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Structural Health Monitoring by Means of Strain Field Pattern Recognition on the basis of PCA and Automatic Clustering Techniques Based on SOM ⋆

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Abstract: A new methodology to perform Structural Health Monitoring (SHM) in complex structures which is based on Data Driven Models (DDM) by means of strain measurements from Fiber Optic Sensors (FOS), in particular Fiber Bragg Gratings (FBGs), was developed by using Principal Component Analysis (PCA) and automatic clustering techniques based on Self-Organizing Maps (SOM) and density methods. The methodology includes techniques to uncoupling the changes in the strain field caused by the damage occurrence and the change in the operational conditions. Those techniques can be classified as Optimal Baseline Selection (OBS) techniques. Several experiments where performed to develop the methodology and demonstrate the whole concept. Some representative results are presented and discussed.

Keywords: Structural Health Monitoring, Strain Field, Patterns, Dimensional Reduction, Classification, Clustering.

1. INTRODUCTION

The origin of the “philosophy” called Structural Health Monitoring may be tracked to the accidents occurred with the Comet aircraft in the 1950s. At that time it was not called “SHM”, but as consequence of the accidents, diverse parties in aviation focused their attention in monitoring the loads for assessment of structural performance. Ikegami and Boller (2009).

The first works on damage detection used identification techniques based on physical models, for example, determination of the stiffness matrix or modal parameters. These approaches deal with deterministic models where all parameters are considered as measurable and different uncertainties are not represented for the model directly. This causes difficulty to assess how reliable the damage estimates are.

More recent techniques estimate the occurrence of damage based on experimental data. Such techniques has received the name of Data Driven Models (DDM). DDM takes experimental measurements for training or learning and assessment of the current state of a structure. These methods are a very robust way to indicate the presence of damage. Fritzen and Kraemer (2009).

In the last decades the aerospace, military and civil industries have developed some proof of concept of different types of SHM techniques. Beyond SHM (and its main goal associated: damage detection), many of those programs have addressed noise control, vibration suppression, shape control and multifunctional structural aspects for spacecrafts, launch vehicles, aircraft and rotor-crafts, wind energy, among others. These techniques have also been applied in civil structures like buildings, tunnels, bridges, highways, oil piping, etc.

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Even though SHM techniques are very promising, there are still some issues and limitations considered as open research fields which need to be solved in order to improve the performance of techniques. A useful system usually requires a large number of sensors distributed throughout the structure. This implies some associated issues like wiring, integrability and compatibility with the structure, etc. Large amount of data produced must be automatically processed and stored. Usually the data gathered include noise, redundant information, outliers, etc. Therefore, sometimes some information must be rejected and other preprocessed or treated somehow in order to extract valuable information from the original data. An additional issue is that there are several external factors which affect the performance of the SHM systems and must be considered. Some common examples include the environmental conditions, variable operational conditions (i.e. variable load conditions), among others.

2. SHM IN PRACTICE

No matter which SHM techniques are used, the steps are always approximately the same. According to Worden and Dulieu-Barton (2004) and Lopez and Sarigul-Klijn (2010) such steps can be summarized as: in a first step an operational evaluation is performed, in a second step the data is acquired, in a third step the data is preprocessed (standardization, cleaning, selection and condensation of information, etc), in a fourth step a model for discrimination of information is implemented and finally, in the fifth step, the situational assessment and the decision making are performed.

Several preprocessing techniques can be found in the literature. Such techniques can deal with data acquisition errors, noise and can perform transformations and condensation of information. The main difference between the different time-frequency methods is the treatment of uncertainty. Baseville et al. (2007).

After data preprocessing, many techniques are used for discrimination of information whose general purpose is to find information and highlight hidden patterns in data. In this way, it is possible to manage the information for optimization purposes, decision support and control processes among others. Staszewski (2001).

Perhaps, the best known technique for extracting information, dimensional reduction and characteristics identification is the PCA, also called sometimes, the Karhunen-Love Decomposition (KLD). The ultimate goal of PCA is to discern which data represent the most important dynamics of a particular system and which are redundant or are simply noise. This goal is achieved by determining a new space that allows re-express the data based on the original data covariance structure. Mujica et al. (2011).

