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# Exploring transfer learning for improving ultrasonic guided wave-based damage localization

Luca LOMAZZI [1], Lucio PINELLO [1], Abderrahim ABBASSI[2], Marco GIGLIO [1], Francesco CADINI [1]

[1] Politecnico di Milano, Dipartimento di Meccanica, Via La Masa, 1, Milano, 20156, MI, Italy. Email: luca.lomazzi@polimi.it.

[2] Institute of Structural Analysis, Leibniz Universität Hannover, Appelstraße 9a, Hanover 30167, Germany. Email: a.abbassi@isd.uni-hannover.de.

**Abstract.** Designing maintenance strategies to reduce the failure risk of plated structures is paramount for increasing the safety level of aerospace, civil and mechanical systems. Although traditional time-scheduled maintenance policies are reliable, they come with costly operations and avoidable downtimes. Recently, more complex condition-based strategies have been studied in the literature. This class of maintenance actions rely on structural health monitoring (SHM) frameworks: a sensor network is installed on the structure diagnostic data are processed to monitor the health state of the structure.

The high dimensionality of data and the limitations of model-based SHM algorithms have led researchers to investigate data-driven solutions for improving the reliability of condition-based strategies. So far, supervised machine learning strategies have mainly been considered. However, since the cost of generating labeled datasets usually turns out to be prohibitive, two alternative solutions have gained attention: unsupervised methods and transfer learning (TL). While the former approach has been proved to provide satisfactory damage detection performance, it requires external knowledge sources to also localize and quantify damage. Instead, transfer learning could be used for performing all the damage diagnosis tasks, without the need for coupling the data-driven method with complex algorithms to restore the information lost by using smaller datasets for training. TL allows adapting pre-trained ML tools to new situations, new tasks and new environments. Moreover, TL can be leveraged when few labeled data are available, or to adapt efficient tools that have already been trained on a slightly different task.

In this work, TL and convolutional neural networks (CNNs) were leveraged for performing damage localization in composite plated structures. That is, domain adaptation and fine-tuning were used to make an in-house CNN-based framework for localizing structural damage flexible enough to work in different domains.

**Keywords:** domain adaptation, transfer learning, damage localization, structural health monitoring, composite.



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## Introduction

It is inevitable that safety and reliability issues appear at some point during the operational life of structures. When this happens, the probability that the structure will fail becomes no longer negligible, and actions must be taken to restore standard safety conditions and avoid intolerable failures [1,2]. In this context, structural health monitoring (SHM) has gained strategic importance for extending the operational life of structures. The main goal of SHM is to detect any damage, anomalies, or changes in the structural behavior through a permanently installed network of sensors.

Particularly promising capabilities have been shown by frameworks that process the information carried by ultrasonic guided waves (UGWs) [3–5], especially when complemented by machine learning (ML) algorithms [6,7]. In fact, ML algorithms allow identifying complex patterns and anomalies that are difficult, or even impossible, to detect manually. In particular, this is made possible by the use of advanced ML algorithms, such as convolutional neural networks (CNNs), that allow processing the diagnostic signals without extracting some damage-sensitive features, which would lead to loss of precious information. This was proven in Refs. [8,9], where a CNN-based framework for damage detection, localization and quantification was presented. The method outperformed ML-based frameworks that relied on extracted features, and traditional tomographic algorithms. Evidence was brought that the CNNs were able to diagnose damage characterized by properties outside the training domain. However, as most of the ML methods used for SHM, the approach required that a large and reliable dataset be available for training the networks. This limitation often results in expensive and time consuming operations that prevent industries from adopting ML approaches in real-worlds scenarios [8,10–12].

To overcome this limitation, transfer learning (TL) has been adopted in the literature [13–15]. To date, TL has helped address specific problems related to the nature of available experimental datasets, including the availability of limited training data, and has made it possible to deal with computational complexity, long training times, and to improve the generalization capability of ML algorithms [16]. This method allows using knowledge learned from a source domain to solve a problem in a related target domain. Ref. [17] introduced a TL approach based on a boosting algorithm to forecast pavement performance with limited data, while Ref. [18] presented a comprehensive approach for detecting open and closed cracks. Ref. [19] used TF to identify and detect structural cracks in images obtained from cameras installed on unmanned aerial vehicles (UAVs). Ref. [20] exploited commercial UAVs equipped with high-resolution vision sensors to detect and identify cracks in deteriorated concrete bridges. Ref. [21] proposed a method that combines CNNs and TL to identify leakage, spalling, and rebar exposure in hydro-junction infrastructure. Furthermore, Ref. [22] presented a method to detect damage on bridges using a combination of TL and vision-based techniques. However, to the authors' best knowledge, no methods have been proposed in the literature that apply TL in the field of UGW-based SHM.

