



Identification and Damage Detection of a Shear Frame Model Based on a Blind Source Separation Method

Minas Spiridonakos, Nishant Yadav, Eleni Chatzi

► To cite this version:

Minas Spiridonakos, Nishant Yadav, Eleni Chatzi. Identification and Damage Detection of a Shear Frame Model Based on a Blind Source Separation Method. EWSHM - 7th European Workshop on Structural Health Monitoring, IFFSTTAR, Inria, Université de Nantes, Jul 2014, Nantes, France. hal-01022976

HAL Id: hal-01022976

<https://inria.hal.science/hal-01022976>

Submitted on 11 Jul 2014

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

IDENTIFICATION AND DAMAGE DETECTION OF A SHEAR FRAME MODEL BASED ON A BLIND SOURCE SEPARATION METHOD

Minas Spiridonakos¹, Nishant Yadav², Eleni Chatzi¹

¹ *Institute of Structural Engineering, D-BAUG, ETH Zurich*

² *Laboratory for Intelligent Structural Technology, Department of Civil Engineering, University of Michigan Ann Arbor*

spyridonakos@ibk.baug.ethz.ch, nisyad@umich.edu, chatzi@ibk.baug.ethz.ch

ABSTRACT

Blind source separation methods have recently emerged as a competitive alternate structural identification method offering a number of advantages when compared to traditional methods. These include the plain underlying model, its computational ease, and its robustness to various types of excitations. The aim of this study, is to experimentally assess the effectiveness of a second order BSS method for the problems of output-only structural identification and damage detection, by its application on the vibration response data of a four-storey shear frame. The structure under study is subjected to various types of input excitation and is tested under its “healthy” and a number of simulated “damaged” states. The results of the study show great potential of the BSS method for the efficient treatment of both problems.

KEYWORDS : *Blind source separation, modal properties, shear frame, structural identification, damage detection.*

INTRODUCTION

Blind Source Separation (BSS) methods have recently gained increased interest among the research community as an alternate structural identification method. The term BSS is used to describe methods that focus on the recovery of unobserved source signals from their observed mixtures [1,2]. The latter are usually considered to be linear and static mixtures of the source signals, leaving a constant mixing matrix as the component to be identified. Toward this end, and depending on the assumptions made on the nature of the unobservable sources, second order or higher order statistics may be used, with the Second Order Blind Identification (SOBI) method [3,4], and Independent Component Analysis (ICA) [2] comprising the most methodological tools from each category.

The applicability of BSS methods on the structural identification problem has only recently been exploited, by linking the mixing matrix to the modal properties of the structure [1,4,5]. The merits of the BSS methods, when compared to traditional identification methods, is that as already mentioned they do not require measurement of the applied excitation (input) while in addition, in the random case, the knowledge of the statistical distribution of the excitation forces is not necessary [1]. Thus, the crude assumption of broadband white excitation [6], which is adopted by the majority of traditional identification methods, may be relaxed to more general types appropriate to describe actual loads like wind and traffic. Moreover, BSS methods are characterized by low complexity since they are based on a simple linear static mixture model, from which the modal properties of the structure may be directly obtained.

BSS methods have been utilized for a number of operational modal analysis and damage detection applications [3,7–9], with the various methods’ robustness for the cases of non-white random excitation sources, noise contaminated outputs and identification of highly damped modes been demonstrated.

