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Procedia Engineering 199 (2017) 1931–1936

Procedia Engineering

www.elsevier.com/locate/procedia

X International Conference on Structural Dynamics, EURODYN 2017

Damage detection in railway bridges using Machine Learning: application to a historic structure

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Abstract

This paper presents a method that uses machine learning to detect and localize damage in railway bridges. Results of the method application to a historical bridge are presented and used to validate the proposed algorithm.
For the application of this technique, both air temperature and deck accelerations data, measured under railway traffic at several locations on the bridge, are needed. The method consists of four stages: (1) collection of such data in both reference condition (i.e. when the state of preservation of the structure is known) and current one; (2) pre-processing of acceleration time histories aimed at extracting characteristics of the crossing train (i.e. running direction, speed and number of axles); (3) training of Artificial Neural Networks and Gaussian Processes using data collected in reference condition and (4) health classification of the bridge in current condition through the comparison between predicted and measured responses. During stage 3, a set of neural networks is trained to predict deck accelerations under every environmental and operational condition (i.e. air temperature and crossing vehicle characteristics, respectively) assuming the reference state of preservation. Then, in stage 4, the current response is compared with accelerations predicted under current environmental and operational conditions. Changes in the behavior of the structure due to damage are thus detected as a discrepancy between predicted and measured responses.
The application of the proposed technique to data collected on San Michele Bridge (1889), in Northern Italy, has shown good agreement with results from previous studies based on mode shape variation. This shows the potential and confirms the possibility of applying the proposed technique to real bridges. This method can thus be used to detect anomalous responses that can be flagged as possible damage as well as give an indication of the location of the decayed structural region.

Peer-review under responsibility of the organizing committee of EURODYN 2017.

Keywords: Damage detection; Machine learning; Railway Bridges.

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Peer-review under responsibility of the organizing committee of EURODYN 2017.
10.1016/j.proeng.2017.09.287

1. Introduction

Civil engineering structures such as bridges have a long design life and, therefore, inevitably encounter material aging and increasing of traffic. Through the Structural Health Monitoring (SHM) technology, early detection of structural anomalies (i.e. damage) is possible with a consequent optimization of maintenance, based on the actual need of the structure. Applying a machine learning perspective to SHM consists in training an algorithm so that it is able to classify the structure state of health based only on data about a given damage-sensitive feature. A detailed model of the considered structure is, therefore, not needed; however, to feed the algorithm in the training phase, data about the chosen feature have to be collected during one or more monitoring periods. During the latters, the state of health of the structure has to be known, since they will represent the baseline cases. When applying such techniques to real bridges, in general, data collected on a structure affected by several levels of damage are not available; instead, it is possible to collect data in healthy condition. Techniques using only one baseline case are called novelty detection methods and, in case the baseline status refers to healthy condition, the detected novelty is flagged as damage. In this field, several methods have been proposed: however, they have been mainly tested with data numerically simulated or produced in laboratory tests [1-5]. Moreover, some of them refer to specific load scenarios [2], [3], [6] that are not usual in real structures; their applicability is, therefore, limited.

2. Methodology

This work uses data collected on a real bridge in Northern Italy for testing an updated version of the novelty detection method for railway bridges presented in [1]. This version expands the original one by taking into account the environmental condition in terms of air temperature. Moreover, in order to allow the application to real data, an algorithm able to extract data about the crossing vehicle has been developed.

For this technique to be applied, it is necessary to install on the bridge a set of accelerometers and thermocouples. The method, then, consists of four stages: (1) collection of data in both reference condition (i.e. when the state of preservation of the structure is known) and current one; (2) pre-processing of acceleration time histories aimed at extracting characteristics of the crossing train (i.e. running direction, speed and number of axles); (3) training of Artificial Neural Networks (ANNs) and Gaussian Processes using data collected in reference condition and (4) health classification of the bridge in current condition through the comparison between predicted and measured responses. In stage 2, signals recorded during the actual train passages are extracted as shown in Fig. 1. Then, knowing the sensors location, the train speed, its length (i.e. the number of axles) and the running direction are computed. Signals are then classified based on running direction and number of axles and those belonging to the most common class are used in the remaining steps. During stage 3, one ANN per accelerometer is trained to predict deck accelerations under every environmental and operational condition assuming the reference state of preservation. No matter how well-trained the ANNs are, they won't be able to perfectly reproduce the measured response; for each train passage and the s-th accelerometer, a small prediction error (pe^s) is computed as:

$$pe^s = \frac{1}{n}\sum_{i=1}^{n}\left[ANN\left(\mathbf{x}_i^s\right) - a_i^s\right]^2 \tag{1}$$