This work aims to bring evidence that TL can be used to make CNNs trained on an experimental dataset of UGWs acquired on a plate work for plates made of different materials. To this purpose, the CNN-based framework already presented in Ref. [8] was trained on signals from the source domain. Then, domain adaptation was used to make the target domain distribution match the source domain distribution, and the CNN was fine-tuned on the few available target domain data.

This paper is organized as follows. Section 1 presents the proposed framework. Section 2 introduces the case study, shows the damage localization results, and discusses the advantages of embedding TL into ML-based frameworks for SHM using UGWs. The conclusions of this work are drawn out in Section 3, where future work is also presented.

## 1. CNN-based framework for damage localization embedded with TL

The CNN-based framework for damage detection, localization and quantification already described in Refs. [8,9] was considered in this work. In the interest of brevity, only the CNNs aimed to localize damage were combined with the TL algorithms to bring evidence of the capabilities of the proposed approach. The framework is shown in Figure 1.

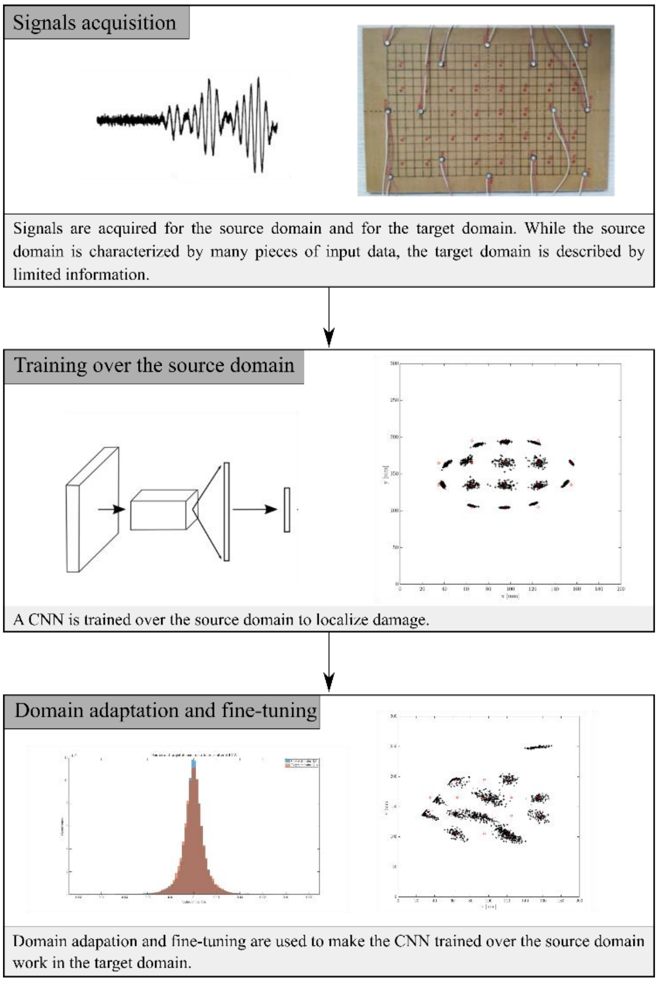



**Fig. 1.** Framework for localizing damage in thin-walled structures by combining CNNs and TL.

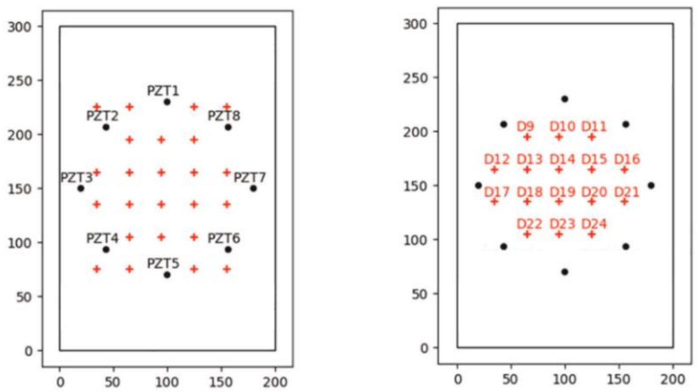
The first step consists of installing the sensor network on the structure and acquiring the diagnostic signals. In order to excite and sense UGWs on plated structures, piezoelectric (PZT) sensors are usually adopted. The pitch-catch technique is suggested to acquire diagnostic signals. That is, one PZT at a time works as actuator, while the other devices sense the UGWs. A full acquisition ends when all the PZT devices have been used for exciting UGWs. The first step needs to be performed for both the source and the target domain, so to have the two datasets ready for the next steps.

