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Deep learning algorithms for delamination identification on composites panels by wave propagation signals analysis

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Abstract. Performances are a key concern in aerospace vehicles, requiring safer structures with as little consumption as possible. Composite materials replaced aluminum alloys even in primary structures to achieve higher performances with lighter components. However, random events such as low-velocity impacts may induce damages that are typically more dangerous and mostly not visible than in metals. Structural Health Monitoring deals mainly with sensorised structures providing signals related to their "health status" aiming at lower maintenance costs and weights of aircrafts. Much effort has been spent during last years on analysis techniques for evaluating metrics correlated to damages' existence, location and extensions from signals provided by the sensors networks. Deep learning techniques can be a very powerful instrument for signals patterns reconstruction and selection but require the availability of consistent amount of both healthy and damaged structural configuration experimental data sets, with high materials and testing costs, or data reproduced by validated numerical simulations. Within this work will be presented a supervised deep neural networks trained by experimental measurements as well as numerically generated strain propagation signals. The final scope is the detection of delamination into composites plates for aerospace employ. The approach is based on the production of images trough signal processing techniques and on employ of an image recognition convolutional network. The network is trained and tested on combinations of experimental and numerical data.

Introduction

Last developments in the modern aerospace industry push towards an improvement in flight efficiency and autonomy leading to a great increment in the usage of composite materials. They allow to lower the weight and obtain easily more complex shapes, but, due to their peculiar composition and fabrication methods, they are affected by delamination and defects. So, every aircraft's component is subject to time-scheduled maintenance sessions even when there is no clear evidence that it is required. This is a very expensive and time consuming process.

In this field, the Structural Health Monitoring technology (SHM system) [1,2,3], based on networks of distributed sensors embedded, or secondary bonded, throughout the whole structure under investigation, could be conveniently used for real-time health monitoring and/or as a data acquisition tool. Structural data, however, may constitute an enormous amount of information that in most cases is difficult to classify. Furthermore, since time is an important factor, the automation of the analysis process could be a significant advantage in this field. From this point of view, intelligent algorithms that can take decision in an autonomous manner reducing the human participation, like Deep Neural Networks (DNNs), may be useful to overcome this impasse.

Structural data may be adequately filtered with the aid of specific Deep Neural Networks designed and trained for the structural context and aimed to the classification and identification of significant parameters [4,5,6]. The DNNs, based on strategic engineering criteria, may represent an effective and efficient analysis tool to promote faster data analysis and classification. In the field of aircraft maintenance, this approach may lead, for example, to a faster awareness of a

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component health situation or predict failures. Neural Networks typically requires a relevant amount of data in order to be trained and to acquire the necessary reliability in classifying and recognizing the occurrence of the selected event but, once trained, they can be extremely effective and low-time consuming in analysing each single scenario to be classified. In this study the potentialities of deep learning with high frequency Lamb waves propagation based SHM methodologies are investigated employing explicit finite element simulations to collect propagation signals due to impact damages on a composite plate; this approach will also be employed in the next future to populate experimental data sets necessary for deep learning algorithm. Previous experimental signals acquired on the real impacted carbon fiber panel have been used to validate a numerical equivalent to allow the expansion of the dataset available [5].

Numerical time history signals have been collected for both the healthy and un-healthy state of the structure and transformed into RGB images. A well-known convolutional algorithm trained on healthy and damaged signals is used to identify anomalies in the form of delamination in the structure. The paper presents the pre-liminary results achieved by the authors..

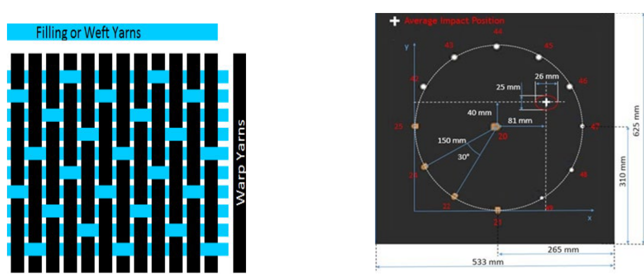
SHM algorithm implementation

The goal of the work is to develop a neural network capable of detecting damage and its position in a composite panel exploiting Lamb waves. For this purpose, a numerical model was used to simulate the propagation of Lamb waves in a flat composite panel. Then, a Matlab algorithm has been created to transform the detected signals into images that the adopted neural network classifies as damaged or intact.

Numerical model, experimental set-up and signal analysis

The composite panel considered consists of 12 plies of three different pre-preg types oriented according to multiple directions [7,8]. The PZT sensors, utilized for lamb waves generation and acquisition, are applied on the panel according to the geometry in Fig. **1**b.

The "pitch-catch" technique has been adopted for signals acquisition and damage detection, that is, a transducer behaves as an actuator, while the remaining sensors detect the signal that has been released inside the panel. Four different positions were considered for impact damage simulation.



