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Statistical methods for damage detection applied to civil structures

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Abstract

Damage detection consists of monitoring the deviations of a current system from its reference state, characterized by some nominal property repeatable for every healthy state. Preferably, the damage detection is performed directly on vibration data, hereby avoiding modal identification of the structure. The practical aspect of using only the output measurements cause difficulties because of variations in ambient excitation due to variability in the environmental conditions, like sea, wind, and temperature. In this paper, a new Mahalanobis distance-based damage detection method is studied and compared to the well-known subspace-based damage detection algorithm in the context of two large case studies. Both methods are implemented in the modal analysis and structural health monitoring software ARTeMIS, in which the joint features of the methods are concluded in a control chart in an attempt to enhance the resolution of the damage detection. The damage indicators from both methods are evaluated based on the ambient vibration signals from numerical simulations on a novel offshore support structure and an experimental campaign with a full scale bridge. The results reveal that the performance of the two damage detection methods is similar, hereby implying merit of the new Mahalanobis distance-based approach, as it is less computational complex. The fusion of the damage indicators in the control chart provides the most accurate view on the progressively damaged systems.

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Keywords: Structural health monitoring; ambient excitation; damage detection; control chart-based algorithm fusion.

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1. Introduction

Online vibration-based damage detection methods are increasingly popular for detecting damages during operational time of large civil and mechanical structures. In particular, for complex public structures such as bridges [1], where human safety is a priority, or for structures difficult to access and inspect, like wind turbine blades [2] or offshore foundations [3]. For given cases, amongst many other examples, the vibration-based damage detection relies on identification of the damage-induced deviations in the damage-sensitive quantities of the collected response signals.

A frequent practice is to use a modal approach, which presumes that the damages are fully reflected by the vibrational characteristics (natural frequencies, mode shapes or damping ratios) identified from the data and thereafter compared between the healthy and current states. However, field work questions the direct use of the modal parameters, arguing that the modal data itself is not sensitive enough to detect the local faults [4], especially when, in practice, the structure is excited by low-frequency inputs. One bypass to the modal framework is to use the statistical methods, where characteristic damage-sensitive quantities are derived directly from the data and evaluated for damages in a hypothesis tests [6].

This paper contributes to the vibration-based statistical damage detection methods with a revision of a new Mahalanobis distance (MD)-based method presented by the authors in [12]. The distance metric is calculated on the output vibration data processed in the framework similar to the subspace-based methods [7], hereby providing an approach that is robust towards changes in the excitation covariance. As such, damage is detected as deviations of the distance from the reference test state. The proposed approach is tested on numerical simulations with a novel offshore support structure, namely, a Mono Bucket (MB) foundation, and an experimental full scale case of a progressively damaged highway bridge in Austria. The performance of the MD-based damage detection approach is compared to the well-known classic and robust subspace-based techniques [6,10], which are implemented in ARTeMIS [11]. The resolution of the damage detection in both numerical and full scale cases is enhanced by a combination of both methods in a Hotelling control chart [8].

The structure of the paper is as follows. The basic principles of the MD-based damage detection approach are presented in Section 2. Both the comparison and joint performance of the methods, with a description of the numerical and full scale cases, are presented in Section 3. The final results are concluded in Section 4.

2. Mahalanobis distance-based damage detection

The square MD between the observations in the data vector $\mathbf{x}_i$ and a reference, baseline model with the sample mean $\boldsymbol{\mu}$ and the covariance matrix $\boldsymbol{\Sigma}$ is defined as

$$MD_i = (\mathbf{x}_i - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x}_i - \boldsymbol{\mu}). \quad (1)$$

