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Laboratory evaluation of a fully automatic modal identification algorithm using automatic hierarchical clustering approach

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Abstract

Earth has been a traditional building material to construct structures in many different continents. In particular, adobe buildings are widely diffused in South America, and in Peru where form part of the cultural identity of the nation. Nowadays, the knowledge of existing adobe buildings is far from a complete understanding of the constructive system and a structural health monitoring (SHM) can quantify and reduce uncertainties regarding their structural performance without causing damage to the buildings. In this process, the implementation of automatic tools for feature extraction of modal parameters is desirable. In particular, the automation is important because, during a long-term monitoring, a huge amount of data is recorded and the direct check of the data of the user is not possible. The present work is focused on the development of an automated procedure for managing the results obtained from the parametric identification method, in particular from the Data-Driven Stochastic Subspace Identification method, which requires an automatic interpretation of stabilization diagrams. The work presents a fully automated modal identification methodology based on the following steps: (i) digital signal pre-processing of the recorded data; (ii) modal parameter identification using models with varying dimensions; (iii) automatic analysis of the stabilization diagram with the application of soft and hard validation criteria and the use of hierarchical clustering approach to eliminate the spurious modes; and (iv) automatic choice of the most representative values of the estimated parameters of each clustered mode: natural frequency, damping and mode shape. The developed algorithm was firstly tested with an inverted steel pendulum to check the accuracy and sensitivity, and subsequently, an earthen wall built in PUCP Structure Laboratory was analysed to determine its dynamic behaviour. The developed algorithm shows high percentages of detected frequencies and high sensitivity to the environmental and structural changes.

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Keywords: structural health monitoring; automatic modal identification; hard/soft validation criteria; hierarchical clustering approach, experimental techniques, adobe structures.

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1. Introduction

Vibration-based Structural Health Monitoring (SHM) allows the extraction of the modal parameters of a structure (natural frequencies, damping ratios, modal shapes) which is useful for increasing the level of knowledge of its structural system and for predicting and localizing damage. In case of checking the safety state of large structures, an automatic and continuous monitoring system is required to be implemented. Nowadays, different ambient-excitation-based methodologies are available and known as Automated Operational Modal Analysis (AOMA). The main challenge of AOMA, when processing the results in time domain, is the automatic interpretation of the stabilization diagrams to separate the physical modes from the spurious ones [1]. This challenge is commonly dealt with the empirical observation that physical modes are stable and close together at every system order. Traditionally, user-defined thresholds are fixed to separate physical from mathematical modes and, then, the physical modes are summarized in a stabilization diagram to manually select the structural modal parameters [2].

The aim of this paper is to evaluate the automatic identification of the developed AOMA algorithm, focused firstly on the Data-Driven Stochastic Subspace Identification method (SSI-Data) to generate the stabilization diagram. The methodology considers then a cleaning step with hard/soft criteria and a grouping step with automatic hierarchical approach to eliminate the spurious modes. Finally, a step where the modal parameters are automatically chosen is introduce to make the methodology fully automatic.

The paper is organized as fallows. Section 2 describes the evaluated methodology. Section 3 describes the case study and the obtained results. Section 4 concludes the paper.

2. Proposed methodology for the automatic identification of the modal parameters

The proposed methodology considers two stages: a preliminary frequency-domain analysis for verifying the quality for the acquired signals and ranges for the expected results and then an automatic time-domain analysis for the final system identification.

The frequency-domain analysis uses the averaged auto power spectrum of the time signal [3] to determine its frequency content. Graphically, the results are plotted in a spectrogram, which is an intensity graph correlating the predominant frequencies vs time (or number of recorded event). This methodology is useful as first step of the dynamic analysis for its complete absence of interaction with the user and for its low time-consuming.

Subsequently, a time domain analysis is used to estimate quantitatively the modal parameters. Firstly, a digital signal pre-processing of recorded data is applied (decimation and filtering according necessities), and then, the data is processed with the SSI-Data method [4]. The SSI-Data interpretation is carried out through the stabilization diagram for which a large range of model orders is analyzed. To decrease the time consumption of the algorithm only even numbers for the model order are used considering that stable poles will still remain aligned. The modes of the stabilization diagram are initially analyzed and partitioned in two groups with the application of hard and soft validation criteria [5]. Four hard validation criteria are used according to equations (1) and (2):

