Chapter 1
Accurate Damping Estimation by Automated OMA Procedures

C. Rainieri and G. Fabbrocino

Abstract Systems and techniques for fast damage detection based on vibration analysis are becoming very attractive in different engineering fields. Modal-based damage detection algorithms are well-known techniques for structural health assessment. However, the lack of automated modal identification and tracking procedures has been for long a relevant limit to their extensive use. The development of several automated output-only modal identification procedures in the last few years has led to a renewed interest in modal-based damage detection. However, robustness of automated modal identification algorithms, computational efforts and reliability of modal parameter estimates (in particular, damping) still represent open issues. In this paper, a novel algorithm for automated output-only modal parameter estimation is adopted to obtain reliable and very accurate modal parameter estimates. An extensive validation of the algorithm for continuous monitoring application is carried out based on simulated data. The obtained results point out that the algorithm provides fairly robust, accurate and precise estimates of the modal parameters, including damping ratios. This may potentially lead to a standardized, extensive characterization of modal damping ratios in structures, which is useful to gain knowledge about damping mechanisms in structures and to develop predictive models.

Keywords Vibration based structural health monitoring • Automated operational modal analysis • Damping • Second order blind identification • Stochastic subspace identification

1.1 Introduction

Vibration based Structural Health Monitoring (SHM) techniques are again gaining in popularity nowadays thanks to the recent development of several algorithms for automated identification [1] and tracking [2] of modal parameters based on Operational Modal Analysis (OMA) methods. Damage detection techniques based on changes of the modal parameters of the monitored structure over time are well-established methods for structural health assessment [3], in spite of some limitations in terms of damage localization and, above all, quantification, as well as drawbacks related to sensitivity to measurement quality and environmental and operational factors [4]. Nevertheless, the continuous monitoring of modal parameters has a large potential in performance and health assessment of civil engineering structures [5]. Applications range from prompt detection of damage and degradation phenomena [6] to post-earthquake health assessment and emergency management [7, 8]. An automated, accurate estimation of modal parameters plays also a primary role in the assessment of the dynamic behavior of complex structural systems such as geotechnical [9, 10] and historical structures [11, 12]. Even if several solutions for automated output-only modal identification are currently available, they show different performance in terms of robustness and accuracy of estimates. This can be addressed also to the drawbacks [1] typically encountered in the algorithms:

- threshold based peak and physical pole detection;
- need of a preliminary calibration phase at each new application;

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- static settings of thresholds and parameters which may be unsuitable to track the natural changes in modal properties of structures due to damage or environmental effects;
- sensitivity to noise, problems of false or missed identification.

Moreover, a number of algorithms do not provide damping estimates; whenever they are able to estimate modal damping, the resulting values are usually very scattered. The fairly large scatter associated to damping estimates, in comparison with that of natural frequency and mode shape estimates, is well documented in the literature. Even if the scatter can be partially addressed to inherent limitations of the estimators and the adoption of an equivalent viscous damping model [13], appropriate data processing procedures have to be adopted in order to minimize the estimation error and enhance robustness and accuracy of automated modal identification algorithms also with respect to the problem of modal damping estimation.

A thorough performance assessment of automated modal identification algorithms is rarely reported in the literature. However, the evaluation of the quality of modal estimates automatically extracted from measurements of the dynamic response of structures under operational conditions is a fundamental step in view of proper post-processing of modal parameters for damage detection and performance evaluation purposes.

In the present paper, a procedure for fully automated output-only modal identification, based on the combination of different OMA techniques, is described. The idea behind the novel approach is the simplification of the analysis and interpretation of the stabilization diagram for the separation of physical from spurious poles taking advantage of the Blind Source Separation (BSS) [14] operated by the Second Order Blind Identification (SOBI) [15, 16] procedure. The main objective of the novel strategy is a robust and accurate identification of modal parameters in operational conditions, including modal damping ratios even if in the limits of the adopted estimator. Its key feature is the absence of any analysis parameters to be tuned at each new monitoring application. In the development of the algorithm, specific attention has been devoted to the control of response time and computational efforts [17], also through a reduction of the length of the analyzed records, without affecting the quality of the estimates. This is relevant, in particular, for SHM applications in seismically prone areas [2].

