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Structural health monitoring of suspension bridges with features affected by changing wind speed

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ABSTRACT

Tools based on multivariate statistical analysis are becoming very popular for automatically revealing the existence of damage in structures using vibration data under changing environmental and operational conditions (typically temperature, humidity and traffic intensity). In this paper, methods of multivariate statistical analysis are newly applied for monitoring the structural health state of the main cables of suspension bridges, with the main contribution of removing non-linear aeroelastic correlations between dynamic features and wind speed.

Considering natural frequencies as damage-sensitive features, an analytical parametric model of suspension bridge with damage in one main cable and subjected to wind loading is formulated, at first, as an extension of previous work. Model predictions demonstrate that apparent frequency variations caused by changes in incoming wind speed can likely be more significant than those produced by a small damage. A technique based on principal component analysis and novelty detection is adopted to cope with this issue and its application to long-term pseudo-experimental buffeting response data, generated by means of the analytical model, is presented. The results demonstrate the feasibility of permanent monitoring systems to reveal the existence of damages in wind-excited long-span bridges producing relative variations in the most sensitive natural frequency smaller than 0.1%.

1. Introduction

Automating the condition assessment process of civil structures is the only practicable solution for the efficient management of aging infrastructure networks. This task can be pursued by Structural Health Monitoring (SHM) systems that link the experimental observation (e.g., by sensors) of the in-service response of a structure to its structural integrity (e.g., damage diagnosis and health prognosis) (Farrar and Worden, 2007).

Although a large number of monitoring systems have been implemented worldwide in strategic bridges (Brownjohn, 2007), there is still an uncertainty related to their ability to effectively inform about the health state of the monitored structure. To date, the main reasons that limit SHM potential reside in a lack of reliable processing strategies able to manage the big data stemming from sensors permanently installed on site and to use such information for performance assessment (Magalhães et al., 2008).

Structural damage is usually associated with local changes in stiffness. Hence, damage sensitive features commonly considered in damage identification strategies are either static responses (Alvandi and Cremona, 2006) or dynamic characteristics of the structure (Deraemaeker et al., 2008; Domaneschi et al., 2013). However, these quantities are affected by changes in environmental and operational conditions (Sohn, 2007; Moser and Moaveni, 2011) and it is necessary to define appropriate strategies able to eliminate such effects in order to allow detection of small damages.

Methods of multivariate statistical analysis and novelty detection have been often proposed for depurating dynamic features from the effects of changes in environmental and operational conditions and for automatically revealing the presence of anomalies in the structural behavior (Worden et al., 2002; Mosavi et al., 2012). Similar methods, such as those based on linear (Yan et al., 2005a) and non-linear Principal Component Analysis (PCA) (Yan et al., 2005b), proved to be effective for eliminating the effects of changes in temperature, humidity and traffic intensity (Bellino et al., 2010).

Removal of environmental effects related to changes in incoming wind speed from monitoring data is an issue that has not been sufficiently addressed in the literature. Yet, it is well-known that wind sensitive slender structures, such as long-span bridges, might exhibit significant apparent variations of their modal parameters with incoming wind speed as a consequence of aeroelastic effects (Hui et al., 2010). Such variations are typically non-linear, which complicates their removal, and, if not properly handled, can be misinterpreted as effects of some structural damage or may hide the presence of

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damage itself. Henceforth, it is mandatory to develop processing strategies for structural health monitoring of bridges able to cope with this issue.

The authors started a research program aimed at the definition of appropriate strategies for continuous structural health monitoring of long-span (suspension) bridges, using operational dynamic response data. A major challenge, in this context, is the susceptibility of the structure to aeroelastic effects, which produces non-linear variations of dynamic features with wind speed. After investigating in Ubertini (2014) the sensitivity of vertical and torsional modal frequencies to damage in one main cable (Cappa, 1988), this paper addresses the process of automatically revealing the presence of main cable damage by application of a technique based on: (i) automated modal identification and frequency tracking, (ii) PCA and (iii) novelty detection (Magalhaes et al., 2012). To the best of the authors' knowledge, this is the first attempt to use PCA and novelty detection for revealing the presence of damage in structures with features being significantly affected by changing wind speed.

Following previous research (Ubertini, 2013, 2014) this work is based on the use of an analytical elastodynamic model of damaged suspension bridge under turbulent wind, that is adopted for generating long-term pseudo-experimental buffeting response data. The model is here extended to consider both vertical and torsional wind excitation and accounts for aeroelastic effects through the self-excited loading model based on indicial functions.

Application of SHM techniques to pseudo-experimental data for validation purposes is relatively common in the literature (see for example Yan et al., 2005a,b) mainly because: (i) it is difficult to collect long-term field data from an actual structure under developing damage and (ii) theoretical analysis allows us to easily test the performance of SHM procedures. It should be mentioned, however, that simulation data may not fully represent actual conditions at bridge site, which might contain complex features such as structural and aerodynamic non-linearities, a variety of operational and environmental conditions and more. All these features represent challenges for both modal identification and damage detection. It follows that the use of artificially generated data poses some limitations and that a full-scale application would be the ideal benchmark validation test for the presented SHM procedure.

