

Application of low-cost instrumentation and output-only modal identification techniques for the structural health monitoring of mechanical systems

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Abstract. Monitoring systems are becoming more relevant to maintain the structural integrity of engineering structures. Structural Health Monitoring (SHM) tools are getting even more important nowadays due to the need of sustainable long-living structures. However, it is safe to say that the large costs involved on the hardware and sensors used to apply SHM techniques are prohibitive for a large scale adoption of these tools. With the popularization of fast prototyping electronic platforms and MEMS sensors, new opportunities are showing up for industrial applications. In this paper, an Arduino Mega 2560 board was used with ADXL335 vibration sensors in order to monitor the structural state of a simple benchmark structure representing a two-storey building. The frequency domain decomposition (FDD) was used to extract the mode shapes and natural frequencies of the structure by measuring the accelerations in different locations. Damage indexes based on natural frequencies revealed the presence of the damage and its propagation. The results showed the viability of using low-cost instrumentation and output-only modal identification techniques as alternative for the SHM of simple mechanical structures.

Keywords: Damage detection, Mechanical vibrations, Low-cost hardware, Output-only modal identification.

1 Introduction

A Structural Health Monitoring (SHM) system typically consists of a dense network of sensors for data acquisition, a central processor and an algorithm for evaluating the structural condition. The system utilizes stored knowledge of structural materials, operational parameters, and health criteria [1]. The most fundamental part of SHM is the damage detection. These techniques methods can be broadly classified in two classes: passive schemes, which rely on the change in structural vibrations to detect damage, and active systems in which the structure is excited by actuators and the subsequent vibration is used to determine whether or not there is damage. Among active schemes, the vibration-based SHM techniques can be cited [2, 3], including modal analysis methodology [4], in which Frequency Response Function (FRF) or mode shapes properties are used to detect the presence of the damage. The use of piezoelectric material as actuator and sensors for monitoring the structural integrity can also be cited, including electrical impedance [5–7], lamb waves methodology [8, 9], among other methods.

This paper is concerned with a passive scheme in which an output-only modal identification technique is used. This type of methodology was already used by other authors to damage identification problems [10, 11]. In this paper a low-cost instrumentation is applied in an experimental test-bed consisting in an two-storey building. Structural damages were simulated through gradual cuts, in order to simulate the damage propagation. Damage-sensitive indexes based on modal properties were used to detect the damage. These features were computed using the Frequency Domain Decomposition (FDD) [12] in which the natural frequencies and mode shapes of the structure can be obtained to each condition based on a set of vibration measurements. The following sections present the proposed SHM technique.

2 Damage detection methodology

To determine whether damage is present or not in the structure, damage-sensitive indexes were used to compare different structural conditions, considered as unknown conditions, with respect to a baseline condition (with no

significant flaws). It is known that the presence of the damage can modify mechanical properties of the structures. In this scenario, the parameters used in the comparison were the resonance frequencies (mentioned as natural frequency, since the system presents a very low damping ratio) and the mode shapes of the structure. The Frequency Domain Decomposition (FDD) was used to extract the mentioned parameters by measuring the accelerations in different locations of the structure. A brief explanation of the FDD method and the damage-sensitive indexes are presented in the following sections.

2.1 Frequency Domain Decomposition (FDD)

The FDD algorithm was first introduced by Brincker et al. [12] in the context of operational modal analysis. This kind of technique can be applied to process vibration signals that are responses to unmeasured or ambient excitation so that modal parameters as natural frequencies and mode shapes can be extracted under certain assumptions. In order to apply the FDD, the input signal should be a white noise or at least a broadband signal that spans the modal frequencies to be investigated [13].

