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THE USE OF NEURAL NETWORKS FOR PIEZOELECTRIC DAMAGE SENSING IN COMPOSITE AEROSPACE STRUCTURES

Chamberland, O.[1*], Bishop, S.[2], and Laliberté, J.[1]
[1] Department of Mechanical and Aerospace Engineering, Carleton University, Ottawa, Canada
[2] Ivan Curry School of Engineering, Acadia University, Wolfville, Canada
* Corresponding author (oliviachamberland@cmail.carleton.ca)

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ABSTRACT

This study discusses a novel manufacturing method that co-cures piezoelectric sensors to the surface of carbon fibre reinforced polymer (CFRP) panels, enabling in-situ cure monitoring, manufacturing inspection, and in-service monitoring. The CFRP panels have been intentionally manufactured with known defects, establishing a reference point for subsequent detection and identification analyses. Using Lamb waves processed with the continuous wavelet transform to perform a time-frequency domain analysis, the ability to recognize and identify delamination, porosity, and foreign object defects was demonstrated. Furthermore, this study extends beyond the traditional analysis of waveforms and employs neural networks to enhance the predictive capabilities for real-time damage assessment. By training the neural network on the acquired signals from the piezoelectric sensors, the objective is to develop a robust predictive model capable of reliably identifying and classifying the various defects present within the panels.

1 INTRODUCTION

Carbon fibre reinforced polymers (CFRP) are a composite material made with carbon fibers embedded in a polymer. Since the 1980’s, CFRP’s have become integral to aircraft construction due to their strength and lightweight properties. Despite their benefits, there is a limited understanding of their failure modes in comparison to more traditional materials. Due to the uncertainty surrounding the failure mechanisms of CFRP, aircraft are subject to extensive non-destructive examinations (NDE) to comply with airworthiness standards. NDE have a significant impact on maintenance budgets and schedules since they result in aircraft being decommissioned for a period of hours to weeks.

To mitigate these challenges, Structural Health Monitoring (SHM) as part of an integrated vehicle health management (IVHM) philosophy offers a proactive approach to managing the health of CFRP composites in aircraft. SHM systems continuously monitor and analyze the integrity of aircraft structures in real-time, identifying potential damages before they become critical. This methodology will not only enhances safety through early detection of structural problems but also streamlines maintenance procedures. By pinpointing exactly when and where repairs are needed, SHM reduces unnecessary downtime and decreases the costs associated with NDE and aircraft being removed from service.

One technique used in SHM systems is Lamb waves. These guided ultrasonic waves can be used to detect and characterize defects in materials, by propagating along the surface of a material. Unlike some other ultrasonic techniques, Lamb waves can cover large areas from a single point of excitation [1]. The waves are sensitive to alterations in the material properties caused by defects like cracks and delamination. By generating Lamb waves at a specific point on a structure and observing how they propagate and alter across different locations, individuals can assess the structure and identify abnormalities. Currently, analyzing these signals is typically a manual process that could benefit from automation. The integration of neural networks into this process could significantly enhance the efficiency and accuracy of analyzing Lamb wave data. Neural networks could be trained to automatically recognize patterns and anomalies in the wave signals to produce near real-time monitoring.

2 Previous Work

Bishop [1], proposed a novel manufacturing method that co-cured piezoelectric sensors to CFRP panels. Panels were manufactured with an out-of-autoclave carbon fiber and epoxy prepreg material (AX-6111-C, Axiom Material Incorporated). The panels were 500 x 200 x 1.2mm and consisted of 8-plies in a symmetric and quasi-isotropic layup, [0/90/+45/-45]s. The panels were intentionally manufactured with known defects to establish a reference point for subsequent detection and analysis. Ultrasonic c-scans were performed on the panels to ensure that the panels manufactured to have no known defects, could be assumed to have no defects.

