Damage detection in composites by AI and high-order modelling surface-strain-displacement analysis

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Marco Enea, Alfonso Pagani, and Erasmo Carrera

Mul^2 Group
Department of Mechanical and Aerospace Engineering, Politecnico di Torino
Corso Duca degli Abruzzi 24, 10129 Torino, Italy.

Abstract. In the recent years, machine learning algorithms have been widely employed for structural health monitoring applications. As an example, Artificial Neural Networks (ANN) could be useful in giving a precise and complete mapping of damage distribution in a structure, including low-intensity or localized defects, which could be difficult to detect via traditional testing techniques. In this domain, Convolutional Neural Network (CNN) are employed in this work along with one-dimensional refined models based on the Carrera Unified formulation (CUF) for surface strain/displacement based damage detection in composite laminates. A layer-wise kinematic is adopted, while an isotropic damage formulation is implemented. In detail, CUF-based finite element models have been exploited in combination with Monte Carlo simulations for the creation of a dataset of damage scenarios used for the training of the CNN. Therefore, the latter is fed with images of the strain or displacement field in a region of particular interest for each sample, which are subjected to the same boundary conditions. The trained CNN, given the strain/displacement mapping of an unknown structure, is therefore able to detect and classify all the damages within the structure, solving the so-called inverse problem.

Keywords: Damage detection · Artificial intelligence · Higher-order finite elements · Carrera Unified Formulation.

1 Introduction

In recent years, the use of artificial intelligence (AI) for structural health monitoring purposes in the aerospace industry is rapidly increasing. The implementation of these methods could result in a partial or full replacement of Non-Destructive Tests (NDT), which are usually performed in the framework of an aircraft maintenance program. The main limitation of these test is the necessity to know in advance the location of the damage to be investigated, which can obviously lead to a misjudgment of the damage distribution in the structure.

One of the most used AI method for structural health monitoring is the Convolutional Neural Network (CNN). CNNs have been first proposed by LeCun et al. in [1], where this method was used for handwritten digit recognition. In the present work, CNNs are fed with images of strain and/or displacement field measurements , which can be a direct indicator of failure in the structure. In real applications, these images are taken through an optic technique called Digital Image correlation (DIC) [2]. Here, the capability of the Carrera Unified Formulation (CUF) [3] to provide very accurate 3D-like solutions with a very low computational demand is exploited in order to create a large database of images for the training of the CNN. Once the network is well trained, the inverse problem is solved: given the strain/displacement mapping of an unknown structure, the network is able to detect and classify the damages within the structure.

The manuscript is organized as follows: Section 2 describes the finite element models employed. Then, Section 3 presents the layer-wise damage modelling; Section 4 illustrates the CNNs training process. Afterward, the results are shown in Section 5. Finally, conclusions are drawn in Section 6.

2 Refined 1D models

In the framework of CUF, the 3D field of displacements can be expressed as a summation of arbitrary expansion functions $F_\tau(x,z)$ and the vector of the generalized displacements $u_\tau(y)$. In the case of one-dimensional beam theories, as in the case of this work, the displacements field is expressed as:

$$\mathbf{u}(x,y,z) = F_\tau(x,z)\mathbf{u}_\tau(y), \qquad \tau = 1,2,....,M \tag{1}$$

where $\mathbf{u}(x,y,z)$ is the displacement vector; F_τ indicates the functions of the cross-section coordinates x and z; $\mathbf{u}_\tau$ is the generalized displacement vector; M indicates the number of terms in the expansion. In this work, Lagrange polynomials are used for the expansion of the displacement across the beam cross-section. Furthermore, the finite element method (FEM) is employed to discretize the structure along it longitudinal axis. Thus, the generalized displacement reads:

$$\mathbf{u}_\tau(y) = N_i(y)\mathbf{u}_{\tau i}, \qquad i = 1,...,p+1 \tag{2}$$

where p is the number of nodes for each element, N_i the shape functions and $\mathbf{u}_{\tau i}$ the nodal unknowns. The stiffness matrix is obtained through the application of the virtual displacement principle. After some manipulations, the virtual variation of te internal work will be written as follows:

$$\delta L_{\text{int}} = \delta \mathbf{u}_{sj}^{\text{T}} \mathbf{K}^{ij\tau s} \mathbf{u}_{\tau i} \tag{3}$$

where $\mathbf{K}^{ij\tau s}$ is the stiffness matrix in terms of fundamental nucleus. Note that no assumption about the approximation order are made for the matrix formulation. Thus, any refined beam model can be obtained with this procedure. The assembled global stiffness matrix is obtained by looping through the indices i,j,τ,s.

