Damage identification in a tubular composite/metal joint through chronology-based robust clustering of acoustic emissions

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Abstract

The aim of this work is to determine the first failure mode of a tubular composite/metal joint, when tested in tension. PWAS are bonded to both the composite and metal parts of the joint for detection of acoustic emissions (AE) during the tensile test. The generation of AE hits is correlated with strain as measured by surface mounted strain gauges and digital image correlation (DIC) during the test. AE data analysis is completed using an unsupervised clustering approach applied to the AE streaming data in order to identify the damage mechanisms. The approach makes use of the Gustafson-Kessel clustering algorithm to identify the clusters with arbitrary shape in the feature space. In the proposed method, different subsets of features are considered, in place of a unique subset as in standard approaches. Each subset provides one clustering result (a partition). An unsupervised information fusion process is then performed to get a representative partition, taking multiple partitions into account. The approach makes use of bootstrapped ensembles to select the number of clusters which allows to both maximise robustness of the results according to the clustering parameterisation and evaluate the uncertainty on pattern recognition results. Subsets of features are optimised to emphasise the chronology about the onsets of AE sources and their evolution. Application of this pattern recognition chain on the AE streaming provides insights on the damage process involved in composite and metal parts of the joint.

1. Introduction

Damage in structural composites can be complex to analyse due to the inherent anisotropy of the material. It is challenging to detect and monitor early damage, particularly where the damage can be very small. The use of acoustic emission (AE) for damage monitoring is well established. Piezoelectric wafer active sensors (PWAS) can be permanently bonded to or embedded in a composite structure to enable detection and localisation of damage, as it occurs, by AE monitoring. It is possible to distinguish between different damage mechanisms including matrix cracks, interfacial debonding, fibre pull-out, and fibre breakage by analysis of AE signal features. Predicting and quantifying damage in composite materials is complex, so the addition of the metal/composite interface is understandably more challenging.

The aim of this work is to distinguish between different damage mechanisms in the early stages of the occurrence of damage to identify the first failure mode. In particular, we focus on characterisation of matrix damage and slippage in the joint. We record strain data with electrical strain gauges and digital image correlation (DIC), and monitor acoustic emissions (AE) using piezoelectric sensors. Parametric analysis and clustering is completed on AE data to further our understanding on the damage process.

1.1 Use of acoustic emission in composites

A rapid release of energy in a material caused by microstructural damage such as a matrix crack causes a transient elastic wave to be generated; this is known as an acoustic emission (AE). The use of AE monitoring for detection of early damage in composite materials is well established [1] and much of the literature available focuses on identifying different damage mechanisms by their AE "signature" [2–6]. Analysis of AE signals has been done by many researchers by isolating features in the time and frequency domains; amplitude, peak frequency, signal duration, and event energy are among the most commonly used [3–8]. Figure 1 shows some of these signal features in the time domain.

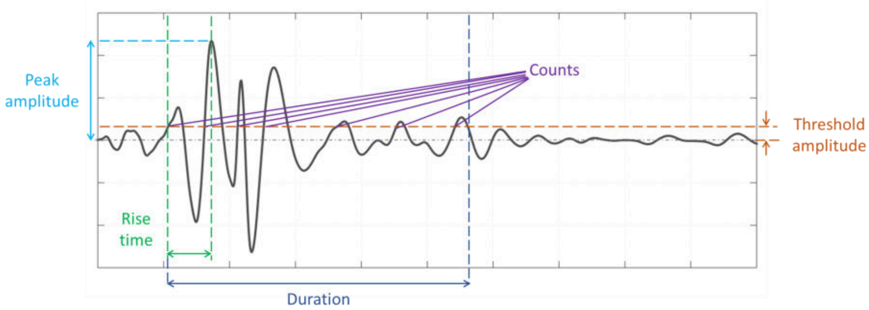


Figure 1. Typical AE signal waveform with labelled features.

Table I shows the general trend observed by researchers for different damage mechanisms in composites. A more detailed compilation of the classification of data points based on their amplitude, frequency, and duration is given in the authors' previous work [7]. It is noteworthy that, although the trend observed by different researchers is similar, it is impossible to compare absolute feature values between specimens. Research has shown that the emission from damaged and undamaged specimens can vary greatly, even when the loading condition is the same [9], so it certainly would not be appropriate to rely on data in the literature if there are differences in the material, specimen geometry, sensor type, sensor coupling, acquisition set-up, environment, etc.

