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AI-BASED ANALYSIS OF AMBIENT VIBRATION DATA FOR THE STRUCTURAL HEALTH MONITORING AND DAMAGE ASSESSMENT IN EXISTING STRUCTURES

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Abstract

An AI-based analysis of vibration time-histories was pointed out in order to assess the damage in structures. In particular, machine learning techniques were applied to extract features that were used to train a regressor based on k-nearest neighbors. A widely accepted Damage Index (DI) computed in terms of decay of the first modal frequency of the building was considered as indicator of the state of damage. The vibration recordings were processed by conventional Experimental Modal Analysis (EMA) techniques. The proposed workflow was validated through the application to shaking table tests of two common construction typologies: a typical Italian rubble masonry building (RMB) and a two-story reinforced-concrete frame (RCF). Seismic tests were performed at gradually increasing intensity from 0.05 g up to specimens failure. They were alternated with dynamic identification white-noise tests (WHN) at 0.05 g. Vibration measurements were carried out through optical markers of a 3D motion capture system (3DVision) with an accuracy of less than 0.1 mm. The first modal frequency of RMB decayed from 11.5 Hz to 2.6 Hz (DI = 95%) and of RCF from 3.5 Hz to 1.1 Hz (DI = 91%). The quality of the obtained regressions were evaluated using the Coefficient of Determination (R^2) and the Relative Percent Deviation (RPD). Moreover, also the fit time and the effect of the time sample length in the signals segmentation were evaluated. Results obtained with the two specimens and with 3DVision data were compared.

Keywords: AI-based analysis, Machine Learning, Damage Index, Shaking Table.

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1 INTRODUCTION

Recent advances in the application of Artificial Intelligence (AI) showed relevant potentialities in many fields of research, including civil engineering. In particular, AI demonstrated very effective when a large amount of input data are available to be processed in order to extract parameters or assessment the state of a system. Thus, a possible and very interesting application to civil engineering would be to process vibration monitoring data for the assessment of the state of damage of a building, e.g. after an earthquake or other critical event. In fact, there already are available very effective methods for processing structural health monitoring (SHM) data. Most of them are mainly based on the estimate of modal parameters (especially modal frequencies) of the building under the assumption that their change over time is due to material and/or structural degradation phenomena. However, the possibility to retrieve similar estimates by AI methods opens new perspectives and constitute a powerful alternative to conventional methods.

The proposed procedure for AI-based analysis utilized machine learning to extract some features from vibration recordings of monitoring sensors located on a building. More precisely, we extracted from the 3DVision data the Mel Frequency Cepstral Coefficients (MFCCs) [1]. MFCCs are applied to many research fields [1-2]. But few experiments are currently been explored for the monitoring of structures [3] and especially for simple cases of classification using cepstral coefficients [4], or neural networks and cepstral coefficients [5] also using autoencoder [6].

Such features were used to train a regressor based on k-nearest neighbors called KNeighborsRegressor. The objective of the AI procedure was to guess the state of damage of the building without having structural information nor using any structural analysis of the available data.

The experimental validation of the proposed procedure was carried out through shaking table tests of a typical Italian rubble masonry building (RMB) and a two-story reinforced-concrete frame (RCF), which represent two very common construction typologies in Italy.

Input data for the AI procedure were generated by providing vibration recordings of optical markers tracked by a high accuracy 3D motion capture system (3DVision) [7].

2 AI PROCEDURE

The AI procedure includes three fundamental parts: pre-processing, feature extraction and regression (see Figure 1). In the pre-processing part, the sensor selection and temporal signal alignment operations were mainly performed, while in the feature extraction part, the temporal segmentation of the signal, the extraction of the MFCCs, and the relative normalizations were performed. Before the application of the regressor, the data were randomly partitioned between training set and test set in a proportion of 70-30% by applying the stratification. To avoid the dependence on the random partition that has an influence especially for low-numbered data sets, the whole procedure was repeated 50 times and the outputs averaged. The details can be found in [8] e [1].

The overall number of features can be calculated by multiplying the number of extracted MFCCs by the amount of considered measurement positions, which in the present case are represented by the number of available markers.

