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DEEP NEURAL NETWORKS FOR UNSUPERVISED DAMAGE DETECTION ON THE Z24 BRIDGE

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Abstract. During their life-cycle, civil infrastructures are continuously prone to significant functionality losses, primarily due to material's degradation and exposure to several natural hazards. Following these concerns, many researchers have attempted to develop reliable monitoring strategies, as integration to visual inspections, to efficiently ensure bridge maintenance and early-stage damage detection. In this framework, recent improvements in sensor technologies and data science have stimulated the use of Machine Learning (ML) algorithms for Structural Health Monitoring (SHM). Among unsupervised learning techniques, the potential of autoencoder networks has been attracting notable interest in the context of anomaly detection. In this light, the present paper proposes two different autoencoder-based damage detection techniques, focused on the Multi-Layer Perceptron (MLP) and the Convolutional Autoencoder (CAE) networks, respectively. During the training, the selected ML models learn how reconstructing raw acceleration sequences acquired from sound conditions. Unknown data, including both healthy and damaged bridge responses, are afterwards used to test the implemented networks and to detect damage occurrence. To this aim, a specific index of reconstruction loss is selected as a damage sensitive feature with the aim to quantify the errors between the original and reconstructed sequences. The performance exhibited by the two approaches is compared and evaluated by application to the Z24 benchmark bridge. Results demonstrate the effectiveness of the proposed methodology to perform feature classification and real time damage detection at the level of macro-sequences as new sensor data is collected, resulting suitable for continuous assessment of full-scale monitored bridges.

1 INTRODUCTION

The increasing number of bridge failures has recently brought to the light the necessity to develop new reliable Structural Health Monitoring (SHM) techniques to perform preventive

condition-based maintenance and automatically detect early-stage damages [1]. During the last decades, vibration-based SHM systems have been widely deployed for this purpose and captured particular attention from many researchers, owing to their non-destructive character and the capability to provide real-time assessment from the monitored structure's response.
With recent ground-breaking advances in the context of computer science, ML algorithms have gained a broad consensus in many engineering fields [2, 3]. They are able to learn knowledge from past data without being explicitly programmed and therefore, they can be adopted in long-term SHM monitoring to automatically gain a wide variety of information, discover hidden patterns, perform damage detection, as well as make future predictions about structural health state [4, 5].
However, when dealing with real-world monitoring scenarios of civil infrastructures, it is worth pointing out the difficulty to acquire measurements from damaged conditions, due to expensive tests or physical constraints issues. This makes unsupervised approaches highly effective in the context of SHM, since input-only data without any labeling (damaged/not damaged) are required to obtain useful information on the monitored structure [6, 7, 8]. Among these techniques, the present paper proposes an innovative ML-based technique, involving two types of autoencoders, for the assessment of full-scale monitored bridges. In particular, a Multi-Layer Perceptron (MLP) and a Convolutional Autoencoder (CAE) networks are implemented to perform damage detection by analyzing, respectively, the single sensor behavior or the whole SHM system with multiple sensors. During the training, the ML model should learn how to correctly reconstruct input acceleration sequences acquired in the healthy period. Then, same-length unknown testing sequences are fed into the trained autoencoder to test and assess model's reconstruction capability. The reconstruction loss is quantified by a specific index, which is considered as a damage sensitive feature, whose distribution in the training period allows to define a proper threshold necessary to investigate newly collected data. However, prior to damage detection, the methodology proposes to group a fixed number of sequences into a unique macro-sequence, in order (i) to consider a longer time frame (of the order of minutes) able to capturing more information on bridge dynamics, (ii) to keep low training computational costs and (iii) to increase model's performance. Therefore, according to the developed procedure, damage detection is carried out by analyzing the percentage of inner damaged sequences exceeding a certain threshold.
While most of researchers test their ML algorithms using laboratorial data, the developed approach is applied to the Z24 benchmark bridge, which represents a realistic monitoring case study [9] widely known in the literature. The performance of the two described autoencoder networks is compared and evaluated through the use of the Receiver Operating Characteristic (ROC) curves, which also enable to find out the optimal threshold minimizing false positives and false negatives [10, 11]. Results remark that the proposed ML-based technique is fast and effective in identifying damage scenarios using a limited number of sensors, demonstrating to be promising for real-time bridge health assessment.