A thorough performance assessment of the algorithm is attempted based on automated processing of a large number of simulated datasets. The herein illustrated results show that the algorithm is characterized by a high success rate. The performance assessment based on simulated data is still in progress. However, the preliminary results seem to confirm the robustness and accuracy of the algorithm, which therefore has a potential in the continuous vibration based monitoring of civil structures.

1.2 Theoretical Background of the Automated Modal Identification Algorithm

The core of the novel automated modal identification algorithm is the Stochastic Subspace Identification (SSI) [18] method for OMA. However, it is not directly applied to the multivariate time series of the structural response but, after a pre-processing step, to the single sources obtained from the Joint Approximate Diagonalization (JAD) [19] of a number of time shifted covariance matrices.

SSI is classified as a time domain, parametric modal identification method. When parametric system identification techniques are used for the estimation of the modal parameters of structures, the definition of the model order, equal to twice the number of eigenfrequencies, represents the key issue. The control theory provides several techniques to automatically set the model order in a way able to maximize the prediction capacity of the identified model [20]. However, when SSI is applied in the context of experimental modal analysis, the attention is not focused on the prediction capability of the model as such, but on the possibility to get accurate and reliable estimates of the modal parameters. In order to find the modal properties of the system it is worth plotting a stabilization diagram. The order of the system is over-specified and the search for vertical alignments of stable poles allows for the discrimination of physical from spurious modes. Even if the stabilization diagram plays a primary role in experimental modal analysis, the selection of physical modes in the alignments of stable poles is often not straightforward, since the quality of the stabilization diagram depends on a number of parameters (number of block rows, maximum model order) and thresholds (allowable scatter between the modal properties evaluated at consecutive model orders) [18, 21] resulting in a relevant role of the analyst's judgement.

The stabilization diagram represents a useful tool for bias errors identification [22], such as the bias of the model, related to spurious modes, and the bias of the modes. Spurious modes can be classified as noise modes, which arise due to physical reasons—measurement noise, characteristics of excitation -, and mathematical modes, due to over-estimation of the system order. The stabilization diagram allows for the discrimination of most spurious modes, since they often do not fulfil stabilization criteria like in the case of physical poles. Other spurious poles can be identified and removed according to physical criteria, for instance, the expected damping ratio range. The bias of the modes can be associated, on the other hand, to the under-estimation of the system order, so that a single identified mode is actually the combination of different modes (either physical or noisy). If the stabilization diagram is plotted until appropriately high values of the model order, the splitting of one column in the stabilization chart into two separate columns, starting from a given model order, is a commonly observed phenomenon. Thus, the mode estimate is biased below this model order since it is the result of the combination of different poles. A bias of the modes may occur also if, for a given maximum model order, the number of block rows is over-specified. In [23] it is shown how, for a given maximum model order, the quality of stabilization first improves and then gets worse for increasing values of the number of block rows. Thus, it is possible to carry out a sensitivity analysis for different values of the number of block rows in order to set it in a way able to minimize the variance of the modal parameter estimates at different model orders.

Evaluation and control of the accuracy of modal parameter estimates are critical in view of modal based damage detection. This basically relies on the comparison between the modal parameters or the modal model of a structure in a damaged state and those in a reference (undamaged) state. Shifts of natural frequencies, increases in damping, changes in mode shapes and other similar damage sensitive features are key parameters to assess the health state of the monitored structure [3]. A comprehensive review of these methods and the issues concerning the removal of environmental effects that also lead to changes in the modal parameters are out of the scope of the present paper. A number of methods for removal of environmental effects can be found in the literature [24, 25]. However, inaccurate identifications of modal parameters may still occur, thus negatively affecting the performance of damage detection algorithms [26], eventually leading to false alarms or missed identifications.

