Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 199 (2017) 2244–2249

Procedia Engineering

www.elsevier.com/locate/procedia

X International Conference on Structural Dynamics, EURODYN 2017

Challenging aspects in removing the influence of environmental factors on modal parameter estimates

Carlo Rainieri[a,*], Filipe Magalhaes[b]

[a] *University of Molise, Viale Manzoni, Campobasso 86100, Italy*
[b] *Construct-ViBest, Faculty of Engineering (FEUP), University of Porto, R. Dr. Roberto Frias, Porto 4200-465, Portugal*

Abstract

Modal based damage detection is a well-established procedure for Structural Health Monitoring (SHM) of civil structures. The development of robust algorithms for automated output-only modal parameter identification and tracking has renewed the interest towards modal based damage detection. However, the influence of environmental and operational variables on modal parameter estimates still represents a relevant shortcoming to their extensive use for SHM, because it can yield changes in the experimental estimates of the same order of magnitude of those induced by damage. As a consequence, there is the need to remove the effects of those factors in order to effectively detect damage. Different approaches can be adopted, some of which do not require measurements of the environmental and operational variable influencing the modal parameter estimates. Nevertheless, the effective removal of the environmental influence on modal parameters still remains a challenging aspect in SHM.

In the present paper, different approaches for compensation of environmental effects are applied to a very large database of modal parameter estimates from a bridge in operational conditions. The objective of the paper is to investigate their performance under the concurrent influence of different environmental/operational variables (for instance, temperature and traffic) on modal parameter estimates. Static (effect on the estimate at time t depends only on the value of the variable at the same time instant) as well as dynamic (effect on the estimate at time t depends on the values of the variable at time t and also at previous time instants) methods are considered. The results of the study remark the relevance of identifying all sources of variability of the modal parameters in operational conditions.

Keywords: Operational Modal Analysis; environmental influence; Second Order Blind Identification.

* Corresponding author. Tel.: +39-0874-404-959; fax: +39-0874-404-952.
E-mail address: carlo.rainieri@unimol.it

1877-7058 © 2017 The Authors. Published by Elsevier Ltd.
Peer-review under responsibility of the organizing committee of EURODYN 2017.
10.1016/j.proeng.2017.09.210

1. Introduction

The development of advanced sensing, data acquisition and data processing techniques has made SHM more and more attractive and widely accepted for the structural diagnosis of bridges and buildings [1]. A variety of damage detection techniques have been developed over the past decade. Among them, modal-based damage detection methods have been widely investigated and they are rapidly spreading after the development of reliable automated OMA procedures [2, 3]. The basic principle of modal based damage detection is very simple. Defining damage as any change (mass change, stiffness change, connectivity change, boundary condition change) of the structure that adversely affects its performance [1], and taking into account that the modal parameters depend on the physical parameters (mass, stiffness and damping), damage can be detected from the variations of the modal parameters.

A number of damage sensitive features based on modal parameters have been defined and tested over the years. Natural frequencies and mode shapes are often used as damage features. The possibility of getting accurate estimates even in the presence of a few installed sensors is one of the reasons of the popular use of natural frequency variations as damage feature. However, the sensitivity of natural frequency estimates to EOVs represents one of the main drawbacks to the extensive application of modal based damage detection [4]. EOVs can cause changes in the natural frequency estimates of the same order of magnitude of those induced by damage. As a consequence, the estimates have to be depurated from the effects of EOVs in order to carry out reliable damage detection [1].

Temperature has been recognized as one of the factors having large influence on natural frequency estimates. In order to compensate its effect, a model representing the functional dependence of natural frequencies from the temperature is required. Regression models can be set by collecting a large number of observations of natural frequencies as well as of the EOV. However, the temperature distribution in actual structures is usually non-uniform and time dependent, as a result of the combined effects of air temperature, solar radiation, wind speed and thermal conductivity of the materials [5]. This can affect the accuracy of regression models based on air temperature, surface temperature only or even on temperature measured on a limited set of internal points of the structure. Thus, there is the need for approaches able to take into account the effect of non-uniformly distributed temperature on natural frequencies. Furthermore, when temperature is not the only parameter influencing the estimates, the selection of the EOVs to use in the development of the model is often not straightforward. Moreover, in many cases they cannot even be measured. In all the previously mentioned circumstances approaches based on alternative statistical tools [6, 7] represent an advantageous alternative to correct the natural frequency estimates without the need of measuring the environmental and operational factors.

