A ROBUST PROCEDURE FOR DAMAGE IDENTIFICATION IN A LATTICE SPACECRAFT STRUCTURAL ELEMENT BY MEAN OF STRAIN FIELD PATTERN RECOGNITION TECHNIQUES

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Abstract

A high stiffness and low weight lattice structure for launcher applications made with high modulus carbon fiber was manufactured by EADS CASA Space by using a new cost efficient fiber placement technology. The structure consisted of a composite lattice of intertwined, unidirectional carbon fiber bars. Several Fiber Bragg Gratings (FBGs) were bonded along these bars in order to measure strain during different tests performed on the structure.

A robust procedure for defect detection based on Principal Component Analysis (PCA) and strain field pattern recognition techniques was used in order to identify different defects induced in the structure during static testing conducted until fracture. A test campaign of smaller, iso-grid structures was conducted with the aim of studying the sensitivity to detect small defects in the lattice structure. A PCA model was built for the healthy structure. Subsequently, different known damage conditions were projected into the PCA model (baseline). From this projection, various damage indices and detection thresholds were calculated. The results showed that even small damages located far away from the sensors could be detected by this technique.

1. Introduction

Nowadays launcher structural elements need to be very light to increment the payload by minimizing the structural weight. An open iso-grid structure, better known for the name of "lattice structure", made of composite material has been demonstrated to be a promising weight efficient structural concept [1].

An integrated health monitoring system could supervise the loads of such a structure and flag possible damages during the testing and instrumentation campaign and could give important information of the structural integrity during the launch phases. Different iso-grid structures have been manufactured before by EADS-CASA Espacio in automatic tape laying process and have been instrumented with embedded FBGSs and compression tested at RT and 200ºC in earlier test campaigns, [2, 3]. In these cases the grid-structure had the function of stiffeners of a skin where they were bonded to.

In the case of the presented paper the lattice structure is open and has no skin where it is bonded to. This kind of structure has an inherent high mechanical efficiency. It can carry higher loads as grid stiffened skin structures because it gets rid of the quite weak grid/ skin interface where the load introduction from skin to grid is only performed by the foot section of the grid. The before mentioned test campaign [2] showed that grid stiffened skins tend to fail locally in this interface. Tests performed on smaller test elements confirmed this result [3]. The open lattice structure avoids this problem because the load is only carried by the bars and seems to be a very promising economical structural element for future launcher structures.

A novel methodology for damage detection and location in structures is proposed. The methodology is based on strain measurements and consists in the development of strain field pattern recognition techniques. The changes in the local strain field may be very intense close to a damage, but smooth out very quickly. So trying to get information about damage occurrence from strain measurements is a difficult task, as the detected strain changes may be very small, and may be masked by external factors. It drives to the need to include a large sensors array into the structure, which is not a difficult when using optical fiber sensors, but then the data treatment has to be done in a fully automated approach, algorithms are needed to compare and extract information from the multiple strain measurements.

This technique have been studied in compression tests of a cylindrical lattice structure that has been tested until rupture. The technique has been able to detect damage occurrence and could identify damaged zones in load tests performed after the rupture of the structure.

2. Strain field pattern recognition techniques.

A time response or strain spectrum obtained through several experimental measurements and features extraction, which is the result of signal processing, allows to create data sets that can be seen as patterns. The study of these groups leads to damage detection based on pattern recognition techniques. The features extraction can be defined as the process of identifying damage-sensitive parameters from the gathered data. This process usually results in some form of data reduction.

The patterns can be continuous variables, discrete variables or a combination of both and, can be expressed in form of vectors, matrices or multidimensional arrays. When pattern recognition techniques are used like a damage detection approach, it must be assumed that each pattern represents a particular damage condition or structural state. The main idea is then, to determine whether a structure is damaged or not and try to assess the damage severity.

For example, when strain field pattern recognition techniques are used, the main idea is to correlate all the strain measurements gathered from a network of sensors in a complex structure and, to discern if something has changed, in particular, the global stiffness and the strain field between different sensors, as product of damage appearance in the structure.

