Mechanical Systems and Signal Processing 87 (2017) 384–400

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

A spectral-based clustering for structural health monitoring of the Sydney Harbour Bridge

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ARTICLE INFO

Keywords:
Structural Health Monitoring
Power Spectral Density
Spectral Moment
Clustering
Anomaly Detection
k-means−−

ABSTRACT

This paper presents the results of a large scale Structural Health Monitoring application on the Sydney Harbour Bridge in Australia. This bridge has many structural components, and our work focuses on a subset of 800 jack arches under the traffic lane 7. Our goal is to identify which of these jack arches (if any) respond differently to the traffic input, due to potential structural damages or instrumentation issues.

We propose a novel *non-model-based* method to achieve this objective, using a spectrum-driven feature based on the Spectral Moments (SMs) from measured responses from the jack arches. SMs contain information from the entire frequency range, thus subtle differences between the normal signals and distorted ones could be identified. Our method then applies a modified *k*-means−− clustering algorithm to these features, followed by a selection mechanism on the clustering results to identify jack arches with abnormal responses.

We performed an extensive evaluation of the proposed method using real data from the bridge. This evaluation included a *control* component, where the approach successfully detected jack arches with already known damage or issues. It also included a *test* component, which applied the method to a large set of nodes over a month of data to detect any potential anomaly. The detected anomalies turned out to have indeed system issues after further investigations.

1. Introduction

With time, civil structures such as bridges experience natural and human-induced damages, i.e. any change in the structure that adversely impacts its performance or safety (e.g. material deterioration, or boundary condition degradation). Many bridges have usually been monitored for such damages using visual inspections at set intervals (e.g. yearly) [1]. This approach has some major drawbacks, e.g. failures could happen between inspections, and incipient damages may go unnoticed during inspections. Thus monitoring the integrity of bridges in a systematic and continuous way is a challenge to the engineering community. Structural Health Monitoring (SHM) systems aim at implementing damage identification strategies for a structure. The information produced by SHM systems allows engineers and asset owners to improve the safety, serviceability, and operational cost of critical structures through their life cycle [2]. A SHM system combines multidisciplinary technologies and techniques, and usually involves the following main steps:

1. Data acquisition is the process of collecting measurements from a structure using an array of sensors. Several issues need to be

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http://dx.doi.org/10.1016/j.ymssp.2016.10.033
Received 24 May 2016; Received in revised form 25 October 2016; Accepted 30 October 2016
0888-3270/

addressed at this step, such as the type or the location of the sensors [3], the sampling frequency, the data transmission and storage, or the energy cost of the systems [4].
2. Feature extraction is the process of selecting the attributes from the data, that are most sensitive to the damages and least sensitive to the operational and environmental variations. The research in this area has focused on time or frequency domain features [5,6], through signal processing techniques, such as data filtering, fusion, or pattern recognition [7–9].
3. Data analysis establishes a statistical framework for decision making to distinguish between damaged and healthy states of the structure. For this purpose, statistical pattern recognition methods using unsupervised or supervised learning algorithms can be implemented [10,11].

Most of the research in SHM has focused on developing and verifying algorithms in a controlled laboratory environment, or on small scale structures [12]. Indeed, deploying and using a SHM system on a large scale structure is prone to significant uncertainties [13]. Furthermore, many of these contributions have been based on short or medium term monitoring, and thus did not capture potential long term variabilities (e.g. sensor failure over time, temperature).

The objective of this paper is to present a novel approach to detect anomalies such as structural damages and system issues in continuously monitored large scale infrastructures. This approach was successfully evaluated on a real iconic bridge, i.e. the Sydney Harbour Bridge (SHB) in Australia. We instrumented that bridge with a unique SHM system, which has monitored more than 400 substructures (i.e. jack arches) since early 2014 [14]. The contribution of this paper is three-fold. First, it presents the recent additional data collection capabilities deployed on SHB. Second, it describes in detail a novel approach to detect structural damages and system issues on this large scale SHM system. This approach uses a novel clustering-based scheme to correlate the location of substructures with their behaviours. Finally, it demonstrates through several case studies the performance and benefits of this approach. While our SHM deployment has collected data for over a year, studying the effect of environmental variability on the system is outside the scope of this paper, and will be presented in future works.

A previous description of the SHB system [15] presented a whole high level overview for infrastructure managers. It briefly reviewed each system component from the on-site nodes to the remote web-based interface for managers and engineers. In contrast, the deployment update in this paper focuses on the data acquisition component only, and provides a technical description of its new functions, which enabled the collection of the data used in this paper.

The remainder of this paper is organized as follows. Section 2 presents some related research works. Then Section 3 provides an update of the new data acquisition functions of the SHB system. Section 4 introduces the theoretical background for the proposed approach to detect structural damages and system issues. Section 5 then presents the results of the successful applications of the proposed method to several case studies. Finally, Section 6 discusses some limits and potential improvements, which are followed by concluding remarks in Section 7.

2. Related works

There have been many contributions related to SHM applications on bridge structures. Many of them studied modal parameters (e.g. natural frequencies, mode shapes and modal damping) for damage identification in bridges. One of the first study proposing such a technique identified some progressive cracks in a three-span highway bridge during cyclic fatigue loading [16]. Other studies focused on the changes in the modal parameters for damage detection [17,18]. They concluded that the identification of higher modes was required to reliably identify damages using modal parameters. Thus, the first few lower modes might not provide useful information about any existing damages [18].

The Los Alamos National Laboratory (LANL) conducted large scale studies on the Interstate 40 (I-40) and the Alamosa Canyon bridges in New Mexico [19,20]. They extracted modal parameters using ambient and forced vibration testing, and reported some of the experienced difficulties. First, the use of eigen-parameters did not provide information about damages, which were located in the nodal points. Second, the identification of the modal parameters was difficult when the modes were not well-separated, which is often the case for bridges. These studies concluded that eigen-parameters were highly dependent on uncertainties in the system, e.g. environmental conditions, traffic loads, excitation source, the identification algorithm and the measurement precision. To account for such variabilities, they suggested the collection of data over a year, in various weather conditions, and with different traffic conditions.

While most of these previous works were based on short-term monitoring, some recent studies reported on long-term SHM applied to bridges with in-service traffic loads [21,22]. They deployed different sensors to monitor various variables and structural responses, e.g. temperature, humidity, wind, corrosion level and input loading using Weight-in-Motion stations. These contributions emphasized the necessity for statistical data analysis to quantify and account for the uncertainties over long time periods [22]. However, they focused on either small structures or had small number of instrumented locations.

SHM systems often only have data from the healthy states of structures, Thus many contributions proposed damage detection methods based on unsupervised or one-class approaches. For example, Worden et al. used a Mahalanobis distance to find data anomalies, which are likely to be structural damages [23]. Other authors proposed clustering approaches for damage detection, which deal with operational and environmental effects, such as Gaussian Mixture Models (GMM), Support Vector Clustering (SVC) and Self-Organizing Maps (SOM) algorithms [24]. Law et al. used a fuzzy c-means clustering approach for structural damage detection [25]. Other methods focused on grouping information coming from sensors distributed throughout the structure. Yin et al. proposed a clustering-based routing protocol to group similar nodes in each span of the bridge [26]. Diez et al. discussed the use of k-means to group bridge substructures with similar behaviour and then detect anomalies [27].