Finally, the situational assessment and decision making is carried out. The situational assessment (and classification) is the one of most important and most significant tasks in SHM development. However, it is perhaps the least developed area between the five generic steps mentioned before. Staszewski (1997), Sohn et al. (2000), Worden and Manson (2000).

3. FIBER OPTIC SENSORS

Optical fibers are cylindrical dielectric waveguides for the light propagation. Usually they are made out from high purity silica or other transparent materials (like some polymers). The optical fiber has a core with a refractive index slightly higher than the surrounding material, called cladding, due to the presence of some dopants. Then, light is confined to the core, since, when the light arrives to the core/cladding interface, with an angle higher than the total reflectance angle (as defined by the Snell law), follows the total reflection and continues confined to the core. Güemes and Sierra (2013).

Fiber optics sensors have a wide variety of advantages such as small size and weight (allowing it to be embedded in composite materials), non-electrical nature (immunity to electromagnetic interference and to electrical noise), high sensitivity, high fatigue resistance, wide operating temperature range, multiplexing ability, etc.

From the sensing point of view the wavelength based sensors, called Fiber Bragg Gratings or simply FBGs, developed at the beginning of the 90's, have concentrated most of the attention from researchers due to their high sensitivity to strain and temperature. The FBGs can measure strains with similar or more accuracy that the standard electric strain gauges and have the main advantages that are more reliable for long term measurements because these do not drifting by aging, and, can be multiplexed since several FBGs can be engraved in the same fiber. The basic idea consists in engrave, at the core of the fiber, a periodic modulation of its refractive index. Kashyap (2009).

When incident light proceeding from a white light source or a LASER passes through a FBG, this behaves as a band-pass filter, promoting the reflection back of a very narrow wavelength band. Each peak is centered on the called Bragg Wavelength (λ_b) corresponding to the first-order diffraction. The Bragg's diffraction law simplifies under normal incidence to the following expression:

$$\lambda_b = 2\overline{n_e}\Lambda_0. \tag{1}$$

Where λ_b is the Bragg wavelength, Λ_0 the pitch or period of the modulation and $\overline{n_e}$ the effective mean refractive index.

4. PRINCIPAL COMPONENT ANALYSIS

PCA 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. Usually, the number of principal components can be much smaller than the number of original variables. Jolliffe (2002).

In all experiments, measurements were performed by using several sensors (J), during certain time interval (K) and, for a discrete number of experimental trials (I). Then the information can be arranged in a tridimensional matrix (X_{3D}). In order to apply a PCA study, this matrix must be re-arranged in a proper way. This procedure is called "unfolding". Kourti and MacGregor (1995).

The global unfolding idea can be appreciated in Fig. 4. Each one of the three tridimensional matrices (corresponding to different operational conditions clustered automatically as will be explained later) should be unfolded in a bidimensional matrix in order to perform a PCA analysis.

When variables with different magnitudes and units are present in experiments, may be desirable to treat the data to reduce the scale effects, as this can hide important information about the system. The most usual way to do it is by normalizing the data. Normalization includes centering and scaling but is often called just "scaling". Centering deals with magnitude differences and scaling deals with differences in units. For a deeper discussion see Jolliffe (2002), Kourti and MacGregor (1995), Nomikos and MacGregor (1994) and Westerhuis et al. (1999).

The projection of the original data over the direction of the principal components (P) is represented by the "score matrix" (T) by the linear transformation given by:

$$T = \overline{X} P_r. \tag{2}$$

Where $\overline{X}$ represents the unfolded and scaled matrix (originally (X_{3D})) and P_r represents a vector containing the first r principal components.

