27th ABCM International Congress of Mechanical Engineering
December 04-08, 2023, Florianópolis-SC, Brazil

COB-2023-0165
TRANSFER LEARNING PERFORMANCE FOR STRUCTURAL HEALTH MONITORING THROUGH BOUNDARY CONDITION INVESTIGATION

Estênio Fuzaro de Almeida
Samuel da Silva
UNESP - Universidade Estadual Paulista, Departamento de Engenharia Mecânica, Ilha Solteira, SP, Brasil
estenio.fuzaro@unesp.br, samuel.silva13@unesp.br

Abstract. *This study explores the impact of boundary conditions on the efficacy of transfer learning in Structural Health Monitoring (SHM). By experimenting with beam structures subjected to a range of boundary conditions, we analyze how these variations modulate the success of transfer learning. A key focus of our investigation is the role of similarity analysis, especially when viewed through the prism of Cosine Similarity. Our hypothesis asserts that a nuanced understanding of similarity analysis can substantially bolster the optimization of transfer learning outcomes. The primary aim is to elucidate the intrinsic relationship between heightened similarity indices of source and target features and the ensuing improvement in transfer learning. Such insights hold promise in significantly enhancing the robustness and precision of structural damage detection systems.*

Keywords: *Similarity Analysis, Domain Adaptation, Transfer Learning, Twin Structures, Damage Detection*

1. INTRODUCTION

Structural health monitoring (SHM) is crucial for ensuring the safety and reliability of structures, involving continuous monitoring to detect potential damage or deterioration. Transfer learning, a machine learning technique that leverages pre-trained models, has shown promise in SHM for efficient and accurate analysis (da Silva *et al.*, 2021; Omori Yano *et al.*, 2023). However, applying transfer learning in SHM, especially for beam structures, requires further investigation, with recent works demonstrating potential (Figueiredo *et al.*, 2023). One aspect that has received limited attention is the influence of boundary conditions on transfer learning performance. Boundary conditions determine the structure's connection to its surroundings and significantly affect structural behavior and response. Understanding this impact is essential for optimizing SHM systems and developing reliable analysis and monitoring models (Farrar and Worden, 2007).

This study aims to demonstrate that optimizing transfer learning performance is achievable through a preliminary similarity analysis of the features involved. The hypothesis is that a higher similarity index between the source and target features directly correlates with improved transfer learning results. Utilizing Cosine Similarity as a straightforward yet effective metric allows us to generalize this approach across various feature-based scenarios. These could range from differing sensor placements and structural geometries to variable environmental conditions. In our particular case, various boundary conditions are applied to a set of beam structures. Vibration data from finite element simulations using the Euler-Bernoulli approach are used for evaluation. Then, similarity analysis (using Cosine Similarity) and transfer learning using Transfer Component Analysis (TCA) (Pan *et al.*, 2011) are applied to validate the previously stated hypothesis.

2. PROBLEM STATEMENT

This work proposes a numerical structural health monitoring (SHM) methodology that focuses on feature extraction from natural frequencies and mode shapes of Euler-Bernoulli beams using the Finite Element Method (FEM). The simulation was made with a custom-design algorithm on MATLAB®, the chosen material was aluminum, and the beams' dimensions were $0.5m \times 0.025m \times 0.005m$. The methodology is structured as follows: First, the mode shape and natural frequency changes caused by different boundary conditions are observed in numerical simulations. The Cholesky method determined the natural frequencies, which involved calculating the generalized eigenvalues of the stiffness and mass matrices. This calculation was based on the Cholesky factorization of the mass matrix after the constrained degrees of freedom were removed. A random force was exerted on the first degree of freedom (DOF), and the resulting displacement at each node was calculated using the Newmark method for numerical integration; these combined displacements on each node form the mode shape. Secondly, similarity analysis using the Cosine Similarity metric (Han *et al.*, 2012) is employed to compare the features before transfer learning, determining the combinations of features with higher and lower similarity. This analysis is also applied to the mode shapes, pairing similar modes for transfer learning. Thirdly, Transfer Component Analysis (TCA) is used for domain adaptation between datasets with different boundary conditions (Pan *et al.*, 2011). The reliability of the similarity analysis prediction of the best and worst cases (based on similarity) for

TCA is evaluated from the difference in the latent feature space graphs. This methodology reduces the empirical approach to transfer learning by preprocessing and correlating data before knowledge transfer.

