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Damage Location in a Stiffened Composite Panel using Lamb Waves and Neural Networks

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ABSTRACT

Neural networks have proved to be very powerful tools in pattern recognition and machine learning and have consequently seen a great deal of applications in Structural Health Monitoring; a field where Pattern Recognition is one of the main lines of attack. The current paper presents a case study of damage detection and location in a stiffened composite panel interrogated by ultrasonic Lamb waves. Rather than work directly on features extracted from the wave profiles, the proposed approach derives secondary features in the form of a vector of novelty indices for the plate. This can be used to train both neural network classifiers and regressors and the use of both for damage location is demonstrated in the paper.

1. Introduction

This work was conducted as part of a European Union project entitled ARTIMA (Aircraft Reliability Through Intelligent Materials Applications). ARTIMA aims to increase the life of in-service aircraft by concentrating on two principal areas: active control of structural vibrations and real-time structural health monitoring. This paper falls into the latter category.

Structural health monitoring involves searching aircraft components for structural damage. A piece of damage within an aircraft could lead to catastrophic failure if undetected, or could lead to the aircraft being taken out of service for an unscheduled maintenance operation. Maintenance constitutes a significant part of the lifetime costs for an aircraft, so any scheme which leads to more efficient maintenance regimes would be advantageous.

In this work a curved carbon-fibre composite panel was studied. The panel included two “omega” stiffeners to make it more representative of a real-life aircraft component. Eight piezoceramic transducers were bonded to the surface of the panel and then used to both generate and receive ultrasonic Lamb waves through the composite panel. The damage was simulated by adding a mass to specific regions of the panel with a force applicator, in order to replicate the local change in stiffness that real-life structural damage causes. The aim here was to predict the location of the damage on the panel.

The statistical technique of outlier analysis [1] was used to initially pre-process the experimental Lamb wave data obtained here. Outlier analysis has previously been used for damage detection by [2] and [3]. This processed data was then used as input data for a multilayer perceptron (MLP) neural network. Two different kinds of multilayer perceptron were used for the structure here: an MLP classification network and an MLP regression network. The classification network defined a small number of convex regions on the panel and then predicted in which region the structural damage lay. The regression network had two real-number outputs which were cartesian coordinate estimates for the location of the damage.
This paper continues as follows. Section 2 introduces the outlier analysis technique and describes how it can be used for damage detection. Section 3 is an introduction to multilayer perceptron neural networks, and section 4 then describes the curved composite panel and the experimental setup. Sections 5 and 6 present the results from the MLP classification and regression networks respectively. Section 7 then discusses the results and gives conclusions.

2. Outlier Analysis

Outlier analysis [1] is a novelty detection method that can be best described as a statistical technique. It is reliant on possessing a large set of data samples indicating “normality” of the system under investigation; in this case, the undamaged state of an aircraft structure. Once new test data become available, these new samples can be tested for “abnormality”, i.e. significant deviation from the normality established by the original data set. Outlier points in the test data may be an indication that this data has been generated by an alternative mechanism, i.e. structural damage in this case.

Outlier analysis can be used equally well for either univariate or multivariate data. Once the initial “normal” data set $X$ has been obtained, the mean $\bar{x}$ and covariance matrix $[S]$ of the data are calculated. Each data point $x_\zeta$ is then assigned a novelty index $D^2_\zeta$. For the multivariate case this novelty index is calculated by the Mahalanobis distance:

$$D^2_\zeta = ((x_\zeta - \{\bar{x}\})^T [S]^{-1} (x_\zeta - \{\bar{x}\})$$

(1)

Every data point can therefore be represented by a scalar novelty value. An appropriate threshold level can then be calculated in relation to the number and dimensionality of the points in the original data set. This threshold level indicates the boundary of normality, so that exceeding the threshold indicates abnormality, i.e. an outlier sample. In [2] and [3] the threshold value was obtained through the use of a Monte Carlo method based on extreme value statistics.

For new data points, the novelty index can be calculated for each of these points using equation (1), and then this index is compared to the threshold value. If the novelty index exceeds the threshold value, this is a clear indication that damage is present within the structure, whereas an index below the threshold suggests that there is no damage present.

