Semi-supervised Learning for Acoustic Vision Monitoring of Tendons in Pre-stressed Concrete Bridges

ALEXANDER LANGE, MAX KÄDING, ROGHUA XU,
STEFFEN MARX and JÖRN OSTERMANN

ABSTRACT

Aging bridge infrastructure appears to become a major challenge in many industrialized countries. Numerous bridges are in bad condition and the current pace of repair and replacement as well as the available financial resources hence demand for a reliable bridge monitoring to facilitate an extended operation period of existing bridges. Nowadays, prestressed concrete bridges are prevalent among other construction types but may suffer from stress corrosion cracking of steel tendons. To detect wire breaks in bridge tendons, recent research suggests the use of acoustic emission analysis. In this work, we propose the use of semi-supervised learning techniques for anomaly detection to detect wire breaks in tendons of prestressed concrete bridges. Particularly, we utilize only acoustic emissions due to traffic and other environmental influences, recorded on a real bridge in operation, to initialize the local outlier factor algorithm. We then apply the initialized local outlier factor algorithm to two separate datasets with more than 500 wire break signals recorded on two different types of bridge girders. It is shown that the anomaly-based approach outperforms a supervised k-nearest neighbors classifier trained using wire breaks from only one girder. An evaluation on the wire break signals from the second bridge girder, not seen during the training phase, shows an improvement of the average recall score from 38 % to more than 99 % for the anomaly-based approach compared to the supervised k-nearest neighbors classifier. Considering the diversity of bridge constructions and the fact that availability of acoustic emission signals due to wire breaks is limited, semi-supervised learning seems to be a suitable approach for wire break detection. Furthermore, acoustic emissions due to normal environmental and operational conditions could be easily and cost-effectively recorded during an initialization phase of any monitoring system and thus be utilized to initialize an anomaly detector for each specific infrastructure.

INTRODUCTION

Aging infrastructure is a major challenge in many industrialized countries. In the U.S., approximately 7 % of all exisiting bridges are declared to be structurally deficient

---

Alexander Lange, Email: lange@tnt.uni-hannover.de. Institut für Informationsverarbeitung, Leibniz Universität Hannover, Germany.

and more than a third of all bridges need to be repaired or even replaced. It is estimated that at current rate, repair and replacement of all these bridges could take up to 68 years and the cost for replacing the structurally deficient bridges could sum up to more than 54 billion US dollars [1]. Due to limited financial resources and the increasing shortage of qualified professionals, it is therefore mandatory to keep existing infrastructure in service as long as possible. However, this can be a serious security hazard when further degradation of the structure remains unnoticed. To that end and with the availability of cost effective compute resources and storage media, automated structural health monitoring (SHM) gained increasing interest. With regard to prestressed concrete bridges, which are prevalent among other bridge constructions, stress corrosion cracking of steel tendons is known to be a serious problem [2]. Therefore, numerous researchers addressed this specific aspect in the context of SHM. *Xu et al.*, for example, designed and tested an electromagnetic device based on magnetic flux leakage to detect broken wires [3]. However, this is a comparatively costly process and most research studies also found acoustic emission testing (AET) to be a valid method to detect wire breaks in bridges. This is reasonable, since it can be assumed that the event of a wire break results in a significant release of energy that is emitted as structure-borne sound waves into the structure and can be detected by acoustic emission sensors. *Käding et al.* recently published a comprehensive analysis of acoustic emission measurements of manually conducted wire breaks at different bridge girders [4]. In [5], the same authors provide some insights regarding the damping behaviour of wire break related acoustic emissions in different frequency bands. Similar observations that the distance-related amplitude decay is decreasing towards lower frequencies were also reported by *Pirskawetz et al.* [6]. In [7], the authors provide the reader with a probability of detection (PoD) analysis for a specific bridge infrastructure. Based on their measurements, they come to the conclusion that for a reliable detection of wire break events (PoD $\geq$ 95 %), the maximum sensor distance should not exceed a limit of approximately eight meters. This is also in agreement with observations made during a long-term acoustic emission monitoring of a tunnel infrastructure in [8]. Considering the dimensions of transport infrastructures, these small sensor distances can make acoustic emission monitoring economically insufficient. It should be noted though that these studies focus mainly, if not exclusively, on traditional acoustic emission analysis in the ultrasonic frequency range. In this work, we are looking at structure-borne acoustic emissions in the audible frequency range below 20 kHz and employ a semi-supervised machine learning technique that learns from acoustic emissions due to environmental influences only. Despite that, our approach does not take any information about the amplitude scale into account and therefore may allow greater sensor distances and hence more economical bridge monitoring using acoustic emissions.