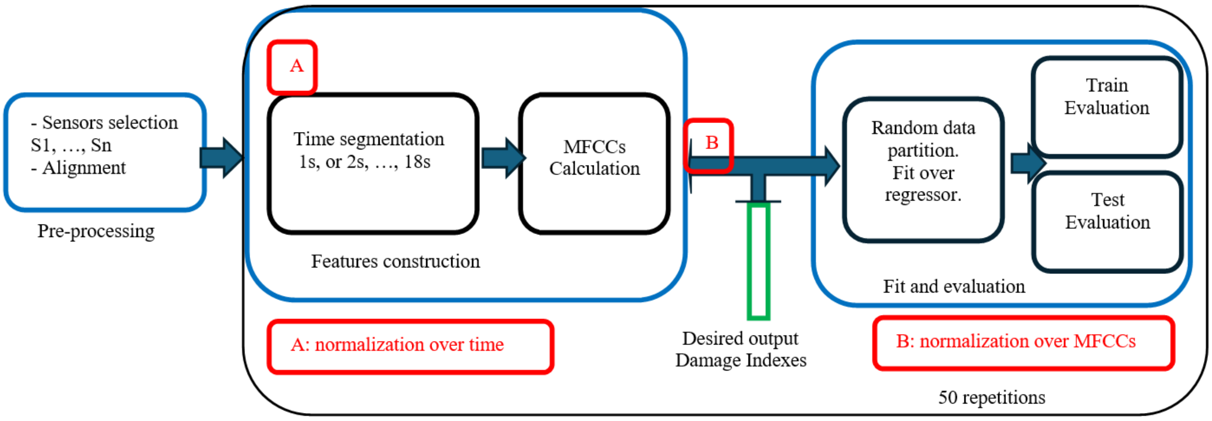

Figure 1: Simplified workflow of the AI procedure.

To predict the DI values, a regressor, commonly used, namely the KNeighborsRegressor was analyzed. KNeighborsRegressor is one of the simplest machine learning methods often applied for data set of low dimensions [9]. It is based on the k-nearest neighbors (k-NN) algorithm. According to k-NN, an object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors, where k is a positive integer, typically small. The k-NN algorithm is here generalized for regression. If k is 1, then the output is simply assigned to the value of that single nearest neighbor, also known as nearest neighbor interpolation. In the present work we have always adopted a value of k equal to 2.

In previous works the KNeighborsRegressor gave a performance quite similar to more complex regressors, while remaining remarkably more simple and fast [1] [8].

We also used a standard scaler to normalize the random data and the MFCCs to speed up the stability and convergence of simulation.

In the application of the proposed AI procedure the data are subdivided into non-overlapped subsamples of various time lengths (time segmentation). In particular, the following time segmentation were considered: 1 s, 2 s, 4 s, 6 s, 8 s, 10 s, 12 s, 14 s, 16 s and 18 s. Shorter time samples give a less representative sample, while longer time samples produce a small amount of examples. Consequently, a compromise should be found.

3 EXPERIMENTAL VALIDATION

3.1 Shaking table tests

The seismic tests for the validation of the proposed AI procedure were performed at ENEA Casaccia research center, near Rome. They consisted in two experimental campaigns on two different specimens representative of the most common construction topologies in Italy: a typical Italian rubble masonry building (RMB) and a reinforced-concrete frame (RCF).

The input signals were based on natural records from the 2016-2017 Central Italy sequence. In particular, for the RMB specimen recordings at Amatrice (AMT, 30/10/2016), Castelsantangelo sul Nera (CNE, 26/10/2016), and Norcia (NRC, 24/08/2016) seismic stations were used. They were scaled with Peak Table Acceleration (PTA) from 0.05 g up to specimens failure, which occurred at PTA equal to 0.50 g [10]. In the case of the RCF specimen only the shake recorded NRC on 30th October 2016 (Mw 6.5) was considered. It was scaled with PTA ranging from 0.10 g to 0.87 g [11]. In both experimental campaigns the seismic tests were alternated with dynamic identification white-noise tests (WHN) at 0.05 g with a duration of about 2 min, which provided the vibration data to estimate the state of damage of each specimen after each shake. A total of 11 dynamic identification tests were carried out on the RMB specimen and 10 on the RCF specimen.

