# Damage Detection in Metallic Beams from Dynamic Strain Measurements under Different Load Cases by Using Automatic Clustering and Pattern Recognition Techniques

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## Abstract

In general, the change in the local strain field or global stiffness caused by damage in a structure is very small and the strain field tends to homogenize very quickly in the field close to the defect. Moreover, other environmental effects can fade the slight changes in the strain field. Only by comparing the response of the structure at several points some information about damage may be unveiled. By means of pattern recognition techniques based on the strain field, this task can be achieved. This is the basis of the strain measurements data-driven models.

The main limitation of the strain field pattern recognition techniques lies in the susceptibility of the strain field to change depending on the load conditions. In the case of dynamic loads, this may reflect even a greater limitation. Robust automated techniques are required to manage these limitations. In first instance, automatic clustering techniques are needed so that data can be classified according to the load conditions and secondly, a dimensional reduction technique is needed in order to obtain patterns that often underlie from data.

Within the context of this paper, a combination of Local Density-based Simultaneous Two-Level (DS2L-SOM) Clustering based on Self-Organizing Maps (SOM) and Principal Components Analysis (PCA) is proposed in order to firstly, classify load conditions and secondly, perform strain field pattern recognition. The clustering technique is the basis for an Optimal Baseline Selection.

An experimental validation of the technique is discussed in this paper, comparing damages of different sizes and positions in an aluminum beam, under a set of combined loads under dynamic conditions. Strains were measured at several points by using Fiber Bragg Gratings.

**Keywords :** *Fiber Optics Sensors, Self-Organizing Maps, Neural Networks, Principal Component Analysis, Strain Field Pattern Recognition.*

## Introduction

When a solid body is subjected to external stimulus (like forces, pressure or changes in temperature for example), it deforms. Deformation implies a change in the dimensions of the solid body and therefore, a strain. Commonly, the engineering structures are made of elastic materials and therefore, the deformation lie in the elastic range. Associated with this elastic deformation are changes in the stress/strain distribution across the structure and changes in the storage of elastic strain energy. As the load increases, some permanent deformations and damage (cracking) may occur, which is accompanied by a release of the stored energy and a change in the strain field. As its name suggests, the strain field refers to the distribution of strains through a region (field) of a body. When a variation occurs suddenly, in in very short distance, the intensity of stress/strain increases abruptly. This condition is known in the literature as “stress concentration”. It is possible to estimate the stress/strain concentration in the region close to a disturbance, that is, the stress/strain concentration in “the near field”. However, when one moves away from the near field to the far field, the scenario changes.

The strain-based damage detection rely on the redistribution of loads and strains in a structure as consequence of the damage apparition. The far field strain in a structure is usually only changed by large scale damage. Damage detection requires measurements very near to the area of damage. For this reason, methods based on fiber optic strain sensors have been usually used only for monitoring structural “hotspots” where high stresses are expected and therefore, a higher probability of damage occurrence. However, also the small changes produced in the far field can be detected by means of the use of appropriated techniques and damage assessment can be performed through the information extracted from such slight changes in the strain field.

The change in the local strain field can be studied experimentally in a very easy way. By mean of studying all the possible correlations between all the possible couples of sensors may be possible to reconstruct the strain field in structure for a given state (i.e healthy structure or a damage case). Using this information in conjunction with pattern recognition techniques would be possible to infer some change in the global behavior of the structure associated to any defect apparition.

An additional issue is the strain field is dependent of the load conditions (i.e. the inertia of the section). For this reason, it is necessary to classify the operational conditions in order to isolate different “strain fields” of a structure due to different operational conditions. This task can be achieved by mean of manual methods (i.e. if the operational conditions are known) or by mean of automatic classification methods.

## 1 STRAIN FIELD PATTERN RECOGNITION TECHNIQUES AND AUTOMATIC CLUSTERING

A time response or 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. 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 severity of damage.

