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LEVERAGING ADVANCED NUMERICAL CALIBRATION TO FILTER OUT TEMPERATURE EFFECTS ON VIBRATION-BASED MONITORING DATA: APPLICATION TO THE MOGADOURO CLOCK TOWER

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Summary. This study investigates the advantages of integrating physics knowledge to enhance traditional data-driven methods for damage detection and early warning in a monitored structure. The implemented method combines the ability to predict variations in modal properties (such as natural frequencies) under changing temperatures, using a highly reliable Finite Element (FE) model calibrated to the experimental response of the structure, with a robust anomaly detection strategy to process new monitoring data and classify it as damaged or undamaged. The relationship between temperature and modal properties, as evaluated through the FE model, is used to normalise the monitoring data. This process filters out the effects of the environmental variation, potentially magnifying the effects of damage, which are then investigated through machine learning algorithms for classification purpose. The procedure is validated by analysing a real case study, the Mogadouro clock tower in Portugal. Several scenarios of available knowledge during the training of the damage detection strategy are simulated, discussing advantages and identifying areas for future improvement.

1 INTRODUCTION

Vibration-based methods have demonstrated their effectiveness and cost-efficiency in identifying damage and informing the preventive conservation of complex existing buildings, including heritage structures. These techniques involve the continuous monitoring and analysis of the dynamic behaviour of the structure over time. By examining its modal properties (i.e. natural frequencies, mode shapes, damping ratios), these methods can detect changes that indicate the progression of damage, allowing for timely interventions [1,2]. Many well-established damage detection methodologies are data-driven and develop behavioural models of the monitored structure based solely on the acquired experimental data [3-8]. Among data-driven methods, statistical control charts are gaining popularity due to their ability to provide rapid and reliable automated damage detection irrespective of the structural typology. These charts assess the health condition of a structure over time by continuously monitoring a predefined statistical distance. Damage is detected when new data present values of the statistical distance that exceed a pre-established threshold. Successful applications to heritage buildings can be found in [9-12]. However, data-driven methods may lack interpretability regarding the underlying phenomena, as they do not account for a physical description of the structure and the events affecting it. Moreover, they have demonstrated a tendency to overfit and a poor capability to generalise to out-of-sample scenarios [13,14]. This is particularly relevant since the extracted modal properties, such as natural frequencies, are significantly influenced by variations in environmental parameters like temperature, humidity, wind speed and direction [1,15-19]. These factors may mask data anomalies caused by damage, leading to substantial delays in detection and warning. Notwithstanding, filtering out the effects of environmental parameters from vibration-based data of historic masonry structures is very challenging, as the underlying phenomena are not yet fully understood [20]. This study explores the advantages of integrating physics-based modelling with data-driven anomaly detection, an approach which has recently emerged in structural health monitoring applications [13, 21]. To this end, the natural frequencies variations under changing temperatures is anticipated through a highly reliable FE model calibrated to the experimental response of the structure. The identified relationship between temperature and modal properties is used to filter out the effects of the environmental variation from the monitoring data, aiming at magnifying the effects of damage, which is evaluated through a control chart. The procedure is validated by analysing data from a real case study, i.e. the Mogadouro clock tower in Portugal, and the influence of the components of the procedure on the final detection performance is assessed aiming at identifying areas of possible improvement.

2 METHODOLOGY

The main steps of a traditional black-box vibration-based data-driven approach for damage detection is presented in Figure 1a. This requires a division of the acquisitions into an initial set of records for training followed by the actual monitoring stage. During the training, acceleration (or velocity) records are collected from the structure under ambient sources of vibration. Records are firstly processed to select and extract one or more features sensitive to damage onset and evolution. In the present work natural frequencies are used for the purpose. Afterwards, a regression model is fitted to the features over the training period and the residuals $r(X)$ are estimated as the difference between the measured (X) and predicted features $(\hat{X})$:

$$r(X) = X - \hat{X} \tag{1}$$

Investigating the residuals instead of the natural frequencies as damage sensitive features is a practical solution to reduce the variability in the monitoring data, by filtering out the effects of non-damage related factors (i.e. operational and environmental variations) to magnify the effects of damage itself. In the present work, a Gaussian Process regression algorithm [22] is adopted to define the frequencies as functions of the temperature due to the well-known influence of environmental variation on modal properties.

