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REAL-TIME STRUCTURAL DAMAGE DETECTION USING PARITY RESIDUE ANALYSIS

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Abstract. *A methodology for structural health monitoring based on subspace identification and residue generation is presented. A parity matrix is initially acquired and adopted to represent the healthy structure. A correlation Hankel matrix, which implicitly contains the modal information of system, is estimated from actual measurements, and a vector of residues is calculated to indicate the possibility of damage. A real-time algorithm is developed to generate the residue vector and accomplish the assessment of its norm on-line. An experimental study case is presented for two similar aluminum beams, using piezoelectric elements as actuators and sensors, simulating the existence of damage in one of them. Further measurements were conducted in order to evaluate the method robustness regarding natural parameter variation with environmental conditions, which is an important issue before the methodology may be used on real structures. For both studies, analysis of the results shows good discrimination from the healthy and damaged states of the beams.*

Keywords: *Structural Health Monitoring, Fault detection, Subspace methods, Parity Residue generation and analysis.*

1. INTRODUCTION

Economic and life-safety issues are the primary driving forces behind the development of structural health-monitoring technology (Doebling et al, 1996), whose techniques may be expected to be applied to all important mechanical and civil engineering structures in a near future. The word damage means, in this context, any material property or geometric change that may affect the present or future behavior of the structure. Fault is in general used as a more comprehensive term, including malfunctions of sensors and/or actuators, besides plant component damages.

From the structure monitoring point-of-view, the state of a system may be described by five levels of knowledge about the system, which may be posed considering the answers to the following questions (Farrar et al, 2001):

1. Is there damage in the system (existence)?
2. Where is the damage in the system (location)?
3. What kind of damage is present (type)?
4. How severe is the damage (extent)?
5. How much useful life remains (prognosis)?

Clearly, the first question is crucial, because the others only make sense if there is a positive answer to the existence of damage. Due to this reason, damage detection has been attracting the main focus of researchers. Despite the intense interest in this area, many topics remain open, and real applications are yet a challenge. Because it is easy to misinterpret regular plant variation with fault provoked altered response, it is a major concern, about monitoring systems, to avoid false alarms, because the operators may loose confidence in the system. Robustness is an important property to achieve a sensible compromise for the fault detection, for any monitoring system to be adopted, when it comes to real applications.

The method here presented aims to obtain the answer about the existence of damage, and the purpose of this work is to develop some way to distinguish efficiently between a "healthy" and a damaged state of the structure, i.e. a robust real time component fault detection procedure. It is assumed that changes in the structure may be indicated by changes in its modal parameters, such as natural frequencies, damping coefficients and mode shapes. A vibration-based parametric method, that take into account implicitly the variation of these parameters, is here presented and extended to include online detection of structural damage.

The proposed fault detection procedure, illustrated in Figure 1, may be separated in two phases and the decision process. On the baseline phase, information reduced to quantifiable indicators is gathered, and signature signals are selected to represent the healthy state of the structure. On the inspection phase, measurements are continuously carried out, leading to actual indicators calculation. An analysis method is then used to decide if the collected data points out a significant difference from the baseline signatures, yielding the conclusion for the evidence of an abnormal state.

For the decision method here proposed, the baseline phase data, considering an average behavior of the structure, is represented by a parity matrix calculated using a subspace identification method. For each new measurement during the

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inspection phase, an autocorrelation matrix is calculated which contains the information of eventual changes of the parameters. In the sequence, a residual vector is generated and a real time algorithm used to process these residues, in order to decide for the existence of damage. An important issue is to guarantee robustness against regular environmental parametrical changes, avoiding these to be detected as false damaged cases.