2 BACKGROUND: MLP AND CAE AUTOENCODERS

An autoencoder is a network composed of two main blocks: the encoder part compresses the input into a lower dimensional representation, containing the informative content of the data, while the decoder is aimed at correctly reconstructing the original input back from the

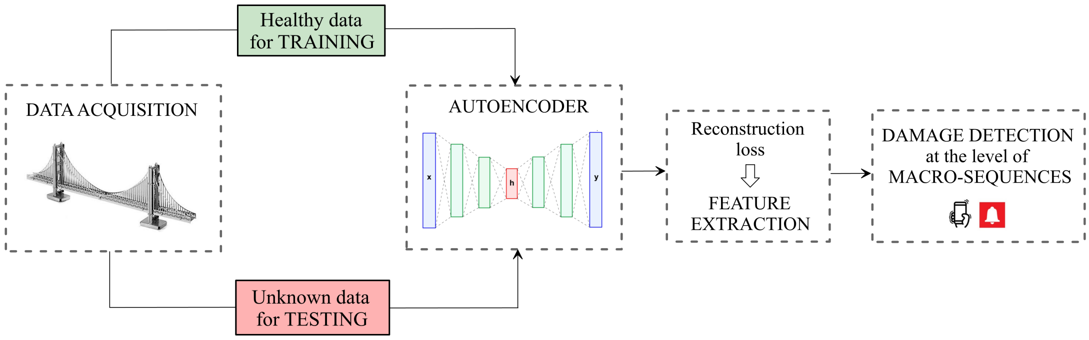

Figure 1: Flowchart of the proposed damage detection technique for bridge health assessment

bottleneck layer.
Two different types of autoencoders are introduced here after, the Multi-Layer Perceptron (MLP) and the Convolutional Autoencoder (CAE) networks, which are adopted for anomaly detection by handling 1D and 2D inputs data, respectively. The MLP represents a fully connected class of feedforward neural network, composed of one or more hidden layers with many neurons stacked together. CAE models stand out for their particular architecture, where convolutional and deconvolutional layers are alternated with pooling and upsampling layers, respectively, in the encoder and the decoder. Within convolutional layers, a filter/kernel sweeping over the input matrix is multiplied by the portion of the input array covered by the filter. Due to the convolution operation, not all the units in the previous layer are connected with the units of the following layer. This represents one of the differences between CAE and MLP autoencoders, the latters characterized by fully-connected layers. Then, pooling layers are employed to progressively reduce data size, usually averaging (average pooling) or taking the maximum value (max pooling) over a certain region of the matrix. Conversely, deconvolutional and upsampling layers gradually reconstruct the dimensions of the data until the input and output layers reach the same size.
During the learning process, the ML model aims at finding a set of parameters (weight matrices and biases for MLP and the elements of the kernel for CAE) that minimize the reconstruction loss, which indicates the difference (i.e. the error) between the input and the reconstructed output. In particular, the mean squared error is selected in this work as objective function or loss function to minimize, employing a gradient-descent based algorithm.

3 THE PROPOSED UNSUPERVISED DAMAGE DETECTION TECHNIQUE

This paper proposes a ML-based approach for bridge damage detection within the unsupervised learning framework. As inferred from Figure 1, the autoencoder is trained to reconstruct healthy data acquired from the bridge in sound conditions and then validated using unknown acceleration time-histories. A specific index of reconstruction loss is extracted and adopted for feature classification and damage bridge health assessment, carried out at the level of macro-sequences.