$$\xi_i > \xi_{min}, \xi_i < \xi_{max} \tag{1}$$

$$f_i > f_{min}, f_i < f_{max} \tag{2}$$

where ξ_i and f_i are, respectively, the damping ratio and the frequency of an identified vibration mode. With these criteria, an upper and lower limit is applied in order to focus the analysis in a specific range of interest. The soft validation criteria consists on verifying frequencies $d(f_k)$ and damping ratios $d(\beta_k)$ distances, modal shapes (using MAC [6]) and then the complexity of the identified mode shapes. The distance criteria is defined according to equations (3), (4) and (5):

$$d(f_i^k) < f_i^k - f_j^{k-1} \tag{3}$$

$$d(\xi_i^k) < \xi_i^k - \xi_j^{k-1} \tag{4}$$

$$MAC(\phi_i\phi_j) < \left|\phi_i^{k^T}\phi_j^{k-1}\right|^2 / \|\phi_i^k\|_2^2 \|\phi_j^{k-1}\|_2^2 \tag{5}$$

where f_i, ξ_i, and ϕ_i are, respectively, the frequency, the damping ratio and the mode shape of an identified vibration mode. The superscript is associated to the model order and the subscript to each mode identified by each model order. This criteria is a comparison between consecutive model orders, and it uses the empirical observation that physical modes have similar modal properties at every model order. The last soft validation criteria is based on the mode shape complexity and takes into consideration that when a structure is proportionally damped, the mode shape components lie on a straight line in the complexity plane[7]. The complexity of a mode shape can be measured with the Modal Phase Collinearity (MPC) where a MPC closer to 1 indicates a correspondence to physical modes while values close to 0 indicates spurious results. The MPC for mode i is defined according to equation (6) as follows [8]:

$$MPC_i = \left[2\left(\frac{\lambda_1}{\lambda_1+\lambda_2} - 0.5\right)\right]^2 \quad (6)$$

where λ_1 and λ_2 are the eigenvalues of the variance-covariance matrix. The modes that fulfill the previous validation criteria go to a next stage that consists in the grouping of the similar modes in a same cluster with the application of a hierarchical clustering algorithm [9]. Firstly, each mode is considered a cluster. Subsequently, the closest clusters are combined into a new aggregate one considering the distance between the clusters (this is a user-defined parameter). In this work, a distance criteria determined by frequencies is used as cluster maxima distance. When all the modes are included in a cluster, a cut level is selected to divided the clusters with a small amount of modes with the other ones. The idea is that the clusters with a small amount of mode represent spurious modes, and therefore, they can be eliminated. This limit is not a fixed parameter because it is possible that spurious modes can pass the clustering filter (in the case of high environmental noise) or real modes can be filtered (especially if the structure is not well excited). In the present application, good results were achieved with a variable clustering limit calculated considering the root mean square (RMS) based limit as a filtering criteria. The final stage is the selection of a single value of the modal parameters in each cluster. In this work, the pole with the highest MPC is chosen as the final result. Fig.1 shows the main steps of this methodology.

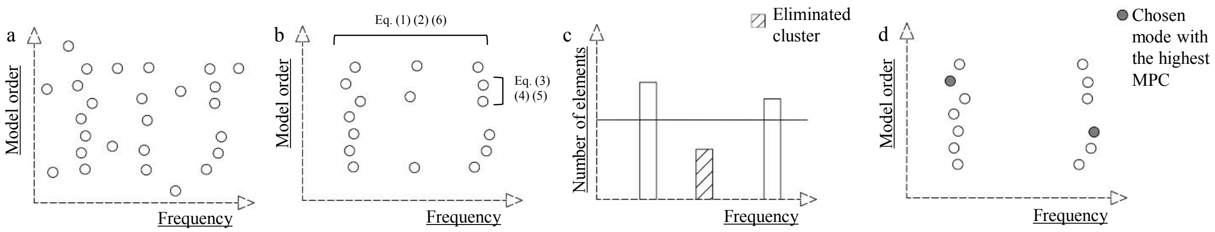

Fig. 1. Summary of the proposed automatic modal identification algorithm (a) Original data; (b) Filtered data by soft/hard validation criteria; (c) Hierarchical clustering approach; (d) Selection of the modal parameters.

3. Validation experiments with laboratory case studies

3.1. Inverted steel pendulum

A SDOF structure given by an inverted steel pendulum was used as a tool to evaluate the performance of the developed algorithm when dealing with historical data consisting of over 2000 files. The pendulum built in laboratory was 1.85m height with a 60x40 mm cross section and a heavy steel plate at the base to assure adequate support conditions (Fig.2a). The structure allows the addition of masses at its top through steel plates (Fig.2b).