METHODOLOGY

Many studies follow the traditional approach of AET and suggest to separate damage-related wire break events from environmental noise by using fixed amplitude thresholds [6,7]. However, due to well-known attenuation effects of acoustic emission signals, the maximum amplitude of any distant wire break signal could lie in the same value range as any near-source signal induced by traffic or other environmental effects. Fixed amplitude thresholds may therefore lead to insufficient sensor network designs for bridge monitoring applications. To overcome this drawback, we use an adaptive threshold technique based on short-time energies of continuous structure-borne sound recordings to preselect any form of *abnormality* in the continuous stream of acoustic emission (AE) measurements (Sec. *Event Detection by Adaptive Thresholding*). The classification of wire break signals among other non-damage related AE events extracted by the the adaptive threshold technique is left for a more sophisticated machine learning algorithm and done in a subsequent step (Sec. *Semi-supervised Learning for Wire Break Recognition*).

Event Detection by Adaptive Thresholding

Let $x[n]$ be a discrete-time signal recorded by an acceleration sensor installed on one of our test specimens (see Sec. *Experiments*). In order to extract acceleration segments with an increased energy compared to the prevailing noise level, we adapt the CFAR algorithm commonly used in radar systems but more recently also studied in the field of AET. Similarly to [9], we first divide our raw acceleration recordings in short non-overlapping segments of approximately 20 milliseconds ($N_{seg} = 1024$) and compute the energy for each of those segments (Eq. (1)). Then, a sliding window method is used to apply the cell-averaging CFAR algorithm as detailled in Eq. (2) to (4) and derived in [10]. Here, N_G are the so-called guard segments and N_T is the number of training segments before and after the *k*-th segment under test that are utilized to estimate the noise power $P_{ref}[k]$. $P_{ref}[k]$ is subsequently used to define the adaptive threshold for the *k*-th segment $\hat{T}[k]$ as stated in Eq. (3), where α is a constant factor that determines the false alarm rate R_{fa} (Eq. (4)).

$$P[k] = \sum_{n=k*N_{seg}}^{(k+1)*N_{seg}} x[n]^2 \quad \text{for} \quad k \in \{0, 1, 2, \dots\} \tag{1}$$

$$P_{ref}[k] = \frac{1}{2N_T} \left(\sum_{n=k-N_G-N_T}^{k-N_G-1} P[n] + \sum_{n=k+N_G+1}^{k+N_G+N_T} P[n] \right) \tag{2}$$

$$\hat{T}[k] = 1.13\sqrt{\alpha} P_{ref}[k] \tag{3}$$

$$R_{fa} = \left(\frac{\alpha}{2N_T} + 1 \right)^{-2N_T} \tag{4}$$

To avoid the extraction of cropped AE events due to leakage in neighboring guard segments, we further apply some postprocessing. Whenever the adaptive threshold $\hat{T}[k]$ is crossed, we extract the corresponding raw acceleration signal $x_k[n]$ according to Eq. (5), calculate the moving root mean square (RMS) of the zero-padded signal $x_k[n]$ and crop the signal to a fixed-length acceleration segment $x_{k,crop}[n]$ as stated in Eq. (6). Here, p_{rms} denotes the argmax of the moving RMS of the zero-padded signal $x_k[n]$. In a last step, we discard all segments with really low maximum amplitudes below 0.1g.

$$x_k[n] = (x[(k - N_G) * N_{seg}, (k - N_G) * N_{seg} + 1, \ldots, (k + N_G) * N_{seg}]) \quad (5)$$

$$x_{k,crop}[n] = (x_k[p_{rms} - \frac{N_{seg}}{4}, p_{rms} - \frac{N_{seg}}{4} + 1, \ldots, p_{rms} + \frac{3N_{seg}}{4}]) \quad (6)$$

$$\text{for} \quad k \in \{ \mathbb{N} \mid P_{ref}[k] > \hat{T}[k] \}$$

TABLE I. DATA SPLITS & PARAMETER SETTINGS FOR PROCESSING PIPELINE

(a) Parameter Grid (GS-CV)

