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Identification and classification of failure modes in laminated composites by using a multivariate statistical analysis of wavelet coefficients



D. Baccar, D. Söffker*

Chair of Dynamics and Control, University of Duisburg-Essen, 47048 Duisburg, Germany

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ABSTRACT

Acoustic Emission (AE) is a suitable method to monitor the health of composite structures in real-time. However, AE-based failure mode identification and classification are still complex to apply due to the fact that AE waves are generally released simultaneously from all AE-emitting damage sources. Hence, the use of advanced signal processing techniques in combination with pattern recognition approaches is required. In this paper, AE signals generated from laminated carbon fiber reinforced polymer (CFRP) subjected to indentation test are examined and analyzed. A new pattern recognition approach involving a number of processing steps able to be implemented in real-time is developed. Unlike common classification approaches, here only CWT coefficients are extracted as relevant features. Firstly, Continuous Wavelet Transform (CWT) is applied to the AE signals. Furthermore, dimensionality reduction process using Principal Component Analysis (PCA) is carried out on the coefficient matrices. The PCA-based feature distribution is analyzed using Kernel Density Estimation (KDE) allowing the determination of a specific pattern for each fault-specific AE signal. Moreover, waveform and frequency content of AE signals are in depth examined and compared with fundamental assumptions reported in this field. A correlation between the identified patterns and failure modes is achieved. The introduced method improves the damage classification and can be used as a non-destructive evaluation tool.

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1. Introduction

In addition to high rigidity and strength, carbon fiber reinforced plastic (CFRP) has good resistance to corrosion and high temperature. These properties make CFRP a good candidate for engineering applications especially in the aviation and aerospace industries. Unfortunately, damage in composites involves multifarious failure modes. Moreover, damage may occur early during manufacture and accumulates throughout the service life [Dzenis01]. In recent years, special attention has been paid to the development of reliable and efficient online condition monitoring systems able to detect and classify different sources of damage. A large number of studies on the use of nondestructive techniques (NDT) to identify and discriminate failure modes in composite materials have been conducted. According to [1], AE is considered as one of the most appropriate NDT methods for in situ health monitoring applications and especially when it is related to examination of dynamic failures.

* Corresponding author.

E-mail address: soeffker@uni-due.de (D. Söffker).

Acoustic emission is defined by American Society of Testing and Materials Terminology for Non-destructive Examinations as “the class of phenomena whereby transient elastic waves are generated by the rapid release of energy from localized sources within a material” [2]. There are many mechanisms including matrix cracking, fiber/matrix debonding, delamination, and fiber breakage that have been identified as AE sources. The challenge is how to assign the specific AE signature to the related failure mechanisms. Different procedures for failure mode identification (FMI) in composite materials have been developed.

