

Optimization of CVAE parameters for the damage assessment of historic masonry buildings

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Abstract – Artificial Intelligence (AI) based on a deep learning procedure through Convolutional Variational autoencoders (CVAEs) have been previously explored to analyze vibration data with the aim of assessing the state of damage of historic masonry structures subjected to seismic shakes. Nonetheless, CVAE application can be optimized by investigating the effect of different sizes of the used latent space and the time sequence length. Therefore, in the present work the optimal size of the two fundamental parameters of CVAE in the analysis of white-noise vibration data as dynamic characterization tool of shaking table tests of a rubble masonry prototype was investigated. The optimization process aimed at finding the best compromised size that leads to the maximum reconstruction capacity of the input and, hence, to the maximum utility for classification tasks. The results show that the used indicators, Mean Squared Error (MSE) and the Original to Reconstructed Signal Ratio (ORSR), lead to a bell-shaped optimization space, for the latent spatial dimension and the length of the time sequence, and therefore to the identification of a maximum point. The above optimization process was applied with remarkable results to vibration data of shaking table tests of a building prototype in historic rubble masonry typical of Central Italy.

I. INTRODUCTION

The development of Artificial Intelligence (AI) methods to analyze experimental data has lately provided very interesting results and opened new frontiers in many fields of scientific research. In fact, many Machine Learning (ML) and Deep Learning (DL) applications have already been explored for several purposes, including the monitoring of structural state of damage [1], [2], [3]. More in particular, the use of Convolutional Variational AutoEncoders (CVAEs) has been recently investigated with successful results to identify and classify damage scenarios [4], [5], [6].

Also, an AI procedure based on CVAE was recently explored to point out new parameters capable of estimating the state of damage of structures, such as historic masonry buildings, subjected to seismic tests on shaking table [7].

Nonetheless, the above studies did not investigate the effect of the size of the used latent space in CVAE

procedure. As a matter of fact, the size of these architectures is often neglected, as the main goal is generally to maximize accuracy [8]. However, this usually causes negative effects, such as a remarkable computational time with remarkably redundant training operations. This means that the efficiency of the overall procedure can be improved by reducing time and effort, while providing best accuracy.

In the present work, an optimal Latent Space Size (LSS) and the Time Sequence Length (TSL) were determined by using two parameters: the Mean Squared Error (MSE) and the Original to Reconstructed Signal Ratio (ORSR).

The above CVAE parameters optimization was applied to a seismic test carried out by shaking table of a typical Central Italy historic masonry building prototype [9]. In particular, the vibration data acquired during the dynamic characterization tests performed before and after the seismic shake were analyzed.

As dynamic characterization tests, a white-noise vibration at 0.05 g of Peak Ground Acceleration (PGA) was used to identify the main modes of vibration of the tested structure. In particular, the modal frequencies are extracted because they are clearly influenced by the material stiffness. As widely known, the state of damage of the historic masonry buildings can be estimated in terms of loss of material stiffness in the structure, caused by the arising of cracks in the masonry, provided that other sources of possible influence on the material stiffness, such as changes in environmental and constraints conditions, are negligible. More specifically, the first mode is usually the one with the higher mass participation, meaning that it substantially takes account of the overall dynamic behavior of the entire structure. Consequently, a global damage index can be formulated in terms of decay of the first modal frequency.

The proposed optimization process was explored in the AI-based analysis of vibration data acquired in a shaking table campaign of a 2/3-scaled building prototype made up of historic rubble masonry typical of the area severely hit by the Central Italy seismic sequence of 2016-2017.

II. METHODS

The main steps of the implemented AI-based procedure are synthetically described in the workflow illustrated in Fig. 1.

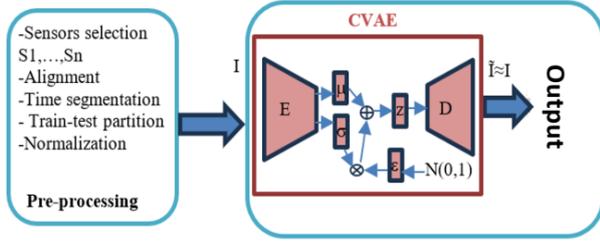


Fig. 1. Workflow of the AI procedure.

Pre-processing operations of the input data I are performed in order to properly prepare the experimental data for the following steps.

Firstly, the data signals to be processed are selected (sensors selection). In fact, this operation is needed to discard bad quality sensors acquisitions that might negatively affect the final results.

Then the selected signals are aligned so as to treat signals of the same duration and referring to the same timing.

Moreover, time segmentation of signals time histories is necessary to provide the CVAE with a proper number of sub-samples for training efficiently the algorithm.

As training is a crucial operation of AI algorithms, the train-test partition is to be chosen properly. In this case the algorithm is trained with the vibration data acquired in undamaged conditions, i.e. before the seismic shakes.

Normalization of input data was applied to each processed signal so as to avoid possible dependence on the intensity level of measurements.

After the above pre-processing operations, the actual AI procedure is applied. The very heart of the overall AI procedure is represented by the CVAE (red block in Fig.1).

