Fully automated OMA: an opportunity for smart SHM systems

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ABSTRACT
Advances in dynamic identification procedures and optimization of hardware performances play a relevant role in the development of Structural Health Monitoring in hazardous areas. Several worldwide applications are reported in the literature and several methods able to assess the health state of a structure exist, some of which are based on tracking the modal characteristics of the structure during service life and especially after damage due to exceptional loads. The most relevant drawbacks of such methods, however, is represented by the need of a user intervention during the modal parameter identification processes, that does not fit requirements of SHM systems.

In this paper, an approach for automated modal parameters identification and tracking is described: the algorithm has been integrated in a fully automated SHM system and is based on a consolidated technique of operational modal analysis, the Frequency Domain Decomposition.

The algorithm has been implemented into a specific software package developed in LabView 8 environment and it is still submitted to extensive tests. Some results obtained since its integration in the SHM system of the School of Engineering Main Building at University of Naples are reported and the potentialities of such algorithm as engine of smart SHM system are described.

NOMENCLATURE
\[
\begin{align*}
[H(j\omega)] & \quad \text{Frequency Response Function matrix} \\
\{\Psi_r\} & \quad \text{Mode shape vector for the r-th mode} \\
\lambda_r & \quad \text{System pole corresponding to the r-th mode} \\
\omega & \quad \text{Circular frequency} \\
Q_r & \quad \text{Scaling factor for the r-th mode} \\
j & \quad \text{Immaginary unit } (j = \sqrt{-1})
\end{align*}
\]

INTRODUCTION
In recent years a growing interest in systems and techniques for early detection of damage based on vibration analysis has raised. Vibration-based techniques aims at tracking changes in structural response directly or indirectly related to the mechanical characteristics of the structure before and after damage, i.e. natural frequencies and mode shapes. However, changes of environmental and operational conditions make structural health monitoring complex and affect modal parameters as well \cite{1, 2}. An alternative approach is based on the post-processing of measures to detect anomalies from recorded time histories (ARMAV modelling, wavelet decomposition, etc.). In both cases, a common trend is to develop methods able to automate detection process and to exploit recent advances in information technologies (IT) \cite{3}. A relevant aspect related to the applicability of damage detection techniques as a part of monitoring practices is an automated identification and tracking procedure. This is not a trivial task since traditional modal identification always requires extensive interaction from an experienced user. Nevertheless, computational loads have to be taken into account in order to evaluate the applicability of modal identification techniques for damage detection purposes. In fact, fast on-line data processing is crucial for quickly varying in time systems (such as a rocket burning fuel). However, a number of vibration-based condition monitoring applications are performed at very different time scales resulting in satisfactory time steps for on-line data analysis.
Interesting examples are related to structural monitoring of large structures such as bridges [2, 4] or offshore platforms [4, 5].

In the present paper, a procedure, implemented in LabView environment and able to overcome some typical drawbacks of classical operational modal analysis, is described. The algorithm and the software are briefly discussed and a specific case study, related to the integration of the software into fully automated SHM systems, is analyzed.

**REVIEW OF AUTOMATED MODAL IDENTIFICATION ALGORITHMS**

The last few years have seen a large effort in the development of vibration based damage detection techniques [4]. In fact, since the dynamic behaviour of a structure is influenced by damage, it is possible to detect occurrence of relevant damage levels through the evolution of modal parameters [6, 7]. However, changes in environmental and operational conditions can affect the modal parameters estimation [8] as well. In this framework, an automated identification and tracking procedure is a fundamental step, because traditional modal identification requires extensive interaction from an experienced user [9]. Currently, there are some advancements in this field, with the development of methods based on control theory (both in time and frequency domain) and methods based on conventional signal processing.

As methods based on control theory are concerned, the model order is usually over-specified to get all physical modes present in the frequency range of interest according to classical modal analysis. However, physical and mathematical poles have to be distinguished. This practice requires large interaction with an expert user [10] and effective tools like the stabilization diagram. Selection of physical poles is not a trivial task: it may be difficult and time-consuming depending on the quality of data, the performance of the estimator (even if there are interesting advancements in this field [11]) and the experience of the user. Extensive interaction between tools and user is basically inappropriate for monitoring purposes. The first proposal for automated modal identification was based on the Least Square Complex Frequency (LSCF) method [9]. In this case the selection of physical poles from a high order model is based on a number of deterministic and stochastic criteria and a fuzzy clustering approach. However, the algorithm for pole selection is quite complex and computational demanding. In 2007 Deraemaeker et al. [12] proposed an automated operational modal analysis procedure based on the Stochastic Subspace Identification (SSI) technique. It is suitable as tracking method but it always requires user interaction because an initial set of modal parameters, using stochastic subspace identification and the stabilization diagram, has to be identified before launching the tracking procedure. Andersen et al. [13], instead, proposed in 2007 a fully automated method for extraction of modal parameters adopting the SSI technique. It is based on the clear stabilization diagram obtained according to a multipatch subspace approach: poles extraction is carried out by the graph theory. This algorithm seems to be very fast, so that it can be used for a monitoring routine, but further work is still needed in order to improve the numerical efficiency of the method.