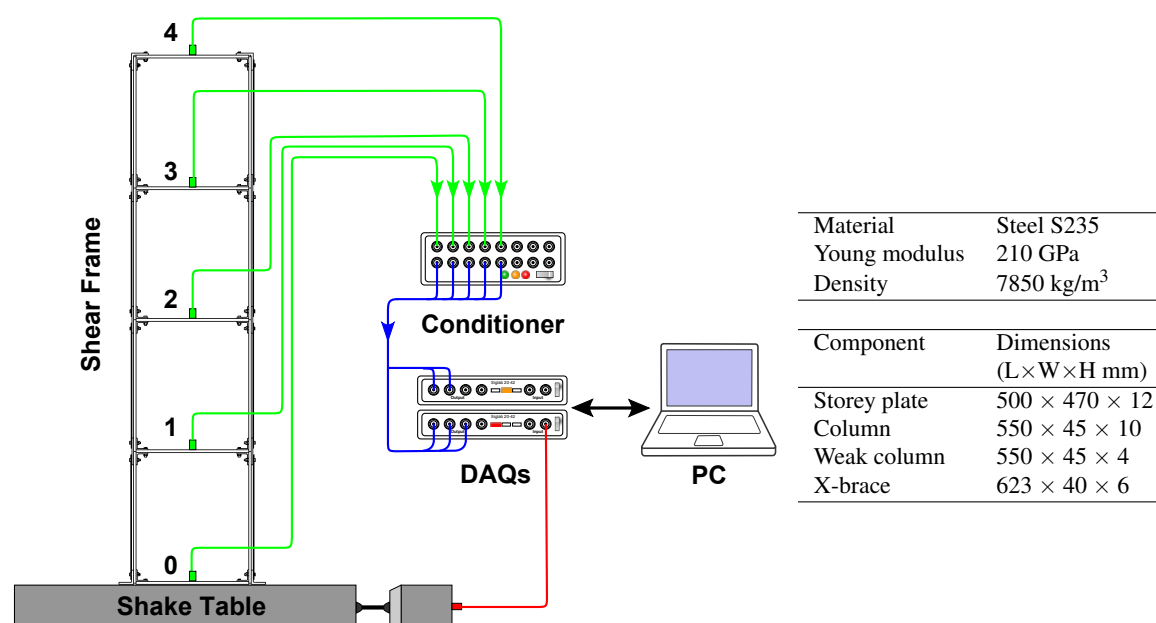


Figure 1 : Schematic diagram of the experimental setup and the physical properties of the shear frame structure.

The goal of this work, is the application of a BSS method for the accurate estimation of the modal properties of a four-storey shear frame model subjected to various types of input excitation and under a number of “healthy” and simulated “damaged” states. More specifically, the SOBI method is used for the estimation of the natural frequencies and the mode shapes of the shear frame based on the dynamic responses of the structure acquired during vibration testing experiments with the shear frame being subjected to random white noise and sine sweep base excitation, while the experiments are conducted for the healthy structure and the structure with three different types of “damages”.

THE SHEAR FRAME, THE DAMAGE SCENARIOS AND THE EXPERIMENTAL SET-UP

The structural system employed in this study is a steel four-storey shear frame model, with lateral force resistance being provided by X-braces. The geometric and material properties of the structure are summarized in Figure 1. The shear frame is mounted through four bolts on a single-axis shake table running on displacement control mode (frequency range 0-100 Hz, force range ± 100 kN, stroke ± 125 mm, max. velocity 0.55 m/s). Sine sweep and random zero-mean Gaussian displacement are used for the excitation of the structure. The vibration response of the structure is measured at the base (actual input excitation, location 0; Figure 1) and each storey of the frame (locations 1-4; Figure 1) through triaxial lightweight MEMS accelerometers (STMicroelectronics LIS344ALH, range ± 2 g, sensitivity 3.3/5 V/g, acceleration noise density $50 \mu\text{g}/\sqrt{\text{Hz}}$) placed at the geometric center of each plate. The identification and damage detection results of the present study are solely based on the vibration response signals measured at locations 1-4 (Figure 1).

