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DAMAGE DETECTION USING PRINCIPAL COMPONENT ANALYSIS APPLIED TO TEMPORAL VARIATION OF NATURAL FREQUENCIES

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ABSTRACT

For preserving existing structures to the extent possible, vibration-based damage detection techniques are gaining more attention. In specific, tracking the changes in a structure's natural frequencies employing the Principal Component Analysis (PCA) seems to be a promising technique. This paper presents an on-going research for developing an approach for damage detection based on identifying the natural frequencies of the structure (via dynamic identification or monitoring) followed by applying PCA on the temporal variation of the identified natural frequencies. The processing of the dynamic monitoring data was carried out using a proposed semiautomatic algorithm able to identify and track the natural frequencies of the monitored structures and their changes over time. The algorithm was applied on one historical structure and two modern ones. PCA will to be carried out. The so far developed approach as a whole was applied on a steel structure model tested in lab. It was subjected to dynamic identification tests with and without damage. It was found that PCA applied to frequency variation seems to be a possible tool to know damages in structures. Nevertheless, the simplified point of view correlating directly the number of PCs with the damage importance seems to be not accurate. First results seem to indicate that the variance percentage explained by each of the principal components could be correlated with the kind of damages and the shake used to excite the structure.

Keywords: damage detection*; PCA;* non-lineal comportment; *modal frequencies temporal evolution.*

1. INTRODUCTION

Damage detection in existing structures (due to aging, environmental actions, earthquakes and other factors) employing the tracking of the changes in modal parameters (natural frequencies, mode shapes and damping ratios) is one of the topics that attracting more importance nowadays. This is because of the need to assess the structural state of a large number of structures (like bridges, tunnels, historical structures, among others) without the full dependence on the traditional visual inspection that is not an effective technique because of its limitations like reliability, precision, accessibility, among others.

Measuring the changes in the modal parameters (especially natural frequencies) before and after the damage is a possible approach for evaluating such damage. This needs that the structure to be instrumented with a dynamic monitoring system active before, during and after the damage. The registered signals can be processed and the variations in natural frequencies, due to damage, could be estimated.

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This could be achieved employing the Principal Component Analysis (PCA) applied to the modal-frequencies temporal variation. PCA is a technique of identifying patterns in data, in addition, to express the data in such a way that highlights their similarities and differences. In case of data of high dimension, finding patters can be hard which makes PCA is a powerful tool for analysing data (Smith, 2002). In theory, the undamaged structure needs only one Principal Component (PC) to explain all modal-frequencies temporal variations; whereas as more damaged is the structure more PCs are needed.

Tibaduiza et al. (2013) showed the application of PCA in not only identifying, but furthermore in classifying the damage. A data-driven statistical approach for damage classification was proposed and validated via experimental campaign using an aluminum plate instrumented with four piezoelectric transducers. Results showed that all the simulated damages were successfully classified both in the baseline undamaged model and in further diagnosis tests in which damage was introduced in the model. Golinval (2017) employed effectively the PCA in detecting damage in structures subjected to forced harmonic response. The case study was a steel truss tested in lab in the undamaged and in the damaged states.

Moropoulou and Polikreti (2009) demonstrated the effectiveness of PCA in the characterization, technology and weathering condition investigation of building materials from historical monuments. They applied the PCA on the bricks of Aghia Sophia (Istanbul, Turkey) for provenance and technology investigation and found that the original clay, used for the construction of the bricks, is not similar to the clay of other contemporary constructions in Istanbul but presents high similarity to the raw material of the bricks from a contemporary church. In the second case study, the PCA helped in presenting a classification of mortars from medieval monasteries based on their microstructural characteristics and strength measurements so that a grouping was established giving an illustrative diagram depicting the correlation between mortar syntheses and resulting characteristics. In the last case, the PCA was used to establish the correlation between environmental pollution data and data from the weathering layers of marble surfaces.

The main disadvantage, however, of PCA is the long necessary monitoring period; generally, half a year could be necessary. In addition, the long time required to carry out the PCA applied to modal-frequencies temporal variation makes it expensive. Therefore, the PCA is mainly applicable to research purposes or to certain types of structures such historical ones.

This paper presents the on-going research on the application of PCA for damage detection in modern and historical structures equipped with dynamic monitoring systems. For that purpose, three structures were instrumented; those were the historical structure of Mallorca cathedral and two modern structures (from reinforced concrete and steel) in the Technical University of Catalonia. For processing the monitoring data, a semiautomatic algorithm was proposed and validated. The other tested structure was a steel frame built in lab and tested under dynamic excitation in the undamaged and damaged states and the PCA was employed to detect the damage.