In order to use PCA like a pattern recognition technique, a baseline must be built firstly, by using data for a known healthy structure. Then, data for unknown structure conditions should be projected into the baseline model (equation (2)). From these projections it is possible to calculate different damage indices and detection thresholds.The two most common statistical tools (also called damage indices) are the T^2 index and the Q index. The first one is a measurement of the variation of each sample within the PCA model. The second one indicates how well each sample fits the PCA model. T^2 index, Q index and their respectively associated damage thresholds (also called Upper Control Limits (UCL)) are defined as follows:

$$T_i^2 = \sum_{j=1}^{r} \frac{t_{sij}^2}{\lambda_j} = \frac{t_{si}\ t_{si}^T}{\Lambda} = \frac{x_i P P^T x_i^T}{\Lambda} \tag{3}$$

$$UCL_{T^2} = \ c^2 = \ \chi^2_{r-2}(\alpha) \tag{4}$$

$$Q_i = \tilde{x}_i \tilde{x}_i^T = x_i (I - PP^T) x_i^T \tag{5}$$

$$UCL_Q = \ \left(\frac{\upsilon}{2m}\right) \chi^2_{2m^2/\upsilon}(\alpha) \tag{6}$$

Where $\chi^2_{2m^2/\upsilon}(\alpha)$ is the upper (100)-th percentile of a chi-square distribution with $2m^2/\upsilon$ degrees of freedom at significance level, with m and υ equal to the mean and the variance of the Q index sample respectively. r is the number of retained principal components in the PCA model.

5. AUTOMATIC CLUSTERING BASED ON SELF ORGANIZING MAPS

Self Organizing Maps (SOM) is a class of unsupervised learning of ANN, which purpose is to discover significant patterns in the input data without a target set. In its basic form, SOM allows to convert the nonlinear relationships between high dimensional data into simple geometric relationships of their image points on a low dimensional display, usually, a regular two dimensional grid of nodes. Kohonen (2001).

One of the most widely used SOM methodologies is the one developed by Kohonen. The goal of the Kohonen SOM is to transform an input pattern of arbitrary dimension in a bidimensional discrete map. Reed (2009).

The main advantage of the SOM is its ability of permitting the grouping of input data into clusters. In order to achieve this goal, the SOM internally organizes the data based on features and their abstractions from input data. SOM uses the training process to organize the two dimensional maps consisting in the topological links between neurons connected by means of weights connections.

One of the most typical visualization SOM tools is the so called U-Matrix. This surface represents the average distance of all cells to its neighboring cells. By means of this tool, it is possible to classify the data in different groups. Sierra-Pérez (2014).

Cabanes and Bennani proposed an efficient method of clustering based on the learning of a SOM. In the first phase the process, a standard SOM is used to compute a set of reference vector representing the local means of the data (weight vectors). Later, in a second phase, the obtained weight vectors are grouped in order to form the final partitioning. Cabanes and Bennani (2010).

The methodology is based on learning at the same time the structure of the data and its segmentation by using both, distance and density information. The main advantage of this methodology lies in the ability of the algorithm to determine automatically the number of clusters during the learning process. Then, no a priori hypothesis for the number of clusters is required. This methodology has been called Local Density-based Simultaneous Two-Level Clustering or DS2L-SOM. For more details see Cabanes and Bennani (2010).

6. FAULT DETECTION METHODOLOGY

A general methodology for fault detection could consist of the following steps: the first step occurs during the clustering stage. If data cannot be classified in any of the baseline data clusters, a fault condition may be assumed as long it is not an isolated case. That is, if only one isolated measurement can not be classified according to the baseline data, it can be assumed as an outlier. If on the contrary, consecutive data start to fall out of the baseline clusters, a fault condition may be assumed.

The second step consists in testing Q index. If Q index is significant, a fault condition may be assumed and the procedure is completed. On the other hand, if Q index is not significant, this is an indication that the PCA model

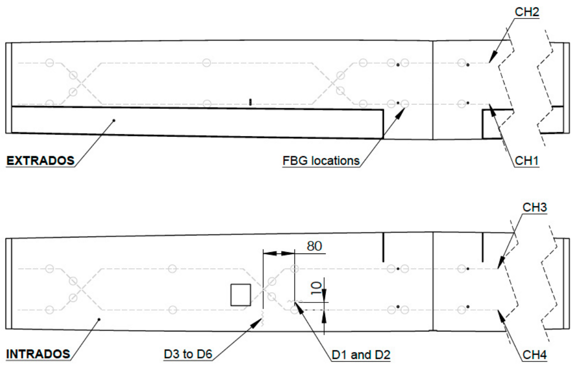


Fig. 1. Sensors and damage locations for a UAV's wing section. 32 FBGs.