In this paper, the MD is calculated on empirical block-Hankel matrices based on output correlations and used directly as a damage indicator, see Eq. 2. The squared MD featured with the Hankel matrices of output correlations is defined as

$$MD_i = vec\big(\widehat{\mathbf{H}}_{p+1,q} - \boldsymbol{\mu}(\widehat{\mathbf{H}}^{Ref}_{p+1,q})\big)^T \left(\boldsymbol{\Sigma}_{\widehat{\mathbf{H}}^{Ref}_{p+1,q}}\right)^{-1} vec\big(\widehat{\mathbf{H}}_{p+1,q} - \boldsymbol{\mu}(\widehat{\mathbf{H}}^{Ref}_{p+1,q})\big). \quad (2)$$

where $\boldsymbol{\mu}(\widehat{\mathbf{H}}^{Ref}_{p+1,q})$ is a mean value of a baseline model and $\widehat{\mathbf{H}}^{\mathrm{Ref}}_{\mathrm{p+1,q}}$ is a reference output block Hankel matrix determined using m merged reference data sets. The proposed metric is robust towards the variations of the excitation covariance and can, therefore, be employed for operational measurements. The formulation of the block-Hankel matrices is adapted from the subspace-based methods.

Consider the system outputs $\mathbf{y_k} = [y_k^1\ y_k^2 \dots y_k^r]^T \in R^r$,where r is the number of sensors, and a subset of r_0 sensors denotes the number of reference channels. Each entry (s,t) of the output correlation matrices $\mathbf{C_i} \in R^{rxr_0}$ yields $\boldsymbol{C}_i^{s,t} = \mathrm{E}\big(\boldsymbol{y}_{k+i}^s \mathbf{y_k^{tT}}\big)/\boldsymbol{\sigma}^s\boldsymbol{\sigma}^t$, where $s = 1, \dots, r$, t comprises all reference channels, and $\boldsymbol{\sigma}^s$ with $\boldsymbol{\sigma}^t$ denote the standard deviation of the signals from sensors s and t, respectively. The correlations can be structured in the block-Hankel

matrix

$$\mathbf{H}_{p+1,q} = \begin{bmatrix} \mathbf{C}_1 & \mathbf{C}_2 & \cdots & \mathbf{C}_q \\ \mathbf{C}_2 & \mathbf{C}_3 & \cdots & \mathbf{C}_{q+1} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{C}_{p+1} & \mathbf{C}_{p+2} & \cdots & \mathbf{C}_{p+q} \end{bmatrix} = \mathrm{Hank}(\mathbf{C}_\mathrm{i}). \tag{3}$$

$\mathbf{H}_{p+1,q} \in R^{(p+1)r\,x\,qr_0}$ where p and q are parameters such $q = p + 1$. Based on the assumption that the damage introduces a change in the distribution of $\hat{\mathbf{H}}^{\mathrm{Ref}}_{\mathrm{p+1,q}}$, it is identified T_m lengths outside the baseline state as an outlier [9], so

$$\begin{aligned} MD_i \leq T_m &\rightarrow healthy \\ MD_i > T_m &\rightarrow damaged \end{aligned}. \tag{4}$$

Here, m designate the reference, healthy data sets and i denotes the tested state. The threshold T_m is defined as one standard deviation above the mean value of the reference state.

3. Numerical simulations

The numerical tests are conducted on a finite element (FE) model of an MB foundation – a new concept for a support structure for offshore wind turbines [5]. The MB structure consists of a circular steel shell forming a skirt, which is installed inside the seabed and closed with a circular plate that creates air-tight conditions inside the so-called bucket. The air-tight feature allows to install the foundation with suction pumps, that is silent and fast to achieve. The shaft is connected to the foundation by steel profiles called webs, which transfer the operational load to the skirt. The welded shaft-web connection is prone to high stresses and carry a significant fatigue load, thus it is considered as a potential damage location.

