Fellow's Research Project - XXXVIII Cycle

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Physics-enhanced machine learning methods for Structural Health Monitoring of bridge networks

Over the past decade, increasing efforts have been made worldwide to provide novel strategies to improve the safety of structures and infrastructures. An area in which the field of civil engineering has in recent years shifted a considerable interest is that of maintenance techniques (i.e. strategies devoted to increase the service life of existing structures). Clearly, the *run-to-failure* approach is not acceptable when life-safety represents a concern. On the other hand, the *time-based* maintenance strategy does not represent an effective approach in the case of large structures. Therefore, the *condition-based* maintenance philosophy is gaining consense and encompassing much research. Structural Health Monitoring (SHM) is a macro-category of non-destructive methodologies which plays a pivotal role in the context of condition-based maintenance strategies. Indeed, the fundamental concept of *condition-based* maintenance is that a sensing system on the structure will monitor the response of the structure and notify when damage is detected, to enable targeted intervention. In that scenario, economic and life losses resulting from the failure of critical elements of the infrastructural network (a prominent example is the Morandi Bridge in Genoa [1]) have pushed governments all over the world to increase investments on infrastructures and promote new regulations in a damage detection-to-maintenance perspective [2-5]. Therefore, SHM is rising rapidly in the world's research context, representing a timely topic in many international conferences in which bridges represent peculiar targets [6].
In this light, Operational Modal Analysis (OMA) is a popular vibration-based SHM technique because of its comprehensive assessment effectiveness, low intrusiveness and automation capability. The core concept of OMA is that to extract the modal features of a structural system (i.e. resonant frequencies, damping ratios and mode shapes) by exploiting acceleration response time series under normal operating conditions in order to infer damages from their permanent variations [7-9]. Therefore, a practical capability and knowledge is required to define the OMA methodology (actually, the most used are time-based methods such as the Stochastic Subspace Identification (SSI)) and the parameters to effectively infer the mode-shapes and distinguish the physical ones [10,11]. Considerable efforts have been also applied into the development of techniques capable of detecting, localize and quantifying damages through continuous and automated OMA [12]. Most recent advances include, among others, continuous supervised damage identification through Machine Learning (ML) [13-15], Physic-guided ML [16] and population-based SHM [17-19].
The data-driven ML [13-15] is a subcategory of the Artificial Intelligence (AI) developing trainable algorithms that are able of learning from available response data (measured or simulated) to provide future predictions [20,21]. ML-based SHM models can be generally categorized as supervised and unsupervised. In supervised learning, an ML model can be trained while using a set of training data with labeled target values (i.e. Bayesian method, deep learning, neural networks, etc.) [20-21]. This learning process requires training data from both undamaged and damaged conditions. Therefore, the main challenge in ML techniques is that recorded data that correspond to a considerable set of operational and damage conditions are hardly

accessible. The methods that are classified as unsupervised learning, do not require explicit training procedures for clustering dataset (i.e. hierarchical clustering, partitional clustering, k-means, spectral clustering, etc.) [22].
A widely applied model-based damage assessment technique in the civil engineering field is Finite Element Model (FEM) updating. That approach implies the effective identification of the frequencies and the mode-shapes of the structure and then the iterative updating of the model to minimize the discrepancies between its response and that of the real structure. The composition of data-driven and model-based techniques generates the strand of physics-guided ML approaches [16,23-24]. In fact, the conjunction of these two methodologies creates an extremely attractive and complementary synergy. The pattern recognition with FE model updating guides and assists the machine learning model, creating more consistent predictions with the engineering principles.
The population-based approach [17-19] aims to expedite the transfer of knowledge between classes of similar systems (i.e. populations). The basic concept is to transfer information from one structure within a population to another similar structure for which data are missing, in order to allow diagnostic inferences on the second structure. Therefore, this methodology would bring significant advantages to practical applications in supplying the lack of data.

