



Nonlinear State Estimation via Machine Learning

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CHAPTER 1

Introduction

Structural Health Monitoring (SHM) is the discipline that, through the acquisition and analysis of data from a structure leads to the assessment of its current and future integrity, it is fundamental to adequately monitor any type of structure such as bridges, buildings, offshore platforms, and wind turbines since the failure of these structures can lead to economic losses and/or human casualties. The techniques used in the SHM may provide early warnings of potential structural damages that are essential in the prevention of catastrophic failures.

The procedures used in SHM may involve the application of sensors, visual inspection, ultrasonic testing or other non-destructive techniques. However, the utilization of sensors seems to be the most practical solution. For example, thinking of the network of infrastructures present in a country, both the number of constructions and their physical size represents a challenge for SHM. Visual inspections coupled with other on-site tests cannot provide continuous monitoring and they become disadvantageous when the time required for these operations is considered. Therefore, sensors are indeed commonly used in SHM because they are relatively inexpensive, easy to install and allow continuous monitoring. As with most other SHM applications, the primary sensors used for infrastructure health monitoring are accelerometers, since through the recorded quantities, it is possible to detect changes in the response of the structure. Thus, damage [3].

In the most general terms, damage can be defined as changes introduced into a system that adversely affect its current or future performance. In the context of structural systems, damage occurs when their material and/or geometric properties change. More precisely, the structure abandons the linear regime and starts responding in the non-linear regime that is characterized by non-linear material behaviour with permanent plastic deformations. An indication of a structure characterized by a non-linear state is the reduction of the system's stiffness as well as the accrual of plastic deformations. According to the given definition, the identification of damage implies a comparison with an initial state which is assumed to be an undamaged state [3]. The state of a point in the structure at a specific time, is given and can be described through different quantities such as displacement, strain, acceleration, temperature, and humidity. Therefore, the definition of the structural state over time, due to various loads and environmental conditions, can involve the use of sensors,

such as; accelerometers, strain gauges, and other types of transducers.

Both the budget allocated for monitoring and its targeted damage types represent two of the elements that lead to the definition of the sensor's number located in a structure. In the specific case of bridges, most studies consider less than 100 sensors but there are bridges that are monitored continuously by over 1000 sensors [3]. In order to make the monitoring practical with a cost-effective number of sensors, some studies focused on the definition for the optimized layout of sensors [8, 5, 9]. The current project aims to use Machine Learning (ML) to extend the state recorded from sensors placed in some nodes of the structure to other locations that have not been provided with a sensor. This brings a reduction in the costs of the SHM program tailored for a structure and allows the monitoring of points that are not accessible. For example, in the case of offshore platforms, the corrosive saltwater environment can adversely affect the sensors and their wiring systems, thus, the elements placed below the water-line cannot be monitored [3].

The number of studies that try to accomplish damage detection and SHM through ML methods is significant. Dang et al. in [2] compared different types of Neural Networks (NN) such as long short-term memory (LSTM), multilayer perceptron (MLP), 1D and 2D convolutional neural networks (1DCNN and 2DCNN). All these methods were applied in the estimation of the section reduction in those points where sensors were recording the acceleration. The study involved structures with sizes and complexity: 1D simply supported beam, 2D steel frame and a bridge. Two other studies presented by Dan et al. [1] and Hamidian et al. [4] aimed to assess the global damage in the considered structures. The former study investigates the utilization of a neural network for the classification of the global damage state of a steel frame and of a bridge in four different categories: undamaged, moderate, mild or severe damage. The inputs used for such prediction were the acceleration signals provided by sensors uniformly distributed on the entire structure.

In the latter study, the focus was to estimate the global damage categories for a three-story steel frame. The considered ML methods of K-nearest neighbours (KNN), artificial neural network (ANN), and support vector machine (SVM), were inputted with one acceleration signal for each floor. However, in this study the raw signals were processed and transformed in correlation functions, and then into entropy which provided information about the complexity and irregularity in a signal.

