e-Journal of Nondestructive Testing - ISSN 1435-4934 - www.ndt.net

EWSHM 2024
11th European Workshop on Structural Health Monitoring

A short-training method for monitoring axially-loaded beams in presence of unknown and large thermal variations

M. BERARDENGO [1], F. LUCA' [2], M. VANALI[3], G. ANNESI[3], S. MANZONI[2]
[1] University of Genoa - DIME, Genoa, Italy, marta.berardengo@unige.it
[2] Politecnico di Milano – Dept. of Mech. Eng., Milan, Italy,
francescantonio.luca@polimi.it, stefano.manzoni@polimi.it
[3]University of Parma – Dept. of Eng. And Arch., Parma, Italy, marcello.vanali@unipr.it

Abstract. This paper deals with the problem of structural health monitoring of tie-rods, which undergo to large changes of eigenfrequencies when temperature changes because of the consequent change of the axial load. An approach for shortening the training period of the monitoring algorithm is proposed, relying on principal component analysis. This new method is compared to a state-of-the-art algorithm to evidence its strengths.

Keywords: structural health monitoring, principal component analysis, vibration, eigenfrequency, Mahalanobis square distance

1. Introduction

Structures are inherently susceptible to degradation and material wear over time, which can ultimately lead to critical damage. When the integrity of a structure is compromised, this can have detrimental effects on both present and future performance of the system. Therefore, the ability to identify signs of damage at an early stage is paramount in order to facilitate timely maintenance interventions, thereby mitigating the risk of structural failure. This aspect holds significant importance not only in terms of ensuring the safety of users but also from an economic perspective. Implementing effective maintenance strategies that are activated only when necessary enables the optimal allocation and utilization of maintenance resources, thus maximizing their efficiency and efficacy.

Structural health monitoring (SHM), focused on devising automated strategies for damage detection, is a major area of research [1]. Thanks to advancements in sensing technologies, data acquisition methodologies, computational capabilities, and data management systems, these strategies predominantly rely on data-driven methodologies. They harness data captured by sensors connected to the structure under observation.

Media and Publishing Partner
https://doi.org/10.58286/29590

However, since no device directly measures damage, a key point is the extraction of damage sensitive quantities, or damage features, from the signals collected by means of sensors [2].

Vibration-based techniques stand out and have undergone extensive study in the literature (e.g., [3–7]). These methodologies extract damage-sensitive parameters from the dynamic responses of the monitored structure, employing techniques such as time series models [8–10] or modal analysis [11]. Fundamentally, they operate on the hypothesis that a damage induces alterations in structural properties (e.g., mass, stiffness, constraint characteristics), which in turn manifest as changes in modal parameters (i.e., eigenfrequencies, mode shapes, and damping coefficients) [12]. One of the main challenges in SHM, and also for vibration-based methods, is to detect damages at an early stage, distinguishing them from the effects of environmental changes.

Tie-rods are axially-loaded slender metallic beams counterbalancing lateral forces in civil structures such as arches and vaults. They exhibit notable vibration levels during operation and, consequently, vibration-based SHM techniques find wide applicability in monitoring tie-rods. However, real-world tie-rods are affected by substantial uncertainties stemming from geometric and material properties, loading conditions, and constraint characteristics. Furthermore, the main problem in deploying unsupervised learning methodologies in real-world structures lies in the large influence of environmental factors [13], with specific reference to temperature variations. Fluctuations in temperature cause changes of vibration behaviour because the characteristics of the beams change (e.g., Young's modulus). However, in the case of tie-rods, the effect of temperature changes is even amplified because they cause changes in the axial load, leading to large variations of the modal parameters and, consequently, of the vibration behaviour [14,15] able to mask the effects of damages.

Some methods have been proposed in the literature to overcome this large influence of temperature (e.g., [16,17]). A method which proved good performances is based on the monitoring of a set of eigenfrequencies and the application of Mahalanobis square distance (MSD). This method (described below) requires to collect training data for a lot of time in order to describe as many temperature values as possible. This implies that at least a seasonal cycle must be collected for training.

This paper proposes a new approach aimed at largely reduce the amount of time required for training when assessing structural integrity by measuring eigenfrequencies. The use of eigenfrequencies allows having even a single sensor to measure tie-rod vibrations and employing operational modal analysis (OMA) without any need of an external excitation (i.e., environmental excitation is exploited).