The second step of the framework consists of training the CNN for damage localization over the source domain. The CNN predicts the x and y coordinate of the damage.

After the training step, TL is used to make the CNN work on the target domain. First, domain adaptation is performed. The method implemented to this purpose belongs to the feature-based methods, and more specifically to the Transfer Component Analysis (TCA) framework [23–25]. This framework aims to identify the principal components of the source and target domain distributions, and to generate a map so to have the principal components of the two distributions match. The algorithm employed in this work relies on the adaptation of the Principal Component Analysis (PCA) for tensor objects, namely the Multilinear Principal Component Analysis (MPCA) [26,27], to find the common features between the datasets in the latent space defined by the eigenvectors of the data. After mapping the target domain into the source domain, the CNN is fine-tuned over the few available target domain data. This procedure allows exploiting the knowledge gained by analyzing the source domain, where several pieces of data are available, to make predictions over the target domain, where information is instead limited.

## 2. Case study

The proposed method was tested against a case study involving experimental structures. Specifically, damage localization was performed for two 4mm thick composite plates with in-plane dimensions 200mm x 300mm [28]. UGWs acquired on a Kevlar plate (K8) were used as the source domain, while signals coming from a Glass fiber plate (G16) constituted the target domain. The sensors employed were 1mm thick PIC255 PZT sensors with diameter 5mm. A circular sensor array with 8 devices was installed on each plate to allow scanning a circular area with diameter 160mm. Damage was simulated by using the pseudo-damage approach described in Ref. [28]. That is, damage was simulated by attaching a vinyl tape at 16 positions, one position at a time. The sensor array and damage positions are shown in Figure 2. The signals sensed over a full acquisition were stacked so to generate a grayscale image (GSI). Each GSI was composed of 7 rows and 10568 columns, i.e., 1 row per sensor and 1321 columns, or samples, per actuator. The dataset consisted of 2400 GSIs, 1600 from the source domain and 800 from the target domain.




| Sensor ID | x [mm] | y [mm] |
|---|---|---|
| PZT1 | 100 | 230 |
| PZT2 | 43 | 207 |
| PZT3 | 20 | 150 |
| PZT4 | 43 | 94 |
| PZT5 | 100 | 70 |
| PZT6 | 157 | 94 |
| PZT7 | 180 | 150 |
| PZT8 | 157 | 207 |

| Damage ID | x [mm] | y [mm] |
|---|---|---|
| D9 | 65 | 195 |
| D10 | 95 | 195 |
| D11 | 125 | 195 |
| D12 | 35 | 165 |
| D13 | 65 | 165 |
| D14 | 95 | 165 |
| D15 | 125 | 165 |
| D16 | 155 | 165 |

| Damage ID | x [mm] | y [mm] |
|---|---|---|
| D17 | 35 | 135 |
| D18 | 65 | 135 |
| D19 | 95 | 135 |
| D20 | 125 | 135 |
| D21 | 155 | 135 |
| D22 | 65 | 105 |
| D23 | 95 | 105 |
| D24 | 125 | 105 |

**Fig. 2.** Damage and PZT devices positions considered in the case study.

MPCA was applied to extract the eigenvalues and eigenvectors of the source and target domains. Particularly, 10 1-Mode and 10 2-Mode eigenvectors and eigenvalues were computed. Here, 1-Mode indicates the extraction performed by compressing the information along the row direction, while 2-Mode stands for the column direction. The eigenvectors were then stacked in a tensor, called eigentensor, which represented the projection of the source and target domains into the latent subspace formed by the 10 principal 1-Mode and 2-

Mode eigenvectors [26,27]. After performing MPCA, the projected dataset was composed of 2400 GSIs with dimensions 7x812. That is, the second dimension of the dataset was compressed by a ratio 10568/812=13. The source and target domain distributions before and after MPCA are shown in Figure 3. Furthermore, the dataset was split into the training, validation, and testing sets, using a ratio 80:10:10, respectively.

