Damage Detection on the Champangshiehl Bridge using Blind Source Separation

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ABSTRACT: This paper addresses the problem of damage detection in civil engineering structures using characteristic subspaces obtained from principal component analysis (PCA) of output-only measurements. Damage detection is performed by comparing subspace features between a reference (healthy) state and a current (possibly damaged) state. The damage indicator used in this study is the angular coherence between subspaces.

The considered damage detection procedure is illustrated on the Champangshiehl Bridge which is a two span concrete box girder bridge located in Luxembourg. Before its destruction, multiple damage levels were intentionally created by cutting a growing number of prestressed tendons. Vibration data were acquired by the University of Luxembourg for each damaged state at many locations on the bridge. As previous studies demonstrated the large importance of environmental factors on modal identification, special care was taken to evaluate this influence during the test campaign.

1 INTRODUCTION

Extracting system dynamic features from a set of measurements can be realized using Blind Source Separation (BSS) techniques such as Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Second-Order Blind Identification (SOBI) etc. (De Boe & Golinval 2003, Nguyen 2011). The main advantage of this type of methods is that they are very simple to use in practice.

With very little increment of computational effort, the extraction of even more sensitive dynamic features may be performed by exploiting the definition of Hankel matrices. An alternative PCA-based method named Null Subspace Analysis (NSA) was proposed and applied in (Yan & Golinval 2006) on the example of an airplane mock-up. This idea was exploited later in (Nguyen 2010) to enhance the use of other BSS techniques. These enhanced techniques were applied successfully to fault diagnosis in industrial systems (Rutten et al. 2009, Nguyen & Golinval 2011).

The aim of this paper is to present an example of application of a PCA-based damage detection technique to a civil engineering structure, namely the Champangshiehl Bridge which is a two span concrete box girder bridge located in Luxembourg.

2 DESCRIPTION OF THE CHAMPANGSHIEHL BRIDGE

The Champangshiehl Bridge shown in Figure 1 is a two span concrete box girder bridge built in 1966 and located in the centre of Luxembourg. The bridge has a total length of 102 m divided into two spans of 37 m (East side) and 65 m (West side) respectively (Fig. 2). It is pre-stressed by 112 steel wires as illustrated in Figure 3. The bridge is supported by two abutments and one pylon made of reinforced concrete. The West abutment consists of an expansion bearing built by a steel roll while the East abutment is fixed. The support at the pylon is made of an elastomer material.

Before its complete destruction, the bridge was monitored and a series of damages were artificially introduced as summarized in Table 1. The four damage cases considered are illustrated in Figure 4a-d. More details on the test campaign can be found in report (Scherbaum & Mahowald 2011).

Figure 1. Side view of the bridge (Scherbaum & Mahowald 2011).

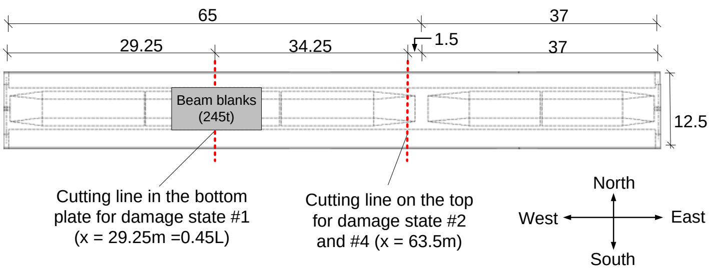

Figure 2. Longitudinal section of the bridge (Scherbaum & Mahowald 2011).

Table 1. Description of the damage scenarios according to the cutting sections shown in Figure 2.

Damage state	Damage	Percentage cutting (100% equals all tendons in the defined section cut)	
		0.45L	Over the pylon
# 0	Undamaged state		
# 1	Cutting straight lined tendons in the lower part of the bridge at 0.45L (20 tendons)	33.7%	0%
# 2	Cutting 8 straight lined tendons in the upper part of the bridge over the pylon	33.7%	12.6%
# 3	Cutting external tendons (56wires)	46.1%	24.2%
# 4	Cutting 16 straight lined tendons in the upper part of the bridge and also 8 parabolic tendons	46.1%	62.12%

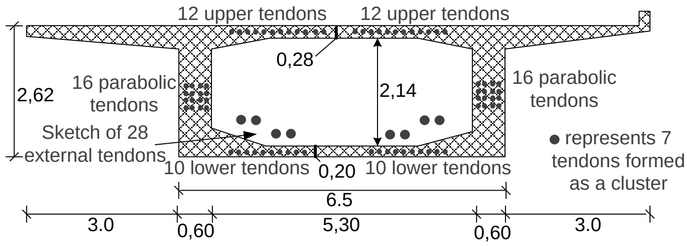

Figure 3. Cross section of the box girder with location of the tendons (Scherbaum & Mahowald 2011).

