Agència de Gestió d'Ajuts Universitaris i de Recerca

Memòria justificativa de recerca de les convocatòries BE, PIV, BCC, NANOS i BP

La memòria justificativa consta de les dues parts que venen a continuació:
1.- Dades bàsiques i resums
2.- Memòria del treball (informe científic)

Tots els camps són obligatoris

1.- Dades bàsiques i resums

Nom de la convocatòria

BE

Llegenda per a les convocatòries:

BCC	Convocatòria de beques per a joves membres de comunitats catalanes a l'exterior (BCC)
BE	Beques per a estades per a la recerca fora de Catalunya (BE)
BP	Convocatòria d'ajuts postdoctorals dins del programa Beatriu de Pinós (BP)
NANOS	Beques de recerca per a la formació en el camp de les nanotecnologies (NANOS)
PIV	Beques de recerca per a professors i investigadors visitants a Catalunya (PIV)

Títol del projecte: ha de sintetitzar la temàtica científica del vostre document.
DETECCIÓ I LOCALITZACIÓ D'IMPACTES A ESTRUCTURES AEROESPACIALS

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2007BE1 00278

Paraules clau: cal que esmenteu cinc conceptes que defineixin el contingut de la vostra memòria.
MONITORITZACIÓ I DETECCIÓ D'IMPACTES - ESTRUCTURES AEROESPACIALS

Data de presentació de la justificació

Resum del projecte: cal adjuntar dos resums del document, l'un en anglès i l'altre en la llengua del document, on s'esmenti la durada de l'acció

Resum en la llengua del projecte (màxim 300 paraules)

Actualment la indústria aeroespacial i aeronàutica té com prioritat millorar la fiabilitat de las seves estructures a través del desenvolupament de nous sistemes per a la monitorització i detecció d'impactes. Hi ha diverses tècniques potencialment útils, i la seva aplicabilitat en una situació particular depèn críticament de la mida del defecte que permet l'estructura. Qualsevol defecte canviarà la resposta vibratòria de l'element estructural, així com el transitori de l'ona que es propaga per l'estructura elàstica. Correlacionar aquests canvis, que poden ser detectats experimentalment amb l'ocurrència del defecte, la seva localització i quantificació, és un problema molt complex.

Aquest treball explora l'ús de l'Anàlisis de Components Principals (Principal Component Analysis - PCA-) basat en la formulació dels estadístics T2 i Q per tal de detectar i distingir els defectes a l'estructura, tot correlacionant els seus canvis a la resposta vibratòria. L'estructura utilitzada per l'estudi és l'ala d'una turbina d'un avió comercial. Aquesta ala s'excita en un extrem utilitzant un vibrador, i a la qual s'han adherit set sensors PZT a la superfície. S'aplica un senyal conegut i s'analitzen les respostes. Es construeix un model PCA utilitzant dades de l'estructura sense defecte. Per tal de provar el model, s'adhereix un tros d'alumini en quatre posicions diferents. Les dades dels assajos de l'estructura amb defecte es projecten sobre el model. Les components principals i les distàncies de Q-residual i T2-Hotelling s'utilitzaran per a l'anàlisi de les incidències. Q-residual indica com de bé s'adiu cadascuna de les mostres al model PCA, ja que és una mesura de la diferència, o residu, entre la mostra i la seva projecció sobre les components principals retingudes en el model. La distància T2-Hotelling és una mesura de la variació de cada mostra dins del model PCA, o el que vindria a ser el mateix, la distància al centre del model PCA.

