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Impact Detection on Composite Plates Based on Convolution Neural Network

I. Tabian[1,a] H. Fu[1,b] and Z. Sharif Khodaei[1,c]

[1]Department of Aeronautics, Imperial College London, South Kensington Campus, Exhibition Road, SW7 2AZ London, UK

[a]iuliana.tabian15@imperial.ac.uk, [b]h.fu14@imperial.ac.uk, [c]z.sharif-khodaei@imperial.ac.uk

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Abstract. This paper presents a novel Convolutional Neural Network (CNN) based metamodel for impact detection and characterization for a Structural Health Monitoring (SHM) application. The signals recorded by PZT sensors during various impact events on a composite plate is used as inputs to CNN to detect and locate impact events. The input of the metamodel consists of 2D images, constructed from the signals recorded from a network of sensors. The developed meta-model was then developed and tested on a composite plate. The results show that the CNN-based metamodel is capable of detecting impacts with more than 98% accuracy. In addition, the network was capable of detecting impacts in the other regions of the panel, which was not trained with but had similar geometric configuration. The accuracy in this case was also above 98%, showing the scalability of this method for large complex structures of repeating zones such as composite stiffened panel.

Introduction

Structural Health Monitoring (SHM) techniques aim to address the shortcomings of current NDI techniques in terms of providing continuous monitoring of structures without the need to have access to all parts allowing for the increase in service life, or decrease in service intervals[1, 2]. By having permanently mounted sensors on the structure, the response of the structure due to an external impact event can be recorded, detected and characterized [3-7]. Subsequently, the structure can be actively excited with guided waves [8] in order to identify whether a barely visible impact damage (BVID) has resulted from the impact e, as well as information on the location and extent of the damage [9, 10].

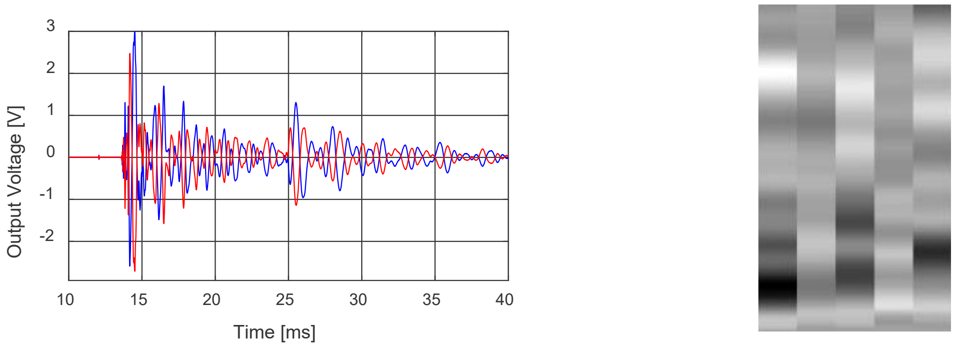
In recent years, a lot of effort has been focused on maturing the SHM technologies and methodologies so that they can be applicable to real structures such as aircrafts. For example, the issue of weight of the sensor wires and connectors has been addressed by technological developments such as smart layer [11] as well as optimization techniques to reduce their numbers while increasing the reliability of the diagnosis [12, 13].

Numerous passive sensing methodologies have shown to be successful in detecting and characterising impact events on simple structures with isotropic properties and limited range of impact energy. Impact detection methodologies in general can be divided into a) trigonometric location techniques, b) Model-based algorithms and c) Machine learning or data-driven techniques. Each category has advantages and disadvantages [2]. The most appropriate category which can be applicable to complex geometries and materials, is the third category which is based on developing meta-models to represent complex non-linear relationships between input and output data. The applicability of Artificial Neural Network (ANN), Probabilistic Neural Network (PNN), Support Vector Machine (SVM) and Extreme Learning Machines (ELM) to detect and characterize impact events has been shown to be successful for simple structures [14-16].