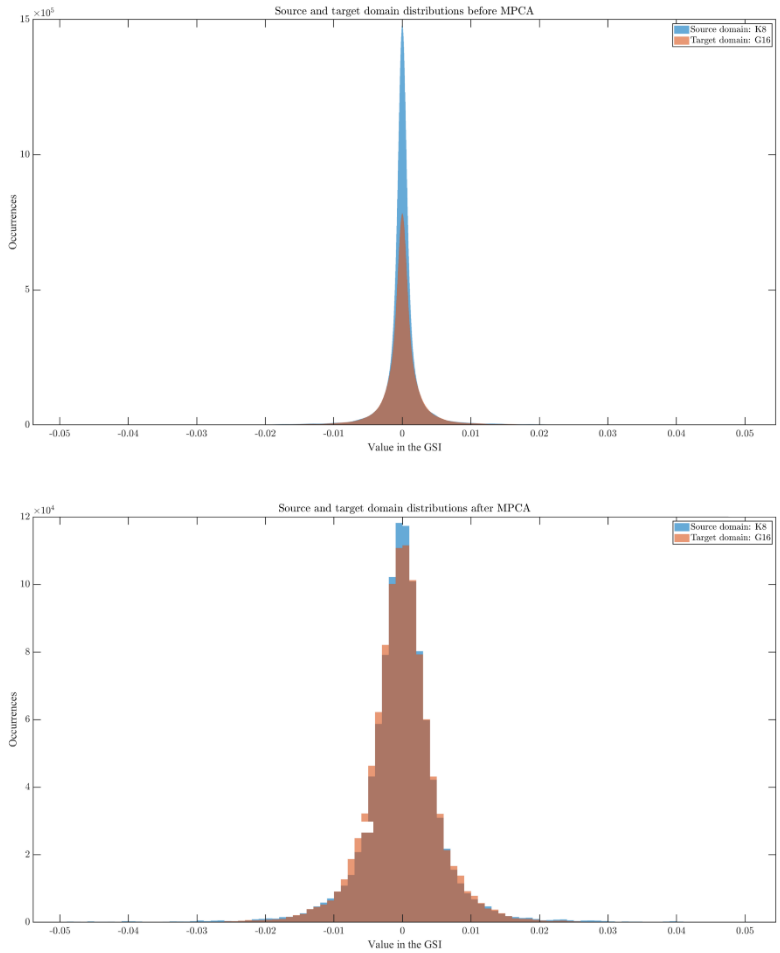



**Fig. 3.** Source and target domain distributions before and after MPCA.

Then, the CNN was trained over the source data in the projected dataset using the MATLAB® Deep Learning toolbox. The network architecture is shown in Table 1.

| Layer | Shape | Kernel Size | Stride | Filters |
|---|---|---|---|---|
| Input Layer | 7x812 | | | |
| Conv2D | | [1, 6] | [1, 3] | 4 |
| Batch Normalization | | | | |
| Max Pooling | | [1, 2] | [1, 2] | |
| Conv2D | | [2, 4] | [1, 2] | 4 |
| Batch Normalization | | | | |
| Max Pooling | | [2, 6] | [1, 2] | |
| Fully Connected | 20 | | | |
| Fully Connected | 10 | | | |
| Fully Connected | 5 | | | |
| Fully Connected | 2 | | | |

**Tab. 1**. CNN architecture.

The damage localization performance of the CNN trained over the source domain is shown in Figure 4 considering the testing set only. Here, red circles indicate expected damage positions, while black crosses show where damage was localized by the CNN.