As the methods based on conventional signal analysis are taken into consideration, Guan et al. [14] proposed in 2005 the so-called Time Domain Filtering method, which is a tracking procedure based on the application of a band-pass filter to the system response in order to separate the single modes in the spectrum. However, the frequency limits of the filter are static and, above all, user-specified according only to the Power Spectral Density (PSD) plots of the response signals: if excitation is unknown, it is sometimes difficult to identify the regions where certain modes may be located according only to power spectrum plots. Moreover, in the case of close modes, it is very difficult, or even impossible, to correctly define such limits in a way able to follow the natural changes in modal frequencies. Finally, in 2007 Brincker et al. [15] presented an algorithm for automation of the Frequency Domain Decomposition procedure in order to remove any user interaction and use it as modal information engine in a SHM system. It is based on the identification of the modal domain around each identified peak in the singular value plot according to predefined limits for the so-called modal coherence function and modal domain function. A good initial value for such limits would be 0.8. However, if the limit value for the modal coherence indicator is somehow justified [15] depending on the standard deviation of the correlation for random vectors and of the number of measurement channels, a few indications are reported for the modal domain indicator.

**THE AUTOMATED MODAL IDENTIFICATION ALGORITHM**

In this section the main ideas underlying the procedure for automated modal parameter identification and some implementation details are reported. A more detailed description of theoretical background of the algorithm and results of its application to a number of different case studies can be found elsewhere [16, 17].

The algorithm starts from the Singular Value Decomposition (SVD) of the output Power Spectral Density (PSD) matrix. The latter is the core of the Frequency Domain Decomposition (FDD) method. By recalling
that, when just a mode is dominant, in its bandwidth the Frequency Response Function (FRF) can be approximated as:

\[
[H(j\omega)] = \{\psi\}, \frac{Q}{(j\omega - \lambda)} \{\psi\}^T, \quad (1)
\]

the amplitude information depends only on the middle term, that is to say on the singular values of the PSD matrix, being the singular vectors of unity length [18]. Thus, by considering the singular vectors in the mode bandwidth, being here \{\psi\}, constant, the MAC index [19] computed at the same frequency line between the two first singular vectors and derived from two subsequent records should be constant and equal to 1 for a stationary and ergodic system. Actually, measurements are always affected by noise, so that specific selection criteria and tolerances must be set. Moreover, it is important to recognize since now that this is a necessary but, probably, not sufficient condition: thus, results of automated identification need some validation.

From a practical point of view, after applying decomposition, the first singular vector at each frequency line is obtained. This step is repeated for a number of subsequent records. Afterwards, the MAC between the two singular vectors at the same frequency line obtained from two different records is computed. However, the MAC index is quite sensitive to noise: in order to reduce the effect of noise, the averaged MAC vs. frequency plot is computed. Averaged MAC vs. frequency plot can be seen as a coherence function: where a certain mode is located, points are located very close each other and to 1 and a nearly flat shape is obtained as shown in Fig. 1. Identification of the bandwidth of each mode is carried out evaluating some statistical parameters related to the MAC value at each frequency line and to the difference between MAC values at two subsequent steps. As shown in Fig. 2, the MAC function is nearly horizontal only at the frequency lines located within a mode bandwidth (Fig. 2b). It has been assumed that such function is horizontal if the assumed statistical parameters are below some predefined limit which are currently under calibration.

In the current implementation of the algorithm, frequency resolution and record length were held constant and equal to 0.01 Hz and 10 minutes for each step respectively. This record length for the single step seems to be the minimum one providing a sufficiently averaged spectrum, thus resulting in a good compromise between accuracy and computational time. However, longer records can result in improved definition of spectra, where most of the noise is averaged out, and therefore of estimated mode shapes, thus reducing noise effects on MAC.
After having identified the bandwidth of a number of modes, within each bandwidth use of peak detection algorithm over the corresponding portion of the first singular value plot leads to the identification of natural frequency for that mode. The corresponding singular vector at that frequency line is a good estimation of the mode shape of the structure [18]. Starting from the SDOF Bell function of the mode [18], damping and natural frequency can be easily determined in an automated way from the correlation function of the isolated SDOF system using only the function down to a certain decay level, as suggested in [15].