The accelerometers installed were PCB 393B31 uni-axial sensors model with a dynamic range of ±0.5 g and 10 V/g sensitivity, with a frequency range of 0.1-200 Hz and a weight of 210 g (Fig.2c). These sensors include a thermal jacket for outdoor protection. The accelerometers were connected to a multi-channel system, cDAQ-9234 (24-bit resolution, 102 dB dynamic range and anti-aliasing filters) (Fig.2d). Three of these accelerometers were in the top metallic plate of the pendulum and one more was placed in the half height. The recording parameters were set to 250 Hz of sampling rate and 360 seconds of sampling time with a recurrence of 20 minutes (a total of 2120 events were recorded). The data processing parameters were set as shown in Table 1. These were selected considering the recommendation of [10].

Table 1 – Used parameters.

Sampling rate	250 Hz	Frequency range	1-100 Hz	$d(\xi_i^k)$	2	Model Order range	20-100
Number of channels	4	$d(f_i^k)$	0.05	Min MAC	0.9		
Decimation factor	1	Damping range	5-1E-5	Min MPC	0.9		

The frequency-domain results in Fig. 2e show the presence of 2 clear frequencies in the range between 5-15 Hz. To test the accuracy of the algorithm a steel plate was added to the top of pendulum from the 530th to the 1160th event. Fig. 2e shows a clear variation of the natural frequencies during this test which is a good indicator of the sensitivity of the proposed methodology for identifying small differences in frequencies.

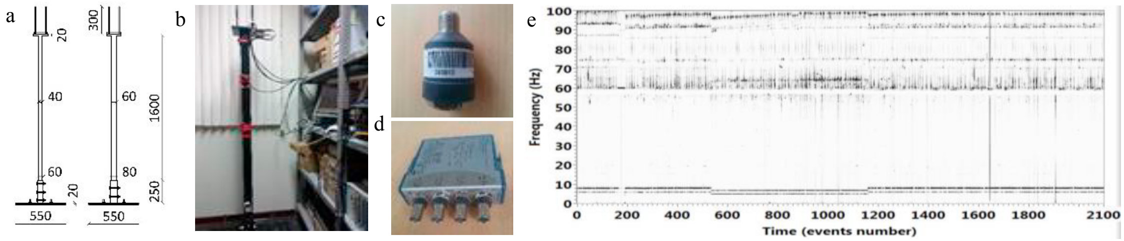

Fig. 2. (a) Geometric details of the pendulum (units: meters); (b) Steel laboratory pendulum; (c) PCB 393B12 – accelerometer sensor; (d) Used cDAQ-9234 acquisition system (e) Frequency-domain approach.

The time-domain analysis in Fig. 3a shows the presence of 4 clear frequencies (5.8Hz, 7.8Hz, 70 Hz and 75 Hz) and, in particular, Fig. 3b allows observing and calculating the frequency jump due to the mass variation and the intensity of the jump for each frequency. The sensitivity of the algorithm is shown also in the Fig.3c, where a zoom of the first frequency is presented and where the daily variation of the frequency for the environmental conditions is calculable. This range variation is about 0,05Hz, 0.05Hz, 0.2Hz and 0.3Hz for respectively the first, the second, the third and the fourth frequency. Furthermore, the percentages of the real identified frequencies in function of all the data acquired and the percentage of all the spurious frequencies in function of the real identified frequencies were calculated. The first frequency was detected in 94.3% of the recorded files, the second in 99.9%, the third in 40.3% and the last in 31.2%. The spurious modes were 8.4% of all the detected frequencies.

