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SHM analysis for damage detection using time series analysis methods

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ABSTRACT: SHM is generally performed using continuous vibration or deformation monitoring. These signals correspond then to time series, whose evolution can be predicted based on their past history. This paper presents such a study on the Austerlitz bridge in Paris: it is a steel bridge, built during the 19th century, and carries the Parisian metro since then. The monitoring is therefore important to detect anomalies in its behavior. For that, it has been instrumented by 24 strains sensors (optic strands) and 4 temperature sensors, which record the corresponding signals during train passages at a 100Hz frequency. The individual passage signals have been extracted, the corresponding data has been gathered (data fusion) and cleaned. Finally, the evolution of the monitoring signals has been predicted based on their evolution with time and temperature. Machine Learning algorithms of type VARMAX have been used to realize the time prediction. The anomalies, defined as differences between the prediction and measured signals, have been identified. This paper will explain the context and the research questions, the work that has been realized and to finish the still-open points.

1 INTRODUCTION

1.1 Background

In France, 10% of the value of the road heritage comes from the engineering structures that are existing in the country (estimated at 200,000 to 250,000 bridges) (Patrick, 2019). This road network is used a lot since it ensures 88% of all trips for freights and people travels, which is why it plays an essential role in the communication and the economy of the country. However, a survey by the IPSOS institute has highlighted an increase in the rate of dissatisfaction of the French people, which has risen from 17% to 22% in two years (Patrick & Michel 2019). This follows the collapse of the Morandi bridge in Genoa in 2018, which revived the debate on the safety of engineering structures and the memory of the Mont Blanc tunnel disaster in 1999. This feeling may be justified when we know that a third of the bridges managed by the French State require repair, according to the Ministry of Ecological Transition and Solidarity in 2018, and that all metal bridges are in non optimal health condition. This leads to traffic restrictions or closures, which is detrimental to economic activity, the environment and the mobility.

This ageing of the French road network is perfectly normal and expected, since the theoretical lifespan of a bridge structure is estimated at 100 years. However, many bridges were built before the year 2000 and the introduction of European standards (Eurocodes, Eurocodes 1992), which means that their lifespan is less than the expected 100 years and tends to be around 70 years. Indeed, a large proportion of the structures were built in the post-war period, in the 1950s and 1960s, and should therefore reach the end of their life very soon and at the same time. This lifespan varies according to several factors such as the type of bridge but also global warming and environmental conditions which can lead, for example, to corrosion (see for example Île de Ré bridge), conditions of use (with the increase in road traffic, some advice of GPS to use the secondary network to avoid slowing down while it has been not designed to receive such loads), or the quality and regularity of maintenance.

The last point tends to be lacking as the inventory of bridges in France is complicated since the managers of some of them are not always known. Moreover, the monitoring of deterioration is only visual, which is far from sufficient to identify certain types of pathologies, such as corrosion, which develops inside the materials. There is therefore a need to address the problem further upstream. However, under-investment and lack of technical skills are a problem as small municipalities do not always have the means and skills to check the condition of their structures and maintain them. It is therefore necessary that the tools used are adapted to all, including local managers, since this emergency management of assets is not good maintenance practice and is neither sustainable nor economically viable in the long term.

A solution which is nowadays widely proposed is the intensive monitoring of structures, also called Structural Health Monitoring. Nevertheless, this monitoring may sometimes lead to (big) amount of data, which may therefore be difficult to be treated. More precisely, it might be difficult to extract pertinent information which would help the infrastructure manager to take decisions related to maintenance, repair, or strengthening actions (Tripura, 2000), (Salawu, 1997), (Seo, 2015).

1.2 *State-of-the-art*

Damage detection is traditionally done through vibration analysis, see (Burgos, 2020), (Lakhdar, 2013) for some examples in the civil engineering domain. Nevertheless, these methods are of various natures, depending on the focus they make, namely on eigenvalues (Belmokhtar, 2022) or eigenmodes, or the mathematical/algorithmic procedures for dealing with the fact that the actions on the structure are unknown (Sadhu, 2017), (Bandara, 2014). Nevertheless, it may be quite difficult to propose or use some criteria to decide if changes/damage in the structure have occurred (Jayasundara, 2019).

