Composites Science and Technology 107 (2015) 89–97

Contents lists available at ScienceDirect

Composites Science and Technology

journal homepage: www.elsevier.com/locate/compscitech

Unsupervised learning for classification of acoustic emission events from tensile and bending experiments with open-hole carbon fiber composite samples

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ARTICLE INFO

Article history:
Received 28 May 2014
Received in revised form 25 November 2014
Accepted 4 December 2014
Available online 11 December 2014

Keywords:
D. Acoustic emission
A. Carbon fibres
Unsupervised learning

ABSTRACT

Widespread use of composites for structural applications is hindered by the inability to fully understand and predict the materials response. The uncertainty in composite materials response is largely due to variability in the initiation and propagation of damage. To develop new tools for design with composite materials, techniques for identifying damage modes during operation are needed. While there is a large body of work on analysis of acoustic emission (AE) from different materials and different loading cases, the current research is focused on applying unsupervised learning for separating AE into a maximum number of groups with distinct evolution. AE data was collected during tensile and bending experiments on carbon fiber reinforced epoxy specimens with different material configurations. The unsupervised learning algorithms successfully identified AE groups with distinct initiation and evolution. With damage mechanisms inferred from load response and from deformation fields obtained with digital image correlation (DIC), strong correlations between the behaviors of the groups and the damage mechanisms were observed and are discussed.

1. Introduction

Composite materials are used extensively in the aerospace industry for their high strength and stiffness to weight ratios and the ability to tailor materials for desired properties. Only relatively recently has the automotive industry become more interested in composite materials for improved fuel economy by light-weighting and improved crash performance by energy absorption. However, unlike metals, fiber-reinforced composites experience many damage types, such as matrix cracking, fiber/matrix pull-out, fiber breakage, and delamination. A major challenge to wide-spread implementation of composites is this wide variety of damage mechanisms associated with composite materials and understanding how those mechanisms initiate and progress. The complicated failure processes in composites precludes the use of current design methodologies.

To develop new and necessary tools for designing with composite materials, it is critical to quantify the damage state at different load levels. Knowing the damage state would allow for an iterative design process and ultimately lead to high fidelity predictive tools. Several methods have been investigated to measure the damage state. For carbon fiber reinforced polymers (CFRPs), these methods can be broadly grouped into the following categories: bulk electrical property sensing, embedded sensing, and surface-based sensing. Electrical methods utilize the fact that initiation and progression of damage cause changes in conduction paths which in turn affects bulk electrical resistance and capacitance [1,2,3]. The most common embedded sensing method is with fiber Bragg gratings (FBGs) which monitor changes in internal strain [4]. In addition, FBGs can sense vibration resulting from damage events [5]. Surface sensing techniques typically require interpretation of either surface deformation or vibration. Surface deformation can indicate localized stiffness reduction and, hence, damage [6]. Surface vibrations can be measured in the form of acoustic emission (AE), which are stress waves resulting from rapid release of strain energy. These waves can be sensed at specimen surfaces with piezoelectric sensors and relevant data acquisition and interpretation apparatus [7].

AE from material damage in composites is relatively easy to monitor and record. However, efficient and effective analysis is still challenging. Efforts have been made to predict failure load based on AE. For example, to predict the final failure load based on AE from loading a sample to about half its expected failure load,

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http://dx.doi.org/10.1016/j.compscitech.2014.12.003
0266-3538/

Sasikumar did supervised learning with an artificial neural network [8]. Others used AE to estimate the location of damage in relatively large structures. Locating damage can be challenging due to the existence of multiple wave modes which propagate with different velocities [9]. The directional effects on the properties of acoustic waves travelling in anisotropic materials also adds to the location estimation challenges.

A different class of AE analyses aims to find the acoustic signature of damage mechanisms. This type of AE analysis involves separating AE signals into groups that represent different damage mechanisms. This process is called clustering. Clustering involves three components. The first is choosing the signal features to base clustering on. The second is identifying the right number of clusters. The third is the technique with which clustering is achieved. These three topics are discussed next.

Different aspects of the AE signals can be used for clustering. Clustering can be based on temporal AE signals. As shown in Fig. 1, relevant temporal features include signal amplitude, duration, energy, and rise time. But AE signals generated by damage (microcracks, debonding, etc.) are generally not stationary [10]. Therefore, clustering is also often based on other signal features, which are extracted from the signal's frequency domain [10]. Such features include the frequency at maximum amplitude and the frequency at center of area under frequency response curve. Frequency domain features are obtained from fast Fourier transform or a more general wavelet transform. Wavelet analysis involves breaking down the signal into a series of orthogonal basis functions of finite length called wavelets instead of breaking it down into harmonic functions [11]. Extra indices can be calculated from combinations of the previous temporal and frequency domain features. These extra indices include average frequency and slope, which is the ratio of amplitude to rise time. Besides focusing on pure AE features, functions combining AE signal features and mechanical information have been used to understand damage progression. For instance, Bakhtiary used the logarithm of the ratio between strain energy and acoustic energy to identify the onset of delamination and its progression in glass fiber/epoxy composite material [12].

