Composite Panel Damage Detection using Ultrasonic Testing and Neural Networks

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Abstract. For modern aircraft, wind turbines, and other aerospace structures composites are replacing metal components. These aerospace structures will be designed and expected to perform well for many years ahead. Therefore, structural health monitoring (SHM) systems are being designed to monitor these structures to improve maintenance, repairing or replacing composites components when the need arises. The focus of this research is on creating an SHM system, using ultrasonic testing methods to monitor damage in a composite panel. The ultrasonic testing consists of either actively scanning the panel by introducing controlled strain waves or passively listening to noises created by damage, which is a technique called acoustic emission. Through acoustic emission, composite coupons with damage introduced in the form of fiber breakage, delamination, and matrix cracking are examined by introducing tensile loading, since these forms of damage are present in aircraft and wind turbines through normal use of the systems. Artificial neural networks are used to analyze the signals received from the ultrasonic testing method. These networks allow for fast processing of the strain waves even with some extra noise present. Through this study, a system, using ultrasonic testing techniques, was shown to be a plausible SHM system for aerospace systems of the future.

1 INTRODUCTION

For aircraft or aerospace structures, maintenance is an important issue. Unlike automobiles and other vehicles, aircraft, wind turbines, or space stations are expected to perform well beyond their designed performance lifetime. This is accomplished through replacing broken parts, usually before failure or inspecting for damage at scheduled times, usually via ground inspections for aircraft. Using simple nondestructive testing techniques, such as visual inspection or coin tap tests, an aircraft is pulled from operation and its components are inspected for damage, resulting in sections being replaced if sufficient damage is found. Current research is being performed on making a structural health monitoring (SHM) system as a means to improve the current maintenance routine. This would consist of a system of sensors and analysis which would scan for damage in-flight, allowing for fewer ground inspections and better real time damage analysis of an aircraft’s structure. If damage is recognized long before failure would occur, then a damage tolerance and prognostic assessment could be implemented, allowing for better determination of the lifetime of components. The current method of inspecting aircraft consists of ground inspections, which search for damage after a set number of flight hours. Although this method is working, an SHM system in-flight would allow for better use of components, as specific lifetimes could be determined, and could be less costly, since an SHM system could be embedded into the aircraft system, reducing or eliminating the ground inspection procedure of taking apart aircraft to scan for damage.

1.1 Ultrasonic Testing

There has been various research investigations of various non-destructive inspection (NDI) techniques, which include small sensors and equipment, easily attachable to the structure of an aircraft or other aerospace system without compromising the loading requirements are in progress. Of the various methods, a form of ultrasonic testing was the subject of the investigation reported in this paper. Ultrasonic testing uses characteristics of Lamb or Rayleigh waves traveling through a thin structural component to determine if any damage has occurred, since the component was placed into service. This method of NDI utilizes piezoelectric sensors to detect the location of crack initiation and/or the severity. The piezoelectric sensor is capable of producing an electric current if the material is deformed. It is sensitive enough to produce and receive strain waves with frequencies in the ultrasonic range. Damage itself will emit these waves as well when increasing in size.

However, these strain wave signals exhibit complex characteristics at high frequencies. For example, a piezoelectric actuator emits a strain wave signal that disperses uniaxially away from it. When the wave encounters a geometric boundary, such as the edge of a panel, the wave will reflect off that boundary, thereby creating a super-position of waves on top of the original wave. Also, strain waves are smooth, continuous shapes,
which can then be broken down into a summation of frequencies and phase modes. From previous research in the field of ultrasonic waves, it has been discovered that each phase mode of the wave will actually travel at different velocities throughout the material [1,2]. These additional changes become part of the response wave received by the array of piezoelectric sensors. Therefore, the optimal strategy found in interpreting strain waves is through conditional based monitoring. Ultrasonic testing in previous research has shown that there was a difference in signals, depending on the location of damage away from sensors [3]. Additional problems are present for composites, such as the direction of fibers affecting how strain waves travel through the material [4]. Other research had shown that there was potential in connecting artificial neural network analysis to this form of nondestructive testing [5].

1.2 Acoustic Emission

The research included in this paper investigates the abilities of a passive ultrasonic scanning system, called an acoustic emission system. This system exists currently, but is still under development, so the focus of this research was looking for a quick, accurate, and precise method of automating such a health monitoring system or to optimize the analysis capabilities of an acoustic emission system. Using the acoustic emission system, an artificial neural network analysis idea is implemented for real-time analysis of acoustic emission data from structural components of aircraft.

