Principal Component Analysis for Fault Detection and Structure Health Monitoring

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ABSTRACT

The aim of this paper is to propose an algorithm for detecting faults such as cracks in an underground structure to ensure its health monitoring. The proposed approach is based on the PCA algorithm. Once PCA components are computed, we can see easily the impact of a crack on their norms. The impact represents a good indication to detect abrupt change.

KEYWORDS : *PCA, sliding windows, fault detection, structure health monitoring.*

INTRODUCTION

In industrial systems, Fault Detection and Isolation (FDI) take a primordial place [1]. Such a problematic can be found in civil engineering structures as well as aerospace [2], aeronautics [3], industrial production [4] or energy production [5]. However, this detection must be ensured promptly and precisely [5].

FDI is also important in SHM (Structure Health Monitoring) because of aging structures, in particular deteriorations and mechanical stress. Such problems, if not repaired, could have disastrous outcomes.

In civil engineering, the systems are generally quite large and complex, that is why an approach without model is preferable. In this state of mind, a first approach is to use ultrasonic waves on the concrete surface are used on SHM [6]; however, this technic can only be used in punctual manner. To ensure proper monitoring of the system, another approach is to implement sensors into the concrete structure, such as Vibrating-Wire Gauges (VWG). This type of sensor has already been used in civil engineering structures such as hydroelectric dams, nuclear power plants or grouted anchor [7-8]. On top of that, as these sensors are inserted into the concrete structure, they allow a permanent monitoring [9].

In this work, the monitoring of concrete liner in underground galleries is studied. Indeed, an underground laboratory[1] was built in order to study the project CIGEO (the Deep Geological Disposal Concept of Andra[2]). It aims at proposing a safe long-term solution for radioactive intermediate-level long-lived waste and high-level waste at a depth of 500 meters. It will be

[1] This laboratory, located in Bure (France), has been created between 2000 and 2005 to prepare the project CIGEO.

[2] french National Agency for Radioactive Waste Management

designed to permanently accommodate radioactive wastes. In these circumstances, the SHM must be ensured thanks to a dedicated instrumentation and processing techniques.
In this paper, an approach based on Principal Component Analysis (PCA) calculated on a sliding window is investigated to detect abrupt changes. The PCA is an algorithm used to find correlations between multiple data. It has been used for example in biologic science [11-12] or physics [13-14] but a very few in civil engineering.
In our case, we will use the PCA algorithm to detect faults on a system presenting characteristics to be unsteady, heavily instrumented and without model. In our case, the PCA is used because of the wide number of data and sensors. The main interest here is to reduce the size of our problem to process it easier.
This paper is organized as follows. First, in section I the proposed approach is described and the interest for fault detection is justified. Section II shows the obtained results by applying this approach on VWG sensors in the presented underground gallery. Finally, concluding remarks and prospects are given.

1 PROPOSED APPROACH

The PCA algorithm is a multivariate technique used to analyse data tables [10]. It is used to generate correlation circles which are studied in term of components norms and angles between components.

1.1 PCA algorithm

The PCA algorithm is a multivariate technique used to analyze data tables [10]. It is used to generate correlation circles in which components norms and angles between components are studied.

Consider a matrix Y [n×m] whose coefficient Y_{ij} represents the i^{th} sample ($1 \leq i \leq n$) of the j^{th} variable ($1 \leq j \leq m$). The first step of the PCA algorithm is to obtain the standardized Matrix Z whose coefficient Z_{ij} is computed by:

$$Z_{ij} = \frac{Y_{ij} - \overline{Y}_j}{\sigma_j}, \quad \begin{matrix} 1 \leq i \leq n \\ 1 \leq j \leq m \end{matrix} \tag{1}$$

where $\overline{Y}_j$ is the mean over time of the j^{th} variable:

$$\overline{Y}_j = \frac{1}{n}\sum_{i=1}^{n} Y_{ij}, \quad 1 \leq j \leq m \tag{2}$$

and σ_j is the standard deviation of the coefficients $\{Y_{1j}, \ldots, Y_{nj}\}$:

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{ij} - \overline{Y}_j\right)^2}, \quad 1 \leq j \leq m \tag{3}$$