3.2 Studied specimens

The RMB specimen was a typical Italian rubble masonry building (Figure 2a). The size was ¾-scaled. Masonry walls were 3.30m wide, 2.40m high, and 0.30m thick. The specimen had one opening at each side, including a 70cm×80cm window at a height of 75cm, and three 0.70m×1.55m door with fir-wood lintels. The rubble masonry was made up of compact marl-stone units with weak natural hydraulic lime mortar and had irregular joints and voids. On top of the RMB specimen timber beams were loaded with 18 steel plates providing a vertical load of 2.5kN/m².

The RCF specimen was a 2/3-scaled two-story reinforced-concrete frame (Figure 2b) designed under the Italian codes of the 1960s and 1970s, so as to represent a common existing building like the ones carried out during the post–war reconstruction in Italy. The compressive strength of concrete was 20 MPa, while the tensile characteristic yield strength of steel bars was 450 MPa. Besides, 12 kN of additional load was added to each floor.

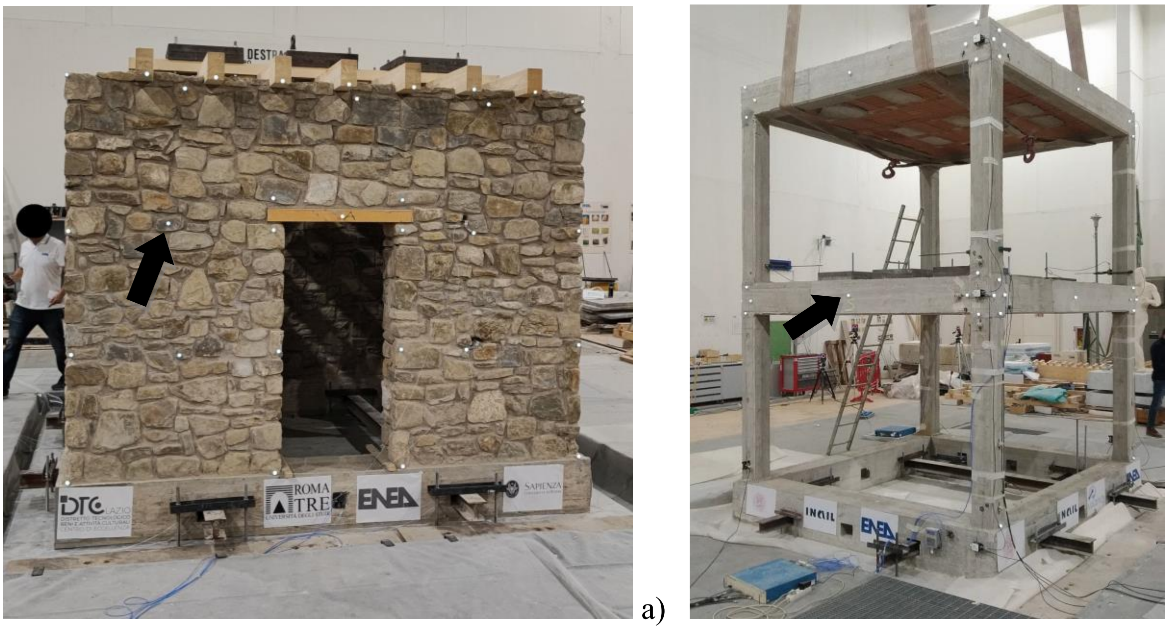
a) b)

Figure 2: View of RMB (a) and RCF (b) specimens on the shaking table. The white small balls indicated by the black arrow are the 3DVision markers.

3.3 Processed data

The data provided in input to the AI procedure were acquired by a 3D motion capture system, named 3DVision. It is capable of tracking the position of 25-mm spherical markers covered with retro-reflecting coating tape with an accuracy in the order of 0.01-0.1 mm. time histories were recorded at 200 Hz of sampling frequency. They can be seen as white small balls located on the specimens in Figure 2. The number of markers was 91 for the RMB and 68 for the RCF. The markers were located at the most relevant positions of the tested structures, according to preliminary numerical analysis of the dynamic behavior by finite element models of the two buildings.