The encoder E converts the input data into a probabilistic latent representation, with mean value μ and variance σ . The decoder part D is used to generate artificial data according to the latent representation of the input data.

CVAE is also characterized by a loss function, which comprises two parts: the one is aimed to minimize the approximation of the input data and the other verifies the latent space distribution deviation from a reference distribution (regularization). This regularization is used to provide a more generalized function. A Gaussian-distributed noise ε ($\varepsilon \sim N(0, I)$) is introduced into the latent space to permit the reparameterization trick, which makes the latent sampling differentiable and compatible with back propagation, according to the following equation:

$$z = \mu + \sigma \times \varepsilon \quad (1)$$

The CVAE was trained to reconstruct the vibration data

acquired during the dynamic characterization test performed before the seismic tests. At this point, the structure is still assumed undamaged. Then, the data acquired in the dynamic characterization tests performed after each seismic shake were also reconstructed. The original data of the dynamic characterization tests were treated to extract the value of DI, based on the decay of first modal frequency of the studied structure according to the following formulation [10]:

$$DI_i = \left[1 - \left(\frac{f_i}{f_0} \right)^2 \right] \quad (2)$$

where f_i is the first modal frequency of i -th test and f_0 is the first modal frequency of the initial test when the structure is still undamaged, i.e. the damage index is assumed as zero ($DI = 0$).

Contemporarily, the AI-reconstructed data were also processed. The meaning of the considered metrics were:

- MSE: it measures the reconstruction error between the input of the CVAE and its reconstructed signal
- ORSR: it is the ratio (quantified in dB) between the magnitude of the CVAE input and its reconstructed signal [4] [5].

Values of MSE and ORSR were calculated for each dynamic characterization test. Then, the centroids representing each dynamic characterization test could be visualized in the MSE vs ORSR plan. Finally, the distance of each centroid from the initial centroid at $DI = 0$ provided a centroid distance (CD).

The more the centroids at different DI values tend to be aligned, the more linearly correlated are CD with DI, which can be quantified by the coefficient of determination R^2 . On the other hand, the higher the slope of the linear regression, the better the sensitivity of CD in the DI approximation, according to the general concept of derivative-based methods of sensitivity analysis [11].

Let's assume the general formulation of the linear regression equation between CD and DI as:

$$CD = a \times DI + b \quad (3)$$

where a is the slope of the linear regression equation with coefficient of determination R^2 .

The optimization process maximized the function P defined as follows:

$$P = a \times R^2 \quad (4)$$

which essentially means that we weighted the slope a with the coefficient of determination.

Several TSLs were explored, from 0.32 s to 2.56 s (corresponding to a number of points from 64 to 512 at 200 Hz of sampling frequency).



Fig. 2. Historic masonry specimen subjected to the shaking table tests.

Ultimately, the considered dimensions of the latent space, for each TSL value, were 16, 32, 64, 128 and 256.

III. EXPERIMENTAL

A specimen representing a typical Italian historic masonry building typology was subjected to seismic tests at the shaking table laboratory of the ENEA Casaccia research center, near Rome. The specimen was a 2/3-scaled building prototype made up of typical Central Italy historic two-leaf ashlar masonry (Fig. 2) [12] made up of stones coming from actual rubble of collapsed traditional buildings in 2016-2017 shakes. In accordance to the mortar commonly investigated on the field in the same area, a lime-poor mortar with similar mechanical and chemical properties was used to produce the specimen.

During the shaking table tests, the vibrations of the specimen were recorded by tracking the positions of 91 passive markers of a 3D motion capture system achieving an accuracy in the order of 0.02-0.03 mm at 200 fps.

The specimen underwent several shakes based on recordings at seismic stations AMT, CNE and NRC of the Central Italy earthquake sequence, 2016-2017. The above shakes were scaled in acceleration with increasing steps of 0.05 g of Peak Ground Acceleration (PGA) up to the specimen failure.

After each incremental step, a white-noise vibration at 0.05 g of PGA was performed as dynamic characterization test. The above dynamic characterization data were processed by conventional modal analysis technique in order to extract the first modal frequency. Such fundamental frequency was 11.6 Hz before the seismic tests (f_0 in initial undamaged condition). Therefore, the vibration data were filtered with a low-pass band at 12 Hz.

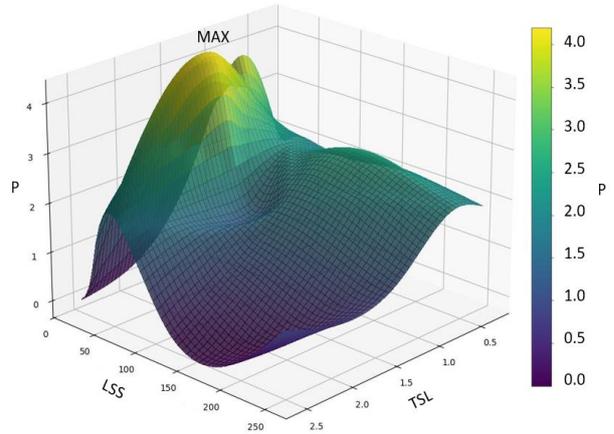


Fig. 3. Graphical representation of the variation of P with LSS and TSL.