The algorithm starts by calculating the power spectral density (PSD - G_{x_n, x_n}) and cross-spectral density (CPSD - G_{x_n, x_m}) of the output signals collected in different positions of the structure. The PSDs and the CPSDs are gathered in the PSD matrix of the output signals $[G(\omega)]$:

$$[G(\omega)] = \begin{bmatrix} G_{x_1, x_1}(\omega) & G_{x_1, x_2}(\omega) & \cdots & G_{x_1, x_N}(\omega) \\ G_{x_2, x_1}(\omega) & G_{x_2, x_2}(\omega) & \cdots & G_{x_2, x_N}(\omega) \\ \vdots & \vdots & \ddots & \vdots \\ G_{x_N, x_1}(\omega) & G_{x_N, x_2}(\omega) & \cdots & G_{x_N, x_N}(\omega) \end{bmatrix} \quad (1)$$

where the diagonal terms G_{x_n, x_n} are the PSDs and the off-diagonal terms G_{x_n, x_m} are the CPSDs, n and m are integer numbers such that $n, m \in [1, N]$ and N is the number of output signals that are being processed by the FDD. The PSD matrix is a 3D array with dimensions of $N \times N \times NF$ where NF is the number of samples of the signal transformed to the frequency domain. After the calculation of $[G(\omega)]$, the singular value decomposition (SVD) is taken for each frequency ω :

$$[G(\omega)] = [U][\Sigma][V]^T \quad (2)$$

where $[U]$ is an $N \times N$ unitary matrix, $[\Sigma]$ is a, $N \times N$ diagonal matrix with the singular values, and $[V]^T$ is an $N \times N$ matrix with the singular vectors.

The SVD has the interesting property of rejecting noise effects and identifying orthogonal components of the matrix to be analyzed [14]. By scanning the calculation through the frequency range of interest, it is possible to plot the first few singular values as a function of ω so that it can be interpreted as the auto spectral densities of the modal coordinates. These singular values can be used to identify amplitude peaks that can be related to the eigenfrequencies of the structure. Meanwhile, for these natural frequencies, the vectors of the matrix $[V]^T$ can be an approximation of the mode shapes of the system. The general idea of the FDD method is illustrated in Figure 1.

More details on the theoretical basis of the FDD algorithm can be obtained in Brincker et al. [12]. In the present paper, the technique was applied to process acceleration data from a simple mechanical structure in order to estimate the natural frequencies and mode shapes.

2.2 Damage indexes

The area of the SHM process that receives the most attention in the technical literature is the identification of data features that allow one to distinguish between the undamaged and damaged structure. A damage-sensitive feature is a scalar value extracted from the measured response data that indicates the presence or not of the damage in the structure. The data acquisition process involves the selection of the excitation methods, the sensors type, number and locations, the data acquisition, storage, and the transmission hardware [15]. Two damage-sensitive indexes were compared using the same experimental data. These metrics were based on the deviation of the response of the structure with respect to the so-called baseline condition ("healthy" structure) and are described in this section.

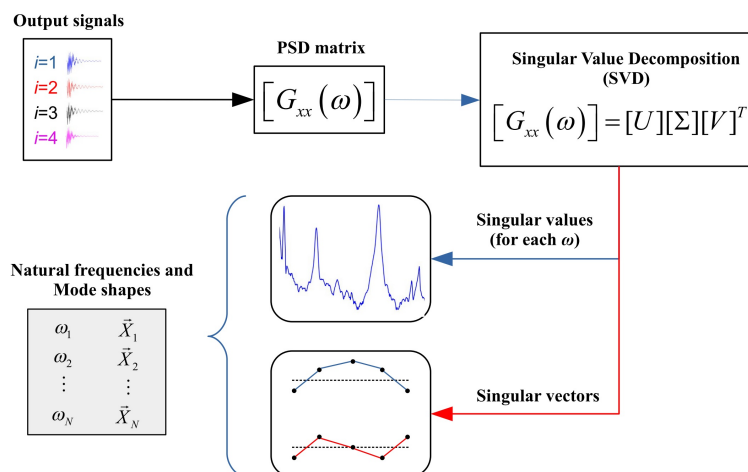


Figure 1. Illustration of the FDD method.

