Damage Localization Frameworks Based on Unsupervised Deep Learning Neural Networks

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ABSTRACT

In recent years ultrasonic-guided waves (UGWs) have been successfully employed in structural health monitoring (SHM) for damage localization due to their high sensitivity to changes in the mechanical properties of the medium they travel through. Lamb waves (LW) are a particular type of UGW that can be generated by piezoelectric transducers placed on thin-walled structures, such as vehicles in general (terrestrial, naval, and aeronautical), and present characteristics that are favorable to SHM. Damage localization using LWs has been commonly accomplished through tomographic algorithms. However, these methods have unresolved issues such as artifacts generation in damage probability maps and a strong reliance on sensor network configuration for signal acquisition. As a solution, data-driven approaches based on supervised machine learning have been suggested. These methods have demonstrated good performance. However, for reliable results, they require large, labeled datasets, meaning that acquisitions must be performed before and after the structure is damaged. These datasets, especially data from the damaged state, are generally not available for real-life structures, given the cost and complexity to experimentally replicate certain damages. Unsupervised machine learning methods might be a solution to this problem, given that the neural network is trained using data acquired from the un-damaged structure only. To this date, no fully unsupervised damage localization frameworks have been proposed. Hence, in this work, two unsupervised data-driven methods are presented to process LWs to localize damage. Specifically, convolutional auto-associative neural networks (CAANNs) and generative adversarial networks (GANs). Both methods process diagnostic signals without requiring any prior feature extraction. After all signals are processed, a damage probability map is generated. The performance of both methods is tested using an experimental dataset of LW acquisitions using a set of piezoelectric transducers on a full-scale composite wing. Results showed that the proposed methods have good damage localization accuracy.

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INTRODUCTION

Recently, research has focused on designing structural health monitoring (SHM) systems for automatic damage diagnosis by analyzing the data acquired from a network of sensors installed on the structure. The SHM process involves selecting the excitation methods, the sensor types, number and locations, and the data acquisition, storage and transmittal hardware. Techniques based on Lamb waves (LWs) are particularly effective for thin-walled structures, being able to detect minor flaws due to their ability to handle high frequency excitation [1]–[5]. In addition to this benefit, SHM systems based on guided waves are also attractive due to their low cost and lightweight sensors, as well as their capability to scan large areas with a relatively small number of sensors [6].

Typically, LWs are excited and detected through a network of piezoelectric (PZT) devices that are attached to the structure. By comparing the wave propagation data obtained from a healthy structure to that collected over time, distortions related to the presence of defects can be identified, allowing for the detection of structural changes. Utilizing guided wave tomography, the work in Ref. [7] localized small impact damages in composite plate-like structures. Statistical damage index technique was applied to the recorded signals and a new image reconstruction approach for tomography was developed. The work in Ref. [8] presented an enhanced LW virtual time reversal method that considered wave-transducer interactions to improve damage detection. This technique was validated through analytical, numerical (using finite element simulations), and experimental studies on an aluminum plate. Finally, Ref. [9] presented a statistical outlier detection technique for accurately localizing LW-based damage in composite plates, which allowed for a reduction in sensor density compared to other imaging techniques.

The complexity of analyzing guided waves has prompted researchers to explore the use of machine learning algorithms for more efficient and accurate damage identification [10]–[13]. Among these algorithms, deep learning (DL) approaches are particularly interesting because they can automatically extract relevant features from raw signals. In recent years, many DL-based methods have been proposed in the literature, with most of them being supervised algorithms. Among these, convolutional neural networks (CNNs) have emerged as the most widely used method. Using CNNs trained on images obtained from LW signals, the work in Ref. [14] successfully detected cracks in thin aluminum plates. Ref. [15] utilized the knowledge obtained from a pre-trained autoencoder to diagnose damage in a carbon fiber-reinforced polymers (CFRP) plate using 1D CNNs.

While supervised algorithms have shown good performance in detecting structural damage, they require a significant amount of labeled data from both healthy and damaged states of the structure under investigation. Such data acquisition is time-consuming and labor-intensive, and obtaining damaged state data for some structures may not be practical. To address this issue, unsupervised DL-based methods can be employed. The use of such methods for LW-based SHM has not been extensively explored in the literature. To the best of the authors' knowledge, fully unsupervised LW-based damage localization has only been studied in Ref. [16]. In this study, the authors presented a technique for localizing damage in a CFRP plate using convolutional autoencoders (CAE) trained on healthy signals. The proposed method was able to identify the approximate location of the localized damage.

