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Anomaly detection and representation learning in an instrumented railway bridge

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Abstract. In this contribution, the strain measurements of a railway bridge are used for anomaly detection, in the context of Structural Health Monitoring (SHM). The methodology used is a combination of a sparse convolutional autoencoder (CSAE) and a Mahalanobis distance. Due to the lack of labeled anomalous data, a simulated fault is used to evaluate the performance of the algorithm. The proposed approach far outperforms the classical feature-based approach. Finally, the latent dimension of the autoencoder is studied and shown to be structured and representative of the underlying physics of the problem.

1 Introduction

Structural health monitoring (SHM) is used to monitor the behavior of a structure, as well as its evolution as a whole. SHM can help reducing the maintenance and repair of an existing infrastructure with condition-based maintenance, saving money on unnecessary maintenance and avoiding unplanned repairs [1]. In addition, it increases the reliability, safety, and lifespan of a structure. Incorporating sensors and SHM systems into new structures should reduce lifecycle costs. In this paper, we consider part of a railway bridge. SHM for such a structure is usually based on vibration or strain measurements where anomalies are detected by spotting variations in engineered features such as the modal parameters [2]. This work aims to build an anomaly detector that is not based on engineered features, but rather on signal patterns directly found in the strain gauge measurements. It is not intended to replace the current approach but rather to complement it to avoid issues otherwise unnoticed by engineered features.

The proposed approach is based on AutoEncoders (AE), where the reconstruction error of the model expressed as a Mahalanobis distance is used as an anomaly index. Simultaneously, the quality of AutoEncoder learned embedding is assessed through visualisation (with t-SNE) and with a surrogate classification task (applying a random forest on the embedding). While this has no immediate purpose for the main anomaly detection, it is used to assess the overall behaviour of the model and serve as a qualitative assessment of the model itself [3].

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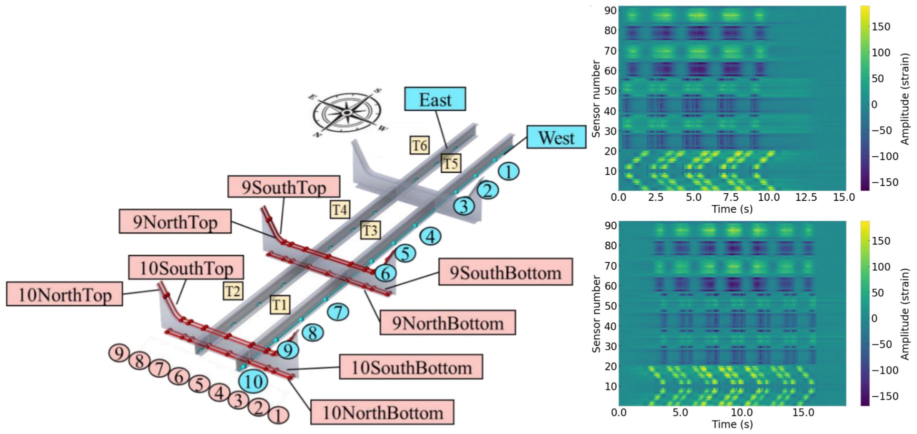

Fig. 1: (left): the location of the three types of sensors installed on the bridge: longitudinal in blue, transversal in red and temperature in yellow [4] . (top right): strain induced by a train passage with 16 axles and in the south direction (N-S). (bottom right): same as (top right) but with 24 axles and in the north direction.

2 Case Presentation and Data Exploration

The data used in this contribution was obtained from 92 strain sensors (Fiber Bragg Grating, FBG) installed on a railway bridge. As can be seen in Fig. 1, each member of the structure is equipped with a set of sensors on the top and bottom surface, more details about the setup can be found in [4]. The measurement campaign started on 07/12/2020 and ended on 14/12/2021. Individual train passages are isolated from the dataset and processed using a procedure detailed in [4]. For this work, all signals were re-sampled to 20 Hz.

Examples of the collected data are shown in the right part of Fig. 1 and some symmetries can be observed in the sensor readings at the bottom of these two figures. First, it is clear that the East (0 to 10) and West (10 to 20) sensors are excited in a similar and progressive manner since they are located in the longitudinal direction. Second, NorthTop10 (20 to 28) and NorthBottom10 (29 to 38) are opposite in sign because when the top of a beam is in compression, the bottom is in tension. One can also clearly see the individual wheels of the train and deduce the direction of the train from the East and West sensors (0 to 20).

