Pattern Recognition for Damage Characterization in Composite Materials

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Composites present additional challenges for inspection due to their anisotropy, the conductivity of the fibers, the insulating properties of the matrix, and the fact that damage often occurs beneath the visible surface. This paper addresses the characterization of damage within composite materials, specifically for structural health monitoring (SHM). Fundamentally, one would like to distinguish between a pristine and damaged structure, however taking a micromechanics view, materials are inherently damaged. Microscopic flaws grow over time, and can be greatly accelerated by events such as overloads or impacts, until a critical damage size is achieved. Therefore a threshold must be introduced, where at some level of detectable flaw size, the structure must be labeled as "damaged". Using one or two recorded features, such as time or frequency domain measurements, to characterize damage may not be feasible, as they may not be linearly separable. While it may be possible to differentiate between "pristine" and "damaged", or between 2 discrete damage modes with limited features, it is not possible to separate the entire mode space. Therefore it is necessary to extract several feature sets to allow multi-dimensional classification of damage modes. The presented research utilized Lamb wave testing coupled with principal component analysis and pattern recognition methods, with the goal of providing the presence, type, and severity of damage with a high degree of confidence. Experiments were performed using quasi-isotropic graphite/epoxy laminates with 2 bonded actuator/sensor pairs. Three types of damage were investigated, each at 4 levels of severity: impact, hole and delamination. A total of 9000 datasets were collected in pulse-echo mode at 100kHz. Training data was collected from 1 plate and testing data from the other plates for each damage type. Subsequently, pattern recognition (PR) algorithms were developed to determine presence of damage, as well as to predict the type and severity of damage. These results have shown that PR methods can be used to successfully characterize damage in composites for SHM, with results that would only improve with additional training data.

Nomenclature

A_0	=	first antisymmetric Lamb-wave mode
ANOVA	=	analysis of variances
EMI	=	electro-magnetic interference
KNN	=	K-nearest neighbor
PCA	=	principal component analysis
PR	=	pattern recognition
PSD	=	power spectral density
SHM	=	structural health monitoring
TOF	=	time-of-flight
U	=	eigenvectors of the co-variance matrix
X	=	co-variance of n-dimensional data
λ	=	eigenvalues of the co-variance matrix

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I. Introduction

Structural Health Monitoring (SHM) is an emerging technology, developing systems capable of continuously monitoring structures for damage to improve safety and reduce life-cycle costs. SHM implies the incorporation of a non-destructive evaluation system into a structure to provide continuous remote monitoring for damage. Various types of SHM systems have been implemented in diverse industries, ranging from industrial machinery to spacecraft[1-7]. As government agencies and companies strive to lower their vehicle operational costs, many have pursued the development of these systems. However, military and commercial vehicles are increasingly using composite materials to take advantage of their excellent specific strength and stiffness properties, which present additional challenges for inspection. Damage detection in composites is more difficult than in metallic structures due to the anisotropy of the material, the conductivity of the fibers, the insulating properties of the matrix, and the fact that much of the damage often occurs beneath the top surface of the laminate and is therefore not readily detectable. Currently successful laboratory non-destructive testing methods, such as X-ray detection and C-scans, are impractical for service inspection of large integrated air and spacecraft subsystems. Lamb wave methods have been proven a reliable technique to collect valuable information about the state of damage within a structure, and several investigators have successfully used Lamb waves to determine the location of damage within composite plates[8-26]. Before this method can be used to facilitate SHM however, further research must be conducted to interpret Lamb wave data. The objective of the present work was to develop an analytical methodology that uses Lamb wave responses from a structure to characterize damage states in composite materials, with the goal of predicting the presence, type and the severity of damage with a high degree of confidence.

II. Defining Damage in Composite Materials

There are several challenges involved in detecting damage in composite materials. Ideally, one would like a simple pristine or damaged categorization at the top level, however taking a micromechanics view, the material is technically damaged as soon as it is fabricated. Those microscopic flaws grow slowly over time, and can be greatly accelerated by events such as overloads or impacts, until a critical damage size is achieved[27-30]. Therefore the concept of a damage threshold must be introduced. At some level of detectable flaw size, the structure must be labeled as "damaged". In composite materials, damage modes of interest include delamination, matrix microcracks, fiber fracture, swelling or brooming, and disbonding from secondary structure. Using one or two features to distinguish between these modes may not be feasible, as they may not be linearly separable, as demonstrated in **Figure 1**. While it may be possible to differentiate between damage and no damage, or between 2 discrete damage modes with limited features, it is not possible to separate the entire mode space for composite materials with only 2 features to classify. It becomes necessary to extract several feature sets to allow multi-dimensional classification of damage modes, as demonstrated in **Figure 2**. Using a very large set of features, however, may lead to the problems of redundancy and computational inefficiencies. In that case, feature–reduction techniques need to be employed to reduce dimensionality. Finally appropriate pattern recognition method must be chosen and trained using this feature data to successfully characterize the damage.