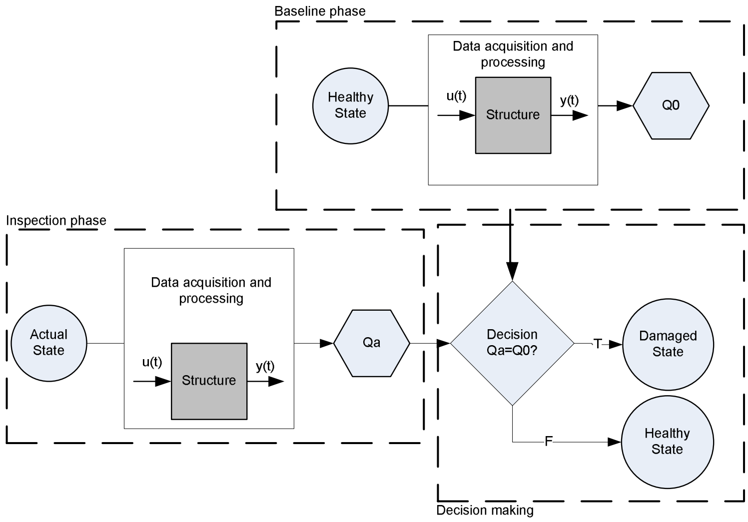

Figure 1: Schematic of the damage detection procedure

2. THEORY REVIEW

2.1. Subspace identification methods

Subspace identification methods were developed for model parameter estimation, based in subspaces of datasets. A brief description is presented here, see Basseville (2000) and DeMoor (1996) for details. A state-space model for the structure, that could be the physical or a canonical model, is admitted and experimentally validated. The identification goal is to calculate parameters contained in the state-space matrices that can describe adequately the system. These methods are used in several areas, and the interest here is its application to fault detection of mechanical and civil engineering structures.

In Figure 2, a structure is depicted by a block where external forces are acting as inputs, and displacements, velocity or acceleration are some of the measured outputs.

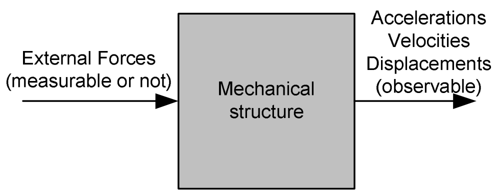

Figure 2: Structure seen as a block.

The forces acting on a system are not always directly accessible or measurable, which gives rise to a special interest to output-only methods. For these methods, we consider just the observable part of the system, represented by the system given in (1).

$$\begin{aligned} \{X\}_{k+1} &= [A]_d \{X\}_k + \{w\}_k \\ \{Y\}_k &= [C]\{X\}_k + \{v\}_k \end{aligned} \tag{1}$$

where $\{X\}$ and $\{Y\}$ are the system state and output vectors, respectively. $[A]_d$ is the discrete state matrix and $[C]$ is the observation matrix. $\{w\}$ and $\{v\}$ are process and sensor noise vectors.

A Hankel matrix of covariances may be calculated by:

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$$[H]_{p,q} \triangleq \begin{bmatrix} [\Lambda]_1 & [\Lambda]_2 & \cdots & [\Lambda]_q \\ [\Lambda]_2 & [\Lambda]_3 & \dots & [\Lambda]_{q+1} \\ \vdots & \vdots & \ddots & \vdots \\ [\Lambda]_p & [\Lambda]_{p+1} & \dots & [\Lambda]_{p+q} \end{bmatrix} \tag{2}$$

where the covariance matrices are given by

$$[\Lambda]_i \triangleq E[\{Y\}_k \quad \{Y\}_{k-i}{}^T]\,. \tag{3}$$

The dimensions p and q are related to the system order, and must be chosen *a priori*, using some preliminary knowledge about the system. The expectation estimator can be seen like a vector projection in a deterministic case (DeMoor, 1996). So, this method can be applied for deterministic excitation as well for stochastic excitation. In order to improve robustness with respect to signal magnitude, it is recommended to normalize the covariance by instantaneous signal power, which corresponds to use the correlation instead of covariance. As it represents just normalization by a scaling factor, the following calculations are made in the same way, using covariance or correlation.