3 Anomaly Detection

3.1 Dataset & baseline model

In this work, the anomaly is simulated by attenuating the amplitude of one of the sensor sets (in real life, this may be caused by a sensor detachment or an asymmetry in the structure, etc.). The data set consists of 1409 measured

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passages of trains with variable compositions, speeds and directions. 1200 of these are considered non-anomalous and are used to train the model. The rest are duplicated and an anomaly is simulated in the duplicates. This yields a test data set consisting of 209 non-abnormal signals and 209 abnormal signals from this test data set. The abnormality index for each train pass is calculated using different models, including the proposed model. These indices are used to calculate the AUC as a performance measure of the final model.

To properly assess model performance, a simple baseline approach using engineered features obtained from the signals is defined. For each train passage, 7 statistical characteristics are extracted (Min, Max, Mean, RMS, crest factor, form factor, impulse indicator) from the 92 sensors, leading to 644 features per train passage. Then, using the training dataset (matrix of 1200 data points in a 644-dimensional hyperspace), we construct a PCA model with 44 principal components (PCs) (indeed, 44 PCs are sufficient to explain 90% of the variability in the data). As proposed in [5], a T^2-statistic and a Q-statistic can be calculated and used as an anomaly index.

3.2 Proposed approach

The preprocessing begins by zero-padding the data set to the same dimension ($\mathbb{R}^{640\times 96}$). The time dimension is padded to 640 samples to accommodate for the longest train passage of $32s$. The sensor dimension is also padded from 92 to 96, to allow for a deeper neural network with a constant stride of 2 for the convolutional layer. These steps are illustrated in the right-hand side of Fig. 2 The model used for anomaly detection is a Convolutional Sparse Autoencoder (CSAE). The encoder part is composed of a 2D convolutional layer with a stride of 2, a kernel size of 3, and the number of filters increases with depth [8,16,32,64,64]. The latent dimension is constructed with a 2D convolutional layer that has 32 filters and a stride of (2,3), resulting in a latent dimension of $32 \times 10 \times 1 = 320$. The latent dimension size is set by applying the elbow rule on the plot of the MSE versus the latent dimension. Finally, the decoder is composed of a transposed 2D convolution and its hyperparameters are symmetric with respect to the encoder. The CSAE residual is used to build an anomaly index using the Mahalanobis distance on the sensor-wise error. Fig. 3 illustrates how the proposed anomaly index is computed: first the model residual is computed, then the part that contains the event is isolated (signal before padding, in orange box), and the mean over time is computed, which yields the sensor-wise error I ($I \in \mathbb{R}^{96}$). After training the model (using MSE as a loss function), the sensor-wise error is computed for the training dataset, then the mean $\boldsymbol{\mu}$ and covariance $\boldsymbol{\Sigma}$ of the sensor-wise error matrix of the training dataset is computed. During testing, the Mahalanobis distance of the sensor-wise error is obtained by using equation 3.1

$$\mathrm{MD}(I) = \sqrt{(I - \boldsymbol{\mu})\boldsymbol{\Sigma}^{-1}(I - \boldsymbol{\mu})^T} \tag{3.1}$$

The motivation for using this anomaly index is, on one hand, averaging over time nullifies the noise of the residual; on the other hand, the Mahalanobis distance

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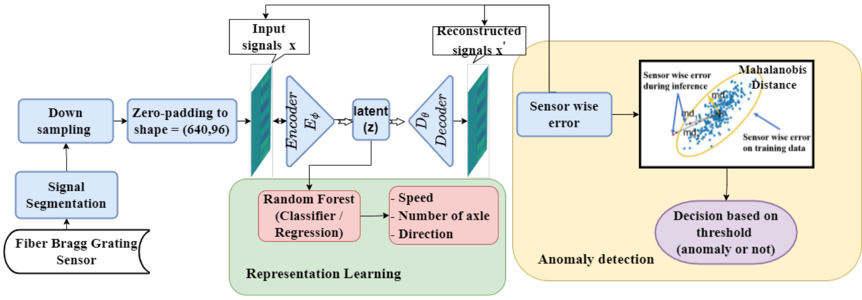

Fig. 2: Overview of the methodology

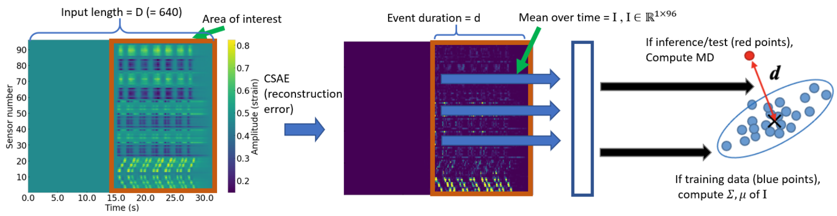

Fig. 3: Proposed approach for computing the anomaly index. MD stands for Mahalanobis distance.

normalizes the residual with respect to the variable performance of the model for each sensor.

Fig. 2 presents an overview of the data flow. The boxes highlighted in yellow are specific to the anomaly detection task. The boxes highlighted in green are specific to the representation learning task and are addressed later in section 4.