2. CASE STUDIES OF THE RESEARCH

2.1 Mallorca Cathedral

Mallorca cathedral is an important Gothic construction built between 14th and 16th century in Mallorca Island in Spain (Figure 1) .The main nave has a length of 77 m distributed over seven bays and the width covered by the naves is 35.3 m. The lateral nave and the central nave spans are 8.75 m and 17.8 m, respectively. The lateral naves are covered by pointed vaults of simple square plan, whereas in the central nave they are of double square plan. The height reached by the vaults at their highest point is about 44 m. The cathedral is unique in being the Gothic cathedral with the highest lateral naves (29.4 m). Currently, almost all kind of the structural elements (walls, columns, vaults, arches) are cracked. Many studies have already pointed out the reasons of such cracking including previous earthquakes, deterioration of materials, low quality of construction materials, among others (Martinez et al. 2007; Pérez-Gracia et al. 2009; Pérez-Gracia et al. 2013; Caselles et al., 2012; Caselles et al., 2015; Elyamani, 2015; Elyamani et al., 2017a and 2017b).

A dynamic monitoring system was installed in the cathedral for about 15 months during 2010-2012.

The system was composed of a digitizer, a Data Acquisition system (DAQ), a Global Positioning System (GPS) antenna, an internet router and the three tri-axial accelerometers called S1, 145station and soil stations (Figure 2). Two of the accelerometers were placed on the top of two of the main nave arches (S1 and 145 station) and the third was placed on the soil inside the cathedral (soil station). The post processing of the monitoring system showed the high correlation between air temperature changes (from -2ºC and 40ºC) and some modal frequencies. As well, some decreases in the natural frequencies were observed under the effect of some seismic events occurred near to Mallorca Island (north of Algeria and Italy) (Elyamani et al., 2017a). These changes were attributed to the opening/closing process of the distributed cracks in the structural elements of the cathedral.

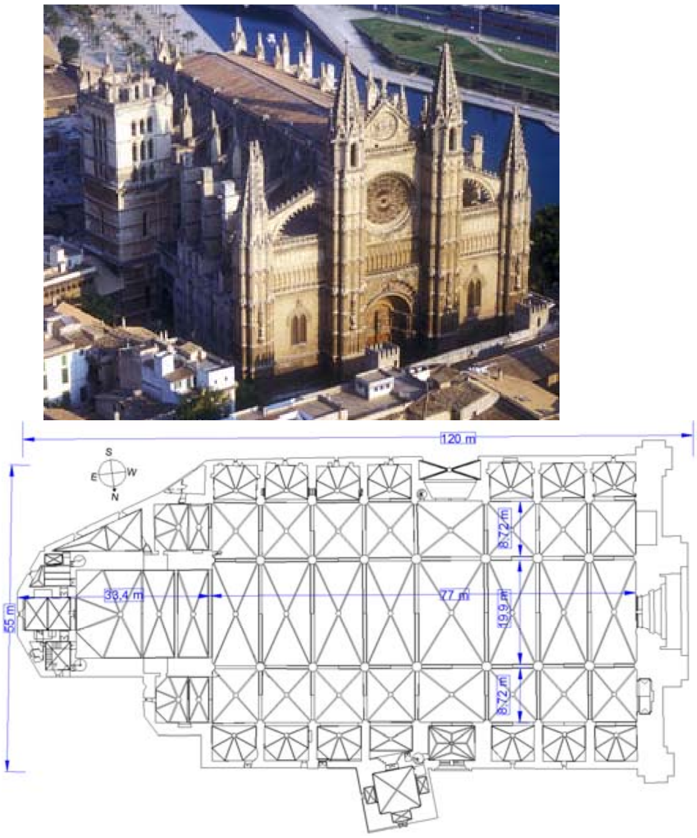

Figure 1. Mallorca cathedral general view (left) and plan (right).

Figure 2.The dynamic system in operation: accelerometer S1, DAQ, router and GPS antenna (left); accelerometer 145-Station and digitizer (middle); and accelerometer Soil-station (right) (Elyamani, 2015).

2.2 University buildings

Two buildings of the Technical University of Catalonia buildings are being monitored since the beginning of 2017. The first one is the Architectural Engineering School building and the second is the Industrial Engineering School building (Figure 3). The first building is made from reinforced concrete in 1962. It has a rectangular plan of about 58×19 m and has 7 floors. The monitoring system consists in one tri-axial accelerometer placed on the roof of the building. The second one was constructed in 1964 from steel and has twelve floors and a U-shape in plan. The total length is about 59 m and the total width is about 47m. The wing width alone is 14m. The monitoring system consists in one tri-axial accelerometer located on the roof.

Figure 3. The Architectural Engineering School building (left) and Industrial Engineering School building (right).

2.3 Reduced steel structure model

Figure 4. The reduced steel structure model.

