Identification of Damage Modes In Glass/Polyolefin Composites By Using Principal Component Analysis On Acoustic Emission Data

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ABSTRACT

This paper focuses on the use of principal component analysis to classify different fracture signals from background noises. PCA is a method used to simplify high order data sets to lower dimension for a simpler analysis. Tensile tests carried out on glass fiber reinforced polyolefin composites and acoustic emissions recorded from these tests. The aim of this study is to classify the acoustic emission signal using PCA. To reduce the multi-linearity among AE parameters (such as peak amplitude, ring-down count, etc) and extract the significant AE parameters, correlation analysis utilized. The experimental results show the successful separation of experimental fracture mode signals from the background noise.

Key words: Acoustic emission, glass/polyolefin composite, Damage mode, Principal component analysis.

INTRODUCTION

An acoustic emission (AE) signal is an ultrasonic wave emitted when materials are strained. Indeed, AE is a transient wave resulting from the sudden release of stored energy during a damage process such as fiber breakage, fiber/matrix interface debonding, and matrix cracking in composite materials. Therefore, any AE signal contains useful information on the damage mechanisms [1]. In the present work, principal component analysis (PCA) used as an unsupervised clustering method for AE transients generated in composite specimens. A principal component analysis performed in order to define new uncorrelated features and to reduce the dimension of the data [2]. The considered damage processes are primarily matrix cracking and local delaminations. The AE waveforms choose as the input of the clustering procedure. PCA utilizes for dimension reduction of AE data. Many works [3-5] have used that AE techniques and multi-variable classification as a pattern recognition tool in the field of non-destructive evaluation. Johnson [6], applied the PCA as an unsupervised clustering method for AE transients generated in composite tensile test specimens. Euclidean distance selected as a measure of the separation between signals represented by vectors in the multi-dimensional space of their descriptors. The numbers of classes and their characteristics are determined empirically. Pure resin samples, 0, 90 and 45 off-axis unidirectional composite samples are used. Tensile tests obtained in order to generate expected damage modes: fiber fracture in pure glass fiber samples, matrix fracture in pure resin samples, mainly matrix fracture with a few fiber fractures in 0 off-axis samples. Mainly matrix fracture with a few debonds in 90 off axis samples and mainly debonding with some matrix fracture in 45 off-axis ones. In these specimens with different configuration two main types of signals are identified, originating from the two expected damage mechanisms i.e. matrix cracking and decohesion. However, it is very difficult strictly separate the clusters within a large quantity of signals.

Materials and Methods

The experimental work carried out on unidirectional glass/polyolefin composite materials (S. S. P. Co., Iran). The density of the glass fiber is 2.6 g/cm3 and ultimate tensile strength and modulus are 2150 MPa and 74 GPa respectively. The density of the polyolefin resin is 1.1 g/cm3 and ultimate tensile strength and modulus are 80 MPa and 2.7 GPa respectively. The laminates were prepared by hand lay-up with compression molding.

All the samples for tensile tests were 25*100*2.5 mm and cut using a diamond wheel saw. This process found to give a suitably smooth surface finish with the minimum sub-surface damage.

Mechanical testing and data acquisition:
All monotonic tensile tests on unidirectional samples were performed at room temperature using an universal test machine (Hiwa Co., Tehran, Iran) with the load cell capacity of 1000 N at the crosshead speed of 0.2 mm/min. Five samples for each type test were used for tensile testing with the ASTM D3039 standard.

Figure 1 shows the experimental arrangement to fiber bundle testing tab, clamping system and AE sensors. As described in previous studies [7,8], to avoid fiber breaking the fiber near the holders, each end of the sample was glued a length of 15 mm to the sample holder.

![Experimental arrangement](image)

**Fig. 1:** experimental arrangement to fiber bundle testing and AE monitoring set up.

Acoustic emission software AEWin and a data acquisition system (PAC) PCI-2 with a maximum sampling rate of 40 MHz used for recording AE events. The testing load and strain recorded in each specimen. Damage initiation and progress in the specimens monitored by an AE system. Preliminary to damage check, the data acquisition system calibrated for each kind of specimens, according to a pencil lead break procedure (ASTM E976) [9].

At the same time, velocity and attenuation of the AE waves can measure. For that, the lead breakage operation was repeated several times and at different locations between the sensors. The difference in arrival times on the sensors deduced. Furthermore, each waveform digitized and stored. After storage and before processing, the signals subjected to a linear location procedure to determine the location of the AE source.