There are two classical categories of approaches to damage detection by means of pattern recognition. The first approach includes the so called “statistical methods” and, the second approach, includes the so called “syntactic methods”. Statistical methods assigns features to different classes using statistical density functions, whereas, the syntactic methods classifies data according to its structural description. Statistical modeling requires a previous statistical characterization of data, before any statistical inference can be reached. The statistical methods are the most used in Structural Health Monitoring (SHM). Many techniques for statistical analysis have been developed for building models under uncertain conditions. However, in SHM applications, all the measurements must be studied together in order to increase the probability of damage detection. Then, it is necessary to use multivariate statistical tools in order to getting some valuable information about the system behavior. [4]

Usually multivariate data are studied grouped in batches. Data processing in batch or semi-batch consists in measuring different variables in function of time. These variables are correlated with each other for each time instant of the experiment and, in turn, are correlated to events occurring during the process being studied.

In order to perform online monitoring of multivariate data, diagnostic and fault detection, several methods have been reported in the literature. These methods are known as multivariate statistical projection methods. To avoid the course of dimensionality (understood like the need of low dimensionality in the feature vectors), data are often projected onto a lower dimensional feature space using specially designed mapping functions. This process is called “data reduction” or “data condensation”. Among the most used projection methods is the Principal Component Analysis (PCA). PCA provides arguments on how to reduce complex data set to a smaller dimension and also reveals simpler patterns or “structures” that may be hidden under the data. The ultimate goal of the technique is to discern which data represent the most important dynamics of a particular system and which data, on the other hand, are redundant or just noise. This is achieved by determining a new coordinate space. This space is based on the covariance of the original data set. For a detailed description of PCA technique the reader is directed to references [5, 6]

PCA is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible). Usually, the number of principal components can be much smaller than the number of original variables. Each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (i.e., uncorrelated with) the preceding components.

There are statistical tools that used along with PCA, allow detection of anomalous behavior in systems. The two most common tools are Q the index (or index SPE Squared Prediction Error) and the $\boldsymbol{T^2}$ index (or index D). The index Q indicates how well each sample fits the PCA model. It is a measure of the difference between a sample and its projection in the main components retained by the PCA model. [5-9]

3. Experimental setup

To conduct this experiment, an open cylindrical isogrid structure also known as “lattice structure” was used. The tested lattice structure had 109.5 cm in height and 80 cm in diameter. This experiment was part of the project “ICARO” leaded by “EADS CASA Space”. [3]

The element was manufactured by “EADS CASA Space” using an out of autoclave epoxy, reinforced with high modulus carbon fiber. An automated tape laying process was used to manufacturing the element. This lattice structure was manufactured without skins trying to avoid the weak grid/skin interface, where the load introduction from skin to grid is only performed by the foot section of the grid. Díaz et al. showed that grid stiffened skins tend to fail locally at the interface between the grid and the skin. [2]

The structure was instrumented with four optical fibers, each one having 9 FBGs with a total 36 FBGs manufactured by the company “FBGS Technologies”. The FBGs were adhered using adhesive X60 (from “HBM Company”) around the perimeter in the upper half of the cylinder to each bar of the grid in the inner side of the cylinder (in clockwise direction). The Figure 1 shows a scheme of the cylindrical isogrid structure and the FBGs locations.

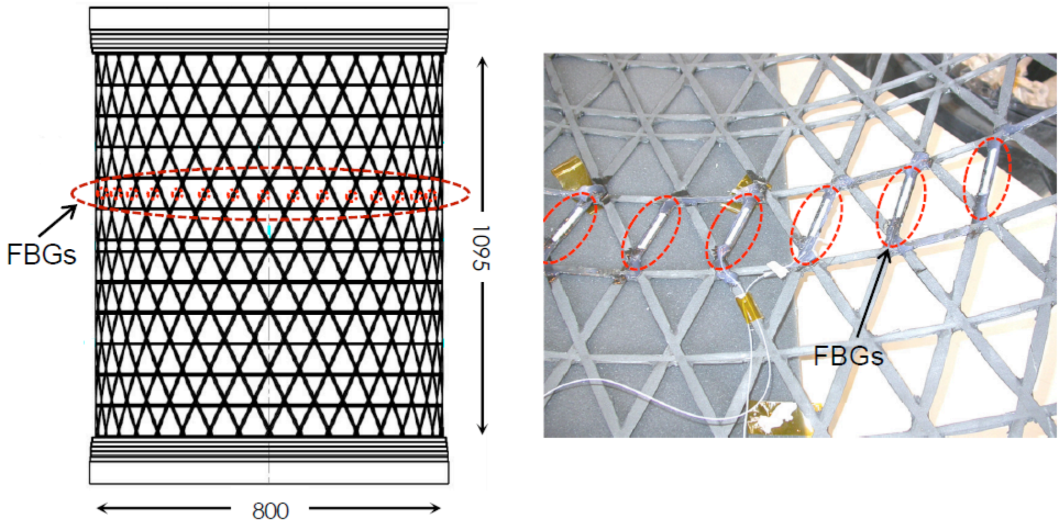

Figure 1. a) Sensors location in the isogrid structure. Adapted from Frövel et al. [3]. **b)** Detail of the instrumented vertical bars in clockwise direction. Adapted from Frövel et al. [3].