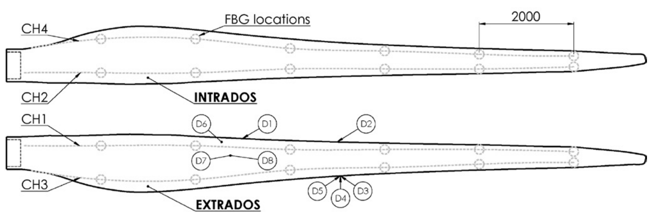


Fig. 2. Sensors and damage locations for a 14 m long wind turbine blade prototype. 24 FBGs.

holds the same characteristics than the actual structure and T^2 index must then be tested.

The third step consists in testing the T^2 index. If T^2 index is significant, a fault condition can be assumed and the procedure is complete. If T^2 index is not significant, then the fourth step must be performed.

In the fourth step, the individual principal components should be tested in order to determine the nature of the irregularity. According to the methodology developed, a normal condition may be assumed if all the previous steps are not able to detect damage.

7. EXPERIMENTAL VALIDATION OF THE METHODOLOGY

Several experiments have been performed with different types of real structures. A couple of full scale wind turbine blades made of composite materials (see Fig. 1) (for mode details see Sierra et al. (2014)), a section of an UAV wing (Unmanned Aircraft Vehicle) made of composite materials (see Fig. 2) (for more details see Sierra et al. (2013)), an aluminum beam (see Fig. 3) (for more details see Sierra and Güemes (2013)) and and other few. For some experiments static loads were used whiles in other ones, dynamic loads were applied to the structures.

In all experiments the procedure was very similar. Several FBGs were installed into the structure. In some cases the sensors where embedded into the composites materials during the manufacturing process. The number of sensors varied between 24 and 36 in all cases. During the experimental phase, the first step consisted in gathering the strain at sensors locations for the healthy state under diverse load conditions and magnitudes. This data correspond to the baseline of the structure and allows to build the PCA baseline model. In a second step, different kind

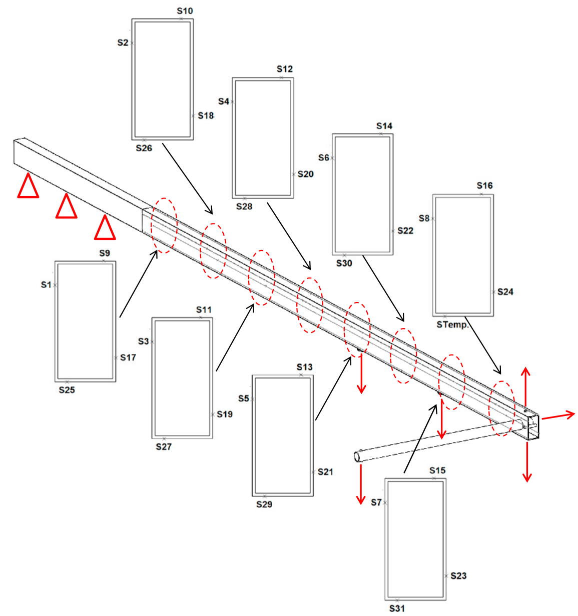


Fig. 3. Sensors distribution across an aluminum beam. 32 FBGs.

of artificial damages were induced into the structures. In some experiments the damages had a cumulative nature and in other, several damages were induced instead of increasing the severity of an existing damage. It is important to notice that damages were intended to emulate a real damage typical for each structure. The severity of damages never exceeded a reduction in the stiffness bigger than 5%. Again, data were gathered for each damaged condition in all the load configurations.