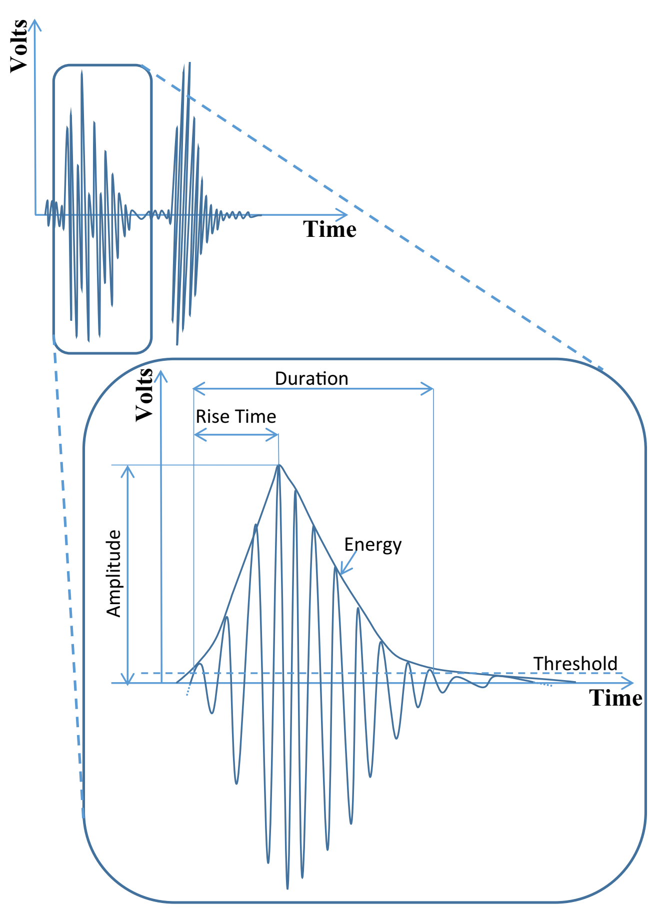

Fig. 1. A schematic AE signal with several AE signal features identified.

Clustering generally requires specifying a desired number of clusters. There exist many cluster validity techniques for determining an optimal number of clusters. These techniques are numerical measures of how unique the resulting clusters are. These numerical techniques include the Silhouette method, Dunn's (DN) index, Davies–Bouldin (DB) index, Krzanowski–Lai index, Hartigan index, and the Calinski–Harabasz index [13]. The DB index is proportional to the ratio of scatter within clusters to their separation. The DN index is the ratio of the minimum distance between two events of different clusters to the maximum distance between events of the same clusters [14]. Each index should have a certain behavior at the optimum number of clusters. For instance, a minimum DB index, a maximum DN index, or a sudden change in either of the two is expected to indicate the optimum number of clusters [14]. The numerical techniques, however, sometimes fail to predict the right optimum number of clusters. For instance, Maulik and Bandyopadhyay showed that even for well-separated clusters, a more complicated index was needed for successful prediction [14].

The clustering process can be achieved through automated data mining which recognizes patterns in complex data sets [15]. This data mining process will henceforth be called unsupervised learning. Unsupervised learning has a wide range of applications including marketing problems [16], motion analysis [17], and speech recognition [18]. Several unsupervised learning techniques exist. One famous technique is the k-means method which formulates the clustering problem as an optimization problem to which a numerical solution can be reached through an iterative process [19]. Another technique is the self-organizing map, which is an application of an artificial neural network that maps the data space onto a two dimensional space where similar data items are located close to each other on the map [13]. Other techniques assume the data follows a distribution density function. Although following a density function is not typically assumed for finding the AE signature of damage, Farhidzadeh et al. developed a criterion for crack classification by assuming that AE data followed a Gaussian distribution [20].

In this paper, numerical clustering-quality indicators are not used for finding the optimum number of clusters which is enforced during clustering. Instead, the maximum number of distinct AE groups is sought. Distinct groups are those that show distinct evolution throughout loading and have statistically representable numbers of observations. Gaussian distribution is assumed for clustering as it was tested on artificial data and found to have better performance than other techniques. This paper is organized into three main sections. The experimental section provides details about the samples and testing equipment used to acquire features of AE signals as well as the deformation and kinetic responses that will represent damage. The section on unsupervised learning explores and compares different methods for choosing the number of clusters and unsupervised learning technique. Then, a separate section presents and discusses the results of clustering performed on AE collected from experiments with CFRP composites. Several distinct groups were separated and correlated to damage mechanisms as inferred from load response and from deformation fields obtained with digital image correlation.