Online Automatic Identification of Modal Parameters of a Bridge using the p-LSCF Method

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**ABSTRACT:** A concrete arch bridge over the Douro River, at the City of Porto in Portugal, is being monitored by twelve accelerometers since September 2007. The present paper describes in detail the methodology used to perform the on-line automatic identification of the modal parameters using the poly-Least Squares Complex Frequency Domain method (p-LSCF). The results obtained with this algorithm are compared with the ones obtained with the previously implemented Covariance driven Stochastic Subspace Identification method using one-year database.

1 INTRODUCTION

The development and validation of tools for automatic identification of modal parameters based on measurement of bridge responses during normal operation is fundamental, as the success of subsequent damage detection algorithms depends on the accuracy of these estimates. Furthermore, it is essential that those routines are robust enough to work on an online basis, in order to permit the evaluation of the structural health in almost real-time.

Therefore, it is opportune to perform practical applications on full-scale bridges with the most advanced commercially available dynamic monitoring hardware and to conjugate that with processing routines that take profit from the latest theoretical developments.

Taking into account, a multi-channel dynamic monitoring system was installed on a long span concrete arch bridge and software was developed to continuously track the variation of its modal parameters using the data that is continuously received at FEUP through Internet.

The monitoring software comprehends routines that perform the on-line automatic identification of the bridge modal parameters using three different approaches: the Frequency Domain Decomposition method (FDD), the Covariance driven Stochastic Subspace Identification method (SSI-COV) and the poly-Least Squares Complex Frequency Domain method (p-LSCF), also known under its commercial name PolyMax.

This paper describes in detail the methodology used to perform the automatic identification of the modal parameters with the p-LSCF method. The results of this algorithm are compared with the ones obtained with the SSI-COV method using one-year database.

2 DESCRIPTION OF THE BRIDGE AND MONITORING SYSTEM

The “Infante D. Henrique” Bridge, over the Douro River, was open to traffic in 2004 to link the cities of Porto and Gaia, located at the north of Portugal. It comprehends a very rigid prestressed concrete box beam, 4.50 m deep, supported by an extremely shallow and thin
reinforced concrete arch, 1.50 m thick (Fig. 1). The arch spans 280 m between abutments and rises 25 m until the crown. In the 70 m central segment, arch and deck join to define a box girder 6 m deep. The arch has constant thickness and its width increases linearly from 10 m in the central span up to 20 m at the springs (Adão da Fonseca and Millanes Mato 2005). Owing to the high stiffness of the deck in relation to the slenderness of the arch, the structure behaves as a beam bridge defined between abutments and with intermediate elastic supports 35 m apart (distance between the concrete elements that provide the connection between deck and arch).

Figure 1: “Infante D. Henrique” bridge view from upstream (Porto at the right side and Gaia at the left).

The dynamic monitoring system installed in the “Infante D. Henrique” bridge is essentially composed by 12 force balance accelerometers (Kinematics, Episensor), 2 digitizers (Kinematics, Q330) and an internet router, which are placed inside the deck box girder and distributed along the bridge according to the scheme presented at Fig. 2. A more detailed description of the hardware is presented in reference Magalhães, Cunha et al. (2008).

The bridge is roughly symmetric and the previously performed ambient vibration test proved that the mode shapes are approximately symmetric. Therefore, as the number of available sensors was twelve, it was decided to instrument just one half of the bridge instead of smearing the sensors along the whole bridge, in order to obtain a good spatial characterization of as many modes as possible. Consequently, those accelerometers were distributed along four sections between the mid-span and the abutment at the Porto bank. Three sensors equip each section: one to measure lateral acceleration and two for vertical accelerations at the downstream and upstream sides (the ambient test showed the existence of torsion modes in the analysed frequency range).

