AN ARTIFICIAL INTELLIGENCE-BASED STRUCTURAL
HEALTH MONITORING SYSTEM FOR AGING AIRCRAFT

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ABSTRACT

To reduce operating expenses, airlines are now using the existing fleets of commercial aircraft well beyond their originally anticipated service lives. The repair and maintenance of these "aging aircraft" has therefore become a critical safety issue, both to the airlines and the Federal Aviation Administration.
This paper presents the results of an innovative research program to develop a structural monitoring system that will be used to evaluate the integrity of in-service aerospace structural components. Currently in the final phase of its development, this monitoring system will indicate when repair or maintenance of a damaged structural component is necessary.

INTRODUCTION

Cyclic mechanical loading causes the progressive development of damage in aircraft structures that can eventually lead to structural failure. If the initiation and development of this damage could be tracked nondestructively, the structure could be repaired or replaced prior to failure. Toward this end, a variety of non-destructive evaluation (NDE) techniques have been developed to detect damage in advanced aerospace composite materials [1-4].

An efficient alternative to these traditional NDE techniques that can be applied to in-service structural components was recently proposed [5,6]. The approach is to measure changes in *global* structural dynamics that result from damage-induced changes in the material properties [7-12]. In reference [12], a sensitive technique was developed to detect small changes in material properties of composite laminates, such as those caused by damage due to mechanical loading. Vibration of laboratory test specimens was monitored, and changes in measured vibration frequencies and damping properties were shown to result from the damage-induced microstructural changes in the composite material.

As part of a Small Business Innovation Research contract with the NASA Lewis Research Center, engineers at Structural Integrity Associates, Inc., recently demonstrated that a personal computer-based pattern recognition algorithm could be "trained," using laboratory test data, to recognize such characteristic changes in structural vibrations and to infer from those changes the type and amount of damage in a structural component. A potential application of this approach to an in-flight airframe monitoring system is shown schematically in Figure 1.

Damaged Blade

Monitoring
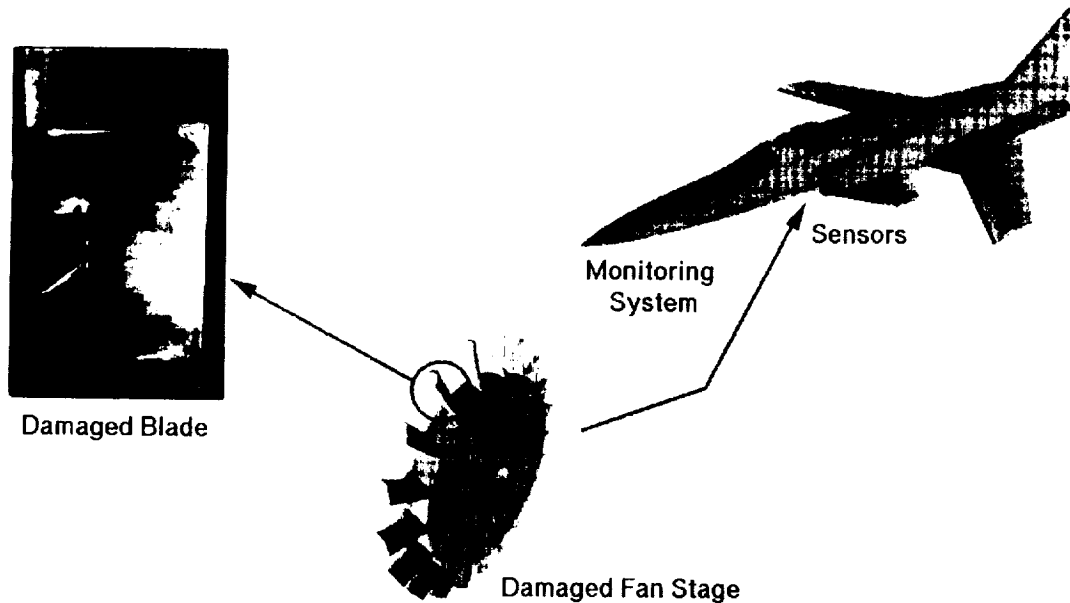System

Sensors

Damaged Fan Stage

Figure 1:   Conceptual Application of Structural Health Monitoring Technology to an In-Flight
                Airframe Monitoring System

The technology described in this paper will be used to monitor the damage development and resulting
structural degradation of aging airframes that naturally occur as a result of the repeated takeoff/landing and
pressurization/de-pressurization cycles that aircraft are routinely subjected to in the course of their duty
cycles.

