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AI-based Structural Health Monitoring procedure for railway bridges

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Abstract

This work exploits unsupervised data-driven AI-based structural health monitoring (SHM) in order to propose a continuous online procedure for damage detection based on train-induced dynamic bridge responses, taking advantage of the large-magnitude loading for enhancing sensitivity to small-scale structural changes. While such large responses induced by trains might create more damage-sensitive information in the measured response, it also amplifies the effects on those measurements from the environment. Thus, one of the biggest contributions herein is a methodology that exploits the large bridge responses induced by train passage while rejecting the confounding influences of the environment in such a way that false positive detections are mitigated. Furthermore, this research work introduces an adaptable confidence decision threshold that further improves damage detection over time. To ensure an online continuous assessment, a hybrid combination of autoregressive exogenous input (ARX) models, principal components analysis (PCA), and clustering algorithms was sequentially applied to the monitoring data, in a moving window process. Since it was not possible to introduce damage to the bridge, several structural conditions were simulated with a highly reliable digital twin of the Sado Bridge, tuned with experimental data acquired from a SHM system installed on site, in order to test and validate the efficiency of the proposed procedure. The strategy proved to be robust when detecting a comprehensive set of damage scenarios. Moreover, it showed sensitivity to early damage levels, even when it consists of small stiffness reductions that do not impair structural safety.

Keywords: Structural Health Monitoring, Damage detection, Artificial Intelligence, Train-induced dynamic responses, Railway Bridges.

1 Introduction

Structural health monitoring (SHM) represents a promising strategy in the ongoing challenge of achieving sustainable infrastructural systems since it has the potential to identify structural damage before it becomes critical, enabling early preventive actions to be taken to minimize costs [1]. A combination of damage assessment technologies is necessary, and new developments in SHM aim at covering as many structures as possible at a reasonable cost. Although most bridges are already monitored using sophisticated measurement systems employing hundreds of sensors, there is a lack of efficient interpretation of the results provided, with frequent difficulty in detecting early damage. Thus, there is a need for data interpretation techniques that provide reliable information to assist engineers in structural management. It is crucial to devise robust online SHM systems that allow structures to be designed and operated safely, without extended downtime periods associated with additional inspection or maintenance. Also, it is important to develop unsupervised SHM systems that can be used in any geometry and that can detect damage in old structures, which already have a changed structural condition, to support the decision making process related to maintenance strategies.

Despite widespread research in this field, up to this date the majority of applications is either based on static responses or ambient vibration [2-4]. Measuring static responses to generate health data cannot characterize the dynamic response, which often has its own unique and sensitive correlations to some kinds of damage. On the other hand, ambient vibration analyses are typically based on small-magnitude responses that do not provide local damage-sensitive information or fail to excite nonlinearities where the damage might be more observable.

Transient signals generated by traffic have not been used efficiently and robustly for damage detection in railway infrastructures. While such large responses induced by trains might create more damage-sensitive information in the measured response, it also amplifies the effects on those measurements from the environment. The unique combination of moving-loads imposed to these structures during short periods can thus be considered an advantage if appropriate analyses are undertaken [5].

In this context, this work exploits unsupervised artificial intelligence (AI)-based SHM to propose a continuous online procedure for damage detection based on train-induced dynamic bridge responses, taking advantage of the large-magnitude loading for enhancing sensitivity to small scale damages. The focus is placed on ensuring robustness and efficiency implementing a hybrid combination of time series analysis methods and multivariate statistical techniques.