Raw data are firstly collected by the network of accelerometers and afterwards rearranged into short sequences of pre-defined length to both capture the bridge dynamics and to limit computational costs. Pre-processing is carried out by applying a standardization (to achieve

zero mean and unit stadard deviation) and a normalization between -1 and 1.
Two ML models are proposed and compared, depending on the characteristics of the input data. On the one hand, when the goal is to create a sensor-based MLP autoencoder, the input is represented by the n-th acceleration sequence, with $n = 1...N$. This translates into a 1D matrix of size $(1 \times J)$, where J is the acceleration length. On the other hand, when considering a single CAE model trained with all sensors, the input is a 2D matrix of size $(N \times J)$, where each row indicates the acceleration sequence associated to the n-th accelerometer.
In order to evaluate the reconstruction loss of the autoencoder, the Original-to-reconstructed-signal ratio (ORSR) is computed for each sequence and then adopted as a damage sensitive feature. This quantity, expressed in decibels, can be defined as:

$$\mathrm{ORSR} = 10 \log_{10} \frac{\sum_{j=1}^{J} x_j^2}{\sum_{j=1}^{J} y_j^2} \tag{1}$$

where x_j and y_j represent the j-th element of the original and reconstructed sequence, respectively. Since ORSR is able to evaluate the amount of noise surrounding a certain signal, it can be conceivably used to detect damage or abnormal conditions which adversely influence and corrupt the reference signal.
Before damage detection, a certain number of short sequences is collected to build a single macro-sequence of user-defined length. Hence, the macro-sequence is classified as damaged when the percentage of inner damaged sequences overcomes a pre-determined threshold $T_2(n)$. It is worth pointing out that, if damaged data are not available, such a threshold can be set equal to a pre-defined percentile of damaged sequences' probability distribution in the training period. In the other cases, it could be convenient to compute n ROC curves by plotting the true positive rate against the false positive rate at different classification thresholds $T_2(n)$ to find out the optimal value $T_{2,opt}(n)$, in correspondence of the maximum Youden index, minimizing false positives and false negatives. Moreover, the evaluation of the area under the curve (AUC), assuming a range from 0 to 1 as damage detection accuracy increases, allows to compare and quantify the ML models associated to the n-th sensor. Further details about ROC curves can be found in [10, 11].

4 CASE STUDY: THE Z24 BRIDGE

The Z24 Bridge was built in 1963 to link the villages of Koppigen and Utzenstorf in Switzerland. It was a post-tensioned concrete box girder bridge characterized by a main span of 30 m, two side spans of 14 m and two concrete piers, clamped into the girder, at the end of the main span. The structure was continuously monitored for almost one year using several sensors located along the deck and the pier. In particular, accelerometers acquired 10 minutes of recordings every hour at a frequency of 100 Hz.
Before bridge demolition in August 1998, a series of progressive damage tests was artificially carried out to study the dynamic behavior of the bridge subjected to different damage scenarios. Detailed description of sensors location, damage tests and the number of corrupted sensors are illustrated in references [9, 12]. In this work, five sensors (S5, S6, S12, S14 and S16) are deployed for bridge damage assessment.

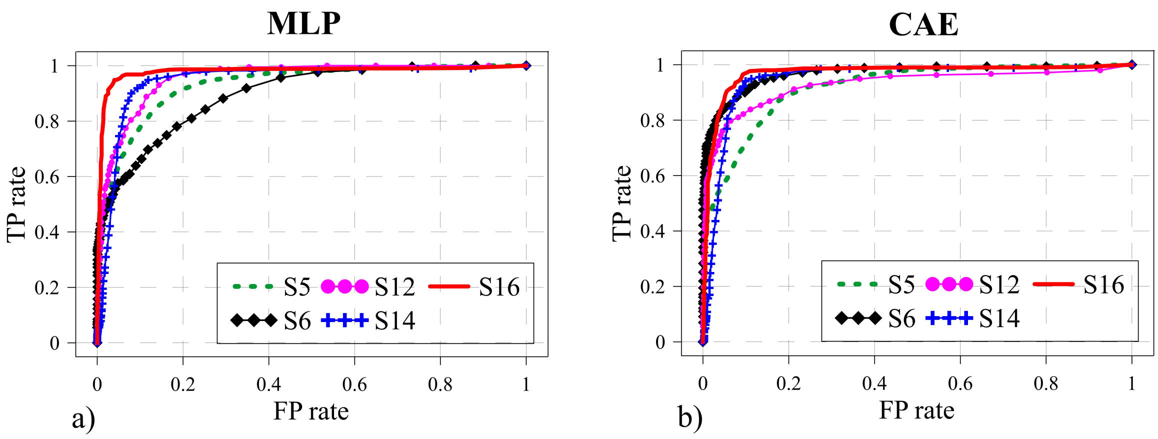

Figure 2: ROC curves computed for each sensor using the MLP and CAE autoencoder networks.

