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Long-time monitoring of the G. Meazza stadium in a pattern recognition prospective

Alessio Datteo[a], Francescantonio Lucà[a], Giorgio Busca[a]*, Alfredo Cigada[a]

[a]*Mechanical Engineer Department, Politecnico di Milano, vi La Masa 34, 20156, Italy*

Abstract

In recent years, the interest for the automatic evaluation of the state of civil structures is increased. The development of Structural Health Monitoring is allowed by the low costs of the hardware and the increasing of the computational capacity of computers that can analyze considerable amount of data in short time. A Structural Health Monitoring (SHM) system should continuously monitor structures, extracting and processing relevant information, in order to efficiently allocate the resources for maintenance and ensure the security of the structure. Considering the latest developments in this field, great attention has been paid to data-based approaches, especially to autoregressive models; these econometric models, born in the field of finance, are usually used to analyze the vibration time series provided by the sensors applied on the monitored structures. Indexes based on these autoregressive models can be used as features by which the structural integrity can be assessed. This work proposes the application of multivariable analysis, the Principal Component Analysis (PCA), to the parameters of autoregressive models estimated on the vibration responses of a real structure under operational conditions. This approach reduces a complex set of data to a lower dimension, by representing the behavior of the structure through the few variables. This work uses the principal components of the autoregressive model parameters as indicators that can effectively describe some important environmental effects. The strategy is applied for the first time on the data collected by the long-time monitoring system installed on the stands of the G. Meazza stadium in Milan. The results will show that this procedure is effective in representing the status of the structure and can be used in a structural health monitoring prospective.

Keywords: statistical pattern recognition, autoregressive models, principal component analysis, structural health monitoring, environmental conditions, operational conditions.

* Corresponding author. Tel.: +39 02 2399 8553; fax: +39 02 2399 8585.
E-mail address: giorgio.busca@polimi.it

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1. Introduction

The main tasks in the field of maintenance of structures are guarantying high security standards and efficiently allocating the available resources for maintenance; in order to achieve these two goals, it is crucial to correctly evaluate the health state of existing buildings. Nowadays, the research is focused on the development of efficient ways to assess and predict structural performances through the extraction of relevant information from huge amount of data collected by acquisition systems. In this scenario, Structural Health Monitoring (SHM) is a research field which deals with the development of automatic damage detection strategies for civil, mechanical and aerospace engineering structures.

Recently, unsupervised learning strategies based on Autoregressive models (AR) have been largely adopted in the literature in the context of vibration-based methods [1]–[5]. A lot of examples of applications of features based on AR modelling to real structures can be found in the literature; these strategies have been tested mainly on bridges, where environmental and operational conditions have significant effects [6][7][8][9][10]. Generally, the responses of the structure are modelled by autoregressive models (AR, ARMA, ARX, etc.) which are used into a data-driven approach for damage detection.

This work investigates on the application of another well-known technique such as the *Principal Component Analysis* (PCA), in combination with AR modelling, with the aim of isolating the damage effect through an effective representation of the state of a structure, taking into account both the impact of environmental and operational conditions.

2. Measurement system of the Giuseppe Meazza Stadium

The Giuseppe Meazza stadium, built in Milano in 1925, is the largest sport arena in Italy by capacity (Fig. 1 (a)). The structure was initially composed of four straight stands with a capacity of 35,000 spectators, increased over the years up to about 80,000 spectators. First, in 1935 the building of the connecting corners completed what nowadays is the first ring. Then, a load-bearing structure was built in 1955; this structure was designed to support a second ring of grandstands that surround and partially cover the stands of the first ring. In 1990, eleven concrete towers were erected around the stadium with the purpose of supporting a third ring and the roof of all the seats. Four towers at the corners of the structure sustain the trusses which carry the roof; the remaining seven towers hold the box girders, made of reinforced pre-stressed concrete, which support the stands of the third ring. As Fig. 1 (b) shows, the stadium could be divided into three substructures.