In the present paper a very large database of modal parameter estimates from a bridge in operational conditions is analyzed in order to assess the performance of SOBI in removing the influence of EOVs in comparison with static (effect on the estimate at time t depends only on the value of the variable at the same time instant) and dynamic (effect on the estimate at time t depends on the values of the variable at time t and also at previous time instants) regression models based on different selections of predictors. In particular, the objective of the paper is to investigate its performance under the concurrent influence of different EOVs (for instance, temperature and traffic) on modal parameter estimates. This is also the reason behind the comparison with regression models: in fact, they require the explicit definition of the predictors, thus identifying the (multiple) EOVs that are responsible of natural frequency variations in the present case. The results of the study remark the relevance of identifying all sources of variability of the modal parameters in operational conditions for effective modal-based damage detection.

Nomenclature

SHM	Structural Health Monitoring
OMA	Operational Modal Analysis
EOV	Environmental and Operational Variable
MLR	Multiple Linear Regression
SOBI	Second Order Blind Identification
PCA	Principal Component Analysis

2. Modal parameter monitoring of the Infante D. Henrique Bridge

2.1. The bridge and the monitoring system

The Infante D. Henrique Bridge, located at the north of Portugal, presents a rigid prestressed concrete box girder, 4.50m deep, supported by a shallow and thin reinforced concrete arch, 1.50m thick (Fig. 1). The arch spans 280m between abutments and rises 25m until the crown. In the 70m central segment, arch and deck join to define a box girder 6m deep [8].

In 2007, this bridge was equipped with a dynamic monitoring system. This is essentially composed by 12 force balance accelerometers, which are installed inside the deck box girder and distributed along the bridge according to the scheme presented in Fig. 1. In order to obtain a good characterization of the lateral bending, vertical bending and torsion modes, each section includes tree sensors. Moreover, temperature sensors embedded in the box girder slabs (Fig. 1) are also present. The collected data is processed by a dynamic monitoring software developed in ViBest/FEUP called DynaMo. Modal properties are continuously estimated based on 30 minute long records of the structural response in operational conditions [9]. The automation of the identification using parametric methods implied the development of a new processing tool that is grounded on clustering techniques and is fully detailed in reference [2]. The identification of the modal parameters is followed by a procedure that links the new set of modes with the ones identified in previous setups, also explained in [2]. In the case of the bridge under analysis this methodology permitted the automatic tracking of 12 vibration modes.

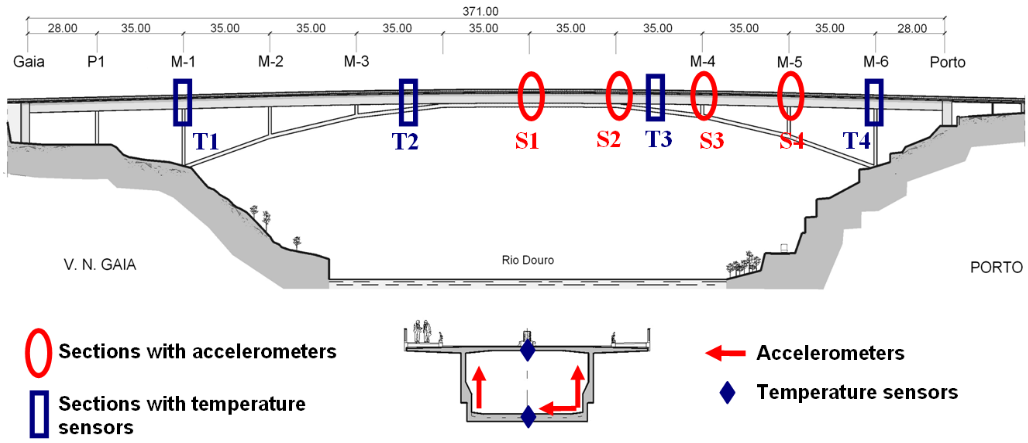

Fig. 1. Elevation of the bridge with the distribution of the accelerometers and temperature sensors.

2.2. Influence of EOVs on modal parameters

Temperature daily and annual variations and traffic over the bridges definitely yield fluctuations of the estimated natural frequencies. The effects of the temperature annual variations are depicted in Fig. 2, using as example the bridge first natural frequency. The inverse proportionality between temperature and frequency is evident.