Table I. Trend of selected signal features for damage mechanisms in composites. Summarised from [7].

Damage mechanism	Peak amplitude	Peak frequency	Signal duration
Matrix cracking (intralaminar)	Low to medium	Low	Short to medium
Fibre pull-out	Medium to high	High	Short
Delamination (interlaminar)	High	Medium	Long
Fibre breakage	High	High	Short

1.2 Clustering algorithms

Data mining methods are generally used for analysis of acoustic emission data due to the sheer volume of data points. They can be supervised, unsupervised, or partially supervised, depending on the amount of prior information available for classification of data points. It is arguably most suitable to use unsupervised algorithms based on the fact that acoustic emission data can be affected by many factors relating to the specimen, loading condition, sensors and electromechanical noise in the environment.

Traditional clustering algorithms tend to be reliant on a single set of parameters, or features, to separate AE data sets into clusters [10–13]. Standard algorithms, such as K-means, Fuzzy C-means, Gaussian mixture models, self-organising maps, and Gustafson-Kessel, cannot take into account the time or space element associated with data points which originate from acoustic emission. In other words, if the order of data points was changed in time, each of these algorithms would produce the same clustering result.

Each of these algorithms relies on assumptions about clusters shapes, and few are actually able to cope with the variation of scattering in different features of AE signals [14].

Damage in composites is often sequential: matrix cracking can lead to fracture of fibres, or failure at the matrix/fibre interface which can lead to delamination. In the literature, there is a limited number of papers where the temporal evolution of AE clusters [13–19] is considered. Though some of the proposed methods allow new clusters to be added dynamically based on the characteristic of acoustic emission hits [13,15,18], the challenge remains that AE hits do not arrive regularly in time; they are unevenly spaced. This adds some complexity to the clustering process. One of the primary aims when clustering AE signals is to get information about the evolution of damage; it is therefore common to represent cluster accumulation over time (or cycles). However, the criterion used to optimise the number of clusters, and to select the unique subset of features, is generally based on a cluster's shape, independent of time. It accounts for the fact that, whatever the order of AE signals, the sequence of clusters will be the same. In this paper, the method optimises the parametrisation according to the way clusters occur during each cycle, so accounting for the order of AE signals is significant.

2. Experimental method

2.1 Tensile loading

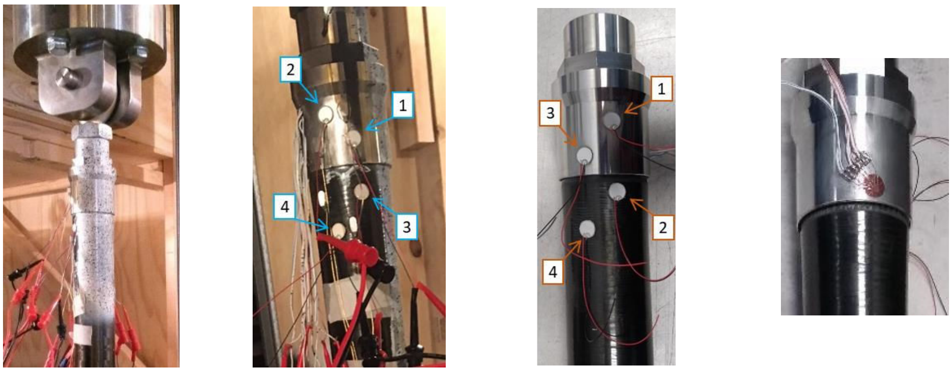
The composite pipe used in this work was manufactured by UTC Aerospace Systems. Three composite/metal joint specimens were tested in a quasi-static tensile loading configuration on an Instron machine equipped with a 600 kN load cell. The tests were performed as described in Table II. The sample was loaded at 0.5 mm/min crosshead speed. The maximum displacement of the crosshead was increased incrementally in successive cycles in order to encourage the progression of damage through multiple loadings.

Table II. Loading information for the composite/metal joint specimens

Specimen	Loading sequence	Breaking load
1	Single cycle to failure	250 kN
2	Single cycle to failure	268 kN
3	Progressive loading cycles to maximum load: (1) 60 kN; (2) 100 kN; (3) 150 kN; (4) 175 kN; (5) 200 kN; (6) To failure	270 kN

2.2 Acoustic emission monitoring

For AE monitoring, piezoelectric wafer active sensors (PWAS) – PIC255 with 10 mm diameter and 0.5 mm thickness – are used [20]. The positioning of PWAS on each of the specimens is shown in Figure 2. Table III describes which data was collected from the sensors on each specimen. AE data was recorded by the software 'AEWin' from Mistras with a sampling rate of 5 or 10 MHz and 20 dB of pre-amplification per sensor. The mismatch of sampling rate is due to a limitation on the acquisition board for recording data streams of 2 channels at 5 MHz per channel.