The first method used for FMI purpose is based on the investigation of signal amplitudes. Recorded AE signals are analyzed in time-domain; amplitude or energy are considered as a unique parameter describing the failure modes. Each failure mode is associated with the related amplitude. Many authors have reported on the use of this method [3–5]. The results reported were different and sometimes contradicting due to the fact that the amplitude depends on fiber orientation, specimen geometry, and sensor location [6]. In consequence, AE amplitude is reported not as a significant descriptor for damage classification. To overcome this limitation, many authors proposed frequency-based analysis approaches using classical methods such as FFT and power spectrum analysis as appropriate alternatives. DeGroot et al. [7] studied damage behavior of unidirectional carbon/epoxy material under tensile load tests. The authors found out that frequencies between 90 and 180 kHz were related to matrix cracking, frequencies above 300 kHz were associated to fiber breakage, and frequencies belonging to debonding and delamination are generated with frequencies between 240 and 310 kHz. These results are in accordance with those reported in [8]. Gutkin et al. [9] applied the FFT to analyze the frequency content for AE signals emitted during various mechanical tests on CFRP. The published results show that based on the peak frequency distribution, certain damage mechanisms could be identified and classified. The authors determined specific frequency bands related to five failure sources (fiber pull-out, fiber breakage, matrix cracking, debonding, and delamination). Frequencies due to fiber pull-out were located in the range of 500–600 kHz, fiber failure was found to reside in the range of 400–500 kHz. Frequencies between 300 and 200 kHz were produced by fiber/matrix debonding where delamination was given in the interval between 50 and 150 kHz, and matrix cracking released frequencies between 50 and 100 kHz. In summary, the above-mentioned studies demonstrate that each failure mode is characterized by a specific frequency range. Frequency-based analysis shows fewer contradictions and better accordance in comparison to amplitude-based analysis because of the non-stationary behavior of AE signals. Some researchers used time-frequency analysis like DWT, CWT, and HHT to obtain more valuable information [10–13]. The study conducted in [12] can be considered as a pioneer in the use of DWT for AE signals analysis. The recorded AE signals were decomposed into 11 levels. Energy change rate and percentage of total energy of each level were calculated. The authors deduced that 98% of AE energy was concentrated in levels 7, 8, and 9 corresponding to frequency ranges 50–150 kHz, 150–250 kHz, and 250–310 kHz, respectively. Each level was assigned to a damage source. Level 9 corresponds to fiber fractures, level 8 is related to fiber/matrix debonding, and level 7 is associated to matrix cracking. Sause et al. [10] demonstrated the ability of CWT to distinguish between AE signals caused from different failure mechanisms in CFRP. Mizutani et al. [14] used wavelet contour maps. Four different types were identified and correlated. Hamdi et al. [15] compared the application STFT, CWT, and HHT. Correlation between failure modes and related frequency ranges was established. Results highlighted the superiority of HHT in processing of non-stationary signals. These outcomes are in close agreement with those obtained by [16]. Eaton et al. [17] and Sause et al. [18] reported the use of frequency content to discriminate between Acoustic Emission signals generated from various damage mechanisms. Several tests were performed on carbon fiber/epoxy plates with different geometries. The experimental results show that the obtained frequencies are still distinctly different for the different failure sources in all experimental setups. Matrix cracking was accompanied by frequencies below 150 kHz whereas fiber failure was accompanied by frequencies above 400 kHz. However, the authors devoted special attention specimen geometry.

With the rapid development of data processing techniques, recent studies have focused on pattern recognition to classify damage mechanisms in composites. Successful applications of multivariate statistical analysis were reported in many studies; Deolivera et al. [19] proposed a two-level clustering approach based on self-organizing map (SOM) of Kohonen and k-means. Overall eighteen descriptors were selected from time and frequency-domain. Six clusters were identified and assigned to the related failure. Sibil et al. [20] presented an optimization of AE data clustering using a genetic algorithm method and PCA. Four clusters were identified and correlated to the damage mechanisms. Loutas et al. [13] introduced a parameter/energy analysis of AE signals clustering process using cluster validity criteria. Additionally, cumulative AE energy and cumulative AE event number were investigated to correlate the identified classes to their failure damages. It was observed that the AE evolution differs from damage to other, which allows, in association with the clustering result, a better classification. Kempf et al. [21] used k-means algorithm for damage characterization and classification. The generated AE signals were analyzed in terms of peak frequency, weighted peak frequency, and partial power. Patterns were classified into three clusters related to the different failure mechanisms. The used PCA-method shows promising AE signal classification. Wang et al. [22] reported the efficiency of cluster analysis associated with neuronal network for damage identification and classification. Features like amplitude, duration, and peak frequency were selected and classified in three clusters using hierarchical and k-means cluster analysis. Artificial neural network was developed to identify three typical failure modes namely matrix fracture, interface debonding, and fiber breakage.

The main drawback of the mentioned procedures lies on the fact that multivariate approaches are mostly based on parameters extracted from signals in time-domain which depend on many factors such as sensor position, attenuation, and structure geometry. In addition, many AE events have to be analyzed in order to extract a sufficient number of parameters. The reviewed approaches are not able to be implemented in real time.

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