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Knowledge transfer between dynamically monitored masonry bell towers

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Abstract. Structural health monitoring (SHM) is really important in cultural heritage (CH) structures, where invasive interventions are often not allowed. An important challenge in data-driven approaches is the lack of data, especially corresponding to damage states, which hampers the development of pattern recognition algorithms in the field of Machine Learning (ML) models. For CH structures, obtaining a complete dataset of health states — including both undamaged and damaged conditions — is often impossible, particularly for damaged states, as it would require harming the structure in situ. Domain adaptation (DA), a sub-sector of Transfer Learning (TL) methods, addresses this problem by adapting data from a more accessible and monitored system (source) transferring information by leveraging data domains to systems with more limited data (target) but with similar properties. In this work, DA techniques are used to expand information on the health state of the special class of monitored structures represented by CH masonry bell towers. In more detail, continuous-time dynamic monitoring data are obtained from a system installed on the masonry bell tower (source) of the Church of S. Maria and S. Giovenale (Fossano, Piedmont, Italy). This tower is currently monitored because, following the evolution of vertical cracking phenomena, in 2012 it was subjected to reinforcement interventions, through the installation of 11 steel tie rods on its four external sides. Another damaged masonry bell tower, belonging to the ancient parish Church of S. Antonio Abate (Montà, Piedmont, Italy), is instead assumed as target structure, with limited knowledge gained from a single testing campaign.

Keywords: Domain adaptation, Cultural heritage, Masonry bell towers, Structural health monitoring, Structural interventions, Numerical models.

1 Introduction

Machine Learning (ML) techniques are increasingly becoming a powerful tool in Structural health monitoring (SHM) [1]. Their ability to manage data and perform predictions makes ML algorithms highly valuable in structural monitoring. Supervised ML algorithms, however, require a sufficient amount of labeled data, which is often unavailable in real-world SHM applications. Modal parameters, commonly used as features in these models, are particularly challenging to obtain for all structural conditions (e.g. damaged or undamaged states). The lack of data prevents the development of reliable ML models for damage detection. To overcome this issue, Transfer Learning (TL) techniques, particularly Domain Adaptation (DA) [2], are frequently used to address data scarcity by transferring or sharing information from data-rich systems (source) to systems with limited knowledge (target) [3]. In this context, finite element models (FEMs) have been employed for data transfer in SHM applications [4]. Detecting damage on cultural heritage (CH) structures is a crucial for their preservation, as these structures are often listed due to their historical, artistic, and cultural significance. Implementing timely monitoring strategies would not only prevent invasive structural interventions but also enable the localization of damage, allowing for the design of targeted, localized repair interventions on the structure.

This paper focuses on structural damage detection in CH structures, specifically masonry bell towers. Two different DA algorithms, namely Transfer Component Analysis (TCA) [5] and Normal Condition Alignment (NCA) [6] are employed to improve damage prediction for two masonry bell towers using a classifier trained on modal parameters extracted from continuous-time dynamic monitoring data, with numerical models used to expand the source features datasets.

Few examples of DA applications on masonry bell towers are present in the literature, one of the most recent studies exploited a single-degree-of-freedom (SDoF) system as source structure to predict different temperature classes on a masonry bell tower [7]. This paper represents a novel investigation in the field of SHM for damage detection in CH structures, specifically masonry bell towers.

In the next section, the theory of DA methods is presented, with a focus on TCA and NCA. Section 3 provides a description of the two masonry bell towers and highlights their datasets, covering both source and target structures. This section also presents the classification results using DA methods, comparing them with the results obtained from non-adapted domain classification. Finally, conclusions are outlined in Section 4.