Thus, the correlation matrix R can be defined:

$$R = \frac{1}{n} Z^T Z, \tag{4}$$

Now, let $\{\lambda_j\}_{1 \leq j \leq m}$ and $\{v_j\}_{1 \leq j \leq m}$ respectively be the eigenvalues of R and their associated eigenvector coordinates in an original basis B_o. Then, using the Gram-Schmidt orthogonalization process, we can obtain from B_o an orthonormal basis B_n. The corresponding change of basis matrix is denoted P. Thus, the eigenvector coordinates C in the orthonormal basis B_n are:

$$C = PZ \tag{5}$$

At present, let us look for the principal components to reduce the problem size, which could be particularly interesting in the case where m is large. If the problem is reduced to a two-dimension subspace, the principal components are associated to the two largest eigenvalues of R. We will subsequently denote these two eigenvalues by λ_a and λ_b, $1 \leq a \leq m$, $1 \leq b \leq m$. Such an assumption about the number of principal components can be considered as satisfied by computing the inertia I_j of each component:

$$I_j = \sum_{i=1}^{n} Z_{ij}^2 , \quad 1 \leq j \leq m \tag{6}$$

Indeed, if the sum of the two inertias I_a and I_b represents at least about 80% of the total inertia, then, the number of principal components can be considered as satisfied. In the opposite case, a more important number of principal components must be considered.

Finally, for the j^{th} variable ($1 \leq j \leq m$), the two principal components are the two coefficients C_{aj} and C_{bj}. For the sake of clarity, we will subsequently denote:

$$X_j = \begin{bmatrix} C_{aj} & C_{bj} \end{bmatrix}^T , \quad 1 \leq j \leq m \tag{7}$$

Plotting the vectors X_j for $j = 1, \ldots, m$ into the same figure leads to a correlation circle as depicted in Fig. 1, where F_1 and F_2 are the two axes corresponding to the two principal components.

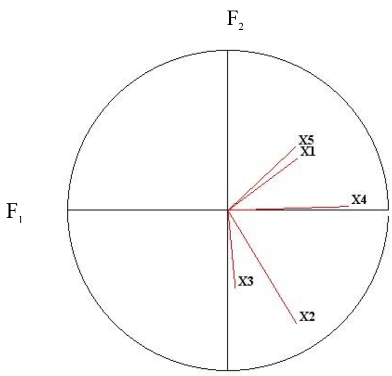

Figure 1 : Example of a correlation circle for $m = 5$

In the above example, vectors pointing in the same direction indicate that they are correlated (here, X_1 and X_5). Vectors in opposite way correspond to anti-correlated measurements and orthogonal vectors to uncorrelated measurements (here X_1–X_2 and X_5–X_2).

The baseline PCA algorithm is an offline method. To use it in a real time setting, one has to consider a sliding window of size h. In other words, at discrete time $k \in \mathbb{N}$, the PCA algorithm is applied to the measurements included between times $k - h + 1$ and k. Thereby, at each time k, a correlation circle as illustrated in Fig. 1 is computed. This circle, and more especially the norms of the vectors X_j, can notably vary with time in the case of faults.

1.2 Exploration of PCA component for fault detection

As stated in the introduction, the PCA algorithm can be used for fault detection and diagnosis. For example, by following the evolution of the reduced parameters obtained in a steady system [15], or coupled with another algorithm to identify signature of a fault when a model is available [16]. An overview of use of the PCA algorithm in fault detection can be found in [17]. Here, the system under consideration is unsteady and no model is known, that's why we are interested in investigating another way to use the PCA algorithm to detect fault.

We assume the healthy case is known. Thus, we have at our disposal the time evolution of each vector norms $||X_i||$ with $1 \leq i \leq m$ in the correlation circle. In absence of fault, the healthy reference and real-time computed norms are very close (but they are not perfectly identical notably because of measurement noise). In presence of fault(s), these two values are different relative to each other for $i \in [1; m]$. We are then able to detect one or several faults. As long as the healthy case and the studied case are close, variation between the two correlation circles in term of norm are negligible or inexistent.

The difference between the two norms can be used to plot a residual that will be used for fault detection procedure. The advantage of this method is to process a wide number of data and sensors easier than if we process them with a conventional method.

2 APPLICATION

The underground laboratory of Bure is installed implemented in clay rock. Galleries are located at 500 meters deep; one of them, the GCR[3] gallery (figure 2) is the gallery considered in this section. This concrete liner used to take charge of the ground.

The ORS[4] section is implemented in this GCR gallery. This section is used to monitoring the behaviors on the clay, the concrete and to observe the evolution of the coating and the retaining. To do this, some sensors technologies are used like optical fibers, TDR (Time Domain Reflectometry) sensors or VWG. All sensors presented here are implemented in-situ.