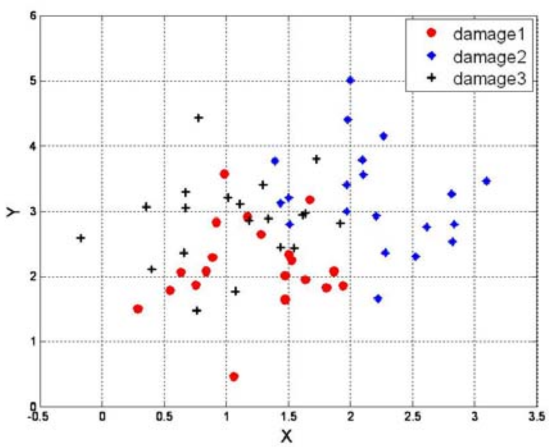


Figure 1: 2D feature space mapping

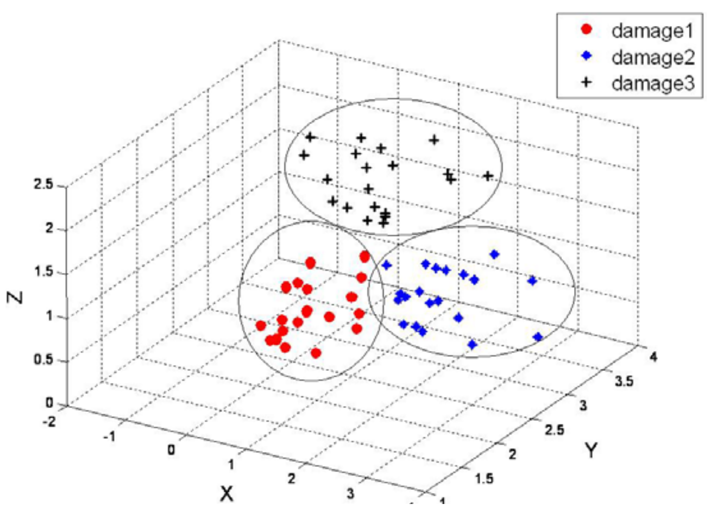


Figure 2: 3D feature space mapping

III. Methodology

The overall methodology consists of several signal processing components, as seen in **Figure 3**. First data is acquired from the sensors. Next the signal is conditioned to remove noise and artifacts such as known boundaries or defects that are not of interest to the analysis. This is followed by feature extraction and selection, where portions of the data from various domains are identified to be utilized in the damage detection algorithm. Next one or more pattern recognition techniques is used to interpret these chosen inputs, and produce state classifiers. Finally, logic is used to predict the overall state of the structure.