The Hankel matrix (2) may be decomposed as the product of an observability and controllability matrices:

$$[\Lambda]_i = [C][A]_d{}^{i-1}[G] \quad (i > 0) \tag{4}$$

$$[H]_{p,q} = \begin{bmatrix} [C] \\ [C][A]_d \\ \vdots \\ [C][A]_d{}^{p-1} \end{bmatrix} \begin{bmatrix} [G] & [A]_d[G] & \cdots & [A]_d{}^{q-1}[G] \end{bmatrix} = [O]_p[\mathbb{C}]_q \tag{5}$$

where the observability matrix is defined as

$$[O]_p \triangleq \begin{bmatrix} [C] \\ [C][A]_d \\ \vdots \\ [C][A]_d{}^{p-1} \end{bmatrix}; [\mathbb{C}]_q \triangleq \begin{bmatrix} [G] & [A]_d[G] & \cdots & [A]_d{}^{q-1}[G] \end{bmatrix} \tag{6}$$

Because the observability matrix contains the information about the modal parameters of the system, the same happens to the respective Hankel matrix. These modal parameters may be calculated by eigenvalue decomposition of the state matrix, according to the following formulation:

$$[A]_d = [\Psi][\lambda][\Psi]^{-1} \tag{7}$$

$$[\lambda] = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_{n_x} \end{bmatrix} \tag{8}$$

$$[\Psi] = \begin{bmatrix} \{\psi\}_1 & \{\psi\}_2 & \cdots & \{\psi\}_{n_x} \end{bmatrix} \tag{9}$$

where $[\Psi]$ is the mode shape matrix and λ_i are the natural frequencies of system.

$$f_i = \frac{\omega_i}{2\pi\tau} = \frac{|\ln(\lambda_i)|}{2\pi\tau} \tag{10}$$

where τ is the sampling period of a discrete-time system.

$$[\Phi] = [C][\Psi] \tag{11}$$

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An observability matrix can be expressed in terms of its modal parameters:

$$[\hat{O}]_p = \begin{bmatrix} [\Phi] \\ [\Phi][\lambda] \\ \vdots \\ [\Phi][\lambda]^{p-1} \end{bmatrix} \tag{12}$$

The observability matrix from Equation (12) corresponds to that of Equation (5) postmultiplied by the eigenvector matrix of state matrix.

2.2. Offline parity residue generation

A residue parity analysis for fault detection in structures consists in generating a scalar or vector-valued function that satisfies the following condition:

$$\begin{aligned} \{r\} = \{0\} & \quad \text{for a healthy case} \\ \{r\} \neq \{0\} & \quad \text{for a damaged case} \end{aligned}$$

As seen in the previous section, the observability matrix, obtained from Hankel matrix decomposition, implicitly contains all the modal parameters. So, a good function to detect changes in modal parameters can be given by:

$$\{r\} = vec([S]^T [O]_p) \tag{13}$$

where $[S]$ is the left kernel of the observability matrix (the null space of $[O]_p{}^T$) and $\{r\}$ is the residue vector. The operator vec is used here to produce a stacked vector-valued function, because the product above can be a matrix, depending on the rank and dimensions of the Hankel matrix. It is simple to verify that both the observability matrix and the Hankel matrix have the same left kernel (using Equation 5). Considering this, it is possible to calculate the residue directly from the Hankel matrix:

$$\{r\} = vec([S]^T [\hat{H}]_{p,q}) \tag{14}$$

As already mentioned, the residue function can tell about the damage state of structure. It must be zero, or near zero, for the normal case or notably different from zero for a damaged case. An important issue is how to choose a value for a threshold, to decide between a normal or a damaged case.

2.3. Online parity residue generation

Using the same principles presented in the previous section, an algorithm was developed to calculate and analyze the covariance matrix online. The proposed parity residue analysis method present as advantages the simplicity of calculations, the volume of data to be processed and the real-time fast response concerning the state of the system being monitored.

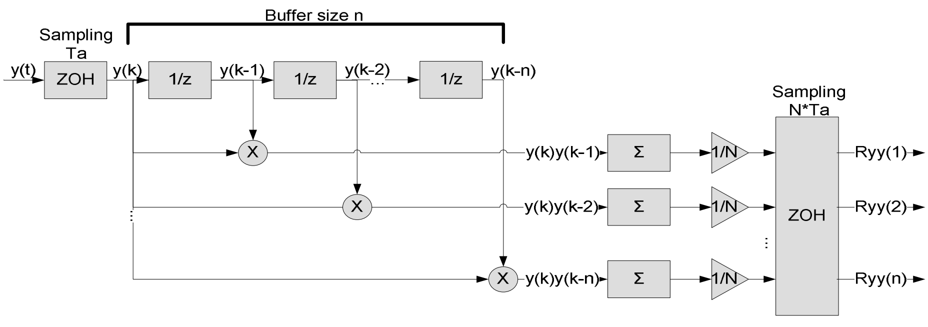

Figure 3: Block diagram for real-time autocovariance calculation

As depicted in Figure 3, the covariance, given by Equation (3), may be estimated by:

$$[\hat{\Lambda}]_i = \frac{1}{N}\sum_{k=1}^{N}\{Y\}_k \{Y\}_{k-i}{}^T \tag{15}$$

