DYNAMIC IDENTIFICATION OF A REINFORCED CONCRETE STRUCTURE BY MEANS OF MODAL ASSURANCE DISTRIBUTION

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Abstract

For time-varying systems in structural engineering, such as bridges with vehicular traffic and structures during construction or seismic events, the application of traditional vibration-based identification methods may not be admissible, since the hypotheses of stationarity of the signal may be far from the real situation. Moreover, in some cases, real-time approaches to visualize the identified parameters are desirable to allow for a rapid decision-making process, which assumes the utmost importance for the early warning in structures near to excavation or demolition sites and strategic infrastructures after seismic events. Time-frequency representations have been largely used for the instantaneous identification of linear time-varying systems. However, traditional algorithms generally suffer from issues related to the identification of closely-spaced modes, which make the modal decomposition a non-trivial task. Moreover, by tracking only natural frequencies, some variations of the dynamic behavior could not be perceived, or the variations induced by other environmental and operational conditions could prevail over those due to a modification in the structural properties (e.g., due to ongoing damage). In this paper, a Decomposition Algorithm based on Modal Assurance (DAMA) is applied to separate modal responses, in order to allow a near real-time identification of modal parameters of structures with time-varying features. In particular, a Modal Assurance Distribution (MAD) obtained from the analysis of multi-variate signals is used to track the variations of modal parameters, considering both natural frequencies and modal shapes. The DAMA is applied to a full-scale structure subjected to a series of dynamic tests performed in different structural conditions. The analysis of multi-variate signals consisting of acceleration recordings collected at different locations of the structure allows the online identification of varying dynamic parameters, which can be used to assess the structural state of health.

Keywords: modal identification; time-varying system; multivariate analysis; time-frequency representation.

1. Introduction

Frequency Domain Decomposition (FDD) is one of the most used identification techniques in the frequency domain, largely applied in the civil engineering field for operational modal analysis (OMA) and structural health monitoring (SHM) [1]. Also, some variants have been introduced to improve the performance and the accuracy of this method, such as the Enhanced Frequency Domain Decomposition (EFDD) [2] which leads to a more robust determination of modal parameters and is the algorithm at the basis of several academic and commercial software. In particular, with respect to the original algorithm, the enhanced version consists of extracting the peaks of the singular values, computed from spectral densities, considering the parts with high Modal Assurance Criterion (MAC) coefficients, i.e., the signal components with similar operational deflection shapes (ODSs), which are assumed as modal shapes at the resonant frequencies. After the selection of separate modal responses, natural frequencies are identified by evaluating the number of zero-crossing of the extracted signals in the time domain.

Due to the assumptions at the base of FDD and EFDD, only stationary structural responses generated by Gaussian white noise excitation can be used to extract unbiased modal parameters of linear time-invariant (LTI) structures. However, in some practical cases, structural responses may be non-stationary, due to a particular excitation (e.g., earthquakes, traffic, and vibration generated by demolitions) or to the time-varying dynamic features, which may evolve in the short time. For such cases, the use of specific algorithms enables the identification of time-varying modal parameters. In the literature, both parametric and non-parametric methods are available. In particular, as concerns the latter category, time-frequency representations (TFR) are largely employed to separate coupled modal responses and extract instantaneous parameters such as natural frequencies and modal shapes. These techniques involve the representation of the energy distribution of the analyzed structural responses in the time-frequency plane and are generally univariate since they consider a single recording channel at a time.

The short-time Fourier transform (STFT) [3] and the wavelet transform (WT) [4] are among the most used linear transforms. More recently, the S-transform [5] has received extensive interest due to its versatility. The Wigner-Ville distribution (WVD) [6] has also been widely studied, however, practical applications on multi-component signals are challenging because of its bilinear structure that creates cross-terms which undermine the distribution readability. Empirical Mode Decomposition (EMD) [7] is a different technique used to extract signal components with different frequencies, i.e., intrinsic mode functions (IMFs), without relying on any basis function. It is especially used together with the Hilbert transform (HT), resulting in the Hilbert-Huang transform (HHT).