2 Domain adaptation

DA is a sub-discipline of TL that enables methods focused on transferring knowledge between two related systems by using data from different domains [2, 5]. The concept of a domain involves two key components: the feature space $\mathcal{X}$ of inputs, and the marginal distribution $P(X)$ of a set of inputs $X = \{\boldsymbol{x}_1, \dots, \boldsymbol{x}_n\}^T \in \mathcal{X}$. In the context of TL, two domains are defined: a source domain $\mathcal{D}_\mathrm{S}$ and a target domain $\mathcal{D}_\mathrm{T}$. Each domain is linked with a task $\mathcal{T} = \{\mathcal{Y}; f(\cdot)\}$, where $\mathcal{Y}$ denotes the label space and $f(\cdot)$ refers to the

predictive function used to estimate the corresponding label. A typical representation of this function is $P(y|X)$, where $y \in \mathcal{Y}$. In DA techniques, it is assumed that both the feature and label spaces are identical for the source and target domains, implying that $\mathcal{X}_\mathrm{S} = \mathcal{X}_\mathrm{T}$ and $\mathcal{Y}_\mathrm{S} = \mathcal{Y}_\mathrm{T}$. In the context of SHM, this suggests that both systems share the same diagnostic properties and structural conditions. Nevertheless, in practice, the marginal distributions between the source and target domains often differ, and this difference is not always related to the conditional distribution. These differences also manifest in the probabilities associated with the occurrence of structural conditions (labels) such that $P(X_S) \neq P(X_T)$, highlighting feature dissimilarities between the two domains. Erroneous results can be derived by training a model on the source domain and directly testing it on the target domain due to discrepancies in their distributions. To overcome this issue, several strategies have been developed to bridge the gap between the source and target domain distributions. These methods typically involve the use of a nonlinear mapping function $\phi(\cdot)$ to align the distributions, ensuring that $P\big(\phi(X_S)\big) \approx P\big(\phi(X_T)\big)$ and $P\big(Y_S|\phi(X_S)\big) \approx P\big(Y_T|\phi(X_T)\big)$.

2.1 Transfer Component Analysis

Transfer Component Analysis (TCA), developed by Pan *et al.* [5], is a method for DA. This technique aims to extract transfer components that span across domains within a Reproducing Kernel Hilbert Space (RKHS) using the Maximum Mean Discrepancy (MMD) as an embedding criterion. The core objective is to align data distributions from different domains by projecting them into a shared subspace defined by these transfer components. In this transformed space, ML models can be trained on source domain data for tasks such as classification or regression, and subsequently tested on target domain data, which can be unlabeled or partially labeled.

TCA operates under the assumption that the marginal distributions between the source and target domains, $P(X_S)$ and $P(X_T)$, are not identical, while the conditional distributions, $P(Y_S|X_S)$ and $P(Y_T|X_T)$, remain the same. Rather than explicitly defining a nonlinear transformation $\phi(\cdot)$, this method leverages the kernel trick, there the kernel function $k(\boldsymbol{x}_i, \boldsymbol{x}_j) = \phi(\boldsymbol{x}_i)'\phi(\boldsymbol{x}_j)$ implicitly maps the data into a higher-dimensional space. The MMD distance between the empirical means of the kernel embeddings for the two domains can thus be expressed as,

$$Dist(X_S', X_T') = tr(KL) \tag{1}$$

where X_S' and X_T' represent the transformed input data from the source and target domains, K denotes the kernel matrix, which includes the kernel matrices of source, target and cross domains. L is the MMD matrix, which is constructed as,

$$L(i,j) = \begin{cases} \dfrac{1}{n_S^2} & if\ \boldsymbol{x}_i, \boldsymbol{x}_j \in X_S \\ \dfrac{1}{n_T^2} & if\ \boldsymbol{x}_i, \boldsymbol{x}_j \in X_T \\ \dfrac{-1}{n_S n_T} & otherwise \end{cases} \tag{2}$$

By using a weight matrix $W \in \mathbb{R}^{(n_S+n_T)\times m}$, with n_S and n_T corresponding to the number of observations from the source and target domains, respectively, and performing a decomposition of the kernel matrix, the empirical kernel map is transformed to $\widetilde{K} = KWW^TK$ [8], effectively reducing the feature vector to an m-dimensional space. Substituting $\widetilde{K}$, the distance between the empirical means of the two domains is,

$$Dist(X_S', X_T') = tr(W^TKLKW) \tag{3}$$

To minimize this distance, a regularization term is used to control the complexity of the weight matrix. Consequently, the kernel learning problem is reformulated as,