Where n is the number of time steps the train passage duration has been divided in (depending on the accelerometers sampling frequency) and, for the i-th time step, $\mathbf{x}_i^s$ contains data about environmental and operational conditions, ANN($\mathbf{x}_i^s$) is the predicted acceleration, while a_i^s is the recorded one. Application of both simulated [1] and real data show that pe^s is affected by the train speed (v); therefore, one Gaussian Process per accelerometer is trained with data collected in reference condition to stochastically characterize pe^s by computing its mean $\mu_s(v)$ and standard deviation $\sigma_s(v)$. Finally, in stage 4, the current environmental and operational conditions are given as input to the ANNs, which predict the vibration data each accelerometer would record in reference condition. The actually measured accelerations are compared with the predicted ones by the means of pe^s and any discrepancy between the two is flagged as structural anomaly. In order to quantify such discrepancy, one damage index (DI) per train passage is computed as:

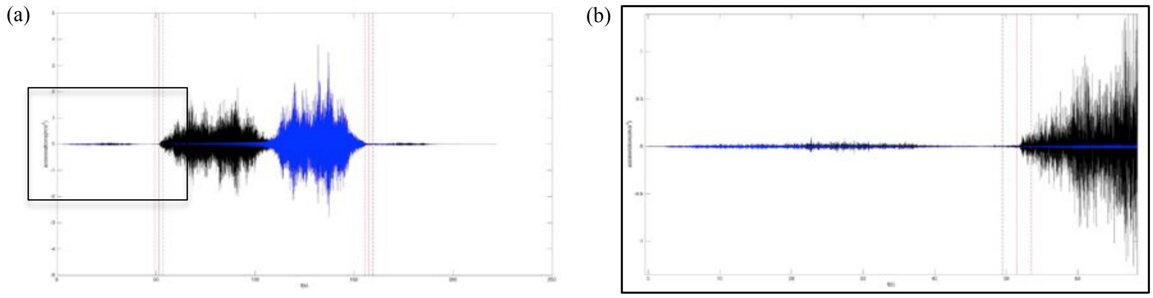

Fig. 1 (a) Sample of accelerations recorded by sensors in the first (black) and last (blue) instrumented sections; (b) detail of the signals at the beginning of the train passage. Red solid lines are placed where the signals should be cut, red dashed lines define the area where the actual cut is made.

$$DI = \frac{1}{n_s}\sum_{s=1}^{n_s}\frac{pe^s - \mu_s\left(\bar{v}\right)}{\sigma_s\left(\bar{v}\right)} \tag{2}$$

Where n_s is the number of accelerometers installed on the bridge and $\bar{v}$ is the train speed during the considered passage (assumed constant). In case *DI* is higher than a threshold value based on costs related to false positives and negatives, the considered train passage results in detected anomaly. The bridge state of health is, thus, predicted at each train passage; however, the reliability of the prediction increases with the number of tested passages.

3. Case study

3.1. The bridge and the monitoring system

The Swiss engineer Julius Röthlisberger (1851–1911) designed the San Michele Bridge (better known as Paderno Bridge) in 1886. It was opened to traffic on 20/05/1889 and it is still used to connect two small towns (Paderno and Calusco d'Adda) not far from Milan [8]. The bridge consists of a main parabolic arch and seven piers supported by the arch and the masonry basement (Fig. 2a). The piers, together with two additional bearings, support a truss box