The paper is organized as follows. Section 2 presents the theoretical background; Section 3 presents the analytical model; Section 4 discusses and compares frequency variations due to changes in incoming wind speed and induced by damage; Section 5 discusses SHM effectiveness and Section 6 concludes the paper.

2. Theoretical background

In this paper, natural frequencies are considered as features enabling condition assessment of long-span bridges and the multivariate statistical analysis technique proposed in Magalhaes et al. (2012) is employed to depurate frequency estimates from the effects of changes in the incoming wind speed and for revealing the presence of a damage. This section is devoted to briefly presenting the theoretical background of the two main tools of the procedure: (i) removal of wind effects from frequency estimates using PCA and (ii) novelty analysis.

2.1. Wind effects removal using Principal Component Analysis

PCA, also known as *proper orthogonal decomposition* (Di Paola, 1998), is a multivariate statistical method *explaining the variance-covariance structure of a set of variables through a few linear combinations of these variables* (Johnson and Wichern, 2007). This method has been often applied in the literature for many purposes, such as reduced-order modeling and modal analysis, and, in more recent years, it has revealed to be particularly effective for damage detection purposes.

In the present study, PCA is adopted to reduce the variability of natural frequency estimates caused by changes in wind speed, by removing linear correlations among the data. Compared to other methods for removing environmental and operational factors from damage-sensitive features, the main advantage of PCA is that it does not require the measurement of the environmental parameters (in the present study, the wind speed), because they are taken into account as embedded variables.

Let us denote with $\mathbf{Y} \in \mathbb{R}^{n \times N}$ the observation matrix containing N samples of the frequency estimates of n vibration modes of the structure. These data can be remapped into the vectorial space generated by the so-called *Principal Components* (PCs) that constitute an orthogonal basis. The remapped matrix, $\mathbf{X} \in \mathbb{R}^{n \times N}$, called the *score matrix*, is written as

$$\mathbf{X} = \mathbf{T}\mathbf{Y} \tag{1}$$

where $\mathbf{T} \in \mathbb{R}^{n \times n}$ is the loading matrix, obtained by performing the Singular Value Decomposition (SVD) of the covariance matrix of the original data as follows:

$$\mathbf{Y}\mathbf{Y}^{\mathbf{T}} = \mathbf{U}\mathbf{\Sigma}^2\mathbf{U}^{\mathbf{T}} \tag{2}$$

and setting

$$\mathbf{T} = \mathbf{U}^{\mathbf{T}} \tag{3}$$

By definition, each row of the loading matrix contains the coefficients of a singular PC, while $\mathbf{\Sigma}^2$ is a diagonal matrix containing the singular values of the covariance matrix, which represent the variance contribution of each PC.

A limited number, l, of PCs usually suffice to reconstruct the major part of the variance, that is assumed to be produced by changes in wind speed. The remaining part of the variance is instead associated to residual random errors in output-only frequency identification. A rectangular reduced loading matrix, $\hat{\mathbf{T}} \in \mathbb{R}^{l \times n}$, is obtained by considering only the first l columns of matrix $\mathbf{U}$ in Eq. (3), in such a way to retain only the PCs that are responsible for the variance produced by changes in wind speed. This matrix is used for model dimension reduction and for re-mapping the reduced-order data into the original space, yielding a modified observation matrix $\hat{\mathbf{Y}}$ as

$$\hat{\mathbf{Y}} = \hat{\mathbf{T}}^T\hat{\mathbf{T}}\mathbf{Y} \tag{4}$$

which only contains the part of the variance that is associated to changes in wind speed. The residual error matrix, $\mathbf{E}$, defined as

$$\mathbf{E} = \mathbf{Y} - \hat{\mathbf{Y}} \tag{5}$$

instead only contains residual random errors, but not those associated to changes in wind speed. A cleaned observation matrix, $\mathbf{Y}^*$, that is, a matrix containing frequency data without effects of changing wind speed, can therefore be obtained as

$$\mathbf{Y}^* = \overline{\mathbf{Y}} + \mathbf{E} \tag{6}$$

where $\overline{\mathbf{Y}} \in \mathbb{R}^{n \times 1}$ is a vector containing the mean values of the original frequency data.

The above described procedure is effective only if the SVD of the covariance matrix is performed on data collected within a training period of sufficient length, t_0, containing a statistically representative sample of wind speed data. Furthermore, if the structure, during this training period, is in the reference healthy state, quantities contained in $\mathbf{E}$ can potentially reveal the presence of a damage by being capable of highlighting anomalies that were not observed during the training period.

Literature results (Magalhaes et al., 2012) referring to bridges subjected to changes in temperature and operational conditions (traffic) suggest that t_0 should be at least equal to 1 year, so that a nearly complete record of environmental and operational conditions is