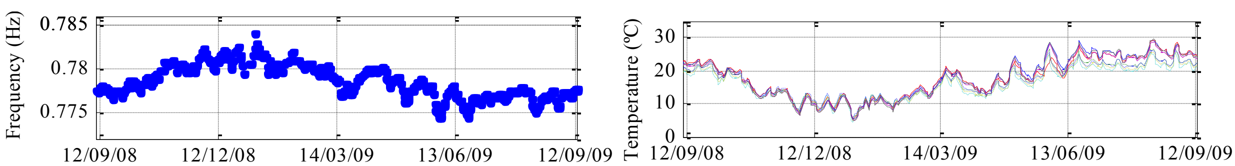

Fig. 2. Left: variation of the first natural frequency daily averages. Right: variation of the temperature daily averages (solid line – sensors at the top slab; dashed line – sensors at the bottom slab). Period from 13/09/2008 to 12/09/2009.

The daily variations of the bridge modal parameters are influenced also by the traffic that crosses the bridge. Due to the existence of friction in the sliding bearings (present in the connection of the deck with the abutments), their stiffness depends on the vibration amplitude that is essentially influenced by the traffic intensity. Since this bridge is one of the main entrances to the Porto city center, it undergoes relevant variations of traffic intensity, with dense traffic during the working days. Furthermore, the existence of traffic lights at the bridge end in the side of Porto motivates important traffic jams over the bridge in the beginning of the morning from 7:00 to 10:00 (Fig. 3).

Looking for example at the typical daily evolution of the first natural frequency (lateral mode) represented in Fig. 3, two effects can be observed: a sudden decrease of approximately 0.003 Hz at the morning rush hour and a variation of about 0.002Hz from daylight to night. The first drop can be explained by the extra mass of the cars stopped over the bridge. Due to the joint influence of temperature and vibration amplitude, the remaining daily variations have to be interpreted with some caution, as both vibration amplitude and temperature decrease from daylight to night.

Fig. 3. From left to right: typical traffic in the periods from 7:00 to 10:00, and from 10:00 to 19:00; daily evolution of the first natural frequency.

3. SOBI and compensation of environmental effects

Different approaches to model the environmental influence on natural frequency estimates can be pursued depending on whether measurements of the EOVs are available or not. If they are available, regression analysis is the simplest approach to model the environmental influence. MLR [10] can be used to identify the relation between some dependent variables (the identified natural frequencies) and several independent variables, the so-called predictors. The established model allows the prediction of future values of the dependent variable when only the predictors are known. In the context of SHM, establishing MLR models requires data collected over a sufficiently long period of time, so that the influence of environmental factors on natural frequencies can be exhaustively characterized. Once the model has been set, predicted natural frequencies are compared to newly collected experimental estimates in order to compensate the environmental influence.

When measurements of the EOVs are not available, statistical methods can be applied. PCA [7] is probably the most popular approach in this class of methods. SOBI [11] is herein applied to remove the effect of EOVs on natural frequency estimates [12]. Natural frequency time series are modelled as a linear combination of sources $\{s\}$ (the unknown environmental factors) plus the residue $\{\varepsilon\}$:

$$\{f\} = [A]\{s\} + \{\varepsilon\} \tag{1}$$

With respect to PCA, which relies on the eigenvalue decomposition of the zero-lag correlation matrix, SOBI is based on the joint approximate diagonalization [13] of several time-shifted covariance matrices. It allows the computation of the mixing matrix [A] and the sources from the collected data. For the theoretical formulation of the method, the sources are assumed to be stationary, uncorrelated, and scaled to have unit variance. Moreover, the sources are assumed to be uncorrelated from the noise [14].

When SOBI is applied to remove the influence of EOVs, starting from a sufficiently large amount of data related to the healthy state of the structure the reference mixing matrix $[A_{ref}]$ is identified. After the estimation of $[A_{ref}]$, newly collected data are processed to estimate the corresponding sources. These are recombined by the $[A_{ref}]$ matrix and the resulting values are subtracted from the experimental ones in order to compute the residues, which are independent of the EOVs so they can be profitably used as damage sensitive features for vibration based SHM.

It is worth noting that the mixing matrix is determined up to a scaling and a permutation of its rows, which prevents the determination of the variances of the identified sources [15]. Thus, in order to remap the identified sources to the original space an appropriate scaling factor has to be determined to avoid bias. It can be computed as the ratio between the first singular value of the reference mixing matrix and that of the mixing matrix estimated from the current data [12].