As a crack propagates in a material, molecular bonds are broken, releasing small amounts of energy. The energy released spreads throughout the surrounding material in the form of strain waves, similar to beat pulse waves. These waves are minute deformations in the material with wave frequencies in the ultrasonic range (500 kHz to 3 MHz). Also an impact event transfers energy into strain waves, resulting in waves similar to crack growth. To detect these strain waves piezoelectric ceramic materials have been created and are currently being produced, for ultrasonic testing sensors. Piezoelectric materials are unique in that a voltage is produced in the material from any deformation. Sensors created from this material are sensitive enough to detect the voltage generated by any small deformations, which is then recorded into a computer database for further analysis. The acoustic emission system uses piezoelectric sensors by passively “listening to” a structural component, recording any waves as voltage over time detected in the ultrasonic range. The system is different from active ultrasonic testing systems in that no strain waves or deformations are produced by the sensors and sent out into the structural component. The acoustic emission system only receives waves, generated by other sources. The recorded waves are then broken down into characteristics of the strain waves, such as amplitude, rise time, and duration, through software provided with the sensors by Physical Acoustics Corporation. These characteristics, along with time recorded for a network of sensors are then analyzed via different software methods to determine if cracks are present and growing, and whether the component needs to be replaced.

Because of complications of geometry and damage location, methods have been developed to analyze these strain waves; however, they may be time and processor consuming. Thus the focus of this paper is on discovering a method through artificial neural networks to look determining the mode of failure. For example differences between fiber breakage and delamination of the composite structures. The abilities of neural networks and acoustic emission sensors have promise in an integrated system to form a structural health monitoring system for aircraft or other aerospace systems.

1.3 Artificial Neural Networks

Artificial neural networks (ANN) were created around the same time as serial computers. These networks are composed of algorithms to mimic the thought processes of an organic brain to analyze a set of inputs in order to obtain a desired output set. Through a fuzzy logic system, the human thought process was emulated mathematically with a network of connected nodes and adjustable weighted values on the paths connecting the nodes, which can establish a relationship of a set of input variables to a set of output variables. Similar to a human brain, this network can be “taught” the relationship of inputs to outputs using example sets of inputs and outputs. After a sufficient number of examples have been introduced, the network can then be used to determine a trained approximation for the output associated with a new input set within the range of the examples used for training. This process approximates the output set, using “fuzzy” logic. The true power of a neural network is demonstrated when used to evaluate complex problems. Because of the training process of neural networks, a complex relationship of inputs to outputs can be found quickly, accurately and precisely if taught well. The advantages offered by the neural network when applied to a structural health monitoring system of ultrasonic sensors allow for quick assessment of the complex strain wave signals generated by the piezoelectric signals. This would result in an accurate, almost real-time damage assessment of structural components, which may


occur when in-service. The focus of the research of this paper consisted of using artificial neural networks to analyze the output of an ultrasonic testing system, being considered as a principle element of a structural health monitoring system for aircraft.

The concept of an artificial neural network was introduced by McCulloch and Pitts in the 1940’s. Rumelhart, Hinton and Williams provided significant improvements of the procedure by including increased learning and solving abilities for complex problems, during their work in the 1980’s [6]. Through these studies, a neural network process was developed, which was suitable for application in the ultrasonic testing addressed in this research.

Kohonen and others developed a common architecture for artificial neural networks, which is called a self organizing map (SOM) [6]. This network type has the ability to categorize data sets into fields, using an unsupervised method with no need for a known output to train. This type of network has nodes, which store group types with matching traits within them. An input set is compared to each node and the node most similar will absorb that input set. The groups can then be used as identifying categories. Consider the basic example with three nodes, illustrated in Figure 1.1 below.

![Figure 1.1: Generic self organizing map architecture for an artificial neural network](image)

In this example the nodes are arranged into a single row. This network learns by first being shown a new input set of data from a training set. The exemplar sets, belonging to each node, which were initially set to small positive random values, are then compared to the input set, or vector. A general comparison method between an exemplar set, \( w_k \), and an input set, \( X_i \), might be performed using the Euclidean distances between the two sets, expressed in Eq. (1.1).

\[
ED_k = \sqrt{\sum_{j=1}^{p} (w_{kj} - X_j)^2} \tag{1.1}
\]

The network nodes then work competitively with the node with the smallest distance winning the input set. For example, let node \( k \) “win” the input set. Afterwards, the exemplar values in \( w_k \) are adjusted to slightly resemble the new input set. This is accomplished using Eq. (1.2), where again a learning coefficient, \( \alpha \), is used.

\[
w_{kj}^{new} = (1 - \alpha) \cdot w_{kj}^{old} + \alpha \cdot X_j \tag{1.2}
\]

Through iterations of all the input sets, this network will adjust itself and group the input sets into categories without any prior knowledge of the data sets. This concept can be expanded further, where a winning node can contain a neighborhood of nodes. In this process winning node \( k \) will adjust its exemplar values, along with neighboring nodes \( k \pm 1 \) for a small neighborhood, or larger surrounding nodes (i.e. nodes \( k \pm 2, k \pm 3, \ldots \)). The concept of neighborhoods, allows for better grouping of input sets as sets similar to each other, but still with slight differences, will be placed in nodes close to one another, but not necessarily the exact same node. The neighborhood concept can be improved upon, by reducing the size of the neighborhood after a set number of iterations. This allows for more defined categories.