Param.	Values
$\mathcal{K}$	{5,10,20,50,100}
S	{MinMax, Std, None}
M	{ℓ_1-norm, ℓ_2-norm, cosine}
C	$\{1, 2, 5, 10, 20\} * 10^{-3}$

(b) CFAR

Symbol	Value
N_{seg}	1024
N_G	2
N_T	48
α	9.59

(c) AE events for Develop., Training & Test

Datasource	Local Outlier Factor			K-nearest neighbors		
	Dev.	Train	Test	Dev.	Train	Test
Wirebreaks box girder	100	-	200	100	100	100
Wirebreaks I-beam	-	-	201	-	-	201
Environmental Noise	1242	1291	3873	1242	1291	3873

Semi-supervised Learning for Wire Break Recognition

For the identification of wire break signals, we first calculate the logarithmic magnitude spectrum for each of those previously extracted segments $x_{k,crop}$ and then obtain cepstral coefficients for each spectrum using the discrete cosine transform. Cepstral coefficients have shown to be a good feature representation in environmental sound classification as well as in condition monitoring [11, 12]. Considering that availability of acoustic emission measurements due to wire break events will presumably always be rare, we propose to utilize a semi-supervised machine learning algorithm, i.e. the Local Outlier Factor (LOF) [13] for the task of wire break signal recognition. We initialize the algorithm with acoustic emission signals due to traffic and other environmental influences only and hence need just some wire break signals to optimize the hyperparameters.

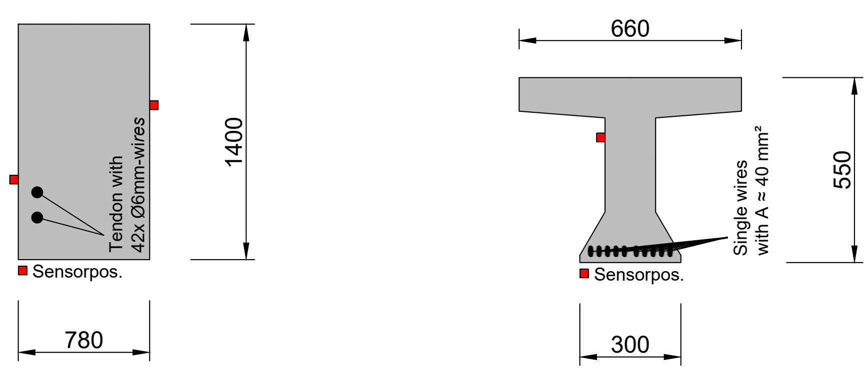
First, we created a dedicated *development* dataset containing approximately 20 % of all available environmental noise and wire break signals and utilized this to tune the hyperparameters of the model using grid search cross validation (GS-CV). The wire break signals are, however, only added to the test folds in case of the semi-supervised LOF algorithm. The considered search space for GS-CV is shown in Tab. Ia, where $\mathcal{K}$ is the number of considered neighbors, S denotes the set of considered feature scaling techniques and M represents the set of investigated distance metrics. C defines the proportion of outliers in the training dataset and is the only hyperparameter that is specific to the LOF algorithm. The best configuration found on this dedicated *development* set is selected and repeatedly evaluated on different train-test splits whose sample sizes are denoted in Tab. Ic. Analogously we trained a fully supervised k-nearest neighbors classifier and compared its results with the ones from the LOF algorithm.

EXPERIMENTS

In this section, the wire break experiments conducted on two different demolished bridge girders (Sec. *Wire Break Measurements*) as well as the acoustic emission measurements due to traffic and other environmental influences (Sec. *Acoustic Emissions due to Environmental Influences*) are described and summarized in Tab. Ic. It should be noted that, in contrast to most other studies, we wanted to investigate the applicability of acoustic emission analysis in the audible frequencies and hence utilized conventional accelerometers with a -3dB cutoff frequency at 17 kHz throughout all experiments. The use of conventional accelerometers with a main sensitivity in the audible frequency range is motivated by the observations in [5, 6], where, for sensors that do not lie in immediate vicinity of the sound source, a significant proportion of the total acoustic emission energy is shown to be present in the lower frequencies below 20 kHz.

