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Sequential projection pursuit for optimal transformation of autoregressive coefficients for damage detection in an experimental wind turbine blade

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Abstract

The performance, and with it, the utility of structural health monitoring systems depends strongly on the efficiency of damage sensitive features (DSFs) for describing the state of a structure. Several approaches are available for extracting DSFs from acceleration response signals, but they are often high dimensional. This affects significantly data processing and storage demands. Therefore, reducing DSF dimensions while maintaining or even improving damage detectability is desired. The present study explores the use of sequential projection pursuit for identifying low-dimensional DSF transformations optimized for structural damage detection. Here, transformation vectors are obtained sequentially using an advanced evolutionary optimization technique. A statistical objective function is employed to facilitate making decisions about the structural state with the help of statistical hypothesis testing. Optimal numbers of transformation vectors are found by fast forward selection. The approach is demonstrated using initial DSFs defined as autoregressive coefficients from acceleration response signals of an experimental wind turbine blade. Wind-like excitations were applied with the help of a pedestal fan, and damages were simulated non-destructively by adding small masses. The results demonstrate that the proposed methodology can considerably reduce DSF dimensionalities without deteriorating the damage detection performance. Conversely, the detectability of some damages could be improved in comparison to using selected original DSFs. This is promising for future developments of efficient vibration-based structural health monitoring methods.

Keywords: Damage detection; Projection pursuit; Wind turbines; Time series methods; Autoregressive models; Statistical hypothesis testing

1. Introduction

Structural health monitoring (SHM) is the process of acquiring measurements, extracting information and knowledge from these observations and determining the current structural performance of a system [1]. Sensing technologies based on different physical principles are available, but the majority are not applicable for continuous, in situ measurements in large structures, e.g. thermal imaging or x-radioscopy, or require dense sensor arrays, such as acoustic emission or dynamic strain methods. Passive vibration techniques based on acceleration responses resulting from am-

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bient excitations are competitive. They are based on the premise that changes in stiffness, mass or energy dissipation mechanisms of a structure, which are often result of damage, affect these global vibration responses. Thus minimal instrumentation using small numbers of sensors can facilitate SHM in large structures.

For describing the structural state in an efficient manner, different damage sensitive features (DSFs) can be extracted from these acceleration signals. Traditionally, structural damage detection (SDD) is performed with the help of modal parameters, i.e. natural frequencies, mode shapes and their spatial derivatives. Nevertheless, the estimation of these parameters using only responses entails practical difficulties due to computational demands and hindrances for automating the process. Data-driven approaches based on parametric and non-parametric time series representations allow avoiding the estimation of modal characteristics. However, DSFs defined in terms of non-parametric time series representations are generally less parsimonious than their parametric counterparts. Therefore, the present study utilizes autoregressive (AR) models obtained from acceleration response signals for the definition of DSFs. Sohn et al. [2] employed AR models for SDD in a laboratory concrete bridge column. The relationship between structural stiffness and AR coefficients (ARCs) was theoretically demonstrated by Nair et al. [3].

Even though, AR models are suitable for SDD, using all ARCs of a model with an identified order may not be optimal because they can be differently affected by damage and noise. Including components in a DSF vector which are insensitive to damage or noisy increases computational efforts for making decisions about the structural state or can blunt the power of an SDD algorithm. Hoell and Omenzetter [4] investigated the selection of ARCs for improving the damage detectability. To further improve the performance, feature transformations can additionally be incorporated. Principal component analysis is widely used for SDD [5–7], but the directions of the resulting transformations are restricted by the variation in the baseline dataset which is not necessarily the same as the variations of DSF due to damage.

Therefore, the present study investigates a general approach for transforming features in order to reduce DSF dimensionalities and to improve the SDD performance. The method is based on sequential projection pursuit (SPP) [8], where transformation vectors are sequentially optimized with respect to an objective function which measures the directions' interestingness. In the present case, the objective function is defined by a statistical distance measure because statistical hypothesis testing is chosen for deciding quickly if a structure is healthy or damaged. The method is applied to dynamic experiments with a small scale wind turbine blade (WTB) made of a glass-fibre reinforced composite. The WTB is excited by a turbulent air stream produced by a domestic pedestal fan, and damage is simulated non-destructively by attaching small masses at selected locations.

The paper is structured as follows. First, the methodology is introduced beginning with statistical hypothesis testing. Time series modelling using AR models and SPP are also discussed. Second, the experiment and the process of feature extraction are explained. Third, the SDD results are presented for previously unseen datasets of the healthy state and untrained damage scenarios. Finally, a set of conclusions rounds up the paper.