The algorithm has been implemented into a software, named Leonida, developed in LabView environment and firstly tested against simulated data [16]. Obviously, this is not a definitive version of the software, but its design and its architecture can be described anyway. A state machine architecture (Fig. 3) has been adopted for software implementation since well-defined stages can be identified. In the first state the MAC vs. frequency plot is computed over a number of subsequent records. Computational time is optimised adopting parallel recording and processing procedures. Moreover, a partial overlap between subsequent records can be considered in the case of data retrieved from file in order to increase the number of averages. In the second state, mode bandwidths are identified according to the predefined limits. At the end of this state, a number of bandwidths are identified through their limit values of frequency. In the third state modal parameters are extracted in a fully automated way by focusing only on the frequency lines defining a certain mode bandwidth. This software can be used for single applications, in order to define the fundamental modes of the structure under test, or as modal information engine for the tracking procedure described in [20, 21]. In this second case, starting from the identified mode shapes for a number of modes, it is possible to track the natural frequencies and the mode shapes of that mode over time, thus performing an effective structural health monitoring. In fact, even if natural frequencies are classically used for damage detection, it is well known that they are more sensitive to the environment than to the damage to be detected. Mode shapes, instead, are less sensitive to the environment and can be easily obtained with a low computational time adopting the above mentioned tracking procedure. Integration of the proposed procedure into a fully automated structural health monitoring system will be discussed in the next section.
A number of case studies related to the application of the algorithm for output-only modal identification purposes are reported in [17]: different record lengths, measurement hardware and structural typologies have been considered for testing the algorithm. Even if results must be considered preliminary, promising results have been obtained in detecting fundamental modes of a number of different structures, thus pointing out potentialities of the proposed procedure, but also limitations, in particular when higher modes are considered and the effects of noise become important. However, if higher modes are not properly excited or noise is relevant, also an expert user probably runs into a number of problems.

INTEGRATION INTO A FULLY AUTOMATED SHM SYSTEM
The proposed algorithm has been extensively applied also to data continuously coming from the permanent SHM system installed on the Main Building of the School of Engineering at University of Naples [22]. The possibility to retrieve data directly from a data acquisition hardware or from a remote database allows an easy integration of the software into a structural health monitoring system. In this section, results obtained from the repeated application of the algorithm to a number of datasets recorded in different days and having different lengths but related to the same structure are reported, and the effect of the record length on the clearness and stability of results is briefly discussed.

Currently, another software is devoted to carry out a continuous tracking of modal parameters for the first three fundamental modes [20, 21]. It allows a fast identification (a few minutes) if compared with Leonida: however, such software package needs a reference mode shape for each mode in order to work. The algorithm proposed in this paper can provide such vectors in a fully automated way, thus overcoming a traditional limitation of modal-based monitoring systems, related to the need of a user intervention: by combining the two software packages, a full integration of output-only modal identification procedures within structural health monitoring systems can be achieved.

The first two fundamental modes of the structure are two close coupled modes [23]. Continuous monitoring of modal parameters over different periods of the year [21] has shown that natural frequencies vary in the ranges reported in Table 1. Results obtained by applying the proposed algorithm to the above mentioned three records, instead, are reported in Table 2:

<table>
<thead>
<tr>
<th>Mode</th>
<th>Observed range [Hz]</th>
<th>Mode of observed natural frequency [Hz]</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.89 – 0.93</td>
<td>0.91</td>
</tr>
<tr>
<td>II</td>
<td>0.97 – 1.00</td>
<td>0.98</td>
</tr>
<tr>
<td>III</td>
<td>1.28 – 1.31</td>
<td>1.29</td>
</tr>
</tbody>
</table>

Table 1: Observed values of natural frequencies of the School of Engineering Main Building over different periods of the year.