The reduced steel model is a two-portico frame of 4 levels, in addition to the base (Figure 4).The model has 1.45m length, 0.77m width and 2m height. The columns have L shape and the beams are rectangular bars. The beams are loaded with 4.5 kg at their mid-spans. The temperature around the model is regulated using an air conditioning keeping it under temperature from 34.5 to 12ºC. The connections between the columns and the beams were screwed at a torque of 5.1 kg.m (the undamaged state). Three tests of damaged states were carried out by changing the level of connection between the columns and the beams by changing the torque value. The first test represented a heavy damage by releasing the connection between one of the beams of the first level and an adjacent column (0 kg.m torque in the connection). The second test represented more damage by releasing the connection of the same column of the previous test with both beams of the same floor (0 kg.m torque in two connections). The third test represented a medium damage in all the beams to the columns connections of the first level (applying a torque of 2.5 kg.m instead of 5.1 kg.m). The shaking of the model was applied in the model's longer direction at the center of its base. For each test, there were two type of shakes. One shaking applying a force of 4 N at the base and the other 2 N.

3. SEMI-AUTOMATIC ALGORITHM

3.1 Spectrogram resolution and averaging

Ambient vibration is usually considered as a white noise vibration. Therefore, the spectrum of the structures excited by this kind of vibration should be averaged. For undamaged masonry structures, and as a rule of thumb, about 20 spectra are recommended to be averaged, but for damaged masonry structures more spectra are needed depending on the level of damage.

Spectral resolution is the inverse of the temporal span (window) used to compute each spectrum. Thus, the total time spent to obtain good averaged spectrum is the inverse of the spectral resolution multiplied by the number of windows required. This time can be reduced by overlapping windows (the overlap is about 33% in the most used Hanning window). In common masonry structures the main frequencies are around 1 Hz and for the dynamic identification of such structures, it is required to detect frequencies variations of about 1% for closely spaced modes. Therefore, a minimum resolution of 0.01 Hz is necessary. This resolution ranks as 163.83 seconds of windows time for a FFT process (2^{14} counts at 100 counts per second). Consequently, good auto-spectrum using Hanning window requires 1136.98 seconds (about 19 minutes) as minimum.

When applied to the case of Mallorca cathedral, the detected variation were about 0.5 Hz per hour (Figure 5), and after averaging 20 minutes of the registered signals from the monitoring system, an appropriate auto-spectrum was obtained involving smooth and real variation. A better solution was to obtain the spectrogram without averaging and using an adequate algorithm to track the value of the modal frequency as will be explained in the following.

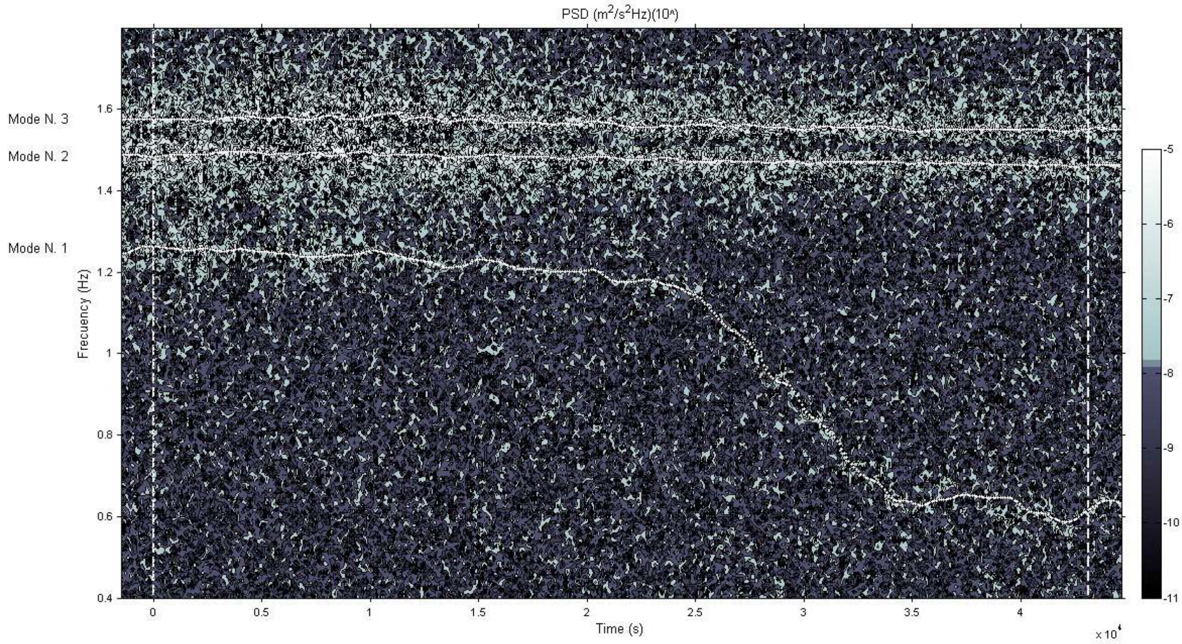

Figure 5. Spectrogram and frequency track of the first three modal frequencies of Mallorca cathedral (19/01/2011 from 12:00 to 24:00 hour).