These studies represent the most relevant examples of ML application in SHM that have been analyzed during the literature review. The overall review led to the conclusion that different types of ML methods can be used to predict various measures of the structural state. However, no clear indications were made in relation to which methods that are able to predict the structural state better than others. This was due to the fact that different ML methods were given different inputs and were then put to predict various outputs. Some outputs were then directly linked to a state, whereas others were indications of stiffness reductions at various locations. However, the majority of the studies used acceleration signals for the estimation and/or localiza-

tion of damage. This is a clear indication of the importance that the accelerometers play in the field of SHM.

For the reasons previously introduced, the present project aims to define a ML model that allows the prediction of acceleration signals in those points of the structure where sensors are not present. More precisely, the considered structure is subjected to an earthquake ground motion and the acceleration response signals are recorded in a few location using sensors. The information collected from the sensors are then used to estimate the acceleration history in another location. In order to provide accurate estimations the ML model needs to be exposed to an adequate number of responses. In order to generate the responses used by the ML method to learn the pattern that links the input signals with the output signals, a Finite Element (FE) model of the considered structure is produced. The structure taken into account for the project consists of a reinforced concrete (RC) frame with 3 stories and 3 bays while the set of ground motions includes 301 different recordings. The selection and the main characteristics of the ground motions have been described in [7, 6]. The RC frame has been modelled with non-linear material properties, thus making the structure able to undertake damage which level depends on the characteristics of the excitation provided by the acting motion. The model evaluation is based on the true response in the same location that the ML method is to predict. These responses then correspond to a structure that is either in the linear or non-linear regime. The ML models that are to be used in the project are a Gaussian Process (GP) and a Neural Network (NN).

References

- [1] Jingpei Dan et al. “Global bridge damage detection using multi-sensor data based on optimized functional echo state networks.” In: *Structural Health Monitoring* 20.4 (2021), pages 1924–1937. DOI: 10.1177/1475921720948206. URL: <https://doi.org/10.1177/1475921720948206> (cited on page 2).
- [2] Hung V. Dang et al. “Deep learning-based detection of structural damage using time-series data.” In: *Structure and Infrastructure Engineering* 17.11 (2021), pages 1474–1493. DOI: 10.1080/15732479.2020.1815225 (cited on page 2).
- [3] Charles Ferrar and Keith Worden. *Structural Health Monitoring : A Machine Learning Perspective*. Chichester West Sussex U.K: Wiley, 2012. DOI: 10.1002/9781118443118 (cited on pages 1, 2).
- [4] P Hamidian, Y J Soofi, and Bitaraf M. “A comparative machine learning approach for entropy-based damage detection using output-only correlation signal.” In: *J Civil Struct Health Monit* 2 (2022), pages 975–990. DOI: <https://doi.org/10.1007/s13349-022-00587-z> (cited on page 2).
- [5] Rongrong Hou et al. “Genetic algorithm based optimal sensor placement for L1-regularized damage detection.” In: *Structural Control Health Monitoring* 26.1 (2018) (cited on page 2).
- [6] EI Katsanos, AG Sextos, and AS Elnashai. “Prediction of inelastic response periods of buildings based on intensity measures and analytical model parameters.” In: *Engineering Structures* 71 (2014), pages 161–177 (cited on page 3).
- [7] Evangelos I Katsanos, Anastasios G Sextos, and George D Manolis. “Selection of earthquake ground motion records: A state-of-the-art review from a structural engineering perspective.” In: *Soil dynamics and earthquake engineering* 30.4 (2010), pages 157–169 (cited on page 3).
- [8] Soon-Jung Kwon et al. “Design of Accelerometer Layout for Structural Monitoring and Damage Detection.” In: *KSCE Journal of Civil Engineering* 7.6 (2003), pages 717–724 (cited on page 2).
- [9] Hoon Sohn et al. “A Review of Structural Health Review of Structural Health Monitoring Literature 1996–2001.” In: *Office of Scientific Technical Information Technical Reports* (2002) (cited on page 2).