(a) **(b)**

Fig. 1. a) 5-Harness Satin Weave Layer; b) composite panel sensors configuration

A key point is the data analysis from rough signals to get a proper identification system. Features (time of flight, group velocity, signal transmission factor, wave energy) are extracted with an appropriate signal processing technique obtaining a diagnosis that presents location and/or severity of the damage.

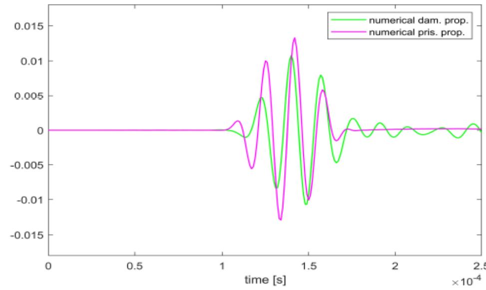


Fig. 2. Signals comparison between pristine and damaged model (path 20_46)

So, if "f" is the particular propagation feature considered, it is possible to define a damage index according to the following formulation:

$$\mathrm{DI} = \frac{(f_d - f_b)\cdot(f_d - f_b)}{f_b \cdot f_b}$$

Where f_d is the value obtained by the signal of the panel as it is at the analysis time, while f_b is the one extracted by the baseline propagation. Then, a damage index (DI) close to zero suggests a healthy-like propagation, while a value over a certain threshold warns for a failure.

RGB images generation ,analysis and results

To implement the convolutional approach, the acquired signals are transformed into RGB images exploiting a MATLAB code. RGB (Red Green Blue) is an additive color model, that is, an abstract mathematical model that allows to represent colors in numerical form, using the red, green, and blue color components. Each image obtained concerns a specific actuator-sensor path and consists of the overlap between the signal detected in the intact panel and that detected in the damaged panel. Going from top to bottom, the signals overlap consists of 10 intact signals, 10 signals in which a damaged and an intact alternate, and finally 10 damaged signals. As shown in Fig. 3, it is clear that the damaged images are characterized by a series of horizontal knurls (that are missing in typical healthy images). The latter are induced by disturbances in signal reception, attributable to damage.

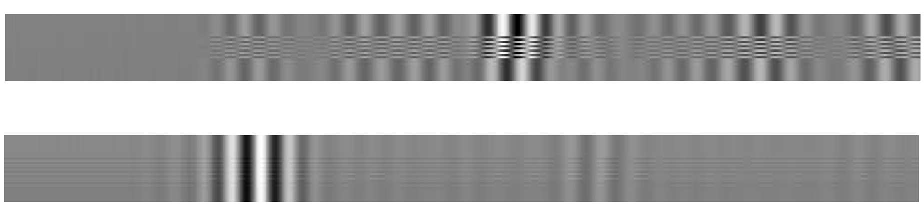


Fig. 3: Generic experimental image damaged (above) and intact (below) obtained by RGB conversion

For images analysis the Google Net neural network, already present in MATLAB, was used. It is a deep convolutional neural network architecture codenamed Inception that achieves the new state of the art for classification and detection in the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14); is a convolutional network consisting of 144 layers, which requires an image as input and returns its classification in output. The network training phase was carried out using MATLAB's Deep Network Designer, a tool that allows to graphically train a neural network, entering the appro-priate training parameters such as learning speed, validation frequency and number of epochs. The network was trained in three different ways to evaluate the recognition efficiency of the experimental images and the relative reliability: numerical, experimental and hybrid training. The most interesting results related to the hybrid training, for which 30 intact images and 30 damaged images were selected, equally divided between numerical and experimental. In this case we were unable to obtain an accuracy higher than 83.3% in the training validation phase; thus, we have not been able to predict the behavior of this network. It was decided to test it anyway and evaluate the results. This condition was also analyzed because we wanted to simulate a situation in which few experimental data were obtained and, therefore, it was necessary to thicken the latter with data obtained numerically. Surprising results were provided by the hybrid network, trained with mixed signals. In fact, overall, it is the network that has shown a higher recognition rate. These results confirmed the high potential that characterizes the hybrid training obtained by combining validated experimental and numerical data.

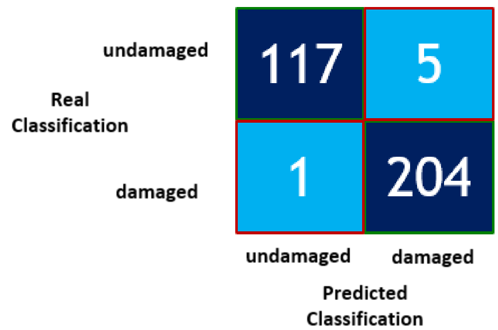


Fig. 4. Results obtained by the Net trained on "hybrid" results

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