After the calibration step, AE signals captured during mechanical testing. Waveforms of AE signals are very complicated objects when dealing with their classification. Therefore, reliable descriptors defined in order to use pattern recognition techniques based on multi-parameter statistical analysis. Six descriptors have been retained account of the important diversity of the waveforms: amplitude, duration, rise time, counts, counts to peak and energy. Among them, the signal amplitude alone measured in real time by the data acquisition system. All the other descriptors were calculated from the waveforms at the

Post-processing step because they are very dependent on the amplitude threshold used to detect the arrival time and the end of an AE signal.

Parameter provided by the PCI-2 system were rejected because a fixed threshold used whatever the signal features, though the end of the signal depends on the source and the sensor characteristics. Therefore, we made use of a floating threshold to determine the duration of the signal. This floating threshold calculated as a percentage (10%) of the maximum signal amplitude.

**Principle Component Analysis:**

In general, a performance of classifier could be affected by input variables that have inter-correlation characteristics (linear dependencies), since a linear dependency between variables is explained by the correlation matrix. In order to eliminate this linear dependency between independent variable, a principal component analysis is usually used. PCA is a mathematical procedure for resolving sets of AE parameters into orthogonal components whose linear combinations approximate the original data. Moreover, PCA expect to reduce the effects of multi-co-linearity between each feature in the process of AE signal classification. Since all principal components are orthogonal each other, we can get new data set from PCA [10].

The principle aim in PCA is to reduce the dimension of data [2]. In addition, a projection into a subspace of a very low dimension, for example two, is useful for visualizing the data. We consider the matrix population composed of the \( n \) patterns \( x_j \):
First, the data centered and reduced (the mean is null and the standard deviation is equal to unity for each column) then we calculate the covariance matrix: 
\[ C_X = E[XX^T], \]
where \( t \) represents the transpose of the matrix. The components of \( C_X \), denoted by \( C_{kl} \) (\( k=1, m \) and \( l=1, m \)), represents the covariance between the variables \( x^k \), \( x^l \): as the covariance matrix is a symmetric matrix, an orthogonal basis can be calculated by finding its eigenvalues and eigenvectors. The eigenvectors \( e_k \) and the corresponding eigenvalues \( \lambda_k \) are the solutions of the equation:

\[ C_X e_k = \lambda_k e_k, \quad k = 1, 2, 3, ..., m. \]

An ordered orthogonal basis can created with the first eigenvectors having the direction of the largest variances of the data. Thus, directions in which the data set has the most significant amounts of energy can found. Instead of using all the eigenvectors of the covariance matrix, we may represent the data in terms of only a few basis vectors of the orthogonal basis. If \( A_K (m \times K) \) is the matrix having the first \( K \) eigenvectors, by transforming the data vector \( X \), we get \( y = XA_K \), which represents the new coordinates of the \( n \) patterns in the orthogonal coordinate system defined by the eigenvectors.

The PCA is applied on the matrix (with \( n \times d \) dimensions) of the time-based parameters collected from AE waveforms. The PCA projection in a two-dimension space highlights the similarities between the patterns. If the data do not overlap, automatic discrimination between the damage classes can considered. Thus, the choice of relevant features to compose the pattern can be validate.

**Results:**

- **Pure polyolefin resin:**

  The primary modes of damage observed in the pure polyolefin resin specimens tested are illustrated. The corresponding amplitude distribution histogram (ADH) shown in Figure2. Most of the AE events recorded below 60dB and were thus associated with matrix plastic deformation and matrix cracking. In addition, no events recorded below 35dB since this was the selected threshold. In this diagram, mean value of amplitude is 39.0857dB and standard deviation is 11.3492dB also mean value of frequency in dominant matrix cracking is 146.6 KHz and standard deviation is 48.17 KHz.

![Fig. 2: ADH of events generated between two sensors during tensile loading in pure polyolefin resin specimen.](image)

**Glass fiber bundle:**

Fiber breakage is a critical mode of damage in the glass/polyolefin composites. Catastrophic fracture of the specimen is usually imminent at the onset of fiber breakage. The AE technique is ideally suited to monitor fiber breaks due to the distinctive stress wave emitted during fiber breakage. It has reported that fiber breakage in fiber-reinforced composites was associated with high amplitude...
events. Glass fiber breakage modes corresponding amplitude distribution show in Figure3. Most of the AE events were recorded between 65-100dB. In this diagram mean value is 75.57dB and standard deviation is 14.75dB.