(a) (b) (c) (d)

Figure 2. Photographs showing: (a) DIC surface of specimen 1; (b) Sensor arrangement on specimen 2; (c) Sensor arrangement on specimen 3 (replicated on bottom joint); (d) Strain gauge positioning on specimen 3.

Table III. Acoustic emission data collected from each specimen

Specimen	Sensors on top joint	Sensors on bottom joint	Joint that failed	Data type recorded
1	Metal: 1, 2 Composite: 3, 4	-	Bottom	Hit data (all sensors)
2	Metal: 1, 2 Composite: 3, 4	-	Top	Hit data (all sensors)
3	Metal: 1, 3 Composite: 2, 4	Metal: 5, 7 Composite: 6, 8	Top	Streaming data (1, 2) Hit data (all sensors)

2.3 Clustering of acoustic emission data

The clustering method proposed here can be broken down into a number of phases, the last of which delivers the final clustering result (Figure 3). Previous work by the authors [14] has shown that use of the Gustafson-Kessel (GK) algorithm in this scheme provides a more accurate clustering result which is robust to parameterisation. The method was able to cope with the feature-sensitivity of different damage mechanisms while capturing the kinetics of damage. Initially, the method in [14] optimised the selection of the number of clusters and of multiple subsets of features according to proportions of clusters. The authors observed that clusters with different onsets generally lead to clusters with different proportions. This heuristic may not always hold true. Here, we go one step further by constraining the occurrence of clusters chronologically, in place of proportions.

3. Results and discussion

3.1 Mechanical test

The load-displacement curves for specimens 1 and 2, and the failure cycle of specimen 3, are shown in Figure 4. In Figure 5 the total number of AE hits received during the tensile tests of specimens 1 and 2, respectively, is plotted against the load. The progressive loading cycles used for testing specimen 3 were identified following mechanical tests on specimens 1 and 2.

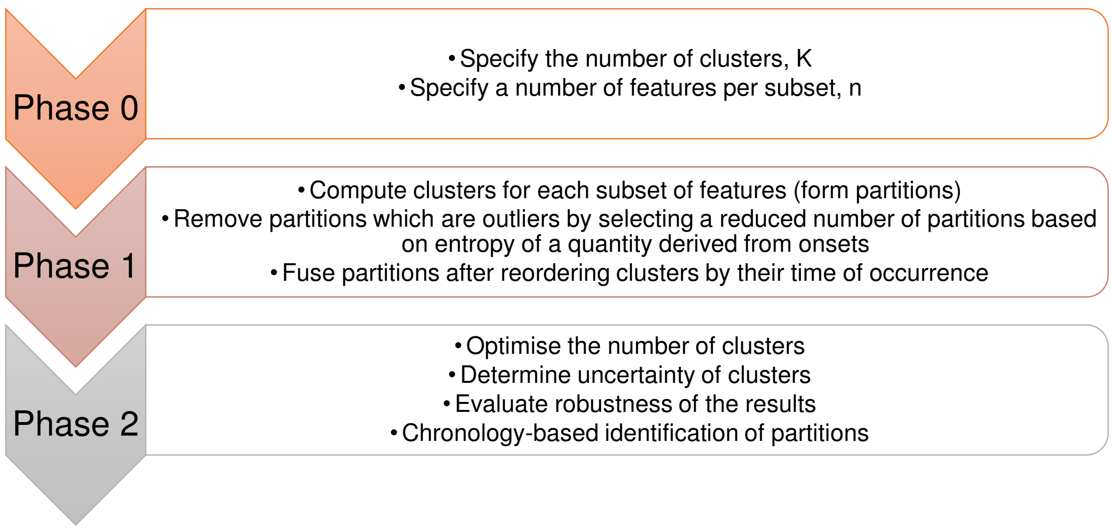


Figure 3. Decomposition of the proposed algorithm into phases.