As the study focused on the estimate of the state of damage of the tested specimens, the AI procedure was only applied to the WHN dynamic identification tests of the two experimental campaigns. More in detail, the natural frequency (f) of each specimen was extracted by the markers signals utilising modal analysis techniques based on the transmissibility function through multi-input multi-output (MIMO) method. Signals from markers located at the specimens base were considered for the input. Percentage decay of squared natural frequency was estimated to build a widely used damage index DI, with values from 0 (undamaged conditions) to 100 (structural collapse). DI was computed according to the following [12]:

$$DI_i = \left[1 - \left(\frac{f_i}{f_0}\right)^2\right] \text{x } 100 \qquad (1)$$

where f_i is the natural frequency for the identification test i and f_o is the initial natural frequency.

For simplicity only displacements in one direction were considered. However, the two specimens were quite symmetric, so that x and y directions provided very similar frequencies.

In the present study the number of considered markers was 27. Consistently with [5], the extracted MFCCs were 13, so that the total features per sample were 351 features (13 MFCCs x 27 markers). Consequently, the data matrix used for the regressor fitting was composed of 351 columns with a number of rows equal to the number of examples mentioned above and dependent on the temporal sub-sampling.

4 RESULTS

The natural frequency of RMB decayed from 11.5 Hz (DI = 0%) to 2.6 Hz (DI = 95%) and of RCF from 3.5 Hz (DI = 0%) to 1.1 Hz (DI = 91%). The consequent DI values obtained are illustrated in Figure 3. Specimen RMB had lower values of DI in the initial tests for PTA lower than 0.3 g and higher DI values for PTA higher than 0.3 g.

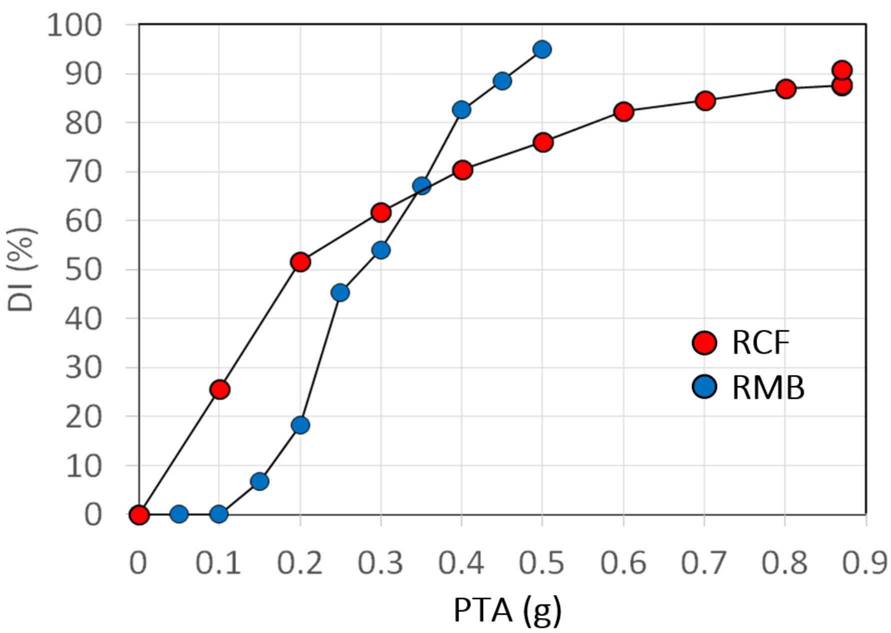

Figure 3: DI obtained for RMB (blue dots) and RCF (red dots) specimens.

In Figure 4 the mean values of R^2 at different time samples are visualized. For the training set (Figure 4a) values of R^2 are very high (0.92-0.99), while standard deviation of R^2 (Figure 5a) is very small (0.01 or less), which confirms that the training step was very efficient. More importantly, R^2 of test set was also very high (Figure 4b), even if lower than in the training, as expected. The tests set provided also quite low standard deviation of R^2 (Figure 5b) with values in the range 0.01 to 0.07. The RMB specimen provided higher R^2 values than the RCF specimen, especially at lower time samples when it gave also smaller variation. However, at time samples higher than 4 s the R^2 values are always greater than 0.9, which indicates a very good estimate of the DI in both specimens. No further relevant improvement was observed at time samples greater than 8 s, with R^2 oscillating in the range 0.94-0.98.

