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Study of cross-correlation signals in a data-driven approach for damage classification in aircraft wings

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Abstract. This paper discusses, experimental results of classifying several mass adding in a wing aircraft structure, using cross-correlated piezoelectric signals, represented by principal components. Piezoelectric signals are applied and recorded at specific points of the structure under analysis. Then, statistical features are obtained by means of principal component analysis to the correlation between excitation and response signals. Unsupervised learning is implemented to the reduced feature space, in order to identify clusters of damaged cases. The main result of this paper is the advantage resulting from using cross-correlated signals, evaluated through the performance of clustering indexes. Experimental data are collected from two test structures: i.) A turbine blade of a commercial aircraft and ii.) The skin panel of the torsion box of a wing. Damages are induced adding masses at different locations of the wing section surface. The results obtained show the effectiveness of the methodology to distinguish between different damage cases.

1. Introduction

An important preoccupation in the aerospace industry is the continuous monitoring of aircraft components to avoid catastrophic failures. In recent years, methods for damage identification in aerospace structures have been focused on analyzing measurements from Fiber Bragg Grating sensors and piezoelectric devices [1], [2], where effectiveness of damage monitoring systems for aircraft structures, using a piezo-diagnostics approach, has been demonstrated. For example in [3], experimental crack extending on a wing panel using vibration deflection shapes can be detected by computing changes in the response from piezo-ceramic actuator patches.

Thus, this paper deals with a previously proposed piezo-diagnostic methodology, for damage detection in aircraft structures [4]. The benefits by including a preprocessing stage based on correlated



piezoelectric signals are discussed, based on experimental results. It is shown that it is possible to obtain a better classification of different damages, when cross-correlation analysis is considered.

2. Aircraft wing damage detection based on Piezo-diagnostic approach

Piezo-diagnostic principle takes advantage of the elastic wave propagation phenomenon to examine the structural signature. Where, piezoelectric devices are used both as actuators and as sensors to detect structural changes. Monitoring technologies using piezo-ceramic devices has been presented by Staszewski et al with beneficial for military aircrafts [5]. Also, some piezo-diagnostic applications include: detection of damage in aircraft joints by processing measurements from piezoelectric patches [6], inspection of rivet cracks or corrosion in aircraft wing structures [7] and, the design of a monitoring scanning system for a carbon fiber composite wing box [8]. Further application for aerospace industry can be found at Adams [9] and Stepinski et al. [10].

In piezo-diagnostics, one of the procedure used to distinguish structural damages, is the application of principal component analysis (**Figure 1**). It consists of computing statistical indices from piezoelectric measurements recorded from several piezo devices attached to the structure surface. Typically, one of the piezoelectric devices (PZT) is excited to induce along the structure a guided wave and the others PZTs are used as sensors to capture it at different locations of the structure. Data from undamaged and damage experimental cases are projected onto the principal components space, and statistical indexes are computed to differentiate several conditions of the structure [11].

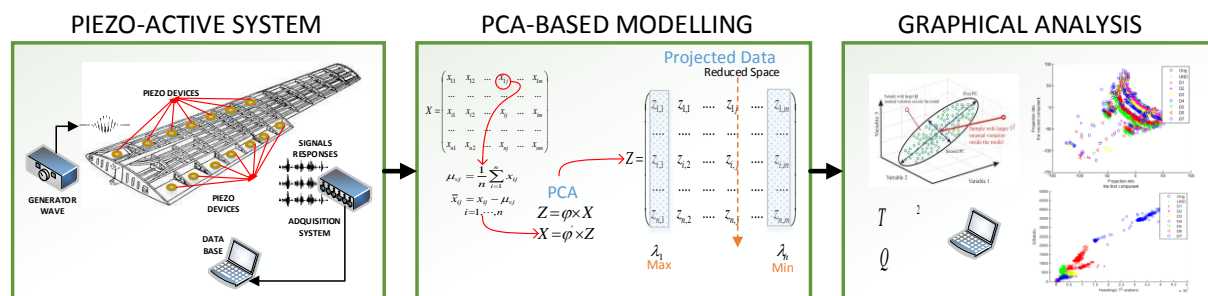


Figure 1. Piezo-diagnostic approach for damage detection by using principal component analysis