$$\min_{\substack{W \\ s.t. W^TKHKW=I}} tr(W^TKLKW) + \mu\, tr(W^TW) \tag{4}$$

where μ is a regularization parameter, H is a centring matrix, and I is an identity matrix. The constraint $W^TKHKW = I$ ensures that the trivial solution $W = 0$ is avoided. By expressing the Lagrangian for the previous equation and following a concise mathematical derivation, it can be shown that Eq. (4) can be efficiently solved by reformulating it as an equivalent trace optimization problem,

$$max_W tr((W^T(KLK + \mu I)W)^{-1}W^TKHKW) \tag{5}$$

The solution for W in the above equation corresponds to the m leading eigenvectors of the matrix $(KLK + \mu I)^{-1}KHK$, where $m \leq n_S + n_T - 1$. These eigenvectors define the transformed feature space, represented by $Z = KW$, where $Z = KW \in \mathbb{R}^{(n_S+n_T)\times m}$.

2.2 Statistical Alignment via Normal Condition Alignment

Rather than operating in a latent feature space like TCA, Poole *et al.* [6] introduced the idea of Statistical Alignment (SA) methods for DA in SHM. These methods present an effective strategy for achieving a shared feature representation across domains. SA approaches work by directly aligning lower-order statistics, such as the mean and standard deviation, through scaling and affine transformations. One specific method, Normal Condition Alignment (NCA), preserves the original feature space while aligning the statistical characteristics of data representing normal conditions, which can be often estimated from small datasets. Additionally, NCA leverages prior knowledge to ensure consistent alignment of data associated with the same class (i.e. health state), making it a practical and efficient solution for addressing DA problems [9]. NCA involves normalizing the source domain data by standardizing it using its mean μ_s and standard deviation σ_s,

$$z_s^{(i)} = \frac{x_s^{(i)} - \mu_s}{\sigma_s} \tag{6}$$

The process of aligning the normal conditions of the target domain with those of the source domain is performed using the following operation,

$$z_t^{(i)} = \left(\frac{x_t^{(i)} - \mu_{t,n}}{\sigma_{t,n}}\right)\sigma_{s,n} + \mu_{s,n} \tag{7}$$

here, $(\mu_{s,n},\ \mu_{t,n})$ and $(\sigma_{s,n},\ \sigma_{t,n})$ represent the means and standard deviations of the normal condition data from the source and target domains, respectively.

3 Application to masonry bell towers

Detecting a damage condition is fundamental, especially in the context of CH. In this paper, two masonry bell towers are selected to identify damaged and reinforced conditions. The source structure is represented by the bell tower of the of the Church of S. Maria and S. Giovenale (Fossano, Piedmont, Italy) (Fig. 1a), which dates to the 14th century and stands 46 meters tall, including its octagonal belfry. The bell tower is currently monitored due to the development of vertical cracking phenomena. In 2012, reinforcement measures were implemented, including the installation of 11 steel tie rods along its four external façades. The bell tower has been the focus of several studies in recent years, revealing key structural properties [10–12]. The target structure is represented by the bell tower of the ancient parish Church of S. Antonio Abate (Montà, Piedmont, Italy) (Fig. 1b), whose construction dates back to 1814 and stands 17 meters tall. A reinforcement intervention was carried out on the tower due to the significant cracking phenomena on the west and north façades, as well as the deterioration of the bell chamber. In detail, mortar injections, steel ties, and the reconstruction of the masonry thickness of a bell tower chamber wall have recently been completed. The source bell tower is continuously monitored since June 2024, with extensive data available regarding the temporary structural intervention carried out in 2012. In contrast, two experimental dynamic testing campaigns were carried out in total on the target bell tower, one for the damaged condition and one for the post-structural intervention condition in May 2024 and January 2025, respectively. While both conditions are represented in the experimental data, few data are present. The DA application to these CH assets aims to improve the recognition of different health states.



(a) (b)

Fig. 1. Bell tower (source) of the Church of S. Maria and S. Giovenale (Fossano, Italy) (a) and bell tower (target) of the ancient parish Church of S. Antonio Abate (Montà, Italy) (b).