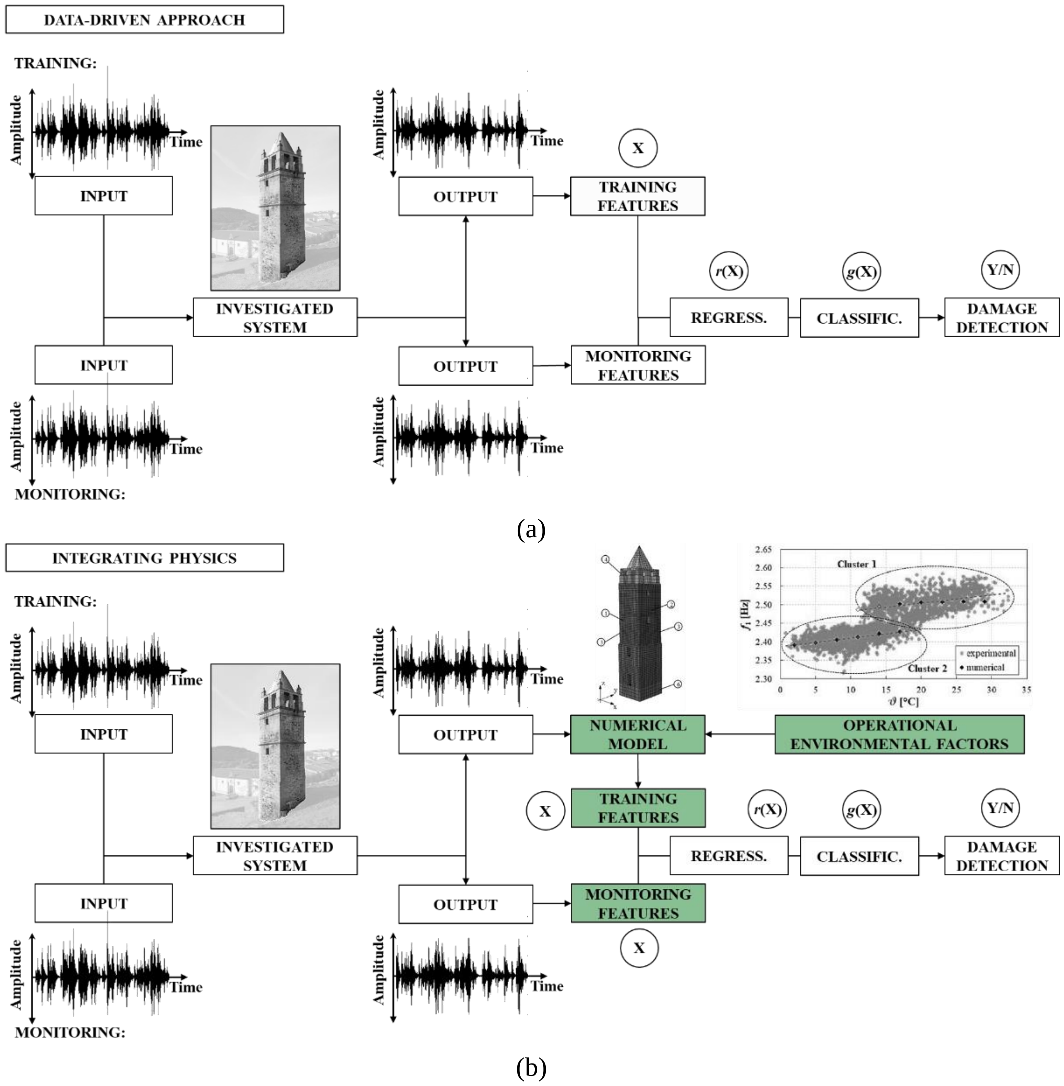


Figure 1: Damage detection strategy: (a) traditional black-box data-driven approach; (b) physics enhanced approach.

Finally the residuals over the training period are used to set the anomaly detection problem as a one-class or binary classification. Here, a Hotelling T^2 control chart is employed for classification. The Hotelling T^2 control chart formulates the classification based on the Mahalanobis statistical distance between the matrix of the new monitored features and the matrices of the mean values and covariance of the training features. For more details on the Hotelling T^2 control chart and the statistical formulation of the threshold, namely the Upper Control Limit (UCL), the interested reader is referred to [23,24]. During the actual monitoring stage, new records are acquired and new features are extracted. The new residuals are estimated by considering the regression model generated over the training data and then are processed by the control chart to conduct the damage detection.

In Figure 1b, the enhancement of this data-driven approach through physics knowledge is pursued by relying on a highly reliable model calibrated upon an initial dynamic identification of the structure. The effect of temperature variations in the expected operational range of the structure (i.e. yearly variations) is estimated on the model and a formulation of the natural frequencies as functions of the temperature is derived from these simulations. The residuals between extracted and predicted frequencies are then used as damage sensitive features in the control chart.

