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Classification of Damage Severity in Natural Fibre Composites Using Principal Component Analysis

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Abstract: The present paper deals with an approach in predicting the classification of damage in natural fibre reinforced composites (NFC) panel using signal processing procedure as indicative parameters and principle component analysis as a learning tool. An impact event produced strain data and the response signal was investigated. An effective impact damage classification procedure is established using a principal component analysis approach. The system was trained to classify the damage class based on the input from the signal features. It has been observed that, the network can learn and classify effectively the damage size in the panel which is the combination features retained at about 84.5% of the variance.

Keywords: Classification, Principal component analysis, damage severity.

1. Introduction

Against the background of worldwide increasing raw material costs and needed higher biodegradability represent important incentives to use natural resources in the future especially in sectors such as automotive and transportation industry, aerospace application, building and furniture and panels application. The use of these fibres instead of glass and carbon is under consideration of their cost-effectiveness in most usage. Although many different types of natural fibres are available, kenaf (Hibiscus cannabinus) is a particularly attractive option due to its rapid growth over a wide range of climatic conditions and its consequent low cost [1]. For the past few years, numerous studies have been performed on kenaf fibre reinforced composite, in order to fully characterize its behaviour. Yousif et al. [2] investigated the effect of fibre surface treatment (6% NaOH) on the flexural properties of long kenaf fibre reinforced epoxy (KFRE). The results revealed that reinforcement of epoxy with treated kenaf fibres increased the flexural strength of the composite by about 36%, while untreated fibres introduced 20% improvement. This was mainly due to the high improvement of the chemical treatment (NaOH) on fibre matrix interaction and the porosity of the composites which prevented the debonding, detachments or pull out of fibres. For untreated KFRE, the fracture mechanisms were debonding, tearing, detachments and pull out of fibres.

In another work [3], the fibre is soaked with 3%, 6% and 9% of sodium hydroxide (NaOH) for a day and then dried at 80°C for 24 hours in order to investigate the tensile properties of the short kenaf fibre composites with maleic anhydride polypethylene (MAPE) and short kenaf fibre with maleic anhydride polypropylene (MAPP). It has been found that the tensile properties of the treated kenaf fibres have improved significantly as compared to untreated kenaf fibres especially at the optimum level of 6% NaOH. Sapuan et al. [4] found an interesting result in their investigation for kenaf fibre reinforced thermoplastics polyurethane composites. It showed that the mechanical properties, namely tensile strength, flexural strength and impact strength decrease with the increasing of NaOH concentrations. Untreated kenaf fibre gave the highest value for all the mechanical properties. In contrast, NaOH fiber treatment resulted in enhancement of fibre morphology as compared to untreated fibres. While Hilmi et al. [5], employed response surface method to find the optimum condition of the alkali treatment on the tensile strength. The result revealed that the highest average reading of kenaf reinforced composite was 26.37MPa from 25% percentage of volume fraction with alkali concentration of 6%. Emran et al. [6] investigated the mechanical performances of twill kenaf woven fibre reinforced polyester composites by using Taguci method. The results showed that by using new angle orientation suggested by Taguchi method the result for tensile strength of kenaf fibre composite improved the. The new value for tensile strength was 58 MPa.

In another view of investigation, vibration techniques have been employed in many applications for detecting the presence and monitoring the progression of damage in structures. For example, De Rosa et al. [7] have reviewed the application of Acoustic emission (AE) for monitoring

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the mechanical behavior of natural fiber composites. It was found that the variability in natural fiber geometry and resistance of natural fiber composites to defect propagation create difficulties to AE techniques. AE techniques also have difficulty is estimating the wave propagation of damage due to the short distance, which subsequently requires high accuracy of stress wave measurement. While Soma & Sekhtar [8] investigated the low-velocity impact damage using lamb wave tomography for thin multi-layered composite plates. It was found that the orientation of delamination was influenced by the fiber direction. For the same intensity of load, the damage extent was greater in cross-ply than quasi-isotropic lay-ups. Zaleha et al. [9] employed passive damage detection for natural fibre using sensor response data. It was found that, PZT sensors can be used to detect the damage extent with the waveform of sensor signals implying the damage initiation and propagation. In other research, Zaleha et al. [10], implemented neural network in the natural fibre composites for damage severity identification. The obtained results showed that the trained networks were capable to predict the damage size accurately, which is the best performance was achieved for Multi-Layer Perceptron network trained with maximum signal features, which recorded the error less than 0.50%.