Boundary conditions play a crucial role in determining the behavior of beams and other structural elements. In this work, four different boundary conditions (Clamped-Free, Pinned-Pinned, Clamped-Pinned, and Clamped-Clamped) were considered for beams modeled using the Euler-Bernoulli approach and solved using the Finite Element Method (Thomas and Abbas, 1975). The boundary conditions characterize how the beam is fixed or supported at its ends, affecting its response to external loads (Inman and Singh, 2008). Figure 1 illustrates the four boundary conditions explored in this study. Changes in boundary conditions lead to alterations in the mode shapes of vibrating beams (Geradin and Rixen, 2015). Consequently, the modal parameters, such as the natural frequencies and mode shapes, are influenced. This work addresses three main questions: (1) Can learning be transferred between structures with completely different boundary conditions when the modal parameters change? (2) Can we measure the similarity between datasets before transferring knowledge based on the similarity of modal parameters? (3) Can we use this information to assess the fitness of transfer learning before its actual implementation?

The overall applicability of transferring knowledge between completely different structures (in terms of boundary conditions) lies on some main reasons: First, for data reuse of continuously monitored structures, it is interesting to explore transfer learning, especially with different boundary and environmental conditions; this leads to generalization of design and optimization. Second, in the context of machine learning methods, using completely different structures and still being able to find patterns is of great interest since FEM is expensive, and predicting the behavior of a not modeled/trained structure using data from a trained structure by transferring knowledge is a powerful tool that can save resources. This is the great purpose of transfer learning in Industry 4.0, especially considering transfer learning applied to Digital Twins, for example.

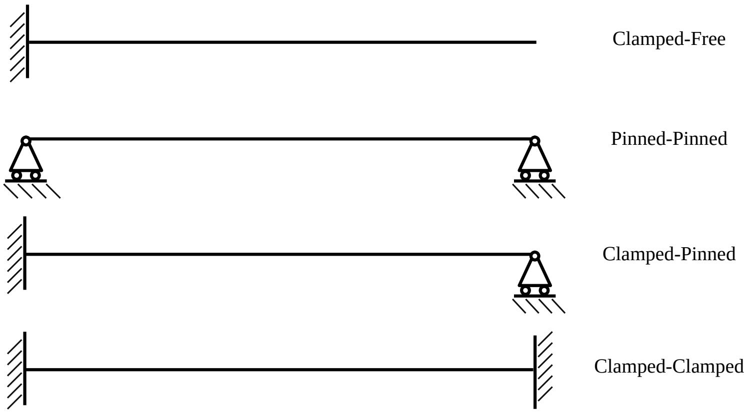


Figure 1. The four boundary conditions explored

The first six natural frequencies and mode shapes for each boundary condition were considered features of interest, as they represent the dynamic behavior of the system (Tahara, 2019). Figure 2 presents the normalized natural frequency feature space for the first six modes (synthetic data was added to the feature space by adding white noise to the extracted natural frequencies), while Figure 3 showcases the first six mode shapes for the different boundary conditions.

Figure 2 shows each mode's natural frequencies (our main features of interest, which will later be used for transfer learning) for every boundary condition. As can be seen, data is normalized by zscore, so every point on the graph is determined by the Equation 1.

$$\frac{x-\mu}{\sigma} \tag{1}$$

In which x is the unnormalized data, μ is the mean of the dataset, and σ is the standard deviation of the dataset; normalization is made to eliminate scale distortions and is mandatory before domain adaptation. The graph also demonstrates that the clusters and histograms of the natural frequencies are shifted linearly with the constraints of degrees of freedom, indicating that the boundary conditions have an impact. Moreover, Figure 3 reveals that modes of the same order from different boundary conditions can have different shapes. Therefore, similarity analysis is essential to examine the similarity of both shape and natural frequencies of modes from different boundary conditions.