<table>
<thead>
<tr>
<th>Mode</th>
<th>Record</th>
<th>Duration [s]</th>
<th>Sampling frequency [Hz]</th>
<th>Natural frequency [Hz]</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>RC1</td>
<td>1200</td>
<td>100</td>
<td>0.92</td>
</tr>
<tr>
<td>II</td>
<td>RC1</td>
<td>1200</td>
<td>100</td>
<td>0.98</td>
</tr>
<tr>
<td>III</td>
<td>RC1</td>
<td>1200</td>
<td>100</td>
<td>1.29</td>
</tr>
<tr>
<td>I</td>
<td>RC2</td>
<td>3300</td>
<td>100</td>
<td>0.93</td>
</tr>
<tr>
<td>II</td>
<td>RC2</td>
<td>3300</td>
<td>100</td>
<td>1.00</td>
</tr>
<tr>
<td>III</td>
<td>RC2</td>
<td>3300</td>
<td>100</td>
<td>1.31</td>
</tr>
<tr>
<td>I</td>
<td>RC3</td>
<td>3800</td>
<td>100</td>
<td>0.92</td>
</tr>
<tr>
<td>II</td>
<td>RC3</td>
<td>3800</td>
<td>100</td>
<td>0.99</td>
</tr>
<tr>
<td>III</td>
<td>RC3</td>
<td>3800</td>
<td>100</td>
<td>1.31</td>
</tr>
</tbody>
</table>

Table 2: Results of automated modal parameter identification.

while the identified mode bandwidths through the RC3 record are shown in Fig. 4a, 4b, 4c. Averaged MAC vs. frequency plot for the RC3 record is reported in Fig. 4d.

The software has been able, therefore, to identify in a reliable way the natural frequency of the first three fundamental modes in all test cases. Also the extension of mode bandwidths is quite stable in all cases apart from the length of the record, as reported in Table 3.

When higher modes are considered, however, a number of wrongly identified frequency ranges disappear for a sufficiently long duration of the record as a result of noise averaging.
<table>
<thead>
<tr>
<th>Mode</th>
<th>Record</th>
<th>Natural frequency [Hz]</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>RC1</td>
<td>0.87 – 0.94</td>
</tr>
<tr>
<td>I</td>
<td>RC2</td>
<td>0.88 – 0.96</td>
</tr>
<tr>
<td>I</td>
<td>RC3</td>
<td>0.87 – 0.95</td>
</tr>
<tr>
<td>II</td>
<td>RC1</td>
<td>0.97 – 1.05</td>
</tr>
<tr>
<td>II</td>
<td>RC2</td>
<td>0.98 – 1.02</td>
</tr>
<tr>
<td>II</td>
<td>RC3</td>
<td>0.97 – 1.02</td>
</tr>
<tr>
<td>III</td>
<td>RC1</td>
<td>1.21 – 1.51</td>
</tr>
<tr>
<td>III</td>
<td>RC2</td>
<td>1.27 – 1.34</td>
</tr>
<tr>
<td>III</td>
<td>RC3</td>
<td>1.26 – 1.37</td>
</tr>
</tbody>
</table>

Table 3: Identified mode bandwidth.

The mode shapes provided by Leonida are used as references for the continuous tracking of modal parameters. In Fig. 5 an example monitoring results in terms of natural frequencies for the first three modes of the School of Engineering Main Building at University of Naples are reported. In Table 4, a comparison between the results of automated tracking and traditional (manual) OMA is shown, pointing out the effectiveness of the algorithm for autonomous modal parameter monitoring.

<table>
<thead>
<tr>
<th>Mode number</th>
<th>Mode [Hz]</th>
<th>Mean [Hz]</th>
<th>Standard deviation</th>
<th>Single test (FDD) [Hz]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.91</td>
<td>0.91</td>
<td>0.0063</td>
<td>0.92</td>
</tr>
<tr>
<td>2</td>
<td>0.98</td>
<td>0.99</td>
<td>0.0062</td>
<td>0.98</td>
</tr>
<tr>
<td>3</td>
<td>1.29</td>
<td>1.29</td>
<td>0.0054</td>
<td>1.29</td>
</tr>
</tbody>
</table>

Table 4: Statistics on values of natural frequencies (Automated FDD) in comparison with single test results.
Fig. 5: Automated identification results of natural frequencies for the first three modes of the School of Engineering Main Building at University of Naples.
CONCLUSIONS
An algorithm for fully automated modal identification of civil structures in output-only conditions has been proposed and discussed in this paper. Even if some aspects of the algorithm must be refined, promising results have been obtained from its application [17] to a number of case studies, allowing a reliable estimation of fundamental modes. Its implementation and integration into the fully automated SHM system of the School of Engineering Main Building at University of Naples have been shown. Reliability of the algorithm in presence of close coupled modes (the first two bending modes of the structure) and effects of record length on results have been investigated. Fundamental modes have been correctly identified in all cases, apart from record length. When also higher modes are considered, as a result of noise, bandwidths are not clearly identified as a whole. However, a number of wrongly identified frequency ranges disappear for a sufficiently long duration of the record as a result of noise averaging, while regions where modes are actually located remain stable notwithstanding record duration. Results of modal identification are used as references for the modal parameter tracking procedure already running as a part of the SHM system.

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