Trendafilova et al. [11] studied the vibration-based damage detection in an aircraft wing, using a modified Principal Component Analysis (PCA) method and simple pattern recognition method. The result revealed that Pattern recognition can recognise between the damage and healthy wing data, whereas the PCA can transformed data from the two categories more differentiable. Recently, Kim et al. [12], investigated damage classification method for delaminated smart composite laminates using PCA. The delaminated smart composite laminate was modelled using the improved layerwise theory. The obtained results showed that the PCA based classification method is efficient in classifying the damage of delaminated smart composite laminates with various layup configurations. Each group of data sets can be clearly recognized from the component plots. Han et al. [13] implemented online multilinear principal component analysis and found out that, the technique supports higher order tensor machine for classification and reduce the computational time for dimension reduction without downgrade the recognition accuracy.

Thus, the work presented here seeks to predict and classify damage in kenaf fibre reinforced epoxy panels subjected to low-velocity impact. The investigation employs principal component analysis to visualize the feature data.

2. Principal Component Analysis (PCA)

Real world data such as signals, digital photographs usually have a high dimensionality. So, in order to handle this type of data, its dimensionality needs to be reduced. Dimensionality reduction is the transform of high dimensional data into meaning representation of reduced dimensionality. As a result, dimensionality reduction simplifies among others such as compression, classification and visualization of high dimensional data.

There are two types of dimensionality reduction techniques, which is linear technique and nonlinear technique. Linear technique such as Principal Component Analysis (PCA) and factor analysis. Whereas nonlinear techniques such as global techniques, multidimensional scaling, local technique and global alignment of linear models. Each technique has their own advantages and advantages [14]. However, in this paper only about PCA will be discussed.

PCA is a classical method for multivariate analysis. The PCA method reduces the dimensionality of a number of interrelated variables and transforms interdependent coordinates into significant and independent variables. The PCA was used to support the Multilayer Perceptron (MLP) classification analysis and illustrate that various classes can be separated. The PCA was applied to signal data features obtained from the PZT sensor. Two major principal component scores were then displayed to visualize five clusters representing impacts severity within five class of damage in NFC panel. The first Principal Component (PC) is a vector which describes the direction of maximum variability in the feature space of the original set of data.

2.1 Structure of PCA formulation

The PCA methods project by a linear transformation, the data into a new q- dimensional set of Cartesian coordinates (z1, z2,., zq). The new coordinates have the following property: z1 is the linear combination of the original x1 with maximal variance, z2 is the linear combination which explains most of the remaining variance and so on as given in equation (1). This technique was adopted as in [15]. The matrices can be extracted using the Singular Value Decomposition (SVD) to obtain the Principal Component transformation as given in equation (2)-(4), where is the mean vector, is the covariance matrix and T is matrix transpose.

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ : \\ : \\ x_p \end{bmatrix} \text{PCA=} \begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ z_4 \\ : \\ : \\ z_q \end{bmatrix} \tag{1}$$

$$[\Sigma]= \sum_{i=1}^{N} (\{x\}_i - \{\overline{x}\})(\{x\}_i - \{\overline{x}\})^T \tag{2}$$

The covariance matrix is then decomposed and rewritten as

$$[\Sigma]=[A][\Lambda][A]^T \tag{3}$$

where [Λ] is a diagonal matrix and [A] is a unitary matrix.