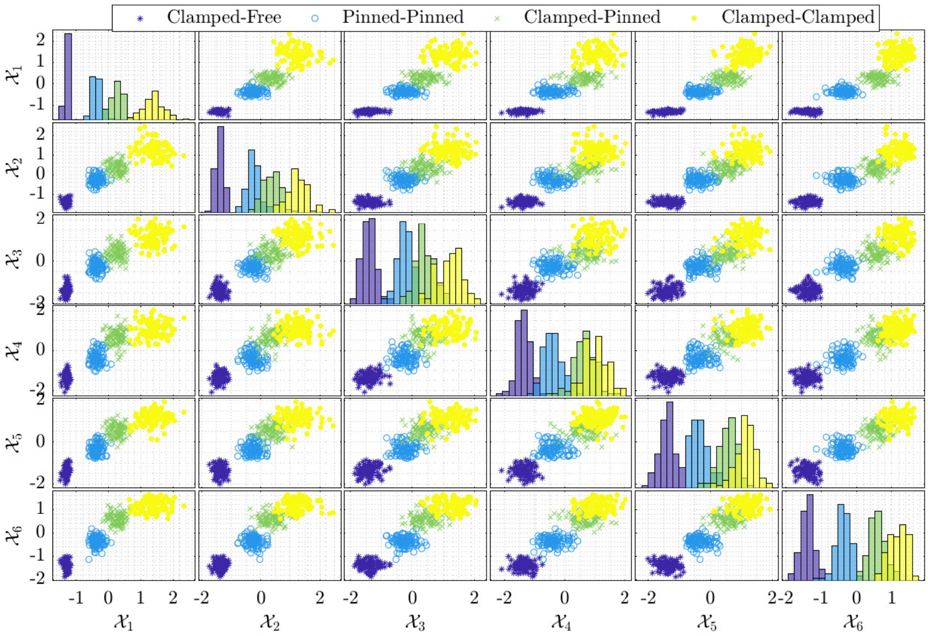


Figure 2. Feature/Histogram plot of the first 6 natural frequencies of four boundary conditions