The autocovariance vector may be continuously calculated using a buffer to store the delayed signal. The length of that buffer is associated to number of autocovariance vector elements. The partial product, calculated for each sampling period (Ta) is accumulated and the result is re-sampled, which gives new calculated autocovariance vectors each period of a complete sampling (N*Ta).

This algorithm may be efficiently and easily implemented using an embedded system, based on a FPGA (Field Programmable Gate Array) module or on a DSP (Digital Signal Processor), which may be used to execute the inspection phase in real time. Once calculated, using recent measurement data, the residue vector has to be analyzed to determine the state of the structure. This analysis is presented on the next section.

2.4. Residue analysis

Basseville et al (2000) propose a statistical chi-square test to make the decision, adopting a threshold that clearly separates the signals. This results in a robust value for the threshold, because it takes into account statistically a large amount of data. A nonparametric version of this test is given by:

$$\chi_r^2 \triangleq \{r\}^T [\hat{\Sigma}]^{-1} \{r\} \tag{16}$$

The major advantage of this test is the estimation of a threshold by the analytic chi-square distribution, to decide for the triggering of an alarm, given a desired probability. However, the residue covariance matrix, $[\hat{\Sigma}]$, is not simple to be estimated and, for the most of cases, there is a dependency between residue vector components, which may produce an ill-conditioned covariance matrix. Techniques like re-sampling and bootstrapping, proposed by Davidson and Hinkley (1997) can improve the results obtained by chi-square tests, but they may not be viable for a real-time application.

For a simple detection procedure, the comparison between residue vector Euclidean norms may be adopted as a simple way to distinguish between healthy and damaged cases.

2.5. Real-time algorithm implementation

The proposed algorithms and calculations previously presented may be synthesized in a complete damage detection procedure, which fits in the two-phase procedure already presented, and depicted in Figure 4. For the first phase, a parity matrix is calculated using data acquired from a healthy structure. The parity matrix, along with the recently calculated autocorrelation matrix, will be used to calculate the residue in the inspection phase, whose norm will be used to distinguish between healthy and damaged states.

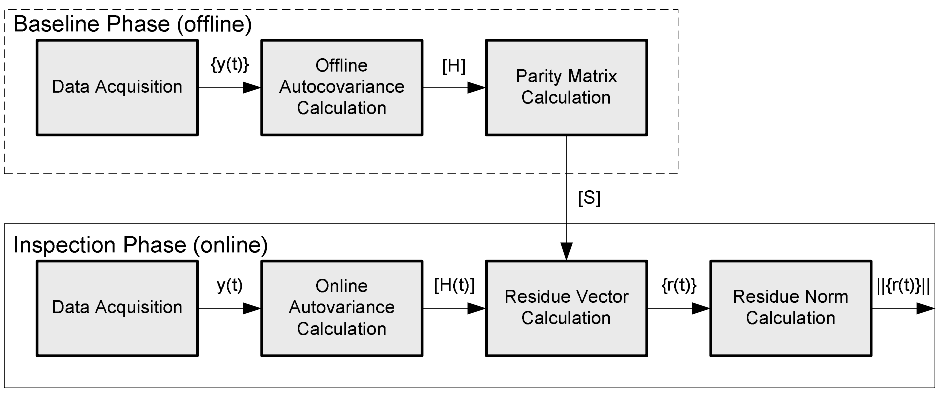

Figure 4: Block diagram for complete damage detection procedure

The method presented in the previous sections was implemented in Simulink®, and used with a data acquisition system. The respective detailed block diagram is presented in Figure 5, which corresponds to the just described block diagram.