3.3 Results

In this contribution, three approaches to tackle the anomaly detection are compared. The first is the baseline model, the second is the proposed approach, the third is similar to the second, but with a MSE as anomaly index instead of the Mahalanobis-distance. As mentioned earlier, the testing dataset is composed of 418 instances of healthy and anomalous data. The anomalies in this dataset are simulated by attenuating the amplitude of 10 sensors in the East sensor set.

Table 1 shows the performance in terms of AUC of the above-described approaches with 2 different level of anomaly severity. The AE with the Mahalanobis Distance (MD) as anomaly index, outperform the baseline model with the two different proposed statistics T^2 and Q.

Commonly in SHM, to track the anomaly index, a control chart is used, see Fig. 4: for each train passage, the anomaly index is calculated and plotted on a time-axis. In SHM, issues are typically persistent in time until a maintenance action is done. So both individual false negatives and positives are typically irrelevant as long as the bulk of data suggests a change in the anomaly index.

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Table 1: Experimental results over testing dataset with two attenuation level. The used metric is AUC

Model / Anomaly	Baseline with T^2 statistic	Baseline with Q statistic	AE with MSE	AE with MD
10% attenuation	0.57	0.56	0.5	0.65
20% attenucation	0.67	0.69	0.5	0.87

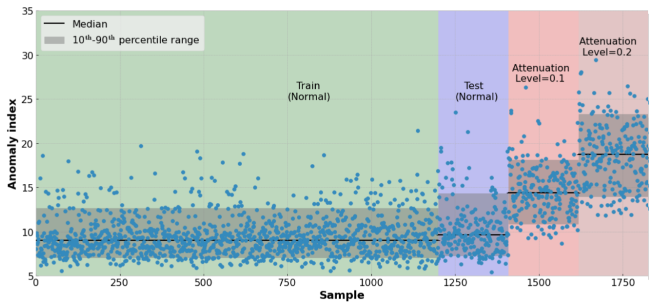

Fig. 4: Control chart for the proposed approach with the two level of anomaly type.

In Fig. 4, a control chart is made by appending the unmodified test data and appending test data with 10% and 20% attenuation on the East sensors. Even for the 10% level, there is a clear and persistent shift in the anomaly index once the anomalies are introduced.

4 Representation Learning

In the following section, the latent dimension of the CSAE is studied to get an overview on the learned embedding of the model, as well as qualitatively assess the model. The discussion proposed herein corresponds to the yellow box in Fig. 2. To visualise the latent dimension, a t-SNE algorithm is used to go from 320 to 2 dimensions. Fig. 5 reveals that the latent space is structured and representative of the problem's underlying physics. Indeed, one can see that there is a clear separation between the two possible directions and the number of axles the trains possess. As shown in Fig. 2, the latent dimension of the CSAE is used to train a traditional machine learning model, namely a random forest, for predicting characteristics of the train passage. The performance of the random forest is an indicator of the quality of the learned features. The data is divided into 1200 training samples and 209 test samples. The model was able to predict (with the latent dimension as a predictor) the train speed with an R^2 of 0.92, when predicting the number of axles the F_1 was 0.94, and finally an F_1 of 1 is achieved when the target is the train direction. Currently, this representation learning step is not part of the SHM strategy and is only used for qualitative

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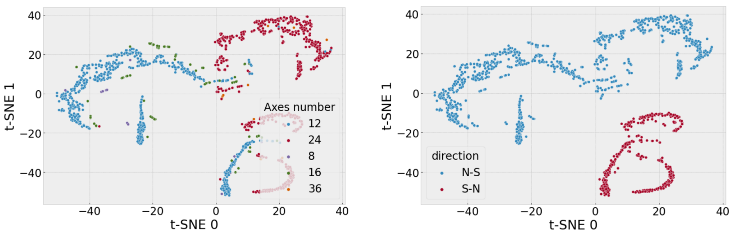

Fig. 5: Latent dimension visualization of the training set using t-SNE, (left) labelled using the train's number of axles, (right) labelled using train's direction.

evaluation of CSAE.

5 Conclusion

This study presents the challenge of anomaly detection in a railway bridges from strain measurements. This problem is addressed using a Convolutional Sparse AutoEncoder (CSAE).

In this contribution, a new anomaly detection algorithm is introduced combining the AutoEncoder (AE) with a Mahalanobis Distance (MD). The method was compared to feature-based statistical model and to an autoencoder with the MSE as anomaly index. Overall, it is concluded that combining the MD and AE has resulted in a more sensitive anomaly detection algorithm for the SHM of a railway bridge.

The learned embedding of the AE is evaluated, and the latent dimension is found to hold information about the characteristics of the train passage.

A future avenue of research would be to build an anomaly index based on the latent dimension.

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