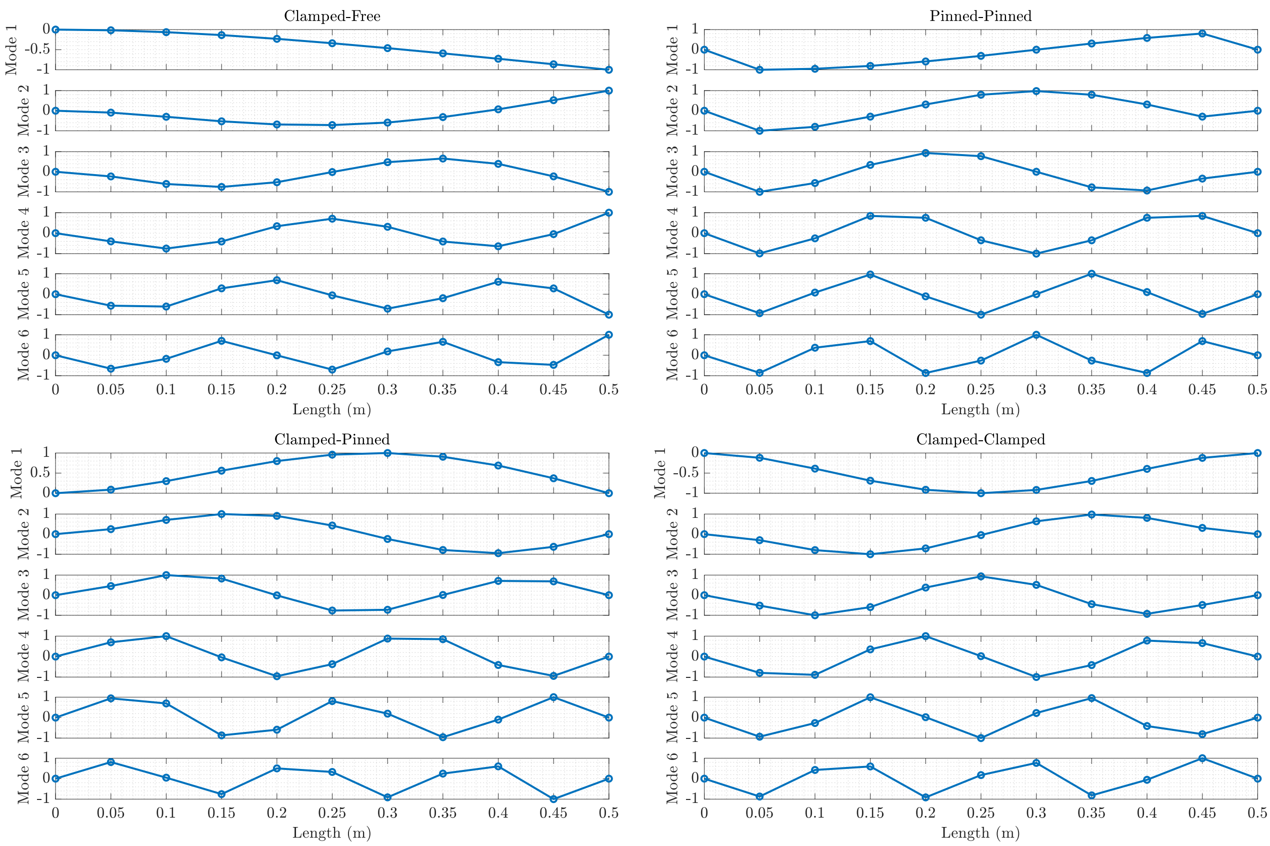


Figure 3. Comparison of mode shapes of four boundary conditions. Euler-Bernoulli beams solved by FE method

3. SIMILARITY ANALYSIS

The cosine similarity metric (Han *et al.*, 2012) is a measure used to quantify the correlation between two vectors. In our case, we organize our features of interest into vectors, specifically a natural frequency vector (one for each boundary condition) and a mode shape vector (six modes for each boundary condition). In this work, the module of the cosine similarity is used. Hence, a value of 1 indicates a perfect correlation, meaning the two vectors are identical, while a value of 0 signifies no correlation at all. This study hypothesizes that a high similarity value (close to 1) between two sets of features implies suitable transfer learning between similar modes, even when considering beams subjected to different boundary conditions. This suggests that the knowledge gained from one set of boundary conditions can be effectively applied to another set of boundary conditions if the mode features exhibit a high level of similarity.

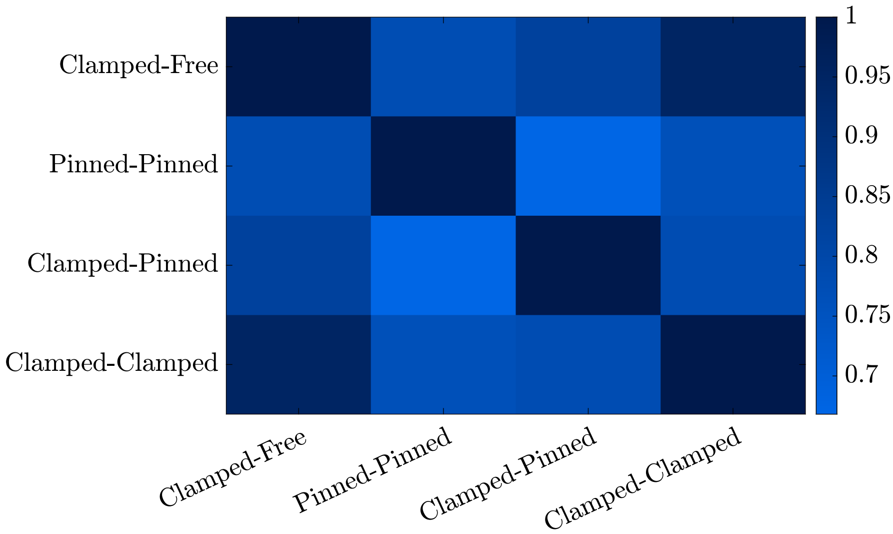
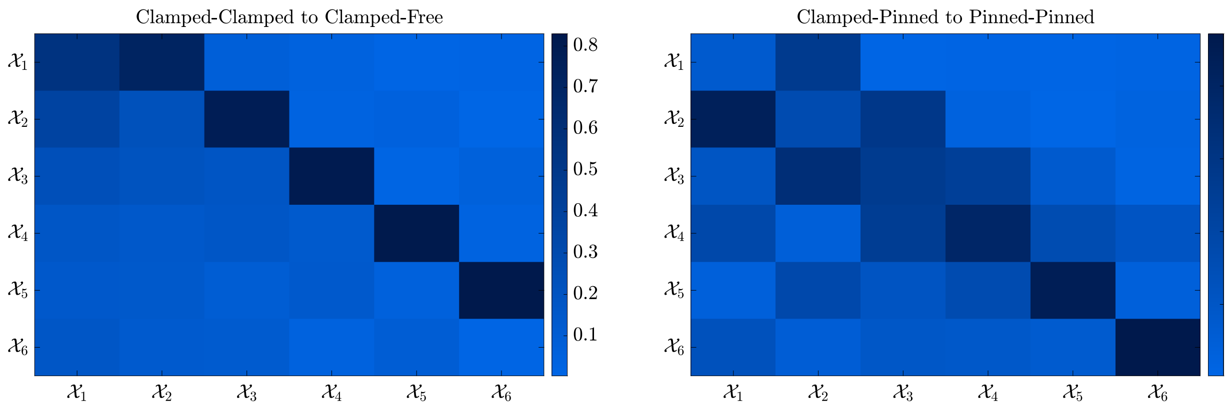