Natural frequency deviation

One of the simplest vibration-based damage indexes can be considered based on the deviation between the natural frequencies of the structure [16]. This is justified by the fact that these modal parameters are sensitive to global changes in the stiffness and inertia of the vibrating system. The deviation of the n -th natural frequency was calculated by:

$$f_n \text{ deviation}[\%] = 100 \left(\frac{f_{n,unk} - f_{n,baseline}}{f_{n,baseline}} \right) \quad (3)$$

where $f_{n,unk}$ and $f_{n,baseline}$ are the natural frequencies of the structure in the unknown and baseline structural conditions. The f_n deviation can be calculated for each of the vibration modes of the system. In the case where the structure is in the healthy state, the value should tend to be near zero while with greater values it is expected that a variation of the mechanical properties of the structures occurred.

Modal Assurance Criterion (MAC)

The second damage feature was the classical modal assurance criterion (MAC) which is a measure of the degree of correlation between two eigenvectors [17]. The MAC is commonly used to quantify the quality of an analytical model in representing an experimental system with respect to the mode shapes of the structure. In this paper, this metric is used to quantify how close the eigenvectors in the unknown condition are to the ones in the baseline state. The MAC can be calculated by:

$$\text{MAC}(\vec{X}_{n,unk}, \vec{X}_{n,baseline}) = \frac{[\vec{X}_{n,unk}^T \vec{X}_{n,baseline}]^2}{[\vec{X}_{n,unk}^T \vec{X}_{n,unk}][\vec{X}_{n,baseline}^T \vec{X}_{n,baseline}]} \quad (4)$$

where T is the transpose operator, $\vec{X}_{n,unk}$ and $\vec{X}_{n,baseline}$ are the eigenvectors representing the n -th mode shapes in the unknown and baseline conditions respectively. In this sense, MAC values near one means that $\vec{X}_{n,unk}$ and $\vec{X}_{n,baseline}$ are well correlated, meaning that the mode shapes in the unknown condition are close to the ones in the baseline structure. Lower MAC values means that these modes are not correlated which can be a symptom of a structural variation.

3 Experimental setup and damage simulation

The test-structure consisted of a two-storey building. Each floor is represented by a square aluminum plate with dimensions of $201 \times 201 \times 12.8$ mm and total mass of 1.444 kg. The floors were linked through four bending metallic aluminum beams with $180.8 \times 21.5 \times 2$ mm. The base of the structure was fixed to a table using a metallic clamp.

To perform the vibration measurements, two ADXL335 accelerometers (sensitivity: 300 mV/g, frequency range up to 1.6 kHz) were attached to the two floors of the building. These sensors were linked to an Arduino Mega 2560 that performed the function of an analog to digital converter. The board was connected to a personal

computer through an USB cable to capture the data, the experimental setup is illustrated in Fig. 2. MATLAB 2019a was used to capture and analyze the acceleration time-series.

A sampling frequency of 200 Hz was used in the acquisition board. Each test consisted of 20 seconds of measured response to an impact excitation caused by a hammer. This test was repeated 8 times in each structural condition in order to verify the repeatability of the experimental results. Only the acceleration of the two floors were captured and the input signal was considered to be unknown. The acceleration of the two floors were processed by the FDD algorithm in order to extract modal information of the system.

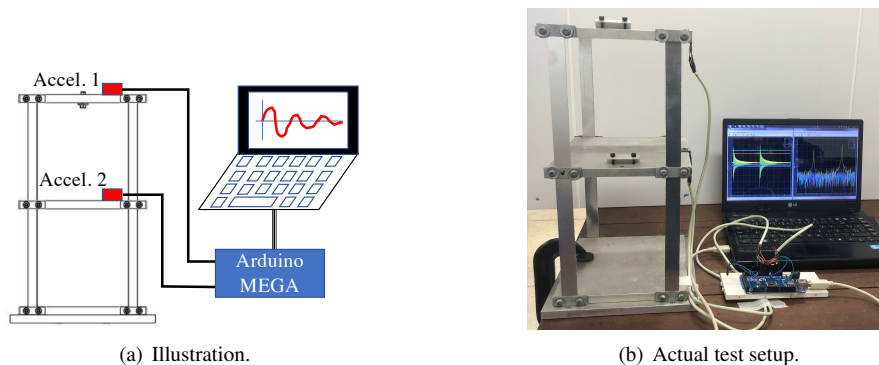


Figure 2. Experimental setup used in the structural monitoring.

