition system supplied by Mistras. Discrete AE waveforms (hits) were recorded using the 'AEwin' software package. The threshold amplitude was set to 55 dB to eliminate sources of extraneous noise, and to account for the 20 dB of pre-amplifier gain per channel. The sampling rate was set at 10 MHz (5 MHz on 2 channels due to hardware limitation) and AE timing parameters set to: peak definition time (PDT) = 200 µs, hit definition time (HDT) = 800 µs, hit lockout time (HLT) = 1 ms, maximum signal duration = 100 ms. Using subsets of 4 from a total of 17 features (as extracted through 'AEwin') per AE hit an unsupervised pattern recognition algorithm (based on the Gustafson-Kessel algorithm [9]) was applied to the full dataset for each specimen. For specimen 1, the five cycles are concatenated in time to form one large dataset. The optimal number of clusters for each dataset is found by maximizing the normalized mutual information criterion (NMI) [10].

3. RESULTS AND DISCUSSION

The time of arrival (ToA) method available within 'AEwin' is used to calculate AE source locations in order to track the growth of damage in the specimens during each loading cycle of specimen 1 (Figure 4). The presence of signals during earlier cycles of loading correlates well with the damage locations observed in the final cycle of loading, suggesting that it may be possible to estimate the failure location before reaching 70% of the breaking strength of the specimen.

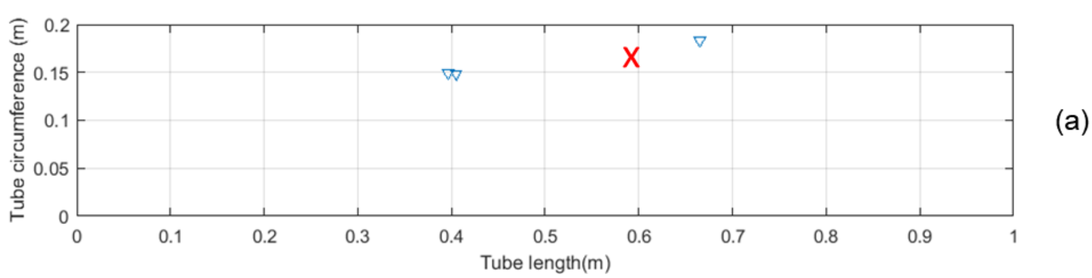

Figure 4 (to be continued). Calculated damage locations during each loading of specimen 1: (a) cycle 1 (blue ∨), (b) cycle 2 (green ∧), (c) cycle 3 (purple >), (d) cycle 4 (lime green <), (e) cycle 5 (turquoise □).