Then the values of f_i gradually decayed with the progressive extension of the damage in the structure, reaching down to 2.6 Hz after the final failure. In the overall shaking table campaign nine dynamic characterization tests were performed, providing nine corresponding DI values.

IV. RESULTS

The applied optimization procedure provided the result illustrated in Fig. 3.

The max value of P was 4.131 as product of $R^2 = 0.958$ by $a = 4.312$. Such optimal solution was achieved in the case of TSL of 1.28 s (i.e. with 256 points) and LSS of 32. The corresponding regression between CD and DI is illustrated in Fig. 4.

Fig. 5 shows the DI clusters on the MSR and OSRS plane for the case corresponding to TSL=1.28 s and LSS=32.

In general, the simulations on all the combinations of TSL and LSS have highlighted that for low and high values of the dimensions of the latent space, there is a flat trend of the distances of the centroids from the centroid with $DI = 0$ as a function of the value of the DI. The same can be said about the length TSL of the time sequence, that is, for values of TSL that do not satisfy the condition [13]:

$$TSL \geq 2 \times f_c / f_i \quad (5)$$

where f_c and f_i are the sampling frequency and the fundamental frequency of the response, respectively.

For example, for TSL equal to 0.32 s in our case, as well as for high values of TSL, the trend is flat with a tendency to better classify the data relating only to the highest DI.

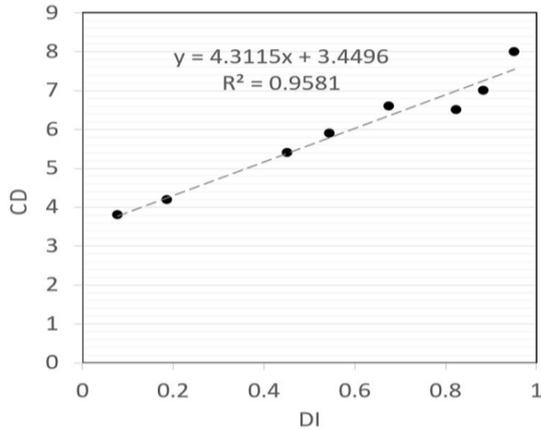


Fig. 4. Optimal solution of linear regression between CD and DI (corresponding to TSL = 1.28 s and LSS = 32).

In fact, in the case of a TSL of 2.56 s, the number of training input data is reduced by a factor of 4 compared to the case of a time length of 0.64 s and this undermines the results since, in general, longer sequences better capture the patterns present in the input data [13].

V. CONCLUSIONS

The present study proposes an optimization strategy of the main internal parameters of the CVAE algorithm applied to an AI procedure implemented to assess the damage in historical buildings.

In particular, the considered objective function in the proposed optimization strategy was the product P between the slope a and the coefficient of determination R^2 of the regression equation between CD and DI.

Maximizing P essentially is a way of providing the best correlation (highest combination of slope and R^2) between the damage assessment by the AI procedure and the damage index DI derived from consolidated methods based on the decay of the fundamental frequency of the studied building. The mathematical formulation defining the goal of the proposed optimization strategy was simple and effective. The corresponding optimized values of the internal parameters (TSL and LSS) are to be considered the best achievable setting of the AI procedure. In substance, the above couple of parameters allowed us to obtain the best usable linear relationship between CD and DI.

For validating the methodology, we evaluated the performance of CVAE to analyze white noise vibration data with the aim of assessing the damage in a specimen of a historic masonry structure typical of central Italy subjected to seismic shakes.

In the above case study, the proposed optimization methodology gave a slope a higher than 4 and R^2 higher than 0.95, corresponding to TSL = 1.28 s and LSS = 32.

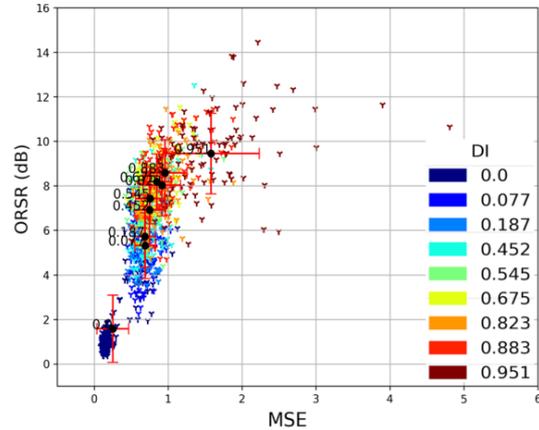


Fig. 5. DI clusters with TSL = 1.28 s and LSS = 32. Black dots indicate the DI centroids.

The above results of the shaking table experimentation are very good and promising for possible application to monitoring real historical structures that undergo earthquakes or other potentially damaging events.

However, further investigation and studies are needed to understand the dependence on the typology and the quality of the processed signals, as well as the influence of changes in the environmental conditions that affect the vibration response in real cases.

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