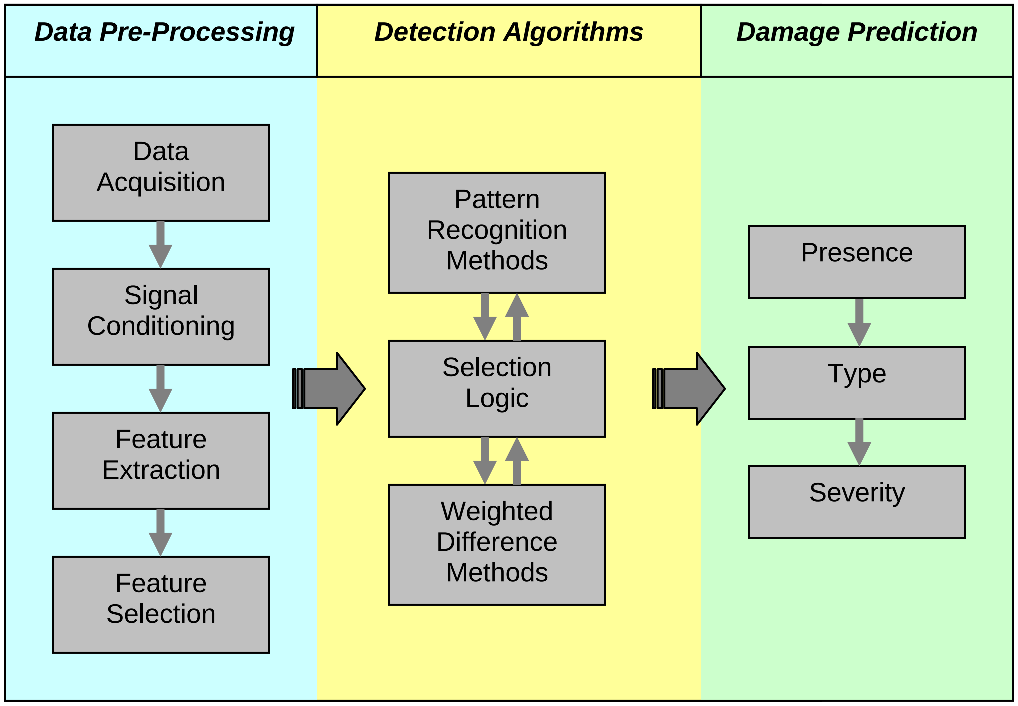


Figure 3: Damage detection methodology

A. Signal Conditioning

Signal conditioning is employed to de-noise the acquired signal from unwanted frequency content. Noise can generally be described by 2 categories: coherent and incoherent. Incoherent noise is typically referred to as "white noise," and can be easily removed through averaging. The source of coherent noise is often more challenging to discover, however can originate from a multitude of EMI sources. While more challenging to identify, coherent noise is also relatively easily extracted within the frequency domain, as long as close attention is paid to not disturbing the phase of the signal. Once the data has been conditioned, another important component of the pre-processing stage is the removal of unwanted artifacts, which could include boundary conditions as well as pre-existing conditions. This is achieved by a variety of techniques in the time, frequency and/or wavelet domains, with the simple goal of eliminating pre-existing characteristics of the signal, typically by using baseline measurements.

B. Feature Extraction

In order to perform pattern classification, a set of discriminative features needs to be obtained from the data. Within the Lamb wave results investigated during the present research, there are 3 main easily identifiable domains from which these features can be extracted: Time, Frequency and Energy. The Time Domain features are amongst the most commonly used in analysis, and include "time of flight" (TOF) and time position of the maximum and subsequent secondary peaks. These features can be observed from the raw data itself with little processing. Frequency Domain features include the maximum value of power spectral density (PSD), shift in frequency response from baseline, as well as the actual frequency and phase at this value. Frequency features can be extracted by using both Fourier transforms as well as Wavelet decomposition, where the effectiveness depends on the shape of the excitation signal. Finally, the Energy Domain features include the mean and standard deviation for the original signal amplitude as well as the 1st and 2nd differences of the signal amplitude. Other features of this domain include the total integrated signal energy, the maximum peak amplitude and the amplitude of other representative envelope locations. These features are extracted through a combination of time and frequency-based functions.

C. Feature Selection

Once a feature set is identified, the next step is to select from amongst this set which features are most representative and discriminative. Using a larger feature set for analysis may not necessarily imply better classification. Often greater number of features requires larger training data sets for error convergence and may otherwise degrade the performance of the classification method. There are many ways to select features, which can produce results with varying accuracy and efficiency. The most traditional method is a balanced one-way Analysis of Variances (ANOVA)[31-32]. This is accomplished by simply comparing the means of two or more columns of data (either baseline to test or amongst various training states) and selecting features based on the probability value of the null hypothesis that a given feature is remains same for all categories of damaged and undamaged plates. Some selected features in the present case were: total energy, frequency and phase corresponding to max power spectral density and time of reflection for near sensor (pulse-echo mode).

During this investigation a second more efficient feature reduction methods was also employed, Principal Components Analysis (PCA)[33]. PCA is a multi-disciplinary technique used for reducing dimensionality of a given dataset. In this technique, the natural coordinate systems of the data, such as voltage versus time or intensity versus frequency, are transformed such that greatest variance is captured by the first coordinate (called first principal component), the second greatest variance by the second coordinate, etc., as illustrated in **Figure 4**.

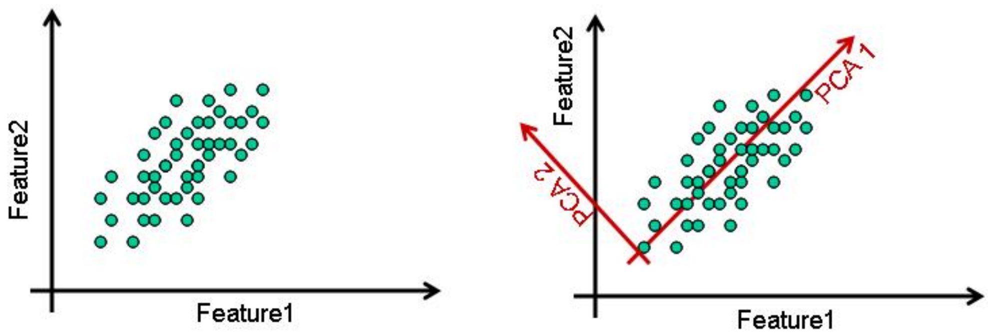


Figure 4: Graphical representation of Principal Component Analysis (PCA)