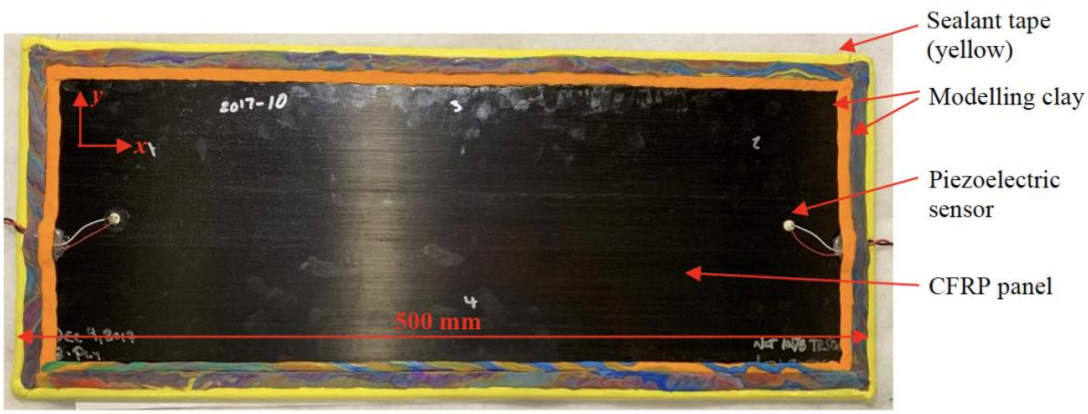

Figure 1. CFRP panel with piezoelectric sensors [2].

Piezoelectric sensors from APC International Limited (model 70-3000) were used for the purpose of this research. They have a resonance frequency of 2.0 MHz and 312 kHz in the thickness and radial directions. The sensors are 6.35 mm in diameter and 0.254 mm in thickness. The two sensors were placed 400 mm apart on the surface of the CFRP panel (Figure 1), where one sensor emits an ultrasonic signal while the other receives the signal after it has traveled though the material being tested.

A Lamb wave signal was generated using a Picoscope function generator (model 3403D). The Lamb waves were initiated by a 3-cycle sine wave combined with a Hanning, which was created in MATLAB and uploaded to the Picoscope. To activate the piezoelectric sensors, a Krohn-Hote wideband power amplifier (model 7602) amplified the signal to +/- 30 V. Figure 2 illustrates this experimental setup.

Additional signal processing was completed using the MATLAB Signal Processing toolbox. The defect identification was performed manually. The research presented within this paper continues the work started by Bishop [2] by automating the detection of damage from the Lamb waves.

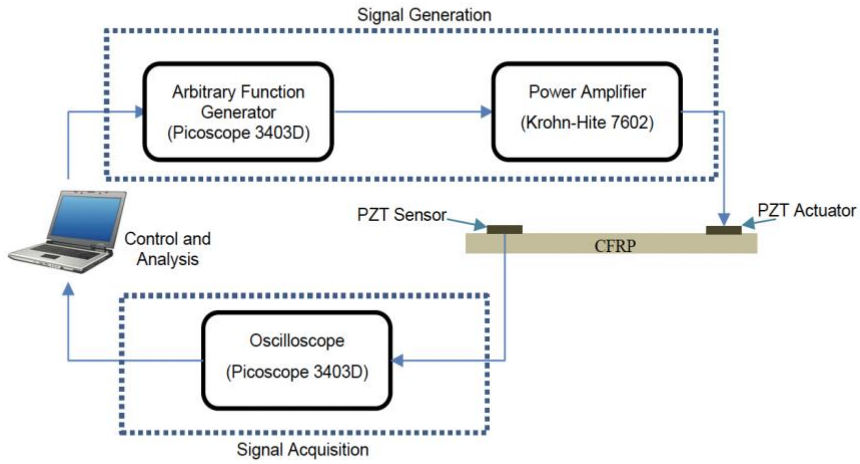

Figure 2. Experimental setup to generate and collect Lamb wave signals [2].

3 Proposed Methodology

In this study, software was developed in Python 3.9 to convert input images into greyscale. These transformed images, depicted in Figure 3, served as the training and testing data for the autoencoder. The autoencoder model consist of 12 layers and was trained with 2000 signal images from undamaged composite panels, and then tested on a set of 5 images which includes both undamaged and damages composite panels. The model was only trained on damaged panels since [3] produced a sensitivity study showing that the accuracy of the model decreased with the addition of damaged images into the training dataset.