Thanks to new regulations, improved data management technologies and instrumentations, the number of bridges being continuously monitored is increasing, making it possible to store databases from which to train ML algorithms. The question that arises is whether it is possible to adapt a neural network to the identification of damages from several similar bridges, in order to provide a more efficient algorithm for that specifical category. In this light, the research project will be centred in the developing of novel methodologies for model-driven damage identification of networks of bridges. Therefore, the approach is to unify the data-driven and model-based techniques in order to run advantages from a physic-based approach and enlarge the method to networks of bridges in a population-based SHM perspective. The target that constitutes the population is that of continuous or partially-continuous multi-span bridges. These structures are particularly challenging for OMA because of the periodicity of the physical and mechanical characteristics [25,26]. The difficulty in identifying the global modes is determined by the fact that the physical frequencies are very close and the modes present similar wavelengths. To better illustrate the problem, some preliminary results derived from the resolution of the free vibration problem of a partially continuous multi-span bridge are given in Figure 1. Figure 1(a) presents the trend of the first and second bending modal orders non-dimensional frequencies Λ as the number of spans n_s of the structure increases. Figure 1(b) shows the characteristic polynomial $\det(\Gamma_{n_s-1})$ that determines the solutions Λ, for the cases of two and five spans. It can effectively be noted that if a bridge is composed by n_s spans, then n_s mode-shapes are to be found according to each modal order. Moreover, the entity of the connection given by the deck and asphalt is a key point to determine the distance between the frequencies. Therefore, the large number of existing highway bridges that fall into that category and difficulties over the identification through the solely FE model updating highlight the scientific interest on that research field.

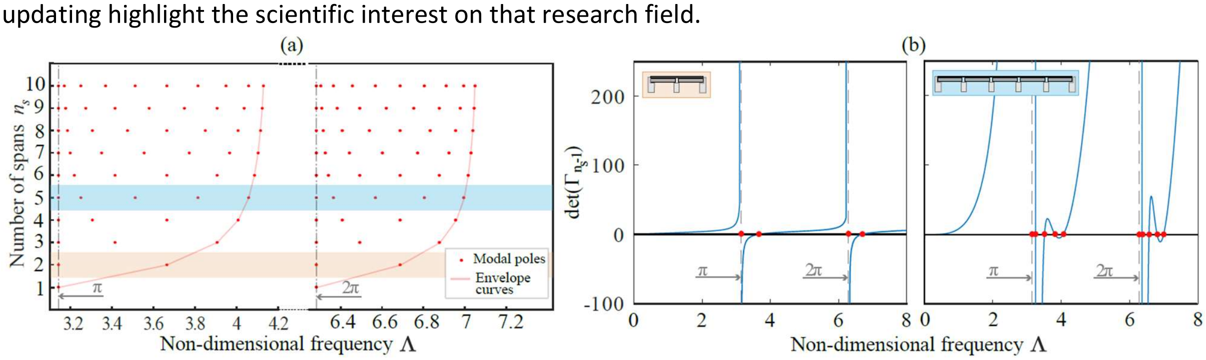

Figure 1: First and second bending modal order non-dimensional frequencies Λ versus number of spans n_s of the structure (a) and characteristic polynomial $\det(\Gamma_{n_s-1})$ that determines the solutions Λ, for the cases of two (left) and five (right) spans (b).

A further objective of this project concerns the processing of data derived from the Discrete State-Space Models and from the Stabilization Diagrams in an SSI method context. The first aim of this point is to speed

up the identification of physical modes (and thus the picking of peaks of singular values) by mean of ML image-correlation techniques. The second purpose is that to acquire other features on which train the ML algorithm, that are not necessarily the raw acceleration data or modal features such as frequencies and mode-shapes.
As a support to this work, the following technologies will be employed: FE modeling software, Matlab and Python programming languages, instrumentations and software to record and analyse through OMA the time histories of real and scaled structures in order to provide data sets and cases study.

Concluding, the scientific and practical utility of this research can be condensed in the following topics: (i) extension of the research in the field of periodic structures, (ii) extension of the research in the field of training from physic-guided AI and population based SHM applied to networks of bridges, (iii) implementation of more efficient techniques into software [27-28] in order to automate modal and damage identification of structures through AI.

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