Principal components that encapsulate most variability can then be selected and be used to reconstruct data with low-order dimensionality, while the remaining components are discarded. In the present work, PCA was used to significantly reduce the raw time-series data consisting of 1000 data points by choosing the first six principal components, which captured more than 99% of the data variance. The first step of PCA is to compute the co-variance of n-dimensional data X (eq. 1). This is followed by finding the eigenvectors (U) and eigenvalues of the co-variance matrix (λ) (eq. 2,3). Next the n eigenvectors correspond to a new set of orthogonal vectors and the corresponding eigenvalue is proportional to the variance captured by projecting along that vector. Finally the eigenvalues are ordered, and the first k vectors are chosen to capture the desired variance (eq. 4,5)

$$X = \begin{bmatrix} x1_1 & x1_2 & . & x1_n \\ x2_1 & x2_2 & . & x2_n \\ . & . & . & x3_n \\ xm_1 & xm_2 & . & xm_n \end{bmatrix} ----- (1)$$

$$\lambda = [\lambda_1 \quad \lambda_2 \quad . \quad \lambda n] -------- (4)$$

$$\lambda X = \lambda U -------------- (2)$$

$$\frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{n} \lambda_i} = 0.99 ------------ (5)$$

$$U = \begin{bmatrix} u1_1 & u1_2 & . & u1_n \\ u2_1 & u2_2 & . & u2_n \\ . & . & . & u3_n \\ um_1 & um_2 & . & um_n \end{bmatrix} ----- (3)$$

D. Pattern Recognition (PR)

PR algorithms are essentially a collection of mathematical models that can be used to associate a set of test data with one of several pre-designated categories. Some of these methods are purely statically-based, and others have learning capabilities, however all PR methods have a requirement for training sets to define a "profile" for each category. Three different pattern recognition techniques were investigated during the course of the present research to evaluate their effectiveness with regards to characterizing damage within the presented methodology: K-Nearest Neighbor, Neural Networks and Decision Tree. Each method was implemented independently, as well as in conjunction with combinations of other methods bound by simple logic (e.g. 2 of 3 must agree, or all must agree).

1. K-Nearest Neighbor (KNN)

KNN is a supervised learning algorithm, in which the category of new data set is determined based on its closest neighbor. The simplest version of KNN is where K=1, and a data set is assigned to the group of the training set that most closely matches, determined by the smallest variance in features or principal components. As K increases, the data set is assigned to the group of the majority category of K-nearest neighbors, as calculated by the mean smallest variance. This is not a true learning algorithm but based on memory where a new instance is determined by input features and training samples. Advantages of KNN include that it is analytically tractable, simple to implement, it uses local information that can yield highly adaptive behavior and it lends itself very easily to parallel implementations. The disadvantages include large storage requirements and computationally intensive recall (both of which get worse as K increases) as well as its sensitivity to noise in the data (particularly at low K values)[34].

2. Neural Network

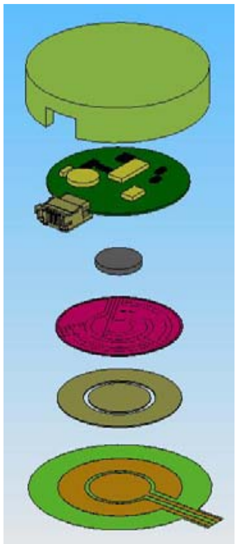
This is a machine-learning technique that uses weighted links. It simulates a network of communicating nerve cells. Input/output data is utilized to train the network and the network links are modified to capture the knowledge, so that after it has been adequately trained, it can be used to classify new input. The advantages of this type of algorithm in clued applicability to multivariate non-linear problems and parallel implementation, there is no need to assume an underlying data distribution (statistical modeling) and it has robustness towards noisy data that this it is inherently well suited for sensorial data processing. The disadvantages include the fact that minimizing overfitting requires a great deal of computational effort, the model tends to be black box or input/output table without analytical basis and there is a need for a large training sets (typically exponentially more sets than defined states)[35].

3. Decision Tree

This method is essentially a series of questions and answers, similar to a "choose your own adventure" approach. Following the metaphor, data enters through the "trunk" of the decision tree, with each "branch" representing conjunctions of features that lead to an ultimate classification, or "leaf." The weight of each decision is implicit in the hierarchy of the branch structure. Several tree structures can be also be assembled into "forest" by using multiple training sets, in order to achieve a statistical consensus. The advantages of this method include that it requires the smallest volume of data, it can accommodate missing features, it has an in-built feature selection and weighing mechanism, the tree structure inference builds domain knowledge and it is nonparametric or "distribution free." The disadvantages include the fact that unstable decision trees may be produced, that data is split only by one variable at a time, the rules deduced may be complex trees, and trees may be overfitted[36].