Therefore, with the development of bigger data volumes, new ways of detecting damages have been proposed (Rasol, 2023) (Wang, 2022): while some works use supervised learning methods (Zhou, 2013), some others propose unsupervised methods (Entezami, 2020). In particular, neural networks are used to predict future time series, and assess the deviation between this predicted data with the “real”, measured one (Manzini, 2021) (Xu, 2015). Changes can then be detected, also via pattern recognition (Yeung & Smith 2005).

It should be noted that other Machine Learning methods are sometimes proposed, like random forests (Zhou, 2013) and XG-Boost (Wang, 2022).

This paper proposes to predict the time series of strain sensors, using the theory of ARMA processes and comparing the predicted values with the measured ones.

2 THE AUSTERLITZ VIADUCT AND ITS MONITORING SYSTEM

2.1 *A steel arch bridge*

The Austerlitz viaduct allows metro line 5 to cross the Seine between the Austerlitz station and the quai de la Rapée (Figure 1).



Figure 1. Photo of Austerlitz bridge.

The viaduct consists of two arches of 20 metres in span with three joints, one at the top of the arch and two at the abutments. This system creates an underpinning at the supports, the span of the arch is thus reduced from CC' to RR' , which is equivalent to going from 140

Table 1. Name of sensors and corresponding structural elements.

| Name of sensor | Monitored structural element |
|----------------|------------------------------|
| S1 | Anchoring beam Austerlitz |
| S2 | Braking tie-rod Austerlitz |
| S3 | Upstream side beam |
| S4 | Downstream side beam |
| S5 | Braking tie-rod Rapée |
| S6 | Inside bottom hanger |
| S7 | Outside bottom hanger |
| S8 | Lower arch |
| S9 | Upper arch |
| S10 | Low diagonal brace |
| S11 | Transverse brace |
| S12 | Diagonal brace Austerlitz |
| S13 | Diagonal brace Rapée |
| S13 | Anchoring beam Rapée |

- The tie rods behave in the opposite way to the opposite to the anchor beams. The tie rod on la Rapée side becomes longer while the tie beam on the Austerlitz side undergoes a shortening.

The characteristics of these sensors in term of period and frequency of acquisition and number of the total data that are recorded by each sensor are various:

- For the strain sensors that are installed on structures S1, S2, S3, S4, S5, S6, S7, S8, S9, S10, S11, S12, and S13, the acquisition period starts from 01/09/2020 and ends 23/09/2021, which means that a whole year of measurement is available. For the sensor installed at S14, the acquisition started on 25/01/2021, which has as consequence that we will not be consider this sensor in the analysis. The acquisition of these sensors is triggered when the subway passes, and the acquisition frequency is 100 Hz. During the acquisition period, each of the 13 strain sensors recorded around 500 million points of data. It is noted that as the acquisition is done at the subway crossings, the recording is not continuous, therefore there exists missing data.
- For the 3 temperature probes, the acquisition started on the 01/09/2020 and ended on 23/09/2021, with one acquisition for 10 minutes. Each temperature probe recorded 56285 pints of data. They are installed on structures S8, S1 and S7, and denoted T1, T2 and T3 respectively.

Data processing has been performed with Python language, in Jupyter notebook, using libraries Numpy, Pandas, Scipy, Sklearn, seaborn and matplotlib. In this article, the study is focused initially on the analysis of data from different types of sensors (strain, and temperature) in order to understand how the different structures of the bridges behave in terms of strain when the subway passes.