2 Methods

The proposed AI-based SHM strategy for early damage detection aims at being generic and robust enough to be applied to any type of railway bridges. A schematic representation of this procedure is depicted in Figure 1. A bowstring railway bridge was selected as case study, and a continuous monitoring system comprising 23 accelerometers installed at the top of each pier, in the concrete slab, and in the steel box girder was installed. To accomplish a fully autonomous and real-time monitoring system, a process involving moving windows was implemented. Within each window, an AI strategy composed by the following four steps is implemented: 1) feature extraction accomplished by fitting autoregressive models with exogenous inputs (ARX) to the accelerations acquired; 2) feature modelling, performed to reduce the influence of environmental and operational variations (EOVs) by applying Principal Component Analysis (PCA); 3) data fusion to enhance sensitivity by implementing a Mahalanobis distance (MD) and 4) feature classification by performing cluster analyses.

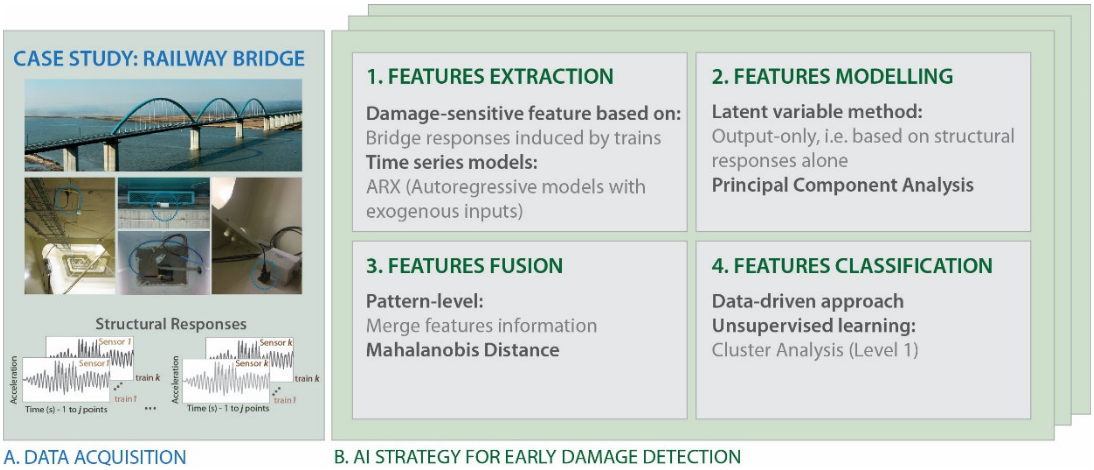

Figure 1: AI-based SHM strategy for early damage detection.

The moving window online procedure, detailed in Figure 2, is divided into three main stages: i) the confidence boundary (CB) build, ii) the baseline coefficients and iii) the online damage detection.

After defining the total number of trains crossings, j, that compose the baseline, and the number of trains crossings within each window, the AI strategy is applied in stage 1A. At the end of this stage, the baseline average distance between clusters (DC) vector is achieved and used to estimate the CB. The purpose of stage 1B is to compute baseline PCA coefficients and baseline covariance and mean matrices for j trains crossings. During the second stage, the moving windows process is implemented in real time. Here, after extracting the ARX parameters, the baseline PCA transformation is obtained, and the baseline covariance and mean matrices achieved in stage 1B are used for feature fusion. The corresponding damage sensitive distances are used as inputs for clustering. The outcome of the windowing process consists of one DC value per window i, and the detection is based on comparing each of these values with the CB. A DC lower than CB suggests that the structure may be assumed to be unchanged during that window. Conversely, a DC higher than the CB suggests the occurrence of damage during the same period. In the case of damage detection, after j train crossings a new baseline may be defined, which will allow identifying when a new type of damage occur.