The data produced by the digitizers is received at FEUP, as ASCII files containing the acceleration time series with a predefined sampling rate and length. For the monitoring of this bridge, a sampling frequency of 50 Hz and a record length of 30 minutes were selected. These files are then processed by software developed in MatLab at the Laboratory of Vibration and Structural Monitoring (www.fe.up.pt/vibest) of FEUP. The software, called DynaMo (standing for DYNAmic MOnitoring), includes the online execution of the following tasks:

− creation of a database with the original data (sampled at 50 Hz) that can be later used to test alternative processing methodologies;
− pre-processing of data to eliminate the offset and to reduce the sampling frequency from 50 to 12.5 Hz (the first 12 modes are below 5 Hz);
− processing of data for automatic identification of modal parameters using three different identification algorithms: FDD, SSI-COV and p-LSCF;
− creation of a database with the results of the processing.

The database with all the results can then be consulted using a graphical user interface (DynaMo Viewer) that comprehends tools to create several types of plots for a given time interval, like the ones presented at section 4.

The dynamic monitoring system is complemented by a static monitoring system that includes strain gages, clinometers and temperature sensors. The data of the temperature sensors is of particular interest for the development of numerical models to eliminate the effect of the environmental temperature on the modal parameters.
3 AUTOMATIC IDENTIFICATION OF MODAL PARAMETERS

3.1 Introduction to the poly-Least Squares Complex Frequency Domain method

The application of the Fourier Transform to the set of second-order differential equations, describing the motion of a linear structure with \( n \) degrees of freedom, gives, after simple mathematical manipulations, the following equation:

\[
Y(\omega) = H(\omega) \cdot X(\omega)
\]  
(1)

where \( Y(\omega) \) is a vector with the Fourier Transforms of the \( m \) measured structural responses, \( X(\omega) \) is a vector with the Fourier Transforms of the excitation loads applied to \( l \) degrees of freedom and \( H(\omega) \) is a \( m \times l \) matrix containing Frequency Response Functions (FRFs).

The FRF matrix can be expressed in terms of the structure modal parameters:

\[
H(\omega) = \sum_{k=1}^{n} \frac{\phi_k^T \cdot l_k^T}{i \cdot \omega - \lambda_k} + \frac{\phi^*_k \cdot l_k^T}{i \cdot \omega - \lambda^*_k}
\]  
(2)

where \( n \) is the number of modes, \( \cdot^T \) is the transpose of a matrix, \( \cdot^* \) is the complex conjugate of a matrix, \( \cdot^{\text{H}} \) is the complex conjugate transpose of a matrix (Hermitian), \( \phi_k \) is a column vector containing the mode shape \( k \), \( l_k \) is a line vector with the modal participation factor of mode \( k \) and \( \lambda_k \) are the structure poles, which are related to the natural frequencies \( \omega_k \) and modal damping ratios \( \xi_k \) through the equation:

\[
\lambda_k = -\xi_k \cdot \omega_k \pm i \sqrt{1 - \xi_k^2} \cdot \omega_k
\]  
(3)

In Experimental Modal Analysis both inputs and outputs are measured, and therefore, it is possible to directly obtain experimental FRFs. In the case of Operational Modal Analysis only outputs are measured. As a consequence, the parametric frequency domain identification algorithms have to be based on output spectra \( (S_{yy}) \), which are related to the FRF matrix by the expression (Ljung 1999):

\[
S_{yy}(\omega) = H(\omega) \cdot S_{xx} \cdot H(\omega)^{\text{H}}
\]  
(4)

The not measured input spectra \( (S_{xx}) \) are assumed to be white noise, which means that the spectra are constant, not depending on the frequency \( (\omega) \). Similar to the FRF matrix, the output
spectra matrix can also be modally decomposed (Parloo 2003):

\[
S_{\gamma}(\omega) = \sum_{k=1}^{N} \phi_k^T g_k^T + \phi_k^T g_k^H + g_k \cdot \phi_k^T \frac{1}{i\omega - \lambda_k} + g_k \cdot \phi_k^H \frac{1}{i\omega - \lambda_k} \tag{5}
\]

In the previous expression, the operational reference vectors \(g_k\) take the place of the modal participation factors. These do not have a special physical meaning and are functions of the modal parameters and input spectra.