The methodology depicted in **Figure 1** has been previously tested and validated using different structures: an aircraft turbine blade, an aircraft wing and an aircraft fuselage [12], [13]. However, the novelty presented in this paper with respect to previous works, is the inclusion of cross correlation analysis as a tool for improving separation boundaries for damage conditions. Thus, cross-correlation between actuation and sensing piezo-signals is estimated previous to the principal component analysis (**Figure 2**). The cross-correlation function between two signals $X(t)$ and $Y(t)$ is defined as:

$$R_{XY}(t, t + \tau) = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{k=1}^N X_k(t) Y_k(t + \tau) \quad (1)$$

Where N is the number of signal samples and τ is the lag time interval used to compute the cross-correlation function.

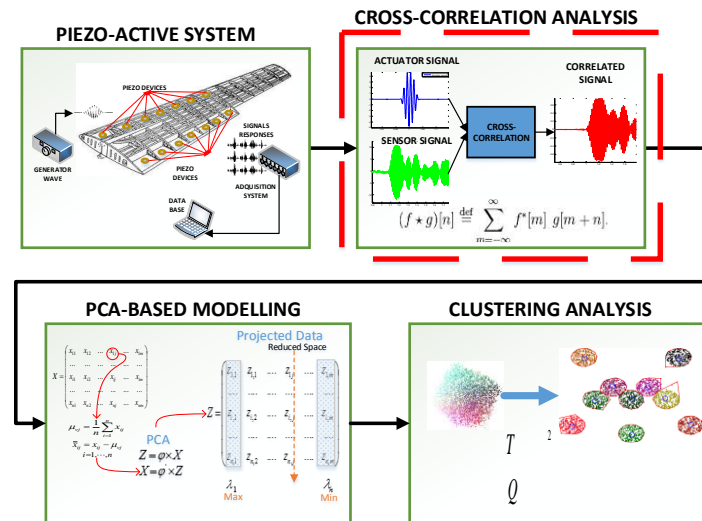


Figure 2. Piezo-diagnostic approach based on cross-correlated features

The K-means algorithm is proposed to organize damage cases into groups and then to evaluate the effectiveness of cross-correlation as preprocessing stage in the damage detection. This algorithm is one of the most commonly used optimization-based unsupervised learning methods. The goal of K-means clustering is to organize the data into k groups, such that the within-group sum-of-squares be minimized [14].

$$\min \left[\sum_{g=1}^k \sum_{i=1}^{n_g} (x_{ig} - \bar{x}_g)' (x_{ig} - \bar{x}_g) \right] \quad (2)$$

Each g_{th} -cluster in the partition is defined by n_g data case members and by its centroid \bar{x}_g , or center. The centroid for each cluster is the point to which the sum of distances from all members in that cluster is minimized. Gap statistic and Davies-Bouldin index are computed to evaluate the data clustering analysis. Therefore, the optimal clustering solution occurs with a largest gap statistic and smallest Davies-Bouldin index values. The K-mean centers represent adequately the data in a cluster if the observations within a group are more similar to each other.

The gap value is defined as [15]:

$$Gap_n(k) = E_n^* \{ \log(W_k) \} - \log(W_k) \quad (3)$$

where n is the sample size, k is the number of clusters, and W_k is the cluster dispersion, defined by:

$$W_k = \sum_{r=1}^k 2n_r D_r \quad (4)$$

where n_r is the number of data points in the cluster r and D_r is the sum of the pairwise distances for all points in cluster r . E_n^* is the expected value determined by a reference distribution and $\log(W_k)$ is computed from the sample data.

The Davies-Bouldin criterion is based on a ratio of within-cluster and between-cluster distances, defined as [16]:

$$DB = \frac{1}{k} \sum_{i=1}^k \max_{j \neq i} \{ D_{i,j} \} \quad (5)$$

where $D_{i,j}$ is the distance ratio between the i th and j th clusters.

In addition to the Gap statistic and Davies-Bouldin index, the quantization error (squared sum of errors) and the dispersion in each cluster (standard deviation) are computed as quality indices to evaluate the clustering process in order to compare the piezo-diagnostic approach when cross-correlation analysis is included.

3. Experimental procedure

Two test structures were used to validate the damage detection approach (**Figure 3**). The specimens are hosted in the “Universidad Politécnica de Madrid” (UPM – Spain). The first structure belongs to an aircraft wing, which is divided by stringers and ribs and the second one to an aircraft turbine blade, which has an irregular form and includes stringers in both faces.