There are two classical categories of approaches to damage detection by means of pattern recognition: “statistical methods” and “syntactic methods”. Perhaps, the statistical methods are the most used in SHM. The main reason is that over the last decade recent advancements like the application of Artificial Neural Networks (ANN) or the so called Machine Learning Techniques (MLT) have proven their effectiveness in real Structural Health Monitoring (SHM) applications. In fact, the pattern recognition techniques are themselves, a subset of MLT.

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. [1]

In MLT, computational rules are inferred or “learned” on the basis of experimental data (evidences), on the contrary to what happened in classical computation where, rules was imposed only by the programmer without an automatically feedback that could modify the rules. The MLT can be divided into two major groups. The supervised MLT and the unsupervised MLT. [1]

In supervised MLT, examples of excitations and responses are required for specific postulated relationship, in this way, real associations between excitations and their associated responses might be learned and the possible errors can be corrected. However, supervised MLT present some issues when are implemented in SHM systems. The main problem is the difficulty in acquiring enough information to ensure that all the possible damage cases are covered. On the other hand, the unsupervised learning is concerned with the characterization of a data set on the basis of measurements and therefore, determining the underlying structure. Common examples of unsupervised techniques include the Learning Vector Quantization (LQV) and the Self Organizing Maps (SOM).

SOM is a class of unsupervised learning 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. [2]

SOM compresses the information while preserving the most important topological and/or metric relationships of the primary data elements on the display, it may also be thought to produce some kind of abstractions. 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. [3]

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. A clustering process can be formally defined as the task of partitioning a set of objects into a collection of mutual disjoint subsets.

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. A traditional clustering method like K-means or hierarchical methods. This approach is called a two-level clustering method. Perhaps, one of the most important task in clustering is to determine the number of clusters K. This task is also known as the model selection problem. If no previous knowledge about the data structure, there is no a simple way to estimate the number of clusters [4].

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 algorithm assumes that a cluster is a dense region of objects surrounded by a region of low density. 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. They called this particular methodology as “Local Density-based Simultaneous Two-Level Clustering” or DS2L-SOM. The main idea of the two-level clustering technique based on SOM, consists in combine the dimensionality reduction and learning capabilities of SOM with another clustering method applied to the reduced space, in order to produce a final set of clusters. The mapping between the input space and the network space is then constructed in such way that two close observations in the input space would activate two close cells of the SOM. To achieve a topological mapping, the neighbors of a winner neuron can adjust their weight vectors towards the input data vector as well, but at a lesser degree, depending on how far away they are from the winner neuron.

In the algorithm each neighborhood connection is associated with a real value $v$ which indicates the relevance of the connected neurons. This value is called “neighborhood value” and is adapted during the learning process. For each data, both best close reference vectors are linked by a topological connection. The value of this connection will be increased, whereas the value of all other connections from the BMU will be reduced. At the end of the training, the set of interconnected reference vectors will constitute an artificial image of well separated clusters.

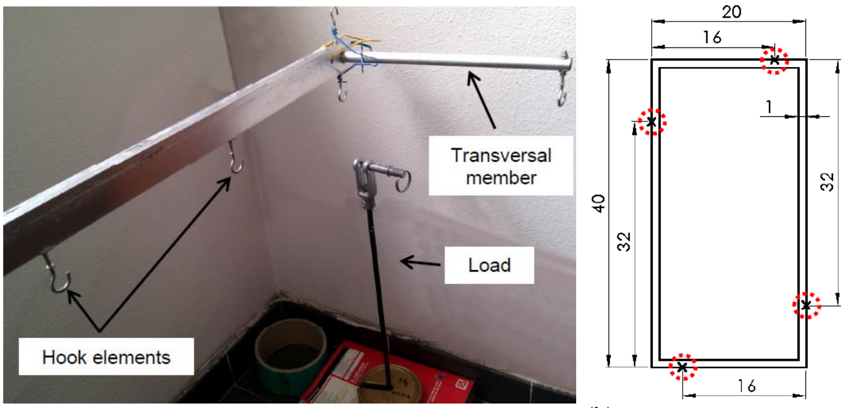
In order to perform online monitoring of multivariate data, diagnostic and fault detection, several methods have been reported in the literature. These methods are known as multivariate statistical projection methods. To avoid the course of dimensionality (understood like the need of low dimensionality 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 [5]