The isogrid was screwed to aluminum inserts in order to guarantee a proper load introduction during the experiments (See Figure 2). A testing machine was used to load the isogrid. A maximum load of 330 kN was reached before the rupture of the structure. Once the cylinder was instrumented, the test phase began. All tests were performed by “INTA” in Spain and consisted in compression loading of the structure. In some tests, several short stops were performed during the loading process in order to stabilize the load.

During all tests, the FBGs were interrogated by means of an SI 405 equipment from “HBM Company”. A sampling rate of 5 Hz was used in all experiments. Several compression tests were performed in order to evaluate the performance of the isogrid structure. A priori, it seems that strain was uniformly distributed in all the bars. However, when a detailed analysis of the strain distribution across the cylinder is conducted, some particular effects, including nonlinearities, can be appreciated. At least, three different tests were carried out before the structure failed without previous notice.

In one of the tests, in which the load level was increased with respect to the preceding tests, the structure failed catastrophic. Some bars and nodes broke instantaneously in the center region of the cylinder. Since there were too many structural elements, the strain was redistributed quickly in the structure and the load was still maintained. It was possible to appreciate how, some of the FBGs, which before the rupture withstood compressive loads, started to withstand tensile loads after rupture. The load was released and some residual strains could be detected in some bars of the structure.

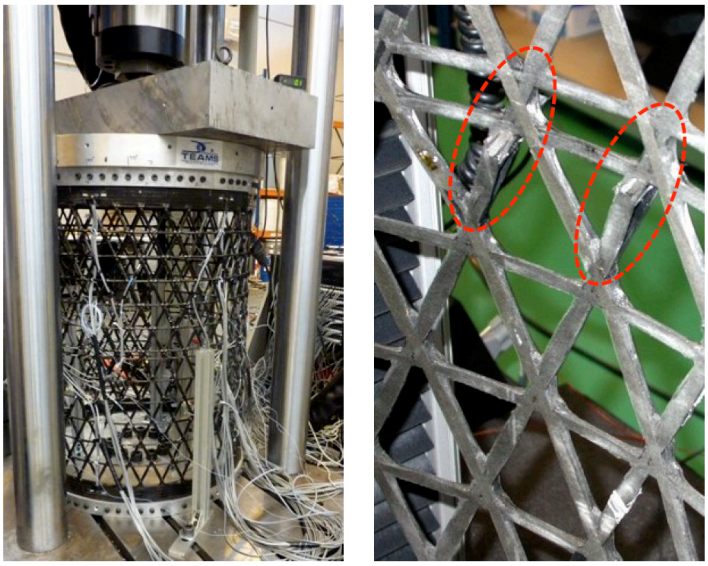

Figure 2. a) Sensors location in the isogrid structure. Adapted from Frövel et al. [3]. **b)** Detail of the instrumented vertical bars in clockwise direction. Adapted from Frövel et al. [3].

After the rupture, two new tests were performed. This time, the structure was loaded to 15% of the failure load in order to determine the residual structural stiffness and the redistribution of the load paths. Data from healthy structure were used for building the baseline model and later, damaged cases were projected into the model.

4. Experimental results

Since all the experiments had different numbers of experimental measurements in function of time, for each one, 800 points were taking homogeneously distributed over the whole experiment. As explained by Sierra et al, data are unfolded and standardized. The first five components were retained, explaining more than 97% of the variance of the system. [5]

As explained before, three tests were performed and during the third test, the structure suddenly did fail (D1). The first two tests were taken as baseline (BL) and validation case (undamaged-UND) and two additional tests were conducted with the damaged structure (D2 and D3). As it can be seen in Figure 3a, the major part of the Q indices for the baseline, the undamaged case and half of the indices associated to experiments named D1, fall within the damage threshold. On the other hand, the indices associated to D1 for the moment where the damage appears (experiment 425 to 800) and the indices associated to the tests performed with the damaged structure (D2 and D3), lie outside the confidence interval.