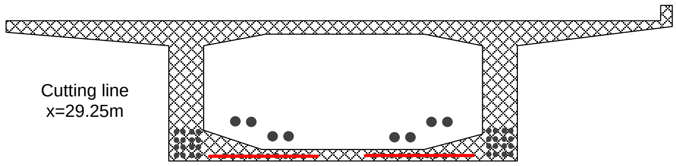

Figure 4a. Damage case # 1.

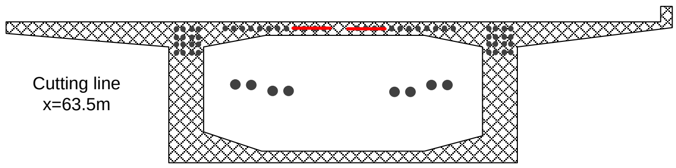

Figure 4b. Damage case # 2.

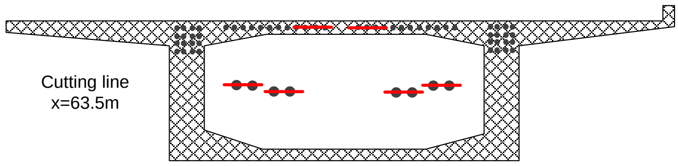

Figure 4c. Damage case # 3.

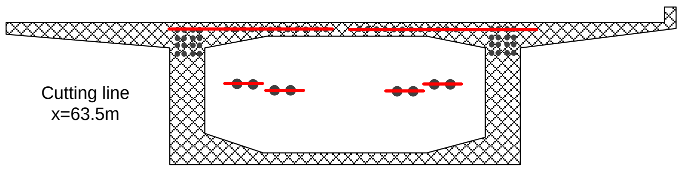

Figure 4d. Damage case # 4.

The measurement setup considered in the present work is given in Figure 5. Twenty sensors were located on both sides A and B of the deck (the distance between each sensor is about 10 m).

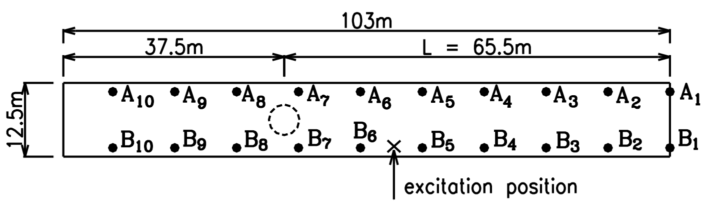

Figure 5. Location of the sensors on the bridge deck.

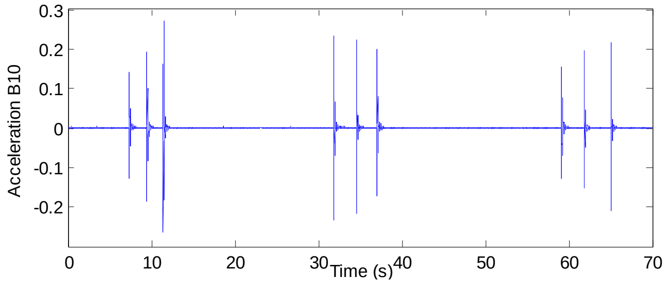

Figure 6. Example of response signal due to impact excitation (healthy state).

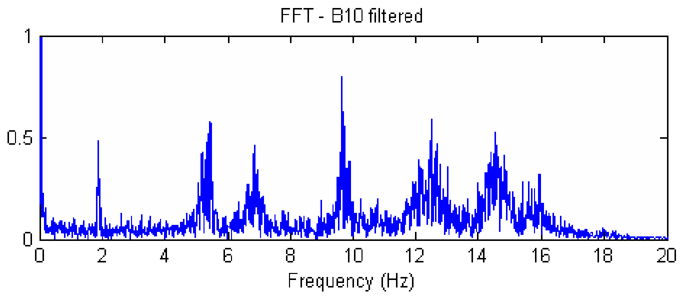

Figure 7. Frequency spectrum at coordinate B10 (healthy state).