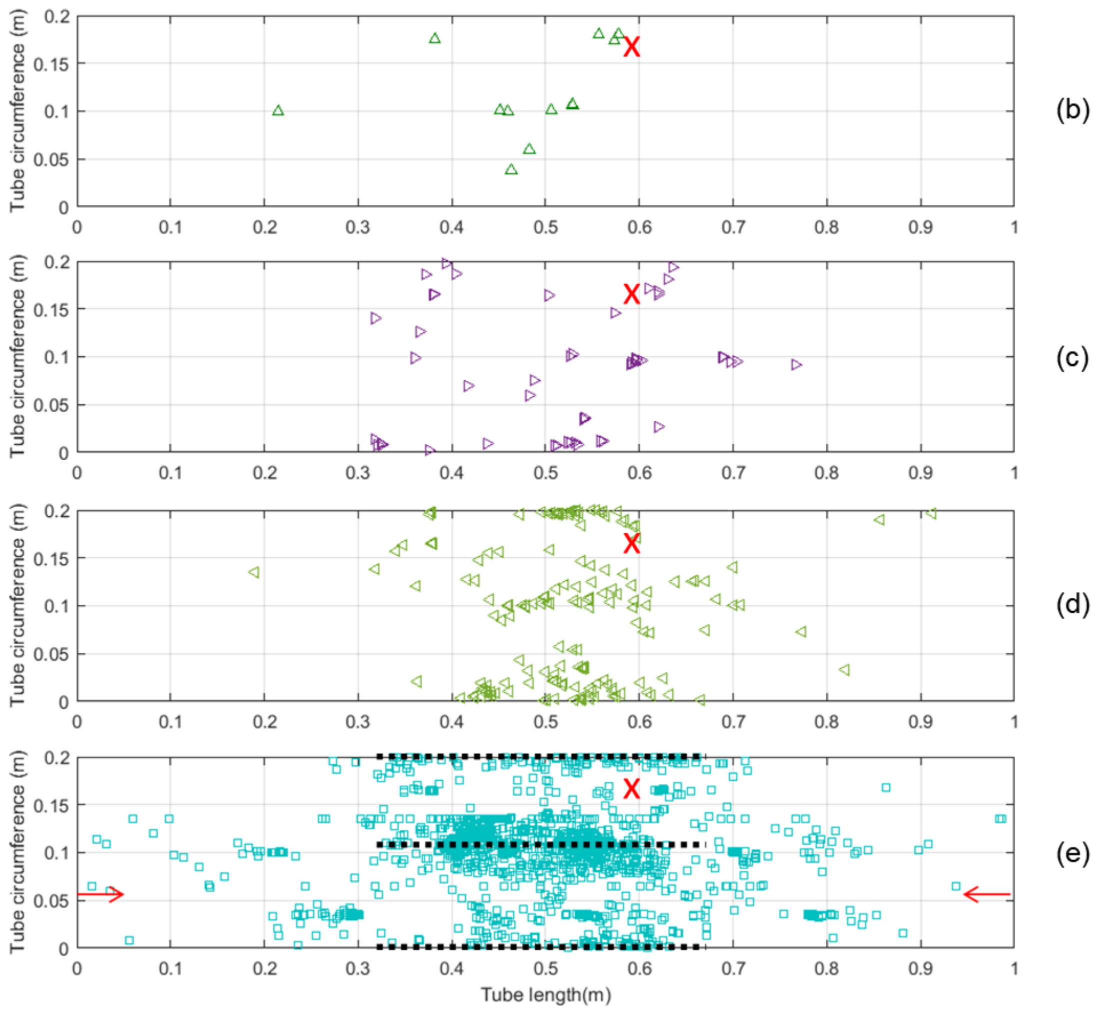

Figure 4. Estimated damage locations during loading of specimen 1: (a) cycle 1 (blue v), (b) cycle 2 (green ^), (c) cycle 3 (purple >), (d) cycle 4 (lime green <), (e) cycle 5 (turquoise □). Dashed lines indicate locations of the through-thickness final failure cracks. Red arrows indicate the top of the specimen.

Application of the unsupervised clustering algorithm on AE hits from specimen 1 results in separation of the data into 9 clusters. The initiation and evolution of signals within each cluster, over the five cycles of loading are shown in Figure 5. A noteworthy observation is that, though the data are separated into these 9 clusters, all clusters do not initiate at the beginning. In the present work, a criterion related to the onset time of different clusters ensures that they are always spread out in time. The reasoning being that damage in composites tends to be decomposed into different phases with cascades during loading. Based on this, it is possible to develop a classification of damage types, for each cluster. It is argued that AE data belonging to cluster 1 are likely to arise due to friction between the specimen and test equipment: this cluster represents the largest group of data points, and data are acquired almost continuously during loading. Similarly, the data in clusters 2 and 3 does not result in a significant change in cumulated energy. AE data belonging to clusters 8 and 9 are more likely related to the final failure of the specimen: an abrupt increase in energy is observed, indicating high energy, catastrophic damage events during these last few seconds of loading. The final failure of the specimen took the form of two longitudinal cracks on either side of the tube – a compression-type failure rather than true bending. This is due to the high proportion of axial fibres greatly enhancing the flexural stiffness of the tube. Clusters 4-7, therefore, likely represent damage signals arising from a combination of mechanisms such as delamination, axial matrix cracking, and breakage of the hoop-oriented glass fibrils and/or fibres.