2. Methodology

2.1. Statistical hypothesis testing and objective function

A generic DSF vector, $\mathbf{v} = [\, v_1\ v_2\ \ldots\ v_m\,]^T$, where superscript T denotes transpose, can be assumed to follow a multivariate Gaussian probability distribution, $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, with a mean vector, $\boldsymbol{\mu}$, and variance-covariance matrix, $\boldsymbol{\Sigma}$. The mean DSF vector of the current state, $\boldsymbol{\mu}_c$, can be tested with respect that of he the healthy state, $\boldsymbol{\mu}_h$, by the following statistical hypotheses:

$$\begin{array}{ll} H_0 : \boldsymbol{\mu}_c = \boldsymbol{\mu}_h \text{ (healthy)} \\ H_1 : \boldsymbol{\mu}_c \neq \boldsymbol{\mu}_h \text{ (damaged)} \end{array} \quad \text{using} \quad \begin{array}{ll} T^2(r,h,c) \leq F^{-1}_{\mathcal{T}^2_{r,n_h+n_c-2}}(1-\alpha) & \Rightarrow H_0 \text{ is accepted} \\ \text{Else} & \Rightarrow H_0 \text{ is rejected} \end{array} \tag{1}$$

where the null hypothesis, H_0, represents the healthy state and the alternative hypothesis, H_1, corresponds to the damage state. Since the true statistical mean vectors are generally unknown, the test can be facilitated by the estimated quantities denoted by the hat and the T^2 static [9]:

$$T^2(r,a,b) = \frac{n_a n_b}{n_a + n_b}(\hat{\boldsymbol{\mu}}_a - \hat{\boldsymbol{\mu}}_b)^T \hat{\boldsymbol{\Sigma}}_{pl}^{-1} (\hat{\boldsymbol{\mu}}_a - \hat{\boldsymbol{\mu}}_b) \sim \mathcal{T}^2_{r,n_a+n_b-2} \quad \text{with} \quad \hat{\boldsymbol{\Sigma}}_{pl} = \frac{(n_a-1)\hat{\boldsymbol{\Sigma}}_a + (n_b-1)\hat{\boldsymbol{\Sigma}}_b}{n_a+n_b-2} \tag{2}$$

The T^2 statistic follows Hotelling's probability distribution function, $\mathcal{T}^2_{r,n_a+n_b-2}$, with r and $n_a + n_b - 2$ degrees of freedom, where r refers to the effective DSF dimensionality. It is the distance between the estimated means, $\hat{\boldsymbol{\mu}}_a$ and $\hat{\boldsymbol{\mu}}_b$, standardized by the estimated pooled variance-covariance matrix, $\hat{\boldsymbol{\Sigma}}_{pl}$ calculated from the separate estimated variance-covariance matrices $\hat{\boldsymbol{\Sigma}}_a$ and $\hat{\boldsymbol{\Sigma}}_b$ in structural states a and b. The sample numbers used for estimation of the statistical quantities in the states a and b are n_a and n_b, respectively. The test can then be performed for the current state, c, with respect to the healthy state, h, by comparing the T^2 statistic with the statistical threshold defined by the inverse cumulative Hotelling's distribution function, $F^{-1}_{\mathcal{T}^2_{r,n_h+n_c-2}}(\alpha)$, at a selected level of significance, α.

To optimize DSFs in a multi-class setting rather than a binary one, an SDD objective function, J_{SDD}, can be defined as the minimum of standardized distances between the reference healthy state and DSFs from C_d damage states as:

$$J_{SDD} = \min\left\{T^2(r,h,1), T^2(r,h,2), \ldots, T^2(r,h,C_d)\right\} / F^{-1}_{\mathcal{T}^2_{r,n_h+n_d-2}}(\alpha) \tag{3}$$

where n_d are the damage state sample numbers. The division by the statistical threshold $F^{-1}_{\mathcal{T}^2_{r,n_h+n_d-2}}(\alpha)$ enables to compare DSFs of different dimensions.

