NullSpace Damage Detection Method with Different Environmental and Operational Conditions

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ABSTRACT

In this paper a damage detection application is presented. The method used is called NullSpace and is based on Subspace Identification. If the traditional time domain based damage detection methods are applied without taking into account the condition that the structure is working, the results can be confusing. In this paper, a soft-clustering method is used in order to be able to create different clusters. These clusters will reflect the different Environmental and Operational Conditions (EOC) as different learning states. In order to test these variations an offshore wind turbine model has been used. Different wind speeds and nacelle orientations have been simulated using Bladed (Garrad Hassan). The results show that the method used for different conditions is able to detect damage correctly, where the traditional method fails.

INTRODUCTION

Structural Health Monitoring (SHM) aims to give, at every moment during the life of a structure, a diagnosis of the "state" of the constituent materials, of the different parts, and of the full assembly of these parts constituting the structure as a whole [6]. The state of the structure must remain in the domain specified in the design. Thanks to the time-dimension of monitoring, it is possible to consider the full history database of the structure, and the changes in the structure can be monitored.

Damages in structures have caused many disasters in the course of history as can be seen in figure 1. These kind of disasters have attracted the attention of the community related to construction techniques and maintenance of structures.

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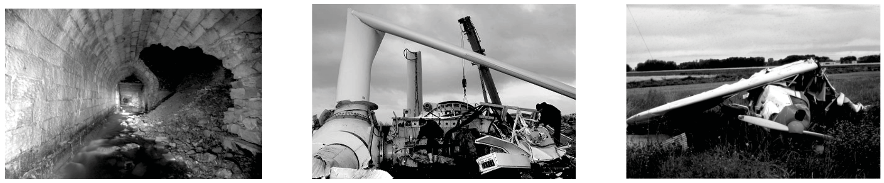

(a) *Tunnel Collapse* (b) *Turbine Collapse* (c) *Airplane crash*

Figure 1: *Structural Disasters*

Among the different application fields of Structural Health Monitoring (SHM), nowadays the wind turbine one can be stuck out. The current trend in this field is to locate the wind power plants off shore, where costs, including maintenance and operations, increase significantly compared to on shore ones. This fact has increased the interest towards the implementation of different concepts of SHM in these structures.

Although many damage detection techniques are successfully applied to scale models or specimen tests in controlled laboratory environments, the performance of these techniques in field is still questionable and needs to be validated [5].

One of the main obstacles for deploying a SHM system for in-service structures is the environmental and operational variation of structures. In fact, these changes can often mask structural changes caused by damage. Often the so-called damage-sensitive features employed in these damage detection techniques are also sensitive to changes in environmental and operational conditions of the structures.

In this paper an application of this problem is presented. It is based on Kraemers work [4]. A soft-clustering method is applied to separate different environmental conditions into different clusters. This clustering method has been tested with a damage detection method based on the work of Basseville *et al* [3], and it is called NullSpace damage detection method.

The data to test the method has been extracted from a mono-pile off shore wind turbine model [2] simulated in Bladed (Garrad Hassan). Different environmental conditions have been simulated: wind speeds; and different operational conditions: nacelle orientations. Some virtual accelerometers have been placed on the tower of the turbine so as to be able to read the vibrations. The damage has been simulated by decreasing the wall thickness of the tower in different percentages.

First, the details of the solution are presented, followed by the turbine model is presentation. Next, the obtained results are shown, comparing them to the unclustered solution. Finally, the conclusions and future work are presented.

