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Automated modal identification for Structural Health Monitoring: a critical assessment

C. Rainieri[1], G. Fabbrocino[1], and E. Cosenza[2]

[1] Structural & Geotechnical Dynamic Laboratory StreGa, University of Molise, Termoli, Italy
[2] Department of Structural Engineering, University of Naples Federico II, Naples, Italy

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 these techniques aim at tracking changes in structural response directly or indirectly related to the mechanical characteristics (natural frequencies, etc.) during service life and especially after damage due to exceptional loads. One of the most relevant drawbacks of such methods is represented by the need of a user intervention during the structural modal parameter identification processes. This specific aspect does not fully fit requirements of SHM systems, which should be fully automated.

In order to overcome this limitation, a number of algorithms have been proposed in recent years. In this paper, after a comprehensive literature review, a critical assessment of the available automated modal identification procedures will be carried out, pointing out advantages and limitations of each method. Finally, the main aspects of an automated FDD-based modal identification algorithm will be described and some sample case studies will be discussed in order to point out its effectiveness. The algorithm has been implemented into a specific software package, named LEONIDA, developed in LabView environment. Some peculiar aspects of software implementation will be shortly reviewed and some issues related to the integration within a fully automated Structural Health Monitoring system will be analyzed.

1 INTRODUCTION

In recent years a growing interest in systems and techniques for fast detection of damage based on vibration analysis has raised. Modal-based damage detection is a well-established methodology for structural health assessment (Doebling et al. 1996), even if changes of environmental and operational conditions can make structural health monitoring complex and affect modal parameters as well (Peeters & De Roeck 2000).

A relevant issue related to the applicability of damage detection techniques as a part of monitoring applications consists of an automated identification and tracking procedure. This is not a trivial task since traditional modal identification generally requires extensive interaction from an experienced user. Nevertheless, computational efforts have to be carefully considered

when applicability of modal identification techniques for damage detection purposes is of interest. In fact, real time on-line data processing is crucial for quickly changing 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 (Peeters & De Roeck 2000) or offshore platforms (Doebling et al. 1996, Brincker et al. 1995).

In the present paper, after a comprehensive literature review, a critical assessment of available automated modal identification procedures will be carried out. The main focus will be on advantages and limitations of each method. Finally, an automated FDD-based modal identification algorithm will be described. A number of different sample cases will be briefly discussed in order to confirm its effectiveness. The proposed algorithm has been implemented into a specific software package, named LEONIDA, developed in LabView environment. Some aspects of software implementation are also described in order to highlight the capability of the procedure to be integrated in a fully automated Structural Health Monitoring system.

2 AUTOMATED MODAL IDENTIFICATION

2.1 Review of existing methods

The first proposal for automated identification of modal properties can be found in (Verboven et al. 2002) but it is just in the last two years that an increasing attention has been paid to this issue, determining a number of proposals for automated identification and tracking of modal parameters (Brincker et al. 2007, Deraemaeker et al. 2008, Rainieri et al. 2007) relying upon modal identification methods based both on control theory or 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 modes have to be distinguished. This practice requires large interaction with an expert user (Soderstrom 1975). Thus, classical modal analysis takes advantage of very relevant and effective tools, such as the stabilization diagram, which is a useful mean to distinguish physical from mathematical modes.

However, 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; see Lanslots et al. 2004) 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 (Verboven et al. 2003). In this case 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 2008 Deraemaeker et al. (Deraemaeker et al. 2008) have 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. (Andersen et al. 2007), 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.

About methods based on conventional signal analysis, Guan et al. (Guan et al. 2005) 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.

In 2007 Brincker et al. (Brincker et al. 2007) presented an algorithm for automation of the Frequency Domain Decomposition - FDD - (Brincker et al. 2000) procedure in order to remove any user interaction and use it as modal information engine in SHM systems. It is based on 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 (Brincker et al. 2007) on the base of the standard deviation of correlation between random vectors and of the number of measurement channels, few indications are reported for the modal domain indicator.

In 2008, the approach to automated modal parameter identification proposed by Brincker et al. has been slightly modified and applied to the permanent monitoring of the “Infante D. Henrique” bridge (Magalhães et al. 2008). In this case, also an automated procedure based on Cov-SSI and on a clustering algorithm for stable pole selection has been proposed. As the modified FDD algorithm is concerned, however, it has been shown (Magalhães et al. 2008) that, when noise level in the spectra increases, the procedure for automatic identification reduces its efficiency.

