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# Damage assessment for wind turbine blades based on a multivariate statistical approach

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**Abstract.** This paper presents a vibration based structural health monitoring methodology for damage assessment on wind turbine blades made of composite laminates. Normally, wind turbine blades are manufactured by two half shells made by composite laminates which are glued together. This connection must be carefully controlled due to its high probability to disbond which might result in collapse of the whole structure. The delamination between both parts must be monitored not only for detection but also for localisation and severity determination. This investigation consists in a real time monitoring methodology which is based on singular spectrum analysis (SSA) for damage and delamination detection. SSA is able to decompose the vibratory response in a certain number of components based on their covariance distribution. These components, known as Principal Components (PCs), contain information about of the oscillatory patterns of the vibratory response. The PCs are used to create a new space where the data can be projected for better visualization and interpretation. The method suggested is applied herein for a wind turbine blade where the free-vibration responses were recorded and processed by the methodology. Damage for different scenarios *viz* different sizes and locations was introduced on the blade. The results demonstrate a clear damage detection and localization for all damage scenarios and for the different sizes.

## 1. Introduction

Vibration-based Structural Health Monitoring (VSHM) has been widely used for damage assessment in a multitude of engineering structures based on the features of the vibration response measured along the structure [1, 2]. Nowadays, VSHM became a trend in the future techniques for monitoring the health of modern civil engineering and aerospace engineering among many others sectors. Indeed, the growth of the off-shore wind turbines place VSHM at the forefront of the contemporary research. The visual inspections of these structures are dangerous, expensive and it might requires a tedious planning, which can be particular and different for each case. The idea of develop an on-line remote system to monitor the health of the structure is the great interest for these structures.

Although failure can happen in any structural component of the wind turbine, one of the most likely parts are the turbine blades [3]. One of the most common failure mechanism in turbine occurs in the glued interface between the two shell parts of the blade. This failure is relative small compare with the total dimension of the blade and it can growth until collapse the entire part. Therefore, it is very important to detect, control and localise this kind of failures.



VSHM can be divided in two groups: model base methodologies [4] and non-model based methodologies [5]. Model based methodologies requires the existence of a model which is able to describe the behaviour of the system. However, the second group is based on pure data-driven techniques to create a reference system space where compare the changes that happen in the system.

Thus the aim of this study is to apply a data-driven technique based on Singular Spectrum Analysis (SSA). This technique is able to separate the stationary and non-stationary components from a vibratory response [6]. SSA divides the data signal in blocks with the same mean and variance over the time. Those blocks called Principal Components (PCs) are used to reduce the dimension of the system by considering the most relevant for each case of study. The projection of the reconstructed signals based on the importance of the PCs is used as a feature for damage detection and localization [7].

The papers is organized as follows: the first sections describe the methodology implemented and the following sections describe the basis and results of the application case.

## 2. Stochastic subspace approach for damage assessment

The stochastic subspace approach presented in this paper is an output-only measurement damage assessment method. The methodology is performed to compare two data sets: one from the undamaged system which is considered as baseline (reference data) and another from the damage system (observation data). The approach is based on Singular Spectrum Analysis (SSA) which is an extension of Principal Component Analysis able to decompose and compress the non-independent values such as time series in their covariance distribution. Stochastic subspace methods are efficient tools for system identification and hence for damage assessment [8, 9]. The projection of the observation data onto the new space reduces the distances between elements from the same system/category and on the same time the distances from different systems/categories increase.

### 2.1. Step 1: Baseline covariance subspace model

The discrete time-acceleration measurements taken from the undamaged system are considered as a reference data to create the new subspace.