These methods may suffer however from several issues, mainly related to the presence of closely-spaced modes, crossing modal responses, and vanishing components, making the modal identification particularly challenging. Moreover, except for the HHT, the other TFRs do not provide any specific algorithm for the extraction of modal responses. The use of further methods is thus necessary, the efficacy of which depends on the quality of the TFR calculated [8]. Also, such methods must be applied considering all the signals collected at different locations of the structure separately. This fact may lead to inconsistency of modal parameters if some modes are not sufficiently excited at particular locations (i.e., at the nodes of modal shapes).

In this paper, the Modal Assurance Distribution (MAD) is presented as an alternative TFR which can be employed for the modal identification of time-varying structures using multivariate signals consisting of the accelerations recorded at different locations. The algorithm presented here is an adaptive extension of the work presented in [9] and used for real-time modal identification in [10,11].

Also, a Decomposition Algorithm based on Modal Assurance (DAMA) is used in this work to extract the modal responses of a full-scale reinforced concrete (RC) building during progressively induced damage.

2. Modal Assurance Distribution for structural identification

Most of the traditional TFRs represent the energy distribution of the signal in the time-frequency plane. Therefore, intervals in which the input excitation is low generally lead to low-valued areas, while strong motions are characterized by high energy terms. The occurrence of strong events may thus lead to scaling problems in the visualization and in the parameter selection for algorithms used for ridge extraction, which has to be performed in order to separate different modal responses prior to the modal identification. Moreover, the presence of recording noise affects the readability of traditional TFRs and is generally undesirable.

In this paper, the concept used in EFDD of selecting the modal responses as the components with similar ODSs is extended to the time-frequency domain. In Fig. 1, the outline of the proposed algorithm for the extraction of non-stationary modal responses is reported. In particular, the wavelet packet transform (WPT) is used to obtain a preliminary TFR for each channel of data collected on the monitoring structure. The possibility of interpreting this transform as a filter bank and its non-redundancy property make it particularly efficient and enables real-time implementations. Each output of the filter bank represents a specific subband of the original signal. Selecting a high transformation level and a suitable filter order (which reflects in the selection of a suitable wavelet function) leads to the decomposition of each acceleration channel into narrow-band signal components. Considering the presence of damping in the modal responses, if the frequency discretization is sufficiently high, a single modal response is divided into different subbands. Nevertheless, the components related to the same mode are characterized by similar ODS. The wavelet coefficients obtained at a given time instant can be interpreted as an estimate of the instantaneous ODSs of the structure. The evaluation of instantaneous MAC coefficients for ODSs associated with consecutive subbands leads therefore to a time-frequency distribution of values in the interval between 0 and 1, denoting orthogonal and proportional consecutive ODSs, respectively. Assuming the presence (and predominance) of white noise in the frequency bands where the structural response is low, the evaluation of MAC coefficients will provide random values in time-frequency regions where modal responses are not present. As a result, the MAD will have persistently high values in the regions where a modal response is present (and divided into subbands), while random values where noise prevails (generating thus random ODSs which may be similar to those of neighboring subbands in scattered time instants).