The transformation to PCs,

$$\{z\}_i = [A]^T (\{x\}_i - \{\bar{x}\}) \quad (4)$$

3. Sample Preparation

The investigation employs the chopped kenaf fibres as the natural fibre and the epoxy as the resin matrix. The dimensions of the kenaf fibre reinforced composite panel were 300mm (L) ×300mm (W) and 3mm thickness. The composites with fibre loading 10% of volume fraction were fabricated using compression technique. The internal surfaces of the mould were sprayed by a release agent in order to facilitate easy removal from the mould. Initially, epoxy resin and hardener were mixed together with ratio 2:1 to form a matrix. Then the chopped kenaf fibres and matrix were mixed together using a mixer for 10-20 minute to disperse fibres in the matrix. The mixture was poured into the mould and closed before manual compression took place. The sample was left to cure for about 24 hours at room temperature. Finally, the panel was taken out of the mould and post-cured in the air for another 24 hours.

3.1 Experimental setup

Experiments were conducted on NFC panels. To introduce impact damage, an impact hammer was held in contact with the NFC panel to serve as an impactor tip and excited the NFC panel. The signal picked up by the receiver PZT sensor was amplified and transferred to the computer via the DEWESoft card. The PZT sensors used were 10 mm in diameter and 1 mm in thickness. The sensors were placed at ten different positions on each plate in order to sample responses at different distances from the impact events as shown in fig. 1. A series of low-velocities, low-energy impacts were performed at different force for 100 plates as illustrated in fig. 2. The data acquisition was triggered when the strain signal produced by the impact hammer exceeded a threshold level of 40 mV. A sampling frequency of 5 kHz was used and the overall time for data acquisition was set to 2s. All strain signals captured from S1 until S10 were transferred to a laptop for further analysis. While the time domain features such as maximum peak, minimum peak and peak to peak value were analyzed for each impact damages. Then these features were used as an input vector for PCA analysis. Two major principal component scores were then displayed in an attempt to visualize five clusters representing the severity of the damage in the NFC panels.

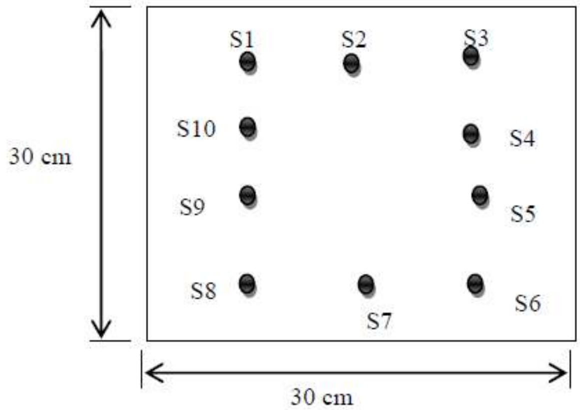


Fig. 1 A schematic diagram for impact investigations in the kenaf natural composite structure.

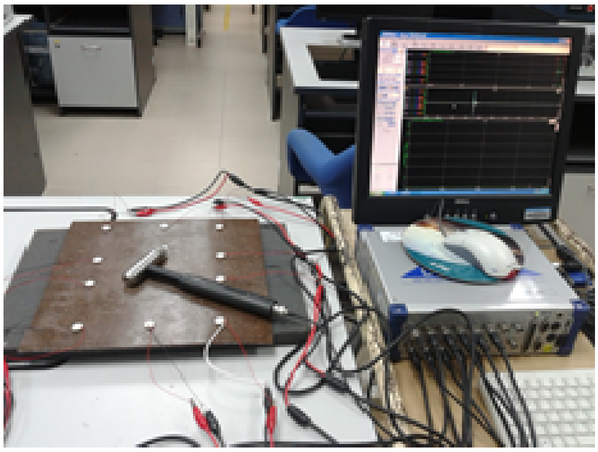


Fig. 2 Experimental set-up for low-velocity impacts

4. Results and Discussion

The PCA analysis involved four different signal features which is maximum peak, minimum peak, peak to peak and the combination of all the features. For every single impact, ten elements were used as an input vector for the PCA analysis. These ten elements were then projected to the first two principal components (PCA1 versus. PCA2). This allowed for a simple visualization of the results.