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 Squared Prediction Error) and $T^2$ index. 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], [6], [7], [8]

## 2 EXPERIMENTAL SETUP

To conduct this experiment, a square cross section aluminum beam was used. The square cross section had dimensions of 20 mm by 40 mm and 1 mm thickness. The beam was attached to a testing bench in cantilever mode. C-clamps were used for fixing the beam. The cantilever length was 120 cm. The beam can be appreciated in Figure 1a. To prevent deformation of the beam in the fixed zone, a wooden block with same dimensions as the inside of the aluminum beam was introduced along the clamping length. Another piece of wood was used to distribute the pressure applied with the C-clamps. A guideline system was used in order to guarantee the clamping conditions were always the same. Different hook elements were added to the beam at different positions to introduce the loads. The first set of hook elements was fixed at 24 mm of the tip. The second hook element was fixed at 250 mm from the first ones and the third one, 250 mm from the second one. A transversal member (at the end of cantilevered end) was also included in order to introduce torque loads. This member had a length of 300 mm. Four optical fibers were bonded to the beam, each one having eight FBGs. 32 sensors were used in total, one of them intended to measure the temperature. The first sensors were located at 50 mm from the clamping end. From this point, all sensors were spaced uniformly each 150 mm. For interrogating the FBGs, a four channels Micron Optics SM130 was used.




(a) (b)

Figure 1: a) Aluminum beam. b) Location of FOS at cross section. Dimensions in mm.

The test consisted in measuring the strains under different load configurations (load cases) using different load magnitudes for each load case. First, experiments were performed for healthy structure (initial condition), and subsequently, after inducing different artificial damages in the beam (damage cases).

The procedure consisted in taking the reference level (zero strain) without any load, then, the structure was loaded. The load was released by means of a trigger device. This device also allows adjusting the displacement at the cantilever tip of the beam. In this way, it was possible to reach the reference level (zero strain) regardless of the load magnitude used. Once the reference level was reached, the load was released instantaneously guaranteeing that load conditions was always the same for all the experimental trials. The acquisition equipment was programmed to save data 200 milliseconds before any sensor reaches more than 5 $\mu\varepsilon$. The strains were measured for five seconds at a sampling rate of 100 Hz. In this scenario, each experiment was performed five times and, for the undamaged case, 20 times (5 experimental trials for baseline and 15 for test it). This procedure was repeated for all the performed experiments. Six load cases were tested and three load magnitudes were used (3.25, 3.75 and 4.25 kg).

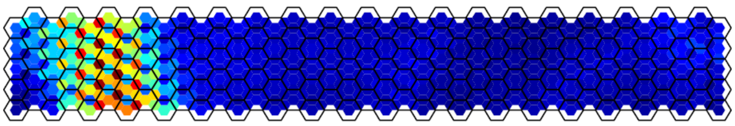
The damages consisted in holes at several positions. In total, three damages were induced in the structure. Damage 2 (D2) with 5.1 mm, damage 4 (D4) with 7 mm and damage 6 (D6) with 8 mm. It is interesting to note that the most severe damage (damage number 6) only reduces the cross area of the beam in the section where is located, by less than 7%; this gives an idea of the severity of damages sought to be detected.