APPROACH

Vibration Testing

To evaluate the effects of ply debonding, or "delamination" on vibration measurements, a series of vibration
tests of delaminated T300/934 graphite fiber/epoxy matrix composite beams was conducted. The test
specimens were of dimension 5 x 0.5 x 0.04 inches, as shown Figure 2. Each specimen was 8 plies thick, and
was laid up in a $[0°/90°]_{2S}$ cross-ply configuration. Ply disbonds
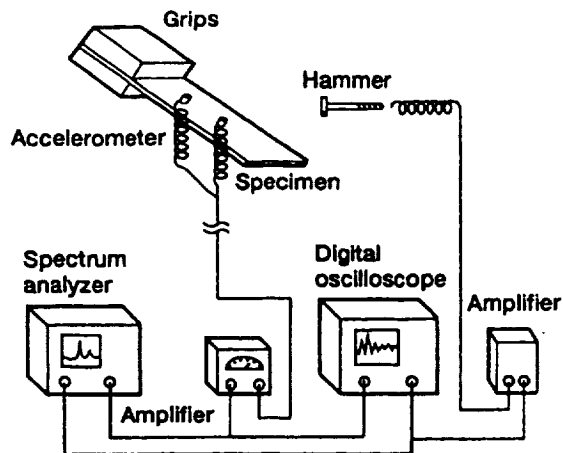

Figure 2: Experimental Apparatus for Vibration Testing

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(delaminations) from one to four inches long were introduced into the material by inserting thin, non-adhesive teflon strips between selected piles of the laminates prior to curing.

The test data contained strain measurements during the first 2.5 seconds of free vibration of beams with delaminations of length 0, 1, 2, 3 and 4 inches along the midplane (neutral axis) [13]. Strain measurements were obtained from a single strain gage oriented longitudinally along the beam and located 0.5 inch from the clamped end. The strain data were digitally sampled at a rate of 800 hz (t = 1.25 msec).

Pattern Recognition

Application of pattern recognition to failure analysis and diagnostic evaluation has increased significantly during the last decade, [14]. Pattern recognition can be considered as one of the many forms in the artificial intelligence (AI) field. The mathematical approaches to pattern recognition may be divided into two general categories [14-16], namely, the syntactic (or linguistic) approach and the decision-theoretic (or statistical) approach.

The majority of the developments in the application of pattern recognition methods to failure detection and diagnostics has used the decision-theoretic approach. This is a process that is generally used to digest a vast amount of data, reduce it into a meaningful representation, and make decision on the outcome of the observation data using a classifier. The types of test data that are used by the pattern recognition algorithm to classify structural damage is shown in Figures 3 and 4.
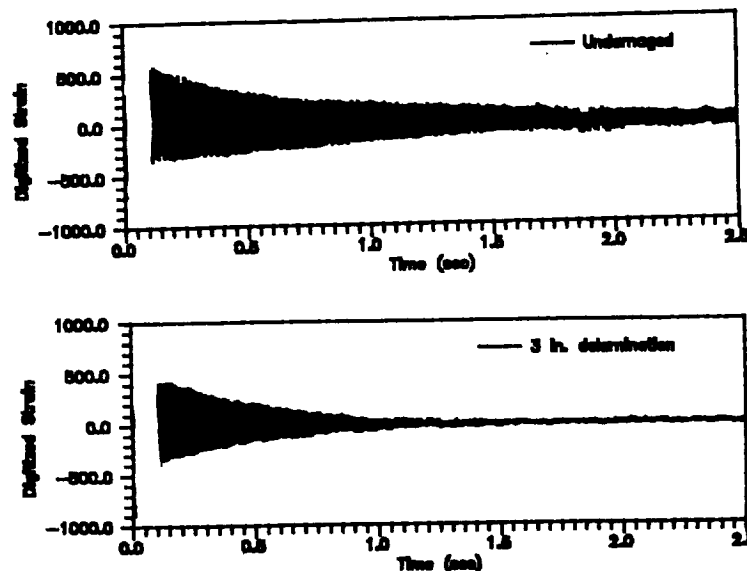