Similar observations can be made on the results obtained for RPD. The experimental results provided tests set RPD values always greater than 3 when time samples were equal to 4 s or more (Figures 6-7). It is good to remember that according to [1] accurate quantitative estimates are characterized by RPD values higher than 3, while for RPD values are less than 2.5 the AI procedure can only be used to provide qualitative indications. Furthermore, RPD values of the RMB specimen are always greater than those of the RCF one, which is substantially coherent with the higher R^2 values achieved, as above mentioned.

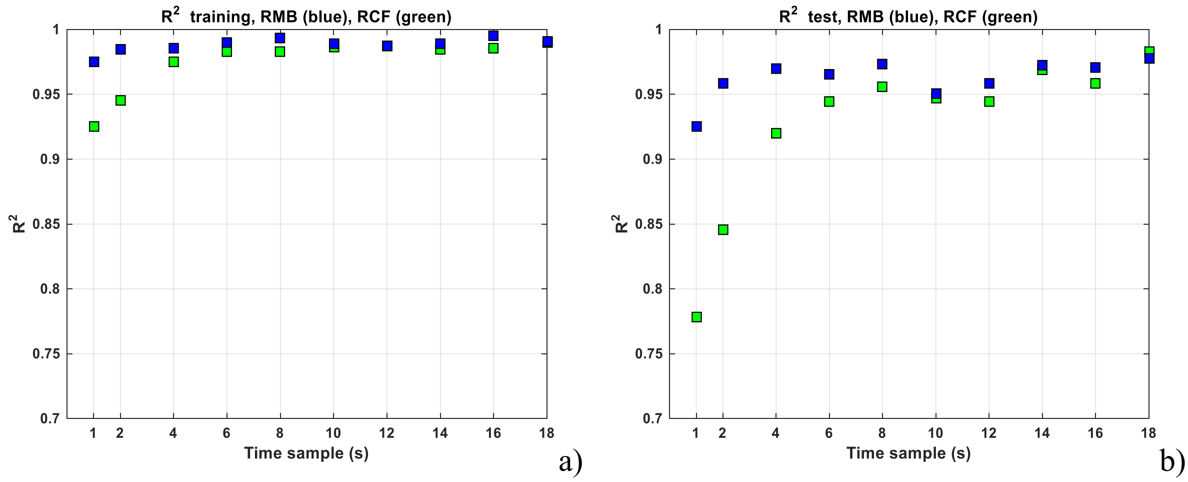

Figure 4: Mean values of R^2 at different time samples for RMB (blue) and RCF (green) for training (a) and test (b) sets.

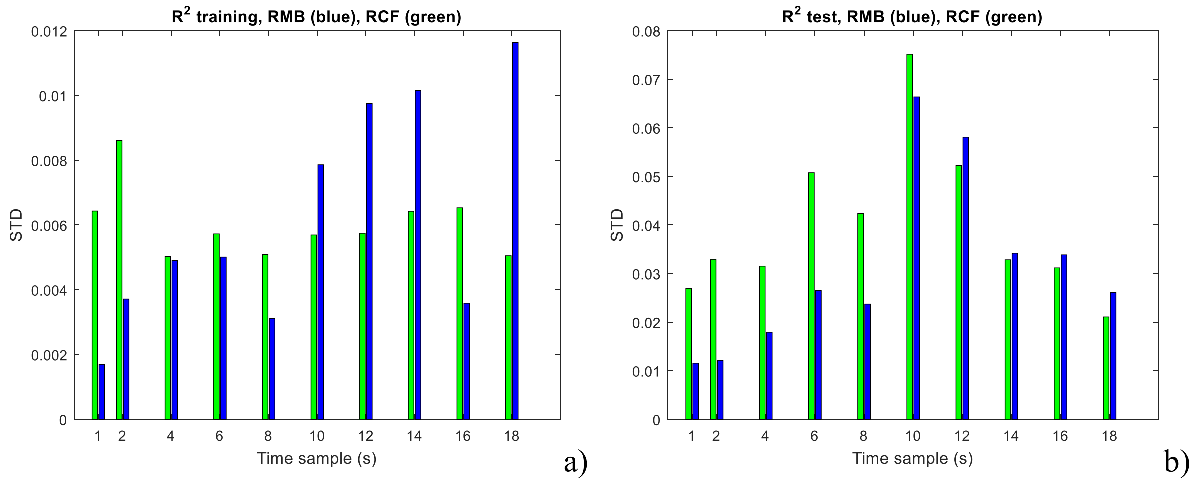

Figure 5: Standard deviation (STD) of R^2 at different time samples for RMB (blue) and RCF (green) for training (a) and test (b) sets.