3.2 Algorithm

The algorithm required to track the modal frequencies should be able to satisfy two conditions. The first one is related to the distribution of the modal frequencies of each structure and the other is related to the employment of non-averaged spectrograms.

Some structures have closely spaced modal frequencies, furthermore, with rapid frequency variation of some of them. On the contrary, some other modal frequencies have very low (almost zero) variations. These facts require the choice of a type of algorithm with some parameters controlling the maximum acceptable variability different for each mode. On the other hand, these parameters should allow high deviation for these modes having rapid frequency variation and low for modes having very low variations. In the same time, these parameters should prevent high-energy modes from overlapping with low-energy modes. These considerations could be sometimes incompatible and making balance between them is almost unachievable. For this reason, the implementation should consider the necessity of manual intervening for adjusting the low-energy modes to their correct frequencies.

Tracking modal frequencies consist of looking for the next probable modal frequency from an initial known or estimated point (frequency at a time). The use of non-averaged spectrograms made the maximum energy of modal frequencies unsteady. For this reason, the chosen frequency cannot be the frequency with higher energy; otherwise the energy distribution over an interval of time should be taken into account.

In this proposed algorithm, it was decided to choose as modal frequency the weight-average of some after and before maximum of the spectra (also weighted by a function). This way assure the control of the smoothing in time and can help to the continuity of the modal frequency. The number of the averaged spectra is a new parameter of the algorithm that had been fixed using the maximum accepted of the rapid variation mode but, could be variable for each mode or structure. The weight of the average for the selected frequencies is a triangular function. The weighting function (Equation 1) of the spectra is a truncated hyperbolic secant function (Figure 6):

$$f_t = \max(y_i)\ where\ y_i = \begin{cases} \operatorname{sech}(d \cdot (f_i - f_{t\pm1})) & if \quad f_i < f_{t\pm1} \pm r \\ 0 & if \quad f_i \geq f_{t\pm1} \pm r \end{cases} \tag{1}$$

where $f_{t\pm1}(t\pm1)$ is the frequency selected or computed at $t-1$ for forward search and at $t+1$ for backward search, d is a coefficient that adjust the decay of the function and r is the truncation distance. High values of d constrain the temporal frequency variability, whereas low values are suitable in the modes that have high temporal variations of frequency and are widely separated from contiguous modes. Besides, the truncation distance can be a coefficient used to prevent mixing up of modes whenever the selected mode is very separate from neighbors or has little temporal variations.

In short, in order to keep a good track of modal frequencies that are far from the neighboring modes, it is possible to choose suitable r or d coefficients without any mixing up with neighboring modes: high r and low d coefficients for modes with quickly temporal variations, and low r and high d coefficients for slow temporal variations. For modes close to others and slow temporal variation low r coefficient or high d can permit a good track of it. The main problem is tracking a mode close to other with high temporal variation. For this last type of modes, it is necessary to use high r coefficient and low d ones that produce the mixing up of both modes. As it has been explained before, to track properly this modes, in the implementation of the algorithm there is the possibility of manually directing the low energy mode to the correct frequency. In this case, the algorithm changes slightly (Equation 2):

$$f_t = \max(y_i)\ where\ y_i = \begin{cases} \operatorname{sech}(d \cdot (f_i - f_x))\ if\ f_i < f_x \pm r \\ 0 \qquad\qquad\qquad\quad if\ f_i \geq f_x \pm r \end{cases} \tag{2}$$

where f_x is the frequency linearly interpolated between $f_{t\pm1}$ and f_s ($t-1$ for forward search and $t+1$ for backward search); f_s is the manually selected frequency.

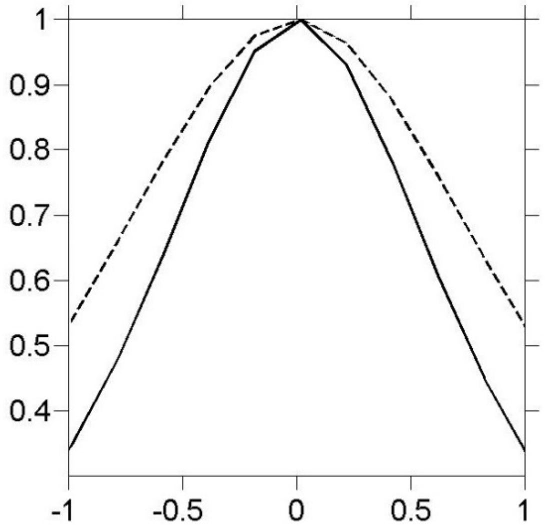

Figure 6. Truncated hyperbolic secant function with two different d coefficients (continuous line: 0.35; dotted line: 0.25)

3.3 Implementation

The implementation of the algorithm was carried out by computing the frequency of each mode at any time from an initial preselected frequency. The preselected frequency can be entered manually or to be loaded from a file with the frequencies of a processed spectrogram before the current signal (t-1 in formulas) or after (t+1 in formulas). For very long time studies, it is not possible computing and drawing the whole spectrogram but it is important to assure the continuity of different parts. Loading the last computed frequency of a previous interval studied (forward search) or the first computed frequency of a past interval studied (backward search) as the preselected frequencies of new interval permit an easy way to assure the continuity of the mode between intervals.