Wire Break Measurements

To evaluate our proposed semi-supervised approach and compare it with a fully supervised machine learning algorithm, we acquired two separate datasets of wire break events on two different types of demolished bridge girders. A cross-sectional view of the girders is shown in Fig. 1. The two demolished sections of the box girder bridge (Fig. 1a) had an approximate length of seven meters and were prestressed with tendons consisting of up to 42 single wires with a diameter of six millimeter. The two I-beam girders (Fig. 1b) were slightly longer and had a length of approximately nine meters. These girders were prestressed with single steel wires whose cross-sectional area was about 40 mm². We equipped all these girders with multiple accelerometers along the length axis in distances between $l_u = 1.2m$ and $l_o = 7.2m$ to the acoustic source. Then, the tendons were manually exposed and single wires of the steel tendons were manually cutted using an angle girder. To increase the diversity of the created datasets, we varied the sensor positions with respect to the wire break location and along the height of the girders multiple times throughout the experiments. Additionally, the exposed length of the tendons differed for different wire break locations along the girders to account for different bond conditions. From these experiments, we obtained 300 wire break signals



(a) Section of box girder (b) I-beam girder

Figure 1. Cross-sectional view of two different types of bridge girders. Only those tendons / wires that were manually cutted during the experiments are shown.

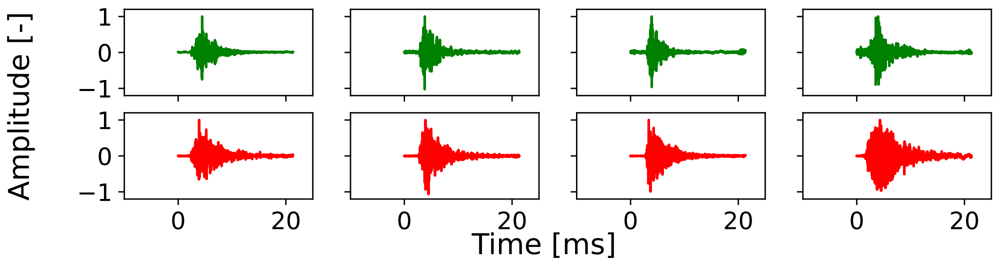


Figure 2. Examples of *environmental noise* signals (top) and *wire break* signals (bottom)

from the box girders and 201 wire break signals from the I-beam girders. A few examples of wire break and environmental noise signals, whose feature representations are fed to the machine learning algorithms, are shown in Fig. 2.

Acoustic Emissions due to Environmental Influences

Additionally, we also installed in total four accelerometers on a box girder bridge in Hagen, Germany that was still in operation back then. We continuously recorded all structure-borne sound signals due to traffic and any other environmental influences over a period of approximately twelve days. Here, the sensor positions remained fixed throughout the whole measurement period. From these approximately 282 hours of continuous recordings, we extract all impulse-like burst signals that are detected by adaptive thresholding, more precisely the constant false alarm rate algorithm. We assume that no wire breaks occured during these measurements on the real bridge and therefore declare all these signals as *environmental noise*.

RESULTS

As stated previously, we train and evaluate the best performing model configuration on the *environmental noise* signals extracted from the CFAR algorithm and the wire break signals from the experiments altogether ten times with different train-test splits. We do this for the semi-supervised LOF algorithm and the fully supervised k-nearest neighbors classifier. For both models, we strictly separated the wire breaks from the box girder, from which a portion of wire breaks were used to initialize the k-nearest neighbors classifier. The wire breaks conducted at the I-beam girder were strictly used for testing. However, the *environmental noise* signals were the same in both test sets for each split. Tab. II shows the resulting statistics for the two models for different numbers of cepstral coefficients. As expected and can be seen from Fig. 3, the fully supervised model shows slightly higher recall scores for the wire breaks of the box girder, partially seen during training, but barely generalizes to new unseen wire break measurements of the I-shaped girder. In contrast, the LOF algorithm, initialized with *environmental noise* signals only, shows a comparable performance for both wire break datasets at the cost of a few more false positives (approx. twelve events per day) and a slight decrease in the average recall score for the wire breaks of the I-shaped girder.