More useful SOM networks increase the number of nodes used and can be expanded to a 2-D field of rows and columns, called a Kohonen layer of a network, named for the creator. The adjustment of weights through learning categories and winning neighborhood concept apply here as well. However, the neighborhood shape then forms into 2-D shapes as well. An example of a common square neighborhood shape is shown in Figure 1.2, where the size is one node away from the winning node. The exemplars to the nodes within the dashed box are adjusted, when the center node “wins” an input data set.
Once the training is completed, a 2-D map of groups is formed. This map can then be used with new data sets and categorized in much quicker speeds. Groups can then be formed with regions of the map, similar to the borders of a country although less specific. Note that once training is completed for a particular training set, the exemplars can be adjusted again, depending on the desired results. Generally though the exemplars remain constant and are not adjusted further for any new data sets introduced to the network. A larger number of nodes used allow for a better defined map, however, a greater amount of computing time is required as well. So, an optimum ratio of number of nodes to processing time is desired when using this form of neural network. This architecture is elegant in using simple equations for learning categorizing data sets, while remaining powerful to discover similarities not easily noticeable in other grouping algorithms.

2 EXPERIMENT

Several experiments were performed, using various composite coupons. Each structural consisted of carbon fiber plies with epoxy resin. Each ply was unidirectional, but the angle difference of a ply layer to the next was +45°. For this series of experiments three composite coupons were manufactured and tested upon. Each coupon had a length of 25.4 cm to 26.7 cm and a width of 3.81 cm with around thirty plies each. The surface layers of all composite coupons used spanned the lengthwise direction and connected the two sensors, since surface waves are affected by fiber orientation [4]. The purpose of this experiment was use artificial neural networks as self-organizing maps to determine the failure modes of a composite coupon to use in estimating whether repair or the structural component is required.

Two acoustic emission sensors were attached to each coupon, which was then subjected to a static tensile loading, provided by an MTS machine. The loading was the result of a controlled displacement increase rate of 0.127 cm/min. The displacement of the two ends was increased at this rate, resulting in an increase on the coupon, until fractured occurred. This point occurred when the fibers and matrix both failed completely and the coupon was split into two separate pieces.

Many strain wave detections were gathered throughout the experiment with various amounts of energy being released, as shown below in Figure 2.1. It was demonstrated that there is an increasing amount of strain waves detected as more internal damage occurred. The damage could have been categorized through various methods into groups, including resin damage, delamination, and fiber breakage. Other studies have determined certain characteristics associated with these different damage types for different structural configurations and have determined the boundaries based on specific values [7]. However, for this experiment, an artificial neural network (ANN) was implemented instead. With an artificial neural network, other trends in the strain waves were seen by the self-organizing map created, grouping the strain waves not just on one parameter of the detected waves, but several at once.
The architecture of the ANN chosen was that of a self organizing map. This allowed the network to categorize the detected strain waves into categories itself. The abilities of this network include using multiple trends or characteristic relationships between various wave detections simultaneously. Essentially, the ANN could be taught a structural component through fracture testing on a laboratory experiment of a copy of the structural component. Using this as an example to learn, the system could then be integrated into an actual structure, used in service, and effectively categorizes detected strain waves in fractions of a second without having to re-teach it again.

### 2.1 Creating and Teaching an Artificial Neural Network

For this experiment the software package Viscovery SOMine was used for this analysis in this experiment. Each strain wave gathered, contained a set of characteristics of the strain wave signals detected by the acoustic emission sensors. Among these properties were rise time, hit counts, energy value, duration, amplitude, and average frequency, including ten characteristics total. These were then fed to a self-organizing map as ten inputs per wave to identify different groups between all the strain waves detected. The first coupon experimented upon became the training example for the network to learn. The network consisted of a Kohonen layer of one thousand nodes. Additional statistical analysis was used, as this was a built-in feature of the Viscovery software. The resulting map from teaching an ANN coupon 1 data is shown in Figure 2.2 below. The points from Figure 2.1 are colored to match the corresponding groups.