4. Results and discussion

The predictive performance of SOBI is herein compared with static and dynamic regression models based on different selections of predictors. Two datasets collected by the monitoring system of the Infante D. Henrique Bridge are considered. They refer to the first (from September 13th, 2007 to September 12th, 2008) and second year (from September 13th, 2008 to September 12th, 2009) of operation of the monitoring system, respectively. The first dataset is used to establish the model of variation of natural frequencies due to EOVs, while comparisons between measurements and predictions are based on data collected during the second year. In particular, the predictive performances of SOBI and regression models are evaluated by computing mean squared value of the residues for each modal frequency (Table 1). Three sources have been identified by applying SOBI to the above-mentioned datasets. Thus, 12×3 mixing matrices have been considered to develop the model. Predictors used to set static (SM#) and dynamic (DM#) regression models are: temperature for SM1, temperature and rms values of lateral and vertical acceleration for SM2, temperature, rms of acceleration and damping for SM3, temperature at different time delays (6, 12, 18 and 24 hours), rms of acceleration and damping for the dynamic model. More details can be found in [16]. SOBI produced much lower residues than MLR, thus confirming its superior performance in describing the variability of the frequencies.

Table 1. Performance comparison of different predictive models (mean squared error).

Mode #	SOBI	SM1	SM2	SM3	DM
1	1.73E-7	1.26E-06	1.04E-06	1.01E-06	1.00E-06
2	8.41E-7	6.84E-06	2.89E-06	2.71E-06	2.02E-06
3	4.59E-7	2.84E-06	1.97E-06	1.91E-06	1.90E-06
4	8.31E-7	1.93E-06	1.52E-06	1.51E-06	9.20E-07
5	7.83E-7	5.49E-06	4.27E-06	4.22E-06	4.22E-06
6	1.34E-6	6.43E-06	4.67E-06	4.67E-06	3.76E-06
7	2.80E-6	1.28E-05	8.78E-06	8.79E-06	6.13E-06
8	2.48E-6	1.65E-05	1.27E-05	1.27E-05	9.53E-06
9	2.54E-6	1.73E-05	1.47E-05	1.47E-05	1.33E-05
10	2.17E-6	3.18E-05	3.01E-05	2.89E-05	2.48E-05
11	1.71E-6	2.07E-05	1.61E-05	1.60E-05	1.24E-05
12	2.72E-6	2.83E-05	2.28E-05	2.28E-05	2.27E-05

Fig. 4 shows the identified sources. Monitoring started on September 13th, 2008 (Saturday) at 00:00. 48 samples per day are collected, thus conversion of sample number into date and time is straightforward. In particular, Fig. 4a shows that the temperature is definitely one of the factors responsible for the variation of natural frequencies. Fig. 4b shows a correlation between one of the identified sources and the rms acceleration. Moreover, peaks occurring in the time of large traffic jam characterize that source. Thus, it is representative of the influence of traffic. The third identified source, instead, is still under investigation. It shows a cyclic behaviour with recurring peaks early in the morning (in the range 4:00 to 6:00 a.m.) and early in the afternoon (in the range 3:00 to 4:00 p.m.).

4. Conclusions

The use of SOBI for compensation of environmental effects on natural frequency estimates has been discussed in the paper. A major advantage of the method is its capacity to model the environmental and operational variability of natural frequencies and, at the same time, to trace the pattern of the EOVs up to a scaling factor and an offset. The performance of SOBI in removing the environmental effects have been assessed in comparison with static and dynamic regression models, obtaining very good results. Moreover, the effectiveness of the method in the presence of multiple EOVs influencing the natural frequency estimates has been demonstrated. Thus, SOBI open interesting applicative perspectives in the characterization of the influence of EOVs on the dynamic response of structures.