Once all data were acquired, the processing step was performed. As mentioned before, in order to isolate the changes in the strain field caused by the load conditions from the changes caused by damage occurrence, the automatic clustering methodology based on the DS2L-SOM algorithm was used as an OBS methodology. Clustering the data according to the operational conditions increases the sensitivity of the whole technique. The idea was to have different baselines corresponding to each load condition or to very similar ones (sometimes the algorithm recognized two or more very similar load cases as one). The idea of having multiple baselines for each load case is presented in Fig. 4. All data corresponding to damage cases were classified according to the operational conditions by means of an inverse DS2L-SOM. Each group was projected into its corresponding baseline model and the defined damage indices were calculated.

8. RESULTS

Next some representative results from all the experiments performed are presented. Since in all the studied cases Q indices were representatives, those are presented alone without other results (i.e. the T^2 index or the principal components alone).

First, an example of the clustering technique is presented in Fig. 5. In this experiment 6 load configurations were used, each one including 4 different load magnitudes. By means of a classic SOM it is possible to obtain the U-

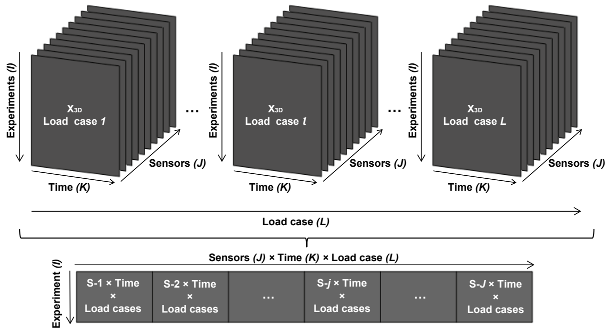


Fig. 4. representation of the OBS methodology. Multiple baselines corresponding to different load conditions to be unfolded.

Matrix (see Fig. 5-a)). As it can be seen, the red ellipses point for some cluster regions. However, it is difficult to discern where the cluster begins and where ends. On the other hand, by means of the DS2L-SOM algorithm it is possible to clearly isolate the clusters (see Fig. 5-b)).

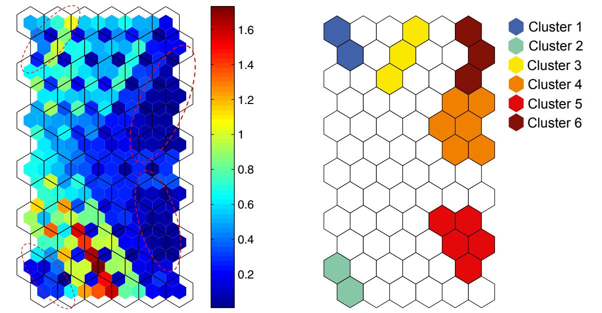
Taking for example only one cluster (corresponding to one specific load case), for example the cluster number 4, the procedure consisted in projecting the damaged data (classified as belonging to cluster 4) into the baseline model for the cluster number 4 and after that, calculating the associated damage indices and their corresponding damage thresholds. The result for the Q index can be seen in Fig. 6. As can be seen, data (indices) corresponding to baseline and undamaged case (verification data) lie inside the damage thresholds whilst indices associated to all damage cases (six in total for this experiment) lie outside the damage thresholds.

Similar results where obtained in all experiments. In Fig. 7 the results for the Q index for one load case in the UAV's wing section experiment are presented. Again, it is possible to see how all indices associated with the damaged cases lie outside the damage thresholds.

As final example, the results for the Q index for one of the wind turbine blades tested are presented in Fig. 8. In this case the results for one load case under under static loads are presented. It is worth to mention that for this experiment the severity of the damage was increased a little bit among experiments in order to estimate how sensitive was the technique as function of a slight change in the damage severity. However, it is still possible to recognize small changes in the Q index for all the damaged cases. Again, baseline data and verification data (undamaged) lie inside the damage thresholds with some few exceptions (outliers).