![Figure 1: An example of a Lamb wave response window used for outlier analysis](image)
The Lamb waves used here were Gaussian-modulated five-cycle sine waves with a frequency of 210 kHz. For each different Lamb wave response sent through the plate, a window of the signal was taken, as shown in Figure 1. Different sampling windows were taken for the different sensor paths through the composite panel, due to different arrival times of the waves, although the same sampling window was always used for a given path. Mean and covariances were calculated for each of these paths, and equation (1) was then used to obtain a scalar novelty index for each different Lamb wave response.

3. Multilayer Perceptron Neural Networks

The earliest type of artificial neural network consisted of a single row of processing nodes, each based on the McCulloch-Pitts neuron [4], and was called a perceptron. It subsequently became clear that the representational capabilities of a single-layer network like the perceptron were limited though, so the multilayer perceptron (MLP) was introduced.

Figure 2: A multilayer perceptron network

Figure 2 shows an example of a multilayer perceptron network. The number of network inputs and outputs is determined by the problem being modelled, and information passes through the network in a forward direction only. An arbitrary number of hidden row nodes can be selected for use, although excessive amounts are likely to be limited by computational expense. An MLP network is often referred to by the number of adjustable weight layers that it uses; for example, the MLP network in Figure 2 is a two-layer MLP.

Multilayer perceptron networks can be used for either classification or regression applications. The network model is trained to a particular system by repeated presentation of example data samples, where the network adaptive weights \( \{w\} \) are updated after each presentation. During the training phase the optimum number of hidden rows will need to be found, as well as the optimum number of nodes in each of these rows. The most common algorithm for training MLP neural networks is the error back propagation algorithm [5]. This can best be described as an adaptation of the gradient-descent technique, specifically for neural networks.

An important requirement for any neural network is generalisation, which involves the network accurately predicting additional data samples that were not included in the original data set. This ensures that the network is representing the underlying system that generated the data, and not just fitting the measurement noise on this data. The standard procedure is to divide the entire measured data set into three sets, respectively labelled as the training, validation and test sets. The final optimum network model is used on the test data set, and the error obtained is the final prediction error of the MLP network [6].

4. The Curved Composite Panel
The specimen structure used here was a curved carbon-fibre composite panel with two omega stiffeners. The panel had a 0-90° fibre orientation, and had dimensions of 600mm x 600mm with thickness 3mm and radius of curvature 2m. The panel was only curved in one dimension, and the two omega stiffeners ran parallel to one another in this curved dimension, traversing the entire length of the panel. The omega stiffeners had their surfaces made of the same carbon-fibre material as the panel itself and contained a polyurethane foam core. Figure 3 shows the dimensions of the composite panel.

![Figure 3: Dimensions of the composite panel and locations of the piezoceramic transducers](image)

Eight piezoceramic transducers were then bonded to the composite panel using Epoxy X60 adhesive. These were SONOX-P5 disc transducers with a diameter of 10mm and thickness of 1mm. The locations of these transducers are also shown on Figure 3. An eight channel multiplexer was used, which in conjunction with a MATLAB graphical user interface enabled any of the transducers to be used as either an actuator or a sensor. This therefore gave 28 different paths between these eight transducers, disregarding reversed paths.

The damage to the composite panel was achieved by using a force applicator, as can be seen in Figure 4. Damage in a structure can be thought of as a local change in stiffness, and this was represented by applying a force to a small localised region of the panel. The advantage to this technique was that it was completely reversible – removing the applied force returned the panel to its undamaged state. The force applicator had a small circular tip and a flat top for supporting masses, enabling the user to select a suitable “damage weight”. In this case, a mass of 3.5 kg was applied (in addition to the small mass of the force applicator itself). A test rig was constructed to ensure that the force was always applied perpendicular to the composite panel. The panel was mounted on plastic “bubble wrap” to isolate it from the test rig. Note that Figure 4 shows an alternative piezotransducer arrangement to that given in Figure 3. This alternative sensor arrangement was tested after the original set of results were obtained for this work, and was found to be less successful so its results were not used here.
For the “normal” data required by outlier analysis, 500 observations were taken for the undamaged plate. 25 different damage locations were then used by the force applicator, as shown in Figure 5, and 100 observations were taken for each of these damage locations. As described in section 2, each Lamb wave response was transformed using outlier analysis into a scalar novelty index. The 8 different sensors in Figure 3 gave 28 sensor paths (ignoring reversed paths), so the input vectors for both the MLP classification and MLP regression networks were 28-dimensional vectors.