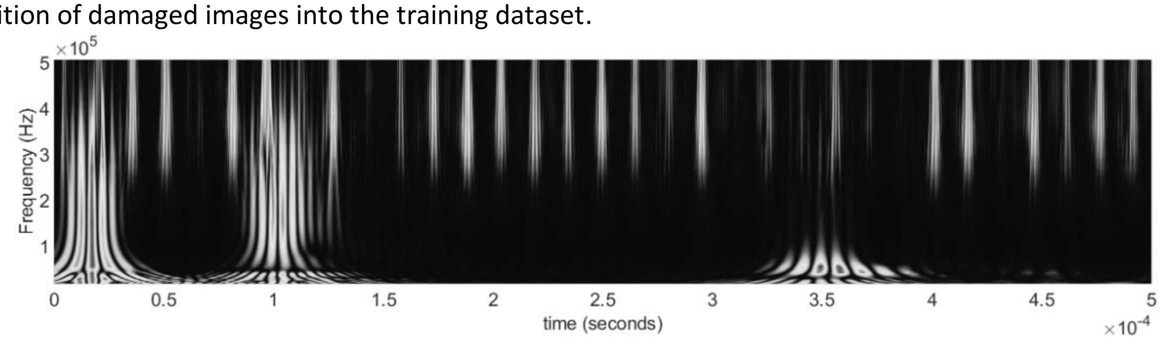

Figure 3. Sample of the images used to train the autoencoder. These signals are presumed to represent an undamaged composite panel.

The architecture of the model (Figure 4) includes 8 layers in the encoder section, which are arranges in alternating sequences of convolutional layers and max pooling layers. Each convolution later has half the number of filters of the processing one. The decoder portion is made up of 4 layers, starting with a flattening layer, followed by 3 dense layers. To match the output dimension with those of the input images, the last dense layer was configured to have the same dimensions. At the latent representation of the data, it is compressed by a factor of ~4187.

Activation functions are critical parameters in neural networks, serving as transfer functions that enable the network to capture complex relationships within the data. In the absence of activation functions, neural networks would essentially function as linear regression models limited to simple, one-degree polynomial relationships. For the purpose of this research, the rectified linear unit (ReLU) activation function was selected for all layers except the

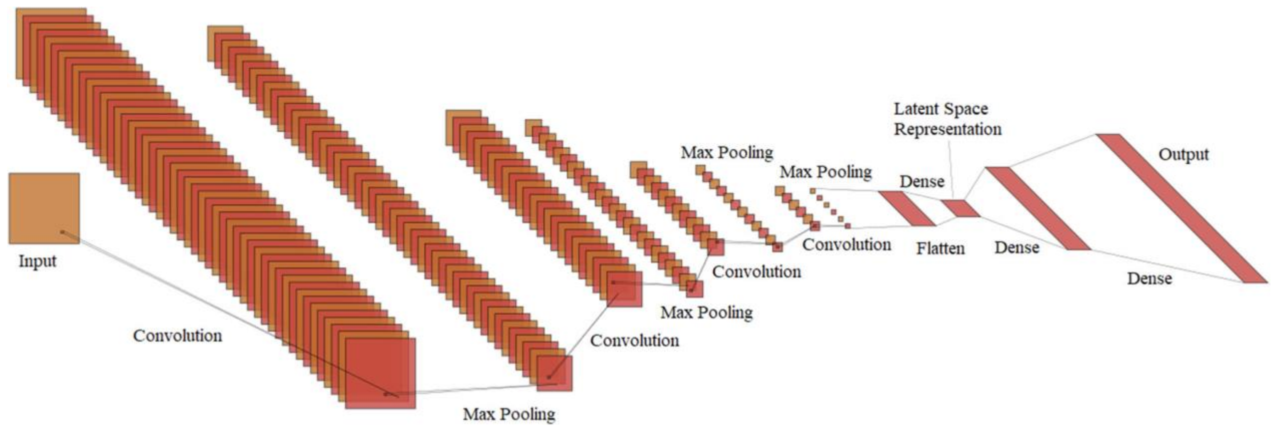

Figure 4. The proposed autoencoder structure.

output layer. For the output layer, the sigmoid activation function was chosen because it constrains the output values between 0 and 1, which is crucial for image reconstruction.

