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An Application of Domain Adaptation for Population-Based Structural Health Monitoring

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An Application of Domain Adaptation for Population-Based Structural Health Monitoring

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Abstract. In the field of civil infrastructure, Structural Health Monitoring generally suffers from a scarcity of labelled damage-state data. To solve this issue, this work adopts a Transfer Learning approach for leveraging information from a source structure, characterised by a rich class of damage labels, to improve inferences on a target structure with limited knowledge. The goal is to train a machine learning algorithm on a bridge undergoing damage and to afterwards transfer the available labelled damage-state data across the members of the investigated population. Given possible differences exhibited by each structure, a domain adaptation technique in the field of statistic alignment, called Normal Condition Alignment (NCA), is applied to match different distributions in a shared feature space. The methodology is validated on a heterogeneous population composed of two numerical bridges of different geometry and materials, representing the Z24 and the S101 benchmark bridges. Finite Element Models are built to simulate healthy conditions and several damage cases. The natural frequencies describing such scenarios are considered as damage-sensitive features and thus employed to characterise the two domains and fed to a supervised learning-based classifier. The presented approach is deemed effective to provide mappings that allow the exchange of health-state information from source to target datasets, becoming a promising approach to be applied within a population of real bridges.

1. Introduction

Vibration-based Structural Health Monitoring (SHM) has been in constant evolution to face the urgent need to manage and preserve the increasing number of ageing infrastructures. Thanks to improvements in sensing technology and computer science, effective strategies are developed to assess structural behaviour in operational conditions by exploiting information from the structure's dynamic response. In this context, Statistical Pattern Recognition (SPR) and Machine Learning (ML) stand out among the most efficient and popular tools, often adopted in the field of aerospace, civil and mechanical engineering [1-3]. In particular, the use of ML algorithms plays a fundamental role for identifying meaningful patterns within damage-sensitive feature distributions, which unveil information about the structural integrity and the presence of any changes in the monitored system. Therefore, these automated techniques, based on unsupervised/supervised learning, attempt to cover multiple SHM levels, with the aim to detect, localise and quantify damage during continuous long-term monitoring activities [4-7].

However, one of the main challenges is that the implementation of a robust ML algorithm requires large amounts of training data. A second drawback is represented by the assumption that both training and testing data are generated by the same underlying distribution; this issue means that typical ML techniques can be considered as case-specific, since they fail when trained and tested on two different structures. Such challenging aspects may cause some limitations when dealing with real monitoring scenarios, where data collection might be discontinuous or significantly costly and labels are often incomplete and scarce. The lack of available data means that most approaches can only address novelty detection or simply the identification of previously-seen conditions. As a solution, Population-based Structural Health Monitoring (PBSHM), represents a promising theory to expand the set of labelled data to train a supervised learning-based classifier [8]. It consists in transferring health-state information across a population of structures, whose features distributions may differ, however, because of variations in design, materials or geometry. To address this issue, Transfer Learning (TL), in terms of Domain Adaptation (DA), allow one to infer a mapping between two domains that harmonises feature distributions within a common latent space [9]. The goal is to improve diagnostic inferences on a target domain by transferring knowledge from a completely-labelled source domain. As a particular branch of TL, DA attempts to reduce the distance between data distributions using defined statistical metrics [10]. In contrast with the most popular TL approaches, such as fine-tuning or those DA techniques aiming to learn a nonlinear transformation from the feature space to a Reproducing Kernel Hilbert Space (RKHS), the method illustrated in this paper aims at aligning the lower-order statistics of source and target domains in the original features space. This idea is called Normal Condition Alignment (NCA), whose benefits are extensively described in Poole et al. [12]. Among them, should be mentioned the improved interpretability of the results and the easier application to data poor and limited datasets. Starting with the new representation, supervised ML classifiers can be trained in the source domain and directly tested on unknown target instances using the transformed features.

In the framework of TL, the current paper applies NCA to transfer damage labels between two FEMs, representing the Z24 and the S101 benchmark bridges [13-16]. The use of FEMs allows one to generate a wide set of labelled data by simulating multiple damage scenarios; this enables to exploit a huge dataset to infer important information on the transferability of specific health-state conditions, thus providing a substantial support for real-world applications. The investigated models are calibrated given the available information on the geometry, materials and dynamic properties and are afterwards employed to simulate representative damage scenarios by progressively reducing the concrete's elastic modulus at specific locations. Damage-sensitive features are aligned via DA and then fed into a K-Nearest Neighbours (KNN) algorithm for detecting and classifying damage typologies, whose performance is assessed in terms of accuracy level. The numerical results show that the proposed approach enables an effective knowledge transfer within the population of FEMs, since damage labels gained from the source domain can be leveraged to predict and classify new monitoring data from the target domain in a supervised-learning context. This tool is particularly promising to become aware of the presence, location and type of damage that occurs within a network of bridges equipped with SHM systems.