Resum en anglès(màxim 300 paraules)

Nowadays, the aerospace and aircraft industry has a main priority in improving the reliability of their structures through the development of novel systems for monitoring and damage detections. There are several potentially useful techniques, and their applicability to a particular situation depends on the size of damage critical admissible in the structure. Any damage will change the vibrational response of the structural element, as well as the transient by a wave that is spreading through the elastic structure. Correlating these changes, which can be detected experimentally with the occurrence of damage, and its location and quantification, is a very complex problem

This work explores the use of Principal Component Analysis (PCA) based on T2 and Q statistic formulation to detect and distinguish damages in structures, correlating its vibrational response changes. The structure used for this study is a blade of a turbine of an aircraft. This blade is excited using a shaker in one side and seven PZT's sensors are attached on the surface. A known signal is applied and the responses are analyzed. A PCA model is built using data from the undamaged structure. A mass is attached on the surface in four different positions. Data from the damaged structure tests are projected on the model. The principal components, Q-Residual and T2-Hotelling's distances are analyzed. Q-residual indicates how well each sample conforms to the PCA model. It is a measure of the difference, or residual between a sample and its projection into the principal components retained in the model. T2-Hotelling's distance, is a measure of the variation in each sample within the PCA model

2.- Memòria del treball (informe científic sense limitació de paraules). Pot incloure altres fitxers de qualsevol mena, no més grans de 10 MB cadascun d'ells.

S'annexa l'article "*PCA based measures: Q-statistic and T2-statistic for assessing damages in structures"* que es presentarà el proper mes de juliol al "*4th European Workshop on Structural Health Monitoring"*

Cover page

Title: ***PCA based measures: Q-statistic and T^2-statistic for assessing damages in structures***

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ABSTRACT

This paper explores the use of Principal Component Analysis (PCA) based on T^2 and Q statistic formulation to detect and distinguish damages in structures. The structure used for this study is a blade of a turbine of an aircraft. This blade is excited using a shaker in one side and seven PZT's sensors are attached on the surface. A known signal is applied and the responses are analyzed. A PCA model is built using data from the undamaged structure. A mass is attached on the surface in four different positions. Data from the damaged structure tests are projected on the model. The principal components, Q-Residual and T^2-Hotelling's distances are analyzed. Q-residual indicates how well each sample conforms to the PCA model. It is a measure of the difference, or residual between a sample and its projection into the principal components retained in the model. T^2-Hotelling's distance, is a measure of the variation in each sample within the PCA model.

INTRODUCTION

Nowadays, the aerospace and aircraft industry has a main priority in improving the reliability of their structures through the development of novel systems for monitoring and damage detections. In the last years, significant efforts are being concentrated in the design of smart structures with the integration of materials, sensors, actuators and algorithms able to monitor the structural state health in real time and detect any defect at an early stage. The basic paradigm is to approach the damage identification via the detection of changes in the propagation of elastic waves through the structure by analyzing time responses in comparison with pattern responses for undamaged structures.

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There are several potentially useful techniques, and their applicability to a particular situation depends on the size of damage critical admissible in the structure. Any damage will change the vibrational response of the structural element, as well as the transient by a wave that is spreading through the elastic structure. Correlating these changes, which can be detected experimentally with the occurrence of damage, and its location and quantification, is a very complex problem.

In SHM, Principal Component Analysis (PCA) [1] has been extensively applied to measured vibration signals for dimensionality studies [2-4], to remove the influence of the environmental effects from the vibration characteristics [5-6], for extracting structural damage features [7-8], to discriminate features from damaged and undamaged structures [9-11], and for clustering a classification of AE transient [12], among others. In the cited papers, from the PCA analysis, just the principal components are studied; however, there exist other measures which give also information about what is going on into the model. The goal of this paper is the analysis of these distances and the influence of the damage over them.

PRINCIPAL COMPONENTS ANALYSIS

PCA is a standard tool for data compression and information extraction which finds combinations of variables or factors that describe major trends in a data set [1]. PCA is concerned with explaining the variance–covariance structure through a few linear combinations of the original variables. Its general objectives are data reduction and interpretation. In this work, the multivariate data are organized in a 3D-matrix $\underline{X}$ (I experiments × K samples per experiment × J sensors). In this way, each frontal slice is a two-dimensional (2D)-matrix X which represents all measurements in one sensor as can be seen from figure 1a. In order to consider the autocorrelation in time by each signal and the correlation between sensors, the 3D-matrix X is unfolded as is shown in figure 1b [2].