The dynamic monitoring system, which consists of two accelerometers for each stand of the second and third tier (one of each direction, vertical and horizontal, as reported in Fig. 1.(b)), records time histories of acceleration of all the stands. The accelerometers used to measure the vibrations are PCB 393B12, ICP seismic accelerometer with sensitivity of 1019,4 mV/(m/s2), measurement range of 4,9m/s2 peak and frequency range (±10%) from 0,10 to 2000 Hz. All the signals needed for the long-time monitoring of the structure are acquired in continuous mode by five

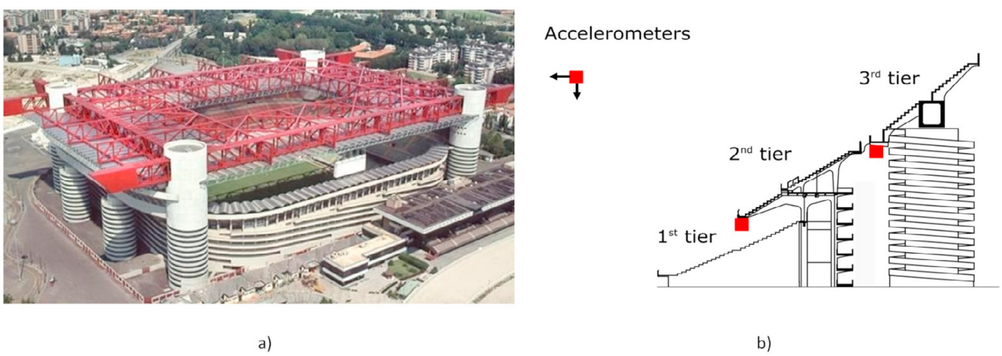

Fig. 1. (a) The Giuseppe Meazza stadium; (b) cross section of the Giuseppe Meazza stadium.

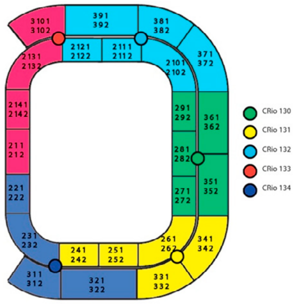

Fig. 2. Layout of the nodes of the monitoring system of the Meazza stadium.

Compact-Rio acquisition units by National Instruments with a sampling frequency of 128Hz. Fig. 2 shows the layout of the measurement system: the stands are signed with different colors accordingly to the Compact-Rio unit that acquires the data. For each stand, there are two channels indicated by a numeric ID: the first digit (2 or 3) indicates the corresponding tier, the second digit the stand, whereas the last one specifies the measurement direction (1 vertical, 2 horizontal).

The data analyzed for this work are recorded from the accelerometers placed on the 11th stand of the second ring (channels 2 11 1 and 2 11 2, with reference to Fig. 2). This choice is made with the aim of investigating the potentiality of the monitoring strategy on just one stand.

3. Long-time monitoring procedure

This section will give a brief theory explanation of the two main tools adopted for the strategy proposed in this paper: Autoregressive models (AR) and the Principal Component Analysis (PCA). The procedure consists in modelling the dynamic response of the structure with an AR model and then performing the PCA of the AR parameters.

By means of an AR model, it is possible to estimate the value of a generic stationary process X at time t by the linear combination of its past values and a random term.

If $x_t, x_{t-1}, x_{t-2}, \ldots$ are the values of the series at equally spaced times $t, t-1, t-2, \ldots$, and $\tilde{x}_t, \tilde{x}_{t-1}, \tilde{x}_{t-2}, \ldots$ are the deviations from the mean value μ, i.e. $\tilde{x}_t = x_t - \mu$, it is possible to express $\tilde{x}_t$ as:

$$\tilde{x}_t = \phi_1 \tilde{x}_{t-1} + \phi_2 \tilde{x}_{t-2} + \cdots + \phi_p \tilde{x}_{t-p} + + \cdots + a_t \tag{1}$$

Where p is the model order, $\phi_1, \phi_2, \ldots, \phi_p$ are the constant coefficients of the autoregressive model and a_t represents the stochastic residual, with constant mean $E(a_t)$ equal to 0 and constant variance $Var(a_t) = \sigma_a^2$.

Once the autoregressive model has been estimated on the vibration time histories, the raw data are summarized by the autoregressive parameters which are related to the dynamic behavior of the system.