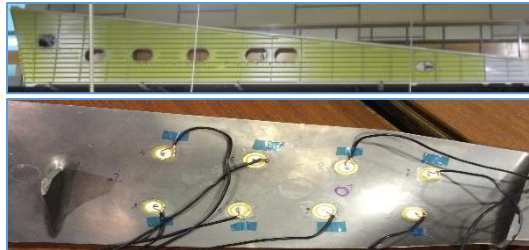


Figure 3. Aircraft section structures used to validate the methodology. Above: skin panel of aircraft wing, Below: turbine blade

The skin panel was instrumented with 10 PZTs, while the turbine blade with 8 PZT's. An 80 KHz burst type signal was configured to produce guided waves along the surface structures. Reversible damages were induced in both structures by adding masses in different positions, four damages for skin panel experiment (D1,..., D4) and five damages for turbine blade case (D1, ..., D5). For both specimens 150 experiment repetitions for each damage were recorded.

4. Results and discussion

Results for each experiment consider a number of clusters for the K-means algorithm equal to the number of damages in the respective structure. Therefore, each damage can be grouped in an individual cluster. In addition, 50 replicates of the K-means algorithm are executed to avoid local minima. Data normalization by means of variance values are used before K-means algorithm to minimize the within-cluster dispersion.

The steps for applying PCA in practice regarding to data collection and organization, baseline model building, scaling preprocessing, statistical indices formulation, model testing, and iterative procedure to estimate principal components, can be found with most detail in previous works [11], [17], and [18]. Thus, data normalization by means of variance values are used before K-means algorithm to minimize the within-cluster dispersion. In addition, NIPALS algorithm is configured to estimate a number of principal components equal to the number of experiments induced for each damage case, i.e. 150.

4.1. Skin Panel Experiment

Variance of the principal components are depicted in **Figure 4**. In which can be observed that the variance evolution is similar for both cases, when cross-correlated functions are used and without it. According to this, 100 components capture most of the principal components variability. In consequence, only 100 components for both uncorrelated and cross-correlated approaches are selected.

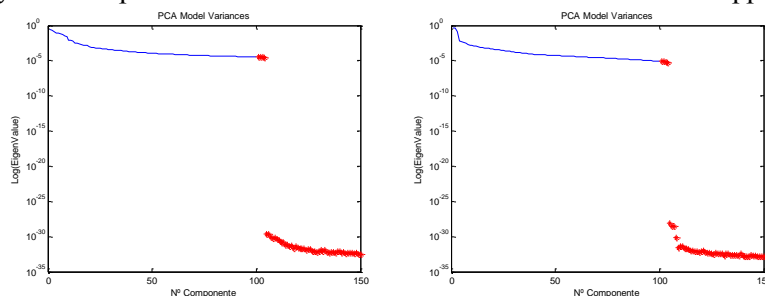


Figure 4. Principal component variances for skin panel experiment. Left: unmodified piezo-diagnostic scheme. Right: cross-correlated piezo-diagnostic approach

The **Figure 5** presents statistical indices and K-means clusters computed for uncorrelated signals. From **Figure 5** can be concluded that atypical data dominate one of the clusters. Besides, damage 2 ('D2') and undamaged cases ('UND') are closer when cross correlation are not estimated. In this case, K-means assigns a cluster for atypical data.