Damage observed in this research can be classified according to five different damage areas. Table 1 summaries the estimated value of the damage area for impact force 100N to 1400N. The general trend observed indicates that the higher of impact force the larger of the damage area. Therefore, it can be concluded that the damage area estimated produced an approximately linear correlation between the impact force and damage area. However, for impact force below than 150N, no damage was detected due to the low energy impacts did not allow enough entry to penetrant into the panel.

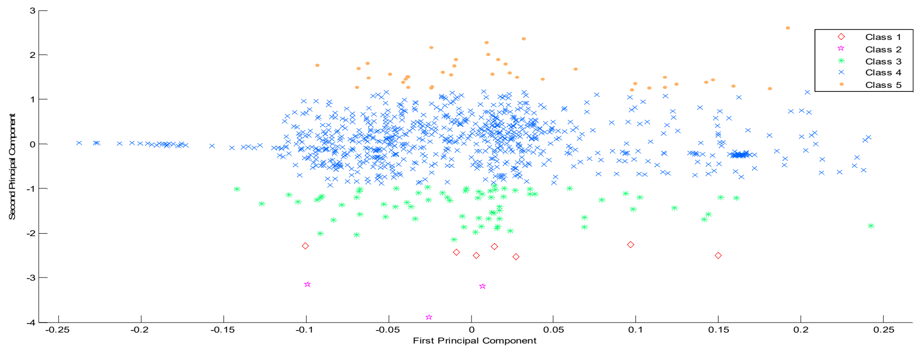
Table 1 Estimated values of damage area in the plate.

Impact Force (N)	Damage area (cm^2)
100	No Damage
200	Dented
300	8
400	8.9
500	13
600	18.25
700	20.6
800	24.3
900	27.7
1000	28.9
1100	30.0
1200	30.5
1300	31.6
1400	32

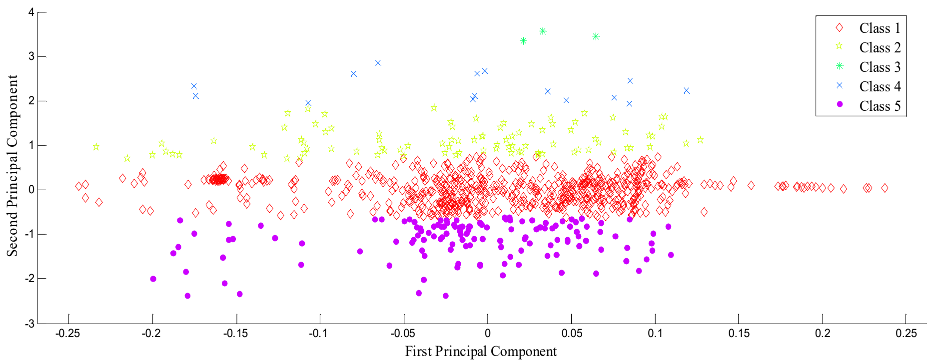
Whereas, table 2 shows the classification and the range of damage area assigned to each class. The class were selected based on the amount of damage area assessed in the experimental work.

Table 2 Damage and code classification

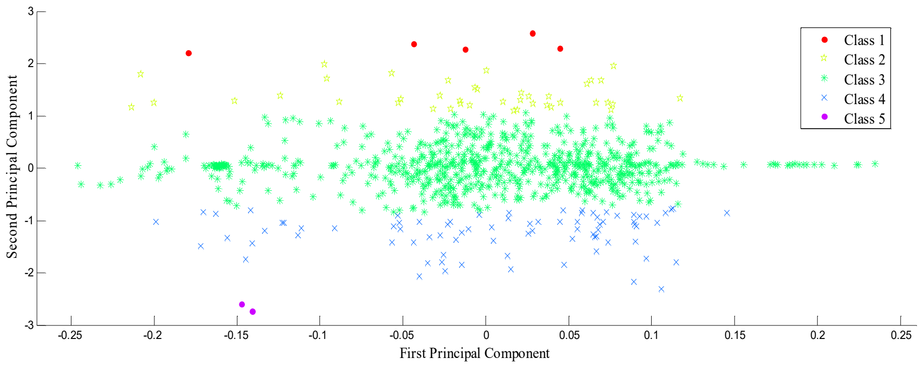
Classification of Damage	Range of damage area(cm^2)	Class
No damage/Scratches	0<DS< 8	1
Small cracks	8<DS<15	2
Moderate Cracks	15<DS<20	3
Intermediate Cracks	20<DS<27	4
Severe Cracks	27<DS	5