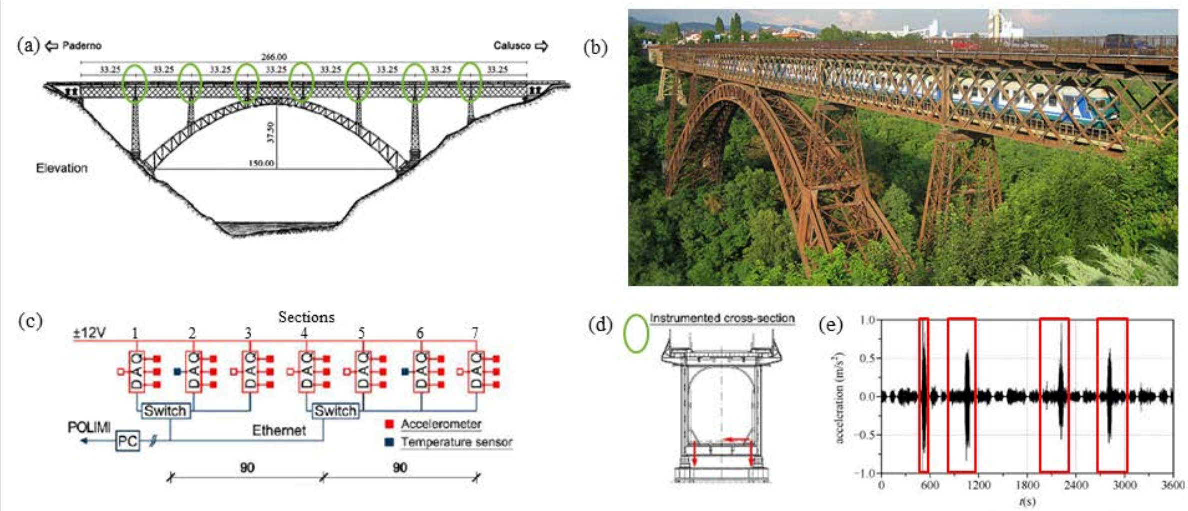

Fig. 2 (a) Elevation of San Michele Bridge, (b) combined railway and road traffic, (c) layout of the installed monitoring system, (d) typical instrumented cross-section and (e) sample of one hour long acceleration record and extraction of signals associated to railway traffic (each red rectangle represent an extracted signal) [9-10].

girder with two slabs: one for pedestrian and alternate road traffic and one for a single-track railway line (Fig. 2b).

A continuous dynamic monitoring system was installed on the railway deck and was active from 28/11/2011 to 30/05/2014. It had been chosen to instrument the seven cross-sections above the bearings of the truss-box girder (Fig. 2a) with three MEMS accelerometers (red arrows in Fig. 2d) and one NI Ethernet DAQ unit. Moreover, sections 2 and 6 (Fig. 2c) were provided with a thermocouple each measuring the air temperature in vicinity of the structure. Each DAQ unit acquired data from the three MEMS accelerometers and the thermocouple, when present. Two switch devices collected the Ethernet cables from the instrumented sections and performed an analog-to-digital conversion of the signals. Digitalized data were transmitted every hour to an industrial PC on site: data from the MEMS accelerometers were stored in the form of binary files containing acceleration time series sampled with a frequency of 200 Hz. Moreover, one value of temperature for each thermocouple was recorded and stored during each hour. At the end of each day, these files were sent to Politecnico di Milano, where acceleration time series associated to railway traffic were automatically identified, extracted and stored. These final files contain the accelerations recorded during the passage of only one train each. Since the extraction was made in correspondence of minima representing red lights for road traffic, the final signals were longer than the actual train passage because they also included an initial and a final part due only to road traffic (Fig. 2e).

3.2. State of preservation of the bridge

In [5], data recorded by the monitoring system installed on the San Michele Bridge were used in order to detect structural anomalies. Mode shape variation in terms of Modal Assurance Criterion (MAC) and Mean Phase Deviation (MPD) showed a gradual variation of the bridge behavior during the monitoring period (Fig. 3a). Such variation is the consequence of the deterioration of the structure conditions, which is mainly localized in the arch crown (Fig. 3b). This deterioration is believed to be the result of corrosion as the coat of protection painting carried out during the last documented intervention (early 1990s) was uneven. Through Fig. 3a, it is possible to identify several periods characterized by stationary behavior of the bridge. Those used in the validation of the method proposed in this research are: Period 1 from 2011/12/01 to 2012/01/31 and Period 2 from 2012/05/01 to 2012/09/30. A part of the data collected during Period 2 was used for the training phase (i.e. as reference condition) because of its longer duration. The remaining, together with those collected in Period 1, were employed to test the algorithm.