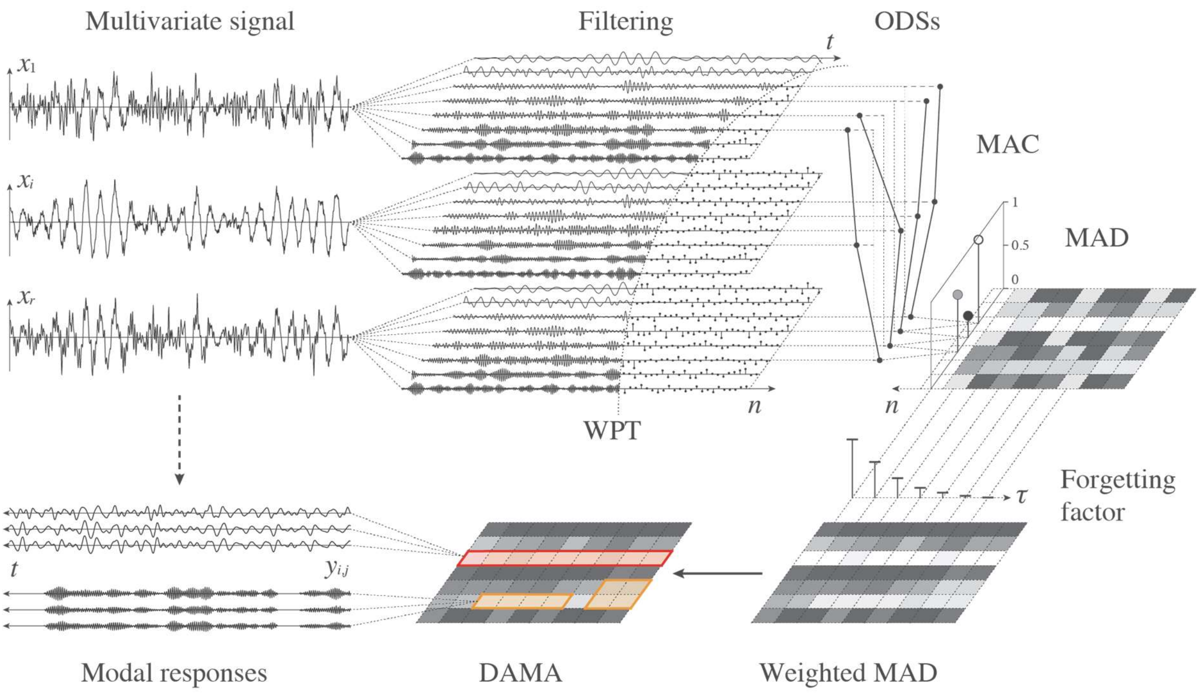

Fig. 1 – Outline of the proposed algorithm for the extraction of modal responses from multivariate signals

The readability of the MAD can be enhanced by reducing the random similarity between noise-generated ODSs. To this aim, each element of the original MAD may be replaced by the weighted average of the previous estimates. The selection of a forgetting factor α (with $0 < \alpha < 1$) is used in this formulation, with the form:

$$wMAD_k\,[n] = (1\text{-}\alpha)\; MAD_k\,[n] + \alpha\; MAD_k\,[n\text{-}1] \tag{1}$$

where $wMAD_k\,[n]$ is the weighted MAD value of the k-th and $k+1$-th subband at time sample n, while $MAD_k\,[n]$ is the original value estimated as described in the upper part of Fig. 1.

Since the proposed TFR consists of instantaneous estimates of the MAC, closely spaced modes that would result in indistinguishable high-valued areas employing the traditional TFRs give here place to two areas separated by values near to zero, due to the orthogonality of different modal shapes. Moreover, the effect of (a modest level of) noise is beneficial in this method, since it covers the effects of mode superposition in the areas between different modal responses, providing random MAC values which can be easily attenuated.

Moreover, the range of values in the MAD is fixed and does not depend on the amplitude of the signal. This fact is of the utmost importance during the extraction of non-stationary components with strongly varying amplitudes. The characteristics of the proposed distribution make it particularly suitable for the application of the watershed transform to identify separate areas representing different modal responses. In particular, the DAMA proposed in this paper consists of the following steps: (1) pre-processing the MAD with a Gaussian filter to remove spurious peaks due to noise, (2) selecting only the MAD regions with values higher than a user-defined threshold, (3) applying the watershed transform to generate a mask which is able to separate high-valued areas with lower-valued boundaries, (4) reconstructing the partial signals associated with each identified area through the inverse wavelet packet transform (IWPT) of the masked distribution, (5) evaluating the modal shape of each part, (6) grouping the areas based on the similarity of modal shapes (using a MAC-based clustering), and (7) summing up all the signal components with similar modal shape. A representation of this procedure is schematized in Fig. 2. This procedure leads to separate multivariate signals representing the modal responses of the signal at the locations where the original signal was collected. Due to the MAC-based clustering, issues related to crossing modes and vanishing components are overcome. Moreover, due to the particular sensitivity of MAD to closely spaced modes, the possibility of extracting of multimodal components is prevented.