After drawing the spectrogram, overlapped by the automatically computed frequencies and the preselected frequencies, there is the possibility of modifying each mode. The main modification is the mentioned possibility of select one or more than one points of the spectrogram where the high energy of the mode made it clearly showed. In fact, the selection of the point not has to be perfectly fitted because of the weighting function is applied to the selected point. If only one point is selected, the non-modified algorithm is applied backward and forward from this point. Whereas, if more than one point are selected, the non-modified algorithms is applied backward from the earlier selected point and forward from the last selected point, and the modified algorithm is applied between selected points.

Each time that a new point of the spectrogram is manually selected the entirely mode is recomputed. Other important modification is the possibility of changing the adjustable parameters of the algorithm d and r. These changes can be applied to the entirely selected points or only one. The other two possibilities are to cancel out the selection of the mode entirely or only in an interval of the time. These possibilities were introduced to avoid selecting frequencies in interval of time where the energy of the spectrum is too low to track it properly. In the implementation, the number of averaged spectra was fixed in 4 before and 4 after the selected point.

4. RESULTS

4.1 Mallorca cathedral results

For Mallorca cathedral, the algorithm seems to be a good tool to track most of the modes automatically; however, some of the modes will require the manual selection of some points to correctly track the frequency temporal variation. For instance, the first mode showed an extremely variability in frequency and in power (Figure 5) that may make its tracking difficult. For this reason, some intervals of time will have to be canceled out for the first mode. For time being, not enough time has been processed with the algorithm. Nevertheless, some preliminary results are presented in Table 1 which were obtained by a previous manual tracking carried out by Grande (2013). These results are good guiding when applying the algorithm to the cathedral in the future.

Table 1. Explained variance of the PCs of Mallorca cathedral (the selected components are in gray)

Component	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
% of variance	57.449	18.296	8.308	5.872	5.455	3.649	0.614	0.224
Cumulative %	57.449	75.745	84.053	89.925	95.38	99.029	99.642	99.866

4.2 Industrial Engineering School building results

The results of the Industrial Engineering School building obtained so far are for the period of about 6 months from 23/11/2016 to 14/05/2017. Twelve modes could be detected with natural frequencies of 0.79, 0.85, 1.14, 1.38, 2.36, 2.43, 2.62, 3.06, 3.37, 3.97, 4.34 and 4.57 Hz. The maximum noticed daily variation range was from 2% (for mode 2) to 6% (for mode 5). The small difference between some modes necessitated the manual selection of points. Modes 1 and 2 had a difference of 7% in frequencies; modes 5 and 6 had 3% of difference, and modes 11 and 12 had a difference of 5%. PCA has not been applied yet, but visual inspection of the spectrograms indicated that more than one PC will be necessary to explain the frequency variability (Figure 7).

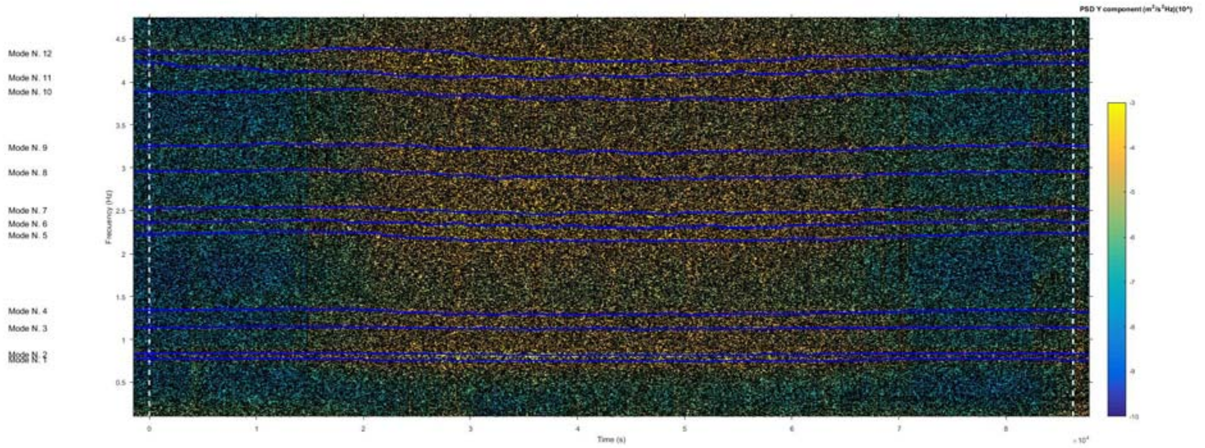

Figure 7. Spectrogram and frequency tracking for Industrial Engineering School building (18/04/2017 00:00 to 24:00 hour).