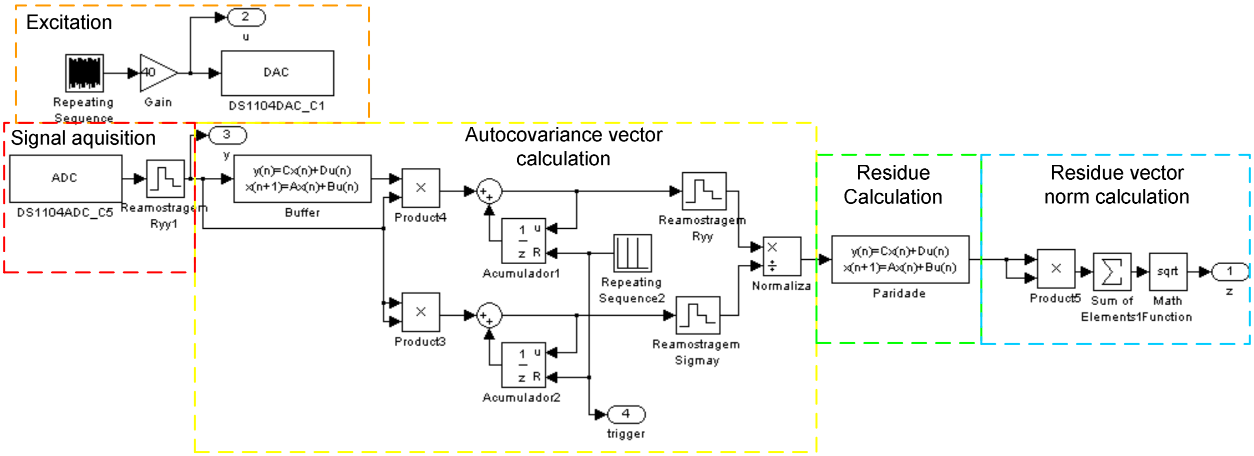

Figure 5: Block diagram for real-time residue norm generation

3. EXPERIMENTAL METHODS

The experimental setup consists in two similar aluminum beams, presenting the same dimensions. One of these beams is intentionally cut, to simulate a structural damage. Both beams are represented in Figure 6.

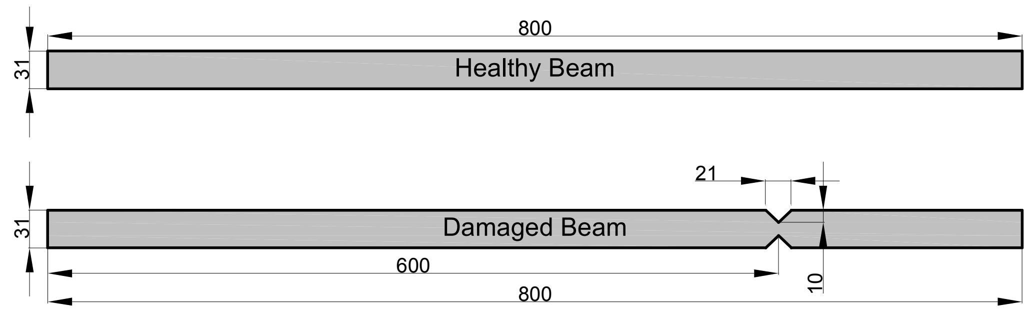

Figure 6: Beams used for tests

The data acquisition and signal generation was implemented using a dSPACE® card, model DS 1104, and respective hardware-in-the-loop software ControlDesk®. The generated excitation signal is amplified and applied to a piezoelectric transducer, used as actuator and positioned at one tip of the beam. The vibration signal is captured by another piezoelectric transducer positioned at the other tip of the beam, amplified and transmitted to the dSPACE® card. The general data acquisition scheme is depicted in Figure 7, and the photography in Figure 8 shows the complete instrumentation setup.