The time-acceleration signals are represented in the frequency domain. The amplitudes values of the frequency spectrum are arranged into a vector as  $\mathbf{z} = (z_1, z_2, \dots, z_N)$ . The new vector is embedding in a Hankel matrix form as bellow

$$\check{\mathbf{Z}}^i = \begin{pmatrix} z_1^i & z_2^i & z_3^i & \dots & z_w^i & \dots & z_W^i \\ z_2^i & z_3^i & z_4^i & \dots & z_{w+1}^i & \dots & z_{W+1}^i \\ z_3^i & z_4^i & z_5^i & \dots & z_{w+2}^i & \dots & z_{W+2}^i \\ z_4^i & z_5^i & z_6^i & \dots & z_{w+3}^i & \dots & \vdots \\ z_5^i & z_6^i & \vdots & \dots & \vdots & \dots & z_N^i \\ z_6^i & \vdots & \vdots & \dots & z_N^i & \dots & 0 \\ \vdots & \vdots & z_N^i & \dots & 0 & \dots & 0 \\ \vdots & z_N^i & 0 & \dots & 0 & \dots & 0 \\ z_N^i & 0 & 0 & \dots & 0 & \dots & 0 \end{pmatrix} \quad (1)$$

where  $W$  is the window length and  $i = 1 \dots M$  the number of realisations considered to build the new subspace. Each  $M$  realisation is performed in the same Hankel matrix form. The group of embedding matrices constructs a large matrix which contains the information about the oscillatory patterns of the undamaged system as  $\check{\mathbf{Z}} = (\check{\mathbf{Z}}^1, \check{\mathbf{Z}}^2, \dots, \check{\mathbf{Z}}^M)$ . The computation

of the covariance matrix of  $\check{\mathbf{Z}}$  distributes the information contained in the dynamics of the undamaged system in vectors with the same mean and variance over the frequency spectrum. These vectors are namely as Empirical Orthogonal Functions (EOFs).

The EOFs are obtained by the eigen-decomposition of the covariance matrix  $\mathbf{C}_{\check{\mathbf{Z}}}$ . The eigenvalues  $\lambda_k$  are then ordered in the diagonal matrix  $\mathbf{\Lambda}_{\check{\mathbf{Z}}}$  in decreasing order and the matrix  $\mathbf{E}_{\check{\mathbf{Z}}}$  contains their corresponding eigenvectors  $\rho_k$  written as columns.

$$\mathbf{E}'_{\check{\mathbf{Z}}}\mathbf{C}_{\check{\mathbf{Z}}}\mathbf{E}_{\check{\mathbf{Z}}} = \mathbf{\Lambda}_{\check{\mathbf{Z}}} \quad (2)$$

The EOFs are considered as the basis for the new subspace. The projection of the reference data onto the new basis yields the Principal Components (PCs) as

$$\mathbf{A} = \check{\mathbf{Z}}\mathbf{E}_{\check{\mathbf{Z}}} \quad (3)$$

The dynamic response is then distributed in  $W \times M$  number of PCs placed into the matrix  $\mathbf{A}$ . The PCs are allocated in the matrix  $\mathbf{A}$  in decreasing order from the ones which contain more percent of the total variance to the components with the lowest percent of variance.

The dynamic response is then reconstructed by the projection of the PCs onto the EOFs. For a given set of indices  $\mathcal{K}$  corresponding to the set of PCs contained in  $\mathbf{A}$ , the Reconstructed Components (RCs) are obtained as is shown in the equation below

$$R_{m,n}^k = \frac{1}{W} \sum_{w=1}^W A_{n-w}^k E_{m,w}^k \quad (4)$$

where  $k$ -eigenvectors give the  $k^{th}$  RC at  $n$ -frequency between  $n = 1 \dots N$  for each  $m$ -realisation ( $m = 1 \dots M$ ) which was embedded in a  $w$ -lagged vectors with the maximum  $W$ -length. The RCs are placed in the  $\mathbf{R}$  matrix.

The RCs are the new reconstructed signals based on the percent of variance contained in the PCs used in their reconstruction. Each RC contains different variance of the total reference signal (original signal). Therefore, the RCs can be used separately and independently for the damage assessment methodology.

