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Monitoring of a Novel Structure using Fiber Bragg Grating Strain Sensors

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ABSTRACT: The aim of this study is to overview the objectives and outcomes of an ongoing structural health monitoring campaign for a novel structure, namely the newly built elephant shelter at the Zurich Zoo. The structure comprises a complex geometry featuring a wooden free form cupola spanning 80 m, which is supported by a post-tensioned concrete ring. The monitoring framework employs strain measurements acquired by a series of Fiber Bragg Grating (FBG) strain sensors embedded into critical locations of this ring, and output-only methods identified for fitting these data. The methods used to this end are based on the Principal Component Analysis (PCA) technique and Vector Autoregressive (VAR) models. The corresponding models are estimated from records coming from a phase in which the structure is undamaged, while the misfit between the model predictions and future measurements may be used as an indicator for the onset of damage.

1 INTRODUCTION

The ever-increasing complexity of modern structures deems rigorous maintenance strategies necessary in order to ensure structural safety under operational as well as extreme loading conditions through its lifespan. Sub-optimal inspection and maintenance strategies may incur a significant monetary burden on infrastructure owners, which can however be minimized on the basis of additional information on the structures condition. The current state-of-the-art on Structural Health Monitoring (SHM) approaches and emerging low-cost sensor technologies allows the acquisition and processing of such information in a financially and practically feasible manner. This information can be used within a damage detection framework to aid in inspection and maintenance planning. This information, which facilitates the use of FBG strain sensors for this specific project, can be used within a damage detection framework to aid in inspection and maintenance planning.

FBG strain sensors are increasingly gaining popularity in civil engineering applications due to their long-term stability, resistance to harsh environments, good mechanical fatigue resistance, potential to be internally embedded, and multiplexing capabilities. The fundamental principle behind FBG sensors relies on the refractive properties of light and the reading and decoding of these refracted wavelengths (Merzbacher 1996). It is important to acknowledge that the Bragg wavelength is not only affected by mechanical loading but also by temperature variations, which should be appropriately accounted for. A single sensor (cable) is insufficient for compensating temperature effects. A possible remedy to this is attained via inclusion of a second (parallel) cable, which exclusively records the wavelength variations due to temperature. Different approaches on temperature compensation are still under investigation (Majumder 2008). Nowadays, both the
sensors and appropriate acquisition units are commercially available for a broad range of application demands.

On the other hand, acting environmental conditions (such as temperature, humidity, wind, traffic etc.) form an important and integral part of structural response affecting its nature in both an expected as well as unanticipated manner. Within such a context, operational effects need to be taken into consideration in devising a robust SHM framework that can successfully monitor structural condition and detect damage. As (Yan 2005) propose, a feature extraction approach such as Principal Component Analysis (PCA), offers the potential of detecting irregular response features without necessitating additional environmental measurements since these are taken into account as embedded variables. However, such an approach is not be suitable in the tracking of structural response when this lies outside the linear or, at best, the weakly-nonlinear range. In tackling this deficiency, an extension to PCA has been proposed (Nguyen 2014) adopting nonlinear kernel functions (kPCA), which allow for the analysis of higher complexity systems. As an alternative, models of the AutoRegressive (AR) class, such as simple AR, or AR with eXogenous input (ARX) models, and variations of these can be used to determine the effect of temperature on the response and extract damage sensitive features (Nandan 2011). Another option resides in adopting a Polynomial Chaos Expansion (PCE) procedure, able to describe the propagation of stochasticity due to changing conditions through the structural system, linked with an independent component analysis for the compression and/or extraction of the salient part of information from structural response signals (Spiridonakos 2014).

As already mentioned, the final goal of this study is the exploitation of the used framework in order to facilitate the owners and operators in decision-making tasks. Complementary to the data acquisition process, a SHM framework has been developed for condition assessment and possible damage detection, which relies on the statistical coupling of strains measured at different locations of the structure with output-only methods. The delivered performance index, tied to the structure’s operational condition, aims to facilitate the planning of regular inspection and additionally offers a warning/alarm trigger in case of damage due to an extreme event. Two different approaches are tested and cross-evaluated to this end, with the respective advantages and disadvantages of each approach being demonstrated.