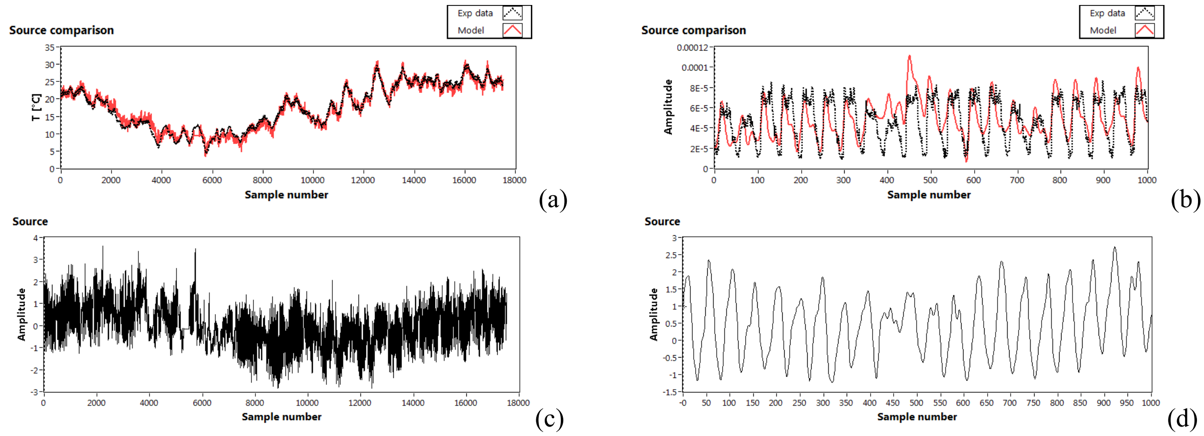

Fig. 4. Identified sources: (a) temperature; (b) traffic jam; Third source - under investigation -: (c) all samples; (d) first 1000 samples.

References

[1] C.R. Farrar, K. Worden, Structural health monitoring: a machine learning perspective, John Wiley and Sons Ltd., Chichester, 2012.

[2] F. Magalhaes, A. Cunha, E. Caetano, Online automatic identification of the modal parameters of a long span arch bridge, Mech Syst Signal Process 23 (2009) 316-329.

[3] C. Rainieri, G. Fabbrocino, Development and validation of an automated operational modal analysis algorithm for vibration-based monitoring and tensile load estimation, Mech Syst Signal Process 60-61 (2015) 512-534.

[4] B. Peeters, G. De Roeck, One-year monitoring of the Z24-Bridge: environmental effects versus damage events, Earthquake Eng Struc 30 (2001) 149-171.

[5] H. Nandan, M.P. Singh, Effects of thermal environment on structural frequencies: Part I – A simulation study, Eng Struct 81 (2014) 480-490.

[6] A. Deraemaeker, E. Reynders, G. De Roeck, J. Kullaa, Vibration-based structural health monitoring using output-only measurements under changing environment, Mech Syst Signal Process 22 (2008) 34-56.

[7] A.-M. Yan, G. Kerschen, P. De Boe, J.-C. Golinval, Structural damage diagnosis under varying environmental conditions – Part I: A linear analysis, Mech Syst Signal Process 19 (2005) 847-864.

[8] A. Adão da Fonseca, F. Milanes Mato, Infante Henrique Bridge over the River Douro, Porto, Structural Engineering International - Journal of the International Asssociation for Bridge and Structural Engineering (IABSE) 15 (2005) 85-87.

[9] F. Magalhães, Á. Cunha, E. Caetano, Dynamic Monitoring of a Long Span Arch Bridge, Eng Struct 30 (2008) 3034-3044.

[10] J.F. Hair, W.C. Black, B.J. Babin, R.E. Anderson, Multivariate Data Analysis, Pearson Prentice Hall, Upper Saddle River, 2010.

[11] A. Belouchrani, K. Abed-Meraim, J.F. Cardoso, E. Moulines, A blind source separation technique using second-order statistics, IEEE T Signal Proces 45 (1997) 434-444.

[12] C. Rainieri, D. Gargaro, G. Fabbrocino, On the use of Second Order Blind Identification for the characterization of the environmental influence on modal parameter estimates, Proceedings of The 8th European Workshop on Structural Health Monitoring, Bilbao, 2016.

[13] J. F. Cardoso, A. Souloumiac, Jacobi angles for simultaneous diagonalization, SIAM J Matrix Anal A 17 (1996) 161–164.

[14] C. Rainieri, Perspectives of Second-Order Blind Identification for Operational Modal Analysis of Civil Structures, Shock Vib (2014), Article ID 845106.

[15] F. Poncelet, G. Kerschen, J.C. Golinval, D. Verhelst, Output-only modal analysis using blind source separation techniques, Mech Syst Signal Process 21 (2007) 2335-2358.

[16] F. Magalhães, Á. Cunha, E. Caetano, Vibration based structural health monitoring of an arch bridge: from automated OMA to damage detection, Mech Syst Signal Process 28 (2012) 212-228.