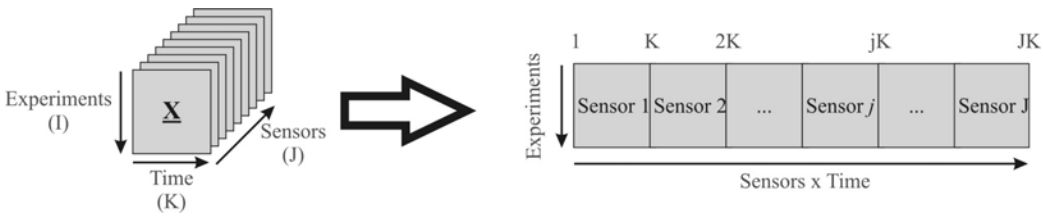

Figure 1. Collected data: (a) 3D-matrix (b) unfolded matrix

The first step in applying PCA is to standardize the data matrix X, since PCA is scale variant. Several studies of scaling are presented in literature: continuous scaling (CS), group scaling (GS) and autoscaling (AS) [13]. According to these studies, GS is selected for this work because it considers changes between variables and does not process independently the variables. The mean trajectories are removed and all variables are made to have equal variance. As a consequence, the experiment trajectories of the sensors and their standard deviations, often non-linear in nature, are removed from the data. Once the variables have been standardized, the covariance matrix S is calculated:

$$S = \frac{1}{l-1} X^T X. \tag{1}$$

The matrix $\widehat{P}$ which its columns are the eigenvectors of S and, the diagonal matrix Λ with eigenvalues of S on the main diagonal, are found:

$$S\widehat{P} = \widehat{P}\Lambda \tag{2}$$

Each eigenvalue is associated to an eigenvector. The eigenvector with the highest eigenvalue represents the most important pattern in the data, i.e. contains the largest quantity of information, therefore this vector is called the ***principal component*** of the data set. Ordering the eigenvectors by eigenvalue, highest to lowest, gives the components in order of significance. In order to reduce the dimensionality, the less important components can be eliminated (information is lost, but if the eigenvalues are small, this information is not much), then only the n first eigenvectors are chosen (loading vectors p_i which are columns of the loading matrix P) and the final data set will be n-dimensional. The projected matrix T (or score matrix) in the new space is defined by

$$T = XP \tag{3}$$

and the projection of T back onto the K-dimensional observation space is

$$\widehat{X} = TP^T \tag{4}$$

The difference between X and $\widehat{X}$ is the residual matrix E:

$$X = \widehat{X} + E \tag{5}$$

$$X = TP^T + E \tag{6}$$

DAMAGE DETECTION INDICES

The score matrix T (its columns consist of score vectors, t_i, associated with the principal component PC_i) and the residual matrix E can be used in order to detect abnormal behaviour in a process or responses. With this aim, the *Q-statistic* (or *SPE-statistic*) and *Hotelling's T^2-statistics* (*D-statistic*) are used to represent the variability of the projection in the residual subspace and the new space respectively. These methods are based on the assumption (generally stemming from the central limit theorem) that the underlying process follows approximately a multivariate normal distribution where the first moment vector is zero (see figure 2).

Hotelling's T^2-statistics: In statistics, *Hotelling's T^2-statistics* is a generalization of *Student's t-statistic* that is used in multivariate hypothesis testing. It denotes the inner change of principal component model. *T^2-statistics* of *i*-th sample is defined by:

$$T_i^2 = t_i \Lambda^{-1} t_i^T \tag{7}$$

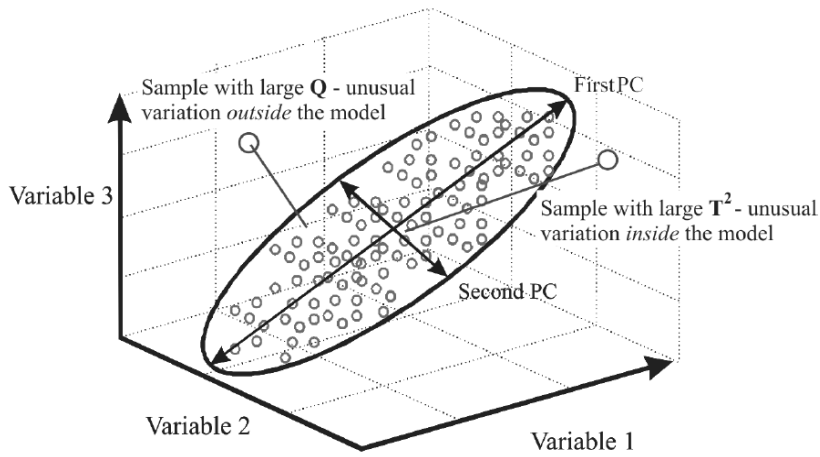

Figure 2. PCA model of three dimensional data set showing Q and T^2 outliers, from [14].

It only detects variation in the plane of the first N principal components which are greater than what can be explained by the common-cause variations. In other words, T^2*-statistics* is a measure of the variation in each sample within the PCA model.

Q-statistic: *Q-statistic* denotes the change of the events which are not explained by the model of principal components. In other words, it is a measure of the difference, or residual between a sample and its projection into the model. *Q-statistics* of *i*-th sample is defined by:

$$Q_i = e_i e_i^T = x_i (I - PP^T) x_i^T \tag{8}$$

where e_i is principal component model errors of *i*-th sample (*i*-th row of *E*) and x_i is the *i*-th sample of the whole set of events (*i*-th column of *X*)

Normally, *Q-statistic* is much more sensitive than T^2*-statistic*. This is because *Q* is very small and therefore any minor change in the system characteristics will be observable. T^2 has great variance and therefore requires a great change in the system characteristic to be detectable.

Information about the events can also be obtained from the plot of scores for the relevant principal components. When there is a change in the system, the scores of the new events will be very different from the previous scores, and the change will be detected. However, this information is also included in the *Hotelling's* T^2*-statistics* since it is calculated using the scores. Moreover, the *Q-statistic* gives us additional information which is not included in the scores plot, because it is related to the variation which is not considered by the model, in this way, the plots of Q and T^2 are a hypothesis test which clearly distinguish any signals with abnormal behaviour whereas the inspection of the scores plot is a qualitative tool [15].

EXPERIMENTAL SET-UP

The structure used in this work is a blade of a commercial aircraft turbine. Unfortunately, due to the origin of the blade, little is known about the specific material and design parameters constituting the structure. However, it could be determined that the blade is manufactured by a homogenous material with a similar density that titanium. (3.57 g/ml). The blade has one stringer in each face. Seven PZT sensors, to detect time varying strain response data, are distributed over the surface; three on one face and, four on the other face as can be seen from figure 3. The blade is suspended by two elastic ropes (free-free configuration). A shaker excites the structure with a vibration signal in one of its borders as can be seen from figure 4. The signal excitation and the dynamic response of the undamaged structure collected in sensor 2 are shown in figure 5. Damages have been simulated adding a mass in four different locations as is shown in figure 6. 300 experiments have been performed and recorded: 100 with the undamaged structure, and 50 per damage. The PCA model has been created using half dataset collected using the undamaged structure. Signals from the other half dataset of the undamaged structure and the whole dataset of the damaged structure were used for testing the approach.