Figure 4. Cosine similarity between four boundary conditions

Figure 4 presents the cosine similarity between the four proposed boundary conditions obtained by comparing their first six natural frequencies. The highest similarity (about 94%) was obtained between the clamped-clamped and clamped-free conditions, which is the darker blue area (excluding the diagonal). Contrarily, comparing the clamped-pinned with pinned-pinned conditions, the light blue area was the one with the lowest similarity (about 66%). The diagonal dark blue blocks are excluded since there is no point in transferring learning between the same structure.

In addition to the boundary similarity, conducting a mode shape similarity analysis becomes relevant for selecting features from the modes. By doing so, it becomes possible to create two distinct feature sets: one with the highest similarity observed between different boundary conditions and mode shapes, and another set that represents the lowest similarity for comparison purposes.



a) Highest boundary similarity b) Lowest boundary similarity

Figure 5. Cosine similarity for the first six natural frequencies for the highest and lowest boundary similarity

Figure 5 illustrates the cosine similarity analysis between mode shapes for the highest and lowest boundary similarities. The similarity analysis of the mode shapes shows that the highest boundary and mode similarity is achieved when comparing modes 3, 4, and 5 of the clamped-clamped condition with modes 4, 5, and 6 of the clamped-free condition (with similarities of about 80%). Contrariwise, the lowest boundary and mode similarity is observed when comparing modes 1, 2, and 3 of the clamped-pinned condition with modes 3, 5, and 6 of the pinned-pinned condition (with similarities below 2%). The intent is to compare the feature set of the lowest overall similarity of natural frequencies and modes with the feature set of the highest overall similarity, then test if transfer learning is enhanced just by using the feature set with a higher similarity. Therefore, the highest and lowest similarity sets can be determined by combining the similarity of the natural frequencies (Figure 4) with the similarity of the mode shapes (Figure 5), resulting in an overall similarity metric.

4. TRANSFER LEARNING

The referenced "highest similarity" and "lowest similarity" sets will be used to transfer knowledge using Transfer Component Analysis to test if cosine similarity indicates optimum feature combinations for transfer learning. From now on, the boundary conditions will only be referred to as their initials (CF stands for Clamped-Free, PP stands for Pinned-Pinned, CP stands for Clamped-Pinned, and CC stands for Clamped-Clamped), and the combinations of boundary/features will be referred to as follows:

The highest similarity set will be called the "best case", the best case features are:

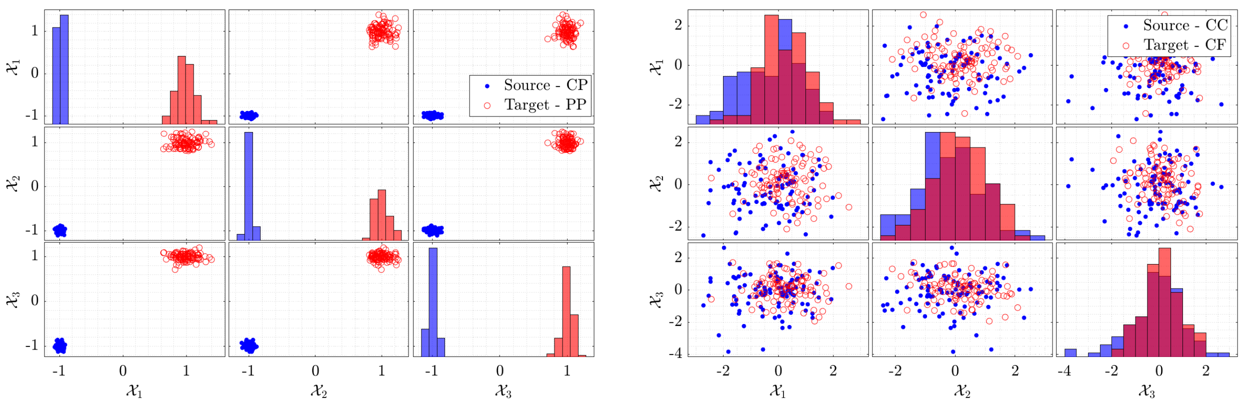
$$\text{Source} = \text{CC}(X_3, X_4, X_5); \quad \text{Target} = \text{CF}(X_4, X_5, X_6)$$