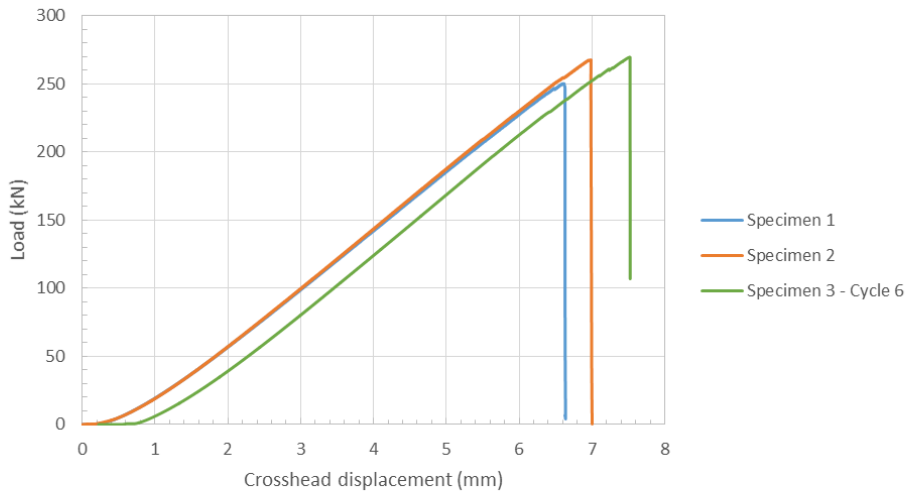


Figure 4. Load-displacement curves for tensile tests on the three specimens.

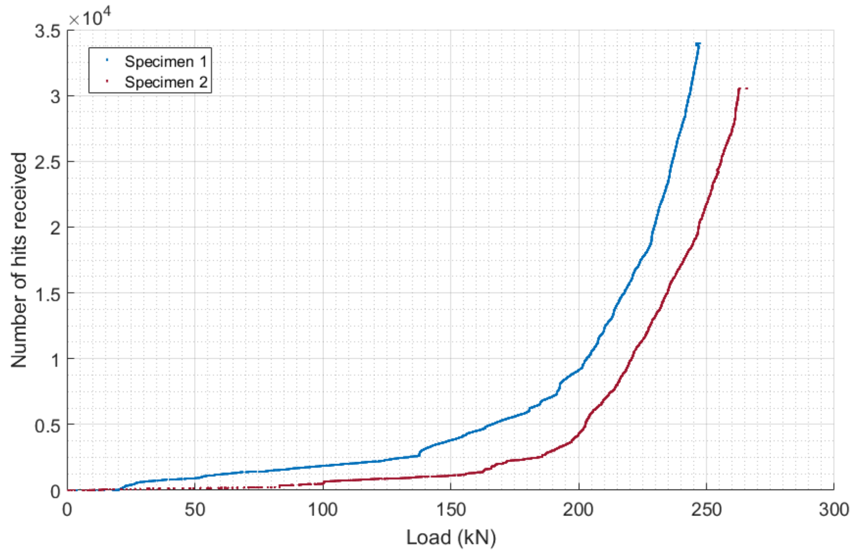


Figure 5. Cumulated acoustic emission hits against load for specimens 1 and 2.

3.2 Clustering of acoustic emission data

The clustering algorithm was run by seaming together the six cycles of loading on specimen 3, as if they had run one after another. In this way, it is possible to identify the load at which clusters initiate, and to analyse the recurrence of signals within a particular cluster, during successive loading cycles. Figure 6 shows the final clustering result obtained after running all phases of the algorithm. The optimal number of clusters was found to be 5 – this was determined by maximising the median values of normalised mutual information (NMI). Though the data has been split into clusters, it is challenging to identify whether a cluster corresponds directly to a damage mode in the specimen. We can say with confidence that cluster 1 is likely not related to damage, since it is activated at the start of the first loading cycle – where no damage is expected to occur – and is active during each of the successive loading cycles, in regions where the cumulated energy of signals does not increase.