Fig. 3: ADH of events generated between two sensors during tensile loading in pure glass fiber.

During tensile loading of the fiber bundle specimens, various distributions of AE amplitudes from the fiber breakage received. The friction between the filaments is a source of additional AE that increases with the gage length. A principal distribution with amplitudes ranging from approximately 80-95 dB can be attributing to the fiber breaks. Again during the analyzing the graph obtained fiber breakage frequency over than 400 kHz but a batch signals appear before the fiber breakage between 150-250 kHz maybe related to the friction between fibers and this friction ranging is from 40 to 70 dB.

AE monitoring of pure matrix cracking under tensile loading shows that the dominant amplitude range of signals is at a lower level (30-50 dB) than the gage length. Generally, source mechanisms are wideband-excited because of the stochastic processes in the structure. The ability to distinguish between matrix cracking, fiber breakage, and interface debonding shall rely on different visco-elastic relaxation processes near the source itself.

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Unidirectional glass/polyolefin (0°):

Unidirectional 0° glass/polyolefin specimen used to determine the correlation between the AE results and fiber breakage. The ADH of this specimen is show in Figure4. It indicated that fiber breakage generated high amplitude events greater than 60dB based on the results of observing the test process during the loading. Note the fluid behavior of the polyolefin when subjected to stress. The separation between the glass fibers and the polyolefin is effectively illustrates fiber/matrix pull out. According to the innumerable studies, AE signal parameters don’t differ so much in the pure glass or in unidirectional glass/ polyolefin (0°) specimen in tensile testing. Indeed Comparison of corresponding frequency distribution histogram shows the debonding appear around 250-320 kHz; few dots appeared above 200 kHz and none above 400 kHz.

Transverse oriented glass/ polyolefin (90°):

Fiber-matrix debonding is a complex process due to the structure of the interface region and this is the dominant failure mode in the 90° specimen. Debonding is. Interfacial adhesion between glass fiber and polyolefin matrix is one of important factors on improving the mechanical properties of the composite materials. Figure5 shows Resulting amplitude from transverse oriented glass/polyolefin under tensile test. The fibers for 90 specimens when tested in tension tend to be separate from the matrix (fiber/matrix debonding without fiber breaking).

Comparison of this ADH with pure resin ADH shows the 50-70dB is not resin deformation or resin cracking, yea this is debonding amplitude and if this test continues fiber break will happen.
Figure 4: ADH of events generated between two sensors during tensile loading in unidirectional glass/polyolefin ($0^\circ$).

Figure 5: ADH of events generated between two sensors during tensile loading in Transverse oriented glass/polyolefin ($90^\circ$).

Figure 5 showed the amplitudes of the collected signals mainly distributed in two zones as can be observe on Figure2. About 70% of them have amplitudes in the range from 35 to 55 dB, with waveforms similar to those observed in the tests on pure resin; we will refer these signals as matrix cracking signals. The 30% left signals have amplitudes in the range of 55–75 dB and waveforms quite different from the waveforms of matrix cracking signals, with shorter decay time and higher energies. These signals will be refer as debonding signals. Moreover, debonding signals are detect only during the second half of the test, whereas the activity of matrix cracking seems quite continuous.

The similarities in parameters found between matrix crack signals in 90 tests and signals from pure resin tests let us think that the source mechanism is the same in both cases. Whereas scanning electron microscopy (SEM) can approve this fact.

Unidirectional glass/polyolefin ($45^\circ$):

The corresponding amplitude distribution is present in Figure6. Matrix deformation and
fiber/matrix debonding can be observed in the same amplitude zones as previously. However, debonding signals found much more numerous than matrix cracking in this test. Indeed, it is clear that these tests have a longer duration than the other tests, and hence more events recorded. The unidirectional tensile test at zero degree usually results in 4000 event points compared with 6500 recorded from the 45-degree test. Therefore, the source of debonding, predominant in this configuration, appears to be debonding.

This is also consistent with their presence in the 90 tests, appearing chronologically after matrix cracking, when matrix fracture occurs around the fibers. The initiation, the growth of matrix cracks and the integrity of matrix cracks appears to create AE events having low amplitude, slowly rising and decaying. On the contrary, the interface debonding leads to signals with higher amplitude, quickly rising and decaying.