Moreover, after having defined the frequency resolution and the frequency interval under analysis, the MAC (Allemang & Brown 1982) rejection level has to be set. Its value has to be identified for each monitored structure by mean of a number of sensitivity tests and, therefore, its calibration could be time consuming. Magalhães et al. have proposed to use a very small value (0.4) but it can be ineffective if the number of sensors is small and similar mode shape vectors for adjacent natural frequencies result from the identification process.

Automation of Cov-SSI method (Magalhães et al. 2008), instead, seems to be more efficient in the case of closely spaced modes but it shows lower ability in the identification of poorly excited modes. The application of the clustering algorithm allows a reliable identification of structural modes. However, also in this case, a number of parameters has to be set after a calibration phase of the system.

Automated modal identification algorithms have been recently proposed also for the Second Order Blind Identification method and for the transmissibility based method.

About SOBI (Poncelet et al. 2008), identification of structural modes is based on rejection of all modes out of the frequency range of interest and of time series of sources characterized by a fitting error higher than 10%; finally, selection of actual structural modes is based on the computation of a confidence factor. The main advantage of the proposed procedure is a lower computational load with respect to SSI methods; moreover, selection of model order is not necessary. Conversely, the main drawback is related to the need of a number of sensors greater than or equal to the number of active modes. Moreover, at now the algorithm has been applied

only against simulated data. Its effectiveness in the case of actual measurements has to be verified.

The automated OMA procedure using transmissibility functions is, instead, based on the combination of Singular Value Decomposition (SVD) and stabilization diagram for selection of structural modes (Devriendt et al. 2008). Computation of the stabilization diagram from transmissibility functions results in stable vertical lines but not all of them correspond to actual system poles, even if they are related to structural characteristics. Thus, another selection tool is needed. In the context of the proposed procedure, the SVD of a two column matrix is computed, where each column consists of a transmissibility function evaluated for a particular load condition.

Since all transmissibility functions converge to the same unique values at the system poles, the matrix will be of rank one in correspondence of each system pole. Thus, by looking at the plot of the inverse of the second singular value, it is possible to distinguish actual structural modes from its peaks. Peak selection can be carried out by defining a threshold. However, in presence of measurement noise this approach is not very reliable. In order to overcome this drawback the use of a smoothing function has been proposed (Devriendt et al. 2008), but it has to be used carefully to avoid distortion. Further refinements of the proposed algorithm are, therefore, needed.

2.2 Fully automated modal identification

The main drawbacks of the available automated modal identification methods can be summarized as follows:

- Most of the methods starts from a threshold based peak detection; as a consequence, a first calibration phase is needed for its proper definition; moreover, just some of the identified peaks correspond to actual modes; performance of peak detection algorithms can get worse in presence of measurement noise;
- Identification of actual modes is based on a number of parameters which must undergo a time consuming calibration process for each monitored structure; moreover, a static identification of thresholds and parameters may be inadequate to follow the natural changes in modal properties of structures due to damage or environmental effects.

Thus, an alternative strategy could be the definition of some objective criteria for identification of mode bandwidth before modal parameter extraction. An FDD-based automated modal identification algorithm is reported elsewhere (Rainieri 2008). It is based on the repeated computation of the SVD of the PSD matrix for a number of records and on the construction of an averaged MAC vs. frequency plot which has the aspect of a coherence function. Inspecting the sequence of MAC values at each frequency line it is possible to identify the actual mode bandwidth to be used for modal parameter extraction.

Currently, the algorithm refers to some limit values affecting MAC and its first derivative. They allow identification of the frequency lines belonging to a certain mode bandwidth. Such limits are the results of a calibration process based on records obtained from different measurement setups, with different durations and related to different kinds of structures. Thus, an objective identification of mode bandwidth is possible. However, a new algorithm, which does not need prior parameter calibration, is under investigation and it will be described in a next paper.

The algorithm is summarized in Figure 1 and it has been implemented into a software package named LEONIDA (Rainieri et al. 2008a), which is able to retrieve data from a measurement hardware, a remote database or a file, thus allowing its integration into a fully automated

monitoring system. The algorithm has been tested against simulated (Rainieri et al. 2008b) and actual data. Results are shown in Table 1 while in Figure 2 the Singular Value plots resulting from manual identification of such structures by FDD are shown. They refer to case studies characterized by increasing complexity. In the first case, a heritage r.c. structure characterized by well-separated modes is considered; in the second case the procedure is applied to the modal identification of a vault belonging to a system of similar vaults in an ancient masonry building. The main issues in such a case were related to a low signal-to-noise ratio and to the interaction effects with the close vaults. Then, a masonry bell tower characterized by two close but not coupled bending modes has been considered; finally, the algorithm has been applied to the identification of the School of Engineering Main Building in Naples, which is equipped with a SHM system based on a remote MySQL database (Rainieri 2008) and is characterized by two close coupled modes.