Vibration monitoring was performed on the healthy structure and at each damage states for different loading conditions and different types of forced excitation (Scherbaum & Mahowald 2011). However, only measurements obtained using impact excitation in the unloaded configuration of the bridge were exploited in the present study. As an example, Figure 6 shows the time response signal recorded at coordinate B10 for a series of nine impacts realised on the deck, between coordinates B5 and B6. Figure 7 gives the corresponding frequency spectrum.

3 IDENTIFICATION OF NATURAL FREQUENCIES USING THE STOCHASTIC SUBSPACE IDENTIFICATION (SSI) METHOD

In many works related to health monitoring of civil engineering structures, a key issue is the extraction of representative features (e.g. modal parameters). A well established modal identification method proposed by Peeters & De Roeck (2001) relies on the use of stochastic subspace identification (SSI). The advantage of SSI is that it can be applied using output-only measurements. In the present work, SSI was applied on the free responses recorded after each impact excitation.

In Table 2, the two first natural frequencies obtained for the four damage cases (D1-D4) are compared to the natural frequencies of the healthy structure.

Table 2. Change in the natural frequencies.

	f1		f2	
	Value (Hz)	Δf_1 (%)	Value (Hz)	Δf_2 (%)
Healthy	1.92		5.54	
D1	1.87	-2.6	5.45	-1.62
D2	1.95	1.6	5.24	-5.42
D3	1.82	-5.21	5.39	-2.71
D4	1.75	-8.85	5.3	-4.33

Table 2 shows that the decrease of the natural frequencies is proportional to the damage level for damage cases D1, D3 and D4. Only damage case D2 exhibits a different behaviour as the first natural frequency increases by an amount of 1.6 % with respect to the healthy structure. However, the second natural frequency is affected by the larger decrease (5.42 %) of all the damage states.

4 DYNAMIC FEATURE EXTRACTION USING PRINCIPAL COMPONENT ANALYSIS (PCA)

Let us consider a dynamical system characterized by a set of vibration measurements collected in the observation matrix **X**:

$$\mathbf{X} = \left[\mathbf{x}_1 \quad \mathbf{x}_2 \ldots \mathbf{x}_k \ldots \mathbf{x}_N\right], \ \mathbf{x}_k \in \Re^m \tag{1}$$

where $\mathbf{x}_k$ is the output vector at time step k, m is the number of output sensors and N is the number of time samples. As defined in (De Boe 2003), Principal component analysis (PCA) provides a linear mapping of the data from the original dimension m to a lower dimension p. The dimension p corresponding to the number of principal components defines the order of the system. In practice, PCA is often performed by singular value decomposition (SVD) of matrix **X**, i.e.

$$\mathbf{X} = \mathbf{U\Sigma V}^{\mathrm{T}} \tag{2}$$

where **U** and **V** are orthonormal matrices, the columns of **U** defining the principal components (PCs). The order p of the system is determined by selecting the first p non-zero singular values in $\mathbf{\Sigma}$ which have a significant magnitude (“energy”) as described in (De Boe 2003). A threshold in terms of cumulated energies is often fixed to select the effective number of PCs that is necessary for a good representation of matrix **X**. In practice, a cumulated energy of 70% to 95% is generally adequate for the selection of the active PCs (De Boe 2003).

The null subspace (NSA) and enhanced-PCA method (EPCA) proposed in (Yan & Golinval 2006, Nguyen 2010) respectively are variant methods of the PCA method obtained by exploiting Hankel matrices of the dynamical system (Overschee & De Moor 1997). The data-driven block Hankel matrix is defined in Equation 3, where $2i$ is a user-defined number of row blocks, each block contains m rows (number of measurement sensors), j is the number of columns (practically $j = N\text{-}2i+1$). The Hankel matrix $\mathbf{H}_{1,2i}$ consists of $2im$ rows and is split into two equal parts of i block rows which represent past and future data respectively. Compared to the observation matrix $\mathbf{X}$, the Hankel matrix is built using time-lagged vibration signals and not instantaneous representations of responses. This enables to take into account time correlations between measurements when current data depend on past data. Therefore, the objective pursued here in using block Hankel matrices rather than observation matrices is to improve the sensitivity of the detection method.