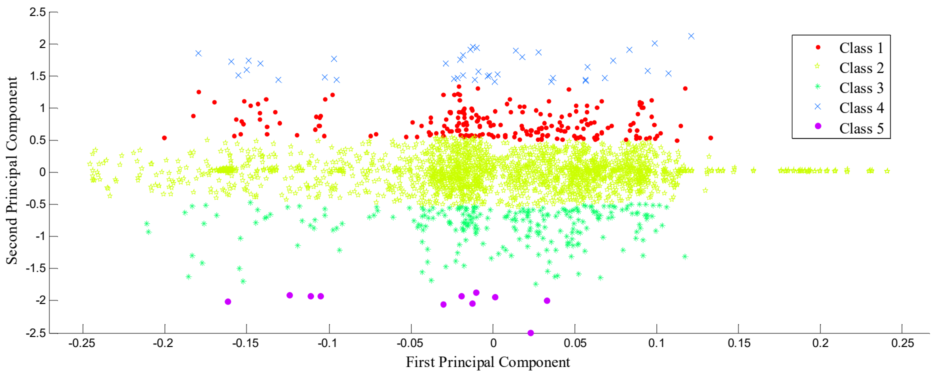
(a)



(b)



(c)



(d)

Fig. 3 PCA plots (PCA1 vs. PCA2) for the time-domain features (a) maximum peak (b) peak-to-peak (c) minimum peak and (d) combination of all time-domain features.

The PCA projected ten elements which have one strain data feature from ten sensors) to the first two principal components. These two components retained 79.4%, 75.6%, 80.2% and 84.5% of the variance for the maximum, minimum, peak to peak and combination features respectively. The results are shown in fig. 3(a)-fig. 3(d). Five clusters, representing impacts severity class can be seen in the figure. The results show that the clusters are fairly separated, and some overlapping can be observed. Each feature gave different type cluster of damage class. When the maximum signal features are used as the input vector, the cluster for class 4 are dominant compared to another class as shown in fig. 3(a). This is agreed well with confusion matrix which depicts that class 4 have the highest classified correctly. However, when peak signal features are used as the input vector as shown in fig. 3(b) cluster for class 1 is dominant. Whereas for minimum signal features, class 3 is dominant as compared to other classes. The good results are obtained for combination features as shown in fig. 3(d), which is the signal are combination of all the signal features obtained from the experimental results. In contrast, the worst results are obtained for the minimum features shown in fig. 3(c). In this case, the PCA failed to recognize and separated uniformly the clusters correctly. Even though there are several points that are separated from their correct group, most of them are still clearly classified.

5. Summary

The patterns of the PCA scores are capable to indicate the cluster which is representing the damage severity class in NFC panels. The covariance matrix of the data gives a rough estimate of the overall orientation of the data cloud in multivariate space. If the first two eigenvalues have more than 80% of the total eigenvalues, which means 80% of the total variance in the original data, the first two components are conventionally considered as enough to represent the data, without losing most of the variance of the original data. This indicates that the behaviour of data pattern recognition for each class of damage can be visualised using PCA as a data visualization tool. Selecting the best feature also can be the crucial task hence it plays the important role for the PCA performance. Generally, a larger data will generate more classes may increase accuracy for extension of this future work. Further research is still required to extend this application for the improvement in terms of their accuracy.

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