4.1 Damage detection results comparing the Multi-Layer Perceptron (MLP) with the CAE autoencoder

The MLP autoencoder, composed of three hidden layers, is independently trained for the n-th sensor to correctly reconstruct the 1D input represented by 10-seconds-long acceleration sequences. During the training, the hyperbolic tangent function (tanh) is used as activation function, the mean squared error as loss function and the Adam optimizer as optimization algorithm. The number of epochs is set to 30 to enable the reconstruction loss stabilization, while the batch size equal to 64.
On the other hand, the implemented CAE autoencoder provides both the possibility to simultaneously analyze all sensors using a unique model and to afterwards extract the single sensor information. It follows that the 2D input is characterized by a matrix of dimension (4×1000), where each rows corresponds to the n-th sensor record of 10-seconds length. The network architecture is symmetric, with the encoder composed of two convolutional layers and two max-pooling layers. In this case, the Leaky ReLu is selected as activation function and, as in the previous case, the mean squared error is employed as reconstruction loss and the Adam as optimization algorithm. The number of epochs and the batch size are fixed at 30 and 128, respectively.
Once trained the models, ORSR is computed for each sequence and each sensor in order to quantify the reconstruction errors between the original and the reconstructed input. Based on the distribution of this feature in the training period, a first threshold $T_1(n)$ equal to the 90-th percentile is set. Then, 60 sequences are grouped together to build a single macro-sequence of 10 minutes. By considering the whole dataset, including healthy and damaged data, ROC curves are built to estimate the optimal threshold $T_{2,opt}(n)$ as well as to compare different sensors and different ML models' performances. As inferred from Figure 2 and Table 1, both approaches lead to similar results in terms of damage detection, showing high performance levels, with AUC values close to 1, and a good capability to minimize false detection errors. In particular, false negatives and false positives are more effectively minimized by using MLP and CAE models, respectively.

Table 1: Damage detection results: AUC values for each sensor, FNr and FPr computed at the optimal threshold.

Sensor	AUC_{MLP}	AUC_{CAE}	FNr_{MLP}	FNr_{CAE}	FPr_{MLP}	FPr_{CAE}
S5	0.93	0.92	0.09	0.12	0.19	0.19
S6	0.90	0.97	0.22	0.07	0.19	0.12
S12	0.96	0.93	0.05	0.20	0.17	0.06
S14	0.95	0.95	0.05	0.06	0.12	0.09
S16	0.98	0.97	0.05	0.04	0.04	0.09

5 CONCLUSIONS

This paper compares the performance of two different types of autoencoders (MLP and CAE) for real-time damage detection of roadway bridges. The methodology is validated with acceleration data from the Z24 benchmark bridge, where the Multi-Layer Perceptron and the Convolutional AutoEncoder models are compared in terms of AUC values and false detection errors rate. While the MLP autoeoncoder is trained for each sensor to reconstruct 10-seconds-long acceleration sequences, the CAE provides the possibility to analyze all sensors together and afterwards extract the single-sensor reconstruction loss. Once trained the ML model with raw acceleration sequences, the reconstruction error between the input and the reconstructed output is quantified through the ORSR feature. Finally, damage detection is carried out at the level of macro-sequences, by selecting the optimal classification threshold through the Youden index. Results obtained from the Z24 bridge highlight that the two proposed ML models are characterized by similar performances, both ensuring high effectiveness in detecting damage using all the five sensors and minimizing monitoring errors. In particular, since the CAE is able to produce the same results of the MLP network by training a single model, it may be recommended due to the reduction of computational burden.

Since the implemented technique requires only raw acceleration data acquired during healthy conditions, it is deemed easily applicable in real-world monitoring scenarios. Moreover, avoiding system dynamic identification and working at the level of single sensor, the procedure is fast and suitable to investigate local damage with a limited number of SHM sensors, proving to be a valid support to integrate visual inspections and to automatically provide real-time bridge health assessment.

Acknowledgements

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