### 2.2. Step 2: Subspace projection. Damage index

The RCs are well separated signals reconstructed by the components which contain the same mean and variance over the whole frequency spectrum [10]. Therefore, the new subspace allows us to project the data from the damaged systems (observation data) onto the new subspace based on the undamaged system. The representation of the data onto the new space is performed by using an inner-product between the RCs and the observation data. This projection is able to characterise the vibratory response into a single point as

$$T = \langle \mathbf{O}, \mathbf{R} \rangle \quad (5)$$

where  $\mathbf{O}$  is the observation data matrix and the matrix  $\mathbf{R}$  is the set of RCs, which correspond to the undamaged system (reference data).

### 2.3. Step 3: Dimensionality magnitude estimation

The data obtained in the projection onto the new space can be utilised as damage index because it contains the information of the dynamic response. The damage index  $T$  is a vector which contains the inner product of the observation data in each RCs. As mention in the previous sections, each RC contains a certain percent of variance from the signals of the reference data. The first RCs contains more variance than the rest of RCs.

Computing the Mahalanobis distance (MD) between the projection of the observation data  $\mathbf{T}_0$  and the projection of the reference data  $\mathbf{T}_z$  onto the new space as the following equation,

$$\mathbf{D}_M(T_z) = \sqrt{(\mathbf{T}_0 - \mu_z)^T \mathbf{S}_z^{-1} (\mathbf{T}_0 - \mu_z)} \quad (6)$$

provides a magnitude used for system identification and hence for damage assessment.  $\mathbf{D}_M(T_z)$  is the Mahalanobis distance to the reference data set  $\mathbf{T}_z$ ,  $\mathbf{T}_0$  is the observation data,  $\mu_z$  is the means of the  $\mathbf{T}_z$  and  $\mathbf{S}_z$  is the standard deviation of  $\mathbf{T}_z$ .

Theoretically, the dimension of the  $\mathbf{D}_M$  can be as much as the dimension of the projection vector  $T$ . However, the dimension of  $\mathbf{D}_M$  is best established by inspecting results from the PCs decomposition of the reference system.

### 3. Application for a wind turbine blade

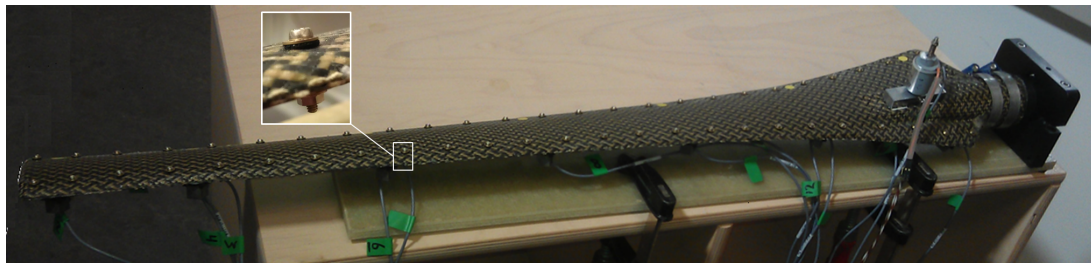
#### 3.1. Description of the experiment

For testing different damage detection and localization algorithms, a dedicated test setup was created. The test object is a 80 cm long rotor blade, which was created in the frame of DTU Wind Car project at Wind Energy department of Technical University of Denmark. The blade consists of two parts: the pressure and suction sides are manufactured separately from composite materials ([11] details the blade design and implementation). In Wind Car projects, the parts are glued together, which very much resembles the manufacturing process of real wind turbine blades. For the described test setup, the parts were squeezed together by means of a big number of small bolts, placed along the leading and trailing edges of the blade approximately 25 mm from each other. This solution greatly simplifies introducing a damage into the blade: one shall simply loose some of the bolts; this way, it is easy to control damage location and size. For damage "repair", the loosen bolts need to be re-tightened. This approach allows us modelling only one type of damage: leading and trailing edge de-bonding, which are quite common for many types of real blades. However, there are other types of damages, which cannot be modelled with the current setup.