For the MLP classifier network, the panel was divided into three regions, as shown in Figure 6. The MLP classifier was assigned the task of distinguishing between these three damage regions and the undamaged case, therefore giving four possible output classes. 200 further samples were therefore taken for the undamaged panel, thus
giving a total test data set of 2700 samples. Each set of 100 observations after the normal set was divided in the ratio 40:40:20 and the data was collected into these three different groups, labelled as the training set, validation set and test set respectively. The training and validation sets therefore each contained 1080 samples, and the test set had 540 samples.

The MLP regression network was only assigned the task of locating structural damage, so it therefore wasn't trained using any samples from the undamaged plate. The sets of 100 samples for all of the 25 damage locations were thus combined to give a data set of 2500 samples for the MLP regression network. These were also separated into training, validation and test data sets.

5. Multilayer Perceptron Classification Network Results

The architecture for this MLP classification network was restricted to 28 input nodes, a single layer of hidden nodes and four output nodes for the four possible damage classes. Softmax activation functions were used by the four output nodes to ensure that their outputs always summed to unity, i.e. they could be viewed as posterior probabilities for the four classes. Each data sample can therefore be assigned to the output class that has the highest posterior probability. The softmax activation function is given by:

\[
y_k = \frac{\exp(a_k)}{\sum_k \exp(a_k)}
\]

where \( k \) is the output node index, and \( a_k \) is the summed input into output node \( y_k \).

The MLP classifier network was trained using the NETLAB neural networks toolbox for MATLAB [7]. As is common with neural network training, the input data was uniformly scaled so that each input dimension was distributed between -1 and 1 with a mean of zero. The single network hidden layer was restricted to a maximum of 20 hidden nodes. For each number of hidden nodes up to 20, ten separate training runs were undertaken using the training data set. A maximum of 1000 iterations was set for the training process.
The ten solutions per hidden node quantity were then all tested using the previously-unseen validation data set, in order to assure that the MLP classifier could generalise. Across all hidden node numbers, the MLP network with the highest validation-set classification rate was then selected as the optimum network, and then tested finally on the test data set.

The optimum MLP classifier found had 5 hidden nodes and gave a successful classification rate of 88.1% on the test set. Table 1 shows the confusion matrix for this MLP classifier, where the four output classes are the undamaged panel and the three damage regions in Figure 6.

<table>
<thead>
<tr>
<th>True class</th>
<th>Undamaged</th>
<th>Damage region 1</th>
<th>Damage region 2</th>
<th>Damage region 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Undamaged</td>
<td>35</td>
<td>0</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Damage region 1</td>
<td>0</td>
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<td>8</td>
<td>5</td>
</tr>
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<td>0</td>
<td>23</td>
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</tr>
<tr>
<td>Damage region 3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>192</td>
</tr>
</tbody>
</table>

Table 1: Confusion matrix for final MLP classifier network

6. Multilayer Perceptron Regression Network Results

As with the MLP classifier, the MLP regression network architecture was 28 input nodes and a single hidden layer with a maximum of 20 hidden nodes. The MLP regression network had 2 output nodes, however, and these nodes used linear activation functions so that the network outputs were real numbers. The input data was uniformly scaled to the range [-1, 1] and the target output data was scaled to [-0.8, 0.8]. The predicted outputs from the regression network were then descaled by the inverse of this transformation.