IV. Experimental Procedures

Experiments were performed using a series of nine 0.1" thick, quasi-isotropic graphite/epoxy laminates, cut to 11.75" square. Each plate contained 2 bonded sensor nodes placed symmetrically along the diagonal at the 1/3 and 2/3 mark. The authors had previously developed a sensor node suitable for performing Lamb wave testing, which was utilized for these experiments[37-43]. The device, called the Monitoring & Evaluation Technology Integration Disk (M.E.T.I.-Disk 3 seen in **Figure 5**) consists of piezoelectric actuation and sensing elements together with integrated electronics for data acquisition and pulse generation, which are encapsulated in a durable urethane package. The devices have a form factor of 1" in diameter, are ~0.3" in height, and use a mini-USB connection for power and communication with a PC. The actuator and sensor consist of a concentrically placed PZT-5A washer and disc. The actuator has an outer diameter of 0.75", the sensor has a diameter of 0.25" and both have a thickness of 30 mils. Each node performed tests separately in pulse-echo mode, with the actuators being excited at 20Vpp using a 100kHz shaped signal, and the sensors acquiring at 1MHz for 0.01 seconds. The nodes were bonded to the structure using a room-temperature curable strain gauge-type liquid epoxy.



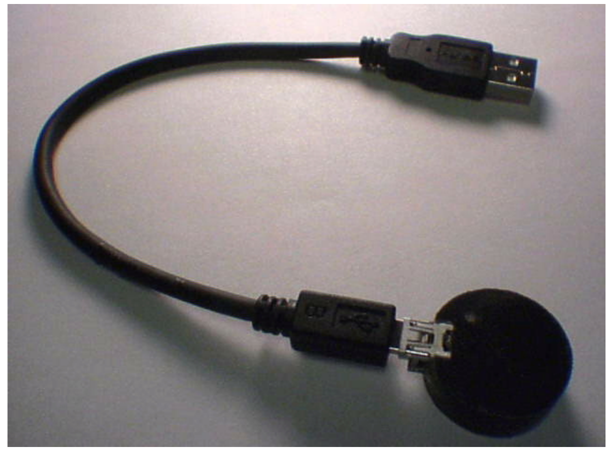


Figure 5: M.E.T.I.-Disk 3 sensor node schematic and photograph

From the composite plates, three types of damage were investigated – impact, hole and delamination. The impact setup consisted of a 5 lbs weight with a ½" diameter ball attached to the bottom. Delamination area and crack lengths as a function of drop-height were predicted based on analytical work found in the literature[44]. Four heights were progressively tested between 4" and 32". Next center drilled holes were cut into the laminates using drill bits and composite machining methods, ranging from $^1/_{32}$" to ½". Last, corner delamination were cut into the center ply of the laminates in the same of isosolese triangles using a box-cutter, ranging from ¼" to 1.5" in side length. For each specimen, 100 pulse-echo tests were performed per node prior to any damage introduction to be used as baselines. Then damage was introduced at each level, 100 more pulse-echo tests were performed, followed by the next progressive damage introduction. Three plates were tested for each type of damage for a total of 9,000 data sets. The test matrix is shown in **Table 1.**

Table 1. Test Matrix

# Plates	Damage Type	Damage Severity
3	Impact (5 lbs dropped spherical weight)	4", 8", 16", 32"
3	Hole (center drilled)	$^1/_{32}$", $^1/_8$", ¼", ½"
3	Delamination (corner cut isosceles triangle)	¼", ½", 1", 1.5"

V. Results

The test matrix presented in the previous section was executed, and all of the experimental results were accumulated on a PC. Representative raw voltage versus time results for the damage type of center-drilled hole is shown below in **Figure 6**. This figure compares signals from the undamaged plate with that from the most severely damaged condition. Upon visual inspection, the signals are very similar making it difficult to discern differences in the time domain. A preliminary analysis was performed using traditional time-frequency based algorithms, which yielded decent results, however with undesirable accuracy levels. Subsequently, a PCA-based approach was used implemented that yielded much improved results. The following sections describe the results for both approaches, as well as presenting the overall "confusion matrix," or table exhibiting the statistical accuracies for the damage predictions as compared to the actual plate configurations.