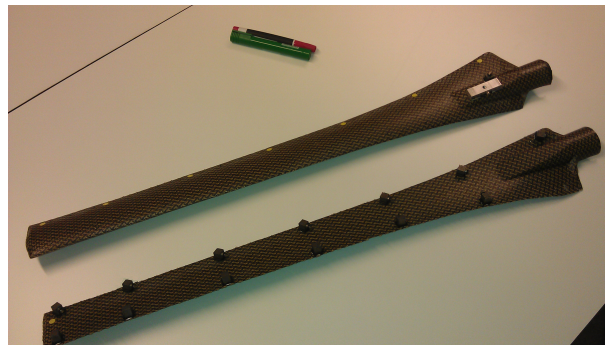
For the experiment, the blade was clamped from the root end, in a similar way as it is supposed to be mounted on the rotor hub (Figure 1(a)). During the tests, the blade was artificially excited by a small electro-mechanical actuator mounted close to the root. The actuator is driven by a signal generator. This setup enables periodic highly repeatable force impulses being introduced into the blade structure. The response due to the actuator strikes was being measured by an array of accelerometers. Fifteen B&K Type 4507 *B* 4 monoaxial accelerometers were used, seven were mounted along the leading edge, another seven-along the trailing edge, and one in a vicinity of the actuator (Figure1(b)). The data acquisition was conducted using B&K Pulse LAN-Xi modules Type 3053 – *B* – 120 and 3160 – *A* – 042, the latter also includes the signal generator. In total, 16 channels were recorded: 15 acceleration signals and the driving signal from the signal generator, the latter to facilitate triggering during the post-processing.

#### 3.2. Data collection

The most of damage detection and localization algorithms heavily rely on statistics in order to improve the robustness and detection rate and minimize the number of false alarms. The described algorithm belongs to the class of unsupervised learning, i.e. the algorithm is trained on healthy state (or also called reference state) of the test object, and the damage state is associated with a deviation from the normal state. First, the statistics for the reference state is collected: when all bolts are tightened, a series of approximately hundred actuator hits is recorded. Then a damage was introduced and expanded. The presented study uses the measurements from three damages: Damage 1 leading edge tip section; Damage 2 trailing edge middle section; Damage 3 leading edge root section. All three damages were introduced following the same scenario: first



(a) Disposition of the bolts on the blade and blade support



(b) Distribution of the accelerometers along the blade

**Figure 1.** Experiment test ring for the wind turbine blade

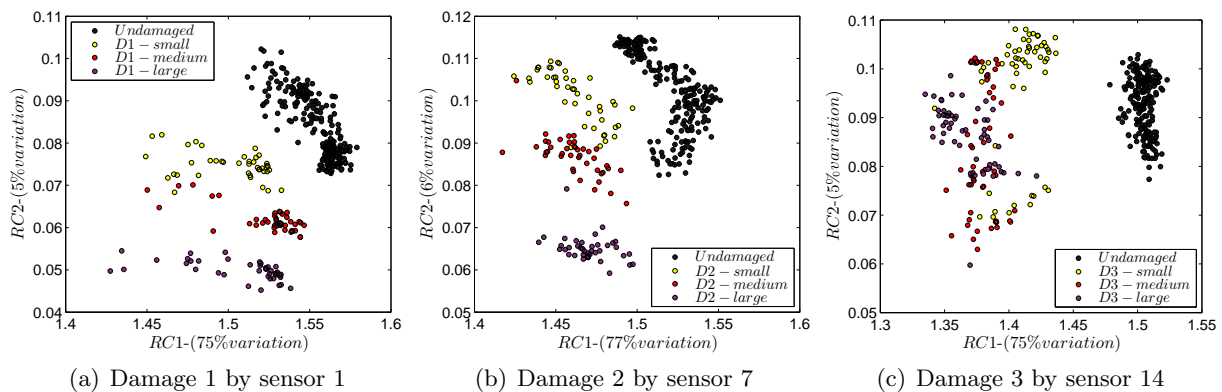
only one bolt was loosened, and a series of new measurements (corresponding to about 60 hits) is conducted. Then a neighboring bolt was loosened, which modeled damage progression. Finally, the third bolt was untightened. After the state corresponding to the biggest damage was measured (namely, three loosened bolts for Damage 1 and Damage 2 cases and four bolts for Damage 3 case), all bolts were re-tightened, thus the structure was brought to the undamaged state, again. We did not test the cases with more than one damage. It is important to note that, when loosening, the bolts were not removed from the blade, thus the total mass of the structure kept unchanged. The soft rubber washers keep the bolts fixed in the holes, thus preventing the bolt rattling. Doing this, we tried to avoid any possible side effects of loosening the bolts, which the algorithm can confuse with the changes in local structural stiffness, which we are trying to detect.