3 MOGADOURO CLOCK TOWER

3.1 Case-study overview

The Mogadouro Clock Tower is a relevant landmark of the homonymous ancient castle in Portugal, built after 1559 to serve as bell tower. It features a 4.7×4.5 m^2 external cross section, a 2.5×2.3 m^2 internal space and 20.4 m of height. The masonry walls present large granite blocks with dry joints in the corners and rubble stones with thick lime mortar joints in the central part of each façade [25]. The belfry is composed by eight masonry pillars forming the only large openings of the tower (Figure 2).

(a) (b) (c)

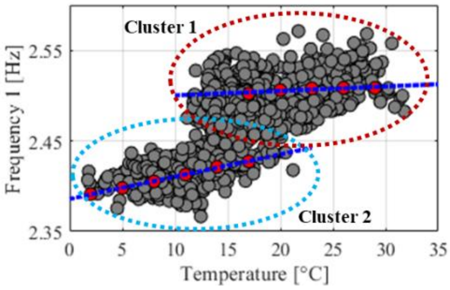
Figure 2: Mogadouro Clock Tower: (a) south view and castle; (b) north-east view; (c) north view.

Due to lack of maintenance, the visual inspection carried out in 2004 highlighted the presence of severe damage and deterioration. Vertical cracks were affecting east, north and west façades, from the base of the belfry, down along the shaft. The most significant ones, in east and west façades, were passing through the wall thickness reaching the base of the tower and separating the cross section into two U-shaped halves [25]. Therefore, an urgent restoration was conducted in 2005 to ensure the safety of the heritage building. The interventions encompassed lime injections, substitution of degraded and lost materials, and installation of lightly pre-stressed external steel belts at the level of the two cornices, namely in the upper part of the shaft and at the base of the belfry [25].

3.2 Dynamic identification and monitoring data

A non-continuous long-term monitoring through three uniaxial piezoelectric accelerometers was conducted between April 2006 and December 2007, after the implementation of the strengthening measures. Ten test series, each one composed of about ten-minute-long hourly acquisitions at 100 Hz of sampling rate were collected during this period [25]. In parallel, ambient temperature and air humidity were recorded as well. The automatic dynamic feature extraction process was carried out through the SSI/Ref method [26].

Figure 3 shows the frequency-temperature relationships for the first two bending modes identified across the monitoring period. Mode 3 and mode 4, torsion and second bending in north-south direction (y direction), respectively, were also identified with sufficient reliability. The results highlighted a non-linear transition from rainy/low-temperature records to dry/high-temperature records, with a shift of about 4% in the natural frequency values, for modes 1 and 2. This reflected in two emerging clusters in their frequency-temperature scatter plots. This peculiar trend has been explained as the result of the water absorption and consequent mass change during the raining season, and the following cycles of wet and dry [25].



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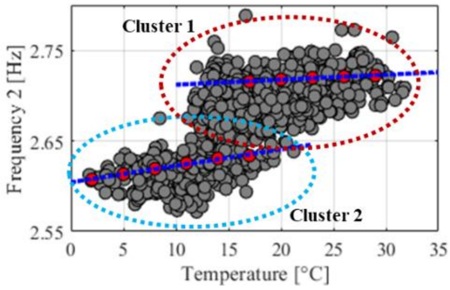

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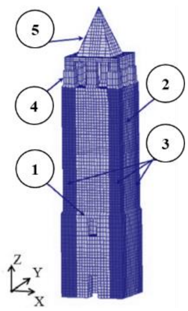


(c)

Figure 3: Long term monitoring: (a) first natural frequency and linear regression from numerical simulations; (b) second natural frequency and linear regression from numerical simulations; (c) FE model of the tower with different materials.