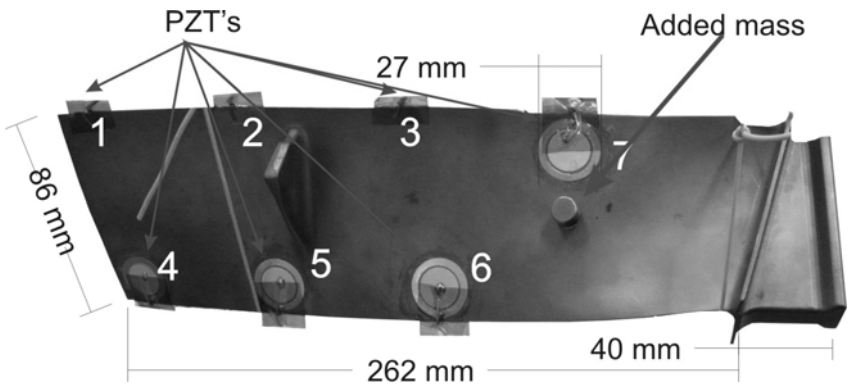

Figure 3: Blade

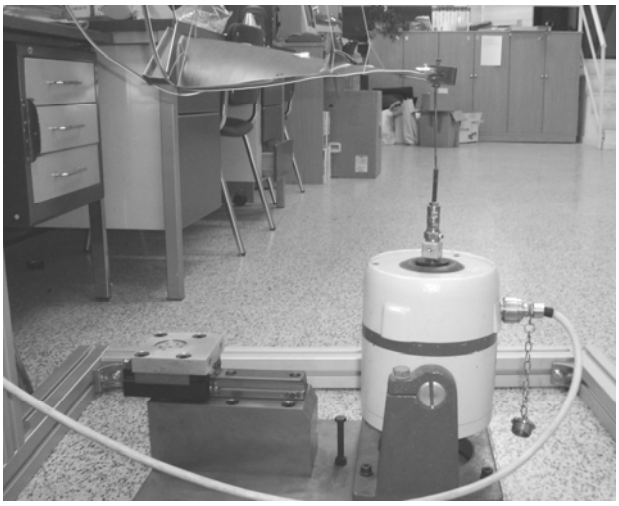

Figure 4: Experimental setup

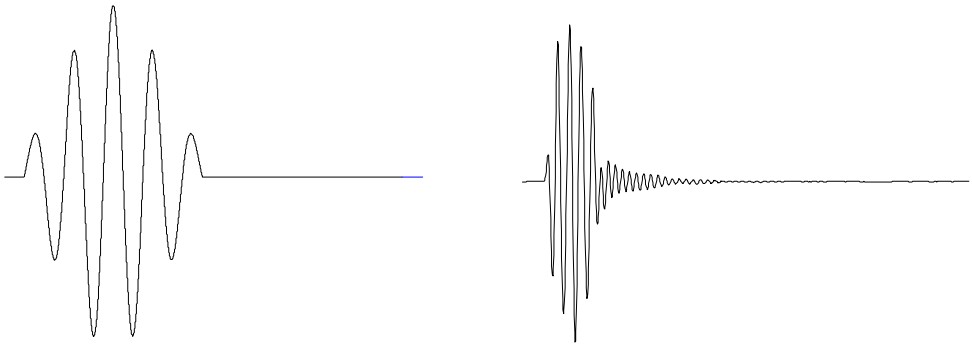

Figure 5. Signal excitation and dynamical response

Figure 6. Added mass locations

ANALYSIS RESULTS AND CONCLUSIONS

Figure 7 shows the two principal components resulting of the projection of the testing dataset (50 undamaged, 50 damages in position 1, 50 in position 2, 50 in position 3 and 50 in position 4) into the PCA model created by undamaged tests. This plot is much clearer in color, but a circular trend of the damages can be appreciated, however, it is not possible to classify or cluster them. Otherwise, from figure 8, which shows a plot of Q-residual and T^2 Hostelling distances of each test resulting from its projection into the PCA model, a clear classification can be performed. It can be observed also the Q-residual much is more sensitive than T^2-Hotelling; undamaged and, damages 1 and 4, would be distinguished using only Q-residual but, damages 2 and 3 (which are very near and over the stringer) do not. Nevertheless, using T^2-Hotelling, these two damages can be discriminated.