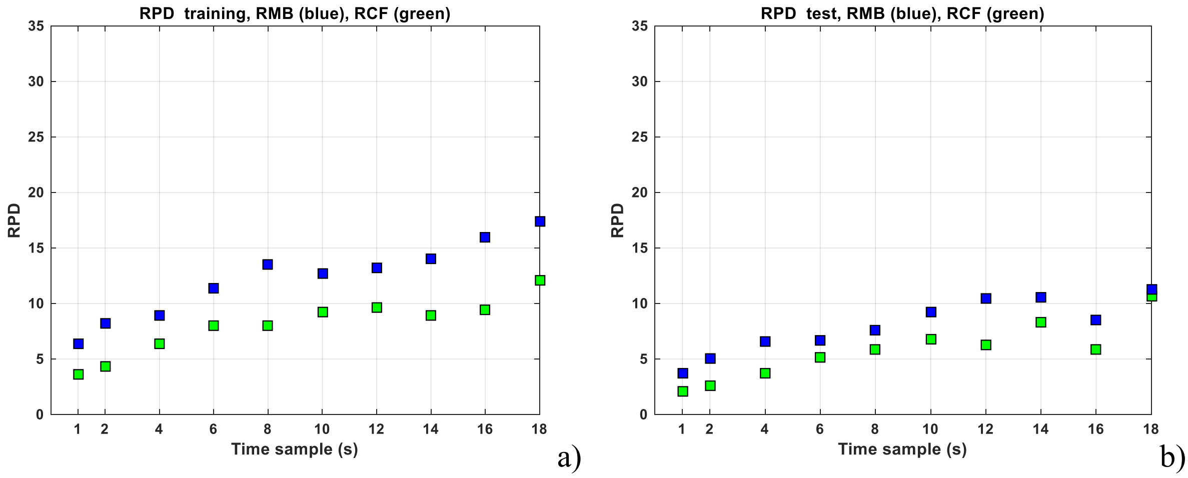

Figure 6: Mean values of RPD at different time samples for RMB (blue) and RCF (green) for training (a) and test (b) sets.

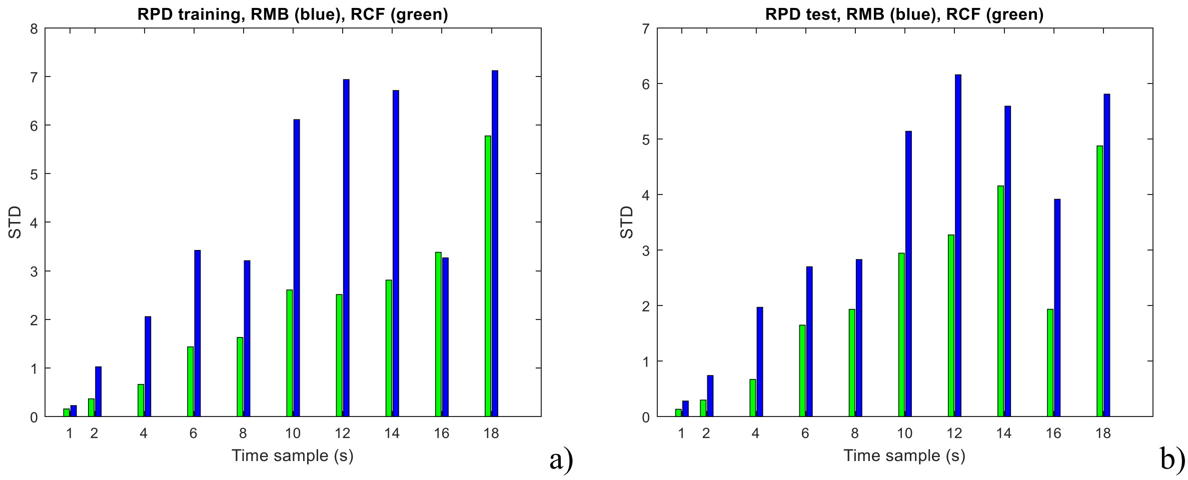

Figure 7: Standard deviation (STD) of RPD at different time samples for RMB (blue) and RCF (green) for training (a) and test (b) sets.