Figure 3: Strain History Measurements from a Vibrating Composite Beam Structure

Figure 3 shows two time domain measurements of the vibration response as measured by a strain gage mounted at some point on the vibrating structure. Comparison of the two signals shows how interply delamination affects the transient response. The vibration response of the damaged beam decays much more quickly due to the energy dissipation caused by friction between the delaminated surfaces. The rate at which the signal decays is dependent upon the extent of the delamination damage in the structure.

Figure 4 shows the results of similar measurements expressed in the frequency domain [17]. As damage develops, a loss in structural stiffness causes a corresponding decrease in the resonant frequencies of the structure, causing this data to shift along the x (frequency) axis. These shifts in frequencies are related to

damage characteristics during the training phase. With sufficient training input, the pattern recognition algorithm can relate typical waveform characteristics (such as vibration decay times and shifts in resonant frequencies) to structural damage levels.
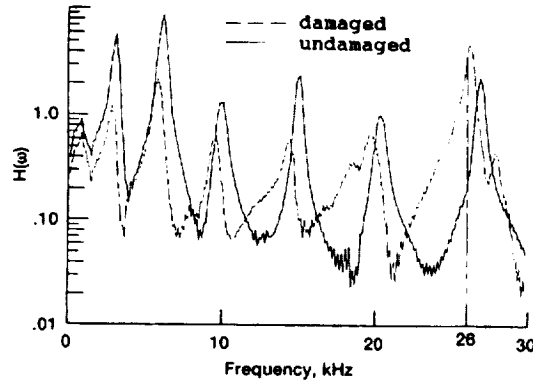

Figure 4: Structural Vibration Response in the Frequency Domain

Four fundamental steps are required to "train" the pattern recognition algorithm:

- Pattern Measurements
- Feature Extraction
- Learning
- Classification

After a set of features (e.g.; frequencies, damping properties) are calculated that characterize the pattern measurements (vibration signals), the classifier partitions the feature space into a number of regions, and associates each region with one of the known outcomes (e.g.; damage levels). Decision making ability is established through a learning process which compiles and retrieves information based on experiences where a priori knowledge of an outcome has been established.

Figure 5 presents a framework of the monitoring methodology for the material degradation of composites using pattern recognition. One key requirement of the methodology is the availability of appropriate dynamic response data of different damage levels. These measurements serve as a database to be used in the feature extraction and learning.
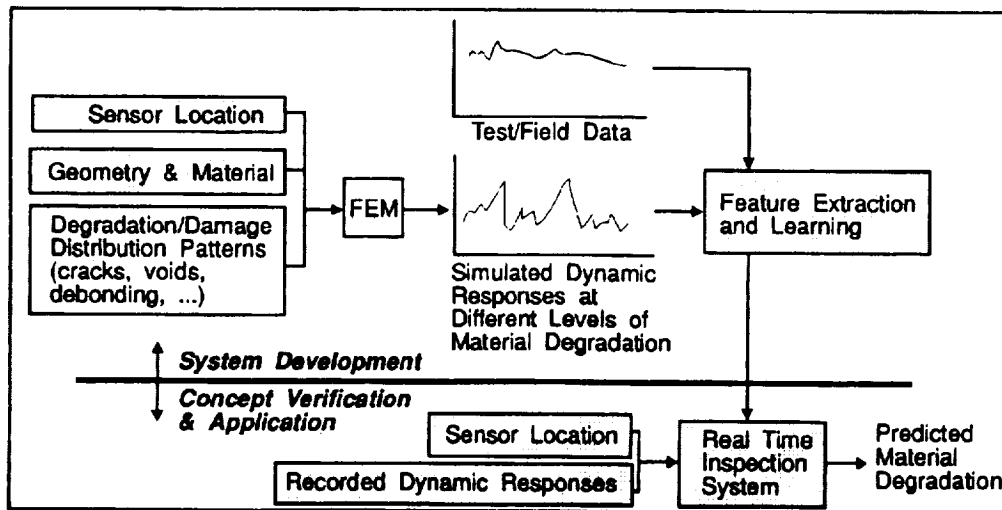

Figure 5: Application of Pattern Recognition Approach to Structural Health Monitoring

Training data can be obtained from actual operation environments of the system to be monitored, or it can be simulated from the dynamic analysis of the components or the structures. The training of the pattern recognition algorithm can be upgraded regularly as additional data with known failure status are added to the data base.