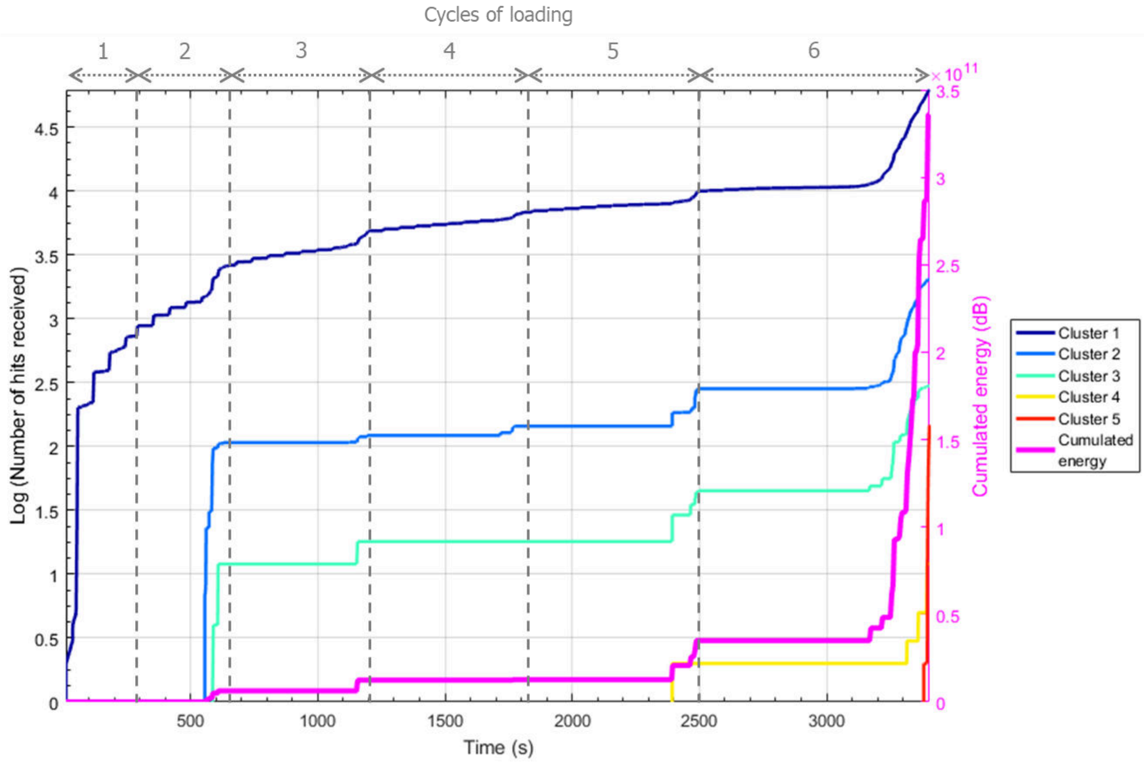


Figure 6. Final clustering partition for all loading cycles of specimen 3: log (number of hits received) curves for each cluster.

4. Concluding remarks

Distinguishing different damage mechanisms in simple composite materials remains a challenge, so a complex structure like the joint studied in this work makes signal interpretation increasingly difficult. It is necessary to consider that signals received by sensors placed on the metal will differ from signals received by sensors placed on the composite; sensors on the metal may record more extraneous noise signals since acoustic waves can travel with lower attenuation over longer durations. Unsupervised clustering algorithms give us the opportunity to analyse data sets from different specimens, made of different materials, without any prior information about the material or about the evolution of damage. Our work has shown that clustering may allow us to separate non-damage-related data points from data which is more likely to be damage-related. In doing so, the size of data to be analysed is reduced. Further work will involve distinction between signals recorded by sensors on the composite and metal, at the top or bottom joint of the specimen, and during individual cycles of loading.