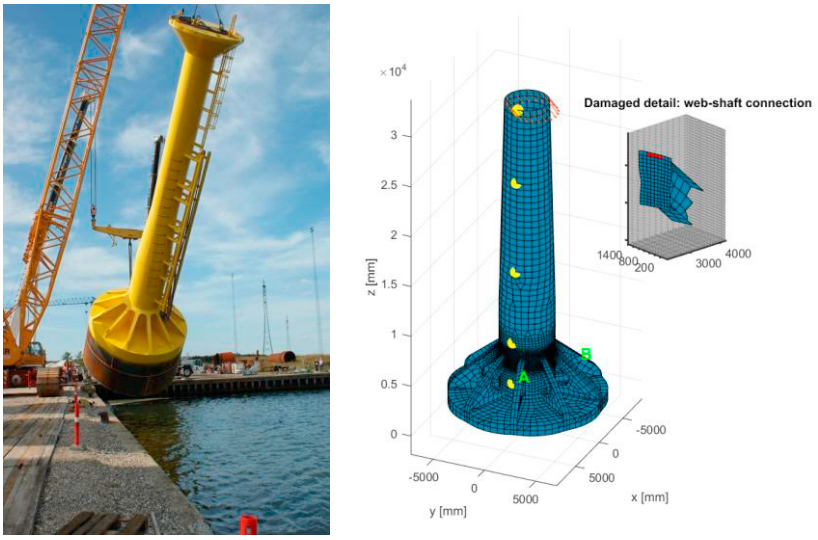

Fig. 1 MB foundation for a mobile met. mast at Horns Rev 2 (2009) (left). FE-model of the MB for numerical simulations (right). Bi-axial x-y accelerometers are illustrated by yellow dots.

The structural responses are simulated by use of the FE model of the structure with a bucket diameter of 14 m and a 32 m long shaft. The translational and rotational boundary conditions are constrained to zero on the skirt plates. In total, the FE model contains 8589 first-order shell elements, 8414 nodes and, consequently, 50484 degrees of freedom (DOF). Output accelerations are simulated using white noise input of variance taken randomly from a normally distributed vector in between [1 100], acting on the nodes on top of the shaft. A single generation of the response is recorded for 250 s with a sampling frequency of 40 Hz in 5 nodes by bi-axial sensors, hereby yielding 10 acceleration channels. In total, the ambient vibrations are simulated for 45000 s, which results in 180 data sets; 50 sets from the

healthy state and 130 sets representing 13 damaged scenarios. To challenge the performance of the damage detection methods, 1% of a Gaussian white noise is added to the response signals.
The damages are simulated as a progressive thickness (t) reduction of the elements in the shaft-web connection, by, respectively, 1%, 5%, 15%, 40% and 85%. Each element is a square of 100mm x 100mm. The damage test scenario along with a corresponding data set are described in Table 1.

Table 1. Damage scenarios during the simulations on the MB model.

Annotation	Description	Sets	Annotation	Description	Sets
A	Healthy state	50	H	t of 4 FE in ALL connections reduced by 15%	10
B	t of 4 FE in A reduced by 1%	10	I	t of 4 FE in A reduced by 40%	10
C	t of 4 FE in A reduced by 5%	10	J	t of 4 FE in A and B reduced by 40%	10
D	t of 4 FE in A and B reduced by 5%	10	K	t of 4 FE in ALL connections reduced by 40%	10
E	t of 4 FE in ALL connections reduced by 5%	10	L	t of 4 FE in A reduced by 85%	10
F	t of 4 FE in A reduced by 15%	10	M	t of 4 FE in A and B reduced by 85%	10
G	t of 4 FE in A and B reduced by 15%	10	N	t of 4 FE in connections reduced by 85%	10

3.1. Damage detection results

The reference state is created using the first 30 data sets from the healthy state. All damage detection tests are conducted with the parameter setting $q = p + 1 = 5$. The damage indicators for the numerical test cases along with the fusion of subspace-based and MD-based methods are illustrated in Fig. 2.