DAMAGE DETECTION METHOD AND CLUSTERING

NullSpace Damage Detection

The key idea of the method relies on the concepts of subspace identification and null subspace. The response data collected from the monitored structure is used to construct the Hankel matrices. If no structural damage occurs, the orthonormality assumption between the subspaces of the Hankel matrices corresponding to different data sets remains approximately valid according to small residues, if not, these residues go wrong, indicating damage. The concept of subspace identification is based on the definition of the Hankel matrix:

$$H_{p,q} = \begin{bmatrix} \Lambda_1 & \Lambda_2 & \cdots & \Lambda_q \\ \Lambda_2 & \Lambda_3 & \cdots & \Lambda_{q+1} \\ \vdots & \vdots & \ddots & \vdots \\ \Lambda_{p+1} & \Lambda_{p+2} & \cdots & \Lambda_{p+q} \end{bmatrix}; \qquad q \geq p \tag{1}$$

Here p, q are user-defined parameters and Λ_i represents the output covariance matrix, which may be estimated from a set of N output data samples y_k as:

$$\Lambda_i \simeq \left(\frac{1}{N-i-1}\right) \sum_{k=1}^{N-i} y_{k+i} y_k^t \tag{2}$$

From the point of view of damage detection, we are not concerned in identifying the modal parameters of the structure. Instead, only relative changes of characteristic features are necessary for structural damage assessment. For this purpose, a method based on the null subspace concept of these Hankel matrices is used. Performing the Singular-Value Decomposition on the Hankel matrix,

$$H_{p,q} = U_H S_H V_H^t \tag{3}$$

U_{H0} must be found, which is the one that makes the next property to be true:

$$U_{H0}^t H_{p,q} = 0 \tag{4}$$

U_{H0} contains the maximum number of independent column vectors that span the column null space of H. The size of this matrix is not fixed.

If the structure is undamaged, the multiplication between null-space (U_{H0}) and the new Hankel matrix should be equal or really close to zero, because both should have similar null-spaces. If damage occurs, the product should be different from zero. We will call this, residue matrix:

$$R_{i,j} = U_{H0}^t H_{i,j} \tag{5}$$

Once the residue matrix is calculated, a vectorization operator is applied, that rearranges the columns of the R matrix (whose size is $m \times n$) into one vector of length $(m \cdot n) \times 1$.

$$\zeta = vec(R_{i,j}) \tag{6}$$

The residual (ζ) has the information about how our structure has changed. This information needs to be quantified, so that the algorithm can deduce if the structure is damaged or not. For that purpose, a Damage Indicator is calculated. Using the different residuals (ζ) of the undamaged structure, the covariance matrix is constructed, in that way how the structure works in the undamaged state is known.

$$\widehat{\Sigma} = \left(\frac{1}{n-1}\right) \sum_n \zeta_n \zeta_n^t \tag{7}$$

where n is the number of residuals that exist for the undamaged structure. In the learning Phase the values of the Null space (U_{H0}) are extracted and the "Covariance Matrix" $\widehat{\Sigma}$ is estimated.

In the detection phase, using the same NullSpace calculated in the learning phase, the residual vector for the structure will be calculated. Subsequently the next formula will be applied in order to detect whether damage exists:

$$DI = \zeta_{n+1}^t \widehat{\Sigma}^{-1} \zeta_{n+1} \tag{8}$$

Fuzzy C-Means Clustering

The Fuzzy C-means (FCM) technique was originally introduced by Jim Bezdek [1] as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters. FCM clustering algorithm is based on the minimization of an objective function called C-means functional. It is defined as:

$$J(X;U,V) = \sum_{i=1}^{N}\sum_{j=1}^{C} (\mu_{ij})^m ||x_i - c_j||^2 \tag{9}$$

where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster, and $|| * ||$ is any norm expressing the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership μ_{ij} and the cluster centers c_j by:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{||x_i - c_j||}{||x_i - c_k||}\right)^{\frac{2}{m-1}}}; \; c_j = \frac{\sum_{i=1}^{N} \mu_{ij}^m x_i}{\sum_{i=1}^{N} \mu_{ij}^m} \tag{10}$$

This iteration will stop when $max_{ij}\left\{||u_{ij}^{(k+1)} - u_{ij}^{k}||\right\} < \varepsilon$, where ε is a termination criterion between 0 and 1, whereas k are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m.