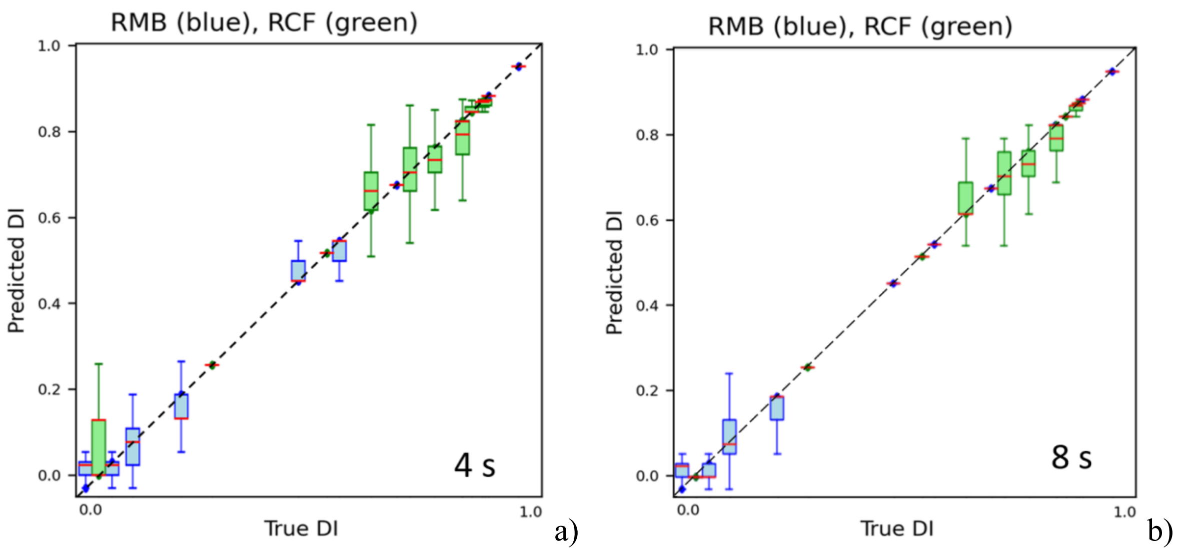

Figure 8: Box plots of RMB (blue) and RCF (red) AI predicted DI values at time samples of 4 s (a) and 8 s (b).

As an example, Figure 8 illustrates the quality achieved by the proposed AI procedure in predicting the DI values at time sample equal to 4 s and 8 s. Box plots visualize the median and the variability of results obtained in the 50 repetitions for the two tested specimens at different DI values. Results were particularly good and associated with low variability for the RMB specimen, especially at high DI values. Conversely, RCF was predicted with higher but still interesting variability (green box plots). However, median DI predictions (red lines) were very good also for RCF, which suggests the importance of performing a reasonable amount of repetitions.

Time segmentation at 8 s (Figure 8b) slightly improved the already good results obtained at 4 s (Figure 8a), as expected.

5 CONCLUSIONS

The proposed AI procedure for the analysis of vibration time-histories gave very promising results. In particular, a very accurate estimate of the structural damage in terms of DI values was achieved with R^2 greater than 0.9 and RPD > 3 at time samples equal to 4 s or more.

On the other hand, the standard deviations of R^2 and RPD were quite relevant, so it is highly recommended to consider the average (or median) value of a reasonably high number of repetitions (we suggest 50 or more).

The results obtained are particularly interesting because the two considered specimens are representative of the two most common existing building typologies in Italy.

Moreover, the two specimens had first modal frequency varying from 11.5 Hz to 2.6 Hz (RMB) and from 3.5 Hz to 1.1 Hz (RCF) so the present study analyzed data with a very wide range of possible frequencies.

Furthermore, the analyzed vibration data were representative of a wide variety of damage levels, from undamaged to DI higher than 90%.

In future work the proposed AI procedure will be tried also on the analysis of accelerometer data of ambient vibration typically used for structural health monitoring (SHM) systems for application to real existing buildings.

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