3 DATA ANALYSIS AND TIME SERIES PREDICTION

3.1 Data analysis

Looking now at the evolution of the strain within the structures that are close (in space), we see that the trend is the same. The correlation matrix (Figure 4) shows that the strain correlation between:

- S1 and S2 is 0.88,
- S3 and S4 is 0.98,
- S6 and S7 is 0.91,
- S8 and S9 is 0.62,
- S10, S11, S12 is between 0.88 and 0.93. However, S13 is less correlated with S10, S11, and S12 with a correlation between 0.57 and 0.64.



Figure 4. Correlation matrix between all sensors (strain and temperature).

As the evolution of the deformation is the same when the structures are close, we have therefore selected to use only the data from the sensors S1, S3, S5, S6, S9, and S10 for the rest of the analysis.

3.2 Time effect removal

The strain within the majority of bridge structures is temperature dependent. It is therefore necessary to correct this effect of temperature, to see the other factors which can influence the deformation of the structures. To eliminate the effect of temperature, the proposed method is as follows:

- Calculate the correlation between strain and temperature values. If the correlation coefficient between the two parameters is close to 1, this means that there is a linear relationship between the two parameters (see Equation (1)):

$$\tilde{\epsilon} = A \times T + B \quad (1)$$

- Apply the Linear Regression prediction model to find the values of A and B of Equation (1) which gives the prediction line, i.e. the predicted strain values $\tilde{\epsilon}$.
- Calculate the difference between the real values of strain ϵ and the predicted one $\tilde{\epsilon}$ to obtain the time evolution of the strain values corrected ϵ_{corr} with no temperature effect.

Figure 5 shows the relation between the real values of the strain of structure S1 and the temperature at the same time: the relationship is linear, which confirms the value of the coefficient of correlation of 0.96 found by the correlation matrix (see Figure 4). The red line in Figure 1 is the predicted strain values $\tilde{\epsilon} = 0.077 \times T - 0.29$. Figure 6 shows the strain time evolution with temperature effect (right graph) and with no temperature effect (left graph): the measured strains are more stable (in amplitude) along time.

3.3 Time series prediction

For temporal signals, we can use ARMA, or ARIMA type models when the signal has to be derived as input. In our case, we have multivariate data for which we wish to use and explore the inter-sensor dependencies. We can then consider multivariate VARMA (Vector Autoregressive Moving Average) extensions. We propose here a variation around these models. We note $x(t)$ the vector of dimension d collecting all the measurements of the d sensors at time t . The model takes the form:

$$x(t) = A_0 x(t) + \sum_{k=1}^p A_k x(t-k) + c + \epsilon(t), \quad (2)$$

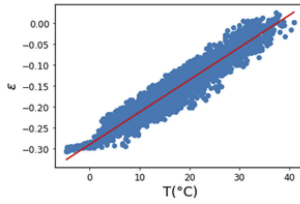


Figure 5. Relationship between strain at S1 and temperature values.

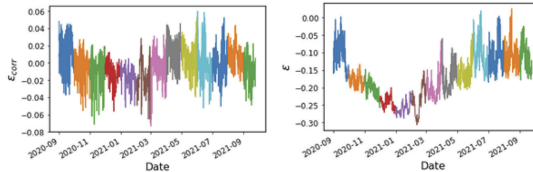


Figure 6. Time strain evolution at structure S1: measured value of strain (right), and corrected strain values with no temperature effect (left).

where matrices have dimension $d \times d$, c is a vector of offsets, and where matrix A_0 is constrained to have zeros on its diagonal. The role of A_0 is to take into account dependencies between signals (sensors) at the same time t . A LASSO regularization is used to stabilize the method and has the interesting property of forcing the coefficients of non-active variables to zero.

A prediction of $x(t)$ can be done according to:

$$\hat{x}(t) = A_0 x(t) + \sum_{k=1}^p A_k x(t-k) + c, \quad (3)$$

where $\epsilon(t)$ is the error or prediction residual. This means that a component j is computed as:

$$\begin{aligned} \hat{x}_i(t) &= \sum_{i=0, i \neq j}^d [A_0]_{i,j} x_i(t) \\ &+ \sum_{i=0}^d \sum_k k = 1^p [A_k]_{i,j} x_i(t-k) + c_j. \end{aligned} \quad (4)$$

A value at time t will be estimated as a function of the outputs of other sensors at the same time, and of all sensors outputs at previous timestamps.