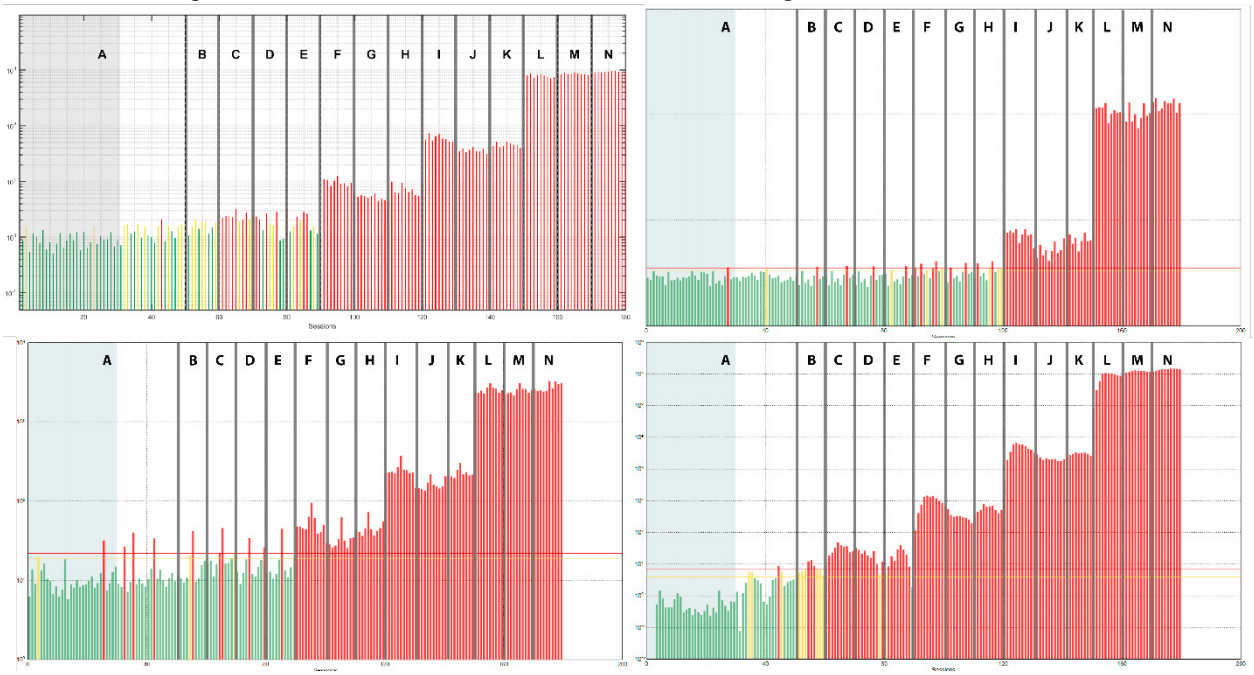

Fig. 2 MD-based damage indicators (upper left). Classic subspace-based damage indicators (upper right). Robust subspace-based damage indicators (lower left). Fusion of the subspace-based and MD-based damage indicators in the Hoteling control chart (lower right).

All three methods detect the cases with 40 % and 85 % reduction of thickness, whereas the 15 % reduction is only detected by the MD-based and the robust subspace-based methods. The first phase with 5 % reduction is detected by the MD-based algorithm, however, along with several false alarms triggered in the healthy state. Only the fusion of all the detection methods in the Hotelling control chart is capable of identifying each damage scenario and does not outline damages in the healthy data.

4. S101 bridge

The instrumentation and employment of a structural health monitoring system on the S101 bridge was described in detail in [1]. This section contains a brief review of the monitoring setup, along with a description of the damages introduced to the bridge and a comparison of the results obtained from the subspace-based methods, similar to the findings in [1], and the MD-based scheme.

The S101 was a prestressed concrete bridge located in Reibersdorf, Austria. With the main span of 32 m, side spans of 12 m, and a width of 6.6 m, it crossed the national highway A1 Westautobahn. Built in 1960, it had to be demolished due to structural problems and to allow space for additional lanes on the highway underneath. That created an opportunity for conducting progressive structural damage tests.

The bridge was artificially damaged and monitored within the "Integrated European Industrial Risk Reduction System (IRIS)" research project. The measurement campaign was conducted by VCE and the University of Tokyo. The purpose of the campaign was to demonstrate the impact of scientific insight and findings with regards to the rehabilitation measures and cost planning of the transportation infrastructure.

Acceleration responses were recorded using 15 tri-axial sensors mounted on the bridge deck. The bridge was monitored continuously from 10-13 December 2008, with a sampling frequency of 500 Hz, hence resulting in a total of 714 data sets (with 165000 samples in each). Naturally, the bridge was closed for any traffic during the progressive damage tests. As a result, the main source of ambient excitation was wind together with vibrations from the highway beneath the bridge. The structural damages introduced in the bridge were of several types and locations. Two major damage scenarios can be distinguished, as outlined in Table 2.