2. The proposed Domain Adaptation-based methodology

The methodology for performing bridge health assessment via TL is outlined in Figure 1; specifically, it focusses on the application of DA to merge different data distributions into a shared feature space. Prior to feature extraction, FEMs of two monitored bridges are built to simulate damage scenarios differing by position and severity. Modal analyses are carried out to extract N natural frequencies, aligned with NCA and used as damage-sensitive features to train and test the KNN algorithm.

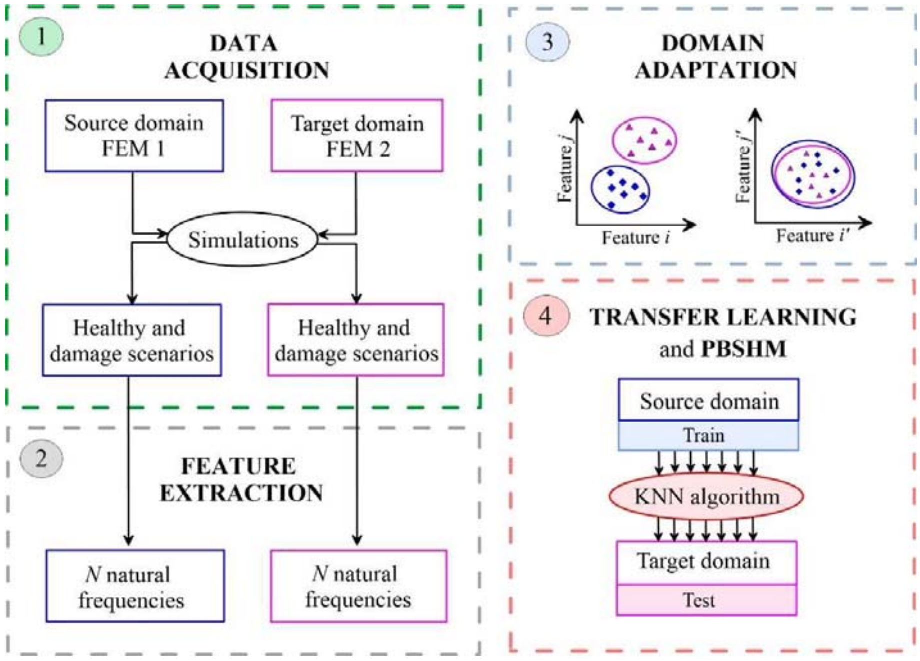

Figure 1. Flowchart of the TL-based methodology.

2.1. Domain Adaptation: Normal Condition Alignment (NCA)

Given a source domain $\mathcal{D}_s = \{\mathcal{X}_s, p(X_s)\}$ with a learning task $\mathcal{T}_s = \{\mathcal{Y}_s, f_s(\cdot)\}$ and a target domain $\mathcal{D}_t = \{\mathcal{X}_t, p(X_t)\}$ with the corresponding learning task $\mathcal{T}_t = \{\mathcal{Y}_t, f_t(\cdot)\}$, domain adaptation aims at improving the target predictive function $f_t(\cdot)$ using knowledge from $\mathcal{D}_s$ and $\mathcal{T}_s$. It is assumed that the feature and label spaces are equal, i.e. $\mathcal{X}_s = \mathcal{X}_t$ and $\mathcal{Y}_s = \mathcal{Y}_t$, while the marginal probability distribution are different, i.e. $p(X_s) \neq p(X_t)$, where $X = \{x_i\}_{i=1}^N$ is a general finite sample from the feature space. The goal is therefore to minimise the distance between source and target domains. Typical DA methods match data distributions by using non-parametric distance metrics, thus requiring enough data to perform accurate density estimation and find a non linear mapping. Working in a latent space, they are also characterised by a limited interpretability of the results. Conversely, this paper focusses attention on Statistic Alignment (SA) [12], that provides an alternative solution to find a shared feature representation across the domains. In particular, Normal Condition Alignment (NCA) keeps the original feature space to align the mean and standard deviation of those data describing normal conditions, which should be able to be estimated with a small data set. It also ensures to align data generated from the same health-state using engineering prior knowledge. This technique involves the standardisation of the source domain according to equation (1), with μ_s and σ_s the corresponding mean and standard deviation,