The paper is structured as follows: Section 2 presents the reference method which already showed to be able to successfully evidence the presence of damages in tie-rods, then Section 3 describes the new method aimed at shortening the training period and, finally, Section 4 discusses some analyses which confirm that the newly proposed approach largely decrease the needed training time.

2. The reference method

The reference method is deeply discussed in [15,18] and requires to identify with OMA a given number of tie-rod eigenfrequencies (e.g., from the second to the fifth). More generally, these eigenfrequencies are indicated here as $f_1, f_2,, \dots, f_m$. These eigenfrequencies are organized into a vector $\mathbf{f} = [f_1, f_2, \dots, f_m]^\mathrm{T}$, where the superscript T indicates the transposed vector/matrix. Doing this for a large amount of time, a baseline can be obtained, constituting the training set:

$$\mathbf{F}^0 = \begin{bmatrix} \mathbf{f}_1^{\mathrm{T}} \\ \mathbf{f}_2^{\mathrm{T}} \\ \vdots \\ \mathbf{f}_r^{\mathrm{T}} \end{bmatrix}$$

Then, for each new observation of the eigenfrequencies $\mathbf{f}^*$, the MSD between $\mathbf{f}^*$ and $\mathbf{F}^0$ can be calculated. The MSD value proved to be a reliable feature to detect the presence of a damage [15,18].

3. The newly proposed method

In this approach, again, OMA is used to collect a set of eigenfrequencies, and repeating this task many times, a baseline $\mathbf{F}^0$ is obtained. Then, this training set undergoes a principal component analysis (PCA) which allows extracting the principal components (PC):

$$\mathbf{Z}^0 = \mathbf{C}^0\mathbf{R}$$

where $\mathbf{R}$ is the rotation matrix and $\mathbf{C}^0$ is the centered version of $\mathbf{F}^0$. Finally, $\mathbf{Z}^0$ contains the PCs. From this new set, the first PCs are discarded because they depend on thermal effects. Usually, the first PC is discarded but, in case also other PCs (e.g., the second) shows long trends related to environmental effects, they are discarded as well. Therefore a new matrix $\hat{\mathbf{Z}}^0$ is extracted from $\mathbf{Z}^0$.

When new observations are available (in the case of this paper a number of observations equal to the number of observations contained in the training set), they are joint to the training set, obtaining a new set:

$$\mathbf{F}^{0*} = \begin{bmatrix} \mathbf{F}^0 \\ \mathbf{F}^* \end{bmatrix}$$

Following the same steps previously described for $\mathbf{F}^0$, the matrix $\mathbf{F}^{0*}$ is centred and the principal component analysis is applied obtaining $\mathbf{Z}^{0*}$. Then, the first PCs are removed, obtaining the matrix $\hat{\mathbf{Z}}^{0*}$. Finally, the MSD is calculated between $\hat{\mathbf{Z}}^0$ and $\hat{\mathbf{Z}}^{0*}$.

This MSD becomes the damage index in which thermal effects are discarded. The detailed description of the mathematical procedure of the newly proposed approach based on PCs is available in [19].

4. Comparison of the methods

This section discusses comparisons carried out with both simulated and experimental data. In both the cases, more details can be found in [19]. Furthermore, the same reference discusses many other comparison tests.

4.1 Comparison with simulated data

Here, the trend of the eigenfrequencies generated by a bi-harmonic temperature trend (with the addition of noise) is generated by means of finite element simulations of a tie-rod. Furthermore, a damage is simulated at a given time by introducing a reduction of 10% of the beam Young's modulus in a given section of the tie-rod.

Figure 1a shows the time trend of the temperature T (shown as a variation with respect to a reference temperature T_0) where the dotted black vertical line shows where the training stop and the dash-dotted red vertical line indicates the damage introduction. Figure 2 presents the results for the two methods (d indicates the damage index), showing that the removal of the PCs related to environmental effects (the first in this case) allows increasing the sensitivity to damage. It is noticed that the damage indexes for both the methods are normalised so that the damage threshold is at 1. Furthermore, the PC-based method is characterised by a threshold range and not by a single value, in order to account also for uncertainty.