Convolutional Neural Networks (CNN) have recently been used in many applications such as image classification, object recognition and computer vision just to name a few. They have also been a subject of recent research in the field of SHM [17, 18]. It's main advantage over other machine learning algorithms in SHM applications such as ANN is that it does not require feature extractions as ANN ; CNN, therefore, is more robust because the optimal feature is extracted automatically from unprocessed data. However, most of the reported research has been on simple structures with isotropic properties [19]. This paper reports, for the first time, the application of CNN for passive sensing of composite plates.

Convolutional Neural Network

CNN is a deep-learning architecture [20] which is inspired by the natural visual perception mechanism of living creatures. There are different variation of CNN but they usually have the following layers: Convolution layer, Pooling layer, fully connected layer and Output layer. The input to the CNN is in form of images, so certain properties are encoded into it. The convolution layer have neurons that learn weights and biases similar to other neural networks. This improves the efficiency of the forward function and reduces the number of the parameters in the network. The convolution layer is made of multiple convolution kernels that learn feature representation of inputs and generate feature maps. The application of CNN in this work is for passive sensing which is impact detection and characterization. For this purpose, the input to the network is the sensor signals recorded by Piezoelectric (PZT) transducers due to an external impact event, which are processed into a 2D image generated as shown in Figure 1 (b). The output is then a certain impact class. Since the CNN can only output a class and not a number, for the purpose of impact location the structure has to be divided into different classes each representing a localized area, as shown in Figure 3 (b). Similarly, for the purpose of impact characterization, the energy levels will be categorized into different classes ranging probable impact energies to identify whether the impact could be alarming for the structure or not.



(a) Sensor signals recorded by one PZT from multiple impact events (b) Greyscale image of 5 sensor readings

Figure 1 Generating 2D images for input to CNN

Each impact will generate different response in the structure represented by signals recorded by the sensors depending on the level of the impact energy and the location. Sensors which are closer to the impact location will experience higher strains and consequently higher amplitude signals. Signals from the sensor network can then be fused to generate a greyscale image as shown in Figure 1 (b) while maintaining important information such as time of arrival and amplitude of the signal.

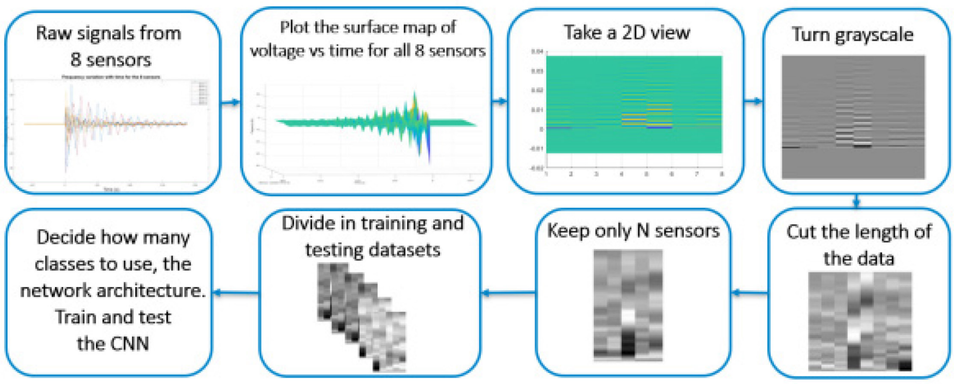


Figure 2 Data input to CNN

The CNN Architecture was optimised for running with very small datasets. A modified version of CIFAR 10 architecture [21] has been adopted in this work to enhance its performance. The first modification is to use only one convolution later from each pair, to reduce the number of parameters required. This is to avoid overfitting for a small training dataset. The second modification is to add the dropout option after each convolution layer also to avoid overfitting. In this paper, the application of CNN for impact localization on a simple composite plate is investigated with experimental data gathered from various impact scenarios.
The data processing for generating the input images for the CNN can be summarized as follows:

1) obtain the raw signals recorded from impact events;
2) plot the surface map of voltage vs time for all of the sensors;
3) generate a 2D image from the surface plots;
4) transfer this 2D image into a greyscale image;
5) apply a time window to the signal (to maintain the time of arrival information);
6) divide the data into training and testing dataset;
7) decide on the output (i.e. number of classes) and network architecture.