The damage scenarios considered correspond to: a) loosening of the bolts (M8) connecting the plate of the 3rd storey with the columns connecting the 3rd and 4th storey through L-brackets, b) replacing two of the columns connecting the 2nd and 3rd storey with thinner ones, and finally c) replacing all these columns by thinner ones (see Figure 2). Thus, three distinct damage scenarios (types) are considered in total which are also summarized in Table 1. The assessment of the SOBI based method with respect to the damage detection problem is based on four experiments for each considered state of the shear frame structure (healthy structure, damage types A, B, and C). The four experiments correspond to two random noise excitation cases (bandwidth 0-30 Hz, standard deviation equal to 0.1 and 0.15 g),

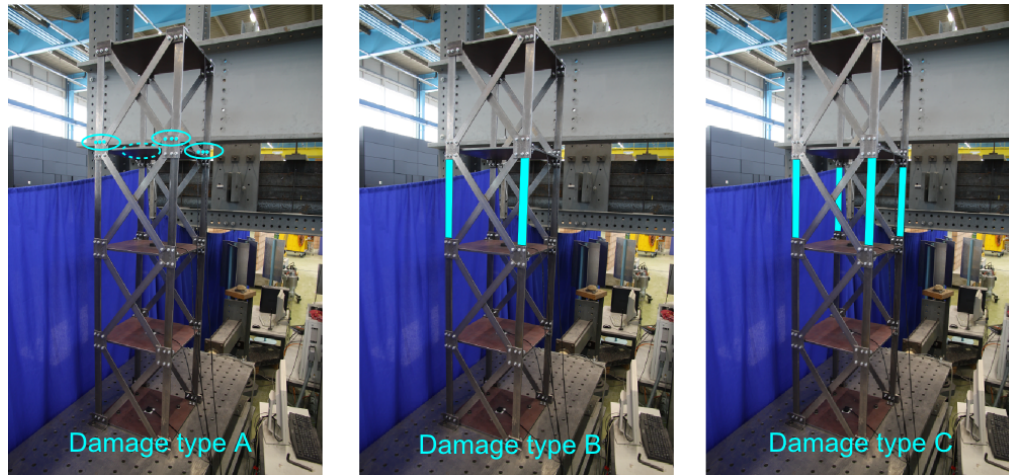


Figure 2 : The simulated damage scenarios.

Table 1 : The damage types and signal details.

Structural State	Description
Healthy	—
Damage type A	loosening of the bolts of the 3 rd storey (from 25 to 15 Nm)
Damage type B	replacing two of the columns connecting the 2 nd and 3 rd storey by thinner ones
Damage type C	replacing all four columns connecting the 2 nd and 3 rd storey by thinner ones
Sampling frequency:	$f_s = 125$ Hz
Signal length:	$N = 5,000$ samples (= 40 s) – random excitation
	$N = 12,500$ samples (= 100 s) – sine sweep excitation

and two experiments with input sine sweep excitation (linear frequency increment between 1 and 30 Hz, maximum displacement equal to 4 mm and 8 mm).

The vibration response acceleration signals are sampled at $f_s = 1250$ Hz. However, the frequency range of interest is 0 - 30 Hz, so the response signals are filtered and downsampled by a factor of 10 before processed (Table 1).

The dynamic responses of the structure subject to sine sweep excitation (maximum displacement equal to 8 mm) are shown in Figure 3 along with the corresponding power spectral density estimates calculated through the Welch method (Hamming window, window size equal to 2048, 80% overlapping, frequency resolution 0.06 Hz). From this figure it may be clearly observed that as expected the shear frame is characterized by four lightly damped modes around 3, 12, 20 and 27 Hz.

BLIND SOURCE SEPARATION METHOD

Blind Source Separation (BSS) methods aim at estimating unobservable source signals and the mixing system from observed output signals. A linear static mixing model of the following form is the simplest and most widely used for this purpose [2]:

$$x_j(t) = a_{(j,1)}s_1(t) + a_{(j,2)}s_2(t) + \dots + a_{(j,n)}s_n(t), \quad \text{for } j = 1, \dots, n \text{ and } t = 0, \dots, N-1 \quad (1)$$

In the equation above it is considered that n observed signals, originate from the linear mixture of n unobserved components $s_i (i = 1, \dots, n)$. By using vector-matrix notation Equation (1) may be rewritten as:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \quad (2)$$

with $\mathbf{x}$ designating the observed signal vector, $\mathbf{A}$ the mixing matrix, and $\mathbf{s}$ the vector of unobserved sources.