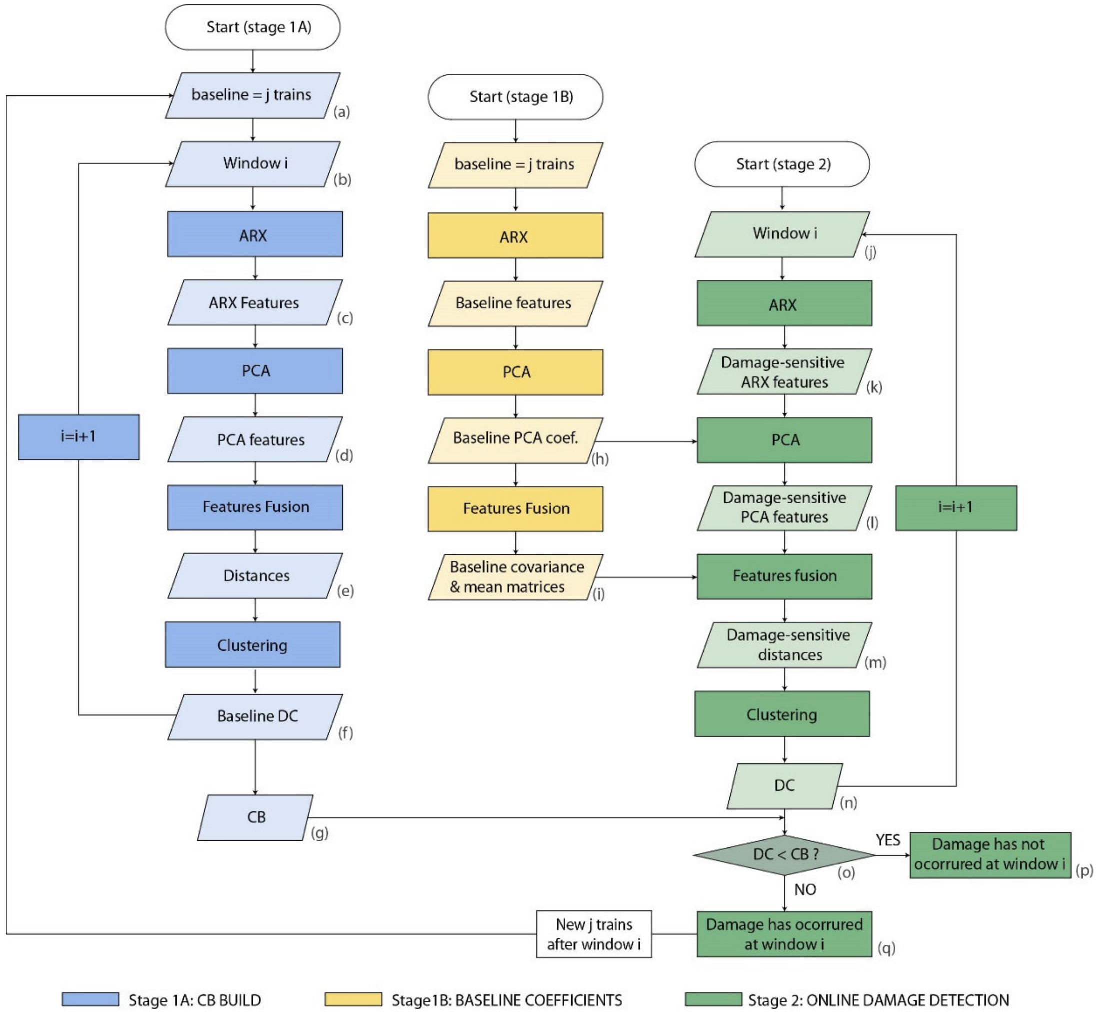

Figure 2: Moving window online procedure for damage detection.

3 Results

To test and validate the strategies proposed herein, a digital-twin of the bridge was implemented to perform a realistic comprehensive simulation of healthy and damage scenarios, since it was not possible to simulate damage scenarios experimentally [6]. The simulations of the baseline (undamaged) condition aimed at reproducing the responses of the bridge taking into account the variability of temperature, speed, loading schemes and type of train. Damage severities of 5%, 10% and 20% stiffness reductions in the concrete slab, diaphragm, and arches were simulated, as well as friction increases in the movements of the bearings. To obtain the most reliable reproduction of the real SHM data, the noise measured on site by each accelerometer was added to the corresponding numerical output.