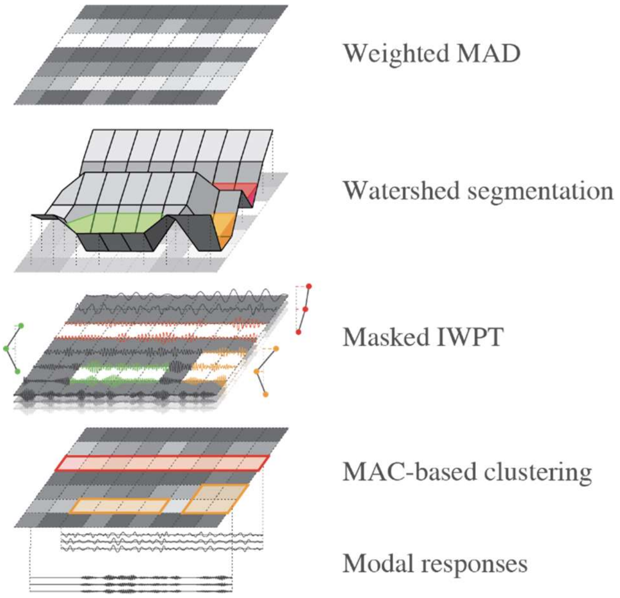

Fig. 2 – Scheme of the DAMA

3. Application

In order to prove the effectiveness and usability of MAD and DAMA, the proposed algorithms were applied to a real-scale building under induced damage scenarios. In particular, the MAD is used to localize the time-varying modal responses in the time-frequency domain, while the DAMA enables the extraction of modal responses, which are then analyzed through the HT as mono-component signals for the identification of instantaneous natural frequencies.

The case study considered in this paper is a five-story RC building tested on a shaking table at the University of California, San Diego, through the George E. Brown Jr. Network for Earthquake Engineering Simulation program (NEES-UCSD) between May 2011 and May 2012. The plan dimensions of the structure were 6.60×11.00 m and the total height was 21.34 m, with a floor-to-floor distance of 4.27 m. The shaking was impressed in the longitudinal (east-west) direction, in which the building had two RC frames as a lateral-load resisting system. The beams had a cross-section of 0.30×0.71 m, with varying connection details, and the floor system consisted of a 0.2 m thick concrete slab on all levels. More details about the specimen can be found in [12–14] and a schematic representation of the geometry is reported in Fig. 3.

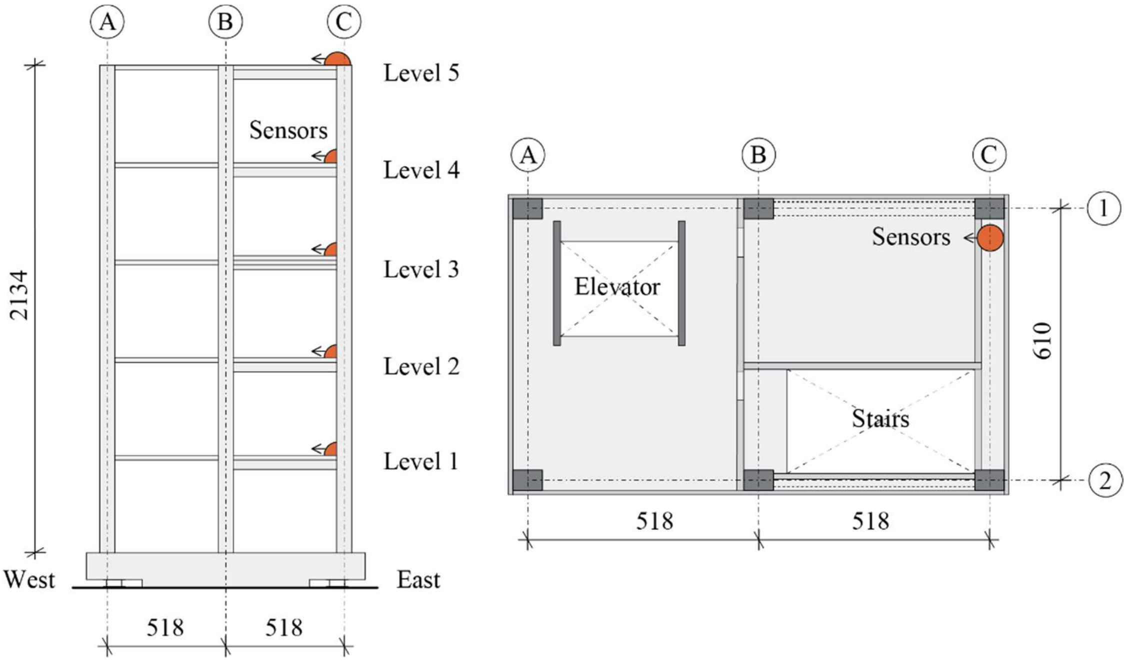

Fig. 3 – Lateral and plant scheme of the specimen, adapted from [12]; dimensions in centimeters.