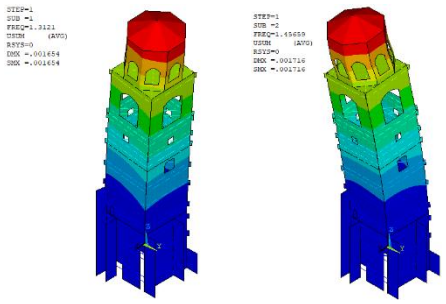
3.1 Source and target datasets

To introduce DA, it is essential to define the source and target domains for the damaged class, henceforth referred to as CL0, and the post-structural intervention class, referred

to as CL1. Consequently, a total of four domains are required. For the purpose of damage detection, this study will focus on the first two natural frequencies associated with the first translational mode in the y and x directions. To address the lack of sufficient experimental data for the CL0 source condition, the Ansys® FEM of the bell tower of the Church of S. Maria and S. Giovenale (Fig. 2) is utilized to construct the CL0 source domain. Specifically, the FEM of the post-structural intervention source bell tower is calibrated using the acquired experimental data identified by means of the Stochastic Subspace Identification (SSI) algorithm [13, 14]. Subsequently, data corresponding to the first translational modes (y-axis and x-axis) of the bell tower in the damaged state, after removing the temporary intervention (CL0), are extracted. To simulate variability of experimental frequencies (i.e. Environmental and Operational Variations (EOVs)), FEM data extraction is performed using Latin Hypercube (LH) sampling [15, 16] of the masonry Young moduli, allowing for a maximum variation of 10%. The results obtained from the calibrated model are presented in Table 1. Focusing on the experimental domains, the identifications performed using signals obtained from continuous-time monitoring during the period from June to October 2024 are used as source dataset for the post-structural intervention class (CL1), resulting in a total of 5595 data. The source CL1 identifications are carried out with a signal length of 10 min, with no overlapping. The same data quantity is then extracted via FEM for the damaged class (CL0). Regarding the target structure, the analysis of signals recorded during the daily experimental campaigns conducted in May 2024 and January 2025 provided a total of 41 features, with 24 corresponding to the damaged class (CL0) and 17 to the post-structural intervention class (CL1). The identifications are carried out with a signal length of 10 min, with an overlapping of 75% and 90% for CL0 and CL1, respectively. The dataset distributions of the source and target domains for CL0 and CL1 are shown in Fig. 3.

Table 1. Results of the calibration process: frequencies obtained from the FE model vs frequencies obtained from the dynamic identification of 2024 campaign.

Identifier	Mode number in FEM	Freq. FEM [Hz]	Freq. ID. (2024) [Hz]	ΔF [%]
1	1	1.31	1.33	1.22
2	2	1.46	1.40	-4.02



(a) (b)

Fig. 2. Experimental calibrated 1st translational mode shapes of the post-structural intervention source bell tower FEM. First translational y-axis mode (a) and first translational x-axis mode (b).

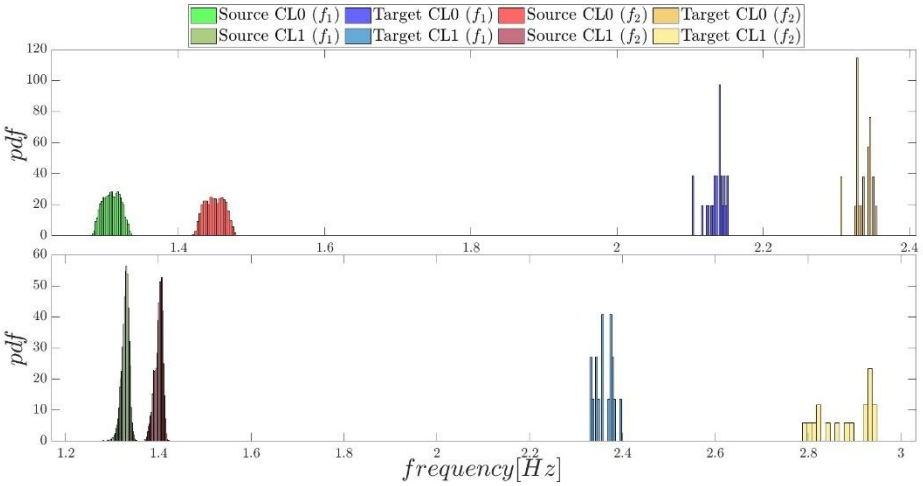


Fig. 3. Dataset distributions of the first two natural frequencies for source and target domains for DA: damaged (CL0) and post-structural intervention (CL1) classes.