And the lowest similarity set will be called the "worst case", the worst case features are:

$$\text{Source} = \text{CP}(X_1, X_2, X_3); \quad \text{Target} = \text{PP}(X_3, X_5, X_6)$$

The original spaces of the best and worst cases are presented in Figure 6 with normalized data, and the latent spaces (after applying TCA) are presented in Figure 7. The latent space has only two features (instead of three from the original space) because TCA reduces the dimensions of the dataset.

From the original spaces, we can see that the worst case has distinct clusters and separate histograms, even with normalized data, meaning that there is a difference between the means of source (CP) and target (PP) data, a difference in the dispersion can be observed as well, transfer learning is necessary to make source and target data approach. On the other hand, the best case source (CC) and target (CF) data have no clear distinction; they have similar mean and variance with superimposed histograms, and transfer learning is not even necessary.



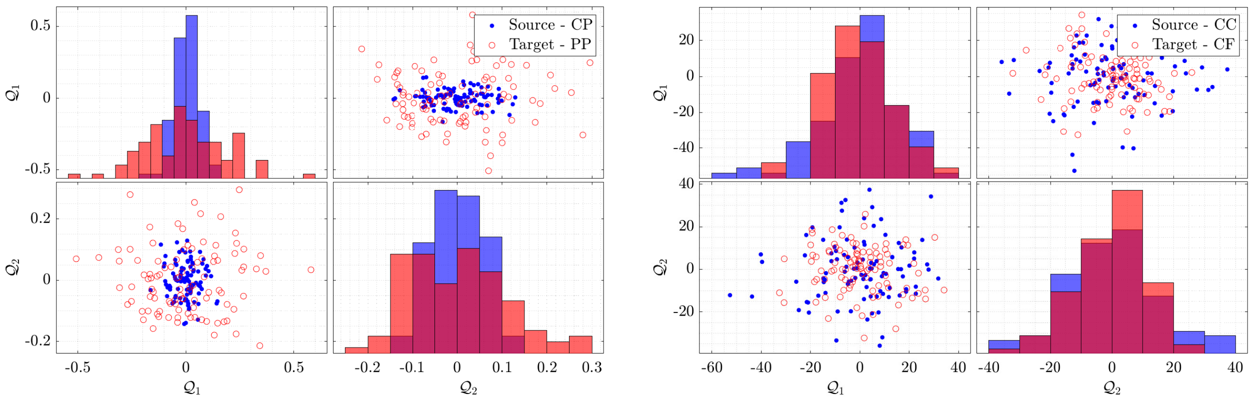
a) Original space of the worst case

b) Original space of the best case

Figure 6. Original space for the best and worst cases

After applying TCA, the latent space of the worst case shows that source (CP) and target (PP) data are matched (as it is supposed to happen after TCA), so transfer learning worked, but the dispersion is different; we have two distinct clusters and histograms, so there is still a difference between source and target data. In the best case, transfer learning was unnecessary. However, we can see that the behavior of source (CC) and target (CF) data remained similar; we have similar means and dispersion, meaning there is practically no difference between source and target data.