The stage 1A of the methodology, which concerns defining the CB, was implemented for a significance level of 1% and for $j = 100$ trains. Figure 3 shows the CB defined for undamaged structural responses under different environmental and operational conditions. The DC series shown in Figure 4 as examples were obtained during the implementation of stage 2 for 100 healthy structural conditions and for 4 types of damage: i) D1 located in the bearings; ii) D2 located in the first mid-span of the concrete slab; iii) D3 located in the diaphragm; and iv) D4 located in the arch. For both stage 1A and stage 2, moving windows with 15 trains and the responses of all sensors installed on site were considered. The effectiveness of the online procedure to detect different types of damage with different severities is shown in Figure 4, since for each type of damage, each symbol represents a different severity, increasing from left to right.

In case a specific type of damage occurs, it is desirable for the CB to adapt in order to detect future damage that may arise over time. Figure 5 shows an application of CB progression, where it is shown the effectiveness of the proposed adaptive CB in automatically detecting new types of damage.

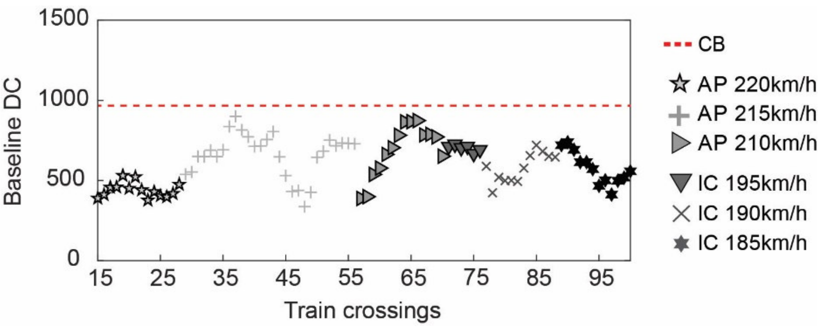

Figure 3: Stage 1A of the procedure: CB build.

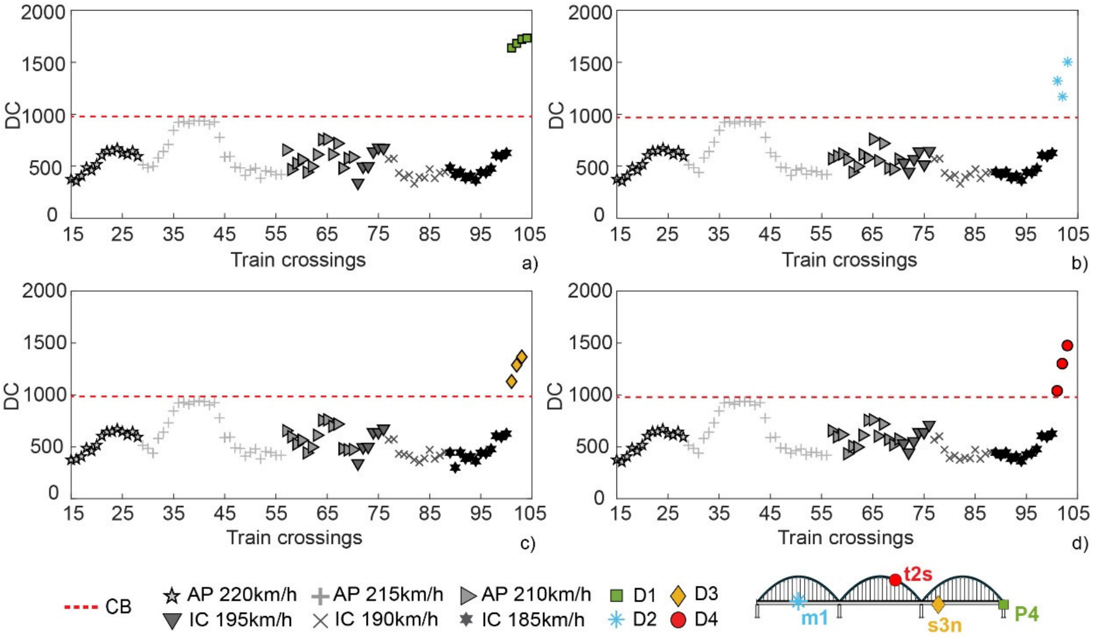

Figure 4: Stage 2 of the procedure: DC values obtained for 100 healthy scenarios and 4 types of damages with different severities.