Clustered NullSpace Damage Detection Method

As most damage detection methods, there are 2 phases: the learning one, and the detecting one. The learning process modelices how the structure behaves for different environmental conditions. The inputs to the algorithm will be the information from the structure, and the environmental conditions, while the output will be a Damage Indicator. The clustering information created in the learning phase will be used in the detection phase, as well as the information about the healthy structure.

Learning Phase

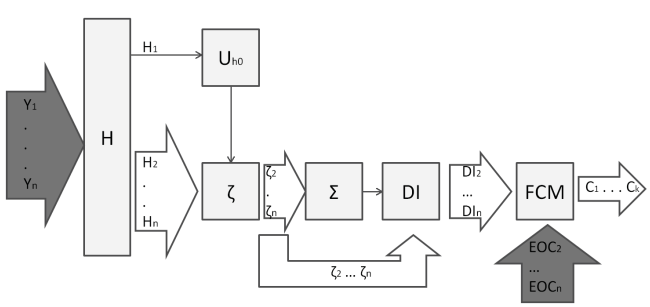

Figure 2: *Learning phase 1*

In this phase, the incoming data will be undamaged, and it is divided into two subphases (Figures 2 and 3). The first step, is to perform a NullSpace damage detection method without the Environmental information, so as to make the classification. First of all, the Hankel matrices are estimated using the equations 1 and 2. The first Hankel matrix, the one corresponding to the first data set, will be used to calculate the NullSpace see equation 4, and after this, the residuals of the rest are calculated (eq. 6). With these residuals, the covariance matrix will be estimated(eq. 7), and also the Damage Indicator (eq. 8).

Using these damage indicators and the EOC data, the fuzzy clustering is performed, and the centers will be calculated.

In the second phase of the learning process the centers (C_X) calculated in the first learning process, the Hankel matrices used in the first phase (H_X) and the Hankel matrices from the centers (H_{0CX}) are used as inputs, along with the environmental conditions (EOC_X). The basic idea is to use the fuzzy clustering centers to estimate how the healthy structure should work in different environmental conditions. The goal of this second phase is to estimate a covariance matrix $\widehat{\Sigma}$ for each cluster.

For each environmental condition, its healthy condition is estimated just by applying the distance to the centers. A Hankel matrix is created that is proportional to the distance to the different centers. That way, a NullSpace for each different environmental condition is calculated. The reference hankel matrix is estimated the next way:

$$H_{sX} = \sum_{k=1}^{K} u_{ij} H_{0Ck} \tag{11}$$

being u_{ij} the distance between the center k and the EOC X of the current data; K the number of centers; and $H_{0Ck}$the Hankel matrix of the center k.

Once the Healthy Hankel matrix is estimated, its NullSpace (U_{h0}) is calculated. There will be a NullSpace for each data set. Next, the residual for the data set is extracted, using the Hankel matrices coming from the data set corresponding to the EOC used for estimating the Healthy Hankel matrix,

$$R_X = U_{h0X}^t H_X \tag{12}$$

The vectorization is applied to the Residual Matrix (eq.6) . All the residuals will construct the Covariance matrices $\widehat{\Sigma}$. There is a covariance matrix per cluster center. The outputs from the learning phase one, will be the centers needed and the Hankel matrices for the centers. From learning phase 2, the covariance matrices are the output. All these variables are going to be needed in the detection phase.