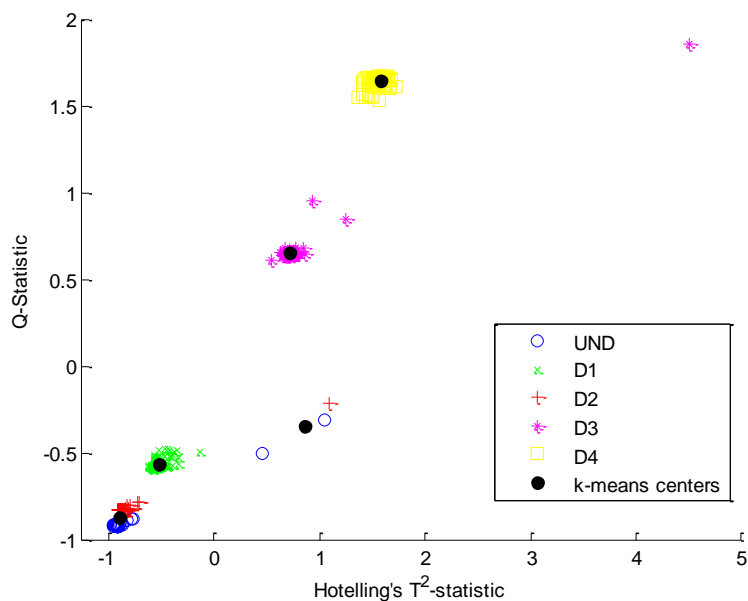


Figure 5. K-means centroids with atypical data with uncorrelated signals for skin panel experiment.

When atypical data are removed from original data matrix, the cluster centers for each damage type are located as it is shown in **Figure 6**.

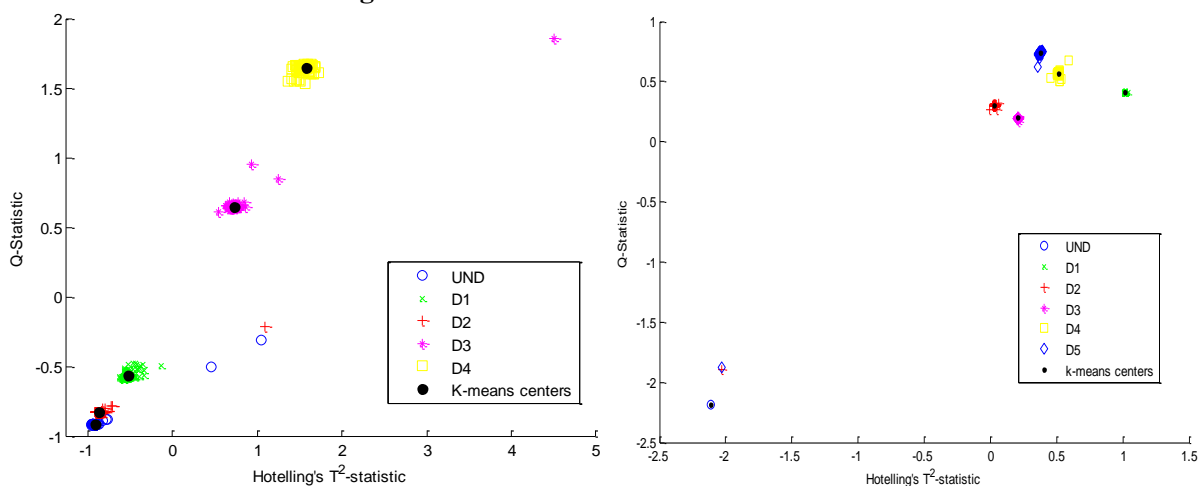


Figure 6. K-means centroids for skin panel experiment. Left: unmodified piezo-diagnostic scheme. Right: cross-correlated piezo-diagnostic approach

In **Figure 6**, it can be observed that more dispersion appears without correlation analysis. Additionally, if correlation analysis is included in the damage classification approach, then the atypical data-cases are filtered. **Table 1** summarizes the quality indexes of the clusters obtained by K-means algorithm.

Table 1. Quality clustering indexes for skin panel experiment.

		Approach		
		Uncorrelated with original data	Uncorrelated eliminating atypical data	Cross-correlated with original data
Index	Gap statistic	3,595	3,504	5,885
	Davies-Bouldin	0,241	0,275	0,089
	Quantization Error	11,798	13,615	0,439
	Dispersion for each cluster	[0.3178, 0.0655, 0.0684, 0.0570, 0.2467]	[0.0335, 0.1315, 0.0147, 0.1032, 0.2467]	[2.2434e-04, 0.0032, 0.0404, 0.0350, 0.0078]

According to **Table 1**, a better dispersion in all clusters and improved clustering indexes are obtained when cross-correlated signals are used instead of raw data. In addition, the uncorrelated approach has comparable clustering indexes values even when atypical cases are removed.

4.2. Turbine Blade Experiment

Similarly than the previous experiment, most of the principal components variability is captured with 100 components as shown in **Figure 7**.