$$z_s^{(i)} = \frac{x_s^{(i)} - \mu_s}{\sigma_s} \tag{1}$$

The alignment of normal conditions of the target domain with those of the source domain is then performed using,

$$z_t^{(i)} = \left(\frac{x_t^{(i)} - \mu_{t,n}}{\sigma_{t,n}}\right)\sigma_{s,n} + \mu_{s,n} \tag{2}$$

where $(\mu_{s,n}\ , \mu_{t,n})$ and $(\sigma_{s,n}\ , \sigma_{t,n})$ indicate, respectively, the means and standard deviations of normal condition data from source and target domains. This process means that those data points describing healthy conditions of the two FEMs will be confined in a common cluster after feature alignment, assuming they are Gaussian.

2.2. Supervised damage detection and classification

Using the new distribution within the original feature space, the KNN is firstly trained to learn the source damage labels and then tested to recognize the unknown damage classes in the target domain.
KNN is a non-parametric supervised ML method that assigns to a certain data point the most frequent label among the K nearest neighbors. The Euclidean distance is used as a proximity metric to evaluate the distance between two points a and b in a *N*-dimensional space and it is defined as:

$$d(a,b) = \sqrt{\sum_{i=1}^{N}(b_i - a_i)^2} \tag{3}$$

Specifically, this ML algorithm is implemented by setting $K = 3$ in order to minimise the number of misclassifications. Since DA should be able to create well-concentrated clusters, thereby including relatively-close data points, low values of K are generally recommended. The effectiveness of knowledge transfer is finally evaluated by computing the accuracy before and after DA, based on the number of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN).

3. Case study: Transfer Learning between the FEMs of the Z24 and the S101 benchmark bridges

Inferring mappings between structures to share damage labels is a key aspect of PBSHM. In this work, source and target domains are represented by the FEMs of two real bridges, namely the Z24 and the S101 bridge, which are illustrated hereafter.

3.1. Z24 bridge: general description and modelling

The Z24 benchmark bridge was a post-tensioned RC bridge, built in 1963 in Switzerland [13]. The structure included a main span of 30 m and two side spans of 14 m, with a global width of 8.6 m. The deck's cross-section was made of two box cells, while two concrete piers, located at the limits of the main span, had a rectangular cross-section and were clamped into the deck's girder. A continuous monitoring campaign was carried out from November 1997 to August 1998 (before demolition), using several sensors measuring accelerations and several environmental parameters. Further description of the experimental data, the monitoring setup and the 14 damage scenarios, progressively applied at the end of summer 1998, can be found in [14].
A simplified model of the Z24 bridge is built and properly calibrated based on system identification results stemming from an Ambient Vibration Test (AVT), which are summarised in Table 1. The deck and the pier consist of 40 and 30 beam elements, respectively. Given a stiffness increase on the top of the piers, as described in the literature [15], the thickness of the girder plate has been slightly increased accordingly. To justify the presence of any additional load, a linear vertical mass and 20 concentrated masses are assigned along the deck.
The model is calibrated by varying the concrete's elastic modulus E_c, the mass values and the thickness of the girder plate to minimise the difference between the FEM and the real bridge in terms of natural frequencies and Modal Assurance Criterion (MAC) values (Table 1).

Table 1. Natural frequencies and MAC values after calibration of the Z24 bridge FEM.

Modes	Exp. natural freq. [Hz]	FEM natural freq. [Hz]	Error [%]	MAC
1	3.851	3.815	0.93	0.98
2	4.911	4.935	0.49	0.90
3	9.772	9.829	0.58	0.89

After calibration, modal analyses are carried out to extract natural frequencies during operational conditions, assuming a variation of E_c in the range $\pm 1.5\%$. Moreover, based on the most common scenarios suffered by bridges, two damage classes are introduced into the model, named as d_1" and "d_2" (Figure 3). They consist in applying ~12% and ~40% reduction of the concrete's elastic modulus, respectively, for three meters along the middle span, which is the region that undergoes a stiffness reduction and a bending moment reduction, and in proximity of the connection between deck and pier, assuming the development of a plastic hinge within a distance equal to 1.5 times the cross-section's height. It should be mentioned that the elastic modulus reduction is simulated in accordance with the national technical guidelines for structural design, asserting that cracking phenomena may produce a stiffness reduction up to 50% [17].