3.3. Validation of the method

Pre-processing of acceleration time histories in Period 2 showed that trains with five wagons running from Paderno to Calusco d'Adda were the most common; therefore, signals characterized by the same train features were extracted also among those recorded in Period 1 and used for the remaining steps. Trains running on this railway line are composed by: one locomotive of the type E464N and several wagons with a mass of 72 tons and 40 tons each respectively. Information about the exact axles loads were not available; therefore, the mass of each part (locomotive/wagon) has been assumed to be equally divided among four axles. The inevitable variability of the axles loads is therefore neglected; however, in [1] it had been proved that the original algorithm was fairly

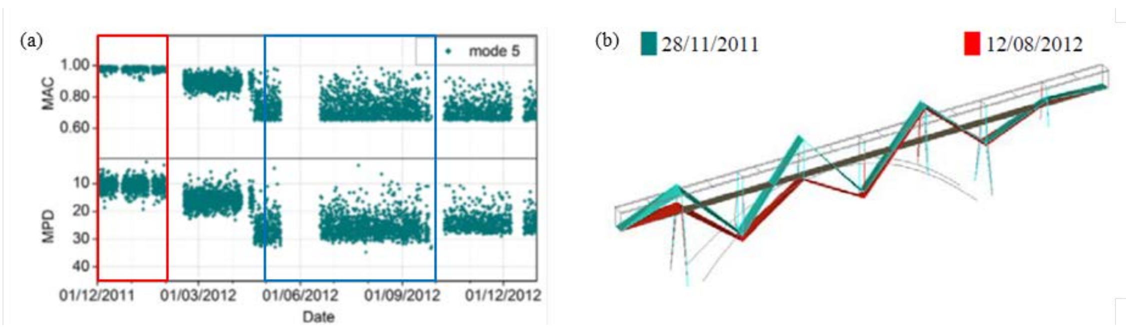

Fig. 3 (a) MAC and MPD tracking for mode 5: The red rectangle refers to Period 1, 2011/12/01-2012/01/31, and the blue one to Period 2, 2012/05/01- 2012/09/30. (b) Comparison between mode shapes at different periods [10].

insensitive to the BWIM inaccuracy in terms of axle loads. Signals recorded during Period 2 referring to 300 and 100 train passages have been used for the training of, respectively, the ANNs and the Gaussian Processes. Two different sets of data have been used to test the method: 100 train passages in Period 1 and 100 in Period 2 (respectively, red asterisks and blue circles in Fig. 4). Results shown in this paper concern sensor measuring the vertical accelerations on the left side of the bridge deck (Fig. 1d); indeed, no considerable differences have been noticed with respect to the others.

Fig. 4a shows prediction errors (pe) plotted against train speed for the accelerometers in sections 1, 3, 4 and 7 (Fig. 1c). Black crosses represent the train passages used to train each Gaussian Process, the black thick line is the mean value $\mu_s(v)$ for the normally distributed pe and the grey area is limited by the curves $\mu_s(v) \pm 2\sigma_s(v)$. As expected, for all four sensors most of the blue markers are within the grey area: indeed, both these train passages and those used for the training have been recorded in Period 2 or, in other words, under the same health conditions of the bridge. Red markers, instead, refer to passages recorded in Period 1 when the structure conditions were different; indeed, they tend to escape the grey area from above showing higher pe values, which indicates that an anomaly has been detected. Also the damage indices computed over all seven sensors show higher values for testing data recorded in Period 1 than for those in Period 2 (Fig. 4b). Thus, one can conclude that the proposed method is able to detect anomalies. Moreover, the separation between blue and red markers is clearer for sensors in sections 3 and 4 (Fig. 4a), which are the closest to the arch crown, where the biggest change in the structure conditions had been noticed (Fig. 3b); therefore, an indication of the location of the detected anomaly is given as well.

A quantification of the detection power of the proposed method is given by the Receiver Operator Characteristic (ROC) curve of Fig. 4c, which is characterized by an Area Under the Curve (AUC) equal to 0,7786. In order to better understand the accuracy of this novelty detection method, let's consider to have a set of trained ANNs and Gaussian Processes and to choose the DI threshold value of the ROC curve of Fig 4b corresponding to the true positive (TP)-false positive (FP) couple 70%-20%. Starting from a small a priori probability of anomaly in the bridge (10^{-6}) and using the Bayesian inference to compute the conditional/posterior probability of anomaly, Table 1 shows that the system can be made arbitrarily reliable over longer periods of time. Indeed, when a total of 15 train passages are considered (note that almost 50 trains cross the San Michele Bridge every day) and 13 out of them result in detected anomaly, there is a 62,5 % probability that the bridge has actually encountered a change in its state of health. Instead, when 20 passages are tested and 17 out of them result in detected anomaly, the posterior probability reach 98,9 %.