It is well known that the spectra are equal to the Discrete Fourier Transform (DFT) of the correlations. Furthermore, it is possible obtain the so-called half spectra by applying the DFT only to the positive time lags of the correlations. The modal decomposition of these spectra is as follows (Peeters and Van der Auweraer 2005):

\[
S_{\gamma}^+(\omega) = \sum_{k=1}^{N} \phi_k^T g_k^T + \phi_k^T g_k^H \tag{6}
\]

As evidenced by the previous expression, the half spectra have the advantage of presenting less poles that the spectra and of having exactly the same structure as the FRFs, making the adaptation of the input-output modal estimation methods into output-only methods straightforward.

The p-LSCF method was firstly developed to perform the identification of modal parameters from FRFs. However, taking into account the previous explanation, its adjustment for Operational Modal Analysis is direct.

The method models the FRF or half-spectra matrix using a right-fraction description in the z-domain (frequency domain model derived from a discrete-time model):

\[
S_{\gamma}^+(\omega) = B(\omega) \cdot A(\omega)^{-1} \tag{7}
\]

\(B\) and \(A\) matrices being polynomials defined as:

\[
B(\omega) = \sum_{j=1}^{p} \beta_j \cdot e^{i\omega \Delta t j} \quad A(\omega) = \sum_{j=1}^{s} \alpha_j \cdot e^{i\omega \Delta t j} \tag{8}
\]

where \(\beta\) and \(\alpha\) are matrices with the model parameters, \(p\) is the order of the polynomials and \(\Delta t\) is the sampling time used to measure the structural responses. The number of lines of the half-spectra is equal to the number of measured degrees of freedom \(m\) and it has as many columns as the number of dof selected for references \(nr\), which is less than or equal to \(m\). \(\beta\) and \(\alpha\) are real matrices with dimensions \(mn\times nr\) and \(ns\times nr\), respectively.

The goal of the identification algorithm is to find the matrices \(\beta\) and \(\alpha\) that minimize the differences between the half-spectra estimated from the measured acceleration time series (represented by \(S_{\gamma}^+\)) and the theoretical half-spectra given by Eq. (7). However, the direct minimization of the difference between both spectra leads to a nonlinear optimization problem. In order to avoid this, the error to be minimized is formulated as (Peeters and Van der Auweraer 2005):

\[
e(\omega) = B(\omega) - S_{\gamma}^+ \cdot A(\omega) \tag{9}
\]

where \(\omega\) (\(i = 1, 2, \ldots, N\)) are the discrete frequency values contained in the frequency range selected to perform the identification and \(e(\omega)\) is a \(mn\times nr\) matrix with the errors to be minimized. Considering all the squared errors on the selected frequency interval, the quadratic function that is minimized becomes:

\[
E = \sum_{i=1}^{N} \sum_{r=1}^{nr} e_{\gamma r}(\omega_i) \cdot e_{\gamma r}(\omega_i)^* \tag{10}
\]

Following the usual procedure of a least squares problem, the derivatives of the error \(E\) with respect to the unknowns (elements of the \(\beta\) and \(\alpha\) matrices) are calculated and forced to become zero. With some simple mathematical manipulations, it is possible to eliminate the unknowns contained in the \(\beta\) matrices from the obtained set of equations, achieving an equation of the type:
\[ M \cdot \alpha = 0 \]  

where \( \alpha \) is a matrix that contains all the \( \alpha_k \) matrices on the top of each other. The full expression of the \( M \) matrix, computed from the measured data, is presented by Peeters and Van der Auweraer (2005). In order to avoid the trivial solution \( \alpha = 0 \), a constraint has to be imposed on the parameters, as for instance, forcing \( \alpha_k \) to be equal to the identity matrix.