9. CONCLUSIONS

The main paradigm in the proposed technique is still if it is more important the number of sensors or the amount of measurements. the opinion of the authors, is that a compromise solution is needed. An appropriate sensor network should be designed for each structure in particular depending of several factors like the size, complexity, expected strain/stress levels, etc. However, being a data-driven methodology, it is required an appropriate amount of information. In the experiments performed the amount



(a) U-matrix. (b) Cluster groups.

Fig. 5. U-matrix and cluster groups for aluminum beam experiment under six different static load configurations, each one including 4 load magnitudes.

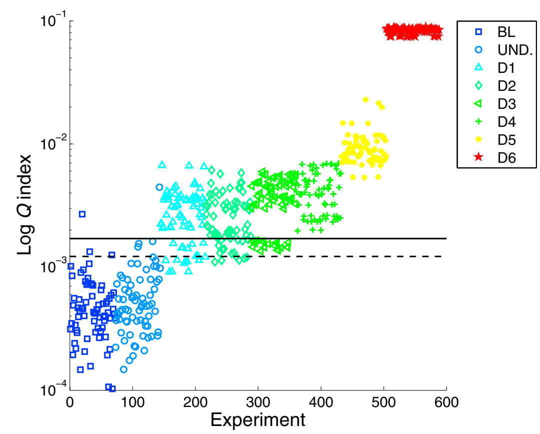


Fig. 6. Q index for cluster 4. Aluminum beam experiment under static loads. 95% confidence threshold (dashed line) and 99% confidence threshold (solid line).

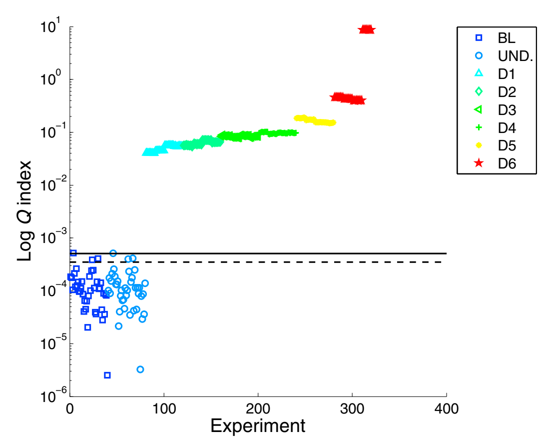


Fig. 7. Q index for load case 1. UAV's wing section under static loads. 95% confidence threshold (dashed line) and 99% confidence threshold (solid line).

of information tended to be preponderant over the amount of sensors.

Since all experiments were performed in laboratory conditions an homogeneous temperature was observed. However, in a real application thermal compensation tech-

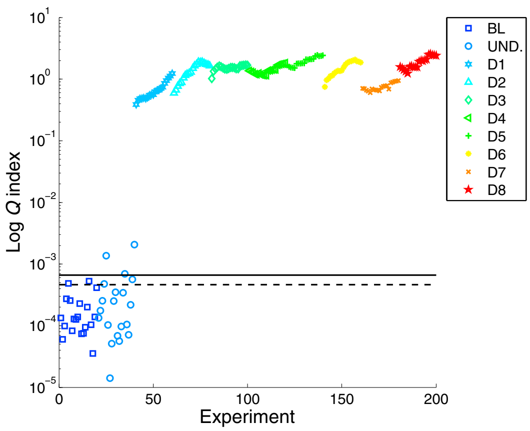


Fig. 8. Q index for load case 1. Wind turbine blade under static loads. 95% confidence threshold (dashed line) and 99% confidence threshold (solid line).

niques should be improved in order to deal with temperature changes and its effect in the strain field. Thermal compensation is not a big issue when FBGs are used but the concept should be probed in a real application.

When the strain patterns for a damage condition for a certain load scenario are very different to those associated to the baseline for the same load conditions, the DS2L-SOM clustering technique is not able to classify the data according to similarities with the baseline. In such cases, the clustering technique becomes in a damage detection method itself. Other automatic clustering techniques should be explored and implemented in order to improve the sensitivity of the technique.

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