3 Damage formulation

In this work, Lagrange expansions have been employed in the CUF framework to build a component-wise approach. The latter allows to model separately each component and/or layer of the structure. Thus, a different degree of detail could be used for the modelling of any component, according to the accuracy required from our model. Moreover, this approach also allows the introduction of different damage intensity for each component, allowing a more localized damage distribution in the laminate, if necessary. In this work, an isotropic damage modelling approach has been implemented, as in [4]. The damage is simulated as reduction of the component stiffness, with no influence on its mass. Thus, the Young moduli E along all three directions are degraded by the same damage parameter d:

$$E_{ii}^{d} = d \times E_{ii}, \text{ with } 0 \leq d \leq 1 \tag{4}$$

where E_{ii}^{d} and E_{ii} are the Young moduli in the three directions for the damaged and undamaged structure, respectively, and d is the damage coefficient. A value of d equal to 1 will result in an undamaged structure, while, if lower, a damage of intensity equal to $(1 - d)$ will be assigned. This parameter will be assigned randomly to create a large database of structures, covering the largest number possible of damage scenarios. Further explanation will be given in the following section.

4 CNN for damage detection

A convolutional neural networks is a particular architecture of deep learning algorithm. Its features makes CNN a very suitable method for image processing. In fact, the main architectural frameworks of CNNs are [5]: local receptive fields, shared weights and spatial subsampling. The combination of these features allows a significant reduction of the number of parameters involved and, at the same time, CNNs have no invariance with respect to input translations and/or distortions.

4.1 CNN architecture

The architecture of a CNN can be built by using three different types of layers. Convolution layers have two-dimensional learnable filters as parameters, which are made slide over the input layer. The convolutional layer computes the dot product between these filters and the current small region of the input, creating the so-called feature maps. These maps will be used as input for the following layers. Then, the pooling layer performs a downsampling operation using maximum or average operations. Finally, the fully-connected layer will compute the weighted sum of input as in classical feedforward neural network. An example of CNN architecture is shown in Fig. 1.

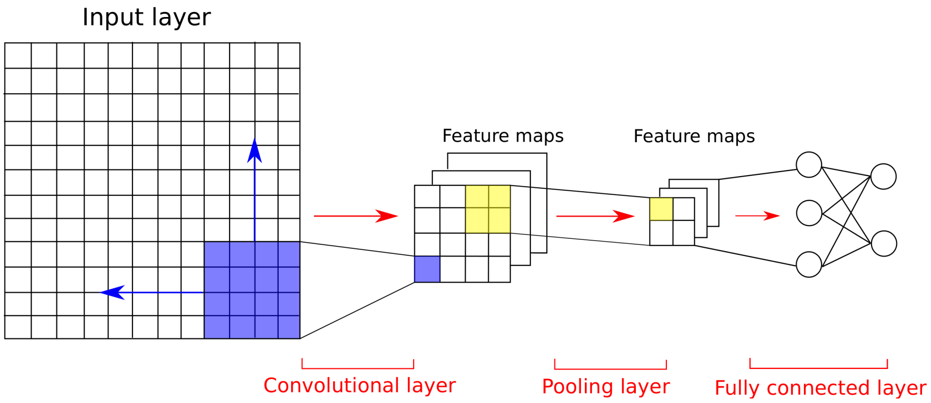

Fig. 1. Example of CNN architecture.

4.2 CNN training process

A large training database is needed for the quantification and localization of damage. In this work, the database has been created through CUF-based Monte Carlo simulations. Damage intensity was assigned randomly to each component, following a Gaussian distribution, with mean and standard deviation equal to 0.1. Then, a linear static analysis is performed for each sample, adopting the same boundary conditions. Thus, the only variable will be the damage distribution. The strain/displacement surface fields images are extracted from the solution files and employed as input for the CNN training.

Once the CNN is well trained, the inverse problem could be solved: given the image of the strain/displacement field, the network will give as output the location and intensity of each damage in the structure. In Fig. 2, the flowchart representing the entire process is shown.

5 Numerical results

The proposed case study is a four-layer composite plate with lamination $[0/45]_s$. The plies are of equal thickness and they are made of an orthotropic material. Four cubic 4-node elements (B4) are employed for the longitudinal discretization, while quadratic Lagrange polynomials (L9) are adopted in the cross-section. The boundary conditions consist of a pressure load applied on the top surface, at the center of the plate. The edges are in clamped conditions.