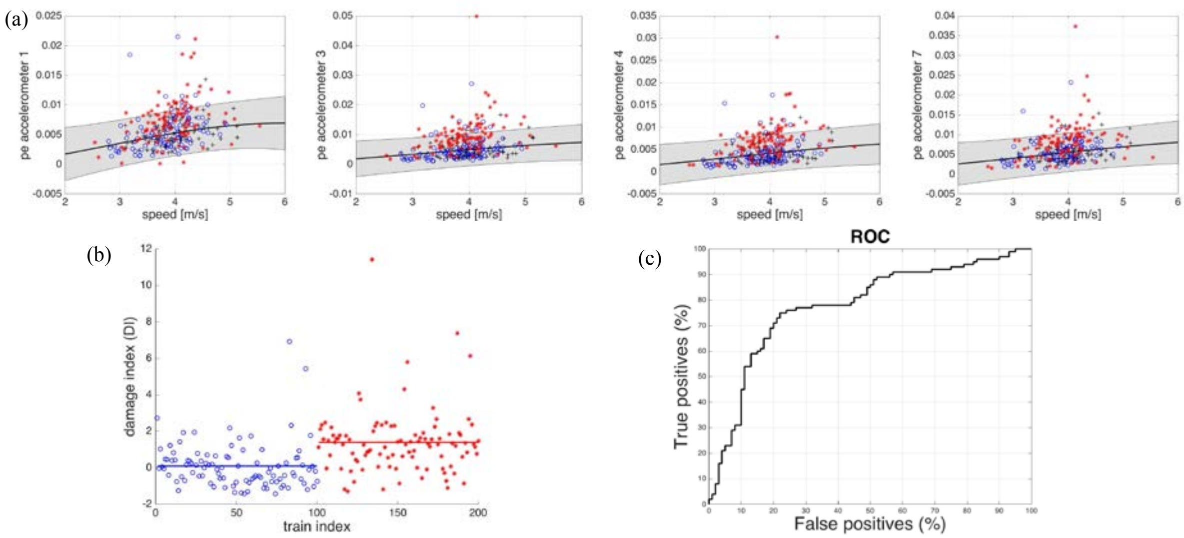

Fig. 4 (a) Prediction errors (pe) plotted against train speed for sensors in sections 1, 3, 4 and 7. Passages marked with black + (collected in Period 2) have been used to train the Gaussian Processes, those with red asterisks (Period 1) and blue circles (Period 2) to test the technique. The black thick line indicates the mean values $\mu_s(v)$ and the grey zone is delimited by the curves $\mu_s(v) \pm 2\sigma_s(v)$. (b) Damage indices. The continuous lines are the mean values of the damage indices of the two sets. (c) Receiver Operator Curve. Positive = detected anomaly (i.e. not belonging to Period 2).

Table 1 Probability of anomaly

A priori probability of anomaly	TP [%]	FP [%]	Train passages resulting in non-detected anomaly	Train passages resulting in detected anomaly	Posterior probability of anomaly [%]
1e-06	70	20	9	1	2,9
1e-06	70	20	13	2	62,5
1e-06	70	20	17	3	98,9

4. Conclusions

In this paper, a novelty detection method for railway bridges has been presented and validated using data collected on a real bridge in Northern Italy.

At first, the algorithm is developed to allow the extraction of acceleration time histories recorded during the actual train passage and the classification of them based on train running direction and number of axles. The same algorithm also computes the train speed. Signals characterized by the most common running direction and number of axles are used for the detection. Then, Artificial Neural Networks (ANNs) are used to predict the deck accelerations given environmental and operational conditions and assuming a given state of preservation of the bridge. Any discrepancy between predicted and measured responses can be interpreted as a change in the structure health/ state of preservation.

Data recorded on San Michele Bridge, Italy, have been used for the validation. Results show the effectiveness of the technique in detecting anomalies at each train passage. However, the reliability of the detection increases with the number of tested passages. Moreover, by applying the technique to several train passages, an indication of the approximate location of the anomaly is possible as well.

Acknowledgements

This research has been carried out at the Department of Civil and Architectural Engineering, at the Division of Structural Design and Bridges, at the Royal Institute of Technology (KTH), in Stockholm. The authors would like to thank the partners in the project: Royal Institute of Technology, Stockholm, Sweden and Politecnico di Milano, Milan, Italy.

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