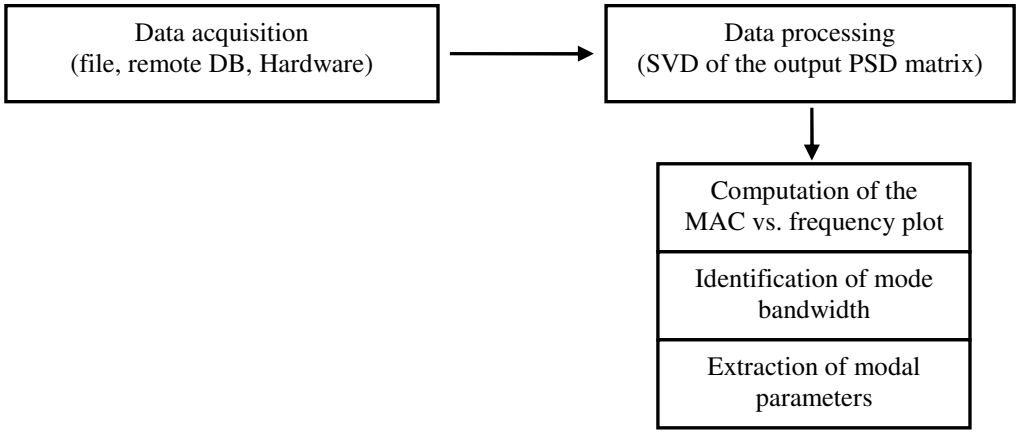

Figure 1. LEONIDA: algorithm for automated modal parameter identification.

Table 1. Automated modal identification by LEONIDA: results

Structure	Mode	Manual identification (EFDD) – natural frequency [Hz]	Automated identification (LEONIDA) – natural frequency [Hz]
Heritage r.c. structure (well-separated modes)	I (Translation)	0.813	0.81
	II (Translation)	1.375	1.38
	III (Torsion)	1.758	1.75
Masonry vault (interaction effects and low signal-to-noise ratio)	I	4.31	4.30
	II	4.94	4.93
Masonry bell tower (two close not coupled bending modes)	I (Translation)	0.70	0.70
	II (Translation)	0.76	0.76
School of Engineering Main Building (two close coupled modes)	I (Prev. Translation)	0.921	0.92
	II (Prev. translation)	0.982	0.98
	III (Torsion)	1.299	1.30