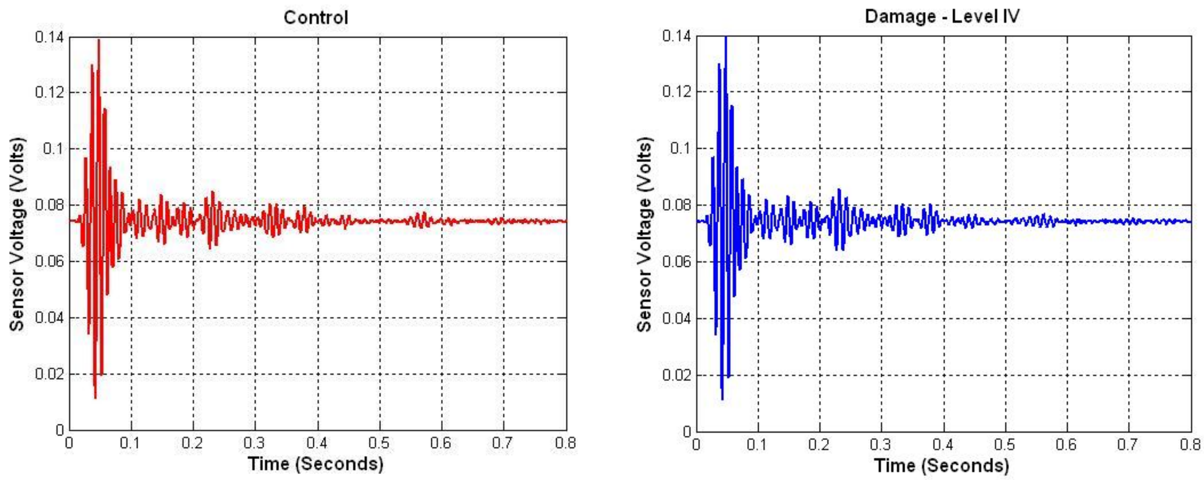


Figure 6: Representative experimental data from specimens with and without drilled holes

A. Time-Frequency Results

Sixteen Time-Domain and Frequency-Domain features were calculated from the collected signal and ANOVA tests was performed on these features to determine their capability as a discriminative feature. A very small P-value indicates that for a given features, it value across various classes was significantly different to distinguish between the classes. It can be seen that most of the features passed the ANOVA test thereby indicating that they were strong features to distinguish between damaged and undamaged structures as well as identify severity of damage. The cluster diagram in **Figure 7** shows the ability of time and frequency based features in identifying damage. Here, using only the first three features that were most discriminative, data from an undamaged plate and those of several levels of damage severity have been plotted in 3-dimensions. It can be seen that though the classes can be separated, the cluster boundaries are diffused instead of crisp, which would lead lower pattern recognition accuracies.