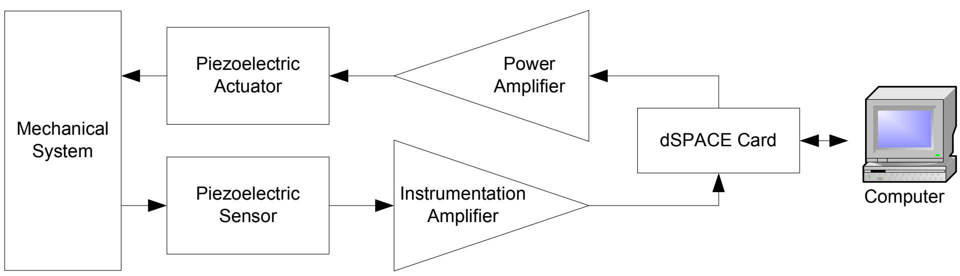

Figure 7: Block diagram of experimental setup

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Figure 8: SHM experimental setup

To determine the better way to excite the beams, a frequency response function (FRF) in the audio frequency range till 25 kHz was experimentally calculated and the result presented in Figure 9.

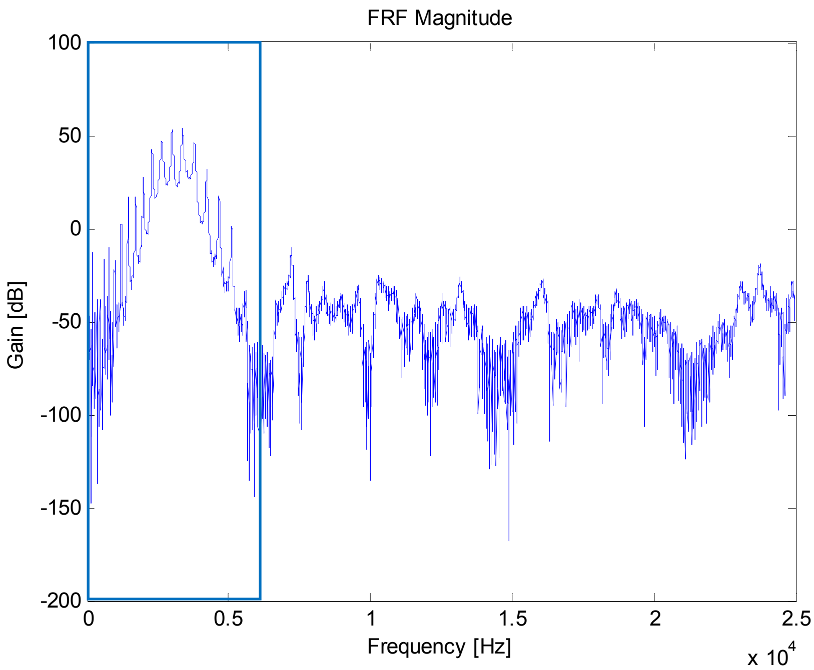

Figure 9: FRF measurement for 0-25kHz.

As may be seen in Figure 9, the response in the frequency range from 1 to 6 KHz presents a clear distinction between the several peaks, and for this reason this band was chosen to be the frequency range of interest for this application. A Schroeder-type signal, with 2^{17} points per period, sampling time of 20μs and frequency range between 1 and 6.25 kHz, was then used to excite the actuators. This type of signal was chosen due to its flat frequency distribution, which assures the uniform excitation for the adopted frequency range.

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4. RESULTS AND DISCUSSION

4.1. Single dataset comparison

Several experimental measurement sessions were conducted using the above described instrumentation facilities. In Figure 10 a typical result for the inspection phase is presented, considering that all measurements presented similar behavior for the curves of the two beams. These curves were calculated using the residue vector norm based on the presented real-time algorithm, with a reference parity matrix calculated for the healthy beam.