During the experimental campaign, seismic excitations, white noise (WN), and double pulse inputs were impressed at the base of the specimen through the shaking table, as listed in Table 1. In particular, a suite of earthquake motions with different peak ground accelerations (PGAs) was used to progressively damage the building, while low-amplitude WN with variable root mean square (RMS) amplitude and double-pulse excitation were employed to apply identification techniques for the purposes of SHM prior to and following each seismic event.

As described in the reports of the experimental campaign, the building was designed to reach its performance targets during the DEN67 motion. Indeed, minimal damage was observed following CNP100 and LAC100 motions, with the structure remaining serviceable, presenting small cracks at level 2 in the inspection phase conducted after the application of LAC100 motion. Limited structural cracking was also observed following the application of ICA100 motion, especially at the bases of the first-floor columns and in the slab of the first level. On the other hand, motion DEN67 involved considerable damage throughout the building, particularly at the first three floors, with cracks and spalling at the base of the first-floor columns.

Table 1 – Summary of motions impressed during the experimental campaign, adapted from [12]

Date	**Excitation**	**Description**
May 7, 2012	WN1	6min WN (RMS: 1.5%g) + 6min WN (RMS: 3.0%g) + 6min WN (RMS: 3.5%g)
	CNP100	1994 Northridge earthquake – Canoga Park (PGA: 0.21g)
May 9, 2012	DP1	Double pulse
	LAC100	1994 Northridge earthquake – LA City Terrace (PGA: 0.18g)
	DP2	Double pulse
May 11, 2012	DP3	Double pulse
	ICA50	2007 Prisco (Peru) earthquake – ICA – scaled at 50% (PGA: 0.21g)
	ICA100	2007 Prisco (Peru) earthquake – ICA (PGA: 0.26g)
	WN2	6min WN (RMS: 1.5%g)
May 15, 2012	WN3	4min WN (RMS: 3.0%g)
	DEN67	2002 Denali earthquake – TAPS Pump Station #9 – scaled at 67% (PGA: 0.64g)
	WN4	6min WN (RMS: 1.5%g)
	WN5	4min WN (RMS: 3.5%g)
	DEN100	2002 Denali earthquake – TAPS Pump Station #9 (PGA: 0.80g)

In this paper, only the accelerations acquired during white noise excitation have been considered as parts of a single recording collected under varying operational and health conditions. In Fig. 4, the multivariate signal used in this paper is reported, consisting of the accelerations recorded during WN1, WN2, WN3, WN4, and WN5 motions collected in the longitudinal direction at levels from 1 to 5 (as indicated in Fig. 3). The original sampling frequency was 200 Hz, while in this paper, a downsampled signal with a factor 4 was used, with a final sampling frequency of 50 Hz.