This paper introduces two new methods for achieving more accurate and fully unsupervised LW-based damage localization in thin-walled structures. The first method combines several convolutional auto-associative neural networks (CAANNs) with a new probabilistic imaging algorithm. The second method utilizes generative adversarial networks (GANs) as another type of unsupervised algorithm to significantly reduce the number of networks required for training, while maintaining high accuracy for damage localization. Both types of networks incorporate convolutional layers to take advantage of their superior feature extraction capabilities. All networks are trained solely on raw signals from the healthy state of the structure, without requiring any information from the damaged structure during training. The proposed methodology is validated against experiments carried out on a full-scale composite wing.

CONVOLUTIONAL AUTO-ASSOCIATIVE NEURAL NETWORKS

CAANNs reduce the dimensionality of the input data through an encoder. The same data is later reconstructed in the output layer based on the low dimension output of the encoder using a decoder. Both the encoder and decoder are CNNs, which are a type of artificial intelligence algorithm commonly used in image processing and computer vision tasks. These networks consist of convolutional, pooling, and fully connected layers. Convolutional layers detect local features in the input data using learnable filters (also called kernels), producing feature maps highlighting specific features. Pooling layers reduce the spatial dimensions of the feature maps while retaining relevant feature information, introducing translational invariance through subsampling. Fully connected layers apply non-linear transformations to the flattened output of the previous layer, eventually producing a vector of scores that correspond to different output classes. Further information on CNNs and CAANNs can be found in the works [17]–[19] and are not reported here in the interest of brevity.

During training, the filters and fully connected layers' parameters are learned through backpropagation, minimizing the error between the predicted output and the actual output. Once trained, the CAANN can classify new inputs by passing them through the network and analyzing the reconstructed output error.

For each actuator-sensor pair a CAANN was trained with data from the undamaged structure, with added 20dB signal-to-noise ratio Gaussian noise to increase the dimension of the dataset. Training allows for the identification of potential anomalies, with a higher discrepancy between input and reconstructed output indicating a greater likelihood of the input data not originating from a healthy structure. This discrepancy is measured using the root mean squared error (RMSE) between the input and the reconstructed output, and its value is assigned to the geometrical coordinates along the path between the actuator and sensor related to the CANN of interest. Additionally, the distance of the points of the structure from the path between the pair of sensors is used to assign them geometrical weights between 0 and 1, which decrease following a Gaussian distribution as the distance to the path increases. The RMSE is multiplied by this geometrical weight and the result is assigned to the geometrical point. After this process is performed for all actuator-sensor pairs, the result is a damage index map, later normalized between 0 and 1. For better visualization, the geometrical area under analysis was divided into a mesh.