3.3 Numerical model

The FE model of the Mogadouro clock tower was generated in NOSA-ITACA software [27] comprising 18,024 isoparametric 8-node brick elements for masonry and 352 thick shell elements for the roof (Figure 3c). Five distinct material properties were considered: (1) South and North façades; (2) East and West façades; (3) walls' corners; (4) belfry; (5) roof; material 1 and 2 were considered linear elastic, while 3, 4 and 5 were modelled as *masonry-like* materials [27]. A fixed base boundary condition was introduced and a thermal expansion coefficient α equal to $5 \cdot 10^{-6} (°C)^{-1}$ was assumed for the whole structure. The FE model was calibrated following a nonlinear approach (linear perturbation analysis), by updating one value of the tensile strength (equal for the three masonry-like materials) and three values of the Young's modulus (different for the three masonry-like materials). The calibration consisted in the minimisation of the difference between numerical and experimental modal properties for the first four modes in a reference scenario taken at 17°C, corresponding to the average temperature during the monitoring period. This reference temperature falls in the overlapping area between the two clusters, therefore the calibration was carried out considering a set of target values in the lower range of cluster 1 and another one in the upper range of cluster 2. Finally, uniform thermal loads were applied to the calibrated models to estimate the modal properties of the tower in distinct expected scenarios between 2°C and 29°C. The numerically estimated frequencies were used to derive the linear regression model as functions of the temperature, for mode 1 and mode 2, as shown in Figure 3a-b. More details on the numerical model and the nonlinear calibration are provided in [20].

3.3 Anomaly detection

For anomaly detection purposes, the acquired dataset is divided into 4 subsets:

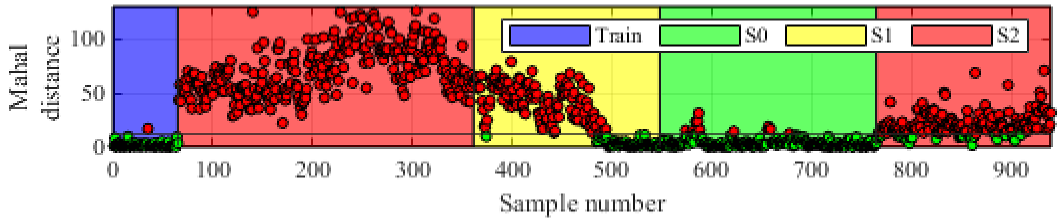
- Training data: initial 18 days
- S0: 74 days in cluster 2 data
- S1: 16 days in the transition interval between clusters 1 and 2
- S2: 116 days in cluster 1 data

This division allows for the investigation of the damage detection strategy performance against samples with similar (S0 samples), different (S2 samples) and intermediate (S1 samples) behaviour with respect to the training data. The subdivision is based on the existing non-continuous sets of acquisitions, and all samples are considered as belonging to undamaged conditions. The control charts of the analysed damage detection approaches are presented in Figure 4.

First, a data-driven approach, without support of the numerical model, is tested. Here, the Gaussian process regression is trained on the first and second natural frequency values and the residuals are processed for the classification. The control chart is shown in Figure 4a. Subsequently, a second approach is tested. In this case, the information provided by the numerical model is leveraged to estimate the natural frequencies as functions of the temperature and calculate the residuals before training the Gaussian process regression. This approach assumes that only the linear regression for cluster 2 is known, as the training data belong to this cluster. The control chart for this approach is shown in Figure 4b. Comparing these two scenarios, it is evident that both fail to correctly classify the samples belonging to S2 and most of the samples belonging to S1. The number of true negatives (correct classifications) and false positives (wrong classifications) is the same for both scenarios. This is because, in the first case, the Gaussian process, despite being trained on a very short period, identifies a trend that largely corresponds to the linear regression derived from the numerical model, in the second case. Moreover, in the second case, the Gaussian process applied to the residuals does not provide any further improvement in classification.

Therefore, a third scenario is analysed, assuming the same approach as the second scenario, but with the linear regression known for both clusters. In a real-world application, this knowledge may result from previous testing on the structure. However, it is worth noting that the non-linear trend exhibited by the tower is uncommon for similar structures and, thus, hard to anticipate in a real fieldwork. Therefore, such extensive knowledge would require an investigation of the tower beyond the short training period considered here. As confirmed by the control chart provided in Figure 4c, the a-priori availability of both linear regression models would significantly enhance the classification performance, minimising the number of false positives.

A further demonstration of the effectiveness of the information provided by the FE model is conducted by considering two additional scenarios. In the first one, the natural frequencies are estimated through the linear regression model based on the simulation, considering cluster 1 knowledge only. In the second scenario, both clusters are considered known. For both scenarios, the residuals between measured and estimated natural frequencies are directly adopted for the classification, bypassing a further processing of the data by using the Gaussian process.