4.3 Architectural Engineering School building results

The results obtained so far for this case are for the period of four months from 18/01/2017 to 17/05/2017. Three modes were detected with natural frequencies of 1.56, 1.99 and 3.22 Hz. Maximum daily variation ranged from 2% (mode 1) to 8% (mode 3) (Figure 8). In general, the automatic track is good and only for high daily temperature variation mode 3 requires manual selection of one point. PCA has not been applied yet.

4.4 Reduced steel structure model results

The PCA of this case has been finished. The acceleration measurements were not taken continuously during shaking test; therefore, semi-automatic data processing was not used. Table 2 shows, as an example, the frequency variation with temperature for the heavy damage (two released connections) under weak shaking test. Applying the PCA on the measured data, the number of PCs needed to explain satisfactorily the variance of the different cases was obtained (Table 3).

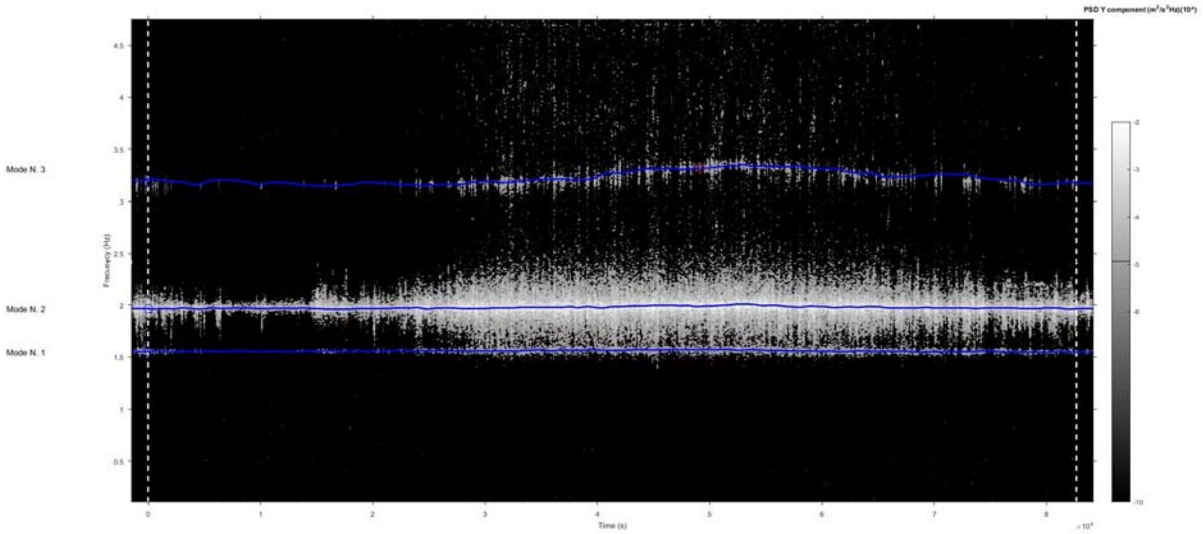

Figure 8. Spectrogram and frequency tracking for Architectural Engineering School building (18/04/2017 00:00 to 24:00 hour).

Table 2. Frequency variation with temperature for heavy damage (two connections released) under weak shaking test.

Temperature		29.0	27.7	26.1	24.5	23.5	20.51	18.8	17.5	14.2
Mode number	1	2.42	2.44	2.42	2.42	2.42	2.45	2.45	2.45	2.44
	2	2.53	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.56
	3	3.63	3.66	3.64	3.64	3.64	3.67	3.67	3.86	3.67
	4	7.59	7.62	7.59	7.59	7.59	7.59	7.59	7.59	7.58
	5	8.75	8.78	8.77	8.77	8.78	8.78	8.80	8.80	8.78
	6	9.19	9.22	9.22	9.22	9.22	9.20	9.22	9.22	9.23
	7	11.98	12.06	12.02	12.02	12.00	12.08	12.08	12.08	12.02
	8	13.08	13.05	13.02	12.98	13.00	13.00	12.97	12.95	12.94
	9	14.17	14.22	14.20	14.20	14.19	14.22	14.20	14.20	14.19
	10	16.64	16.73	16.75	16.77	16.77	16.75	16.75	16.75	16.77
	11	17.67	17.64	17.66	17.62	17.61	17.44	17.48	17.42	17.56
	12	20.97	20.98	20.95	21.02	21.02	21.00	21.02	21.02	21.05
	13	23.64	23.73	23.87	23.95	23.98	23.97	23.84	23.84	23.95
	14	24.44	24.45	24.533	24.52	24.55	24.48	24.45	24.52	24.53
	15	25.27	25.34	25.41	25.47	25.50	25.47	25.50	25.53	25.53
	16	25.48	25.56	25.67	25.75	25.80	25.73	25.75	25.77	25.77
	17	26.77	26.80	26.87	26.98	27.09	27.02	27.17	27.199	27.30
	18	29.02	29.08	29.12	29.16	29.25	29.19	29.19	29.22	29.27