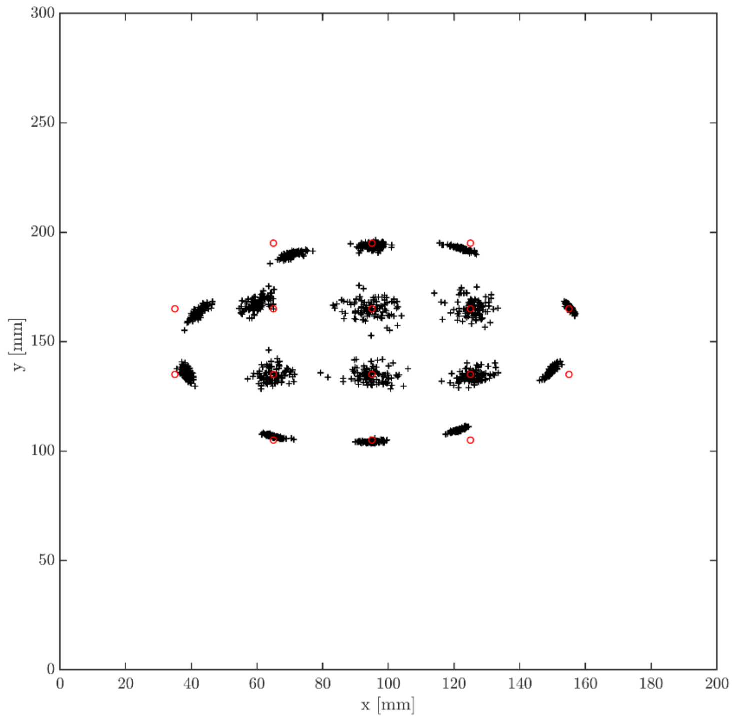
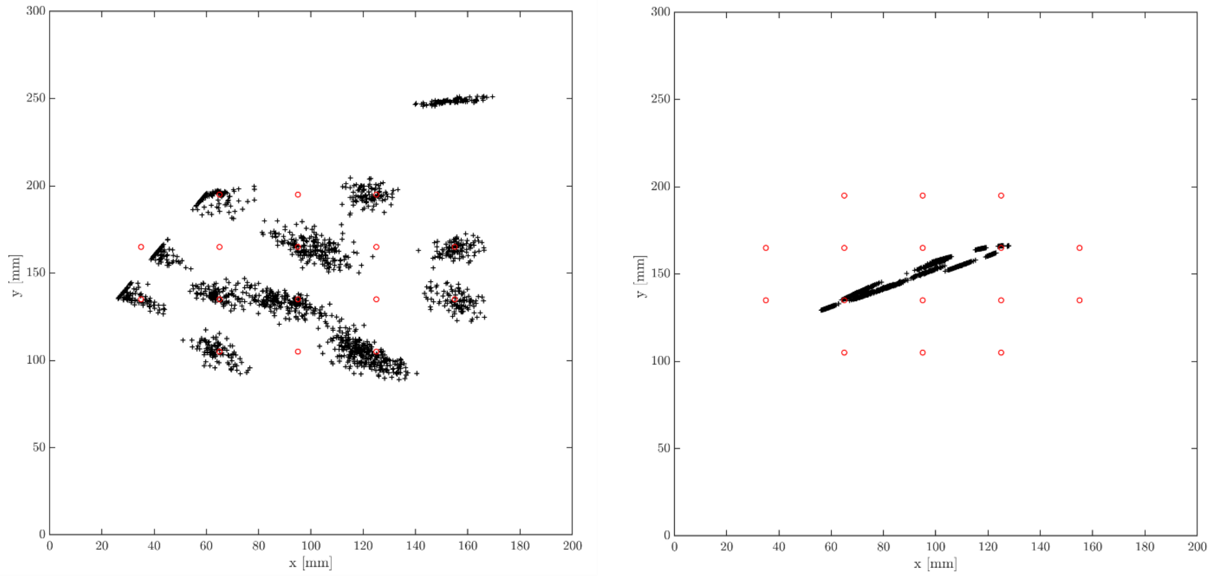



**Fig. 4.** Damage localization performance over the testing set of the source domain.

After training, the fully connected layers of the CNN were fine-tuned over the target domain data in the projected dataset, while the convolutional part was kept frozen. Furthermore, a new CNN was trained from scratch over the target domain projected dataset as a reference to compare the TL performance with. The damage localization performance of the fine-tuned CNN and of the newly trained CNN over the testing set of the target domain projected dataset is shown in Figure 5.




(a) (b)

**Fig. 5.** Damage localization performance over the testing set of the target domain. (a) Fine-tuned CNN. (b) CNN trained from scratch.

The results brought evidence that TL was fundamental for making the CNN work on the target domain. In fact, without TL, the pieces of data available for the G16 plate were not enough to guarantee satisfactory localization accuracy, as shown in Figure 5(b).

## 4. Conclusion

This paper has presented a CNN-based framework for damage localization embedded with TL. The workflow is constituted of the following steps:

1. Signals need to be acquired on the structures. The structure for which many pieces of data are available is the source domain, while the structure with limited information is the target domain.
2. A CNN is trained to localize damage in the plate of the source domain.
3. Domain adaptation and fine-tuning are used to make the CNN trained on the source domain work on the target domain.

The results have shown that the proposed framework successfully allows CNNs to work in different domains, or for different structures.

Future work will aim to test the proposed framework against more complex tasks, such that of making a CNN trained on a numerical model of the structure work on the real structure.

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