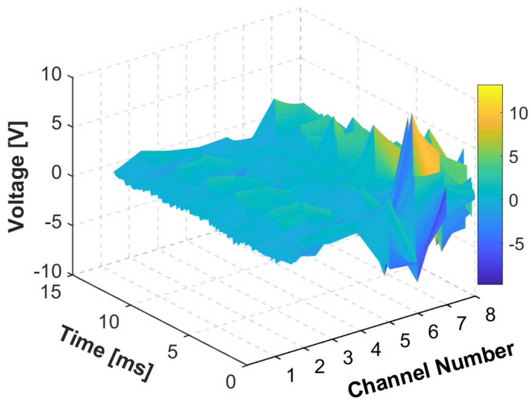
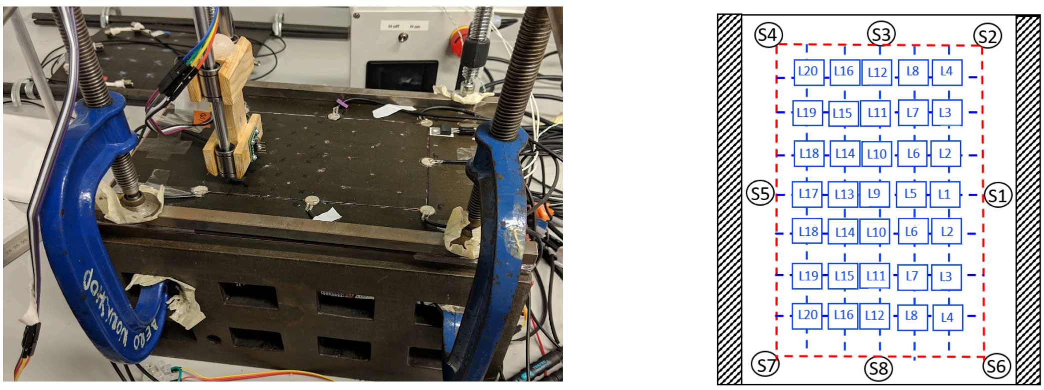


Figure 3 Example of surface map of the sensor signals recorded by all 8 sensors

Experimental Set Up

The composite plate used in this work is quasi-isotropic ($[0/+45/-45/90/0/+45/-45/90]_s$ layup) carbon fibre (M21 T800s) of size 200 mm x 290 mm) with 8 PZT sensors bonded to the top side of the plate. The plate is impacted with a dropping ball on a sliding mechanism, with a manually adjustable height and location [4]. The data from the piezoelectric sensors (PZT) is recorded using a NI PXI-5105 8 channels oscilloscope and NI Signal Express software.



(a) Impact fixture (b) Impact location classes

Figure 4 Composite plate with surface mounted PZT sensors

The plate was impacted inside the region highlighted by the red dashed line indicated in Figure 4 (b) to generate 2 datasets A and B. The impact area is 120 x 160 mm with a grid of 20 x 20 mm. Dataset A consists of 35 impact locations, each impact location repeated 4 times with two different impact heights 50 and 100 mm each corresponding to a different impact energy. Dataset B also consists of 35 impact locations but for 10 different energy levels generated by impact height varying from 10 mm to 100 mm in steps of 10 mm. It is worth noting that each repeating set is slightly different because of the tolerance in adjusting the height of the impactor and locating it.

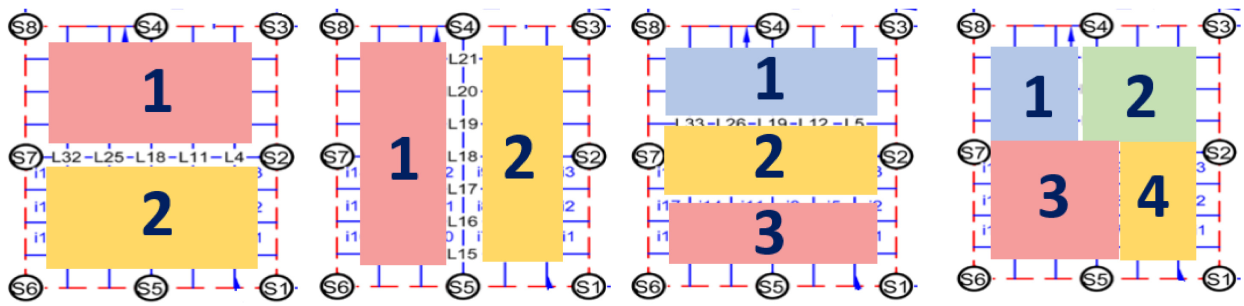
Table 1 Experimental data

Dataset	Total no. of images	No. of sensors	No. of impact locations	No. of energy levels	Repeats	Classes	Images per class
A	280	8	35	2	4	35	8
B	160	8	35	10	4	4	70