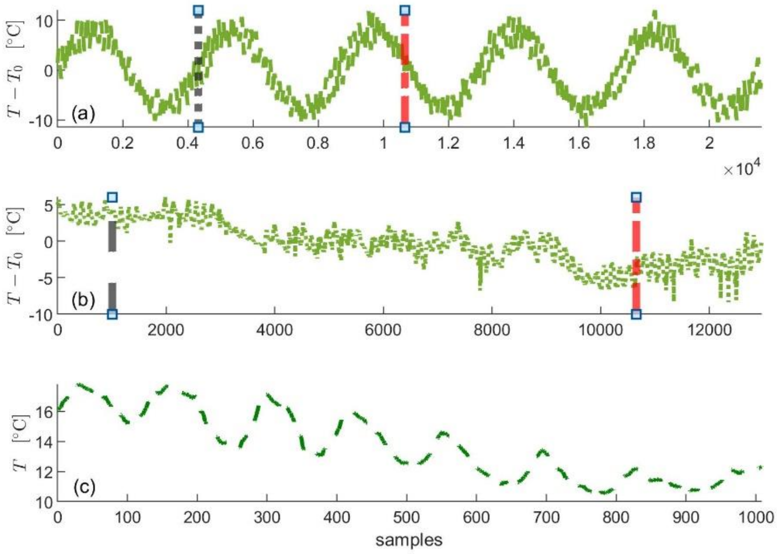

Fig. 1. $T - T_0$ simulated trend for the first (a) and second simulation (b) and measured trend of T during the experiments (c).

Then, a more complicated temperature trend was considered (Figure 1b). It is evident that the training set covers only some values of the temperature trend (i.e., only the largest temperature values). The damage was a Young's modulus reduction of 30% at midspan. Figure 3 shows the results and it is evident that the PC-based approach allows filtering out the temperature effects, while the traditional reference method highlights a damage before it actually occurs and this is due to temperature effects.

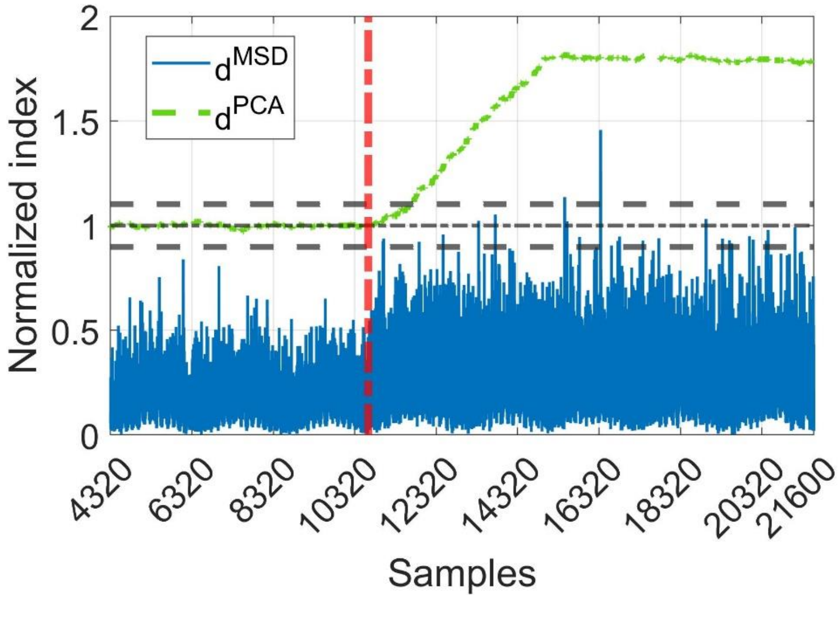

Fig. 2. Trends of the two damage indexes d for the PC-based and the reference method (referred here to as MSD) for the T trend in Figure 1a.