### 3.3. Damage detection

The discrete time-acceleration measurements (free-decay responses), from the undamaged blade, were recorded and processed by the methodology explained in §2. The new subspace based on the undamaged blade was used as reference state where the vibratory responses measured from the different damage locations and sizes can be compared. Ten signals were used to build the new subspace and the window length was selected as  $W = 10$ . The reason to choose this window length follows similar considerations than [12]. The statistical model was created by using only the undamaged responses for one sensor. The signals from the damaged blades were recorded from the same sensor and consequently projected onto the new subspace. This procedure was separately repeated for each sensor.

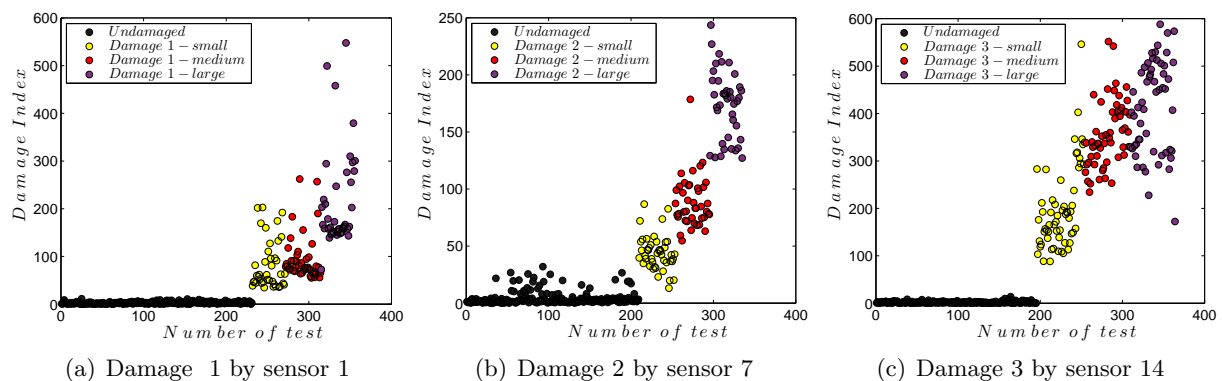
Figure 2 represents the projection of undamaged and damaged responses characterised in a single point onto the new subspace. Each damage location was studied separately. For the case of Damage 1 (damage located on the tip of the blade) and Damage 2 (damage located on the middle of the leading edge) can clearly be observed that the values cluster within groups of the same

category. The distances from elements of the same category reduces their distances meanwhile elements from different categories increase the distances from the other categories groups (see Figure 2(a) and 2(b)). Therefore, the detection between undamaged and damaged blades is achieved as well as the detection between different damage sizes. However, the clustering effect in the case of the Damage 3 (damage located on the trailing edge close to the support) does not clearly differentiate between different damage sizes. Although, the detection between damaged and undamaged is clearly achieved (see Figure 2(c)).



**Figure 2.** Projection of all damages location and sizes (small, medium and large) onto the new subspace based on undamaged structure.