The NETLAB toolbox was once again used to train the data here. The network error was given by:

$$ E = \frac{\sum_{i=1}^{N} 4|\Delta x_i| \cdot |\Delta y_i|}{A} \cdot 100 \quad (3) $$

where $\Delta x$ and $\Delta y$ are the respective prediction errors in the x and y directions, $A$ is the total area under investigation (in this case, one quarter of the entire panel area) and $N$ is the number of data samples. This is a modified version of the mean-squared error function (MSE).

Ten training runs were undertaken for each number of hidden nodes up to the maximum of 20. These solutions were then all tested using the validation data set, and the optimum solution over all hidden node quantities was the one with the lowest validation-set value of (3). This was then tested on the test data set to give the final error for the MLP regression network.

The optimum MLP regression network found here had 8 hidden row nodes and gave a test-set MSE value of 3.2%. Figures 7 and 8 are photographs of the test panel showing the maximum prediction error from this MLP regression network for two arbitrary data samples. They were obtained by taking the predicted damage locations for those samples from the network, and then creating rectangular areas from these errors around the two true damage locations. These rectangular error areas are shown by the white sections on the panel.
7. Discussion and Conclusions

In this work multilayer perceptron neural networks were used for damage localisation within a stiffened carbon-fibre composite panel. Piezoceramic transducers were used to send ultrasonic Lamb waves through the panel, and the Lamb wave responses were pre-processed by the statistical technique of outlier analysis. Damage was added to the panel through the use of a force applicator and masses, and this damage was completely reversible. A MATLAB graphical user interface was used to acquire the data with a PC data acquisition card, and the MLP networks were trained by the NETLAB neural networks toolbox.

Both of the two main types of MLP network were used here: a classification network and a regression network. The classification problem involved defining three convex regions of the panel, and then determining whether the panel was undamaged or had damage in one of these three regions. The MLP regression network had two real-number outputs for the estimated cartesian coordinates of damage on the panel, in relation to the top-left corner of the panel. By contrast with the classification network, the data set for the regression MLP network did not include any undamaged data, so the aim of the regression MLP was to estimate the location of structural damage, not to predict whether or not damage had occurred.
The raw experimental Lamb wave response data needed to be pre-processed here because it would have been hugely impractical to feed the entire response signal into an MLP network, and would have featured a large amount of redundant data. Outlier analysis was effective for this pre-processing because it converts windowed signals into scalar values, and gives a clear indication of signals which are significantly different from “normality”. It enabled all 28 sensor paths to be simultaneously provided to the MLP networks as input vectors. Outlier analysis was also selected here due to its success in previous damage detection work by the authors.

The MLP classification network defined three relatively large regions on the panel, although it did also offer the ability to state that the panel was undamaged. Only half of the total panel area was used for these three damage regions, with all of the damage locations lying within this area. After a suitably rigorous training process, an MLP classification network was found which gave a successful classification rate of 88.1% on the test data set. This is a relatively high figure given the unpredictable behaviour of anistropic composite materials.

It is usually the convention for MLP classification problems to have balanced data sets, i.e. each output class has the same number of samples within the data set. For the 2700-sample data set used here, however, this is not the case. An alternative data set with 2000 samples equally balanced with 500 samples per class was thus created, using many of the same samples from the original 2700-sample set. As described by Tarassenko, the outputs of this balanced data set were modified to represent the true posterior probability outputs of the original set. The classification performance for this balanced set was inferior to the 2700-sample set though, so the imbalance of the classes in the data set used here did not have a detrimental effect on the MLP classification network result.

The optimum MLP regression network found for the composite panel had a mean-squared error value of 3.2% on the test data set. This gave much more specific damage localisation results than the MLP classification network, although was only designed to be used with damaged data. A general heuristic for mean-squared error is that 5% is “good” and 1% is “very good”, so the MLP regression network obtained here is a good one. Figures 7 and 8 give a physical demonstration of the damage localisation performance of the MLP network.

This work has therefore shown that multilayer perceptron neural networks can efficiently locate damage in a stiffened carbon-fibre composite panel, for both classification networks and regression networks. It has also been shown that outlier analysis makes an effective pre-processor of experimental Lamb wave response data for a neural network.

References