3.2 Classification results for damage detection

Once the datasets have been defined and the objective of the DA established, an additional subdivision is pointed out within the target dataset. Since the datasets represent the focus of the DA process, and to ensure statistically valid results, a 1:3 ratio has been selected for splitting the available data per class into training and testing datasets for the target structure, respectively.

The classifier used in this study is a Support vector machine (SVM) with a linear kernel. The performance of the classifier is evaluated by computing the accuracy, which is calculated as the ratio of correctly predicted labels to the total number of test samples. The target testing data are used to compute such metric, and a confusion matrix is employed to illustrate the comparison between the true class and the predicted class, representing the ground truth and the prediction of the model, respectively. The result of the SVM model are shown in Fig. 6a and in Table 2.

Domain adaptation: Normal Condition Alignment. NCA is proposed to align the source and target domains based on the normal-condition. Then, a SVM model is used to classify CL0 and CL1 on the target testing data, as shown in Fig. 4a and Fig. 4b.

Domain adaptation: Transfer Component Analysis. The DA technique via TCA is applied to the testing data of the target bell tower of the ancient parish Church of S. Antonio Abate. Adaptation is performed with a number of transfer components m equal to 2, a regularization parameter $\mu = 0.1$, and a linear kernel. The target and source adapted domains are shown in Fig. 5a and Fig. 5b, respectively.

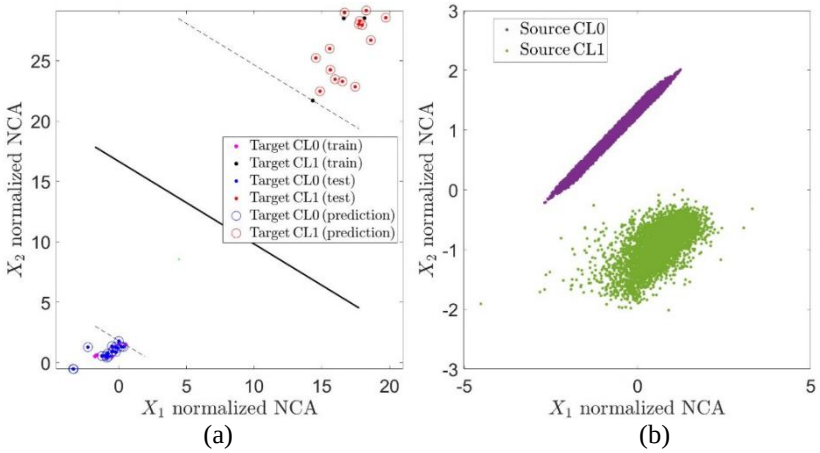


Fig. 4. Support vector machine (SVM) model inferred in the normalized target components (X_1, X_2). The models are trained using the non-circled data and tested on the remaining data, with circle colors indicating the model predictions for damaged (CL0) and post-structural intervention (CL1) classes (a). Source dataset with normalized target components (X_1, X_2) (b).