3.2. S101 bridge: general description and modeling

Built in the 1960s, the S101 benchmark bridge was a post-tensioned RC bridge located in Austria and composed of a main span of 32 m and two 12 m long side spans [16]. The cross-section is characterized by a 7.2 m wide double-webbed t-beam, with the height varying from 0.9 m in the mid-span to 1.7 m over the piers. Before demolition, the bridge was continuously monitored for four days in December 1998 by using fifteen three-axis accelerometers with a sampling frequency of 500 Hz. After the first day in which the bridge was in sound conditions, progressive damage tests, including the lowering of the north-western pier and a cut of four tendons, were carried out to evaluate any change in the structural dynamic behaviour.

Regarding the modelling, the deck cross section is composed of shell elements describing two longitudinal rectangular beams with variable height, the slab and two rectangular cross beams above the piers. On the contrary, beam elements are employed to represent the four rectangular RC piers. The model is discretised using 112 shell elements for the deck and 28 beam elements for the piers. The mass values and the concrete's elastic modulus are used as calibration parameters with the aim to minimise the differences between the experimental natural frequencies and those estimated from the FEM, shown in Table 2.

Table 2. Natural frequencies and MAC values after calibration of the S101 bridge FEM.

Modes	Exp. natural freq. [Hz]	FEM natural freq. [Hz]	Error [%]	MAC
1	4.042	4.01	0.79	0.98
2	6.28	6.322	0.67	0.84
3	9.713	9.834	1.25	0.86

Although the Z24 and the S101 bridges belong to a heterogeneous population, showing different absolute values in natural frequencies, they show some similarities in the modal responses. As inferred from Figure 2, they have in common the first three identified modes, including a symmetric (Mode 1) and non-symmetric (Mode 3) bending mode and a lateral/torsional mode (Mode 2).

As described for the FEM of the Z24 bridge, natural frequencies are extracted from modal analysis during pristine and damage conditions by considering the same simulated scenarios, in terms of extension, location and severity (Figure 3).

3.3. Domain Adaptation results

The structural domains, characterised by the first two natural frequencies of the Z24 and the S101 bridges, i.e. F1 and F2, are represented in a 2D plot in Figure 4a. Such feature distributions allow one to identify three clusters, each one associated to the investigated health-state classes, where "0" indicates data from pristine conditions. However, the clear shift between the two domain distributions is the reason why the classifier exhibits an insufficient performance when it is trained on the S101 and tested on the Z24 bridge and vice versa, showing 45% and 27% accuracy, respectively (Table 3). Such an outcome remarks the need to perform feature alignment to find a mapping between the two domains.

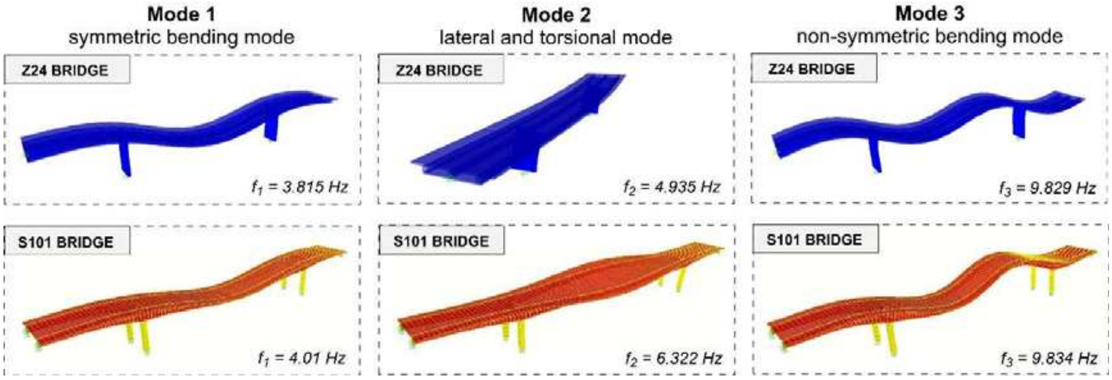

Figure 2. Mode shapes obtained from modal analysis carried out via the FEMs of the Z24 and the S101 bridges.