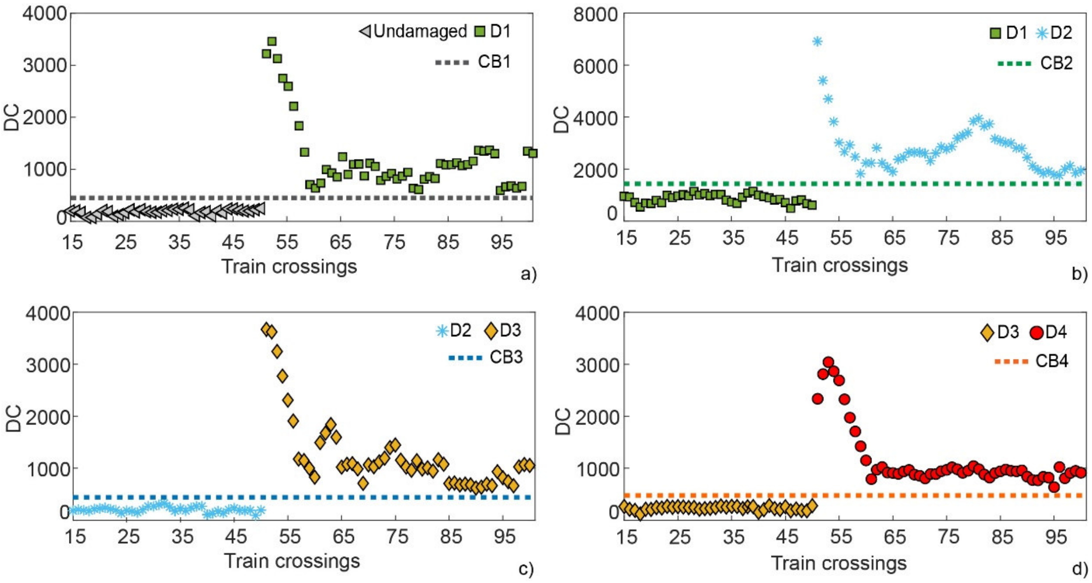

Figure 5: Adaptive CB for different types of damage: a) undamaged vs D1, b) D1 vs D2, c) D2 vs D3 and d) D3 vs D4.

4 Conclusions and Contributions

This paper presents a comprehensive SHM procedure for conducting continuous online damage detection, using train-induced dynamic responses, integrating several algorithms that address detection, EOVs, and online, autonomous classification. The unsupervised AI strategy proposed includes the sequential application of ARX models, PCA transformation, and clustering algorithms to the observed data, using a moving window procedure. This strategy also includes an innovative approach to define an adaptive confidence boundary, which can be automatically updated to detect new damage that would progressively occur.

The following conclusions can be drawn from the research work herein presented:

- The performed time-series analysis showed to be able of accurately generalize the information present in data, while performing significant compressive fusion.
- The importance of feature modelling was demonstrated, when the effects of EOVs were considerably reduced without the features losing sensitivity to damage.
- The results strongly suggest that the proposed methodology is, in fact, robust and may be used for damage detection throughout the entire structural system.
- Changes as small as 5% of stiffness reduction may be detected.
- Finally, using several train-induced responses from the bridge comprising progressively different types of damage, the effectiveness of an original adaptive CB in detecting new structural changes that may occur in a structure already damaged was successfully demonstrated. Also, the procedure proved to be robust in avowing false damage alerts.

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