2 THE STRUCTURE UNDER STUDY

The structure of interest is the Kaeng Krachan Elephant Shelter of the Zurich Zoo (Figure 1), which has been in operation since June 2014. It comprises a complex geometry featuring a wooden free-form cupola spanning 80 m, which is supported by a post-tensioned concrete ring. Several features have been monitored during different construction and operation phases and reported to the design engineers in order to validate and further refine the model of the structure.
A major component of this deployment, essentially the only continuous monitoring system, relies on the use of FBG strain sensors that have been embedded into critical locations (Figure 2) of the concrete ring, attached to the steel reinforcement, and which serve the purpose of long-term monitoring of the strain evolution within the post-tensioned concrete sections. Chains of 4 Micronoptics embeddable os3600 strain sensors (Figure 2) of a 20cm active length, have been used at each indicated cross section, at 10 different locations. Special attention was given to the selection of the nominal wavelength of each FBG so that no overlapping signals are obtained when connecting to the Data Acquisition (DAQ) unit. Few of the embedded sensors at locations F1, F3 and F9, indicated in Figure 2, were damaged during the construction phase due to various causes (including mishandling of the equipment by the construction workers, high pressure self-compacting concrete etc.), which is an inevitable reality when dealing with out-of-laboratory deployments. The sensors are then collected via fiber optic cables at the DAQ system location. Records are obtained using a 1 Hz sampling frequency and 5-minute averages are transmitted to an ftp-server shared and operated by MAGEBA AG. Additionally, operational condition variables, namely ambient temperature, humidity of the wooden roof and force of specific foundation anchorages, are also measured and uploaded on the same server, while all these measurements are available to the client through a graphical web-interface. However, the present study focuses on output-only methods which are based solely on structural response measurements, and for this reason the operational variables are not used in the subsequent analysis.

The measurement campaign started in April 2013, just before post-tensioning of the ring tendons and has been ongoing ever since. In the work presented herein, the period from September 2014 to March 2015 has been implemented for the overviewed condition assessment framework, since the structure is primarily subjected to operational loads within this period and is free of other effects such as creep, shrinkage, post-tensioning, and construction phases.

3 STRUCTURAL HEALTH MONITORING METHODS

As already mentioned this study focuses on SHM methods which rely on structural response measurements. Nonetheless, output-only methods may be further classified as static or dynamic in regard with their “memory” on past structural response values. In the first category, it may be assumed that the input variables (features), have only a short-time effect on the structural behavior, while in the latter the structure has a memory on the history of its operational conditions and past values of its response. The thermal capacity of a structural material, or the humidity trapped in a wooden structure are significant factors which may attribute a structural memory to the recorded variables.
In the present study, a static and a dynamic output-only method is utilized and compared for their ability on the accurate modelling of the strain time-histories of the structure. These are the PCA technique and the VAR models, which are briefly outlined in the next sections.

3.1 **Principal Component Analysis (PCA)**

PCA is a technique used for the projection of possibly high-dimensional datasets of correlated variables onto compact coordinate systems, resulting in this way in a smaller group of independent variables. Let us consider a set of $N$ centered observations $\mathbf{x}_i$ with $\mathbf{x}_i \in \mathbb{R}^K$ and $t = 1,...,N$ corresponding to the measured structural responses, which are the FBG sensor strain measurements at various locations of the concrete ring for our case study. The original dataset $\mathbf{x}_i$ may be transformed into another set of $m$ variables $\mathbf{y}_i$ by Equation 1.

$$\mathbf{y}_i = T \cdot \mathbf{x}_i$$  \hspace{1cm} (1)

where $T$ is a $m$-by-$k$ orthonormal matrix that applies a rotation to the original coordinate system. This is achieved by solving an eigenvalue problem in order to estimate a small number of principal components (Jolliffe 2002). These principal components should correspond to the input variables (features) that are highly correlated with the structural response measurements.

The PCA extracts the principal components of the original dataset by diagonalizing its covariance matrix as in Equation 2.

$$C = \frac{1}{N} \sum_{i=1}^{N} \mathbf{x}_i \cdot \mathbf{x}_i^T$$ \hspace{1cm} (2)

Toward this end, the eigenvalue equation $\lambda \mathbf{v} = C \mathbf{v}$ has to be solved for eigenvalues $\lambda \geq 0$ and eigenvectors $\mathbf{v} \in \mathbb{R}^K$. The singular value decomposition may be used for this reason as presented in Equation 3.

$$C = U \Sigma U^T$$ \hspace{1cm} (3)

By selecting the $n_1$ largest eigenvalues of $\Sigma$ the previous equation may be factorized as follows:
\[
C = \begin{bmatrix}
U_1 & U_2 \\
0 & \Sigma_2
\end{bmatrix}
\begin{bmatrix}
\Sigma_1 & 0 \\
0 & \Sigma_2
\end{bmatrix}
\begin{bmatrix}
U_1^T \\
U_2^T
\end{bmatrix}
\]  (4)

with \( \Sigma_1 \) denoting the submatrix containing the \( n_1 \) largest eigenvalues and \( U_1 \) the corresponding eigenvectors. The transformation of the original data may then be achieved by setting \( T = U_1 \). The accuracy of the projection may be validated by re-mapping the selected components \( y_i \) back to the original space, by means of the reduced matrix \( U_1 \) that is shown in Equation 5.

\[
\hat{x}_i = U_1 U_1^T x_i
\]  (5)

The misfit of the projected to the original data values may be quantified by the residual error vector \( e_i = U_2 U_1^T x_i \), while the accuracy of the projection approximation has to be validated by using new data which were not included in the estimation (training) dataset.