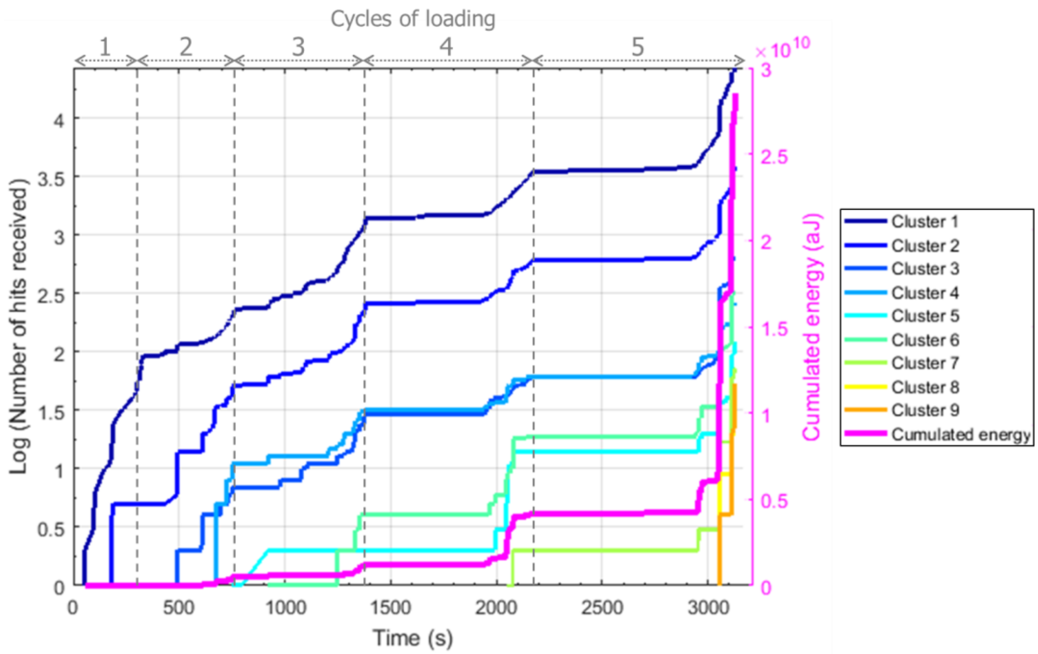

Figure 5. Number of AE hits recorded by all channels, separated into clusters, for specimen 3.

When the clustering algorithm is applied to specimens 2 and 3, both tested in a single cycle until failure, the data is separated into 8 and 15 clusters, respectively. The behaviour of clusters in these two specimens is shown in Figure 6. Although the specimens are assumed to be almost identical, the AE signals recorded during loading can be affected by small variations in: material properties, specimen geometry, sensor placement, sensor bonding, positioning with respect to the machine, and noise in the environment. Number of clusters aside, the most obvious difference when comparing the plots is the behaviour of clusters 2 and 4 on specimen 2. The exponential increase in signals at around 400 s likely result from extraneous noise since the change in cumulated energy is negligible. The envelope of each damage profile provides an assessment of uncertainty related to the final clustering result.

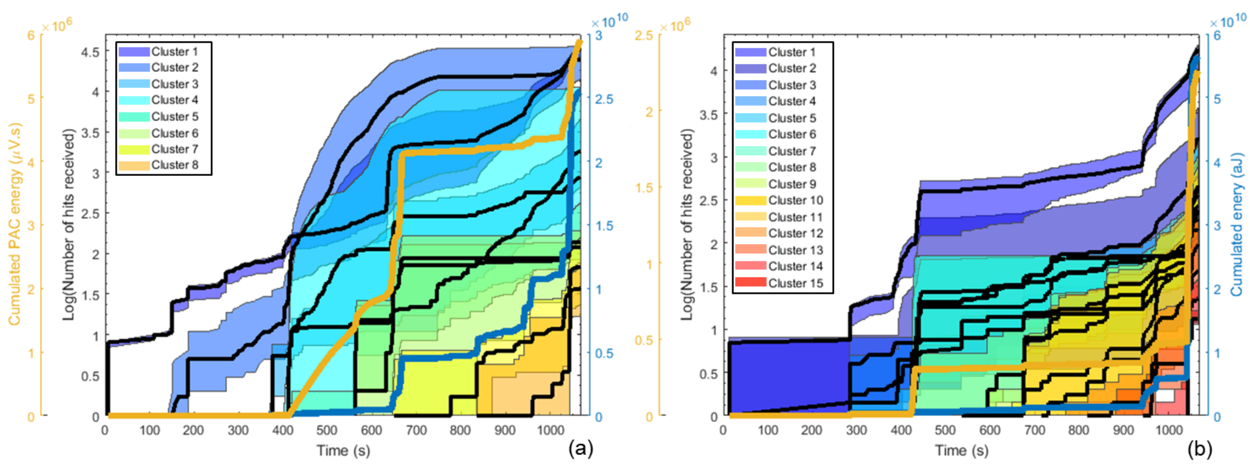

Figure 6. AE hits from all channels separated into clusters for (a) specimen 2 and (b) specimen 3.

4. CONCLUDING REMARKS

In the present work, the potential for the use of acoustic emission is demonstrated as a tool for detecting, localising, and classifying damage mechanisms arising during quasi-static loading. The use of an unsupervised clustering algorithm eliminates any operator bias and reduces the time taken to obtain a final result. Further work is required to develop a means of linking data clusters to individual damage modes in the composite, by means of destructive and non-destructive validation via, for example, x-ray computed tomography. Identifying the location, size and type of damage is of great importance in the effort to estimate residual life and long term performance of the composite tube [11].

5. ACKNOWLEDGEMENTS

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