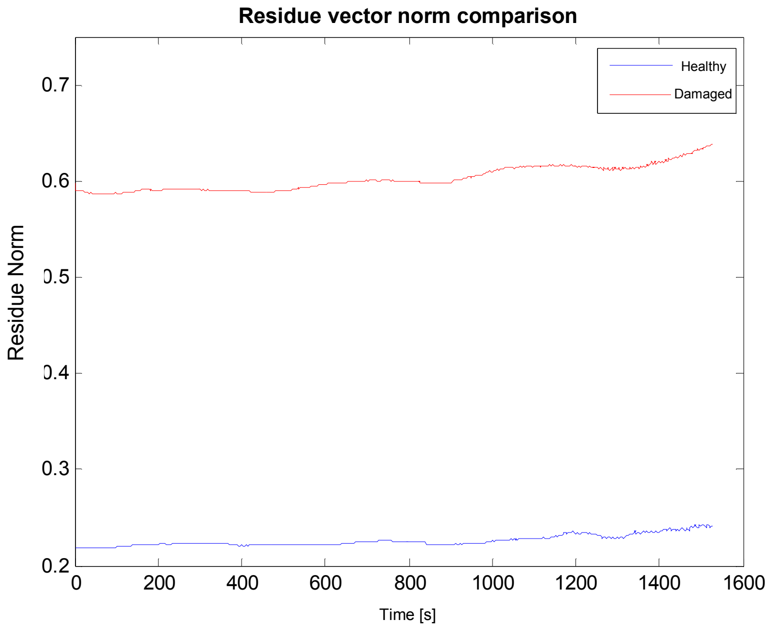

Figure 10: Residue vector norm comparison for healthy and damaged cases

It is possible to notice, in Figure 10, that the residue norm for the damaged case presents a higher value, and clearly separated, from the undamaged case.

4.2. Robustness analysis

The proposed detection method is based on the fact that damage in any structure causes changes in its modal properties, but environmental factors can modify also the physical properties of the structure material. The possibility of false alarms must be avoided, which may be achieved through improvement of the detection method robustness. An analysis of the behavior of the beam aiming to assess the method robustness was conducted and is described in the following.

The measurements were repeated for eight different days, and the beam frequency response function (FRF) results may be seen in Figure 11, for the damaged and healthy cases, respectively in the lower and upper panel. It is possible to notice some variation from one day to another, but it is clear also that the measurements are consistently presenting a block behavior. The variations on each curve may be associated to environmental conditions (temperature as a main factor) because care was taken to ensure that the instrumentation conditions were maintained. It is possible to notice that in the same day, a similar variation occurred in general to both beams, but the difference in the respective FRFs provides as well the separation of the residues. Nevertheless, it is important to check if a higher signal level for the undamaged beam may mislead the interpretation considering a lower level for the damaged beam. Balmes et al (2008) suggest considering an average Hankel matrix, in order to concentrate information for different environmental conditions. Adopting this method, a parity matrix for the whole of measurements was calculated and residues were generated through a correlation vector for each day, using the real time algorithm. The residue vector norms are plotted in Figure 12, which gives a good indication about the algorithm performance.

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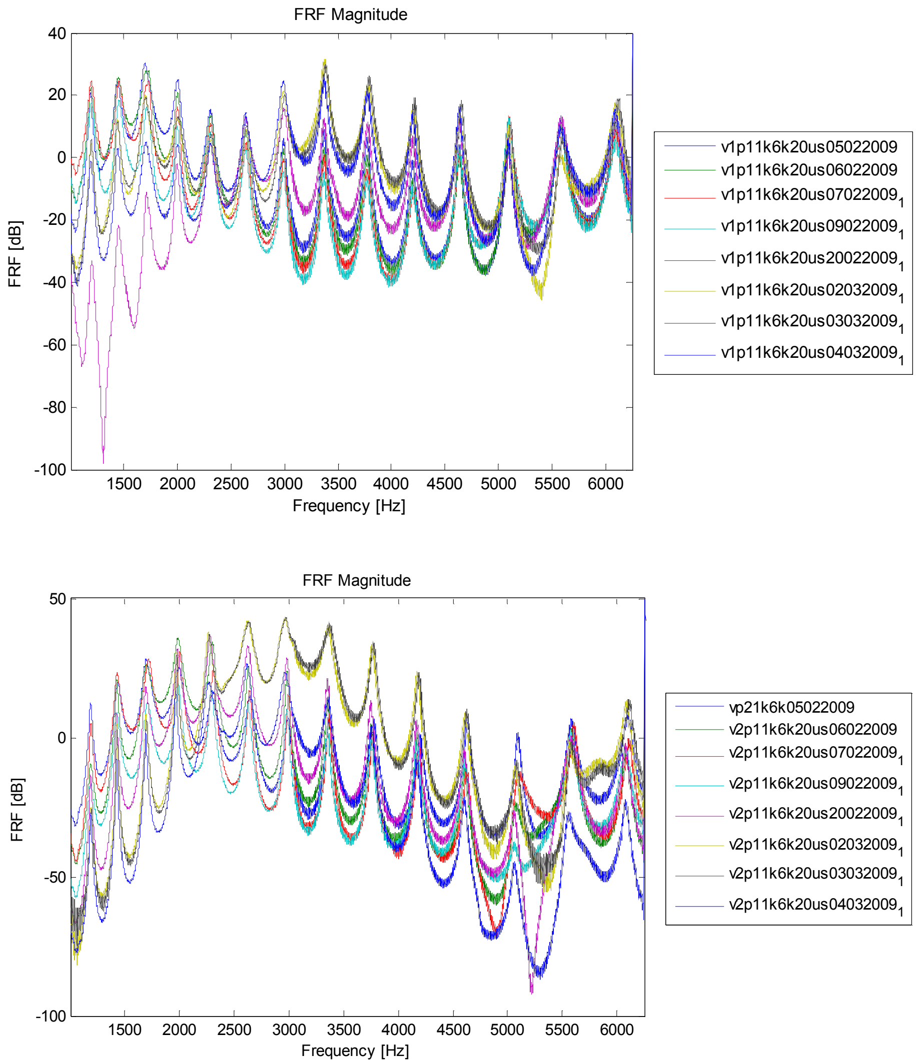