A number of simulation studies have pointed out how the modal parameter estimates provided by parametric methods such as SSI are by far more accurate than those provided by non-parametric procedures [27, 28]. However, the automated interpretation of stabilization diagrams is a very complex activity and a lot of research efforts have been spent on this task [28]. In the present paper a novel approach to the automated output-only modal parameter identification is proposed and it is extensively tested in order to assess the robustness, accuracy and precision of estimates in view of continuous monitoring applications. The method is based on SSI and the selection of physical poles in the stabilization diagram by clustering techniques, but it takes advantage of the BSS operated by SOBI at a preliminary stage in order to simplify the interpretation of the stabilization diagram. In fact, as a result of the BSS phase, the raw data associated to the measured structural response are transformed into sources [15] which can be well-separated (they show the contribution of a single mode to the structural response), not well-separated (noise or minor contributions from other modes could be superimposed to the contribution of the main mode) or just noise sources [17]. The sources are obtained through JAD of p time-shifted covariance matrices until the sum of the off-diagonal terms is under a user-defined threshold t [19]. The idea under the proposed approach for automated output-only modal identification is to take advantage of the BSS to simplify the analysis of the data and the interpretation of the stabilization diagram by extracting the modal information from the single sources and not the multivariate time series of raw data. The sources are analyzed one-by-one according to the SSI method and the physical poles are separated from the spurious one by means of clustering techniques and mode validation criteria. The interpretation of the stabilization diagram, therefore, becomes easier since it basically reports information about only one mode at the time.

The flowchart of the proposed algorithm is shown in Fig. 1.1. The JAD phase leads to a preliminary discrimination between modal contributions and noise. The sources, including both modal and noise sources, are then passed, one-by-one, to the SSI-based step for the estimation of natural frequencies and damping ratios and identification of noise sources. This step of the algorithm takes advantage of advanced clustering techniques [29] to identify the physical poles. For each source, the poles provided by the SSI are grouped into clusters according to the hierarchical clustering method. The cluster characterized by the largest number of elements is selected as representative of the mode. At the end of this phase a further selection and validation of the poles in each cluster is carried out. Clusters that do not fulfil the validation checks are removed from the dataset. In particular, the average damping ratio in each cluster has to be in the range $0 \div 5\%$ and the corresponding coefficient of variation not larger than 10%. The first limitation is based on an empirical observation about the behaviour of civil structures in operational conditions, which are usually weakly damped. The second limitation comes from the observation that physical modes are characterized by small standard deviations, while spurious modes show much larger values of this parameter [28]. Checks about the physical significance of the estimates are also carried out (for instance, checks of the sign of damping). As a final stage, the natural frequency and damping ratio estimates in each cluster are normalized in the range [0, 1] and a k-means clustering algorithm with $k = 2$ cluster is applied, allowing the presence of empty clusters. This last step eventually removes still present spurious poles and slightly improves the accuracy of estimates. It is worth pointing out that the validation criteria have to be applied after the hierarchical clustering stage, since they might remove all the spurious poles and a number of physical poles could be separated and lost as a result of the clustering stage.

The final values of the natural frequency and damping ratio for the identified modes are obtained by a sensitivity analysis with respect to the number of block rows in SSI, for a fixed value of the maximum model order in the stabilization diagram. The cluster characterized by the minimum variance of the estimates when i ranges in a certain interval with a certain step Δi

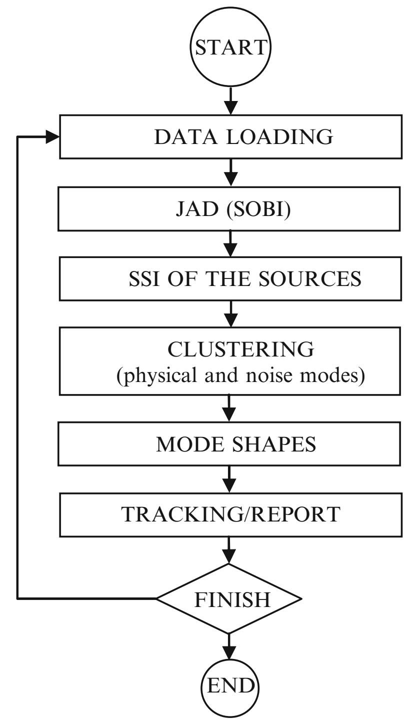

Fig. 1.1 Flowchart of the automated modal identification algorithm

is finally selected as the one providing the best estimate of the modal parameters for a given structural mode. Mode shape estimates are finally obtained, in the current stage of implementation, from Singular Value Decomposition (SVD) of the output Power Spectral Density (PSD) matrix at the previously estimated frequency of the mode [30].

The previous considerations about the automated identification algorithm highlight how the source separation at the first step makes the discrimination of physical and noise modes easier and more reliable. The sensitivity analysis with respect to the number of block rows and the grouping of the poles in clusters leads to a robust identification of modal parameters and to a quantification of the precision of the estimates.