2.2. Autoregressive time series modelling

For extracting time series-based DSFs, the proposed methodology assumes that the vibration responses are stationary. To reduce effects of varying excitation characteristics, signals can be normalized by removing estimated means and dividing by estimated standard deviations. For an AR(p) process of order p, a stationary, zero-mean, Gaussian distributed times series, $z[t]$, at time instant t can be expressed as the weighted sum of p previous values and a noise term $e[t]$:

$$z[t] = \sum_{i=1}^{p} a_i z[t-i] + e[t] \tag{4}$$

where a_i are the ARCs and $e[t]$ is a zero-mean, normally distributed, independent, random noise term. The ARCs and the variance of the noise term, σ_e^2, are the system unknowns. An appropriate model order can be estimated with the help of the Akaike information criterion (AIC). The sample-size normalized AIC can be calculated as [10]:

$$AIC(p) = \ln(\hat{\sigma}_e^2) + 2(p+1)/n \tag{5}$$

where $\hat{\sigma}_e^2$ is the estimated noise variance which measures the model likelihood. Then, validation of the identified model is required to assure the model adequacy. This is usually done with the help of the model residuals, $\hat{e}[t]$, which can be obtained by modifying Eq. (4) as:

$$\hat{e}[t] = z[t] - \sum_{i=1}^{p} \hat{a}_i z[t-i] \tag{6}$$

where $\hat{a}_i$ are the estimated ARCs. Additionally to investigating the residuals by normal probability plots, testing them as a whole can be done using the modified Ljung-Box-Pierce statistic, $Q(K)$, as [10]:

$$Q(K) = n(n+2)\sum_{k=1}^{K} \hat{r}_e^2[k]/(n-k) \quad \text{with} \quad \hat{r}_e[k] = (n-k)^{-1}\sum_{i=1}^{n-k} \hat{e}[i]\hat{e}[i+k] \tag{7}$$

where K is the total number of lags of the estimated residuals autocorrelation function, $\hat{r}_e[k]$, to be considered, and n is the number of samples. For a valid model, the Q statistic follows a $\mathcal{X}^2_{K-p}$ probability distribution with $K - p$ degrees-of-freedom, thus statistical hypothesis testing can be utilized for the validation. An initial DSF vector, $\mathbf{v} = \left[a_1\ a_2\ \ldots\ a_p\right]^T$, can then be defined using the p ARCs, a_i, of an identified AR(p) model. In the present study, the Burg method [11] was used for estimating ARCs.

2.3. Sequential projection pursuit

SPP tries to identify an transformation matrix, $\mathbf{P} = \left[\mathbf{p}_1\ \mathbf{p}_2\ \ldots\ \mathbf{p}_r\right]$, containing r transformation vectors, $\mathbf{p}_i$, with p dimensions, where $r \ll p$. Matrix $\mathbf{P}$ is used to project initial DSFs $\mathbf{v}$ onto a lower dimensional subspace for generating transformed DSFs, $\mathbf{v}_p$, as $\mathbf{v}_p = \mathbf{P}^T\mathbf{v}$. An optimization problem can be formulated for obtaining the transformation matrix $\mathbf{P}$ as:

$$\mathbf{P} = \arg\max_{\mathbf{P}}\{J_{SDD}\} \ \text{ subject to } \ \mathbf{P}\mathbf{P}^T = \mathbf{I} \tag{8}$$

where $\mathbf{I}$ is the identity matrix of appropriate dimensions. The orthonormality constraint is introduced in order to avoid information redundancies between singleton transformations. To reduce the problem complexity, the $(p \times r)$-dimensional problem is split into r consecutive problems of p dimensions in SPP [12]. In the original approach, structural removal is applied to the data between the sequential steps. However, this removes also interrelations between the transformed DSFs, which are important for evaluating the overall performance with respect to the defined SDD objective function, J_{SDD}. The proposed approach evaluates the objective function in the $(i+1)$-th step of the sequence, $i = 1, 2, \ldots, p-1$, using the transformation matrix $\mathbf{P}_{i+1}$ which contains the i already found transformation vectors as fixed entries and the $(i+1)$-th vector subject to optimization. This reduction allows employing an evolutionary inspired global optimization technique, which reduces the risk of being trapped in local optima. In the present study, the covariance matrix adaptation-evolutionary strategy by Hansen and Ostermeier [13] is employed. The algorithm generates offspring individuals in each generation by sampling from a multivariate Gaussian probability distribution, where the statistical characteristics are adapted in order to guide safely the optimization towards the global optimum.

3. Experiment and damage sensitive feature extraction

Dynamic experiments are performed with a WTB of a small wind turbine with 5 kW rated power output in order to demonstrate the proposed methodology. The WTB is 2.36 m long and has a constant 15 cm wide solid cross-section defined by the aerofoil E387, see Figs. 1(a) and (b). It is made of a glass-fibre reinforced epoxy composite. The material's mass density is calculated as 2.30 g/cm^3 from the measured total mass of 7,110 g. Cantilever-type boundary conditions are created by attaching the WTB rigidly to a massive steel base sitting on a concrete floor. Contact-free wind-like excitations are generated using a pedestal fan with a maximum power of 40 W, where the second out of three selectable power levels is used. Damage is introduced non-destructively by attaching small masses at selected locations on the trailing edge, leading edge and tip with 10 g to 100 g masses in increments of 10 g for the edge damages and 20 g and 50 g masses at the tip.