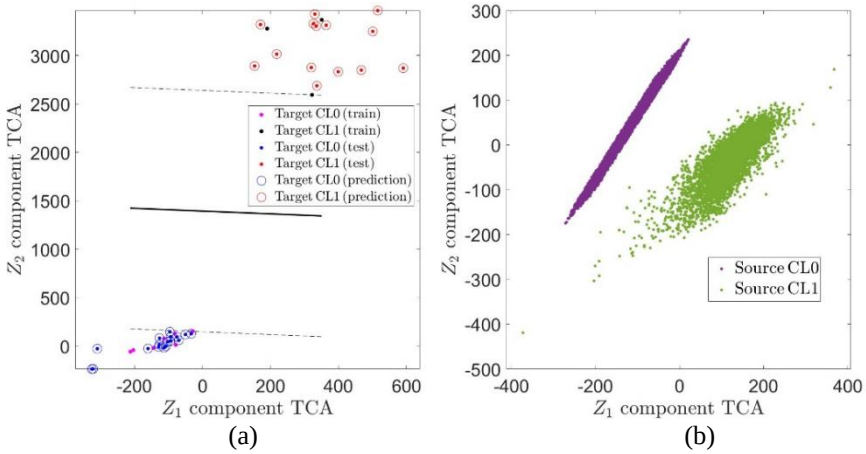


Fig. 5. Support vector machine (SVM) model inferred in the latent subspace representation (Z_1, Z_2). The models are trained using the non-circled data and tested on the remaining data, with circle colors indicating the model predictions for damaged (CL0) and post-structural intervention (CL1) classes (a). Source dataset in the latent subspace representation (Z_1, Z_2) (b).

Models comparison. The SVM model, without DA, faced difficulty in detecting CL1 in the target domain, resulting in a misclassification rate of 42.9%. Although the overall accuracy reached 80.65% (Table 2), but this metric does not fully investigates the issues highlighted in the confusion matrix (Fig. 6a).

In contrast, DA — both using SA (specifically with NCA) and TCA — showed excellent performance by perfectly classifying both the damaged and the post-structural intervention conditions (Fig. 6b, Fig. 6c), with a global accuracy of 100% (Table 2).

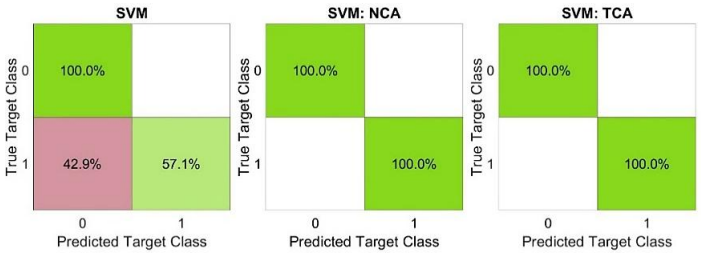


Fig. 6. Target testing confusion matrices: SVM (a) SVM: NCA (b) SVM: TCA (c).

Table 2. Target testing classification model accuracies.

Model	SVM	SVM: NCA	SVM: TCA
Accuracy	80.65%	100%	100%

4 Conclusions

This paper investigates two DA approaches (i.e. NCA and TCA) for damage detection in SHM, with a focus on vulnerable CH structures, such as masonry bell towers. The effectiveness of the methodology is demonstrated on two different masonry bell towers, namely the bell tower of the Church of S. Maria and S. Giovenale (source structure), and the bell tower of the old parish Church of S. Antonio Abate (target structure). NCA and TCA algorithms are applied to detect damage in the target bell tower, with the results summarized as follows:

- NCA maintains the original feature space to align the mean and standard deviation of the data representing normal conditions. Using a SVM model, target testing data achieved a 19.35% improvement in prediction accuracy compared to the non-adapted one, reaching a prediction accuracy of 100%.
- The second DA strategy, using TCA to adapt the domains in a latent feature space, achieved the same 100% prediction accuracy as the NCA algorithm.

The results demonstrate the effectiveness of both DA algorithms in detecting damage on the proposed masonry bell towers. In particular NCA, despite being a simpler algorithm that does not require a latent feature space (e.g. TCA), achieved the same prediction accuracy. In general, this suggests that both DA algorithms can be systematically applied in monitoring CH structures.

Future work will focus on identifying the most suitable source domain for the specific target structure. Additionally, the use of data extracted from calibrated FEMs for the target structure will also be considered to expand the limited available datasets, without compromising the overall properties of the experimental domain distributions.