1.3 Performance Assessment of the Algorithm Against Simulated Data

The performance of the proposed algorithm in terms of accuracy and reliability of estimates has been investigated through a statistical analysis of the results obtained from simulated data continuously generated through the application of a Gaussian white noise to a 4-DOF system. The mass and stiffness matrices of the system are given by Eqs. (1.1) and (1.2):

$$[m] = \begin{bmatrix} 5 & 0 & 0 & 0 \\ 0 & 5 & 0 & 0 \\ 0 & 0 & 5 & 0 \\ 0 & 0 & 0 & 10 \end{bmatrix} kg \tag{1.1}$$

$$[k] = \begin{bmatrix} 400 & -200 & 0 & 0 \\ -200 & 400 & -200 & 0 \\ 0 & -200 & 400 & -200 \\ 0 & 0 & -200 & 600 \end{bmatrix} \frac{N}{m} \tag{1.2}$$

$$[c] = a_0\,[m] + a_1\,[k] \tag{1.3}$$

while Rayleigh damping is used to model structural damping. Thus, the damping matrix has been obtained as per Eq. (1.3). The a_0 and a_1 coefficients in Eq. (1.3) have been computed by setting a value of 1% of the modal damping ratio for the first and last mode of the system. Thus, the simulated 4-DOF system is characterized by the following modal properties (Table 1.1):

Table 1.1 Modal properties of the simulated 4-DOF system

Mode #	Natural frequency (Hz)	Damping ratio (%)
I	0.668	1.00
II	1.137	0.88
III	1.526	0.92
IV	1.879	1.00

Table 1.2 Success rate of automated modal identification over 1000 runs

Mode #	Success rate (%)
I	99.7
II	99.6
III	99.5
IV	99.8

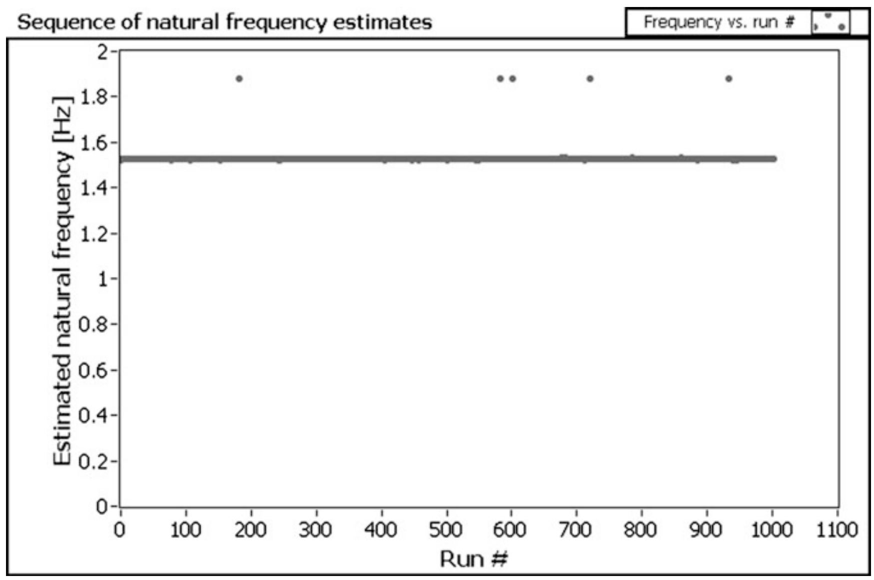

Fig. 1.2 Sample sequence of values of estimated natural frequencies in 1000 runs

The system matrices and, therefore, the associated modal parameters have been kept constant in all runs in order to focus the attention only on the uncertainties associated to inherent limitations of the estimator. The performance of the method when uncertain system matrices are adopted, so that the modal parameters can slightly change at each run as an effect of the deviation of the system matrices from their nominal values, is out of the scope of the present paper and it will be discussed elsewhere.