Table 4 shows the variance of the PCs of the structure for all type of damages and shakings.
In general, a PC has to be taken into account when explaining enough variance compared with the aleatory variability of the data that can be specified by plotting the accumulated variance in a graph (Figure 9). The number of PCs to be selected is determined by the change of the last inflection in the graph. In this case, heavy damage (one connection released) under weak shaking test shows a continuous decrease of the variance that introduced difficulties in the choice of the number of PCs to be considered (Figure 9c). On the contrary, heavy damage (one connection released) under strong shaking test (Figure 9d) shows a clear inflection being absolute in the case of generalized medium damage under strong shaking test (Figure 9h). The unexplained variance of the selected PCs may be related to the quality of the data or other non-linear behavior.
There was a clear different behavior between weak and strong shaking in all the tests. This difference

could be attributed to the non-linear behavior of the screwed joints. The most curious result was for the generalized damage where weak and strong shakings have opposite characteristics. Whereas weak shaking demanded lesser PCs and that the two first PCs explained very low variance, strong shaking needed more number of PCs and the first PC explained most of the data variance.

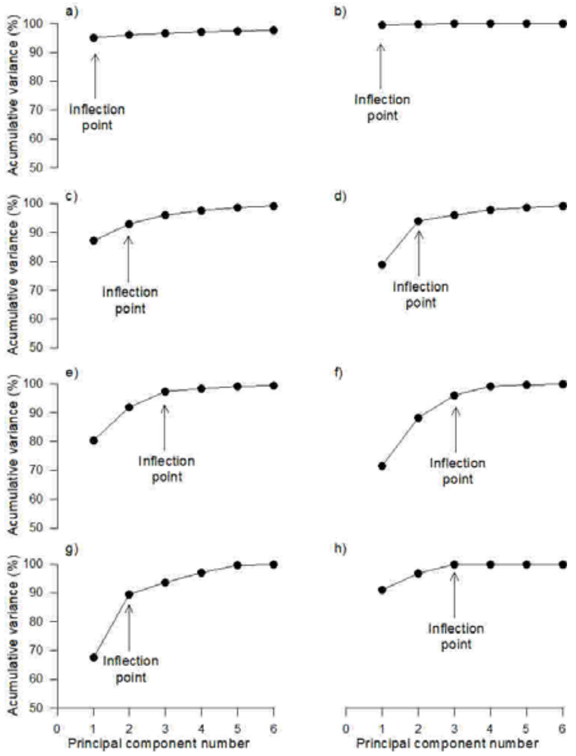

Figure 9. Accumulative variance versus PC number and chosen inflection point. a: test of undamaged model under weak shaking, b: test of undamaged model under strong shaking, c: test of heavy damaged model (one released connection) under weak shaking, d: test of heavy damaged model (one released connection) under strong shaking, e: test of heavy damaged model (two connections released) under weak shaking, f: test of heavy damaged model (two connections released) under strong shaking, g: medium damage test under weak shaking, h: medium damage test under strong shaking.

Table 3. Number of selected PCs for each test and level of damage.

	Steel structure model state			
Shaking type	Without damage	Heavy damage (one connection released)	Heavy damage (two connections released)	Generalized damages
Weak	1	2	3	2
Strong	1	2	3	3

5. CONCLUSIONS

The paper presented an approach for damage detection based on identifying the natural frequencies of the structure (from dynamic monitoring or dynamic identification) followed by PCA on the variations of these natural frequencies.

For processing the dynamic monitoring data, the paper presented a semiautomatic algorithm based on a truncated hyperbolic secant function with variable parameters able to identify and track the natural frequencies of the monitored structures and as well their changes over time. The algorithm was tested for processing the monitoring data of three structures. Those were the historical structure of Mallorca cathedral and two modern buildings in the Technical University of Catalonia; the first was the

Architectural Engineering School building and the second was the Industrial Engineering School building. It was found that for structures with clear, constant, and enough separated modal frequencies, automatic tracking is usually good and, we need using manual selections only occasionally, as for the case of Architectural Engineering School building. Otherwise, structures without large temporal variations of the modal frequencies but not enough separated need only sometimes mark points manually to adequately track these frequencies. Moreover, structures with closely spaced natural frequencies and large temporal variations of them usually need manual selection of few points to do it properly.