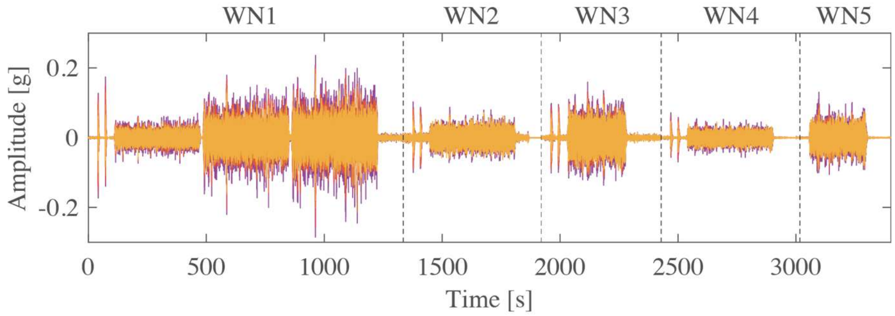

Fig. 4 – Multivariate signal collected in the longitudinal direction

The MAD was thus calculated by selecting the Fejér-Korovkin 22 wavelet function with a decomposition level 8. Due to the random similarities in noise-generated ODSs, in Fig. 5(a) the MAD presents a consistent number of spurious peaks. To smoothen the distribution before the application of DAMA, a forgetting factor of 0.9 was adopted, which leaves the frequency resolution unchanged but removes abrupt variations on the time axis, introducing however a slight delay in the extraction of modal responses. In fact, the mask generated by the DAMA can be seen as an adaptive filter bank with time-varying cutoff frequencies. The definition of such parameters depends on the values of the MAD and is, therefore, more responsive using a forgetting factor close to zero. On the other hand, a prompt adaptivity (in the order of fractions of a second) is not necessary for medium- to long-term monitoring applications (as the one shown in this paper). The selection of a high forgetting factor is indeed preferable here to avoid the extraction of local peaks due to noise or short-time effects. A lower value may be chosen to study structural behavior during seismic events.

A threshold of 0.5 was then selected for extracting only high-valued areas and the watershed segmentation was performed after applying a Gaussian filter with standard deviation 1. After extracting segmented areas, a MAC-based clustering procedure with sensitivity 0.15 has been applied, i.e., couples of ODSs with MAC values higher than 0.85 have been associated with the same cluster. In this way, the components obtained by reconstructing the partial signals related to each area have been assigned to a different vibration mode. In this way, the areas shown in Fig. 5(b) have been obtained. In this experiment, a total number of 3 vibration modes have been identified.