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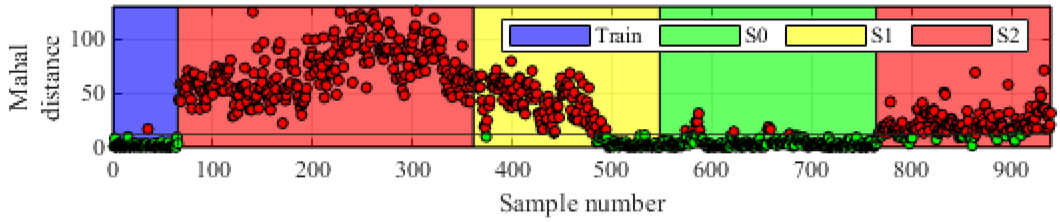

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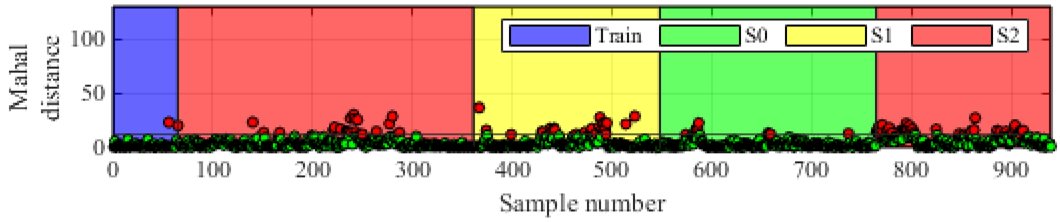

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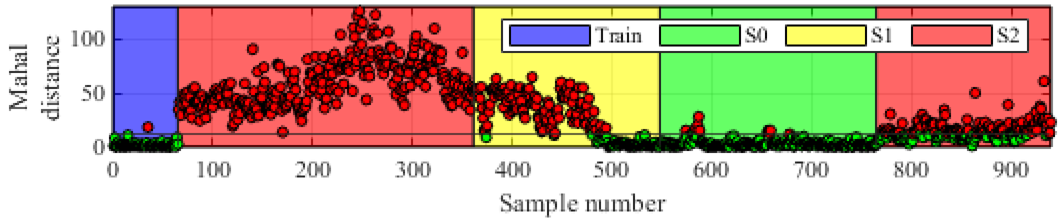

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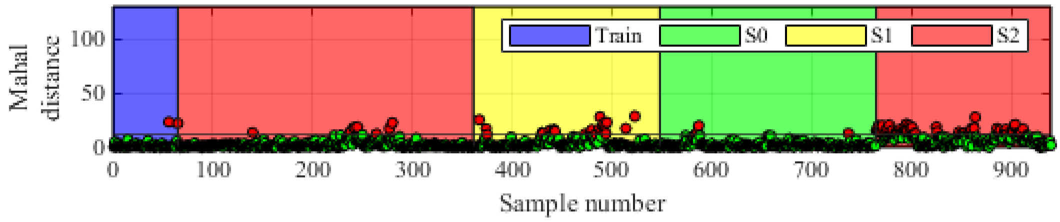

(e)

Figure 4: Control charts (green dots are true negatives, red dots false positives): (a) Gaussian process regression of frequencies; (b) features normalised according to cluster 1 equation, Gaussian process regression of residuals; (c) features normalised according to cluster 1 and 2 equation, Gaussian process regression of residuals; (d) direct classification of features normalised according to cluster 1 equation; (e) direct classification of features normalised according to cluster 1 and 2 equation.

Comparing the control charts in Figure 4d and 4e, with Figure 4b and 4c, respectively, an improvement in the final classification emerges, suggesting that the linear regression models are sufficiently effective in explaining the dependency of the natural frequencies on the temperature variation.

Comparing all the considered scenarios, it is worth noting that the performance of all regression models (Gaussian process and linear) in reducing the data variability is strongly affected by the large scatter in the samples. This scatter is likely influenced by several factors, beyond the ambient temperature, which is the only parameter considered in the present study.

4 CONCLUSIONS AND FUTURE SCOPES

In the present work the advantages of integrating physics knowledge to enhance traditional data-driven methods for damage detection and early warning are investigated. To this end, an accurate calibrated FE model is utilised to simulate environmental conditions otherwise unknown during the training period. The clock tower of Mogadouro serves as a relevant case study. This tower presents an extremely peculiar response under varying environmental conditions due to a change in the behaviour between rainy and dry seasons. The development of reliable models for the dependency of the natural frequencies on the temperature through numerical simulations demonstrated to be an effective approach to integrate and/or substitute the information obtained solely from experimental data. However, for real world case studies, such as the one analysed here, a single extrinsic parameter, like the temperature, is not sufficient to completely explain the variability of the monitored data. More research is required to ensure more accurate simulations of thermal variation effects and to incorporate on the FE model additional operational and environmental factors that influence the structural response.

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