Flap-wise acceleration responses at the tip are measured using a piezoelectric miniature accelerometer model Metra KS94B-100 with 100 mV/g sensitivity and a frequency range between 0.5 Hz and 28 kHz, which is attached to the WTB with adhesive wax. Acceleration signals are acquired with a National Instruments data acquisition card NI-9234 connected to a National Instruments chassis cDAQ-9174 and a laptop with National Instruments software package LabView.

Acceleration signals are acquired in sequences of 30 min length at a constant sampling rate of 2,048 Hz for the healthy and selected damage states. An eight order Chebyshev type I low-pass filter with a cut-off frequency of 204.8 Hz is applied to the signals before resampling at 256 Hz. To create a database, each signal is divided into 400 segments of 5 s length with an overlap of approximately 10%. The segments are normalized by removing their estimated means and dividing by their estimated standard deviations.

For AR time series modelling, an appropriate model order can be selected using the AIC, which is calculated for 400 time series segments of the healthy state for AR orders from one to 100. The results are shown in terms of the estimated means and standard deviations in Fig. 1(c). Although no clear minimum can be identified, an AR order of 40 is selected because higher orders cannot significantly improve the results. The model is validated by investigating model residuals with normal probability and autocorrelation plots, but they are omitted here for brevity. Additionally, the modified Ljung-Box-Pierce statistic is calculated for residual autocorrelation coefficients up to lag 240 with a value of 213.23, which is below the 95% confidence bound of 233.99. Thus it can be concluded that the model is valid.

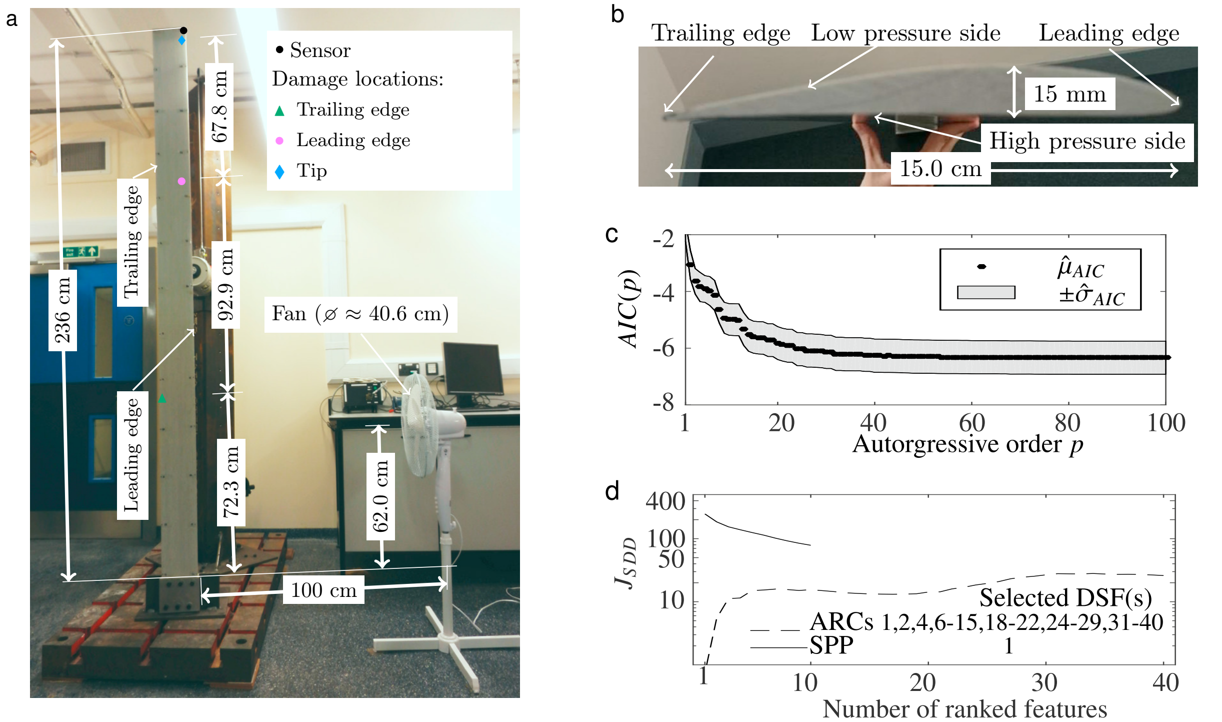

Fig. 1. (a) Experimental configuration; (b) wind turbine blade cross-section; (c) mean and standard deviation of Akaike information criterion; (d) ranking and selection of ARCs and SPP DSFs (y axis in log scale).