When developing a neural network, the loss function and optimizer must also be considered. Optimizers are used to adjust the weights of the model during training based on feedback from the loss function. For the purpose of this study, Mean Square Error (MSE) was chosen as the loss function, and the adaptive moment estimation (Adam) [4] optimizer was selected to update the weights. To prevent overtraining, an early stopping mechanism was implemented to stop training if the loss did no decrease by 0.001 for 3 consecutive epochs. Once satisfied with the compression and reconstructive abilities of the autoencoder, the mean absolute error (S_i) associated with each reconstructed image was calculated using the following:

$$S_i = \frac{\sum_{i=1}^{a}\sum_{j=1}^{b}\left|y_{ij} - x_{ij}\right|}{ab} \quad (1)$$

where a and b is image pixel dimensions, y_{ij} is the predicted pixel value, and x_{ij} is the true pixel value. The S_i is then clustered to predict whether an image represents a damaged or undamaged panel.

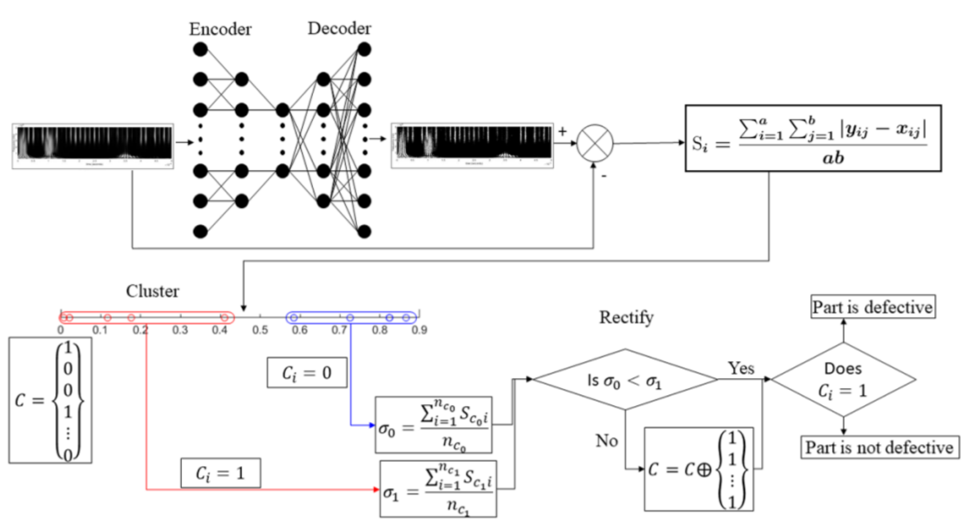

Figure 5. Schematic of the proposed analysis methodology.

Table 1 and Figure 5 summarize this process and rectifies the output from the cluster if the cluster was reversed. The recreate function represents the autoencoder which generates a reconstructed version of an input image. The score function then assesses each image and assigns a numerical value based on the S_i. These S_i scores are then grouped into two categories using the Scikit KMeans clustering algorithm [5], referred to here as the cluster function. This clustering process aggregates similar S_i values and labels them with either a 0 or 1. To ensure accurate identification, the average S_i for images labeled as 1 and 0 is calculated. The cluster with the higher average S_i is considered to contain the defective components under the assumption that a greater error indicates a higher likelihood of defects.

To investigate the results of this research, the precision, recall and F1 scores were calculated using the corresponding metrics from Scikit [5]. These metrics give insight into the number of true positives, true negatives and false positives produced by the model.

Table 1. Proposed algorithm.