The Principal Component Analysis (PCA) is a technique coming from multivariate analysis; applying an orthogonal projection to a given data set, the PCA allows a reduction of its dimensionality, maximizing the variance of the projected data, onto a lower dimensional linear space. The new variables, the principal components (PCs), are uncorrelated and they are ordered so that the first few components retain most of the variation present in the original data set.

The use of PCA on the autoregressive model parameters allows a simple representation of the behavior of the structure through few variables, without consistent losing of information. As it is explained in the following, the information contained in collected data can be resumed and represented by mean of the first three principal components, proving the effectiveness of this strategy on providing synthetic features for damage identification.

4. Results and discussions

The data refer to a period of eight months, precisely from the August, 13th 2015 to April, 19th 2016. Among the grandstands managed by the cRIO 132, the vibrations of the 11th grandstands are considered (see Fig. 2). Fig. 3 shows the Power Spectral Densities (PSDs) of the selected channels during the night of September, 13th 2015, as an example of its dynamical behaviour.

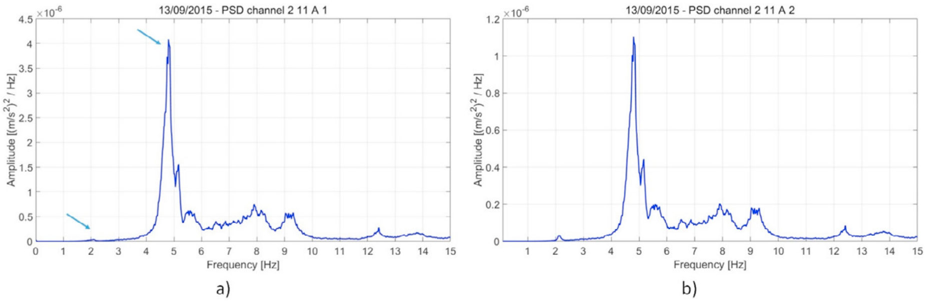

Fig. 3. Power Spectral Density of the selected stand on 13/09/2015: (a) vertical direction; (b) horizontal direction.

The second mode around 5 Hz is the preeminent one since the first mode around 2 Hz, which is mainly horizontal, is lightly excited by operational conditions. Because the horizontal direction is scarcely forced, the analysis is focused only on the vertical accelerometer on the 11th Stand of the second tier of the stadium.

Time histories of one minute duration of the system response are considered to compute the AR model. In this way, it is potentially possible to represent the effect of short time events on the structure dynamic, like the celebration of a goal during a football match or the people dancing during a performance at a concert. The time histories are filtered at 15 Hz with a sixth order Butterworth zero phase filter, since the main dynamic of the stand due to the ambient excitation is under 10 Hz, as shown in Fig. 3.

The first step of the procedure is to estimate the AR parameters on the time histories. The filtered time histories are initially normalized by removing their mean value and dividing them by their standard deviation. Another required pre-operation is to establish the optimal AR order for the considered time histories. For all the time histories, the AR model order is fixed at 40 by the BIC criterion.

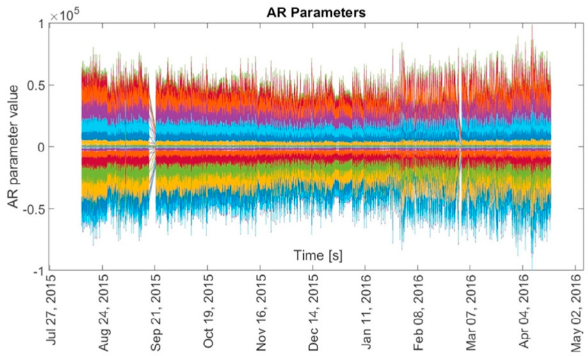

Fig. 4. Evolution of the 40 AR parameters from 13/08/2015 to 19/04/2016.

Looking at the evolution on time of all the AR parameters together (Fig. 4), it is difficult to extract useful information on the progression of the system during the considered period. The PCA on the AR parameters will allow to maximize the variance of the information carried by the data, projecting the multivariate problem on few principal directions, as it will be seen in the following sections.

The second step of the procedure performs the PCA of the AR parameters. The principal component analysis provides also the amount of the variance of the original data for each principal component. Fig. 5 shows the first three principal components from August, 13th 2015 to April, 19th 2016. From this figure, it is possible to notice two different behaviours: a slow variation on the long-term and a daily oscillation with higher variance. The long-term trend can be seen better by estimating the moving average of the principal components.