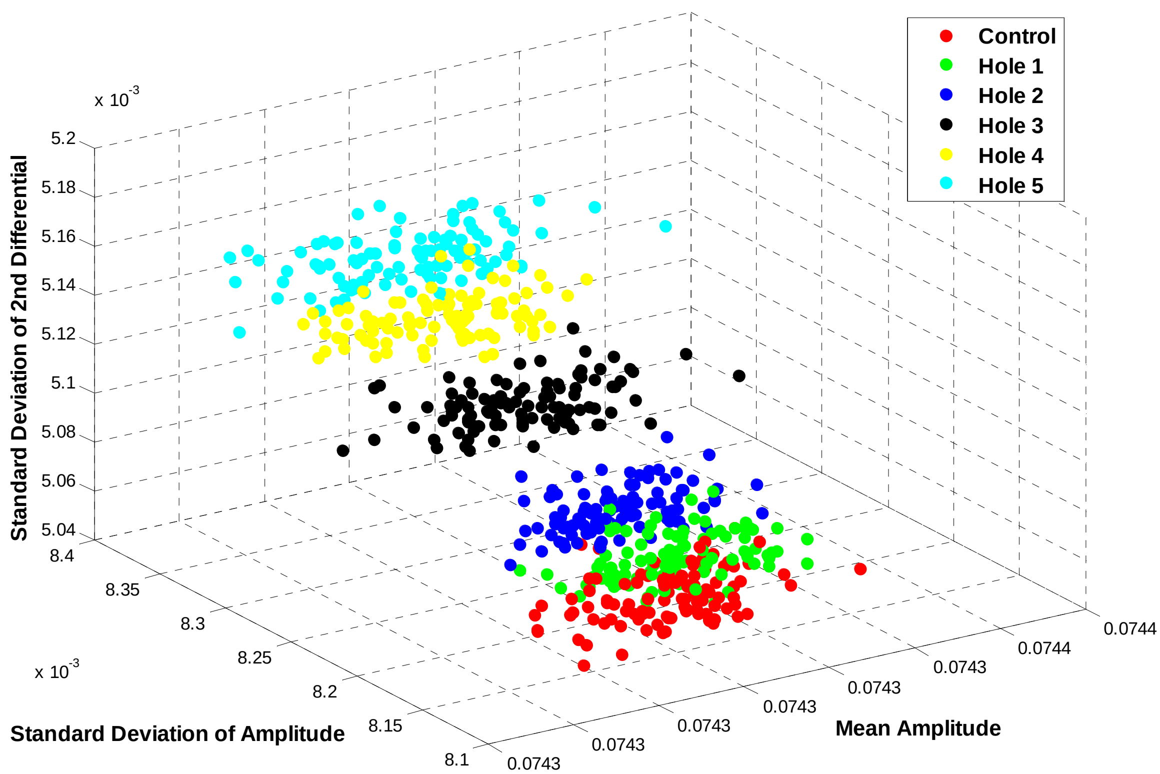


Figure 7: Time/frequency cluster diagram for representative data from specimens with drilled holes

B. PCA Results

Similar to the previous approach, PCA was also used to extract features as an alternative to the traditional time/frequency resultants. Each data set contained 800 points which were treated as 800 dimensions, and using the previously presented method they were transformed into 800 new dimensions which were the eigenvectors of covariance matrix of the input data. These 800 transformed vectors were used to generate the principal components. The top 20 principal components that contributed to nearly 70% of the data variance were then selected. These 20 components were the new features that were passed into the pattern recognition methods. The cluster diagram in **Figure 8** demonstrates the ability of PCA to assist in the identification of damage. Here, using only the first three principal components, data from an undamaged plate and those of several levels of damage severity have been plotted in 3-dimensions. It can be seen that not only all the classes can be clearly separated, but clearly separated with a greatly reduced dimensionality. PCA proved to increase both the efficiency and accuracy of the pattern recognition methods.

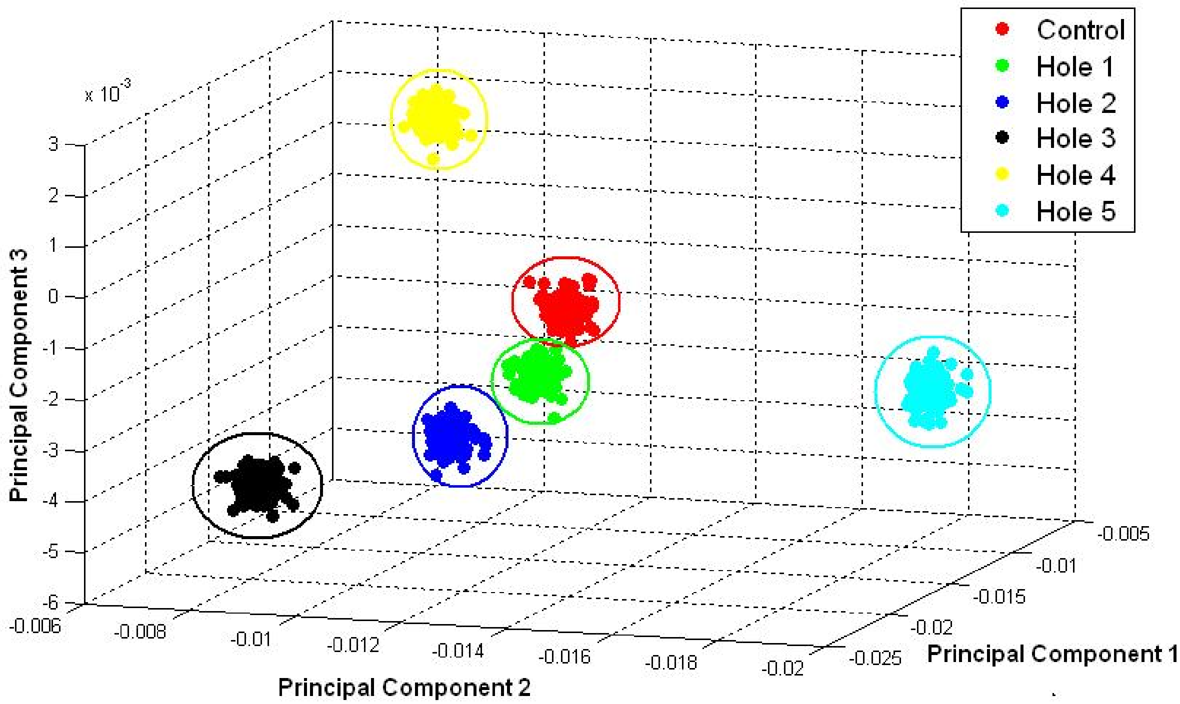


Figure 8: PCA cluster diagram for representative data from specimens with drilled holes