For our experiment, we learn the model, i.e. we determine the coefficients, on a part of the data and compute the residuals on the whole data, which allows us to test the predictive capacity on data that have not been used for learning. The data are thus split into a learning part (from September 2 to May 17: two thirds of the data) and a test part (the last third, from May 18 to September 23, 2021). In order to test the capacity of the model to detect anomalies, we have introduced:

- An attenuation of 0.97 on AMPL-AS between the first and 14 of July,
- A factor of 1.05 on AMPL-TFR between 12 and 20 August.

For $p = 0$, the model only explores the interactions between sensors at the same time. In other words, the output of a sensor is only computed from the outputs of the other sensors at the same time. The coefficients of the sensors, and thus the dependencies they reveal, are given in Figure 7.

The residuals are computed, and we note that the introduced anomalies are correctly detected (the “boundaries”, related to the derivation, appear clearly between July 1 and 14 for AMPL-AS and on several other sensors, and from August 12 to 20 for AMPL-TFR). Other points are detected around February 10, when an exceptional freezing period is known to have occurred.

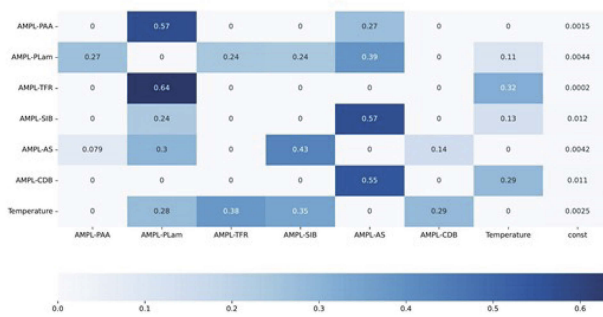


Figure 7. Coefficients of sensors for $p = 0$.

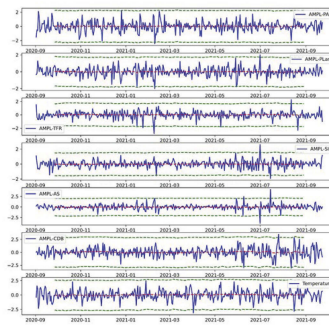


Figure 8. Residuals of prediction for $p = 6$.

For $p > 0$, the results are very similar. The coefficients associated with the time lags are small, and the improvement in the residuals remains tenuous (Figure 8). This indicates that there is in fact little temporal dependence between the samples; or at least that it has been removed by the initial derivation operation.

The predictions obtained show that the model allows to correct the effect of the artificially introduced defects (see Figure 9).

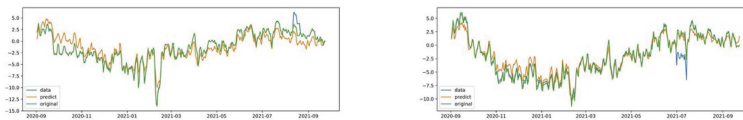


Figure 9. Prediction obtained for a defect on TFR and AS, for $p = 0$.

4 CONCLUSIONS

This work has shown a simple and yet effective method, using time series prediction, to detect changes in behaviour of structures. For that, the time series are analysed and simplified, first by considering only data which is non- (or less) correlated with other, then by removing the effect of temperature which is a big issue in civil engineering.

By experimenting on these data and introducing artificially anomalies into the measurements – which would simulate either a true structural anomaly or a sensor anomaly; we show that the regularised VAR statistical model learned on a portion of the data, is able to (a) detect anomalies on the unseen portion of the data, (b) correct the effect of these anomalies on the data; thus being able to compensate for a deficient sensor.

Future work are on the possibility to introduce physical/mechanical calculations in the analysis, especially for structures like Austerlitz bridge which are quite easy to model.

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