On the period taken into consideration, it is available the maximum, minimum and average temperature for each day, and also the daily humidity. Therefore, the first idea is to check if these long-term trends could be related to the environmental seasonal effects. Considering the variation of temperature, Fig. 6 reports the moving averages of the three principal components estimated over a time window of a week and the daily temperature time history, both given with the same time resolution.

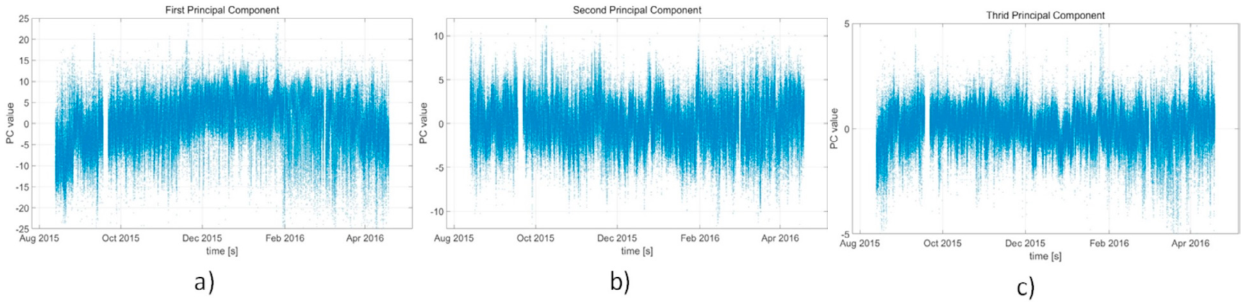

Fig. 5. Evolution of the PCs from 13/08/2015 to 19/04/2016: (a) first PC; (b) second PC; (c) third PC.

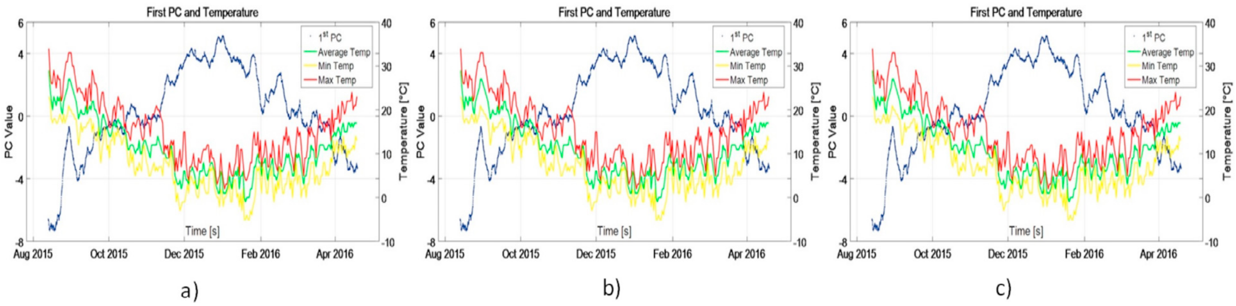

Fig. 6. Filtered evolution of the PCs with the temperature evolution from 13/08/2015 to 19/04/2016: (a) first PC; (b) second PC; (c) third PC.

It is possible to state that the first principal component is inversely correlated to temperature, whereas the second and the third principal components seems to be less correlated to this quantity. To quantify this correlation, the index of linear correlation (Pearson's index) between the principal components and the temperature is calculated.

The values of the index of Pearson for the minimum, maximum and the mean temperature are reported in Table 1. The same considerations are made for the humidity, again just the first component reveal a possible correlation with the humidity. In this case the Pearson's index reaches the value 0.44 for the first PC.

Referring to Table 1, it is possible to state that the first principal component has a strong correlation with temperature and a moderate correlation with humidity those could justify its trend on the long period. Conversely, the other two components seem to be less sensitive to environmental changes.

Now, it is analyzed the trend of the PCs on a short-term period by reducing the observation window, for instance from the September, 30th 2015 to October, 6th 2015. The first three principal components with the superimposition on the RMS values during this week are reported in Fig. 7. All the three principal components show a daily trend. Fig. 6 is suitable to state a low variation of the PCs due to the effect of the temperature; for instance, a 30°C temperature difference between winter and summer entails a change in the PC scores of just few units. On the contrary, the daily trend is much higher than the long-term trend.