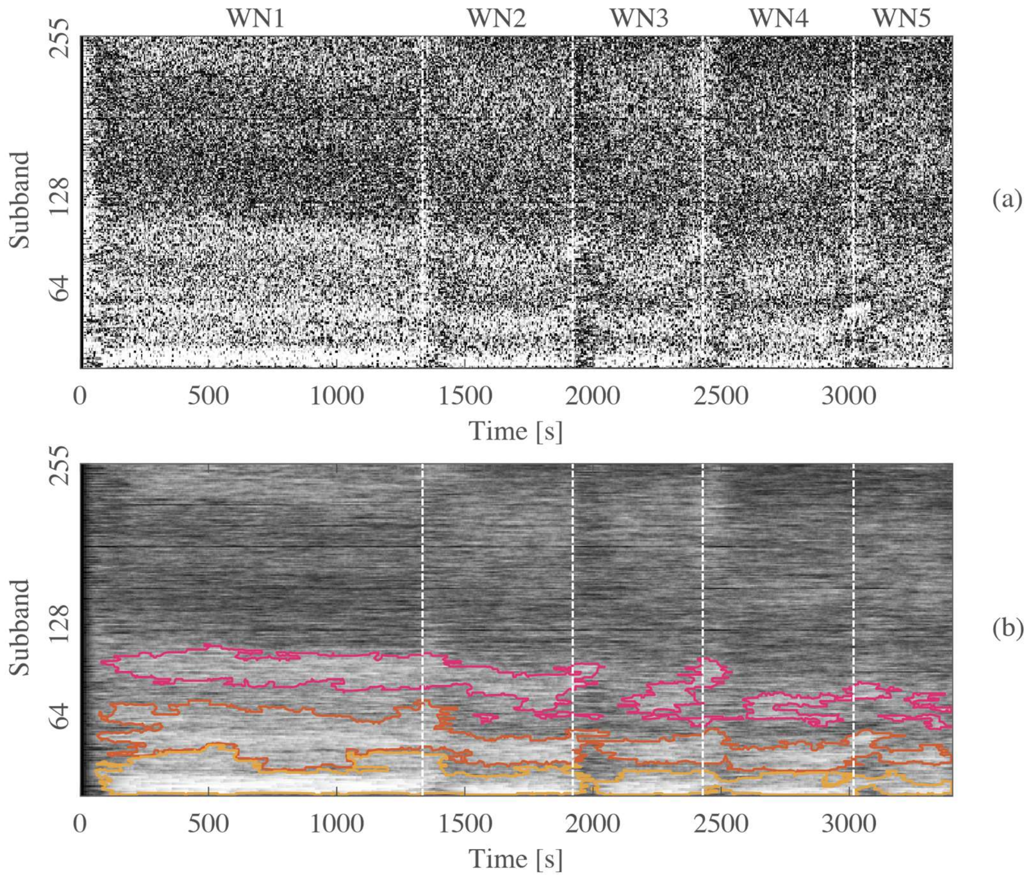

Fig. 5 – Original (a) and weighted (b) MAD with mask generated through the DAMA

The instantaneous frequencies identified by applying the HT to the modal responses associated with the areas represented in Fig. 5(b) are reported in Fig. 6, superimposed on the reference values (dashed lines) identified during the 1.5%g RMS WN excitation in reference [13]. A median filter with a window size of 1000 samples was applied to the instantaneous frequencies before plotting, in order to improve the readability of the figure.

As a comparison with literature methods for adaptive signal decomposition, the EMD was considered. The instantaneous frequencies obtained by applying the HT on the IMFs extracted from the signal collected at level 5 are reported in grey in Fig. 6. Here, the same median filter used for extracted modal responses is employed.

It is possible to notice that the instantaneous frequencies identified through the proposed method are in agreement with the reference values identified in [13]. On the other hand, IMFs show more variable instantaneous frequencies, which are generally more distant from the reference values, with evident mode mixing problems for the first modal response.

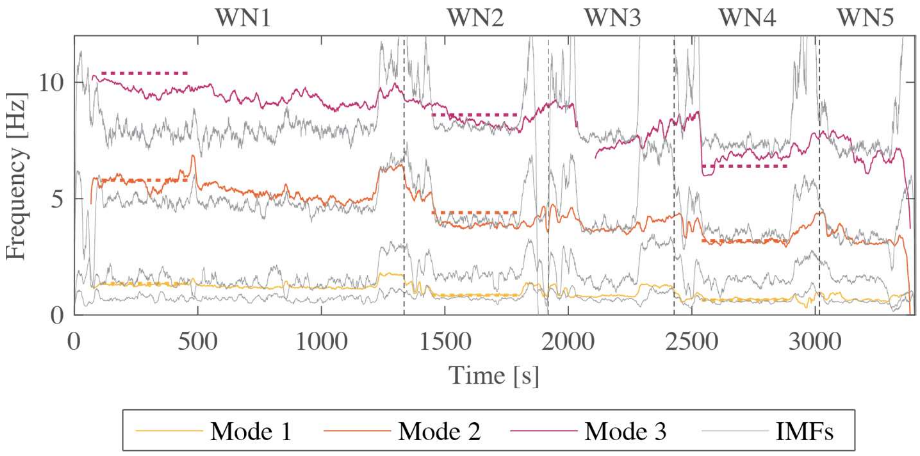

Fig. 6 – Instantaneous frequencies extracted through the proposed algorithm (colored) and the HHT (grey)

As in the case study analyzed in [10], a clear correlation between frequencies and excitation amplitude is noticeable, since shifts in identified values occur within the same damaged condition when the RMS of the excitation changes, also for the undamaged scenario.

The instantaneous amplitudes of the decoupled modal responses can be used for estimating time-varying modal shapes. In Fig. 7, the instantaneous modal shapes calculated by normalizing the identified amplitudes to the values associated with the sensor at the higher level are reported. Here, the same median filter used for instantaneous frequencies is employed.