C. Overall Results

Once the previous steps of the damage detection methodology—signal conditioning, feature extraction and feature selection—had been completed, the resulting signal features were used within several combinations of the PR schemes previously described. For each damage type, a single sensor node on single plate was designated as the "training node," and all data collected from this node before damage as well as at each level of damage severity was used to train the PR algorithm. The other node on the same plate as the training node, as well as all of the other nodes on the other plates were all "testing nodes," and used to collect experimental data for predictions. All of the PR results provided decent accuracy, however the most reliable method determined in the present study was using KNN alone. The KNN parameters were optimized in MATLAB to obtain the best mean accuracy using all of the collected data. The master confusion matrix in **Table 2** presents the best results using the optimized KNN algorithm, displaying the percentage predicted severity of damage versus actual severity of damage combined for all damage types. Horizontal lines in the matrix sum to total 100% of the actual severity levels (e.g. the second line would be read as 86% of the 1/32" drilled holes were correctly diagnosed and the remaining 14% were predicted to be 1/8" holes).

Table 2: "Confusion Matrix"—results from damaged composite plates using pattern recognition techniques to determine presences, type and severity

PREDICTED		**No Damage**	**Drilled Hole**				**Delamination**				**Impact**			
ACTUAL		ND	1/32"	1/8"	¼"	½"	¼"	½"	1"	1.5"	4"	8"	16"	32"
No Damage	ND	**100%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Drilled Hole	1/32"	0%	**86%**	14%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	1/8"	0%	53%	**47%**	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	¼"	0%	0%	0%	**44%**	56%	0%	0%	0%	0%	0%	0%	0%	0%
	½"	0%	0%	0%	0%	**100%**	0%	0%	0%	0%	0%	0%	0%	0%
Delamination	¼"	0%	0%	0%	0%	0%	**99%**	1%	0%	0%	0%	0%	0%	0%
	½"	0%	0%	0%	0%	0%	58%	**30%**	12%	0%	0%	0%	0%	0%
	1"	0%	0%	0%	0%	0%	1%	9%	**58%**	32%	0%	0%	0%	0%
	1.5"	0%	0%	0%	0%	0%	0%	0%	0%	**100%**	0%	0%	0%	0%
Impact	4"	0%	0%	0%	0%	0%	0%	0%	0%	0%	**76%**	23%	1%	0%
	8"	0%	0%	0%	0%	0%	0%	0%	0%	0%	6%	**33%**	61%	0%
	16"	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	**98%**	0%
	32"	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	14%	**86%**

VI. Conclusion and Recommendations for Future Work

As seen from the maser confusion matrix, the results of this PR-based methodology have been very successful. For determination of presence of damage, this methodology has predicted with **100%** accuracy without any false positives or missed damage. For determination of type of damage, this methodology has also predicted with **100%** accuracy without any mis-classifications. Both of these results were obtained using an optimized K-Nearest Neighbor code. Finally, for determination of severity of damage, this method has predicted the correct severity 77% of the time, with 11% overpredicting the damage size and 9% underpredicting the damage size. When considering not only the exact severity, but also include the directly adjacent severity levels, this accuracy improves to **99.9%**. This simplification is reasonable since the damage was not introduced in a very controlled fashion, so the damage levels themselves were not very well exclusively defined (e.g. there is little difference between a 0.03 in^2 and 0.13 in^2 when delaminating composite plies with a razor, which resulted in one of the largest sources of "adjacent" error). Alternatively, these improved results could be achieved in a real application simply by intelligently selecting the boundaries for severity levels through additional experimentation and iterative refinement. Overall these results would be sufficient for a technician to be able to make a knowledgeable decision about the necessity to perform a repair. Of particular significance, these results were achieved using training data from one plate and testing data from a separate plate. This has broad implications for the feasibility of commercial usage, where a single set of validated training data would need to be implemented on multiple vehicles. This verifies the ability of this methodology to account for slight variability in sensor fabrication and placement, as well as accommodating "real" uncontrollable damage types such as delamination and impact. Future research will be aimed at executing this methodology for built-up structures, as well as including an adaptive module to account for maintenance, repair and ageing. Robust integrated SHM systems will be an important component in future air and spacecraft designs to increase safety and reduce life-cycle costs, and pattern recognition driven Lamb wave methods will likely play an important role in their success.

Acknowledgments

The research presented in this paper was preformed at the Metis Design Corporation in Cambridge, MA under a contract from the Air Force Research Laboratory, Materials & Manufacturing Directorate FA8650-06-M-5026).

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