## 3 RESULTS

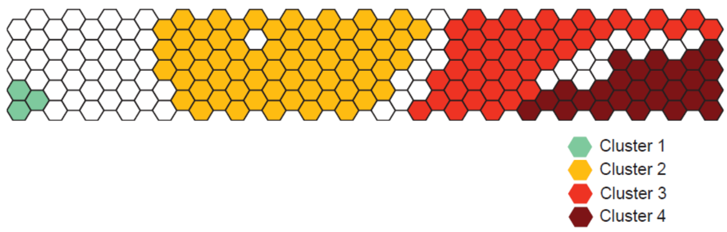
In order to classify the information according to the operation variables (load case), the two-level clustering method based on SOM, proposed by Cabanes and Bennani was used in this work [4]. The methodology can be summarized as follows:

- For each damage case data for all load magnitudes and all load conditions were put together in a matrix where the rows was experimental trials (measurements) and the columns variables.
- The matrices were parametrized by subtracting from each element, the mean of its corresponding row and later, rows were randomly reordered.
- Standard SOM algorithm was implemented on the baseline matrix. The SOM toolbox developed by Vesanto et al. was used for this purpose. [9]
- The Two-level clustering proposed by Cabanes and Bennani was implemented on the SOM for the baseline matrix. The DS2L-SOM algorithm developed by Cabanes was used for this purpose. A new "improved SOM" with separated clusters (corresponding to different load cases) was obtained for the baseline. Each cluster is a new specific baseline for one load case. In this sense, this methodology can be considered as an "Optimal Baseline Selection" or OBS.
- All the matrices for the damage cases were projected into the new improved SOM for the baseline. In this way, the data in those matrices was compared with the data into the baseline. As a result, the data for all damage cases could be classified according to the load cases initially separated for the baseline.
- After having the different baselines corresponding to each load condition and the damaged cases classified according to the same load conditions than the baseline, a PCA study was performed.

The Ds2L-SOM algorithm automatically calculates the optimal number of cells, resulting in a 5 × 39 map. A 90º rotated view of the U-Matrix for this map can be appreciated in Figure 2a. The results for the clusters found are depicted in Figure 2b. In this case, four clusters were recognized. After the data for the baseline were clustered, the data corresponding to the different damage cases were classified according to the four clusters previously mentioned. Only the results for the cluster number 4 are presented in this article. It is important to notice that the best results of this experiments were obtained for the cluster 1 since all the measurements included in "cluster 1", really belonged to load case included in this cluster. For instance, the cluster 4 has a combination of similar samples which really do not belong to the load cases included in the cluster 4. This can be explained because the damage occurrence modifies the strain patterns in the structure and it is possible these patterns become more similar to other patterns for the healthy structure (baseline) as product of the disturbances induced by damage.



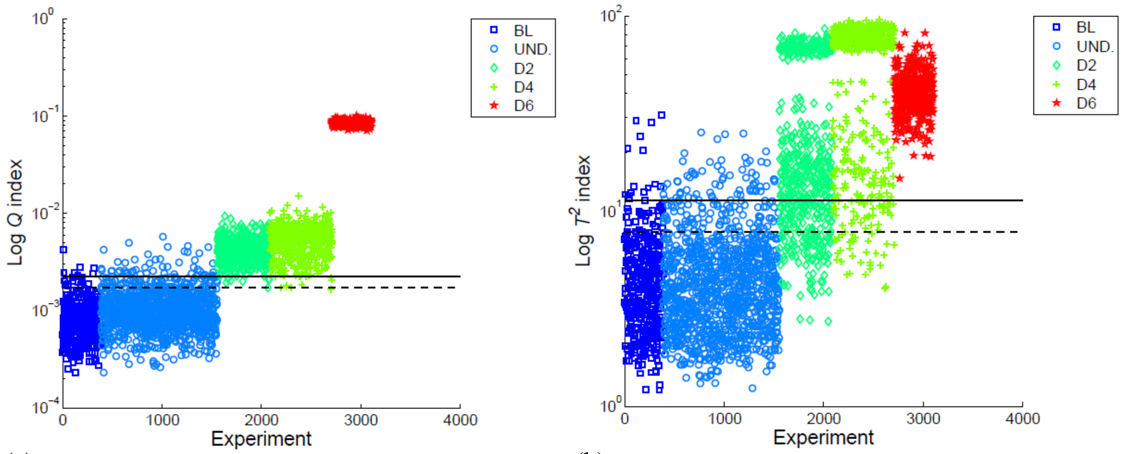
(a) U-matrix. 90º rotated view.