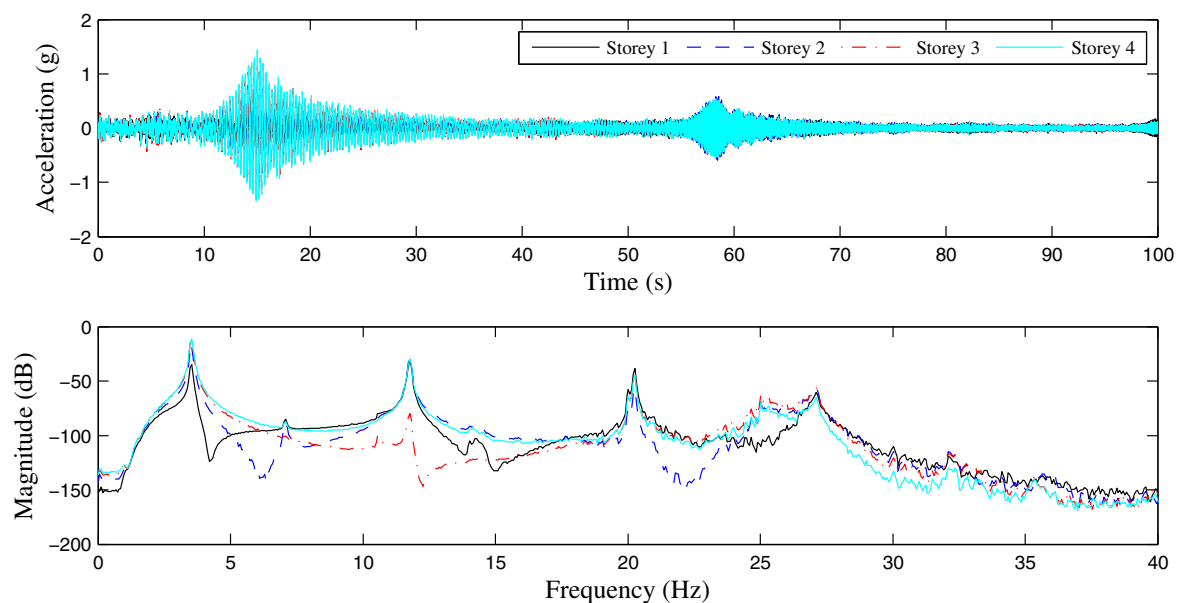


Figure 3 : Dynamic responses of the shear frame structure subject to sine sweep excitation (upper plot) along with the Welch-based estimates of the power spectral densities.

BSS methods have recently found fertile ground in the field of operational modal analysis, since the linear mixing model may be directly linked with the equation relating the vibration response of a structure and its normal modes [1, 5]

$$\mathbf{x}(t) = \mathbf{\Phi} \mathbf{q}(t) \quad (3)$$

where $\mathbf{\Phi}$ stands for the modal matrix and $\mathbf{q}(t)$ the modal responses. Although the above equation is valid only for the case of a real-valued modal matrix, corresponding to zero or proportional damping [5], recent studies have dealt with the development of BSS methods able to estimate complex modes, while they have also been shown to be able to accurately estimate highly damped modes [5, 10].

The unobserved sources $\mathbf{s}$ (or equivalently $\mathbf{q}$) are unknown and have to be estimated by the random vector $\mathbf{x}$ and the also unknown mixing matrix $\mathbf{A}$. More accurately, noting that by inverting the mixing matrix $\mathbf{A}$, say $\mathbf{W} = \mathbf{A}^{-1}$, the vector of the unobserved sources $\mathbf{s}$ may be readily obtained as:

$$\mathbf{s}(t) = \mathbf{W} \mathbf{x}(t) \quad (4)$$

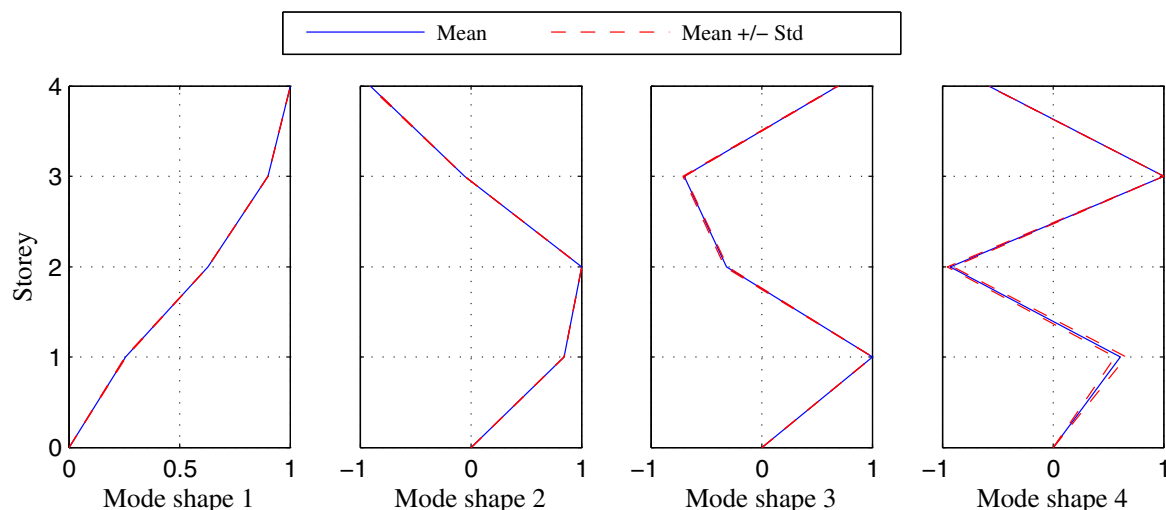
the estimation problem may be more compactly defined as the problem of estimating the mixing matrix $\mathbf{A}$ based on the observed signals $\mathbf{x}$ and assumed properties of the unobserved sources.

Therefore, BSS methods may be distinguished into those using higher order statistics, such as Independent Component Analysis (ICA) method which assumes independent unobserved sources which are estimated by maximizing their non-Gaussianity, and those using second order statistics, with main representative the Second Order Blind Identification (SOBI) method, which consider mutually uncorrelated sources. The latter method is much simpler, based on weaker assumptions and better fitted to the problem of structural modal analysis [10]. Actually, SOBI has been successfully applied in a number of structural identification applications and has been proven to offer a number of advantages over alternative methods such as ICA [4], or even other second order methods such as AMUSE [3].

For this reason, SOBI is presently employed for the structural identification of the modal properties of the shear frame model, while also its potential for damage detection is examined. The estimation details of the method may be found elsewhere [4, 10].

Table 2 : Estimated natural frequencies (mean value $\pm$ one standard deviation) of the healthy structure.

Nat. freq.	mean $\pm$ std (Hz)
ω_{n_1}	3.5367 ± 0.0111
ω_{n_2}	11.8067 ± 0.0225
ω_{n_3}	20.2528 ± 0.0613
ω_{n_4}	27.0500 ± 0.0244

Figure 4 : Estimated mode shapes (mean value $\pm$ one standard deviation) of the healthy structure.

IDENTIFICATION & DAMAGE DETECTION RESULTS

Identification of the shear frame under its healthy structural state is first considered. SOBI algorithm is employed for the estimation of the modal properties of the structure, and more specifically its natural frequencies and the corresponding mode shapes. The latter may be directly obtained by the columns of the estimated mixing matrix A without any further processing being required, while the natural frequencies may be obtained by locating the strongest component of the power spectral density of each of the estimated sources.

Applying the SOBI algorithm to the dynamic responses of the structure for each of the four input excitation cases, a set of equal number of estimates of the modal properties is obtained. The mean value and standard deviation of the healthy structure natural frequencies estimates are summarized in Table 2, while similarly the mean mode shapes along with the corresponding standard deviations are depicted in Figure 4. The small standard deviation of the estimates highlights the robustness of the SOBI method to the different excitation cases considered.