The damage conditions considered a gradual variation of 3 mm cuts at one of the bending beams 10 mm distant from the base of the building in order to simulate damage propagation. Seven different structural conditions were considered: Baseline (no damage), DC 1 (3 mm cut), DC 2 (6 mm cut), DC 3 (9 mm), DC 4 (12 mm), DC 5 (15 mm) and Repair as illustrated in Figure (3). The Repair case was performed when the beam in the DC 5 state was replaced by a new one with the same dimensions as the previous. To verify the dispersion of the results, 8 realizations were performed to each condition as summarized in Tab. (1).

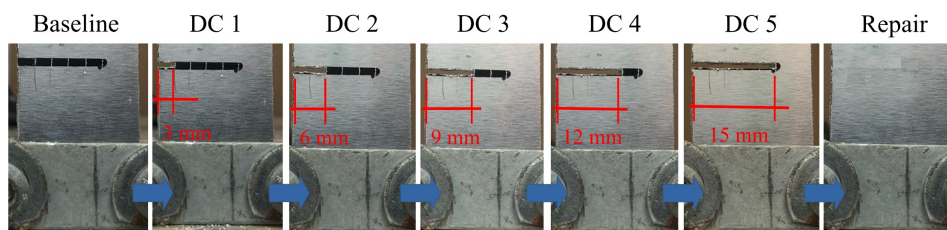


Figure 3. Damage propagation during the experimental tests.

Table 1. Damage scenarios

Test Number	1 - 8	9 - 16	17 - 24	25 - 32	33 - 40	41 - 48	49 - 56
Condition	Baseline	DC* 1	DC 2	DC 3	DC 4	DC 5	Repair
Damage	none	3 mm cut	6 mm cut	9 mm cut	12 mm cut	15 mm cut	none

*Damage Condition

4 Results and discussion

This section presents the results obtained through the FDD method through which the natural frequencies and mode shapes were obtained. Moreover, a comparison between baseline, repair and damage conditions was performed.

Figure (4) presents the PSD obtained by processing the accelerations for all the presented conditions. It is possible to observe that the resonance frequencies (to each vibration mode) decrease for the cases when damages were present in the structure. This fact is justified by stiffness decreasing due to the progression of the cuts. Moreover, it is possible to observe that the 2nd and the 4th modes were the most affected (sensitive) by the presence of the damages.

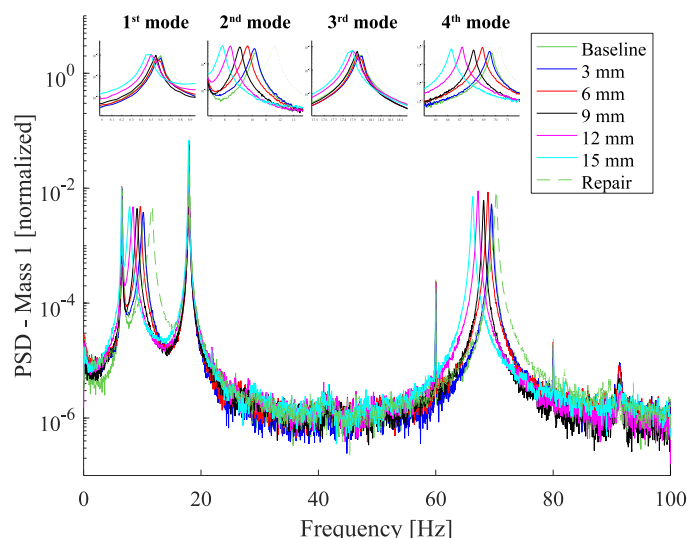


Figure 4. Power spectral density of structure obtained through the low cost accelerometers.