The operational reference vectors and the poles, and as a consequence the natural frequencies and the modal damping ratios (Eq. (3)), can be obtained from the calculated \( \alpha \) matrix (Heylen, Lammens et al. 2007). The mode shapes are then, usually found with another least squares problem using Eq. (6) adapted to include two residual terms to approximate the effect of the modes below and above the frequency band of interest (Heylen, Lammens et al. 2007). This is a linear problem because the only unknowns of the equation are the mode shape components and the residual terms.

### 3.2 From a right-matrix fraction description model to a state-space model

During the development of the Dynamic Monitoring software for the “Infante D. Henrique” bridge, the Covariance driven Stochastic Subspace method (SSI-COV) together with an algorithm to perform the automatic identification of the modal parameters was implemented before the p-LSCF. In order to take profit from the developed automatic identification procedure also with the p-LSCF, the estimated right-matrix fraction description model is converted into a z-domain state-space model, with a structure that is similar to the one obtained with the application of a SSI method.

The state-space representation of a stochastic (input not measured) linear system in the discrete frequency domain (z-domain) is (Juang 1994):

\[
\begin{align*}
\dot{x}(z_k) &= A \cdot x(z_k) + w(z_k) \\
y(z_k) &= C \cdot x(z_k) + v(z_k)
\end{align*}
\]

where \( z \) is equal to \( e^{i\omega t} \), \( x(z_k) \) is the z-transform of the state vector; \( y(z_k) \) is the z-transform of the outputs, \( A \) is a discrete time state matrix, \( C \) is a discrete time output matrix and \( w(z_k) \) and \( v(z_k) \) are the z-transforms of vectors that represent the noise due to disturbances and modelling inaccuracies and the measurement noise due to sensor inaccuracy.

Before doing the conversion, the \( \beta \) matrices have to be calculated from the \( \alpha \) matrix given by Eq. (11). This is easily achieved using the expressions presented by Peeters and Van der Auweraer (2005). Then, matrices \( A \) and \( C \) of the stochastic state space model are given by the equations:

\[
A = \begin{bmatrix}
-\alpha_{k-1} & -\alpha_{k-2} & \ldots & -\alpha_{p-k} & \alpha_0 \\
I & 0 & \ldots & 0 & 0 \\
\vdots & \ddots & \ddots & \vdots & \vdots \\
0 & 0 & \ldots & I & 0 \\
\end{bmatrix}
\]

\[
C = \begin{bmatrix}
\beta_{p-1} & -\beta_{p} \cdot \alpha_{k-1} & \alpha_{p-2} & \ldots & -\beta_{p} \cdot \alpha_{p-k} \\
\end{bmatrix}
\]

which were adapted from the ones derived by Juang (1994) for the case where the basis functions of the polynomials are \( e^{i\omega t} \). From this point, the identification follows the classical steps of the SSI algorithms.

### 3.3 Algorithm for Automatic Identification of Modal Parameters

The identification method presented before requires the definition of an order for the polynomial used on the right-fraction description model (\( p \) in Eq. (8)) and for real structures, it is not possible to predict the order that better fits the experimental data. Therefore, an appropriate way to overcome this difficulty is to estimate the modal parameters using models with orders within an interval previously fixed in a conservative way (the upper limit is much higher than the number of physical modes of the system within the frequency range under analysis). However, the higher order models contain numerical modes (also called spurious or
noise modes), which do not have physical relevance but are needed to model the noise existent in measured data.

Separation of physical and spurious modes is then a crucial step of the identification algorithm. The most popular approach to achieve this is based on a stabilization diagram (Fig 3). However, the stabilization diagram by itself does not solve the problem of modal parameters identification; it is just a graphical tool to help on the manual selection of the poles that are more likely to represent the structure physical modes. In the context of continuous monitoring, it is crucial to develop tools to achieve the identification without any user interaction.