The identification of optimal DSFs is performed using three healthy and eight damage datasets, i.e. 20 g, 50 g and 80 g masses attached at the trailing and the leading edge locations as well as tip masses with 20 g and 50 g. Then, SPP is employed for obtaining a transformation matrix optimized with respect to the objective function J_{SDD} and the training dataset. To limit the computational efforts, the number of transformation vectors is limited to ten. The covariance matrix adaptation-evolutionary strategy by Hansen and Ostermeier [13] is employed for the optimization of subsequent transformation vectors. For finding the optimal number of these vectors, a ranking is established for increasing numbers of DSF components, see Fig. 1(d). This is additionally done for ARCs to create a competitive DSF for assessing the performance of the proposed procedure. For the SPP DSFs, it can be seen that using one DSF gives the highest objective function value. The ranked ARCs show a different behavior, where increasing the number of ARCs improves the performance. A local optimum is obtained for seven ARCs, while the global one occurs for 34 ARCs. The optimal DSF subsets are also provided in Fig. 1(d).

4. Structural damage detection

The SDD performance of the optimal DSF subsets is assessed for single samples of previously unseen healthy and damage datasets using the $T^2(r,h,c)$ statistic. The statistical properties of the healthy reference were estimated from the healthy training data. To be able to compare directly the results of the two DSFs with different dimensionalities, i.e. one and 34 dimensions for SPP and ARC subsets, respectively, the $T^2(r,a,b)$ statistics were scaled by the corresponding statistical threshold, $F^{-1}_{\mathcal{T}^2_{r,n_h+n_d-2}}(\alpha)$, at 5% significance levels, see Fig.2. It can be seen that most samples of both DSFs fall below the detection threshold for the healthy state indicating low false positive rates. The results for the trailing edge and tip damages are very similar for the SPP and ARC DSFs leading to almost identical SDD performances for these cases, where masses with 20 g or more can be reliably detected. However, differences can be observed for the leading edge damages, which appear to be more difficult to detect. Here, the SPP transformed DSFs allowed detecting masses of 60 g or more with negligible false negatives. This is not the case for the ARC subset, where only damages with 90 g and 100 g could be detected.

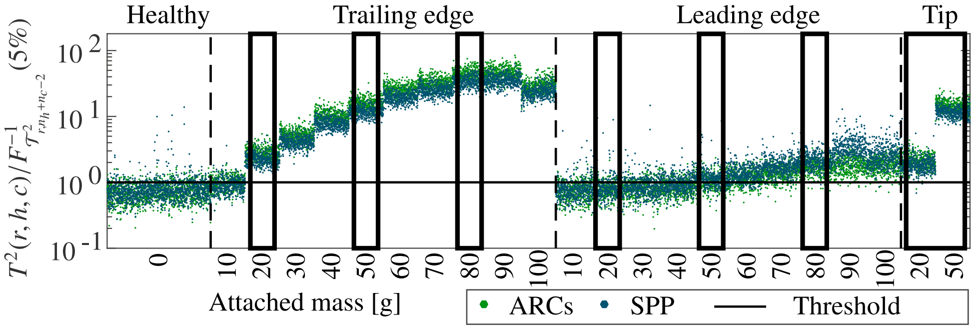

Fig. 2. Structural damage detection results for previously unseen healthy data and damage scenarios used and not used in training (y axis in log scale; trained damage extents indicated by bold frames).

5. Conclusions

This paper presented a novel methodology for improving the detectability of structural damages by means of DSF transformations obtained by SPP and a specialized objective function. Decisions about the structural state were made with the help of statistical hypothesis testing. The approach was applied to ARCs as initial DSFs estimated from acceleration responses of a small WTB which was excited by the air stream generated by a domestic pedestal fan. Damage was simulated non-destructively by attaching small masses. The advantages of using SPP transformed ARCs have been demonstrated in comparison to an optimally selected original ARC subset. The DSF dimensionality was significantly reduced, i.e. to a single dimension, while the detectability of damage could be improved enabling to detect smaller damage extents. These results are promising and further research may lead to beneficial applications under realistic conditions.

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