(b) Cluster groups. 90º rotated view.

Figure 2: U-matrix and cluster groups. a) U-matrix. b) Cluster groups.

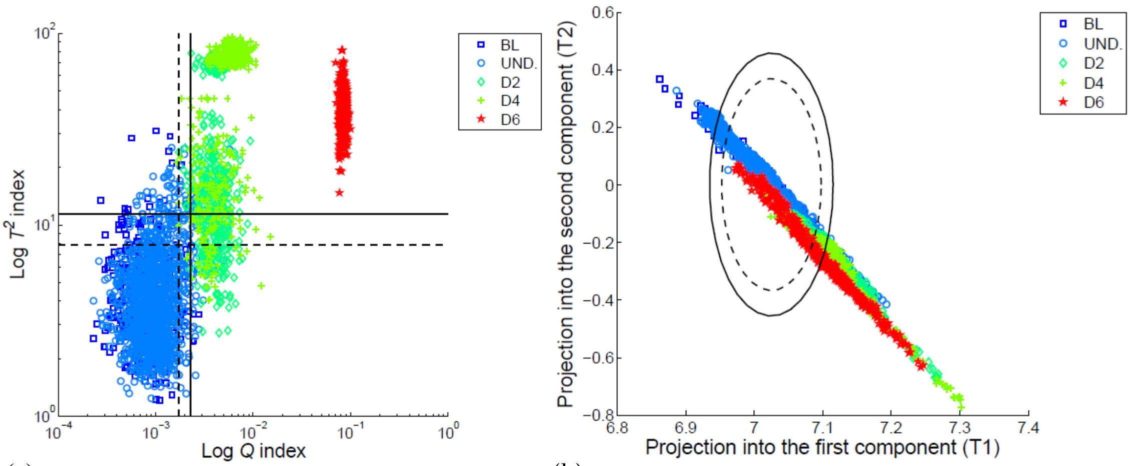
The $Q$ index is depicted in Figure 3a. As it can be seen, there is a good separation of all the damaged cases from the baseline in both models. Some undamaged indices lie outside the confidence intervals or in within 95% and 99% of confidence. However, it is possible to classify these indices as abnormal indices. The $T^2$ index for both models can be seen in Figure 3b. Some deviations can be appreciated with respect to the baseline.




(a) (b)

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

Finally, $Q$ index vs. $T^2$ is presented in Figure 4a and the the two first scores are presented in Figure 4b.




(a) (b)

Figure 4: a) $Q$ index vs. $T^2$ index with damage thresholds for 95% and 99% of confidence (dashed line and solid line respectively). b) Projection into the two first principal components with damage thresholds for 95% and 99% of confidence (dashed line and solid line respectively).

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## CONCLUSIONS

In order to achieve the first level of SHM (damage detection) by using strain measurements in a structure under different load cases and 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 model was built using the responses for the healthy structure. In subsequent steps, several experiments were performed by inducing different artificial damages to the structures. 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. FBGs showed to be very sensitive to small strain changes in the structure, which makes it suitable for the proposed technique.

By including several load conditions at the same time in one model, caused a decrease in the damage detection sensitivity since a “more general” model was built instead of “specific models” for each load condition. This propitiated the necessity of developing the proposed classification and clustering techniques and the “Optimal Baseline Selection” methodology. The automatic classification technique based on SOM and DS2L-SOM algorithms probed to be very accurate and promising when classifying the data according to operational variables is not possible.

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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