**Fig. 6:** ADH of events generated between two sensors during tensile loading in unidirectional glass/polyolefin (45°)

**PCA clustering results:**

PCA was performed on AE signals in order to explore its ability of clustering signals generated due to different damage mechanisms in unidirectional glass/polyolefin composites. The analyzed data set approximately consisted of 6000 AE transients in each waveform; so that the number of variables in each point was 6. This variables are amplitude, duration, rise time, counts, counts to peak and energy. The selection covers about 25 microseconds and done to eliminate the influence of reflections coming from the clamping of the specimen also because it found that this part of the signal bore the characteristics of signals. The types of signals considered have a positive first arriving peak; therefore, all signals were time shifted to have this pick at the same position in time. This is necessary because damage sources having separated origins along the specimen will result in different arriving times on a transducer, which did not trigger the system.

In most cases, different damage mechanisms will generate AE transits of different peak amplitude and waveform characteristics. In addition, the same damage mechanism acting in the same lay-up configuration but with different ply thicknesses will result in change in peak amplitudes. It is however, reasonable to believe that the signal remains its characteristic waveform in such a case. Hence, the signals in this investigation were not desire to let the pick amplitude play an important role on the clustering process. There for, each signal was normalize the influence of the discrepancies in the attachment of the transducers to the specimen the gain setting of the AE system and the signal attenuation on the clustering results. The PCA was performed which was implemented in MATLAB code. The analysis of complete data set, i.e. unidirectional glass/polyolefin (0, 90 and 45) resulted in score plot for PC1 and PC2 as can be seen in Figure 7.
Figure 7: Score plots of the complete data set. a- PC1 versus PC2 in Unidirectional glass/ epoxyL160 (0°) b- PC1 versus PC2 in Transverse oriented glass/ epoxyL160 (90°) c-PC1 versus PC2 in Unidirectional glass/ epoxyL160 (45°)

Figure 7.a plot clearly shows that class A and class B are two well-separated clusters. This as correspond to the two types of signals generated due to matrix cracking and fiber breakage in the Unidirectional glass/ polyolefin (0°) specimen influence of tensile testing but we don’t know which cluster was related to which damage. Any undefined signals from another subgroup picked up by the transducer prior to final failures that can separate with score plot of PC1 versus PC2 in any subject but there are not predominant.

Comparison of Figure 7.a and Figure 7.b characterized that class A is belong to matrix deformation such as matrix cracking because it is common and joint in waveform of Unidirectional glass/ polyolefin (0°) and Transverse oriented glass/ polyolefin (90°) specimen under tensile testing. In following, we can estimate class C is Fiber /matrix debonding and we established that class B related with fiber breakage.
The remaining signals from any classes do not fall into clusters, which can be discriminated from each other in PC1 versus PC2 score plot for the computed data set. It should emphasize that for an experiment without prior knowledge about the different possible damage mechanism the signals would not labeled as they have been here. However, if PC1 versus PC3 is plotted, a may be identified as a subgroup which corresponds to the signals generated due to initiation of matrix cracks.

This is essential in PCA, which aims to improve and enhance the characteristics borne in the signals and to reduce as much as possible of noise generated during the experimental measurements.

In following for supplementary classification results, if unidirectional glass/ polyolefin (45°) specimen is pulled up to absolutely fracture under tensile test and adding AE transients and afterward classification of AE data with PCA technique, class A, class B and class C clusters can be observed in the same amplitude zones as previously(Figure7.c).

Because of same position of classes in this clustering with previously score plots we reached the damage modes without SEM micrograph and results of PCA in tensile test of unidirectional glass/polyolefin composites can save and introduce as a database. Thus PCA can satisfy strictly correlate the AE signal classification with SEM observations.

This work proved that identify the failure mode signals using only one parameter such as amplitude should be so difficult but PCA solved this problem and analysis using several AE waveform parameters will be necessary for their identification.

Conclusion:

In the present work, tensile test on unidirectional glass/polyolefin composites carried out and damages mechanisms analyzed by AE. Several damage modes activated and primarily, matrix cracking and fiber/matrix debonding further studied and there were predominant modes. The aim was to use the AE waveforms picked up during the tensile testing using broadband transducers as the input data for the analysis instead of conventional AE parameters commonly be used for clustering purposes. PCA successfully distinguished different signal waveforms along the test.

PCA utilize a majority of the AE signals in the test set were correctly classified. This achieved using the measured time history of the generated AE transients as inputs, which gives the classification method the advantage of being an objective method. This work shows the AE and PCA offers an effective tool in the field of non-destructive testing.

References

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