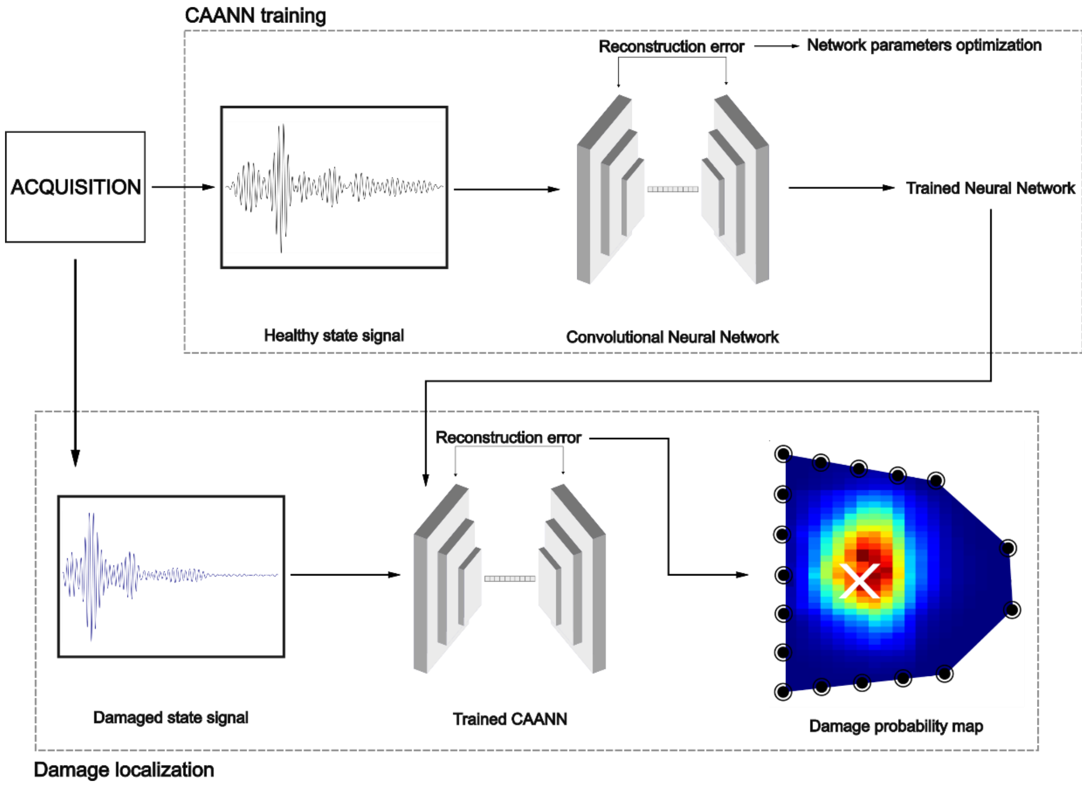

Figure 1. Illustration of the CAANNs-based damage localization.

GENERATIVE ADVERSARIAL NETWORKS

The architecture of a GAN consists of two sub-networks: a generator and a discriminator. The generator creates new examples for a dataset by receiving samples from a latent space. The discriminator receives samples from the dataset (real samples) and the generator (fake samples) and tries to distinguish between them by outputting 0 for fake data and 1 for real data. Both the generator and discriminator are artificial neural networks composed of convolutional and/or fully connected layers. During training, the parameters of one network are updated while the parameters of the other network are fixed. The discriminator aims to increase its accuracy by discovering the features of the training data samples and learning their distribution. Meanwhile, the generator learns to map samples in the latent space to output samples and tries to fool the discriminator into accepting the generated samples as real data. This can be expressed as a two-player minimax game [20], [21].

Conventional GANs suffer from not being able to control the class of generated samples. This limitation is addressed by Conditional Generative Adversarial Networks (CGANs), which are a type of GAN that can produce samples of desired classes. This is achieved by combining the input data of both sub-networks with labels. The generator learns to create samples of each class given the corresponding label, while the discriminator learns to differentiate between real and fake samples of different classes. In this paper, CGANs with convolutional layers are utilized to detect damage in thin-walled structures using PZT devices for acquiring diagnostic signals.

Similar to the CAANN method, the models were trained using the healthy state signals with added Gaussian noise of 20 dB signal-to-noise ratio. By creating a grid, the area surrounded by PZT devices is divided and each cell of the grid is then assigned a score based on the average score of the paths that intersect it. The region with the highest score is the region with the highest probability of damage. For better visualization, Hanning interpolation was applied to the grid cell limits.

RESULTS

The full-scale composite wing open database for the analysis was produced in Ref. [22]. LWs were stimulated and sensed at the lower panel of the wingbox during four distinct phases: prior to wingbox assembly, post-assembly, after the application of fatigue cycles, and following impact tests conducted with an air gun. The impacts may cause delamination, a type of damage that reduces the strength and longevity of composite structures. In addition, it is often concealed and not detectable through visual inspection. Detecting this hazardous form of damage is a major concern when using composites in aerospace structures, which are frequently exposed to impacts.

In this study, the signals obtained after wingbox assembly were considered as reference signals, signifying the undamaged structure. Conversely, the signals collected post-impact were analyzed using the proposed framework to pinpoint delamination. The wingbox skin comprised three distinct layups: unidirectional Uniweave (UN) laminae, woven fabric 5-Harness (5HS) laminae, and NCF-biaxial (NCF) laminae. The completed wingbox structure measured 4.5 meters in length, with a width ranging from 1.2 to 2.3 meters. A network of 133 transducers was installed within the interior portion of the lower panel, organized into eight bays (A1, A2, B, C, D1, D2, E1, E2). Bays A2 and E2 were chosen for this study to demonstrate the effectiveness of the proposed framework.

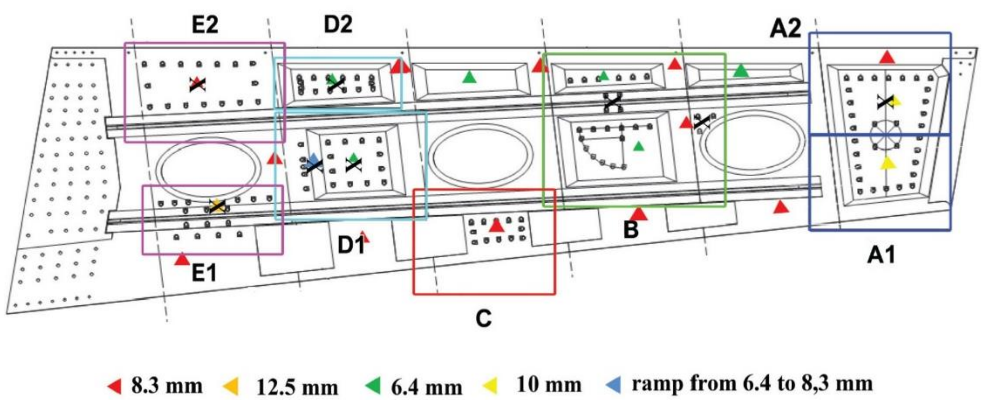

Figure 2. Depiction of the lower wing panel showing the different bays, the position of the transducers and the positions of impact (X symbols). The colored triangles indicate the measured thicknesses. Reprint from Ref. [22].