The system response to Gaussian white noise N(0,1) has been simulated 1000 times. The input has been applied at DOF #1. Each simulated dataset consisted of four measurement channels; the total record length was 3600 s and the sampling frequency was 10 Hz. Gaussian white noise has been added to the system response in order to simulate the effect of measurement noise. The obtained datasets, characterized by a SNR equal to 5 dB, have been then processed by the proposed algorithm in order to automatically extract the modal parameters of the system. The analysis of the simulated datasets has been carried out considering a number of block rows i ranging between 20 and 80 with $\Delta i = 2$ and considering a maximum model order of 16 in the construction of the stabilization diagram for each analyzed source.

The analysis of the obtained results has pointed out that the algorithm carries out automated output-only modal identification in a very robust way. In fact, a success rate [31] larger than 99% has been obtained for all modes (Table 1.2). Just in a few runs the modal parameters have not been properly identified (Fig. 1.2). However, such wrong estimates can be easily removed through the analysis of the extreme values in order to identify modal parameter estimates, which are outside the 3σ range.

In Tables 1.3 and 1.4 the results obtained from application of the proposed algorithm to the simulated data after removal of extreme values (associated to wrong modal parameter estimates) are summarized. They point out how the estimates are very close to the nominal values in at least the 50% of the cases. In fact, the median values are very close to the nominal ones and the interquartile range is very narrow and in the order of 0.001 Hz for natural frequency estimates and 0.1% for damping ratios.

Larger errors are associated to damping estimates, as expected. However, the analysis of the scatter of the natural frequency and damping estimates with respect to the nominal values point out that, with the exception of the previously

Table 1.3 Summary of automated modal identification results (after removal of extreme values): natural frequencies

Mode #	$f_{nominal}$ (Hz)	μ_f (Hz)	σ_f (Hz)	f_{min} (Hz)	25th centile	50th centile	75th centile	95th centile	f_{max} (Hz)
I	0.668	0.668	0.000745	0.666	0.667	0.668	0.668	0.669	0.670
II	1.137	1.137	0.000901	1.135	1.137	1.137	1.138	1.139	1.141
III	1.526	1.526	0.001164	1.520	1.525	1.526	1.527	1.528	1.531
IV	1.879	1.879	0.001467	1.873	1.878	1.879	1.880	1.881	1.884

Table 1.4 Summary of automated modal identification results (after removal of extreme values): damping ratios

Mode #	$\xi_{nominal}$ (%)	μ_ξ (%)	σ_ξ (%)	ξ_{min} (%)	25th centile	50th centile	75th centile	95th centile	ξ_{max} (%)
I	1.00	1.02	0.11	0.70	0.94	1.02	1.10	1.21	1.36
II	0.88	0.89	0.08	0.67	0.84	0.89	0.94	1.02	1.13
III	0.92	0.93	0.07	0.73	0.88	0.93	0.98	1.05	1.15
IV	1.00	1.01	0.08	0.79	0.96	1.01	1.06	1.14	1.23

Table 1.5 Summary of automated modal identification results (after extreme values removal): frequency scatter

Mode #	Δf_{min} (%)	25th centile	50th centile	75th centile	95th centile	Δf_{max} (%)
I	0.000025	0.04	0.07	0.13	0.23	0.36
II	0.000010	0.02	0.05	0.09	0.16	0.29
III	0.000036	0.02	0.05	0.08	0.15	0.38
IV	0.000006	0.02	0.05	0.09	0.15	0.30

Table 1.6 Summary of automated modal identification results (after removal of extreme values): damping scatter

Mode #	$\Delta\xi_{min}$ (%)	25th centile	50th centile	75th centile	95th centile	$\Delta\xi_{max}$ (%)
I	0.02	3.7	7.4	12.8	22.5	36.1
II	0.01	2.8	5.9	10.3	17.6	28.0
III	0.01	2.6	5.5	9.0	15.5	24.3
IV	0.01	2.4	5.1	8.7	15.4	22.7

Table 1.7 Analysis of coefficient of variation of identified natural frequencies (after removal of extreme values)

Mode #	$\gamma_{f,min}$ (%)	25th centile	50th centile	75th centile	95th centile	$\gamma_{f,max}$ (%)
I	0.0003	0.002	0.004	0.01	0.03	0.18
II	0.0002	0.002	0.006	0.01	0.03	0.09
III	0.0002	0.003	0.006	0.01	0.03	0.07
IV	0.0005	0.004	0.008	0.01	0.04	0.51

Table 1.8 Analysis of coefficient of variation of identified damping ratios (after removal of extreme values)