VWG sensors are particularly used in this paper. The aim of these sensors is to observe deformation of a concrete structure. This kind of sensors delivers a discrete time signal $\{y_k\}$ where k is the discrete time and $k \in \mathbb{N}$. An abnormal change of the deformation reported can be interpreted as a system fault.

[3] Rigid Conception Gallery.
[4] observation of the coating and retaining

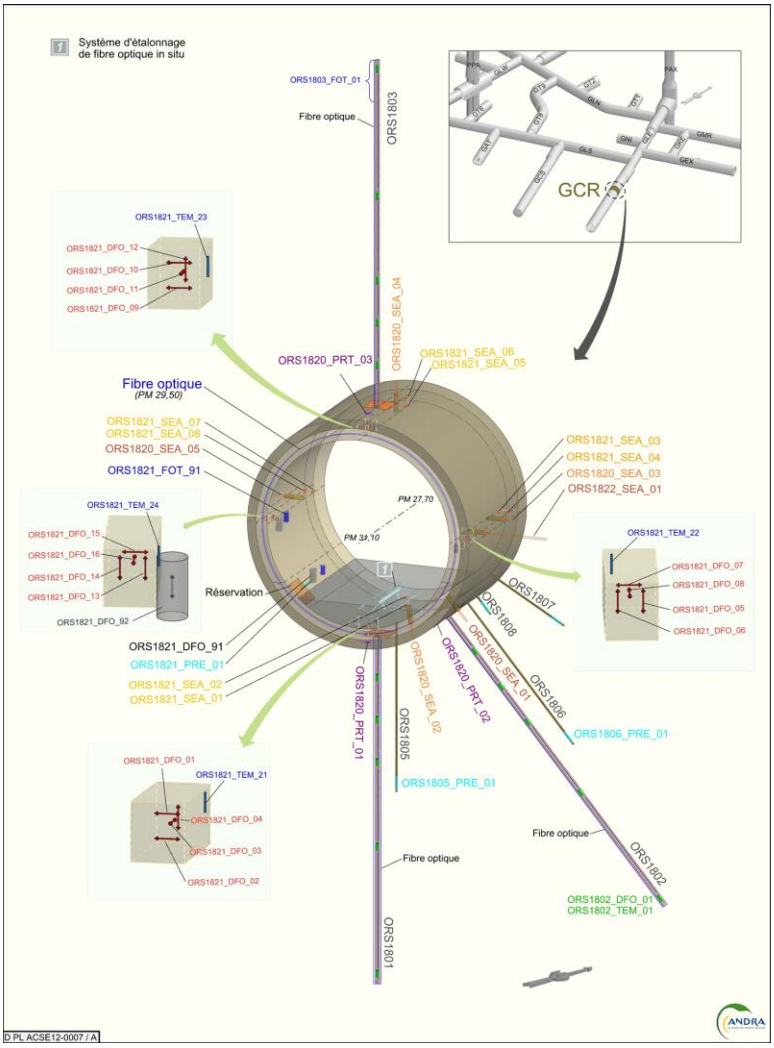

Figure 2 : View of the ORS section

Sixteen VWG like one presented figure 3 are inserted into the ORS section under consideration. In the health case, the time-evolution of their measurements during 12 weeks is plotted in fig. 4.

Figure 3: A vibrating wire gauge

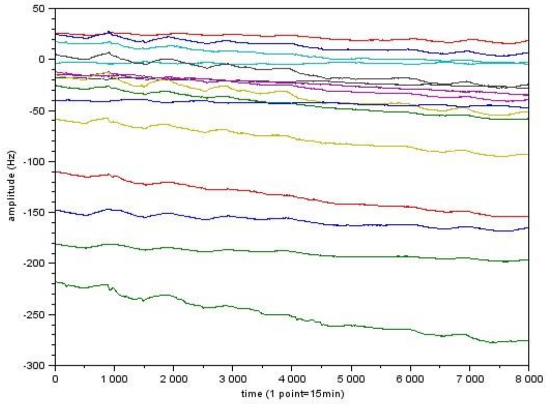

Figure 4: VWG measurements in the nominal case.

Applying the PCA algorithm regarding the method given in 1.2 allow to trace correlation circles of sensors measurements. This circle for … is shown in fig. 5.