The results can be seen in Figures 3 and 4. For both bays, both methods had similar results. For bay A2, the higher damage indices are spread in an area that surrounds the impact position while for bay E2 the higher damage indices are concentrated at the impact position. It can be noticed in the c-scan images extracted from Ref. [22] and depicted in Figure 5 that the damaged area for bay A2 is smaller and not concentrated in the damaged area center. That is reflected by the localization results, as the higher damage index is not located at the impact position. As for bay E2, the damaged area is larger, and damage is highly concentrated at its center. As a result, both localization methods point to the impact position.

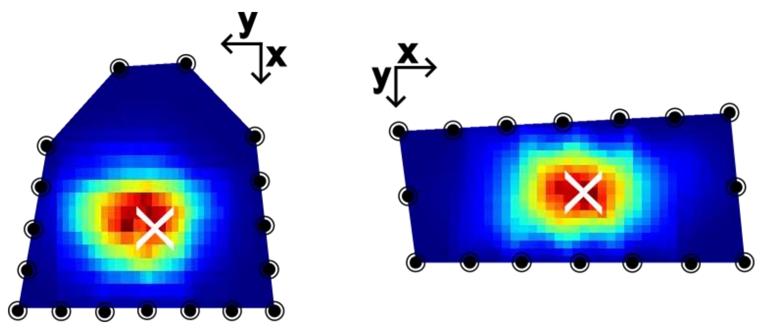

Figure 3. CAANNs-based damage localization results: bay A2 (left) and bay E2 (right). The black circles represent the PZT transducers and the white X represents the point of impact.

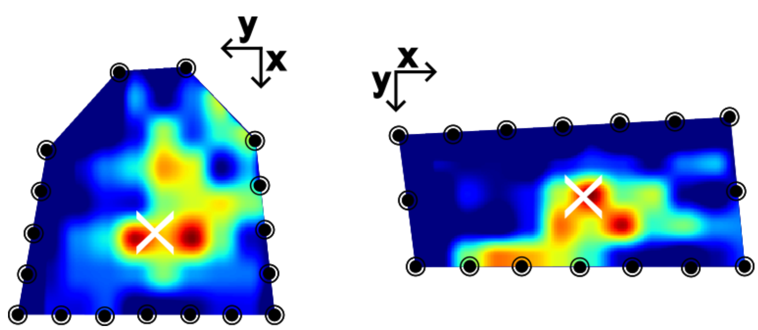

Figure 4. CGANs-based damage localization results: bay A2 (left) and bay E2 (right). The black circles represent the PZT transducers and the white X represents the point of impact.

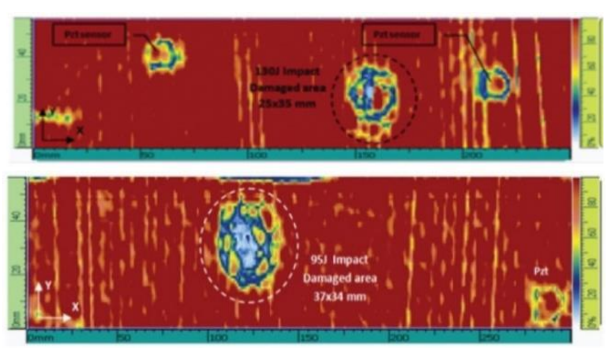

Figure 5. C-scan images: bay A2 (top) and bay E2 (bottom). Reprint from Ref. [22].

CONCLUSION

In this paper, two unsupervised methods for damage localization based on LWs have been proposed and validated against experimental data. One method is based on CAANNs while the other is based on CGANs. Given the unsupervised nature of the data-driven approaches employed, the dataset generation cost is reduced since only undamaged structure data is needed to set up the method.

Experimental data for validation derives from an experimental campaign conducted on a full-scale composite wing. Two different sections of the wing's lower panel were considered, at two different states: after assembly (healthy state) and after being subjected to impacts (damaged state).

The results attest to the methods efficiency, as both methods could localize the damaged areas. Difference in the results for the different sections can be accounted to the different delamination patterns, while the difference between methods can be accounted not only to the machine learning method itself, but also to the different technique for the assignment of damage indices to the grid points.

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