It is important to remember that measurements for the whole load spectrum were used to carry out this analysis. Because of this, some nonlinearities found for the lower load magnitudes (during the initial loading stage) were included in the model. As it can be seen, due such nonlinearities, the indices associated to the lower load magnitudes lie outside the damage thresholds. Besides the found nonlinearities, it is a fact that for lower load magnitudes, the SNR decreases and as consequence, the accuracy of the technique also does.

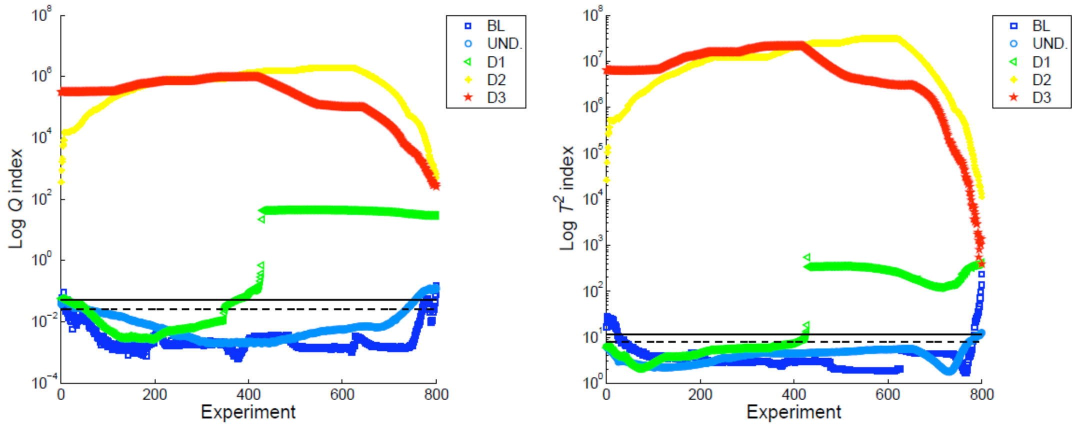

Figure 3. a) Q index for PCA model with damage thresholds for 95% and 99% of confidence (dashed line and solid line respectively). **b)** T^2 index for PCA model with damage thresholds for 95% and 99% of confidence (dashed line and solid line respectively).

The T^2 index is represented in Figure 3b. From this index can be concluded that the PCA model is not optimum for such samples which are located close to the starting and ending of spectrum. In general terms, in both sub-figures presented in Figure 3, it is possible to appreciate how the indices corresponding to the middle-high load range of the load spectrum, remains approximately constant and their tendencies give a clear idea of the damage onset in the structure.

An example of the found nonlinear effects is depicted in Figure 4. In the Figure 4a the strain distribution for all the sensors for several load magnitudes during a loading cycle is depicted.

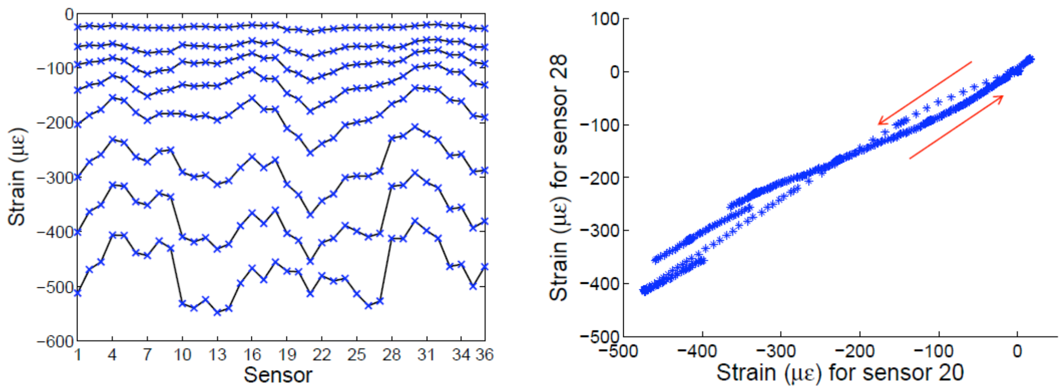

Figure 4. a) Strain as function of load increase for all the 36 FBGs for the baseline. **b)** T^2 Strain vs. Strain for couple of sensors (20 and 28).

In the perfect case, the strain should increase homogeneously, that is, instead of the irregular strain distribution shown in the Figure 4a, the distribution should be flat since the load is supposed to distribute along all the bars of the structure equally. The real problem is the distribution changes as the load increases in a nonlinear way. These phenomena can be detailed by studying the response of a pair of sensors. The Figure 4b shows such study for a couple of sensors during a whole test (loading plus unloading). It is possible to appreciate how nonlinear effects appear during the loading stage along with a hysteric behavior. On the other hand, it is possible to appreciate a linear behavior during the unloading stage.