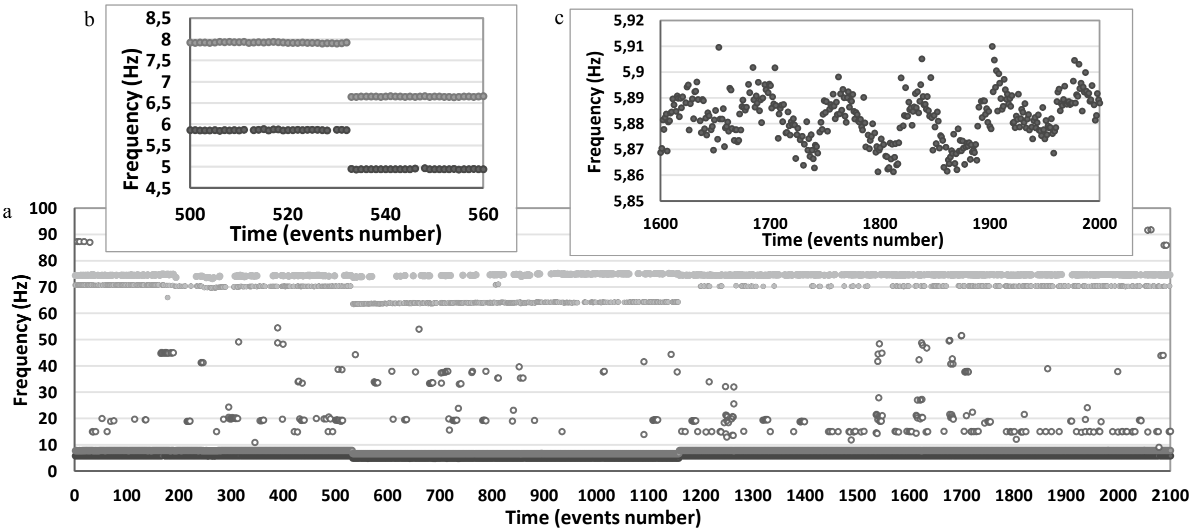

Fig. 3. (a) Time-domain approach; (b) Detail of the first and second frequency jumps; (c) Detail of the diary variation of the first frequency.

3.2. Adobe walls

Adobe blocks were built in the laboratory and exposed to environmental conditions for drying for a period of 50 days. Three full-scale walls (Fig. 4a) were built using this material and they were continuously monitored for more than 4 months. For a matter of extension, this paper reports only the results of one of the adobe walls. The dimensions of the analyzed wall are shown in Fig. 4b (1660 x 2000 x 220 mm). A concrete plinth was considered as the wall foundation to avoid the filtration of water through ground and to create a non-deformable support for the wall. The accelerometers installed and the data acquisition system have the same characteristics as in the previous case study. Two accelerometers were placed in one face at the top of the wall for measuring the out of plane behavior and one extra sensor was placed also in the top but in transverse direction. The data acquisition parameters were set as 256 Hz of sampling rate, 600 seconds of sampling time and the recurrence of events of 1 hour (a total of 2900 of events were recorded in 4 months). Table 2 shows the used parameters for the time-domain analysis.

Table 2 – Used parameters.

Sampling rate	256 Hz	Frequency range	1-100 Hz	$d(\beta_i^k)$	2	Model Order range	20-150
Number of channels	2/3	$d(f_i^k)$	0.05	Min MAC	0.9		
Decimation factor	1	Damping range	5-1E-5	Min MPC	0.9		

The frequency-domain results in Fig. 4c show the presence of six frequencies in the range between 0-80 Hz. An interesting trend is detected in any case in several frequencies, which is certainly due to the drying effect in the adobe structural system.

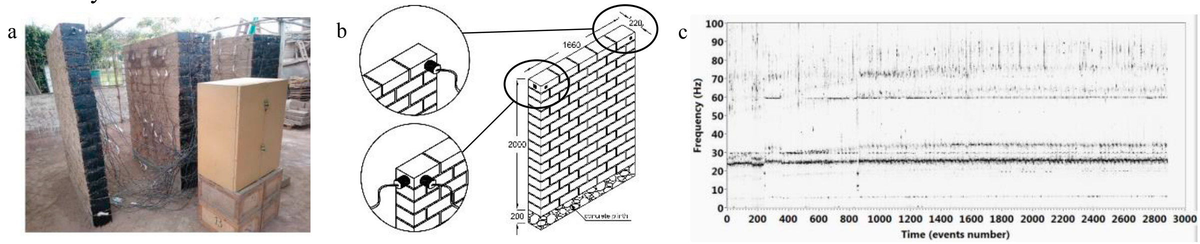

Fig. 4. (a) The three full-scale adobe walls; (b) Geometric details in mm and accelerometer positions of the adobe wall; (c) Frequency-domain approach.

The time-domain analysis in Fig. 5a shows the presence of 6 clear frequencies (6.1Hz, 21 Hz, 25.7 Hz, 34.2 Hz, 64 Hz and 76 Hz) and confirms the trend, detected in the previous analysis, in all the six frequencies (with more clear results in the higher frequencies). Furthermore, in Fig.5b a zoom of the increase of the fifth frequency is presented where the frequency increases from 49Hz until 59Hz. Additionally, a zoom of the daily frequency variation of the fourth frequency due to the environmental conditions is shown in Fig.5c. This range variation is of about 1 Hz (from 33.75 to 34.75 Hz). The same sensibility is shown also in the other frequencies where the daily range variation is about 0.2 Hz, 0.5 Hz, 0.7 Hz, 2 Hz and 3 Hz for respectively the first, the second, the third, the fifth and the sixth frequency. Finally, the percentage of each detected frequency in function of all the data recorded and the percentage of the spurious frequencies in function of the identified frequencies were calculated. The first, the second, the third, the fourth, the fifth and the sixth frequency were detected respectively in 99.8%, 79.7%, 98.7%, 97.2%, 70.1% and 22.8% of all the recorded data. The spurious modes were 8.6% of all the detected frequencies.