Data: Image Set I
Result: A vector C of booleans where 1 indicates a defective part
initialization
foreach I **do**
  $y_{ij} \leftarrow$ `Recreate(`I`)`
  $S_i \leftarrow$ `Score(`y_{ij}`)`
end
$C \leftarrow$ `Cluster(`S`)`
$\sigma_0 = 0$; $\sigma_1 = 0$; $n_{c_0} = 0$; $n_{c_1} = 0$; **foreach** *image* **do**
  if $C_i == 1$ **then**
    $\sigma_0 = \sigma_0 + S_i$
    $n_{c_0} = n_{c_0} + 1$
  else
    $\sigma_1 = \sigma_1 + S_i$
    $n_{c_1} = n_{c_1} + 1$
  end
end
if $\frac{\sigma_0}{n_{c_0}} < \frac{\sigma_1}{n_{c_1}}$ **then**
  $C = C \oplus ones$
end

4 Results and Discussion

Table 2 denotes the proposed autoencoder structure. With a total of thirteen layers, the model has 1,966,894,562 parameters to train. Beginning with an input layer shape of 332 by 1176, each max pooling layer decreases the size by half. The model architecture was determined through trial and error, considering the available computational power. The model was trained on a 2021 Apple M1 - Max, 32GB Macbook Pro. The model took 10 epochs to converge to a loss of 0.0023 and a validation loss of 0.0065.

Table 2. Proposed autoencoder architecture.

Layer type	Output shape	Number of parameters
Input layer	[332,1176,1]	0
Convolution layer	[332,1176,48]	480
Max pooling	[166,588,48]	0
Convolution layer	[166,588,24]	10,392
Max pooling	[83,294,24]	0
Convolution layer	[83,294,12]	2,604
Max pooling	[42,147,12]	0

Convolution layer	[42,147,6]	654
Max pooling	[21,74,6]	0
Flatten	[9324]	0
Dense	[1000]	9,325,000
Dense	[5000]	5,005,000
Dense	[390432]	1,952,550,432

The model can accurately reconstruct the undamaged panels but struggled to reconstruct those that are damaged. This is the desired behavior that will allow the clustering algorithm to differentiate between defective and non-defective panels.

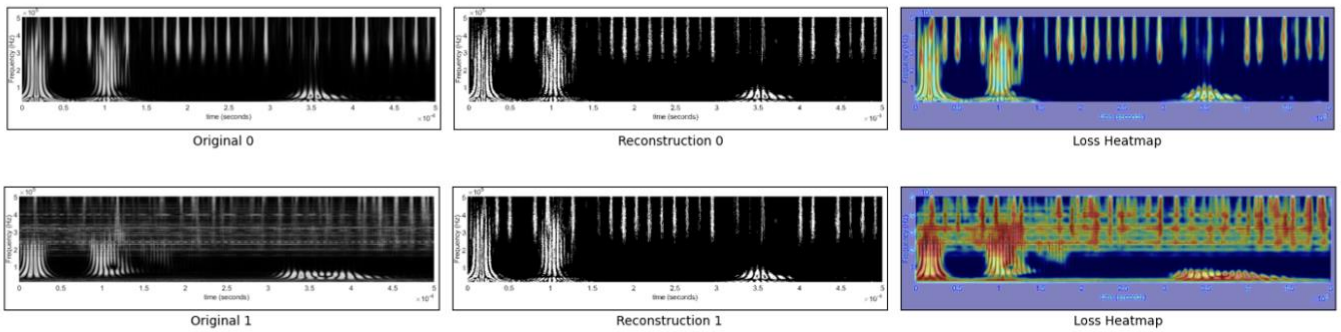

Figure 6. Example of panels which were correctly classified by the proposed method. The numbers “0” and “1” represent a non-defective and defective panel respectively. The damaged panel was known to have a delamination defect under the second ply.

The above figure shows two samples that were accurately classified by the proposed method. The model obtained a recall, precision and F1 score each of 100% indicating that the model classified the samples correctly.

5 Conclusions and Future Work

The findings of this study suggest the possibility of combining piezoelectric embedded sensors and neural networks to act as SHM systems on composite aerospace components. Future studies should include generating more data to further validate the proposed method. Additionally, another neural network should follow the results of this method to differentiate between the different types of damage present within the panels. The images classified as defective could then be passed through the same procedure multiple times with different training datasets to determine what type of damage is present.

6 REFERENCES

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