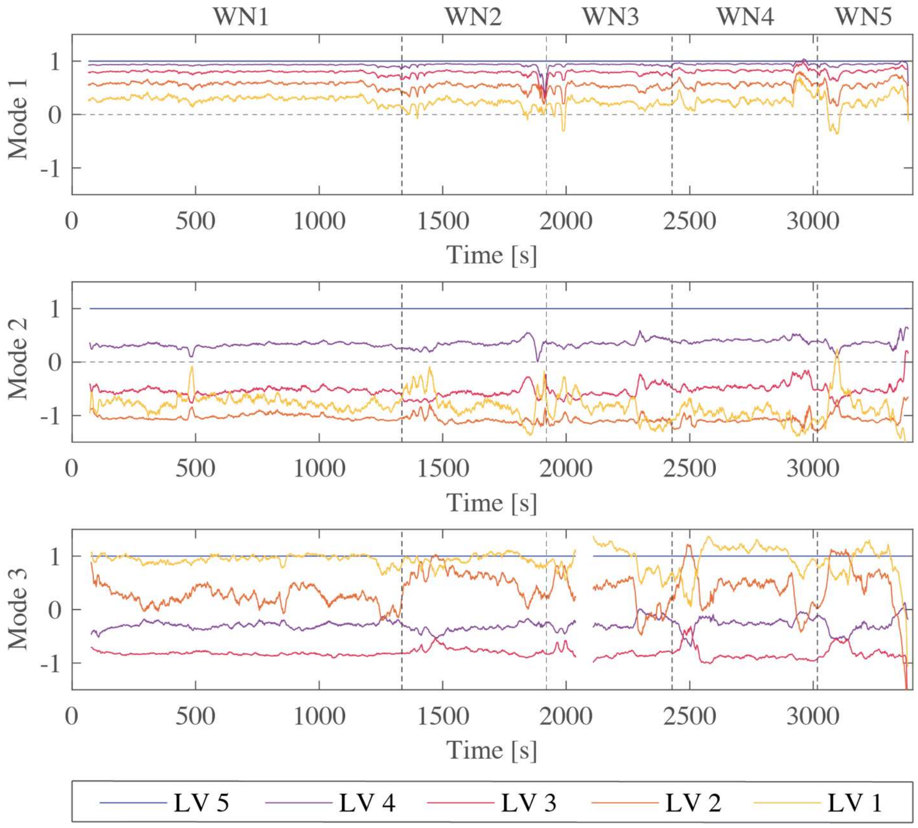

Fig. 7 – Normalized amplitudes of the instantaneous modal shapes extracted through the proposed algorithm for the different levels (from LV1 to LV5)

While modal frequency shows a visible dependence on the excitation amplitude, modal shapes appear to be almost independent, showing a noisy trend when passing from a condition to another. The reason for such variability may be due to the abrupt passage from a recording to another, which is not smoothed in the ending parts through any windowing function. Thus, the wavelet coefficients evaluated in the transition intervals may be corrupted. Moreover, the adaptive filter bank generated through the weighted MAD presents a delay and, therefore, the first part of each recording is decomposed through the filters adapted on the final part of the previous segments.

Furthermore, a variation of instantaneous modal parameters with the ongoing damage is notable. The identified values may indeed be employed in real-time algorithms for SHM aimed at early warning when dynamic features of structures present anomalies, or to check the state of health of civil structures and infrastructures in critical situations (e.g. in the period after the occurrence of an earthquake or during invasive interventions).

4. Conclusions

In this paper, a new time-frequency representation for multivariate signals is presented, based on the similarities between instantaneous ODSs related to narrow-band signal components. The use of the wavelet packet transform allows the implementation of the method through efficient algorithms for real-time applications. The modal assurance distribution has proven to be particularly suitable for the watershed segmentation, as the areas associated with different modes are well separated by low values in the distribution. Furthermore, the use of a forgetting factor significantly improves the readability of the modal assurance distribution, introducing however a delay in the adaptability of the equivalent filter bank, which is nevertheless negligible for long-term monitoring applications.

In this study, the decomposition algorithm based on modal assurance was applied to a full-scale RC building. The natural frequencies identified through the proposed method were compared to the outcomes obtained for a stationary interval of the analyzed signal using a traditional FDD algorithm. The results show a good agreement between the average frequency values. Also, the proposed algorithm is able to estimate the instantaneous variations of modal parameters due to operational, environmental, and damage effects. The proposed method was also compared to the EMD, which is currently widely used for the instantaneous evaluation of modal parameters in several SHM applications. However, in this application, EMD showed serious mode-mixing problems, together with the identification of non-physical modes.

The idea of measuring similarity in neighboring ODS has already been successfully used in the EFDD algorithm for modal identification in the frequency domain and is extended here in the time-frequency domain, enabling the identification of instantaneous parameters for time-varying systems.

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