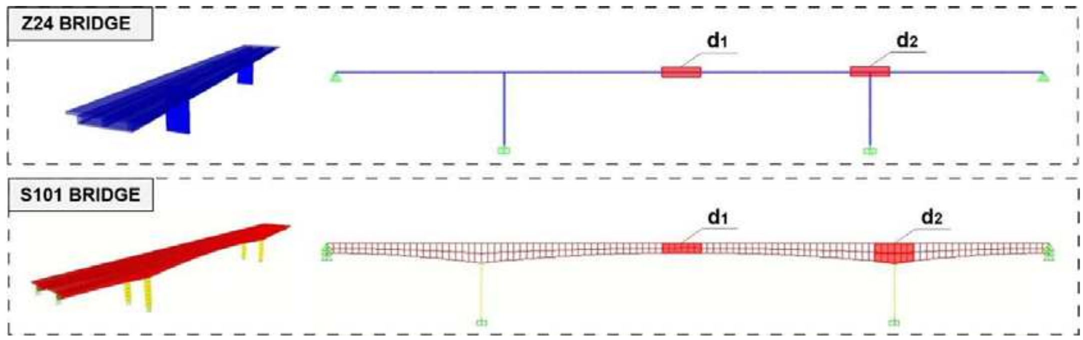

Figure 3. Two damage scenarios are introduced into the FEMs: d_1 and d_2 indicate ~12% and ~40% reduction of E_c, respectively, in the mid span and at the connection between the deck and the pier.

NCA is therefore applied to align and group healthy data of source and target bridges to make them coincide within the single black cluster (Figure 4b), by using Equation (1) and (2). It follows that new instances gained by the monitoring system, including healthy and damage data, can be transformed and projected onto the shared feature space.

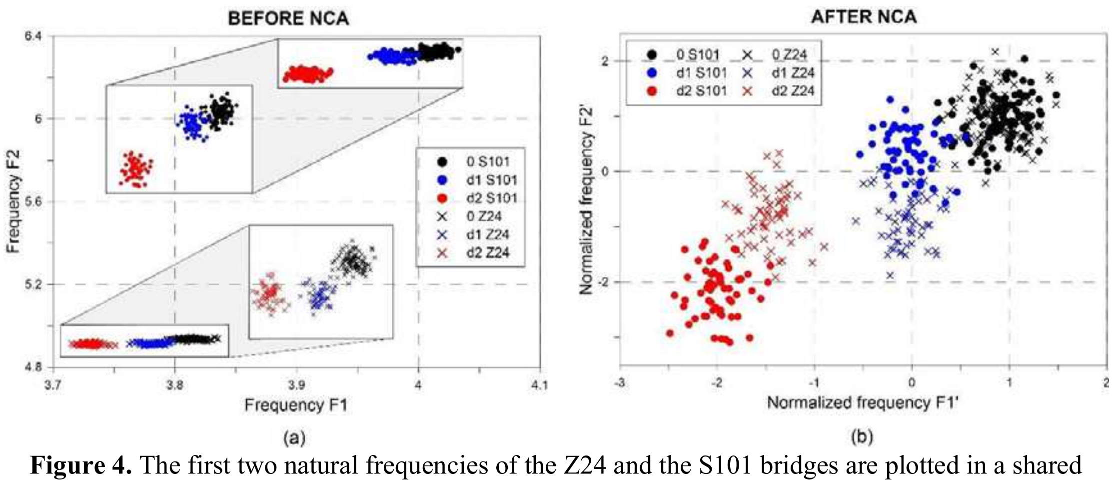

Figure 4. The first two natural frequencies of the Z24 and the S101 bridges are plotted in a shared feature space before DA (a), and after aligning the normal conditions with NCA (b).

By looking at the new distributions, the effectiveness of NCA is demonstrated by the capability to identify common clusters including the corresponding data of the two bridges. As a result, using the transformed features, the KNN algorithm is firstly implemented one single time to learn the source damage labels and afterwards used to identify the same damage classes in the target domain. A single ML model can thus supply information on both structural health. Figure 5 illustrates the predictive performance by computing confusion matrices, where each row contains the number of instances in an actual damage class and each column contains the corresponding number of instances in a predicted damage class. The results highlight an accuracy improvement after DA, showing, however, different performances if the algorithm is trained using the S101 or the Z24 bridge data. In the first case, the alignment produced by the NCA ensures an almost perfect classification, with 95% accuracy and a total of 5% misclassifications, mainly occurring when predicting “d2” data.

Table 3. KNN performance, in terms of accuracy, before and after NCA using different source domains.

Source domain	Accuracy	
	Before NCA	After NCA
S101 bridge	27%	95%
Z24 bridge	45%	89%

In the second case, the KNN perfectly predicts those instances belonging to “d2” and “0” classes, while all the misclassifications come up when labelling the features of the damage scenario “d1”, leading to a global lower performance with 89% accuracy.