The mean values of the estimated modal properties are used as nominal (reference) values for the subsequent damage detection procedure. This involves the application of the SOBI algorithm to the dynamic responses of the “damaged” structure acquired during an equal number of experiments for each damage scenario, the derivation of the corresponding modal properties estimates, and the comparison with the nominal values. Damage detection is then based on testing for significant changes in the modal properties between the nominal (healthy) and current state of the structure.

The mean $\pm$ one standard deviation values of the estimated natural frequencies corresponding to the healthy and the damaged shear frame are contrasted in Figure 5 (four experiments per structural state). Evidently, damages may be correctly detected for all test cases, as the estimated natural frequencies, particularly for the higher modes and for damage types B and C, shown large deviations from the nominal values. The percentage change of each natural frequency estimate ($\omega_{n_i}^u$ with $u = A, B$, or

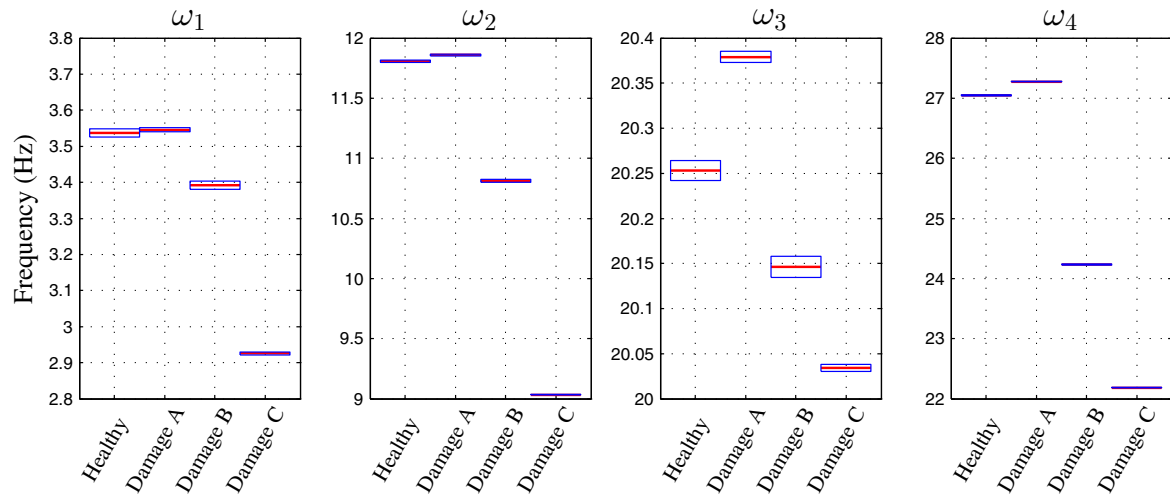


Figure 5 : Natural frequencies estimates (mean $\pm$ one standard deviation) for all structural states.