Computational Analysis

An extensive experimental database exists that shows the effect of delamination damage on vibration characteristics of composite laminates [5,6,13]. No such database exists that shows the effects of matrix cracking. Therefore, computational structural analysis was used to augment the existing experimental database to include the effects of matrix cracking on vibration behavior.

Free vibration analysis of the cantilevered composite beams was conducted using the modal superposition method available in the general purpose finite element code ANSYS [18]. Localized matrix cracking in the material was simulated by decreasing the flexural modulus over a specific region in the structure. These calculations were performed using a three-dimensional finite element model of the test specimen, with isoparametric solid elements that have orthotropic material properties. The finite element model had eight elements through the thickness and 10 elements along the longitudinal axis of the beam.

RESULTS

The initial step in applying the pattern recognition method is to conduct the system training (learning). During this phase, a priori knowledge of the correct output classification of the data for a given set of input is needed. In this case, the results of the vibration tests and finite element analyses were used as the training data. The knowledge gained during this learning process can then be used by the decision processor (classifier) to evaluate future input when the output status is unknown.

To develop this training base, the strain histories recorded from the vibration tests were characterized, both in the time domain and the frequency domain, and then correlated with the known levels of damage in the test specimens using the 71 different waveform classification features available in the TestPro monitoring system [19]. Time domain classifiers included mean, standard deviation, maximum amplitude and rise and fall time characteristics. Frequency domain classifiers included direct power spectrum features and cumulative distribution functions.

To assess the applicability of this approach to damage monitoring in composite structures, several different classification schemes were evaluated. These were the classification of

- Damage Modes
- Damage Severity
- Damage Location

The objectives are, therefore, to train the system such that it can classify the different types of damage (damage modes) in the structure, quantify the severity of the damage, and determine the location of the damage. This section summarizes the effectiveness of the monitoring system in each of these areas.
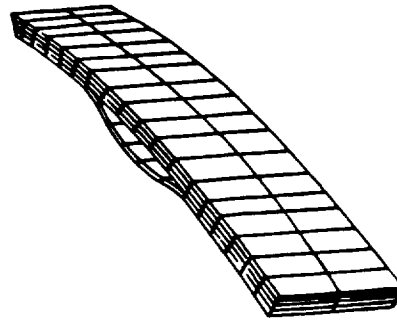
Damage Modes

The data used to train the pattern recognition algorithm came from composite beam structures with three different categories of damage:

- Undamaged
- Localized matrix cracking
- Delamination

Each of these damage modes are depicted schematically in Figure 6.

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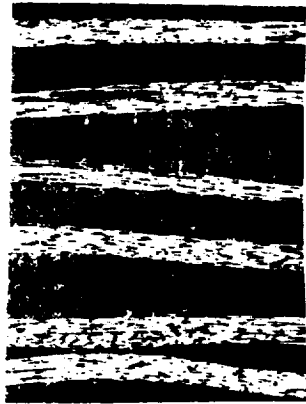
matrix cracking   delamination

Figure 6: Typical Damage Modes in a Polymer Composite

The pattern recognition algorithm was used to identify, based on the vibration signal, the damage that exists in the structure. For the purpose of this investigation, each test specimen was assumed to be characterized by one of the three damage states listed above.

The data base was divided into two groups: Training and Analysis, Table III. The data in the training group, Table III, were put through the learning step to determine the optimum feature(s) to be used in the classifiers for damage status classification. The optimum waveform feature was determined in this manner to be "Mean Value of the Normalized Enveloped Function," a time domain feature. The enveloped function is represented graphically by a curve connecting the positive amplitude peaks of the waveform. It is therefore always positive and represents a low pass filter or integration process. The actual damage status of the structure was compared with that obtained using the pattern recognition algorithm. The results shown in Table I indicate that 98 percent of the total damage classifications were correct, using the nearest neighbor classifier.