Figure 11: FRF for consecutive-day datasets. Up: Healthy case. Down: Damaged case.

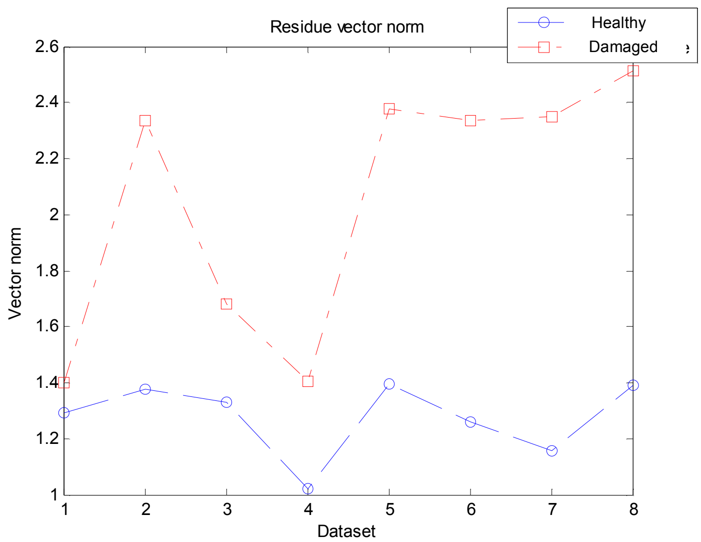

Figure 12: Residue vector norm, for several datasets

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It is possible to see in Figure 12 that the residue vector magnitude in the damaged case is greater for all days. For two measurements, the low level for the damaged beam is close to the average level of the undamaged beam, but it is possible anyway to distinguish these points from the curve representing the healthy state of the beam. Considering a larger number of datasets, it may be expected to improve the statistical data representing the undamaged case, leading to more clear results.

5. CONCLUSIONS

A system monitoring recursive method is here proposed and its performance experimentally analyzed using an aluminum beam setup. The idea is to develop an algorithm that may be used in an embedded monitoring system, aiming real-world applications. The method is based on a parity subspace residue generation, calculating a correlation matrix representing the recent measurements, and a parity matrix based on data from a healthy state of the monitored beam. Two beams were used, one representing the damaged beam and the second, an undamaged beam, representing the healthy state. The analysis results comparing the two parity residual norm curves, generated on real time from measurements of the two beams, show a clear separation between them. An assessment of the robustness of the method is presented also, based on FRF measurements repeated for eight different days, showing some variation related to parameter changes due to environmental conditions. The residual norm curves separation is not so clear in two of the eight days, but it is possible to notice the altered condition of the beam. An extended study dedicated to improve the analysis of the robustness of the method, using more statistical significant data, is being conducted and will be related in a future work.

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