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References

1. Farrar CR, Worden K Structural Health Monitoring: A Machine Learning Perspective. https://doi.org/10.1002/9781118443118
2. Pan SJ, Yang Q (2010) A Survey on Transfer Learning. IEEE Trans Knowl Data Eng 22:1345–1359. https://doi.org/10.1109/TKDE.2009.191
3. Crocetti A, Scussolini L, Miraglia G, Ceravolo R (2024) Multi-class Damage Detection on Experimental Frames through Transfer Component Analysis. e-Journal of Nondestructive Testing 29: https://doi.org/10.58286/29791
4. Coletta G, Miraglia G, Gardner P, Ceravolo R, Surace C, Worden K (2021) A Transfer Learning Application to FEM and Monitoring Data for Supporting the Classification of Structural Condition States. In: Rizzo P, Milazzo A (eds) European Workshop on Structural Health Monitoring. Springer International Publishing, Cham, pp 947–957. https://doi.org/10.1007/978-3-030-64594-6_91
5. Pan SJ, Tsang IW, Kwok JT, Yang Q (2011) Domain adaptation via transfer component analysis. IEEE Trans Neural Netw 22:199–210. https://doi.org/10.1109/TNN.2010.2091281
6. Poole J, Gardner P, Dervilis N, Bull L, Worden K (2022) On statistic alignment for domain adaptation in structural health monitoring. Struct Health Monit 22:1581–1600. https://doi.org/10.1177/14759217221110441
7. Cavanni V, Ceravolo R, Miraglia G (2024) Knowledge Transfer between Oscillators and Real Vibrating Structures to Enrich Dynamic Monitoring Datasets. Structural Health Monitoring in the Light of Climate Impact and Data Science Research and Review Journal of Nondestructive Testing Vol. 2(2): https://doi.org/10.58286/30525
8. Schölkopf B, Smola A, Müller K-R (1998) Nonlinear component analysis as a kernel eigenvalue problem. Neural Comput 10 (5), pp 1299–1319
9. Giglioni V, Poole J, Venanzi I, Ubertini F, Worden K (2024) A domain adaptation approach to damage classification with an application to bridge monitoring. Mech Syst Signal Process 209:. https://doi.org/10.1016/j.ymssp.2024.111135
10. Civera M, Pecorelli ML, Ceravolo R, Surace C, Zanotti Fragonara L (2021) A multi-objective genetic algorithm strategy for robust optimal sensor placement. Computer-Aided Civil and Infrastructure Engineering 36:1185–1202. https://doi.org/https://doi.org/10.1111/mice.12646
11. Ceravolo R, Pistone G, Fragonara LZ, Massetto S, Abbiati G (2016) Vibration-Based Monitoring and Diagnosis of Cultural Heritage: A Methodological Discussion in Three Examples. International Journal of Architectural Heritage 10:375–395. https://doi.org/10.1080/15583058.2013.850554
12. Scussolini L, Foti V, Civera M, Ceravolo R, Pistone G (2023) Redesign of Strengthening Interventions on Historical Buildings. The Case Study of an Earthquake-Damaged Bell Tower. In: Limongelli MP, Giordano PF, Quqa S, Gentile C, Cigada A (eds) Experimental Vibration Analysis for Civil Engineering Structures. Springer Nature Switzerland, Cham, pp 708–717. https://doi.org/10.1007/978-3-031-39109-5_72
13. Van Overschee P, De Moor B (1996) Subspace identification for linear systems. Theory, implementation, applications. Incl. 1 disk. In: Springer Science & Business Media. p xiv + 254
14. Pecorelli ML, Ceravolo R, Epicoco R (2020) An Automatic Modal Identification Procedure for the Permanent Dynamic Monitoring of the Sanctuary of Vicoforte. International Journal of Architectural Heritage 14:630–644. https://doi.org/10.1080/15583058.2018.1554725
15. Stein M (1987) Large Sample Properties of Simulations Using Latin Hypercube Sampling. Technometrics 29:143–151. https://doi.org/10.1080/00401706.1987.10488205
16. Ferrari R, Froio D, Rizzi E, Gentile C, Chatzi E (2018) Model updating of a historic concrete bridge by sensitivity- and global optimization-based Latin Hypercube Sampling. Eng Struct 179:139–160. https://doi.org/10.1016/j.engstruct.2018.08.004