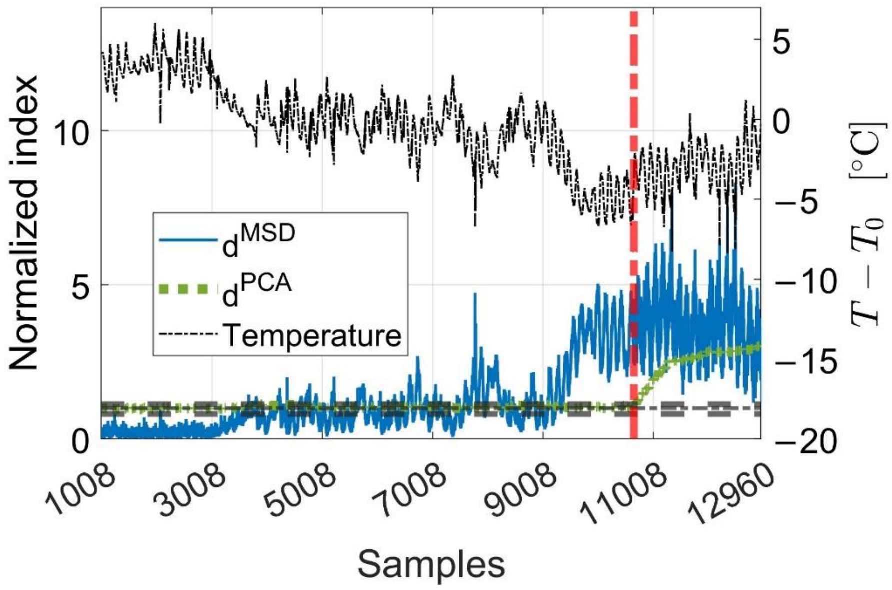

Fig. 3. Trends of the two damage indexes *d* for the PC-based and the reference method (referred here to as MSD) for the *T* trend in Figure 1b.

4.2 Comparison with experimental data

Here, a lab tie-rod [15] with length of approximately 4 m is used. Eigenfrequencies were extracted through OMA. The trend of T in the baseline is shown in Figure 1c. The damage was obtained by adding a concentrated mass (of 1% of the total mass of the tie-rod) close to one of the two fixed ends.

Figure 4 shows the results for the two methods. evidencing that the newly proposed approach highlights the presence of the damage at the correct time while the reference method is not fully able to point out the presence of a damage.

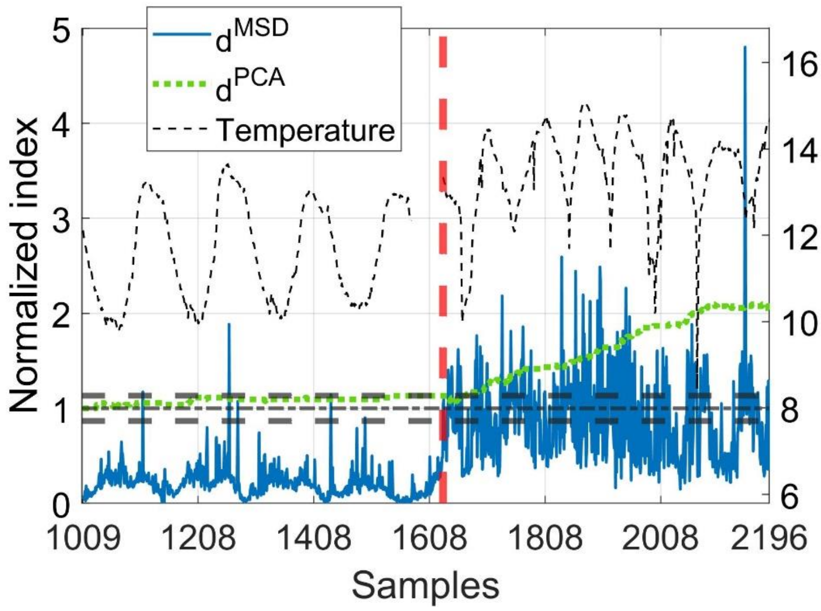

Fig. 4. Trends of the two damage indexes *d* for the PC-based and the reference method (referred here to as MSD) for the *T* trend in Figure 1c.

5. Conclusion

The paper has introduced an approach for shortening the training time when SHM of tie-rods is performed. These beams are critical because temperature changes generate large effects of beam dynamics because of the consequent change of axial load. The new proposed method, based on principal component analysis, is successfully compared to state-of-the-art methods through both simulated and real data. This new method is widely described and tested in [19].

Acknowledgment

This research is supported by the European Union – NextGenerationEU, M4C2 I1.1, Progetto PRIN 2022 "CHIMERA?" (grant n. 20225PKHWJ, CUP D53D23003070006).

References

[1] C.R. Farrar, K. Worden, An introduction to structural health monitoring, Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences. 365 (2007) 303–315. doi:10.1098/rsta.2006.1928.

[2] C.R. Farrar, K. Worden, Structural Health Monitoring: A Machine Learning Perspective, 2012. doi:10.1002/9781118443118.