Mode #	$\gamma_{\xi,min}$ (%)	25th centile	50th centile	75th centile	95th centile	$\gamma_{\xi,max}$ (%)
I	0.03	4.24	4.81	5.75	6.92	9.66
II	1.21	1.82	2.29	3.05	4.19	6.99
III	0.18	0.91	1.19	1.63	2.57	5.51
IV	0.15	1.18	1.52	1.99	3.28	9.14

mentioned extreme values which affect less than 1% of the estimates, in the 95% of the runs the error is lower than 0.25% for frequencies (Table 1.5) and 23% for damping ratios (Table 1.6). Moreover, the typical scatter of damping ratio is in the range [2%, 10%] (50% of the values of scatter associated to damping estimates are in this range).

The natural frequency and damping ratio estimates provided by the proposed algorithm are average values of the poles grouped in a cluster representative of the identified mode. The analysis of their coefficient of variation shows that the modal estimates provided by the algorithm are not only fairly robust and accurate, but also precise. In fact, the coefficient of variation is typically well under 0.1% for natural frequencies (Table 1.7) and 10% (the rejection limit set in the algorithm) for damping ratios (Table 1.8).

The distributions of the identified damping ratios after 1000 runs for the four modes are depicted in Fig. 1.3. The associated means, modes and medians are reported in Table 1.9. They are very close each other and to the nominal values of modal damping ratios. Taking into account the uncertainty associated to damping estimates, the mode of damping values is given with one decimal place only.

The statistical analysis of the results can be eventually further refined by removing also outliers. However, the results after outlier removal are very consistent with the previous ones (to this aim compare Tables 1.3, 1.4, 1.10 and 1.11). The marginal refinements associated to outlier removal confirm the robustness and accuracy of the algorithm.