The proposed methodology for the automatic selection of the best modal parameters from a set of modal parameters provided by models of several orders is based on a hierarchical clustering algorithm. This statistical tool groups the mode estimates with similar natural frequencies and mode shapes and allows the selection of the groups associated with physical mode estimates (the ones that contain more elements). The final estimates are then obtained by averaging the estimates inside the selected groups, after the elimination of possible outliers, taking into account the modal damping ratios. A full description of the algorithm together with a literature review of alternative methods is presented by Magalhães, Cunha et al. (2009). Its practical application is illustrated in the next section.

### 3.4 Practical application of the p-LSCF method

Before the application of the identification method, the time series collected at the “Infante D. Henrique” bridge, with a length of 30 minutes and a sampling frequency of 50Hz, were detrended, low-pass filtered and resampled with a frequency of 12.5Hz.

The first step of the p-LSCF method is the calculation of the spectra matrix, whose elements are the Fast Fourier Transform of the positive lags of the time series correlations, after the application of an exponential window to reduce the leakage errors. In the present application, correlations with 1024 positive time lags were calculated using a fast implementation of the summation formula. An exponential window was applied with a factor of 0.1 (ratio between the values of the window at the correlation last point and at zero). As all the measured degrees of freedom were selected as references, the spectra matrix has dimensions 12x12.

Then, the fitting of the theoretical spectra was performed in the frequency range 0.5 - 5 Hz, using polynomials with orders between 1 and 18. The stabilization diagram presented at Fig. 3 shows, for one setup collected by the continuous monitoring system, the modal parameters estimated by all the used polynomial orders after the conversion of the right-fraction model into a state-space model. This plot also illustrates the ability of the p-LSCF method to deliver very clear stabilization diagrams, due to the fact that most of the numerical poles have negative damping and therefore are easily separated (small yellow circles).

![Stabilization Diagram](image1)

Fig. 3: Stabilization diagram of the data collected at 12:00 24/10/2007

![Clusters](image2)

Fig. 4: Clusters associated with the analysis of the stabilization diagram of Fig.3

Fig. 4 characterizes, for the same setup, the clusters formed with all the mode estimates extracted from all the fitted models. These were organized in such way that all the mode estimates inside each group respect the following: the distance to the closest point is lower than 0.02; being the distance between two mode estimates given by the natural frequency relative difference plus one minus the MAC (0 - orthogonal shapes; 1 - the same shape) of the mode shapes. The 12 groups that contain the physical estimates clearly stand out.

Finally, the 14 groups with more elements are selected (two extra groups are selected to improve the capability to identify lowly excited modes). After the elimination of mode
estimates with extreme modal damping ratios (outlier analysis), the average natural frequencies and mode shapes of each group are compared with 12 reference mode estimates (previously obtained from the analysis of several setups). Then, the new estimate for each reference mode is chosen, using the MAC ratio as selection criterion, from a group composed by all the selected clusters mean estimates that have a natural frequency that does not differ more than 15% from the reference value. The estimate is only accepted if the MAC ratio is higher than 0.8. In this way, the link between estimates of the same physical mode is achieved and simultaneously, possible frequency shifts lower than 15%, motivated by environmental variables or possible damages, are allowed.

4 RESULTS OF ONE YEAR OF CONTINUOUS MONITORING

The dynamic monitoring system of the “Infante D. Henrique” bridge has been working since the 13th of September of 2007. Therefore, the database of the results contains the variation of the bridge modal parameters, identified with three different methods, for more than one year. In this section the results delivered by the p-LSCF method are presented and compared with the ones provided by the SSI-COV. The comparison between the results of the FDD and SSI-COV methods has been already presented by Magalhães, Cunha et al. (2008).