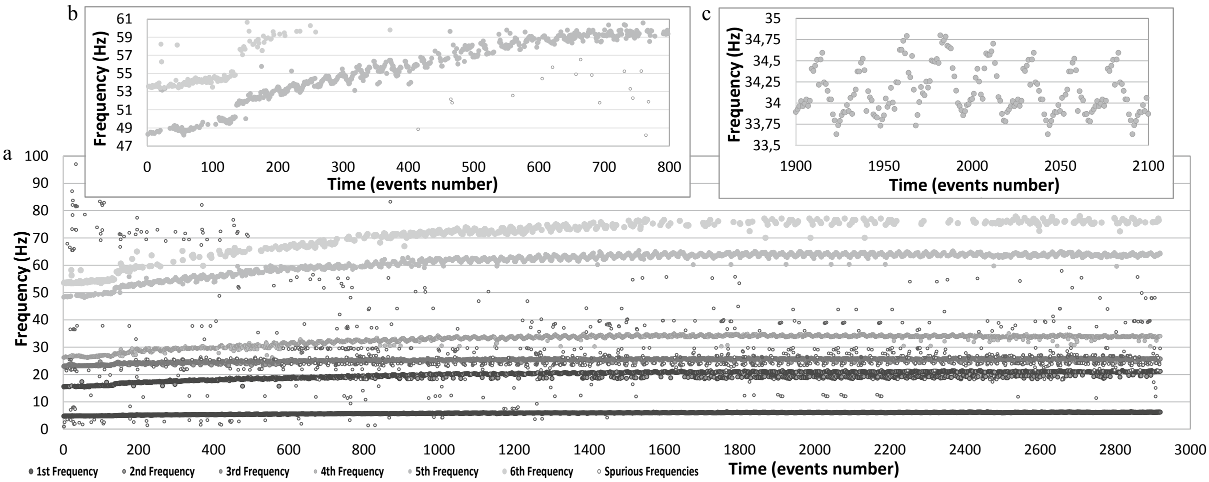

Fig. 5. (a)Time-domain approach; (b) Details of 4th frequency; (c) Detail of 5th frequency.

4. Conclusions

In this work, a fully automatic modal identification algorithm using hard and soft validation criteria and automatic hierarchical clustering approach was evaluated with months of recorded data to test its efficiency and accuracy. The results indicate a high efficiency of the hard and the soft validation criteria in the cleaning of the stabilization diagram. Furthermore, the use of an automatic hierarchical clustering approach with a not fixed group limit that has the mean feature of being flexible and to change automatically acquisition for acquisition is able to increase the elimination of spurious modes without deleting the real ones. It is shown by the high percentages of the detected frequencies; 99.9% and 94.3% are the percentages of the times that the first two frequencies of the pendulum are detected in function of all recorded data, and 99.8%, 79.7%, 98.7% and 97.2% are the percentages for the first four frequencies of the adobe wall. Moreover, the amount of not-deleted spurious modes in function of the real detected frequencies is 8.4% in the case of the steel pendulum and 8.6% in the case of the adobe wall. These results show the subsequent need to introduce an additional step to improve these percentages.

In addition, the inverted steel pendulum and the adobe wall results show that the algorithm is able to identify dynamic parameters with a very useful sensibility in the case of frequency changes due to mass or stiffness variation or due to environmental effects. It is possible to observe changes of frequency with a sensibility of 0.05 Hz due to environmental conditions and also to measure numerically the influence of these conditions for every identified frequency. Furthermore, the high sensibility of the algorithm is able to measure quantitatively the variation of each frequency in the case of mass or stiffness changes. Additionally, in the case of adobe wall, it is possible to calculate exactly the hardening period and to understand the frequencies that are more affected to this process.

Finally, the similar accuracy and sensibility of the algorithm in the case of the inverted steel pendulum and the adobe wall, built starting from the production of the adobe blocks, make the developed algorithm a useful tool for monitoring adobe buildings and for reducing uncertainties regarding their structural performance.

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