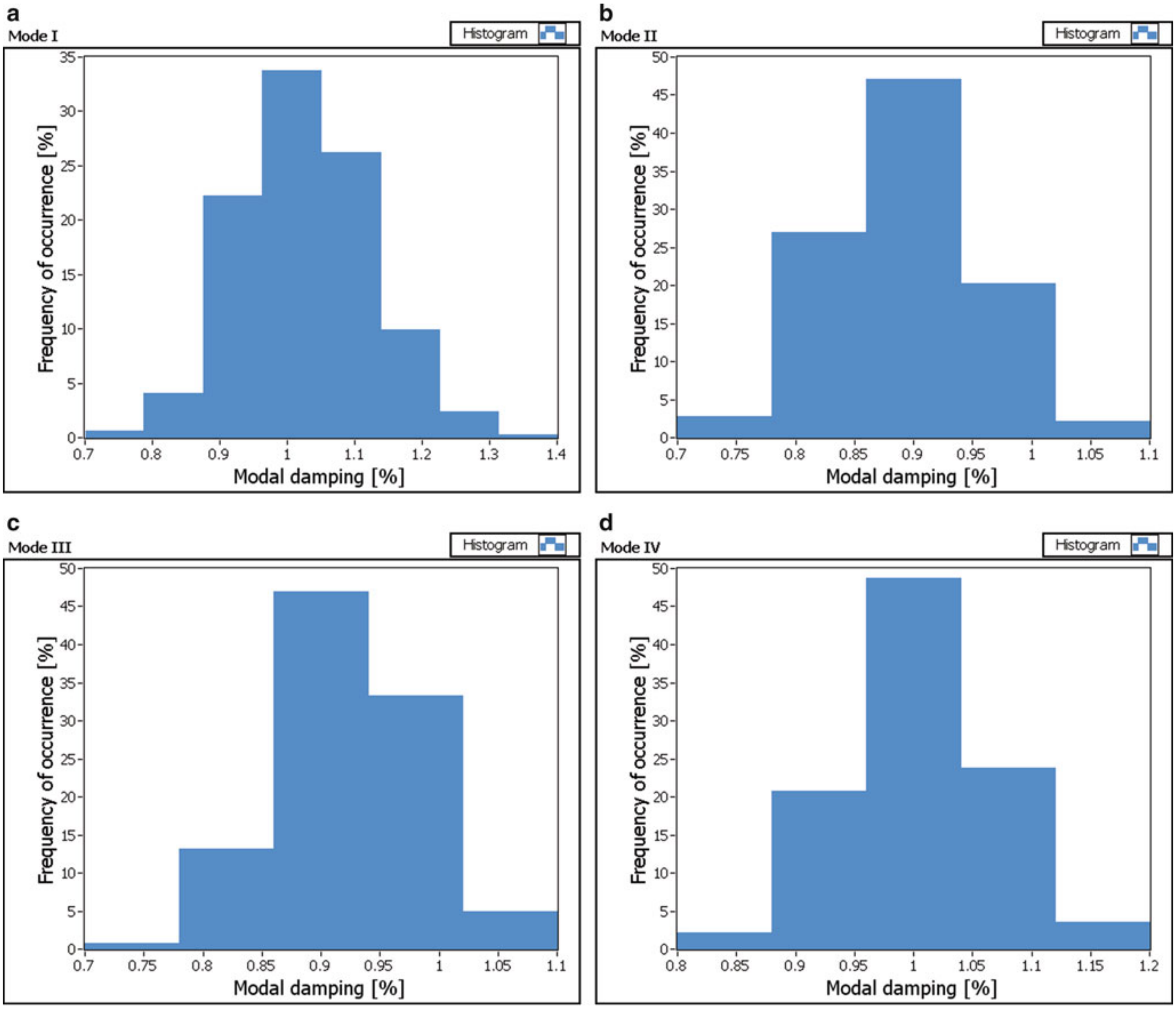

Fig. 1.3 Histograms of modal damping ratio estimates (after removal of extreme values): mode I (**a**), II (**b**), III (**c**), IV (**d**)

Table 1.9 Comparison of mean, mode and median of identified damping ratios with the corresponding nominal values (after removal of extreme values)

Mode #	$\xi_{nominal}$ (%)	μ_ξ (%)	ξ_{median} (%)	ξ_{mode} (%)
I	1.00	1.02	1.02	1.0
II	0.88	0.89	0.89	0.9
III	0.92	0.93	0.93	0.9
IV	1.00	1.01	1.01	1.0

Table 1.10 Summary of automated modal identification results (after outlier removal): natural frequencies

Mode #	$f_{nominal}$ (Hz)	μ_f (Hz)	σ_f (Hz)	f_{min} (Hz)	25^{th} centile	50^{th} centile	75^{th} centile	95^{th} centile	f_{max} (Hz)
I	0.668	0.668	0.000723	0.666	0.667	0.668	0.668	0.669	0.670
II	1.137	1.137	0.000863	1.135	1.137	1.137	1.138	1.139	1.140
III	1.526	1.526	0.001045	1.523	1.525	1.526	1.527	1.528	1.529
IV	1.879	1.879	0.001339	1.875	1.878	1.879	1.880	1.881	1.883

Table 1.11 Summary of automated modal identification results (after outlier removal): damping ratios

Mode #	$\xi_{nominal}$ (%)	μ_ξ (%)	σ_ξ (%)	ξ_{min} (%)	25th centile	50th centile	75th centile	95th centile	ξ_{max} (%)
I	1.00	1.02	0.11	0.74	0.94	1.02	1.10	1.21	1.33
II	0.88	0.89	0.08	0.69	0.84	0.89	0.94	1.02	1.09
III	0.92	0.93	0.07	0.73	0.88	0.93	0.98	1.05	1.12
IV	1.00	1.01	0.07	0.82	0.96	1.01	1.06	1.13	1.20

1.4 Conclusions

A novel, hybrid approach to automated output-only modal identification for SHM applications has been described in the present paper. It is based on the combination of selected OMA techniques and clustering strategies for the discrimination between structural and noise modes and the selection of the dynamic properties of physical modes. Its performance has been assessed against simulated data generated by a 4-DOF system excited by a Gaussian white noise. The results obtained from 1000 runs have been analyzed in order to assess the performance of the algorithm in terms of robustness, accuracy and precision. Encouraging results have been obtained, in particular as the possibility to estimate damping ratios in an accurate and fully automated way is concerned. Further investigations are in progress to assess the performance of the algorithm in the case of uncertain system matrices, when the modal parameters slightly change at each run as an effect of the deviation of the system matrices from their nominal values. All these tests will provide an extensive characterization of the performance of the algorithm in view of continuous, long term vibration based SHM applications.

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