In order to determine whether damage is present or not in the structure, the previously presented damage-sensitive indexes were computed to each condition. Figure (5) presents the variation (in percentage) of the natural frequency of the structure under different damage conditions. The percentages were calculated in comparison to the baseline condition.

The results showed the damage influence and the dispersion of the natural frequencies to the baseline condition, to each damage condition and to the repaired structure. By inspecting the natural frequencies variations, it is possible to observe that the natural frequencies decrease when increasing the length of the cuts, probably caused by the stiffness decrements. This fact can be better noticed for the 2nd and 4th natural frequencies, since they are the most sensitive to the presence of the damage as previously seen in Fig. (4). Moreover, the damage propagation revealed a nearly linear trend for the 2nd natural frequency variation and an almost exponential trend for the 4th natural frequency variation. Also, it can be observed that the natural frequency increases when the damage was repaired. The main cause for that, was probably due to the replacement of the bending beam. This modification of clamping imposed a different boundary condition than what was present in the baseline condition.

Figure (6) presents the variation of the MAC for the first four mode shapes. Inspections of this figure reveals that the mode shapes were not considerably affected by the presence of the damage since no conclusions can be obtained with respect to the presence and propagation of the damage.

5 Final remarks and conclusion

An SHM damage detection technique was performed in a two-storey building using only the output acceleration signals. The FDD was used to determine the natural frequencies and mode shapes of the system in each condition: baseline, damage and repair. The damage was simulated through gradual cuts at the floor links. The results showed that the variation in natural frequency is more sensitive than the mode shape variation. A damage index based on natural frequencies revealed the presence of the damage and its propagation that can be better viewed using the 2nd and 4th vibration modes. However, no considerable changes were verified at the mode shapes and no conclusions about the presence of the damage could be obtained using the MAC index.

Considering the SHM scenario presented in this paper, the use of low-cost instrumentation and output-only modal identification technique showed to be an interesting alternative for the SHM of simple mechanical structures. It is also important to emphasize that the hardware used in this paper has some important limitations like the number of bits of the ADC of the Arduino Mega (10 bits only) which can bring some quantization errors. The ADXL335 is also a very limited sensor in terms of frequency range and maximum acceleration. Despite of these drawbacks, the proposed methodology has the advantage of being more economically feasible when thinking about large-scale applications.

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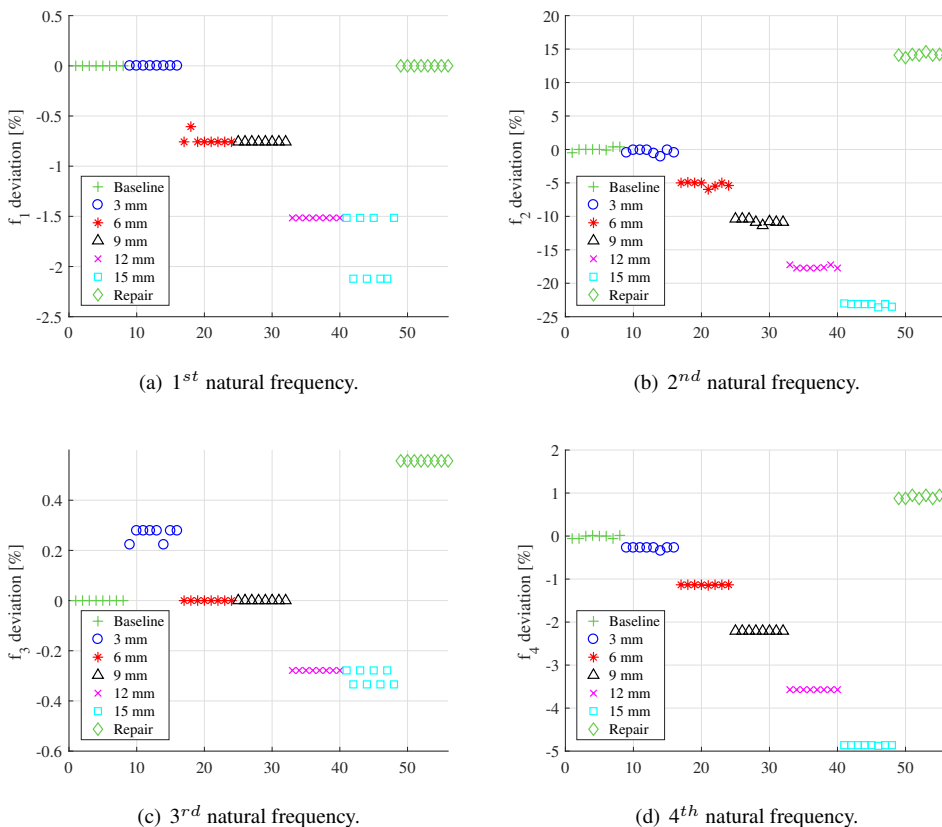