Result and Discussion

In this section, the results of Impact detection with CNN is discussed. Developing a CNN for passive sensing consists of training the CNN with a set of images and their corresponding classes (labels) and testing it with another set of images which are new to the network. The accuracy of the CNN is measured by how many classes it has predicted correctly. For the location prediction a "class" means a certain location or region in the plate. For the purpose practical application of the passive sensing to realistic structures, the location accuracy of an impact event is not as important as accuracy of the localization methodology. It is more important to detect an impact event with high certainty than being able to localize it with high accuracy. Therefore, several different network architecture has been investigated in this work in terms of the output class as shown in Figure 5:

- 35 classes: each class corresponding to one impact location as shown in Figure 4 (b) with 20 mm distance between each impact.
- 4 classes: corresponding to 4 corner zones, impacts on the mid line of the plate had to be grouped with one of the classes, hence the classes are non-symmetric at the end, Figure 5 (d).
- 3 classes: corresponding to top, middle and bottom regions of the plate, Figure 5 (c).
- 2 classes: which can be either top/bottom or left/right as shown in Figure 5 (a) and (b).



(a) (b) (c) (d)

Figure 5 Division of composite plate in different classes

To find the optimum network architecture, different runs were carried out for each class. For example for dataset A and the 35 class output CNN, 3 different networks were investigated. The data was divided in 210 images for training, and 70 for testing, meaning that 3 repeating sets are used for training, and the last one for testing. With 35 location taken as classes, the accuracy reached was 91 % for 20 epochs and 98.5 % for 50 epochs. Thus, since 50 epochs give a satisfactory accuracy and does not take too much training time, this will be used for the next trainings. For the scenario with only 4 classes corresponding to the four corners, training with 210 images and testing with the 4th set resulted in 100% accuracy.

As the location prediction has proven to be successful and highly accurate when training with images covering all the locations on the plate, the up-scalability issue is investigated. In a real aircraft, the metamodel cannot be trained with data from every single location of the wing/fuselage, for example, so the metamodel should be able to predict the approximate location by being trained with images from a few locations along the frame. Then, using symmetry with respect to the sensor configuration, boundary conditions and others, it should be able to correctly predict the location of the impact. For this, the plate has been divided into more regions, for example top/bottom or left/right as shown in Figure 5 (a) and (b). The training for this CNN was done with one of the regions only (e.g. top), and tested with the other region (e.g. bottom) to explore the generalization and scalability of the network. For this to be possible (the top images should encapsulate a similar physical meaning as the bottom images), the symmetry about the horizontal was enforced. The results achieved using different sets of locations, divided into Left and Right showed and accuracy of 95 % and 100 %, for two different training sets which is similar to the other trained CNNs.

Summary

In this paper, a novel metamodel based on Convolutional Neural Networks for passive sensing in composite plates has been successfully developed and optimised. The application of the metamodel has been demonstrated for impact localization on a composite plate with surface mounted PZT sensors. An innovative representation of the recorded sensor data allowed the signals form a network of sensors to be transformed into a 2D image and used as inputs to the network. The metamodel accuracy reached values of 98.5% when predicting impacts on the same locations that has been trained with.

The advantage of the proposed CNN-based metamodel for passive sensing in this paper is that it can achieve high accuracy with limited data set. Moreover, the up-scaling and generalization capability of the CNN is of high interest for passive sensing. This means that for large complex structures, the network can be developed for data trained by one region but used on other regions of similar geometry and sensor architecture which is very attractive for large structures such as composite stiffened panel. In future work, the applicability of CNN on composite stiffened panel will be investigated, in particular its generalization capabilities.

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