Fig. 5 shows the time evolution of all the natural frequencies identified by the p-LSCF method in the frequency range 0.5-4.5 Hz from September 2007 to November 2008. Fig. 6 contains a zoom of the previous plot to illustrate the increase of the first frequency during the winter and its decrease during the summer. It is relevant to note the ability of the used procedure to well characterize such low frequency variations, contained in a narrow band of 0.01Hz.

![Figure 5: Variation of the first 12 natural frequencies identified with the p-LSCF method from 13/09/2007 to 30/11/2008](image)

![Figure 6: Variation of the first natural frequency identified with the p-LSCF method from 13/09/2007 to 30/11/2008](image)

![Figure 7: Variation of the modal damping ratios of the first 12 modes identified with the SSI-COV method from 10/11/2008 - 14/11/2008](image)

![Figure 8: Variation of the modal damping ratios of the first 12 modes identified with the p-LSCF method from 10/11/2008 - 14/11/2008](image)

At Table 1, the results of the SSI-COV and p-LSCF methods are compared using the identification success rate (S. R. is the ratio between the successful identifications and the total number of analysed setups) and the mean and standard deviation (std) values of the estimates obtained during the period under analysis. From the examination of this table it can be concluded that, in average, the performance of the two methods is similar, both presenting very high success rates, almost coincident mean values and close standard deviations. However, a detailed observation of the modal damping ratios estimates shows that the p-LSCF can provide
better results, as proven in Figs 7 and 8. In Fig. 8, the daily variations of the damping of the second mode (represented in green, higher values) with the bridge vibration amplitudes (high during the day and low at night) are much clearer than in Fig. 7. Fig. 8 also clearly shows a localized increase of the damping of the remaining modes at the beginning of the morning. This happens because at the Porto side bridge end there are traffic lights that induce traffic jams over the bridge at this time. The increase of the damping, which consistently occurs at the same hour, is certainly motivated by the suspension of the vehicles stopped over the bridge.

Table 1: Results synthesis of the SSI-COV and p-LSCF methods outputs from 13/09/2007 to 30/11/2008

<table>
<thead>
<tr>
<th>Mode</th>
<th>S. R.</th>
<th>f (Hz)</th>
<th>std(f)</th>
<th>ξ (%)</th>
<th>std(ξ)</th>
<th>S. R.</th>
<th>f (Hz)</th>
<th>std(f)</th>
<th>ξ (%)</th>
<th>std(ξ)</th>
</tr>
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<tr>
<td>1</td>
<td>99.99</td>
<td>0.778</td>
<td>0.002</td>
<td>0.453</td>
<td>0.111</td>
<td>100</td>
<td>0.778</td>
<td>0.002</td>
<td>0.439</td>
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<tr>
<td>2</td>
<td>100</td>
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<td>0.005</td>
<td>1.190</td>
<td>0.373</td>
<td>99.99</td>
<td>0.821</td>
<td>0.004</td>
<td>1.187</td>
<td>0.377</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
<td>1.146</td>
<td>0.003</td>
<td>0.471</td>
<td>0.117</td>
<td>100</td>
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<td>0.441</td>
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</tr>
<tr>
<td>4</td>
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<td>0.004</td>
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<td>0.114</td>
<td>100</td>
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<td>100</td>
<td>4.380</td>
<td>0.015</td>
<td>0.536</td>
<td>0.112</td>
</tr>
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</table>

5 CONCLUSIONS

This paper presented the procedure used to include the p-LSCF method in the framework of the dynamic monitoring system installed in a long span concrete arch bridge. The implemented algorithm made possible the online automatic identification of the modal parameters of the bridge first 12 modes, contributing to the construction of a database with results of more than one year. The implemented alternative algorithm of the p-LSCF has the advantages of avoiding the resolution of a second least-squares problem, of performing the automatic identification using the mode shapes, instead of operation reference vectors without physical meaning and of not making the identification of all the mode shapes dependent on the correct selection of all important poles. The comparison of the results of this method with the ones provided by the SSI-COV method showed that it delivers slightly better modal damping ratios estimates.

REFERENCES