Structural Health Monitoring

Subjects: Engineering, Civil
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Recent advances in sensor technologies and data acquisition systems opened up the era of big data in the field of structural health monitoring (SHM). Data-driven methods based on statistical pattern recognition provide outstanding opportunities to implement a long-term SHM strategy, by exploiting measured vibration data. However, their main limitation, due to big data or high-dimensional features, is linked to the complex and time-consuming procedures for feature extraction and/or statistical decision-making. To cope with this issue, in this article we propose a strategy based on autoregressive moving average (ARMA) modeling for feature extraction, and on an innovative hybrid divergence-based method for feature classification. Data relevant to a cable-stayed bridge are accounted for to assess the effectiveness and efficiency of the proposed method. The results show that the offered hybrid divergence-based method, in conjunction with ARMA modeling, succeeds in detecting damage in cases strongly characterized by big data.

Keywords: Structural Health Monitoring ; Big Data ; Statistical Pattern Recognition ; Time Series Analysis ; Kullback–Leibler Divergence ; Nearest Neighbor ; Large-Scale Bridges

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1. Introduction

Civil structures are currently facing issues related to aging, material deterioration, excessive loading conditions unexpected at the design stage, inappropriate usage, environmental actions and natural hazards. Under such circumstances, they may get affected by serious damages which threaten their structural performance and safety. To avoid irreparable events and guarantee the serviceability of the structures, structural health monitoring (SHM) represents a practical tool to evaluate the structural conditions both at global and local levels [1][2][3]. To achieve this objective, relatively dense sensor networks need to be designed and data acquisition must be exploited to continuously collect information in terms of, e.g., structural vibrations [4][5][6][7][8][9][10].

2. Result

Recent advances in sensor and information technologies have opened up the possibility of exploiting big data, in order to shift the focus from sensing and instrumentation to the analysis and interpretation of sensor network outcomes via data-driven methods [11]. Big data is a term associated with a large volume of high-dimensional data, whose size is beyond the ability of commonly used software and hardware to analyze the samples in a limited amount of time [12]. The concept of big data has received remarkable attention when dealing with complex engineering problems, also within the civil engineering community [13][14][15]. Big data may arise for SHM in the case of long-term monitoring strategies, use of dense sensor networks, exploitation of multiple dynamic tests on the structure and high sampling rates [16].[16][17][18][19][20][21][22][23][24][25][26][27][28][29][30][31][32][33][34][35][36][37][38][39]

Big data analytics for SHM is a relatively new research topic. In [16], challenges related to big data were discussed on the basis of their characteristics like variety (type and nature of data coming from different sources), volume (size and quantity of stored data), velocity (speed at which the data are processed) and complexity (related to uncertainties and inaccuracies in them). In [17], the computational sensitivity of common SHM procedures was assessed in relation to system identification and damage detection, in the case of large volumes of vibration measurements to be processed. A machine learning algorithm was proposed in [11], based on cross-correlation and robust regression analyses, for processing data collected from the mechanical components of movable bridges. A method was also offered in [18], based on the statistical pattern recognition paradigm to include the use of multivariate analysis, sensor data fusion and machine learning for damage detection from a large volume of data acquired from distributed piezoelectric sensors. Damage detection using distributed parallel processing was implemented in [12], with the aim of addressing the issues linked to the volume and variety of the data. Big data analytics were carried out in [19] for the condition evaluation of highway bridges, by roughly considering one million data samples obtained from the National Bridge Inventory. In [20], the focus was on structural damage detection and localization by handling big data through an iterative spatial compressive sensing algorithm.

The processing of data in long-term SHM may be a complex and time-consuming procedure, often preventing the monitoring system to work in real-time. Further to that, a large volume of high-dimensional data (e.g., the acceleration time histories acquired by a dense sensor network) needs a vast storage space, detrimentally affecting the performance of the software used for data analytics [21]. What precedes must also deal with issues related to uncertainties such as noise, environmental and operational variability due to temperature fluctuation, humidity variation and mass changes caused by traffic loads [18][22][23]. For a long-term SHM program, the measurement of vibrations takes place under different environmental and operational conditions, leading in some cases to changes in the structural response similar to those caused by damage, and hence providing false alarms [22].

Data-driven methods for SHM have been inspired by the theory of statistical pattern recognition [23][24][25][26][27]. These methods consist of two main steps: extraction of damage-sensitive features from periodically spaced vibration measurements over a period of time, and analysis of these features via statistical approaches, to assess the current state of the structure. The reason to move to damage-sensitive features lies in the fact that the direct use of raw vibration data may not be sufficiently informative [11]. As vibration data are acquired in time, time series analysis provides an efficient tool for feature extraction [28][29][30][31][32].

The analysis of the damage-sensitive features for damage detection is usually carried out via statistical techniques. In fact, the definition of a meaningful relationship between damage and the features extracted from the raw vibration data, on the basis of physical laws or numerical models of the structure, proves difficult if not impossible [25]. The analysis of damage-sensitive features is usually known as statistical decision-making or feature classification (see [18][22][23][29][33][34][35]). Within SHM, this process aims to compare the features relevant to two different structural conditions, one of which is assumed normal or undamaged, and then make a decision about the current state of the structure, which may be either undamaged or damaged. From a statistical viewpoint, distance metrics for feature classification have to provide a measure of the discrepancies between two sets of data samples, handled as random variables, in terms of, e.g., their probability distributions [36]. There exist effective univariate and multivariate distance metrics that can be adopted in SHM analysis [22][23][25][29][30][31][37][38]; however, their use does not always guarantee an accurate and reliable feature classification, particularly in the case of big data analytics.

Having considered the above-mentioned limitations, the main objective of this work is to propose a data-driven method for SHM based on statistical pattern recognition in the presence of big data. First, ARMA representations are adopted to model, in the time-domain, the vibration responses, which are assumed to consist of large volumes of high-dimensional data, and reliably extract damage-sensitive features in a low-dimensional space. Second, a hybrid divergence-based method is used to take a decision about damage occurrence. Such a method is a combination of a partition-based Kullback–Leibler divergence (PKLD) and the nearest neighbor (NN) rule, and is, therefore, termed PKLD-NN. It stands as an improvement over a classical hybrid method obtained by combining the Euclidean-squared distance (ESD) and the NN rule (ESD-NN), as proposed in [39]. Furthermore, the PKLD improves the conventional Kullback–Leibler divergence (KLD) in measuring the discrepancy between two sets of time series samples, to enable addressing the main limitations for random samples and coping with high-dimensional features for damage diagnosis. The high detectability of damage and the utility of long-term SHM methods are shown for the proposed PKLD-NN approach, accounting also for ambient vibrations and environmental and/or operational variability conditions. A major strength of the proposed approach is its capability to provide a novelty detection on the basis of the measured data and low-dimensional feature samples, independently of the specific type of damage. Experimental datasets of a large-scale cable-stayed bridge are adopted to verify the effectiveness and efficiency of the proposed data-driven method. Through comparison with state-of-the-art techniques, the newly proposed strategy is reported to be highly successful in detecting damage and handling big data.

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