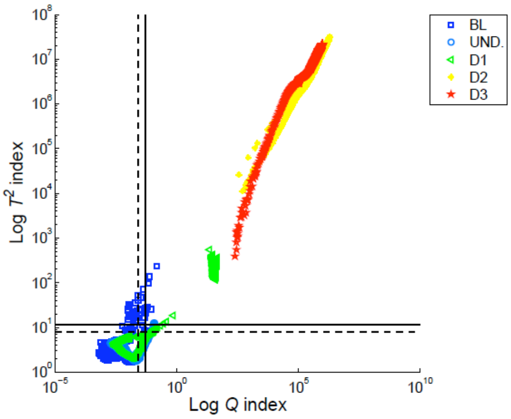

Figure 5. Q index vs. T^2 index for PCA model with damage thresholds for 95% and 99% of confidence (dashed line and solid line respectively).

The Figure 5 shows the Q index vs. the T^2 index plot. This plot serves as additional tools in order to understand in a more graphic way the existing correlations between the Q index and the T^2 index. Again, it is possible to see how the indices associated to the different healthy states (BL, UND. and half of D1) lie inside the lower left region (normal operation region). All other indices lie in the upper right region (majorly), indicating a clear fault condition.

5. Conclusions

In order to achieve the first level of SHM (damage detection) by using strain measurements in an isogrid structure under different load magnitudes, readings gathered from FOS and by means of the application of PCA and different damage indices, several scenarios were experimentally analyzed.

A PCA baseline models was built using the responses for the healthy structure. In subsequent steps, experiments were performed for the damaged structure. All these experimental data were projected into the PCA model, for which, a selected number of principal components were retained. Finally, different damage indices and thresholds were calculated.

The FOS offer unique advantages including small size, easy of embedment in composite structures, immunity to electromagnetic interference, excellent multiplexing capabilities, excellent accuracy and sensitivity. All this advantages make the FOS the ideal choice for strain-based SHM techniques. Precisely these advantages convert the strain-based techniques, based in turn in FOS, in a promising field of research in SHM.

In all the experiments performed it was possible to detect deviations among different indices associated to the baseline (and the undamaged case) and the different damage cases. The Q index showed more sensitivity in this study to detect anomalies. On the other hand, the T^2 showed a good potential to discern if a model is well defined since it is able to give an idea of the variability inside the model.

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References

[1] V.V. Vasiliev, V.A. Barynin, A.F. Razin, S.A. Petrokovskii and V.I. Khalimanovich. Anisogrid composite lattice structures – Development and space applications. Proceedings of the International ARA- days, 2009

[2] V. Díaz, E. del Olmo and M. Frövel. Design & development of advanced composite isogrid structural solutions for primary structures of future reusable launch vehicle, proceedings ECSSMMT, 11th European Conference on Spacecraft Structures, Materials and Mechanical Testing, Toulouse, France, 2009

[3] Malte Frövel, Encarna del Olmo, Antonio Fernández, Fernando Quero, Gabriel Carrión, José María Pintado and Alfredo Güemes. Damage detection by load path changes in reinforced composite panels using local FBGS and distributed sensing, 6th EWSHM, Dresden, 2012

[4] W. Staszewski and K. Worden. Signal processing for damage detection, Encyclopedia of Structural Health Monitoring, 533-539. 2009

[5] J. Sierra, A. Güemes and L. Mujica. Damage Detection by Using FBGs and Strain Field Pattern Recognition Techniques. *Smart Materials and Structures.* 25011-25020. 2013

[6] J. Sierra. SMART AERONAUTICAL STRUCTURES: Development and Experimental Validation of a Structural Health Monitoring System for Damage Detection. Doctoral Thesis Universidad Politécnica de Madrid. 2014

[7] J. Jackson and G. Mudholkar. Control procedures for residuals associated with principal component analysis. *Technometrics.* 341-349. 1979

[8] K. Villez, K. Steppe and D. De-Pauw. Use of Unfold PCA for On-line Plant Stress Monitoring and Sensor Failure Detection. *Biosystems Engineering.* 23-34. 2009

[9] D. Burgos, L.E. Mujica, A. Güemes and J. Rodellar. Active piezoelectric system using PCA. Fifth European Workshop on Structural Health Monitoring. Sorrento. 2010