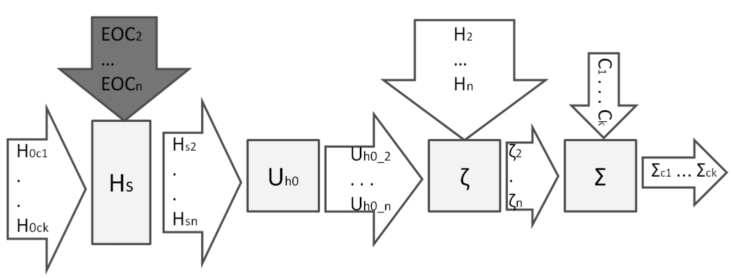

Figure 3: *Learning phase 2*

Detection Phase

The detection phase is shown in Figure 4. In this phase, the classification decision is made: it is decided if a data set belongs to the healthy structure or not. The detection phase is very similar to the second phase of learning, but with the difference that instead of estimating the covariance matrix, using the covariances from the learning phase, the Damage Indicator (DI) is calculated.

The first part of the detecting phase is the same that has been done in the second phase of learning. The estimation of the healthy Hankel matrix is done in this first part, to know how the healthy structure should work for those EOC. With this Hankel matrix, the NullSpace (U_{h0}) is found, just as done in the learning phase. The input signal is transformed into Hankel matrices. With these Hankel matrices, and using the estimated NullSpace, the residual matrix is found using the equation 12 and the residual using the vectorization shown in equation 6.

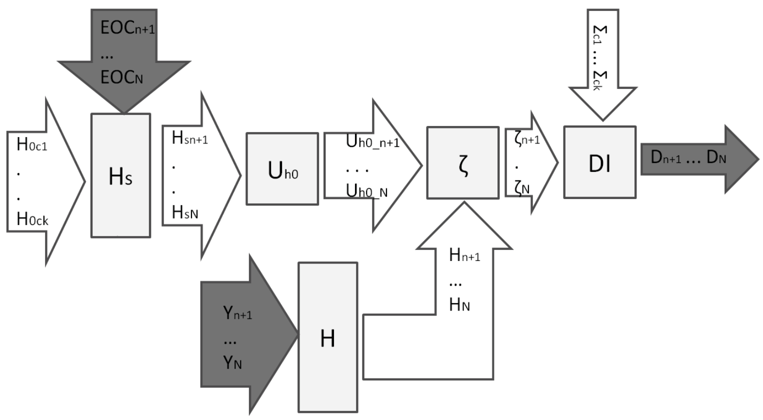

Figure 4: *Detection phase*

Finally, for the Damage Indicator, the covariance $\widehat{\Sigma}$ calculated in the second phase of the learning process is used. There are more than one covariance matrices, one for each center. The one that belongs to the closest center is applied. The Damage Indicator is found the next way:

$$DI = \zeta_{n+1}^{t} \widehat{\Sigma}_{CX}^{-1} \zeta_{n+1}$$

TURBINE MODEL

The method explained in the previous section, has been tested in a modeled wind turbine. This wind turbine is based on the UPWIND project [2], and it is implemented for the software Bladed (Garred Hassan). The tower properties of the monopile version for the NREL 5-MW baseline wind turbine are the next ones: the base diameter ($6m$) and thickness ($0.027m$), top diameter ($3.87m$) and thickness ($0.019m$). The height above ground is $107.6m$, $20m$ of those are flooded; finally the total mass is $697.46Kg$.

Simulation Parameters and Data

In the software different EOC are simulated using different winds and nacelle orientations.

The winds used, are Turbulent winds with different means. In this case, the winds are centered in $5m/s$,$13m/s$,$19m/s$,$25m/s$ speeds, while the Nacelle orientation changes between $0^o, 15^o, 30^o\, and\, 45^o$ from north.

To simulate the damage, the wall thickness has been reduced. The tower is divided into different tower stations. The wall thickness of one of those stations has been reduced in different percentages $1\%\, 5\%\, 10\%\, 20\%\, and\, 30\%$.

Simulated vibration data from the structure is extracted from different tower stations. In each station a simulated biaxial sensor (X,Y) is placed. Four locations have been used, located in$17.71m$, $41m$, $64.3m$ and $87.6m$.