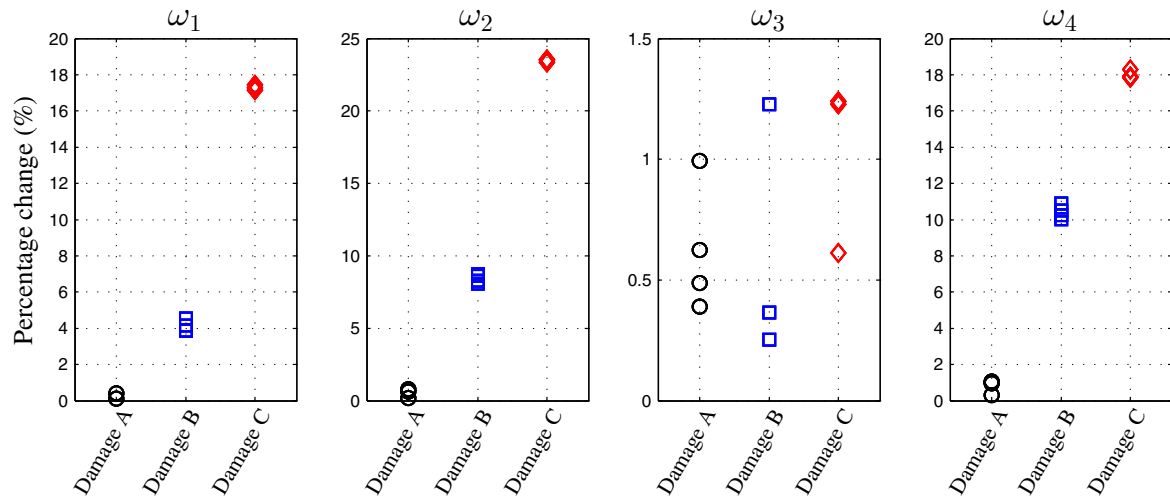


Figure 6 : Percentage change of the damaged structure natural frequencies with respect to the nominal values of the healthy structure.

C) with respect to its nominal value ($\bar{\omega}_{n_i}^o$), is calculated through the following equation:

$$C_{\omega_{n_i}} = 100 \times \frac{|\bar{\omega}_{n_i}^o - \omega_{n_i}^u|}{\bar{\omega}_{n_i}^o} (\%) \quad (5)$$

and shown in Figure 6. This plot highlights the previous comment by showing deviations of up to 25 % from the nominal values for the case of damage type C, which as expected is the one to cause the largest changes in the dynamic properties of the structure. On the other hand, damage type A causes changes, which are for all natural frequencies, lower than 2 %.

The damage detection may also be based on the comparison of the estimated mode shapes for the healthy and damaged states of the structure, through the Modal Assurance Criterion (MAC). The MAC value is a measure of the correlation between two mode shapes, which for the comparison between an estimated real-valued mode shape of the damaged shear frame, let ϕ_{u_i} , with the corresponding nominal

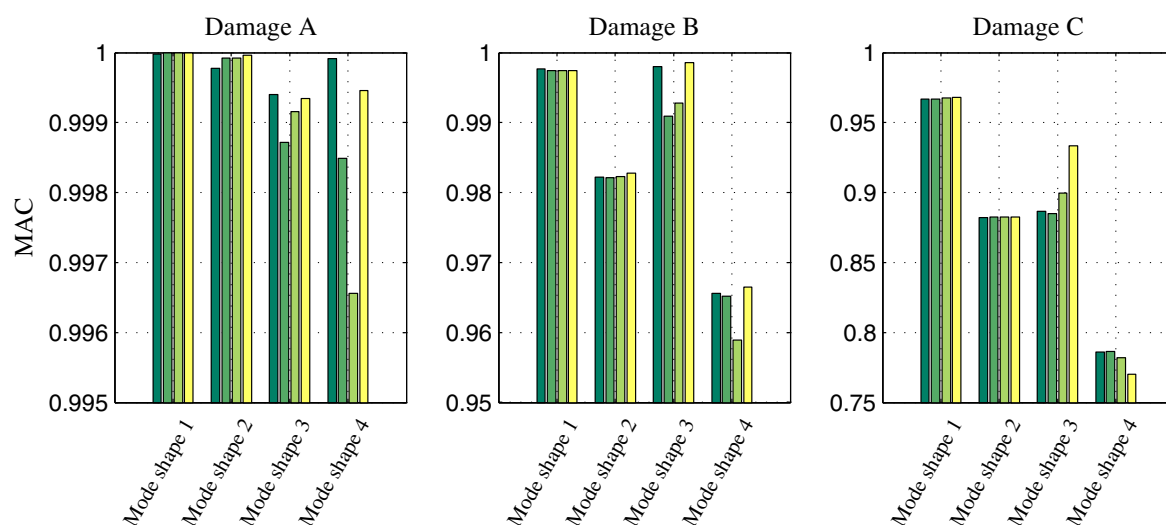


Figure 7 : Modal assurance criterion values of the damaged structure mode shapes with respect to the mean values of the healthy structure estimates.