Table 2. Damage scenarios during the progressive damage test of the S101 bridge.

Damage case 1	Damages	Sets	Damage case 2	Damages	Sets
B	First cut through the left pier	5	I	Exposing the tensioning cables, 1st tendon cut	20
C	Second cut through the left pier	15	J	2nd tendon cut	178
D	Settlement of the left pier (1st) – 1cm	10	K	3rd tendon cut	23
E	Settlement of the left pier (2nd) – 2cm	21	L	4th tendon partly intersected	6
F	Settlement of the left pier (3rd) (final settlement) – 3cm	9			
G	Lifting the left pier - +6mm above the 0.00	186			
H	Strengthening the left pier with a steel plate	45			

4.1. Damage detection results

The reference state is created using the first 100 healthy data sets. Output acceleration signals are decimated to 12.5 Hz and all damage detection tests are conducted with the parameter setting $q = p + 1 = 16$. To reduce the computational time, 4 reference, or so-called projection, channels are chosen based on [1]. In total, 680 out of 714 data sets were investigated for damages. The comparison of the damage indicators for the robust subspace-based and MD-based methods is illustrated in Fig. 3.

The results in Fig. 3 show that the MD-based method identifies the healthy state up to 150 data set, which agrees with the structural testing scheme, and classifies the damages to the respective periods seen in Table 2. When comparing

the results from both methods, the MD-based damage indicators are more sensitive to the local, less significant, damages- I, J, K, whereas the major damage events- C, D, E, F are less pronounced, yet identified.

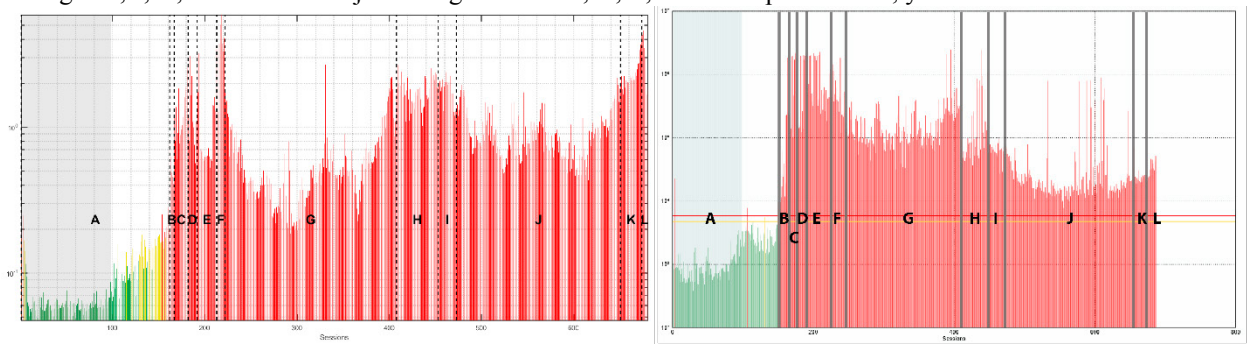

Fig. 3 MD-based damage indicators (left). Robust subspace-based damage indicators (right).

5. Discussion and conclusions

This paper presents a revision of a recently developed MD-based damage detection method, whose performance has been compared to well-established subspace-based damage detection approaches. The methods were tested on the basis of an FE simulation model of a novel offshore support structure and an experimental campaign with a full-scale artificially damaged bridge.

Despite the changes in the variance of the ambient excitation, tested methods have proven to be effective in detecting the damages in both the simulations and the full scale experimental cases. The performance of the new MD-based damage detection appears similar to the robust subspace-based scheme in both cases. Both the subspace-based and MD-based algorithms successfully identify the initial point of each artificially introduced damage scenario, proving the capabilities of both methods to detect the damages and to be ready to deploy in online health monitoring systems.

Future work will focus on the use of empirical Hankel matrices based on different statistical transformations of the output data as damage sensitive quantities. The fusion of the methods enhanced the performance of damage detection, hence research on this subject will also be expanded.

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