3.2 Vector AutoRegressive (VAR) models

Vector AR models are conceptual extensions of the corresponding AR models which are used for fitting a vector of output variables onto its past values. More specifically a VAR model may be described by Equation 6 as follows:

\[
x_t + A_1 x_{t-1} + A_2 x_{t-2} + \ldots + A_{n_a} x_{t-n_a} = x_t + \sum_{i=1}^{n_a} A_i x_{t-i} = w_t ;
A = \begin{bmatrix}
a_{i,1} & \ldots & a_{i,k} \\
\vdots & \ddots & \vdots \\
a_{k,1} & \ldots & a_{k,k}
\end{bmatrix}
\]  (6)

where \( A_i \) are the \( k \times k \) are the AR matrices, \( n_a \) the AR model order, and \( w_t \) the vector series of residual errors which are normally identically distributed with zero mean value and diagonal covariance matrix \( \Sigma_w \). The AR matrices may be estimated through ordinary least squares by writing the VAR model into linear regression, while the model order \( n_a \) may be selected by using criteria based on the prediction ability of the model such as the residual sum of squares and the Bayesian information criterion (Lütkepohl 2005). The model’s one-step-ahead prediction is given by Equation 7.

\[
\hat{x}_{t+1} = -\sum_{i=1}^{n_a} A_i x_{t-i}
\]  (7)

while the corresponding prediction error \( e_t = x_t - \hat{x}_{t+1} \) coincides with the residual vector \( w_t \). The model may be validated by its prediction for new datasets not used during the estimation (training) of the model.

4 RESULTS

The results presented in this section concern the fitting and prediction of the strain measurements collected from seven different locations of the concrete string of the structure (sensor locations 2.2, 4.2, 5.2, 6.2, 7.2, 8.2 and 10.2). The time-series of these measurements as recorded during the first six months of monitoring are shown in Figure 3. Various reasons related with power
supply interruptions, data transmission problems and malfunction of the web access device led to missing data for large periods of time, especially during the first months of operation of the monitoring system. For this reason, as indicated in Figure 3, the data used for model identification (estimation set) correspond to the continuous measurements that were obtained between December 2014 and January 2015 (1400 samples) while the recordings obtained during 19 days (February and March 2015) were selected as the validation set (900 samples).

Based on the estimation set and the singular value decomposition, the normalized eigenvalues of the covariance matrix $C$ and the corresponding variance explained for an increasing number of principal components is shown in Figure 4. The first two principle components have the highest influence on the strain measurements with the corresponding explained variance exceeding 99.5%, and thus are retained for the projection of the original data onto the PC space. This projection for both the estimation and validation set may be shown in Figure 5.

For the VAR modelling, a model of AR order equal to 10 is selected based on the BIC criterion (Figure 6). The VAR(10) one-step-ahead predictions for both the estimation and validation set are presented in Figure 7 along with the corresponding Euclidean norm of the complete prediction error vector. As it may be observed by comparing Figures 5 and 7, the much richer structure of the VAR model which accounts both the dynamic effects that are involved in the structural behavior but also the spatial relation between the various strain measurements results in better fitting of the data and better performance for future values.

**Figure 3:** Strain measurements from the structure measured at the indicated locations recorded during the first six months of monitoring.

**Figure 4:** Normalized eigenvalues and the corresponding explained variance of the strain measurements covariance matrix.
Figure 5: Measured strains and the corresponding estimates based on the PCA technique for sensors 7.2 and 2.2 (top) and the norm of the corresponding errors for the complete vector of strain measurements (bottom).

Figure 6: VAR model order selection based on the Bayesian information criterion.

Figure 7: Measured strains and the corresponding one-step-ahead predictions based on the VAR(10) model for sensors 7.2 and 2.2 (top) and the norm of the corresponding errors for the complete vector of strain measurements (bottom).
CONCLUSION

The procedure and outcomes of an SHM framework on a novel structure has been introduced, which resulted in enabling a good medium for clients to be continuously informed about the structures condition and detect possible damages. FBG strain sensors and a static (PCA) and a dynamic (VAR) output-only model have been implemented to obtain a misfit between the prediction and the measured value which can be used as a damage indicator able to warn for possible irregularities/anomalies. The VAR model achieved a better fitting and prediction performance since it accounts for the dynamic effects that are involved in the structural behavior and the spatial relation between various strain measurements.

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