Acknowledgments

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References

1. Hamstad, M.A., "Testing Fiber Composites with Acoustic Emission Monitoring", J. Acoust. Emiss. **1982**, 1, 151–164.
2. Mehan, R.L.; Mullin, J. V, "Analysis of Composite Failure Mechanisms Using Acoustic Emissions", J. Compos. Mater. **1971**, 5, 266–269.
3. Godin, N.; Huguet, S.; Gaertner, R., "Integration of the Kohonen's self-organising map and k-means algorithm for the segmentation of the AE data collected during tensile tests on cross-ply composites", NDT E Int. **2005**, 38, 299–309. doi:10.1016/j.ndteint.2004.09.006.
4. Masmoudi, S.; El Mahi, A.; El Guerjouma, R., "Mechanical behaviour and health monitoring by acoustic emission of sandwich composite integrated by piezoelectric implant", Compos. Part B Eng. **2014**, 67, 76–83. doi:10.1016/j.compositesb.2014.05.032.
5. Masmoudi, S.; El Mahi, A.; Turki, S.; El Guerjouma, R., "Mechanical behavior and health monitoring by Acoustic Emission of unidirectional and cross-ply laminates integrated by piezoelectric implant", Appl. Acoust. **2014**, 86, 118–125. doi:10.1016/j.apacoust.2014.04.011.
6. Gresil, M.; Saleh, M.; Soutis, C., "Transverse crack detection in 3D angle interlock glass fibre composites using acoustic emission", Materials (Basel). **2016**, 9, 699–718.
7. Chandarana, N.; Sanchez, D.M.; Soutis, C.; Gresil, M., "Early damage detection in composites during fabrication and mechanical testing", Materials (Basel). **2017**, 10,. doi:10.3390/ma10070685.
8. Kotsikos, G.; Evans, J.T.; Gibson, A.G.; Hale, J., "Use of acoustic emission to characterize corrosion fatigue damage accumulation in glass fiber reinforced polyester laminates", Polym. Compos. **1999**, 20, 689–696. doi:10.1002/pc.10392.
9. Ono, K., "Acoustic Emission Behavior of Flawed Unidirectional Carbon Fiber-Epoxy Composites", J. Reinf. Plast. Compos. **1988**, 7, 90–105. doi:10.1177/073168448800700106.
10. Sawan, H.A.; Walter, M.E.; Marquette, B., "Unsupervised learning for classification of acoustic emission events from tensile and bending experiments with open-hole carbon fiber composite samples", Compos. Sci. Technol. **2015**, 107, 89–97. doi:10.1016/j.compscitech.2014.12.003.
11. Sause, M.G.R.; Gribov, A.; Unwin, A.R.; Horn, S., "Pattern recognition approach to identify natural clusters of acoustic emission signals", Pattern Recognit. Lett. **2012**, 33, 17–23. doi:10.1016/j.patrec.2011.09.018.
12. Kostopoulos, V.; Loutas, T.; Dassios, K., "Fracture behavior and damage mechanisms identification of SiC/glass ceramic composites using AE monitoring", Compos. Sci. Technol. **2007**, 67, 1740–1746. doi:10.1016/j.compscitech.2005.02.002.
13. Pomponi, E.; Vinogradov, A., "A real-time approach to acoustic emission clustering", Mech. Syst. Signal Process. **2013**, 40, 791–804. doi:10.1016/j.ymssp.2013.03.017.
14. Ramasso, E.; Placet, V.; Boubakar, M.L., "Unsupervised Consensus Clustering of Acoustic Emission Time-Series for Robust Damage Sequence Estimation in Composites", IEEE Trans. Instrum. Meas. **2015**, 64, 3297–3307. doi:10.1109/TIM.2015.2450354.
15. Doan, D.D.; Ramasso, E.; Placet, V.; Zhang, S.; Boubakar, L.; Zerhouni, N., "An unsupervised pattern recognition approach for AE data originating from fatigue tests on polymer-composite materials", Mech. Syst. Signal Process. **2015**, 64–65, 465–478. doi:10.1016/j.ymssp.2015.04.011.
16. Dzenis, Y.A.; Qian, J., "Analysis of microdamage evolution histories in composites", Int. J. Solids Struct. **2001**, 38, 1831–1854. doi:10.1016/S0020-7683(00)00138-4.
17. Silversides, I.; Maslouhi, A.; LaPlante, G., "Acoustic emission monitoring of interlaminar delamination onset in carbon fibre composites", Struct. Heal. Monit. **2013**, 12, 126–140. doi:10.1177/1475921712469994.
18. Placet, V.; Ramasso, E.; Boubakar, L.; Zerhouni, N., "Online segmentation of acoustic emission data streams for detection of damages in composites structures in unconstrained environments", 11th Int. Conf. Struct. Saf. Reliab. **2013**, 1–8.
19. Zhou, W.; Chakraborty, D.; Kovvali, N.; Papandreou-Suppappola, A.; Cochran, D.; Chattopadhyay, A., "Damage Classification for Structural Health Monitoring Using Time-Frequency Feature Extraction and Continuous Hidden Markov Models", 2007 Conf. Rec. Forty-First Asilomar Conf. Signals, Syst. Comput. **2007**, 848–852. doi:10.1109/ACSSC.2007.4487337.
20. PI Ceramic, "Piezoelectric Ceramic Products", **n.d.**,. http://www.piceramic.com/download/PI_Piezoelectric_Ceramic_Products_CAT125E.pdf.