The approach as a whole was applied on a steel structure model tested in lab. It was subjected to dynamic identification tests with and without damage. It was found that PCA applied to frequency variation seems to be a possible tool to know damages in structures. Nevertheless, the simplified point of view correlating directly the number of PCs with the damage importance seems to be not accurate. First results seem to indicate that the variance percentage explained by each of the principal components could be correlated with the kind of damages and the shake used to excite the structure.

Table 4. Explained variance of the PCs for different damages and shakings (the selected components are in gray).

Steel structure model state	**PC number**	**Weak shaking**		**Strong shaking**	
		% variance	% accumulated	% variance	% accumulated
Undamaged	1	95.168	95.168	99.513	99.513
	2	0.899	96.067	0.312	99.825
	3	0.698	96.765	0.142	99.967
	4	0.474	97.239	0.017	99.984
	5	0.207	97.447	0.014	99.998
	6	0.187	97.633	0.002	100.000
Heavy damage (one connection released)	1	87.132	87.132	78.779	78.779
	2	5.927	93.059	15.086	93.865
	3	3.098	96.157	2.249	96.114
	4	1.472	97.629	1.785	97.899
	5	0.965	98.594	0.835	98.734
	6	0.669	99.263	0.513	99.247
Heavy damage (two connections released)	1	80.435	80.435	71.501	71.501
	2	11.389	91.824	16.673	88.174
	3	5.482	97.306	7.879	96.053
	4	1.091	98.397	3.099	99.153
	5	0.723	99.121	0.562	99.715
	6	0.376	99.497	0.285	100.00
Medium damage (all connections of the first floor are not fully screwed)	1	67.449	67.499	91.015	91.015
	2	22.045	89.449	5.680	96.695
	3	4.013	93.507	3.305	100.00
	4	3.565	97.072	0	100.00
	5	2.426	99.498	0	100.00
	6	0.502	100.00	0	100.00

6. ACKNOWLEDGMENTS

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REFERENCES

Caselles O, Clapes J, Roca P, Elyamani A (2012). Approach to Seismic Behavior of Mallorca Cathedral. In15th World Conference of Earthquake Engineering, Lisbon, Portugal, 24-28 Sep 2012.

Caselles O, Martínez G, Clapés J, Roca P, Pérez-Gracia V (2015). Application of particle Motion Technique to Structural Modal Identification of Heritage Buildings, International Journal of Architectural Heritage, 9: 310–323.

Elyamani A (2015). Integrated monitoring and structural analysis strategies for the study of large historical construction. Application to Mallorca cathedral, PhD thesis, Technical University of Catalonia, Spain.

Elyamani A, Caselles O, Roca P, Clapes J (2017a). Dynamic investigation of a large historical cathedral. Structural Control and Health Monitoring, 24(3).

Elyamani A, Roca P, Caselles O, Clapes J (2017b) Seismic safety assessment of historical structures using updated numerical models: The case of Mallorca cathedral in Spain. Engineering Failure Analysis 74, 54-79.

Golinval JC (2017). Damage detection in structures based on Principal Component Analysis of forced harmonic responses. Procedia Engineering:199: 1912-1918.

Grande CJ (2013). Correlation between weather conditions, heating of structural elements, and the dynamic behaviour of Mallorca cathedral, *Master Thesis*, Civil Engineering School, UPC, Barcelona, Spain.

Martínez G, Roca P, Caselles JO, Clapés J, Barbat AH (2007). Determinación experimental y analítica de las propiedades dinámicas para la Catedral de Mallorca, Intersections/IntersecţiiInt. J., 4(2), 65-74.

Moropoulou A, Polikreti K (2009). Principal Component Analysis in monument conservation: three application examples. Journal of Cultural Heritage: 10(1):73-81.

Pérez Gracia V, Caselles JO, Clapés J, Osorio R, Martínez G, Canas JA (2009). Integrated near-surface geophysical survey of the Cathedral of Mallorca. J. Archaeol.Sci. 36: 1289–1299.

Pérez-Gracia V, Caselles JO, Clapés J, Martinez G, Osorio R (2013). Non-destructive analysis in cultural heritage buildings: Evaluating the Mallorca cathedral supporting structures, NDT&E International 59: 40–47.

Smith LI (2002). A tutorial on principal components analysis. Cornell University, USA, 51(52), 65.

Tibaduiza DA, Mujica LE, Rodellar J (2013). Damage classification in structural health monitoring using principal component analysis and self-organizing maps. Structural Control and Health Monitoring. 2013 Oct 1;20(10):1303-16.