An isotropic damage is then introduced in four components of the structure, identified along the beam axis (Fig. 3). Each component contains all four layers of the plate. The damage d is assigned through Monte Carlo simulation, with both mean and deviation standard equal to 0.1. A database of 6000 samples has been built, with 5300 samples used for the training set, 600 for validation and 100 as test set. The images employed were the vertical displacement field of the

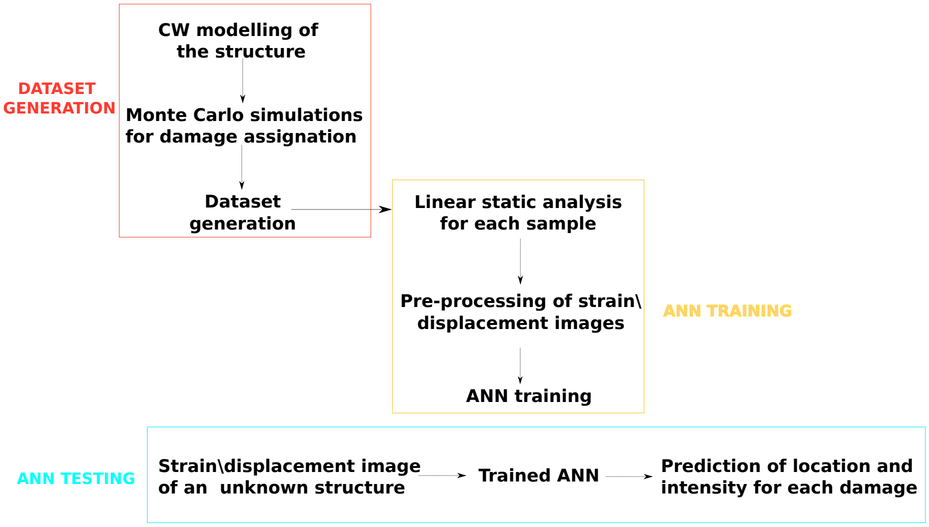
DATASET GENERATION
CW modelling of the structure
Monte Carlo simulations for damage assignation
Dataset generation
Linear static analysis for each sample
Pre-processing of strain\ displacement images
ANN training
ANN TRAINING
ANN TESTING
Strain\displacement image of an unknown structure
Trained ANN
Prediction of location and intensity for each damage

Fig. 2. Flowchart representing the entire process for damage detection.

bottom surface, with resolution of 1012 × 1012 pixels. An example of images for two different damage scenarios are represented in Fig. 4.

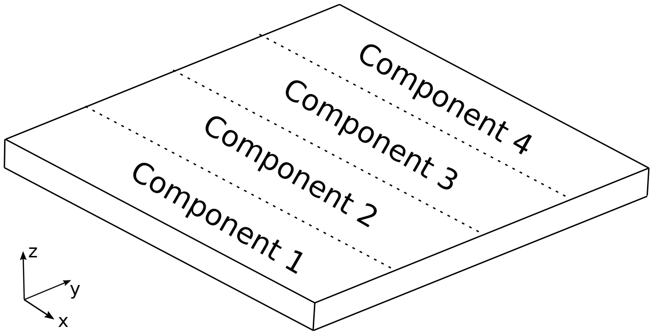

Fig. 3. Component's numbering in the composite plate.

Thereafter, some results are presented for the current case. A significant number of unknown structure has been fed into the trained neural network to verify if the latter was able to retrieve location and intensity of each damage in the structure. The regression curve is shown in Fig. 5. The regression coefficient R has a value near the unity, demonstrating a very high accuracy in predicting the correct value of the CNN targets (i.e. damage). Figures 6 and 7 show a comparison between the target value of damage intensity (red bars) and the CNN prediction in each component of the structure (blue bars). In the vertical axis, the intensity of the

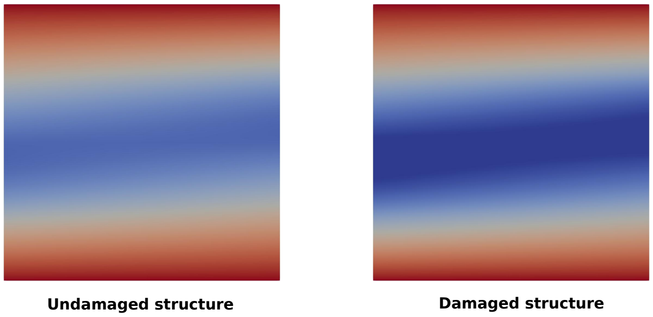

Fig. 4. Vertical displacement fields of an undamaged and damaged structure, respectively.