$$\mathbf{H}_{1,2i} = \left[\begin{array}{ccccc} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \cdots & \mathbf{x}_j \\ \mathbf{x}_2 & \mathbf{x}_3 & \cdots & \cdots & \mathbf{x}_{j+1} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \mathbf{x}_i & \mathbf{x}_{i+1} & \cdots & \cdots & \mathbf{x}_{i+j-1} \\ \hline \mathbf{x}_{i+1} & \mathbf{x}_{i+2} & \cdots & \cdots & \mathbf{x}_{i+j} \\ \mathbf{x}_{i+2} & \mathbf{x}_{i+3} & \cdots & \cdots & \mathbf{x}_{i+j+1} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \mathbf{x}_{2i} & \mathbf{x}_{2i+1} & \cdots & \cdots & \mathbf{x}_{2i+j-1} \end{array}\right] \equiv \left[\begin{array}{c} \mathbf{H}_p \\ \hline \mathbf{H}_f \end{array}\right] \equiv \frac{\text{"}\,past\,\text{"}}{\text{"}\,future\,\text{"}} \qquad (3)$$

where the subscripts of $\mathbf{H}_{1,2i}$ denote the subscript of the first and last element of the first column in the block Hankel matrix.

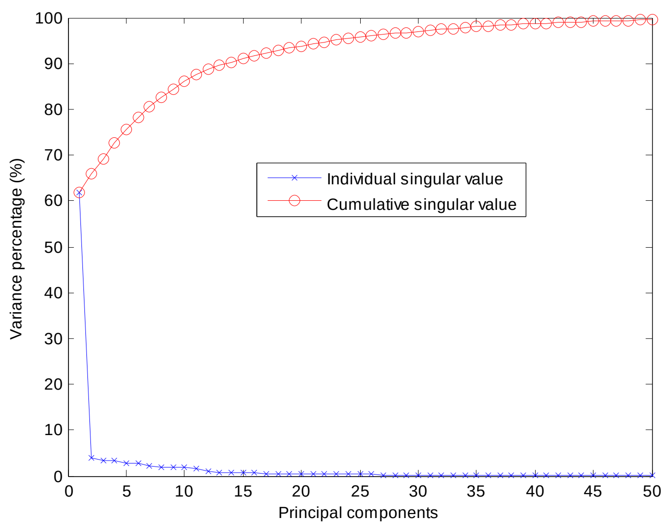

Figure 8. Energy diagram for the healthy structure.

Figure 8 gives the singular value (or energy) diagram constructed with a number of 50 blocks in the Hankel matrix of the healthy structure. It can be observed that the first principal component concentrates the largest part (more than 60%) of the total energy of the system compared to the other principal components which correspond to much lower singular values. A slight decrease of the energy can also be observed between the 4th and the 5th singular value.

5 DAMAGE DETECTION BASED ON THE CONCEPT OF SUBSPACE ANGLE

The principal components contained in matrix $\mathbf{U}$ span a subspace which characterizes the dynamic state of the system. Without any damage or variation of environmental conditions, the characteristic subspace $\mathbf{U}$ remains unchanged. Any change in the dynamic behaviour caused by a modification of the system state modifies consequently its characteristic subspace. This change may be estimated using the definition of subspace angles (Golub & Van Loan 1996).

As illustrated by a two-dimensional case in Figure 9, the concept of subspace angle can be seen as a tool to quantify existing spatial coherence between two data sets resulting from observations of a vibration system. It was used in (De Boe & Golinval 2003, Yan & Golinval 2006, Nguyen 2010) to detect changes in the dynamic behaviour of a structure (e.g. damage, onset of nonlinearity).