In order to quantify the results obtained in the projection figures above, the MD was computed to measure the distances between undamaged elements to the different damages locations and sizes. Figure 3 shows separately the MD for each damage location. It can be observed within the three damage locations that the damaged was successfully detected. Also, the progression of the damaged is well observed even for the case of Damage 3 (Figure 3(c)) where the cluster classification in Figure 2(c) was not very well achieved. Figure 3(a) and 3(b) demonstrate that as much as the damage increases the distance from the undamaged state also increase. Moreover, the distance between different sizes of the damages is also distinguishable. For the three cases the damage progression is perfectly described.

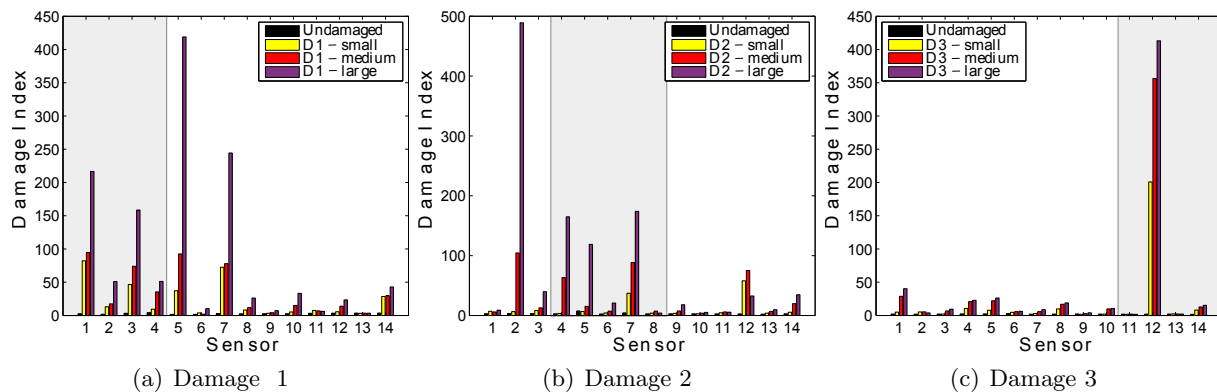


**Figure 3.** Mahalanobis distance from the undamaged scenario to different damage sizes (small, medium and large) for each damage location.

### 3.4. Damage localization

Other important aspect to consider for VSHM is the localization of the damage along the blade. The damage index described in the previous sections and the localisation of the sensors along the blade are correlated to determinate a potential location of the damage. The sensors which are located close to the damage are more prone to detect such damage [13]. Therefore, the sensors which obtain larger value of MD index indicates that damage occurs close to the region where such sensor is located.

Figure 4(a) shows the sensitivity of the sensors on the Damage 1. It can be observed that the largest values of the MD occurs between sensors 1-5. These sensors are located around the area close to the tip of the blade which is the region where Damage 1 was performed. Similarly, Figure 4(b) represents the sensitivity to the Damage 2. It can be observed that although damage 2 occurs between sensor 5 and 7, the sensors around the area are more sensitive to damage. Finally, Figure 4(c) shows clearly the sensitivity of the sensor 12 on the Damage 3. The area where Damage 3 occurs is exactly in this position. As a general comment, the growth of the damage, in all the damages scenarios, is clearly observed in all sensor of the structure.



**Figure 4.** Mahalanobis distance for each damage location and size corresponding to each sensor. The grey region involves the sensors which are closer to the damage.

## 4. Conclusion

The study presented in this paper is focused of using a multivariate signal processing technique for damage assessment in turbine blades. The experimental lab data on a turbine blade was used to evaluate the effectiveness of the methodology for damage detection and localization. The damage detection is fruitfully achieved for the different damages scenarios. The methodology is also able to monitor the progression of the damage being clearly detected the different sizes introduced during the experimental test procedure. The correlation of the damage index and the location of the sensors along the blade provides a high potential for damage localization. The damages were approximately located in the regions where each damage was performed. Further studies in this direction are extremely recommend due to the successful results obtained. It is also important to pointed out that the test data used in this study is focus on the low frequency damage data. As a conclusion, the methodology clearly present an high potential for on-line damage assessment in wind turbine blades.

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