From the latent spaces feature/histogram plot, we can conclude that similarity analysis could previously identify which combinations of features would result in better transfer learning by selecting modes and boundaries with higher similarity, so there is a correlation between feature similarity and transfer learning efficiency. Even though the "worst case" source (CP) and target (PP) data mean matched, the datasets remained different in the dispersion, while in the "best case," source (CC) and target (CF) data matched perfectly.



a) Latent space of the worst case

b) Latent space of the best case

Figure 7. Latent space for the best and worst cases

5. FINAL REMARKS

This article analyzed the impact of boundary conditions on transfer learning performance for structural health monitoring, specifically focusing on beam structures. The study conducted a comprehensive analysis by applying various boundary conditions to a set of beam structures and evaluating transfer learning performance using vibration data and similarity analysis. It was observed that using some similarity metric computed in the function of the features map can indicate the best combinations of parameters and the definition of the target and source domain dataset. These results provide valuable insights for designing more effective transfer learning approaches in structural health monitoring. Future research could explore additional boundary conditions, consider different types of structures, evaluate performance using real-world data, and investigate the practical implementation of the proposed methodology in structural health monitoring by adding damage to the structures since damage could change the behavior of the features and, therefore, similarity itself. It is worth noting that similarity could follow the severity level of the damage, i.e., if the damage is early or extensive.

6. ACKNOWLEDGEMENTS

This work was funded by São Paulo Research Foundation (FAPESP) under grant number 2021/06133-9 and 19/19684-3, and National Council for Scientific and Technological Development (CNPq) under grant number 306526/2019-0.

7. REFERENCES

da Silva, S., Yano, M.O. and Gonsalez-Bueno, C.G., 2021. "Transfer component analysis for compensation of temperature effects on the impedance-based structural health monitoring". *Journal of Nondestructive Evaluation*, Vol. 40, No. 3, p. 64. ISSN 1573-4862. doi:10.1007/s10921-021-00794-6.

Farrar, C.R. and Worden, K., 2007. "An introduction to structural health monitoring". *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, Vol. 365, No. 1851, pp. 303–315. doi: 10.1098/rsta.2006.1928.

Figueiredo, E., Yano, M.O., da Silva, S., Moldovan, I. and Bud, M.A., 2023. "Transfer learning to enhance the damage detection performance in bridges when using numerical models". *Journal of Bridge Engineering*, Vol. 28, No. 1, p. 04022134. doi:10.1061/(ASCE)BE.1943-5592.0001979.

Geradin, M. and Rixen, D.J., 2015. *Mechanical Vibrations: Theory and Application to Structural Dynamics*. Mechanical Vibrations: Theory and Application to Structural Dynamics. Wiley, 3rd edition.

Han, J., Kamber, M. and Pei, J., 2012. "2 - getting to know your data". In J. Han, M. Kamber and J. Pei, eds., *Data Mining (Third Edition)*, Morgan Kaufmann, Boston, The Morgan Kaufmann Series in Data Management Systems, pp. 39–82. Third edition edition. ISBN 978-0-12-381479-1. doi:https://doi.org/10.1016/B978-0-12-381479-1.00002-2. URL `https://www.sciencedirect.com/science/article/pii/B9780123814791000022`.

Inman, D.J. and Singh, R.C., 2008. *Engineering vibration*. Prentice Hall Englewood Cliffs, NJ, 3rd edition.

Omori Yano, M., Figueiredo, E., da Silva, S. and Cury, A., 2023. "Foundations and applicability of transfer learning for structural health monitoring of bridges". *Mechanical Systems and Signal Processing*, Vol. 204, p. 110766. ISSN 0888-3270. doi:https://doi.org/10.1016/j.ymssp.2023.110766. URL `https://www.sciencedirect.com/science/article/pii/S088832702300674X`.

Pan, S.J., Tsang, I.W., Kwok, J.T. and Yang, Q., 2011. "Domain adaptation via transfer component analysis". *IEEE*

Transactions on Neural Networks, Vol. 22, No. 2, pp. 199–210. doi:10.1109/TNN.2010.2091281.

Tahara, L., 2019. *Um estudo da influência do comportamento não linear na análise modal experimental*. Master's thesis, Universidade Estadual Paulista, Ilha Solteira, São Paulo.

Thomas, J. and Abbas, B., 1975. "Finite element model for dynamic analysis of timoshenko beam". *Journal of Sound and Vibration*, Vol. 41, No. 3, pp. 291–299. ISSN 0022-460X. URL `https://doi.org/10.1016/S0022-460X(75)80176-3`.

8. RESPONSIBILITY NOTICE

The authors are solely responsible for the printed material included in this paper.