[3] W. Fan, P. Qiao, Vibration-based damage identification methods: A review and comparative study, Structural Health Monitoring. 10 (2011) 83–111. doi:10.1177/1475921710365419.

[4] R. Hou, Y. Xia, Review on the new development of vibration-based damage identification for civil engineering structures: 2010–2019, Journal of Sound and Vibration. 491 (2021) 115741. doi:10.1016/j.jsv.2020.115741.

[5] O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, D.J. Inman, A review of vibration-based damage detection in civil structures: From traditional methods to Machine Learning and Deep Learning applications, Mechanical Systems and Signal Processing. 147 (2021). doi:10.1016/j.ymssp.2020.107077.

[6] J.M.W. Brownjohn, A. de Stefano, Y.-L. Xu, H. Wenzel, A.E. Aktan, Vibration-based monitoring of civil infrastructure: Challenges and successes, Journal of Civil Structural Health Monitoring. 1 (2011) 79–95. doi:10.1007/s13349-011-0009-5.

[7] M.P. Limongelli, E. Manoach, S. Quqa, P.F. Giordano, B. Bhowmik, V. Pakrashi, A. Cigada, Vibration Response-Based Damage Detection, 2021. doi:10.1007/978-3-030-72192-3_6.

[8] A. Entezami, H. Shariatmadar, A. Karamodin, Data-driven damage diagnosis under environmental and operational variability by novel statistical pattern recognition methods, Structural Health Monitoring. 18 (2019) 1416–1443. doi:10.1177/1475921718800306.

[9] A. Entezami, H. Sarmadi, B. Behkamal, S. Mariani, Big data analytics and structural health monitoring: A statistical pattern recognition-based approach, Sensors (Switzerland). 20 (2020). doi:10.3390/s20082328.

[10] B.S. Razavi, M.R. Mahmoudkelayeh, S.S. Razavi, Damage identification under ambient vibration and unpredictable signal nature, Journal of Civil Structural Health Monitoring. 11 (2021) 1253–1273. doi:10.1007/s13349-021-00503-x.

[11] T.T.X. Tran, E. Ozer, Automated and model-free bridge damage indicators with simultaneous multiparameter modal anomaly detection, Sensors (Switzerland). 20 (2020) 1–25. doi:10.3390/s20174752.

[12] C.R. Farrar, S.W. Doebling, D.A. Nix, Vibration-based structural damage identification, Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences. 359 (2001) 131–149. doi:10.1098/rsta.2000.0717.

[13] B. Peeters, J. Maeck, G. De Roeck, Vibration-based damage detection in civil engineering: Excitation sources and temperature effects, Noise and Vibration Worldwide. 35 (2004) 33.

[14] L. Collini, R. Garziera, K. Riabova, Detection of cracks in axially loaded tie-rods by vibration analysis, Nondestructive Testing and Evaluation. 35 (2020) 121–138. doi:10.1080/10589759.2019.1649400.

[15] F. Lucà, S. Manzoni, A. Cigada, L. Frate, A vibration-based approach for health monitoring of tie-rods under uncertain environmental conditions, Mechanical Systems and Signal Processing. 167 (2022) 108547. doi:10.1016/j.ymssp.2021.108547.

[16] F. Cadini, L. Lomazzi, M. Ferrater Roca, C. Sbarufatti, M. Giglio, Neutralization of temperature effects in damage diagnosis of MDOF systems by combinations of autoencoders and particle filters, Mechanical Systems and Signal Processing. 162 (2021) 108048. doi:10.1016/j.ymssp.2021.108048.
[17] C. Roberts, L.D. Avendaño-Valencia, D. García Cava, Robust mitigation of EOVs using multivariate nonlinear regression within a vibration-based SHM methodology, Mechanical Systems and Signal Processing. 208 (2024) 111028. doi:10.1016/j.ymssp.2023.111028.
[18] F. Lucà, S. Manzoni, A. Cigada, S. Barella, A. Gruttadauria, F. Cerutti, Automatic Detection of Real Damage in Operating Tie-Rods, Sensors. 22 (2022). doi:10.3390/s22041370.
[19] M. Berardengo, F. Lucà, M. Vanali, G. Annesi, Short-Training Damage Detection Method for Axially Loaded Beams Subject to Seasonal Thermal Variations, Sensors. 23 (2023) 1–27. doi:10.3390/s23031154.