RESULTS

The figure 5 shows the Damage Indicators of the NullSpace Algorithm without any type of clustering. Different colors show different cases. The green data sets are the ones used for the learning phase, the blue are the healthy ones not used for learning. The next four colors are the ones corresponding to each damage (red 1% reduction, cyan 5%, fuchsia 10%, yellow 20% and black 30%). The black line corresponds to the mean value of each case.

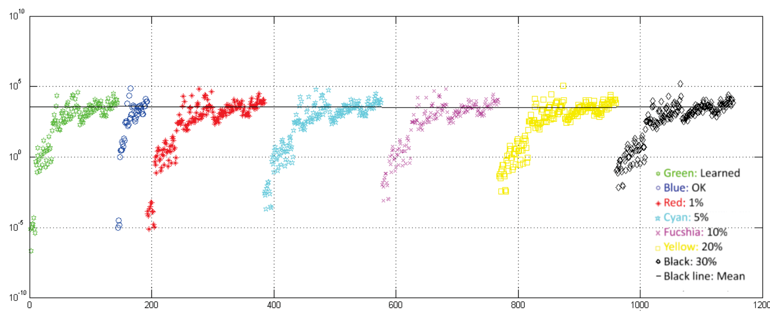

Figure 5: *Results with Unclustered NullSpace*

The first thing to see is that the variations concerning the EOC are larger than the ones corresponding to the damage itself. The data sets with the same EOC have nearly the same DI value (note that the scale is logaritmic). This results in a really close value of the mean value for each case, and being impossible to be able to detect damage properly.

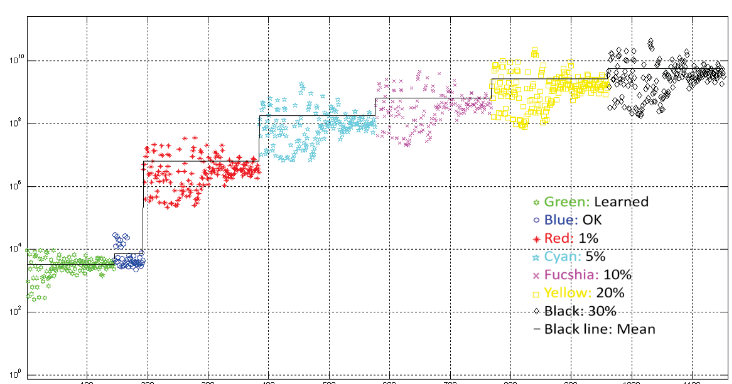

Figure 6: *Clustered NullSpace results*

In the figure 6 the results of the clustered NullSpace method are showed. The color classification is the same as in figure 5. It is clear that the damage is well detected. The gap between damaged and undamaged is big.

Among the undamaged data sets, the green ones have a really close value to the blue ones. The damaged cases show similar responses, but the values for higher amount of damage are bigger in general and the mean value corroborates that fact.

CONCLUSIONS AND FUTURE WORK

The application to a wind turbine model of the clustered NullSpace damage detection method has been able to correctly detect damage in the structure in different environmental conditions. We also see that the mean value of the metric indicating failure has higher values in the cases where the damage is more severe.

In the results we can see that if a unclustered solution is used, the results obtained are not logical, and that too many false alarms are created. On the other hand, a good application of a clustered version of the same method shows how the method is able to detect damage. Although it is not easy to cuantify the damage because the dispersion of the damage indicators is big. The NullSpace method needs long datasets in order to have a stable damage indicator. This tells us that the simulations should have been longer.

The tower used was a monopile offshore model; nowadays the mayor wind turbine enterprises are modeling jacket based offshore wind turbines. It would be interesting to see how the damage detection method works in this case. The next step would be to try it with a jacket based offshore model.

On the other hand, it would be interesting to do a feature selection to the raw data in order to select the most sensitive data for the damage detection.

Finally, as a conclusion, we have implemented a damage detection method valid for the severe climate in the offshore demanding conditions, where maintenance costs are high.

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