Table 1 Pearson's index value between the Principal Components and temperature, humidity and RMS.

CASE	Pearson's Index Value	CASE	Pearson's Index Value	CASE	Pearson's Index Value
PC 1 vs average Temp	-0.77	PC 1 vs Humidity	0.44	PC 1 vs RMS	-0.47
PC 2 vs average Temp	0.31	PC 2 vs Humidity	-0.02	PC 2 vs RMS	-0.75
PC 3 vs average Temp	0.15	PC 3 vs Humidity	-0.05	PC 3 vs RMS	-0.74

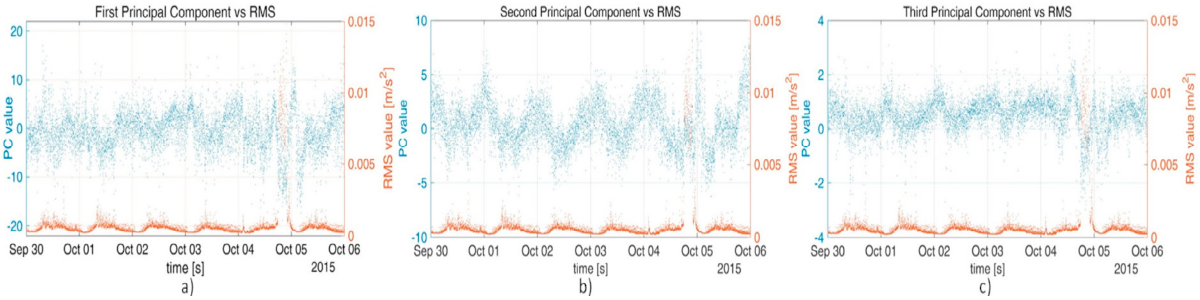

Fig. 7. Weekly evolution of the PCs against RMS values of acceleration from 07/09/2015 to 14/09/2015: (a) first PC; (b) second PC; (c) third PC.

Therefore, it is unreasonable to explain the short-term evolution of the PCs by a change of the environmental conditions. The source of the strong variability of the PCs' scores could be due to the operational conditions affecting the structure, like a change of the traffic intensity around the stadium from day to night. To prove that, the RMS values estimated over a time window of 10 minutes are plotted in Fig. 7 together with the PC scores. There, the correspondence between the PCs' and RMS time evolutions can be easily seen. It can be also seen a discontinuity on both PCs and RMS on October, 4th 2015 when a football match took place in the stadium. Therefore, the plots show a clear correlation among the PC scores and the intensity of the vibrations inducted on the structure.

This correlation could be quantified by the Pearson's index between the scores of each PC and the RMS values. Table 1 reports these values; the first PC has a moderate inverse correlation with RMS, whereas the second and the third PC have a strong correlation with the operational conditions. It is worth to remember that the first PC has also a strong correlation with the environmental conditions, while this dependency is lower for the other two components. Therefore, it could be assumed the first PC mainly carries information on the long term seasonal evolution, while the other two components are more linked to the vibration level in the stadium. This clear dependency on environmental and operational condition is fundamental for a SHM prospective. It means that the procedure is able to correctly describe the system and its variation due to external contributions through a deterministic trend.

5. Conclusions

The application of a long-term monitoring strategy based on the PCA of the AR parameters modelling the vibration response of a stand of a stadium is presented in this paper. The results have shown a good correlation between the PCs and the main environmental conditions, such as temperature and humidity. More specifically, it has been observed that the first PC seems to be more influenced by the change of the weather conditions, while the other two components have shown a clearer dependency from the operational conditions. This dependency has been verified by quantifying the entity of the excitation of the structure with the RMS of the signals themselves. In a SHM prospective, it is crucial to isolate the deterministic effect of environmental and operational conditions on the PC scores for a successful damage detection. Since the relationship is deterministic, that some approaches for data normalization can be proposed and tested in order to filter out these effects, overcoming the main application limit of unsupervised techniques. Solving this issue, the proposed technique could be efficiently used also for SHM purposes, being included into an automatic damage detection process.

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