Figure 5. Variation of the first four natural frequencies of the structure.

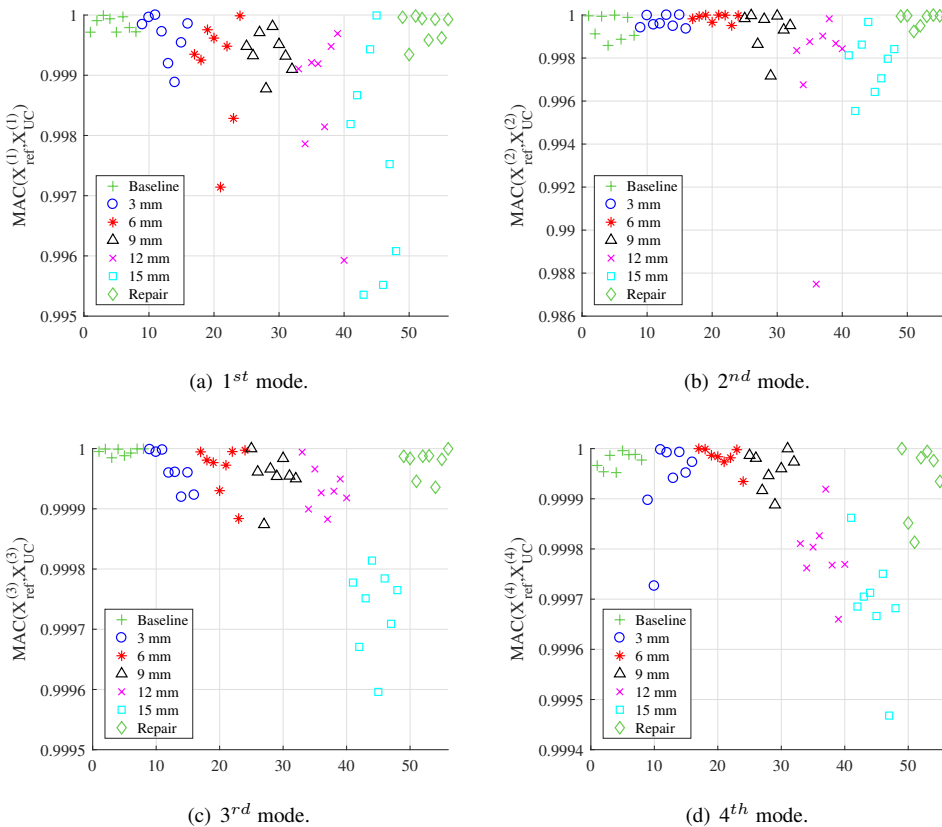


Figure 6. Variation of the MAC for the first four mode shapes.

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