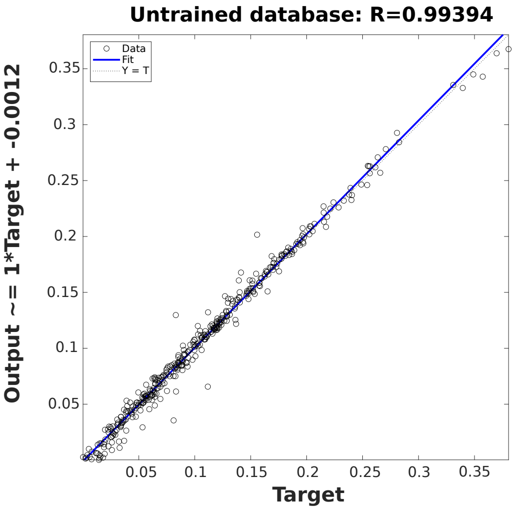

Fig. 5. Regression curve

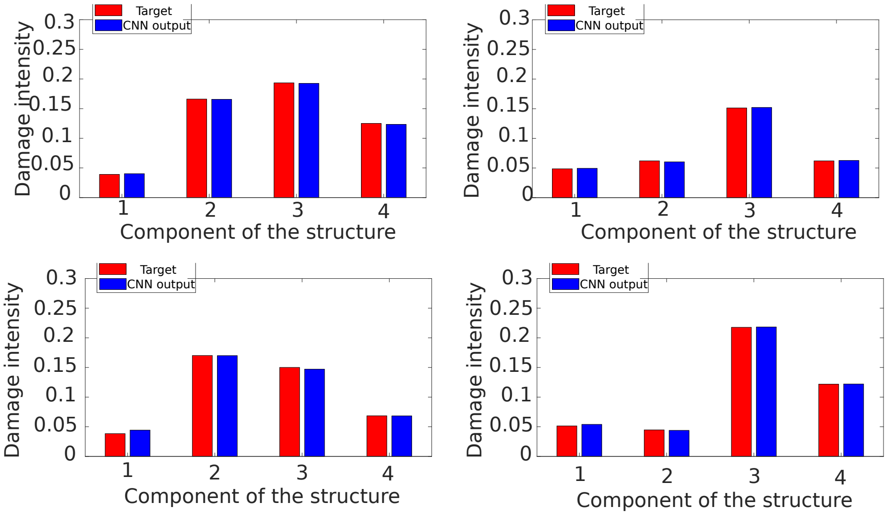

Fig. 6. Comparison between target value and ANN prediction in structures with all components damaged.

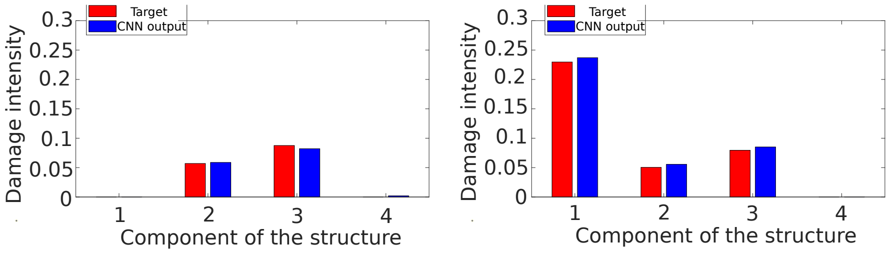

Fig. 7. Comparison between target value and ANN prediction in structures with two and three components damaged.

damage is represented. In the horizontal axis, the numbering of the components is displayed, following the repartition reported in Fig. 3. Note that the CNN is also able to predict with great accuracy even when structures have only some components with damage.

6 Conclusions

In this manuscript, a displacement-based damage detection method is proposed. The features of Convolutional Neural Networks (CNN) are combined with refined 1D models in the framework of the Carrera Unified Formulation (CUF). In fact, several linear static analysis have been carried out for the creation of a database covering the largest number of possible damage scenarios. This database has been used for the training of the CNN. The proposed model provided good results for a four-layer plate in which an isotropic damage has been introduced. After the network's training is completed, the latter is able to predict location and intensity of damages in unknown structures.

Note that in the proposed numerical example, only displacement field images were employed for CNN training. In future research, the authors will propose examples of damage detection through strain images and through a combination of displacement and strain mapping. Moreover, the authors will introduce a new damage model, which takes into account the difference between damages in longitudinal and transversal directions.

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