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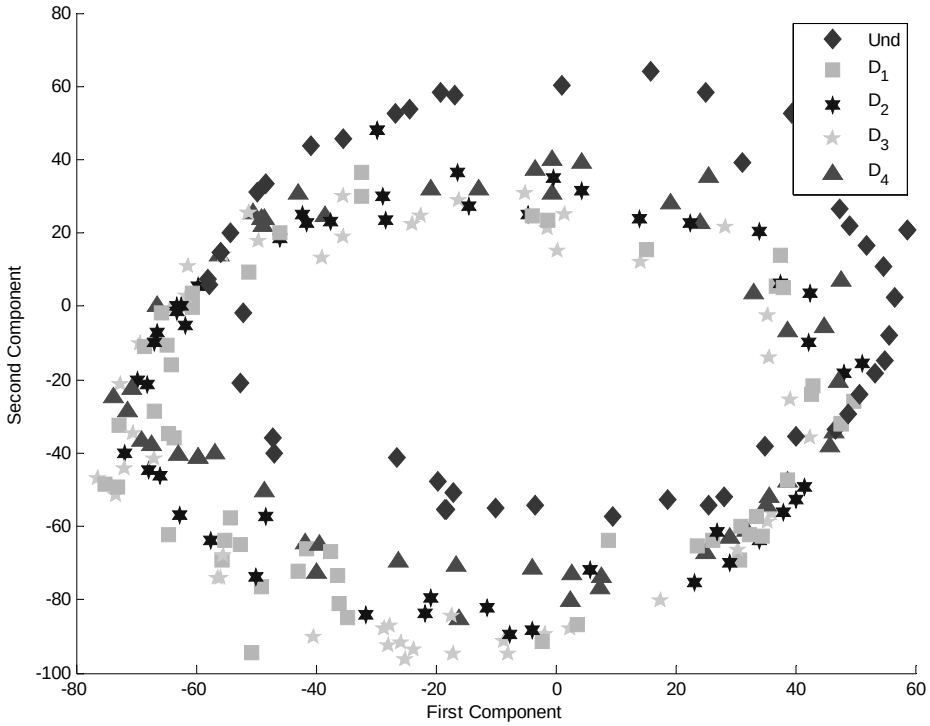

Figure 7. Two principal components

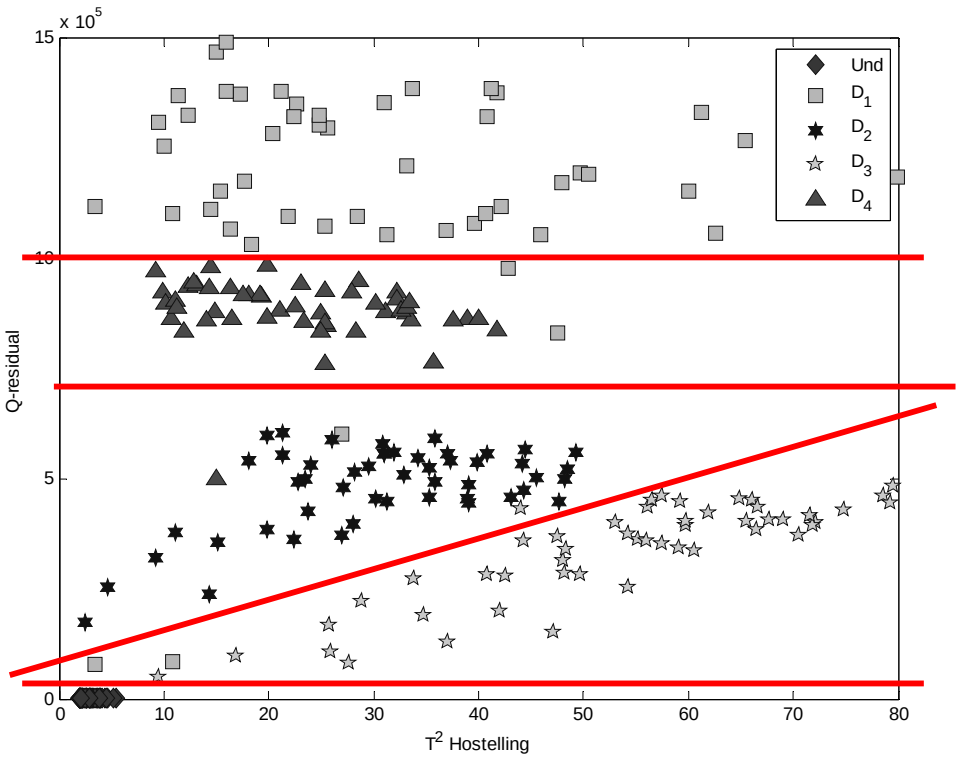

Figure 8. Q-residual and T^2 Hotelling distances

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