mode shape of the healthy structure $\bar{\phi}_{o_i}$ may be written as follows:

$$MAC_i = \frac{(\bar{\phi}_{o_i}^T \cdot \phi_{u_i})^2}{(\bar{\phi}_{o_i}^T \cdot \bar{\phi}_{o_i}) (\phi_{u_i}^T \phi_{u_i})} \quad (6)$$

The calculated MAC values for all the experiments conducted and all damaged states and are shown in Figure 7. Also in this case, the MAC values are not really low for the type of damage A, however they are significantly lower than unity (fully correlated) for the rest of the damage types. In general, the larger sensitivity of the higher modes to damages is validated by the results of this figure.

It must be noted that the damage detection method could be automated by using a statistical framework and an appropriately hypothesis test based on the probability distribution function of the modal properties estimates. However, a larger number of experiments would be required in order to be able to empirically derive an accurate estimate of such distribution.

CONCLUSION

The effectiveness of a second-order BSS method for the output-only structural identification and damage detection problems was experimentally examined through its application on the dynamic response data of a four-storey shear frame model excited at its base. Three distinct damage scenarios were considered, and the modal properties of the structure under its various damaged states were compared to their nominal values corresponding to the healthy structural state. All damages could be readily detected as the deviation of the estimated modal properties were detected by the employed SOBI method. Future research will focus on the use of more advanced BSS methods for the same problem and the development of a statistical damage detection framework.

ACKNOWLEDGEMENTS

Rafael Dubs, Alessandra Eicher, Rebekka Habegger, and Severin Haeffliger, master students of ETH Zurich, who designed, constructed and tested the shear frame structure under the supervision of the authors, are gratefully acknowledged.

REFERENCES

- [1] G. Kerschen, F. Poncelet, and J.-C. Golinval. Physical interpretation of independent component analysis in structural dynamics. *Mechanical Systems and Signal Processing*, 21(4):1561–1575, 2007.
- [2] A. Hyvärinen and E. Oja. Independent component analysis: algorithms and applications. *Neural Networks*, 13(4-5):411–430, 2000.
- [3] W. Zhou and D. Chelidze. Blind source separation based vibration mode identification. *Mechanical Systems and Signal Processing*, 21(8):3072–3087, Nov 2007.
- [4] F. Poncelet, G. Kerschen, J.-C. Golinval, and D. Verhelst. Output-only modal analysis using blind source separation techniques. *Mechanical Systems and Signal Processing*, 21(6):2335–2358, 2007.
- [5] S.I. McNeill and D.C. Zimmerman. A framework for blind modal identification using joint approximate diagonalization. *Mechanical Systems and Signal Processing*, 22(7):1526–1548, Oct 2008.
- [6] P.T. Brewick and A.W. Smyth. An investigation of the effects of traffic induced local dynamics on global damping estimates using operational modal analysis. *Mechanical Systems and Signal Processing*, 41(1-2):433–453, Dec 2013.
- [7] S. I. McNeill and D. C. Zimmerman. Blind modal identification applied to output-only building vibration. In *28th IMAC, A Conference on Structural Dynamics*, pages 157–176. Springer, 2010.
- [8] B. Hazra and S. Narasimhan. Wavelet-based blind identification of the ucla factor building using ambient and earthquake responses. *Smart Materials and Structures*, 19(2):025005, Feb 2010.
- [9] V.H. Nguyen and Golinval J.-C. Damage detection using blind source separation techniques. In *29th IMAC, A Conference on Structural Dynamics, Jacksonville, FL, USA*, pages 45–56, 2011.
- [10] J. Antoni and S. Chauhan. A study and extension of second-order blind source separation to operational modal analysis. *Journal of Sound and Vibration*, 332(4):1079–1106, Feb 2013.