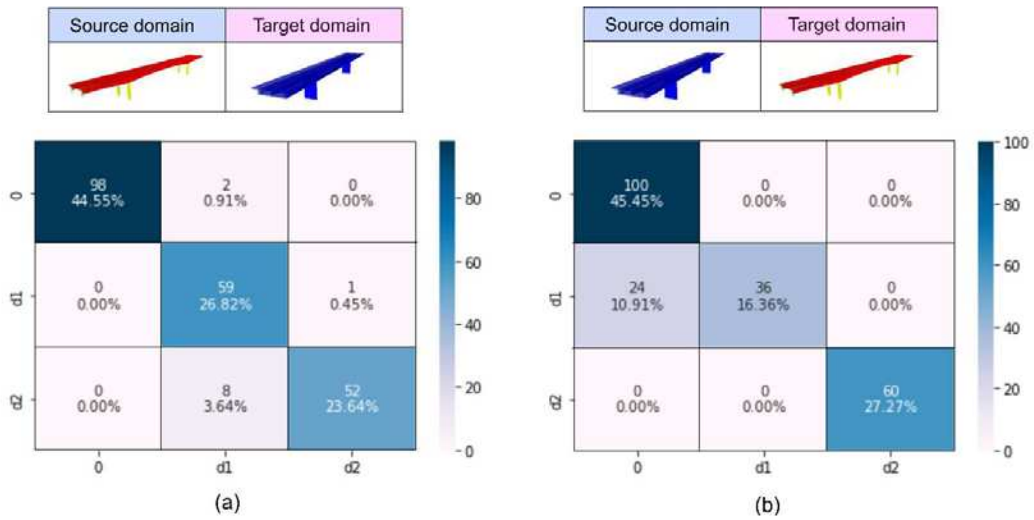

Figure 5. Confusion matrices when applying the KNN after NCA using as source domain (a) the S101 bridge or (b) the Z24 bridge.

It should be remarked that these different outcomes strongly depend on the shape of the input data and on the aligned distribution after NCA. Further studies will apply and compare other supervised/unsupervised ML algorithms and different DA techniques, as well as select the optimal number of features to align, in order to analyse how all these parameters affect the final outcome in terms of damage classification performance and false predictions. Furthermore, to obtain a reliable TL, it is important to underline the importance to ensure the similarity between the investigated structures and between the simulated scenarios, allowing TL handle consistent labels and better comprehend the

type of transferable information. This is the reason why the FEMs of two continuous-beam bridges, having the same static scheme and similar modes, are used as case studies in this work.
Although the use of FEMs provides an idealised representation of real-world scenarios, the successful results suggest that the presented approach could potentially work when expanded to a real population of monitored bridges. It should be considered as a promising solution to overcome the limited availability of health-state labels. A rich variety of labels gathered from a specific bridge can be exploited to help a ML classifier predicting and recognizing, in real time, data of a new bridge that is measured by a permanent SHM system. However, practical applications are inevitably characterised by some additional challenges that deserve future investigations, such as the influence of environmental effects, the presence of signal noise and possible non-linear behaviours.

4. Conclusions

This paper proposes a DA-based strategy for damage classification with the aim to provide a population-level damage detector which leverages health-state information across a population of bridges.
Especially when dealing with civil infrastructure, the implementation of a robust classifier requires a large set of training data from the SHM system, stemming from both healthy and damage conditions, which can be significantly costly for the authorities. To address this issue, a labelled source domain can be exploited to infer diagnosis on a different target domain, characterised by unknown (unlabelled) monitoring data. In this framework, the proposed approach is tested to transfer knowledge between the FEMs of two real bridges, namely the Z24 and the S101 benchmarks. The methodology is aimed at merging the distributions from both domains using the NCA technique, which statistically aligns damage-sensitive features into a shared bi-dimensional space. After the alignment of the first two natural frequencies, it becomes easy to identify common clusters helping to discern between healthy and simulated damage scenarios. With this aligned space, the KNN is deemed effective to classify specific scenarios of a target domain after being trained on a labelled source domain, yielding high accuracies and low values of false predictions. Particular attention should be given to the bridges' similarity assessment and to the evaluation of the most suitable features to align via DA, as well as to the challenges to be addressed in real-world scenarios. Overall, the possibility to successfully transfer damage labels may revolutionise the way to perform SHM of bridges and becomes promising to develop SHM strategies at the scale of a network of bridges, that is, move to PBSHM, with the associated savings in investment and operation costs of permanent SHM systems.

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