Table 1: Monitoring System Indicates Damage Mode
with 98 Percent Accuracy

Training	Analysis	Total
27/28 *	22/22	49/50

* correct classifications / total cases analyzed

Damage Severity

After the damage mode has been identified, as described in the previous section, an evaluation of the extent of that damage can be made. To quantify the extent of localized matrix damage in the structure, the problem was again posed as a three-class problem:

- Undamaged
- Minor Damage $(E/E_0 > 0.9)$
- Major Damage $(E/E_0 < 0.9)$

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Physically, a uniform degradation of the elastic moduli would represent distributed damage such as matrix cracking.

The data in the training group were assigned to the appropriate classes for the training exercise. After training, the "Mean Value of the Normalized Enveloped Function", was again determined to be the optimal discriminator for classification. Table 2 summaries the evaluation results for classification of the degree of modulus degradation. Using the nearest neighbor criteria, the pattern recognition algorithm correctly classified the level of modulus degradation in 41 of the 46 cases examined, an 89 percent average.

Table 2: Monitoring System Indicates Damage Severity
with 89 Percent Accuracy

Training	Analysis	Total
22/24 *	19/22	41/46

* correct classifications / total cases analyzed

Damage Location

To conduct the system training, a two-class problem was defined, which classified the damage location as within either O inches to 3 inches or 3 inches to 5 inches of the clamped end of the cantilevered composite beam, as shown in Figure 7.
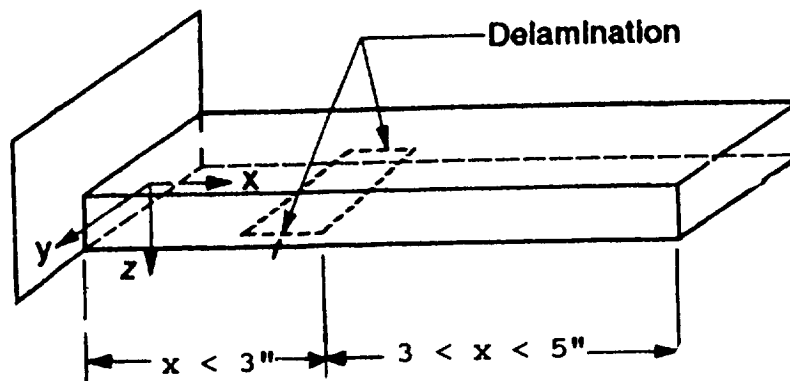

Figure 7: Classification of Damage Locations

The length of the damaged zone was not considered. The data in the analysis group has damaged zones overlapping the two defined regions.

The optimum feature was determined to be the "Difference between 50% Level and 25% Level" of the Waveform Cumulative Distribution. The results, summarized in Table 3, indicate that 80 percent of the damage locations were classified correctly by the pattern recognition algorithm using the nearest neighbor criteria classifier [17].

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Table 3: Monitoring System Indicates Damage Location
with 80 Percent Accuracy

Training	Analysis	Total
22/24 *	19/22	41/46

* correct classifications / total cases analyzed

Since the primary objective of this project was to demonstrate the feasibility of using the pattern recognition approach as a means of damage detection, only a limited amount of system training was conducted. The percentage of correct classifications should improve significantly if a more extensive set of test data were used to train the system.

CONCLUSIONS

It was demonstrated that a pattern recognition algorithm can be trained to interpret structural vibration measurements in terms of damage characteristics in a composite structure. This approach can therefore be used together with a measurement system to monitor damage development in aerospace structural components. Potential applications include in-service structural monitoring, or routine material inspections for quality control applications during manufacturing. In either application, the results would provide information needed to schedule maintenance and to make decisions for repair or replacement.

Due to the success of this work, the project has recently received substantially increased funding from NASA to continue work on a Phase II program, which was awarded to Structural Integrity Associates, Inc. in August. During this two-year development program, a pattern recognition algorithm for a prototype "Structural Health Monitoring System" will be developed and demonstrated on a specific aerospace structural component.

ACKNOWLEDGEMENT

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THE GROUND PROCESSING SCHEDULING SYSTEM

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