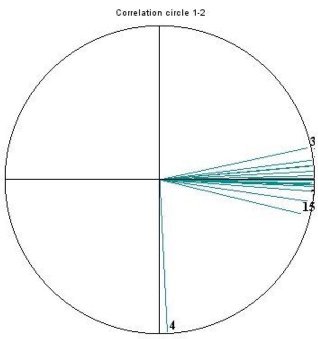

Figure 5 : Correlation circle in nominal case for time k = 1

Now, a fault is introduced on these measurements. The fault is added between k=1000 and k=1200, these 200 points correspond to two days. The size of the fault is 70Hz.

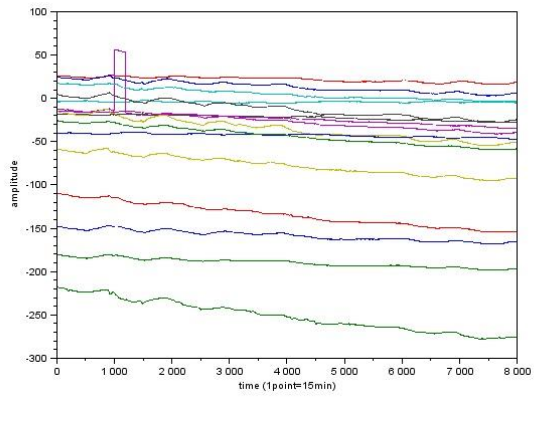

Figure 6: VWG measurements in the faulty case.

The new correlation circle is plotted in fig. 7. We can clearly see a difference with the nominal correlation circle in fig. 5. Then, a change in the norm of some vectors occurs, allowing the detection of the fault. This is confirmed in fig. 8 and 9 where the blue lines correspond to the time-evolution of the vector norm and the red ones to the faulty case.

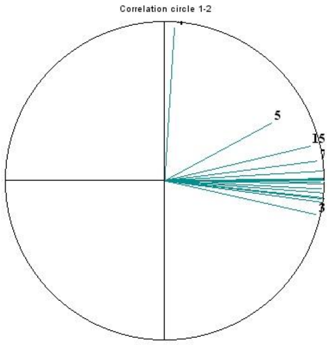

Figure 7: Correlation circle at time k = 1 in the nominal case

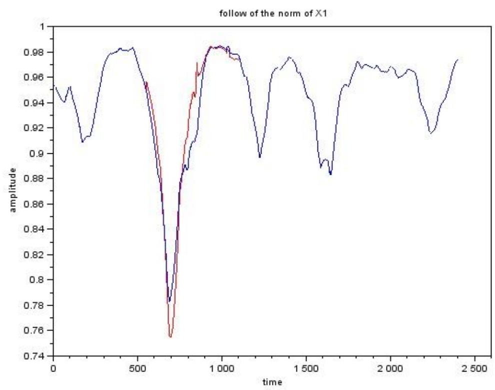

Figure 8: Comparison between healthy case and faulty one (not directly affected by the fault)

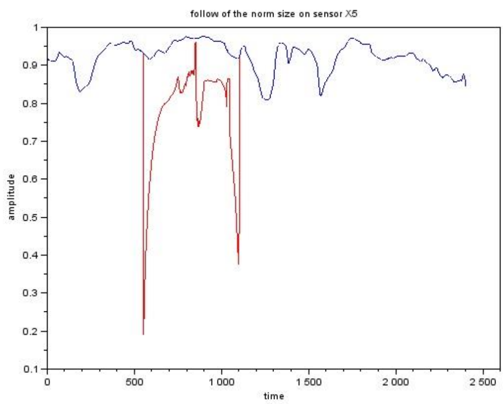

Figure 9: Comparison between healthy case and faulty one (directly affected by the fault)

Two cases can be distinguished if a sensor is directly affected by a fault or not:

- In the first case: the evolution of norm curves, for faulty and nominal measurements, is almost the same (fig. 8),
- But, in the second case: the norm curves are spaced relative to each other (fig. 9).

In this work, the results have been obtained in the case of a unique sensor fault. It permit to obtain a good detection indicator.

3 CONCLUSION AND PERSPECTIVE

In this paper, a PCA based algorithm has been proposed for sensor fault detection. It consists in comparison between the norm curves for faulty and nominal cases. The case of a unique sensor fault has been considered. The detection of the fault is feasible by using, for example, residual. As outlook of this work, on the one hand, it is very important to resolve the fault isolation problem in the case of a unique sensor fault. On the other hand, the case of multiple faults is very interesting to be considered.

Then, all of these results can be easily extended for micro-crack detection in the concrete.

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