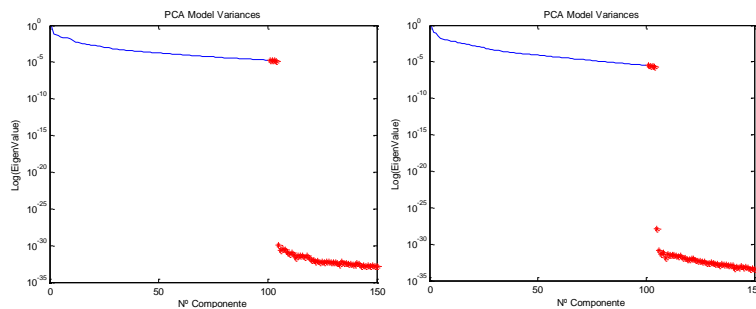


Figure 7. Principal component variances for turbine blade experiment. Left: unmodified piezo-diagnostic scheme. Right: cross-correlated piezo-diagnostic approach

Immediately after, the cluster procedure is performed. The final clusters for damages in turbine blade experiments are depicted in **Figure 8**. Here it is possible to highlight a clear separation between different types of damage when cross-correlation analysis are included in the piezo-diagnostic approach.

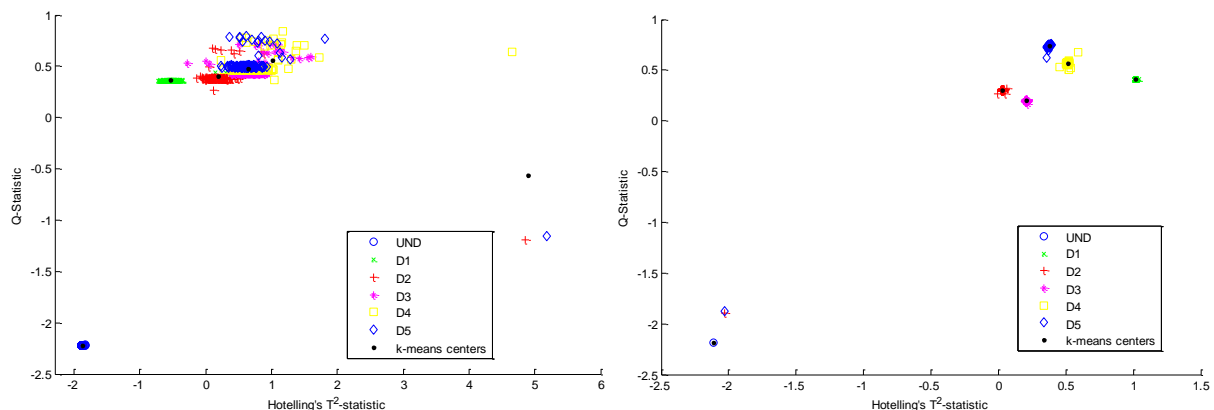


Figure 8. K-means centers for turbine blade experiment. Left: uncorrelated piezo-diagnostic scheme. Right: cross-correlated piezo-diagnostic approach

The respective clustering errors are summarized in **Table 2**. According to these results, the clustering indexes confirm the best performance for cross-correlated analysis.

Table 2. Quality clustering indexes for turbine blade experiment.

		Approach	
		Uncorrelated	Cross-correlated
Index	Gap statistic	3,681	6,865
	Davies-Bouldin	0.4054	0.0618
	Quantization Error	16,787	0.2909
	Dispersion for each cluster	[0.0092, 0.1236, 0.1362, 0.0828, 0.8833, 0.2380]	[0.0357, 0.0069, 0.0090, 0.0168, 0.0147, 0.0050]

5. Conclusion

In this paper is shown that by using common clustering techniques is possible to distinguish damages in a simple way. However, a better damage differentiation can be obtained if cross-correlation technique is used as preprocessing technique. This effectiveness was validated by computing the error clustering.

In order to avoid abnormal data, dispersion preprocessing was achieved filtering typical cases by using cross-correlated piezoelectric signals, where an adequate rejection of abnormal data was obtained.

Related to evolution of variances for principal components it can be concluded that no differences are presented for both structures of different properties. Also, since, K-means centers are assigned to damage types when cross-correlation analysis is included, classification can be achieved representing damage cases with this optimal value.

Effectiveness of cross-correlation was validated with the error clustering calculation where improvements were obtained for the two experiments.

6. Acknowledgments

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