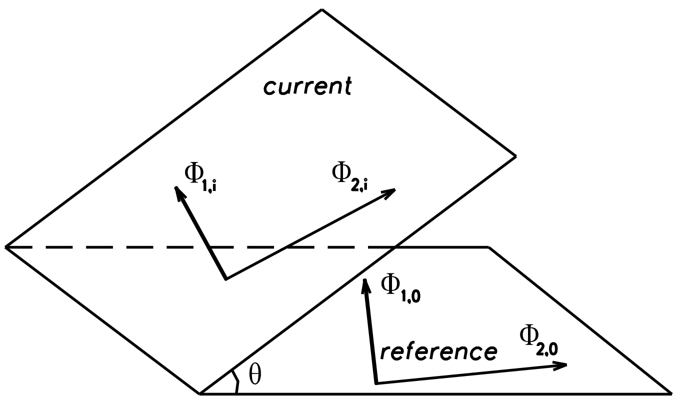

Figure 9. Illustration of the concept of subspace angle in a 2D-case. The reference and the current subspaces are defined by the active components $\mathbf{\Phi}_1$, $\mathbf{\Phi}_2$ of the corresponding Hankel matrices.

The application of the concept of subspace angle on the Champangshiehl Bridge data allows to detect all the damage cases (D1-D4) using the single first principal component (PC) of the Hankel matrix. The detection remains good and even more evident when 2, 3 and 4 PCs are used.

On the other hand, the use of more PCs (higher than 4) deteriorates the quality of the distinction between the damaged and the healthy states. Indeed, the highest PCs (associated to small singular values i.e. low energy) come from noise present in the data and are not dynamic features of the system. As an example, the detection results obtained on the basis of 3 PCs is shown in Figure 10. In this figure, a total of 20 tests were considered: eight tests on the healthy structure (H) and twelve tests corresponding to the four levels of damages D1-D4. It can be observed that all the damage cases are well detected and that damage cases D2 present the largest damage indexes.

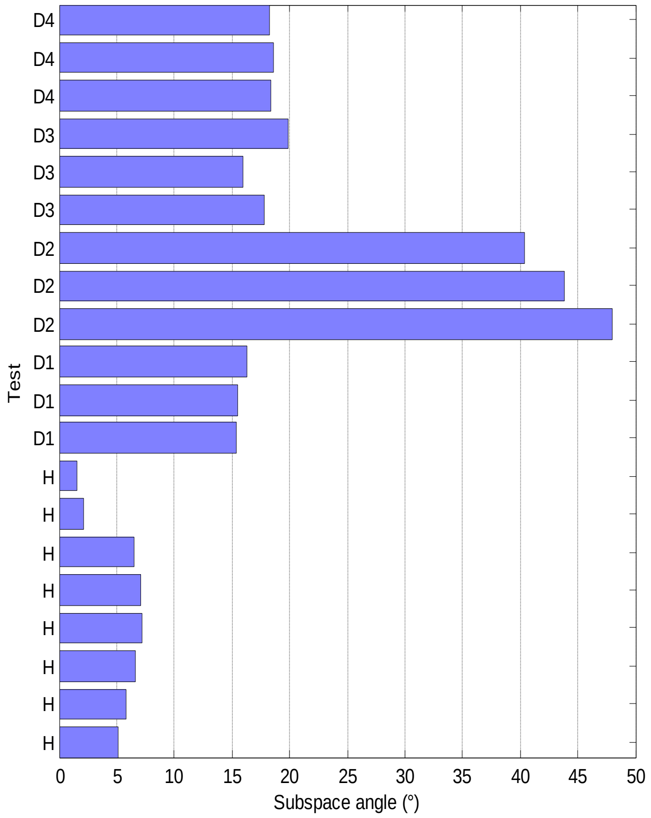

Figure 10. Damage detection results using EPCA.

6 CONCLUSION

The philosophy pursued throughout this paper is to exploit experimental vibration measurements to extract dynamic features of a system without resorting on modal identification results (i.e. natural frequencies and/or mode-shapes). To this purpose, techniques of the Blind Source Separation (BSS) family are considered and especially here, a variant of Principal Component Analysis based on the definition of Hankel matrices is used. In this method, the order (number of active principal components) is determined by looking at the cumulated variance in the singular value diagram. Thus the problem of damage detection is tackled using the subspaces spanned by the active principal components. It consists in determining the angular coherence between subspaces obtained in current states with respect to a reference (healthy) state. The advantage of PCA over classical modal identification methods relies on its easiness of use. First results obtained on the Champangshiehl bridge are encouraging.

In further studies, the influence of environmental conditions on the damage detection results will be considered.

7 ACKNOWLEDGEMENT

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