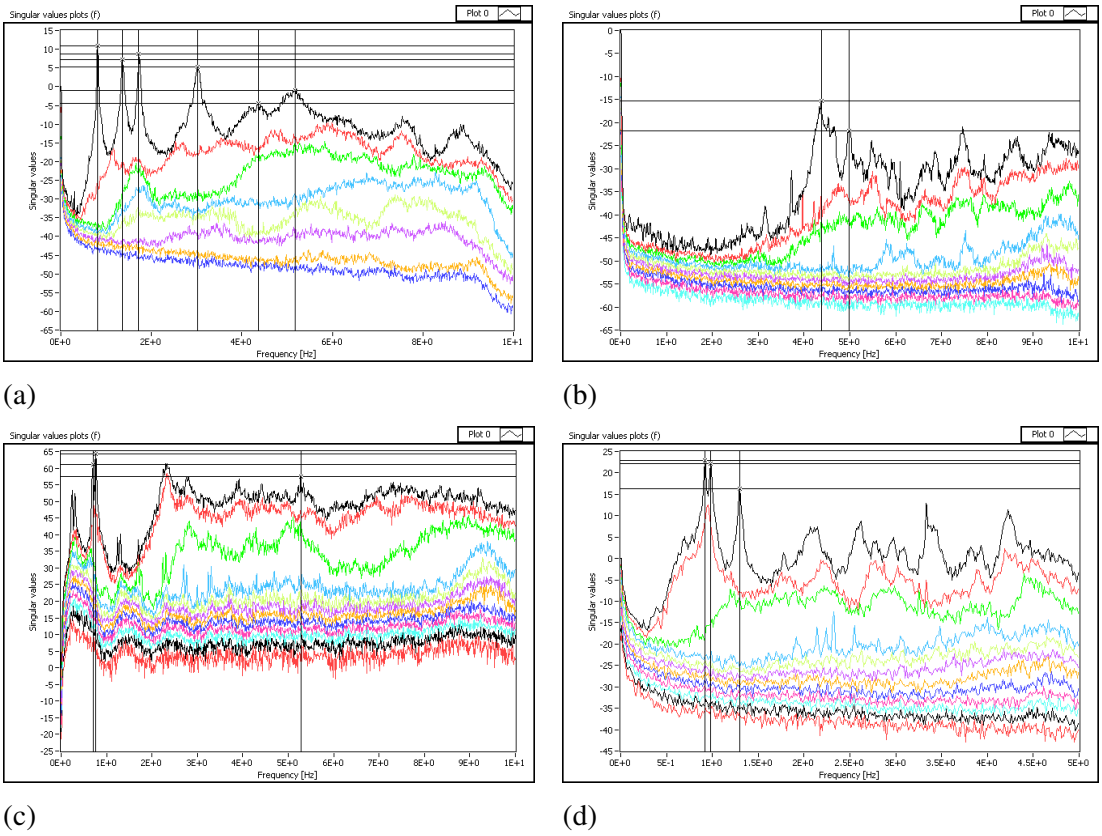

Figure 2. SV plots: heritage r.c. structure (a); masonry vault (b); masonry bell tower (c); School of Engineering Main Building (d).

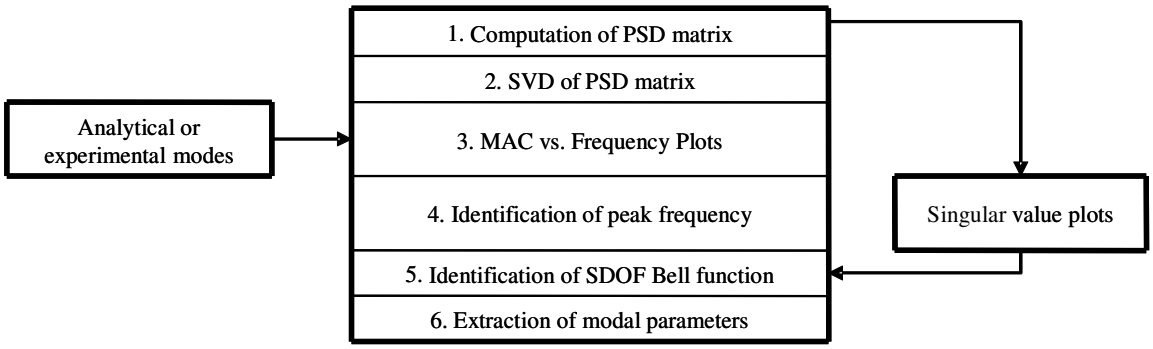

Figure 3. AFDD-T: algorithm for automated modal tracking.

Thus, the software is able to carry out a proper identification process in a fully automated way. Since it is somewhat time consuming, a faster modal tracking can be carried out by using its results (namely, the mode shapes) for a spatial filtering of data. A reliable procedure for modal tracking based on this concept (called AFDD-T) is described elsewhere (Rainieri et al. 2007, Rainieri 2008) and summarized in Figure 3.

Such algorithm is able to follow the natural changes in modal parameters due to damage or environmental effects. A new reference can be provided by LEONIDA periodically or on demand (namely, after an extreme event). The two algorithms for automated modal parameter

identification and tracking have been integrated into the SHM system of the School of Engineering Main Building in Naples. Some monitoring results are reported in Table 2 for the last summer; all statistics are computed on 7132 samples.

Table 2. The School of Engineering Main Building: monitoring results (summer 2008)

Mode number	Natural frequency (mode) [Hz]	Natural frequency (mean) [Hz]	Natural frequency (standard deviation) [Hz]
I	0.92	0.92	0.00979
II	0.99	0.99	0.008094
III	1.29	1.29	0.008367

3 CONCLUSIONS

Advantages and limitations of a number of recent procedures for automated modal identification for structural health monitoring applications have been reviewed. Some of the mentioned drawbacks can be overcome by mean of the proposed algorithm for fully automated modal identification of civil structures in output-only conditions.

Even if some aspects of the algorithm must be refined and possible further improvements are under investigation, promising results have been obtained from its application 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.

Results of modal identification are used as references for a faster modal parameter tracking procedure, based on a spatial filtering approach. Effectiveness of the proposed strategy for continuous and fully automated modal identification for structural health monitoring purposes has been pointed out by showing the results obtained from its application within the SHM system of the School of Engineering Main Building at University of Naples.

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