![Self organizing map topography](image1)

![Energy of detected waves over elapsed time](image2)

**Figure 2.2: Resulting map of groups from artificial neural network for coupon 1**

(a) Resulting map from learning; (b) Figure 2.1 color coded with groups from part (a)

The ANN learned four distinct groups from the data, and placed them accordingly in the resulting 2D map (see Figure 2.2). In this map, the wave detections with the highest energy levels were placed in the upper left corner of the map, labeled as “Upper” in the figure and colored green. Traveling outward from this corner, energy levels decrease over the map, until the lower levels are placed into the upper right side, labeled as “Lower (2)” and colored yellow. There were much more detections in lower levels, resulting in their regions of the map being much
larger. The ANN itself created groups with general boundary lines of set energy values, as shown in Figure 2.2b. However, these are not definite values, but instead more of a “fuzzy” boarder, allowing for better categorization of detected waves. The regions are also shown to overlap slightly, which is not affected by the abilities of the ANN. The next step became counting these waves through time by the groups formed by the ANN and creating a warning system to alert for failure.

2.2 Post-processing of the Artificial Neural Network

A time window, consisting of a small time step, was created. This time window could slide or travel through the time domain, representing real-time monitoring. For each window or time step, strain waves were detected from the composite coupon by the acoustic emission sensors. These detections were then presented to the ANN, learned on solely coupon 1, to place all detections into one of the four categories. Next a histogram count of the number of detections per group was determined. From this process, a threshold value for the four count data array was then made to signal or alert when failure of the composite coupon was eminent. From Figure 2.2b, it is shown that the upper region, or the green section did not receive any detections until a certain amount of failure has occurred, while the lower three regions increased in density or number of detected hits. This proposed system allowed for a simple, fast method to develop a warning system for when a composite structural component is nearing a breaking point and would require repair or replacement.

3 RESULTS AND DISCUSSION

In order to test the abilities of the artificial neural network (ANN), created in the previous section, the two additional composite coupons were statically loaded in the same method as first coupon. The detected strain waves of coupons 2 and 3 were then presented to the SOM network, taught on coupon 1. For the time window analysis, a time step of 2 seconds was chosen and the results are displayed below in Figure 3.1.

![Graphs showing count of hits detected per group over time, using 2 second windows](image)

**Figure 3.1: Count of hits detected per group over time, using 2 second windows**

*Colors match categories in Figure 2.2, and time windows of 2 sec were chosen*

Coupon 2 behaved similar to coupon 1. Thus a similar graph was generated as the one for coupon 1, showing in increase in the density of the number of points for each group as the composite coupon reached the fracture point. However, coupon 3 experienced some sensor malfunctions. Because of this, detections between times 110 sec to 138 sec and around 180 sec point were found to be acceptable with the equipment operating properly. For coupon 2, all four levels could be marked with individual threshold limits, which once they were exceeded, could be the warning or alerting signal that the composite failure was eminent. For example, on coupon 2 for the “Middle” group, colored red in the figure, any signal above 200 counts would indicate that the coupon was approaching a fracture. For the “Upper” group, colored in green, any strain wave detection in this region would signal the onset of breaking. Thus a smaller threshold count of 1 to 5 could be used. Monitoring all the different categories and their count levels together could allow for an early detection system with the ability to alert for any critical growing damage in a composite structure.
4 CONCLUSIONS

This paper presented a novel method of using artificial neural networks with an acoustic emission system to monitor strain wave detections of growing damage within a composite structure. Three composite coupons experienced an increasing static tensile loading, until fracture occurred. During this time, the acoustic emission sensors detected various strain waves released by internal growing damage. An artificial neural network was able to categorize the various waves into four distinct groups by learning one coupon test, and then apply its gained knowledge to further coupons, which experienced similar loading and fracture. The ANN learned on its own the categories with no external assistance, using the first coupon. The second and third coupons were then presented to the learned network and again it could categorize each individual strain wave detected. A count of number of detections per group over small time windows was conducted, and a pattern of increasing detections as the structural component led to fracture was recognized. Using a threshold to define when failing would occur for each category, an early warning system of failure was produced, effectively monitoring a composite structure with only detections from acoustic emission sensors. This novel method of combining non-destructive inspection and artificial neural networks is the initial stage towards obtaining a structural health monitoring system, improving the future maintenance routines on aerospace systems.

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REFERENCES

[3] D Mateescu, Y Han, A Misra, Analysis of Smart Structures with Piezoelectric Strips Subjected to Unsteady Aerodynamic Loads, McGill University, Montreal, Quebec, Canada; AIAA 2007-2001