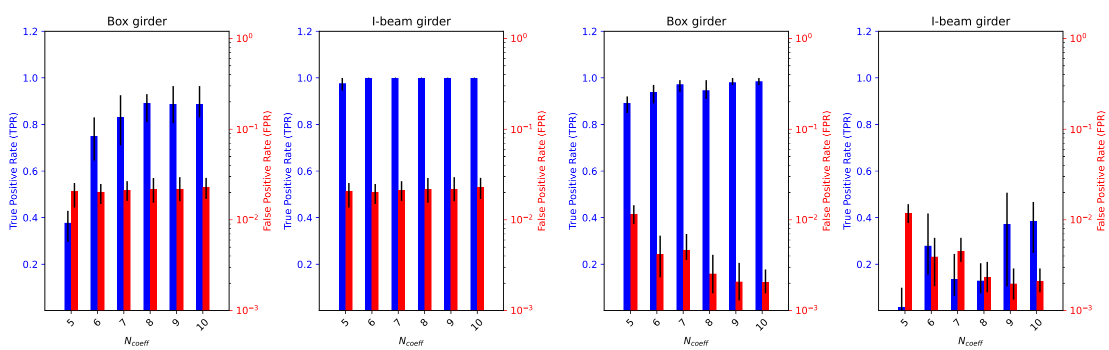
TABLE II. EVALUATION RESULTS ARE AVERAGED VALUES ACROSS TEN REPEATED EVALUATIONS. BEST RESULTS IN TERMS OF THE MEAN F1-SCORE ACROSS BOTH WIRE BREAK DATASETS ARE MARKED IN **BOLD**.

Wirebreaks	N_{coeff}	Local Outlier Factor			K-nearest neighbors		
		TPR[1]	**FPR**[2]	**F1**[3]	**TPR**[1]	**FPR**[2]	**F1**[3]
Box girder	5	0.378	0.021	0.422	0.893	0.012	0.764
	6	0.750	0.020	0.700	0.940	0.004	0.895
	7	0.833	0.021	0.742	0.972	0.005	0.904
	8	**0.894**	**0.022**	**0.772**	0.947	0.003	0.926
	9	0.888	0.022	0.768	0.981	0.002	0.952
	10	0.889	0.023	0.764	**0.984**	**0.002**	**0.954**
I-beam girder	5	0.977	0.021	0.822	0.017	0.012	0.026
	6	1.000	0.020	0.837	0.279	0.004	0.407
	7	1.000	0.021	0.831	0.137	0.004	0.221
	8	**1.000**	**0.022**	**0.828**	0.129	0.002	0.219
	9	1.000	0.022	0.826	0.372	0.002	0.518
	10	1.000	0.023	0.821	**0.384**	**0.002**	**0.536**

[1] True Positive Rate; [2] False Positive Rate; [3] F1-score

CONCLUSION AND OUTLOOK

To the authors best knowledge, this work is the first approach to apply semi-supervised learning to the task of wire break detection in tendons of prestressed concrete bridges. We show that supervised learning algorithms may suffer from poor generalization performance in low data regimes like acoustic emission analysis of wire breaks. This is reasonable, considering the diversity of bridge constructions and tensioning systems and the complex nature of wave propagation. Therefore, we evaluated the performance of the LOF algorithm, which is initialized with acoustic emissions due to traffic and other environmental influences only and can therefore be easily adapted to each specific infrastructure under test. We obtain average recall scores of 89 % and 100 % for the wire break events of two different bridge girders, while having approximately twelve false positive detections per day. This is slightly worse than the results of a supervised approach applied to wire breaks of one type of bridge girder reported in [14]. However, our method also does not rely on the amplitude scale of the signals and therefore may allow a more economic design of sensor networks for acoustic emission monitoring.



(a) Local Outlier Factor

(b) K-nearest neighbors

Figure 3. Evaluation results on two different wire break datasets for a) semi-supervised and b) fully-supervised approach. The errorbars denote the minimum / maximum scores across all ten repeated evaluations. *Note the logarithmic scale of the ordinate for FPR.*

ACKNOWLEDGEMENTS

This research was partially supported by the German Federal Ministry for Economic Affairs and Climate Action (research project *"AI-supported acoustic emission monitoring for automatic damage detection in supporting structures of wind turbines"*, FKZ: 03EE2025B). The authors also thank Prof. Dr.-Ing. Thomas Braml and Matthias Haslbeck, M. Sc. for faciliating the experiments.

REFERENCES

1. Black, P. and ARTBA. 2022, "2022 Bridge Report," `https://artbabridgereport.org/reports/2022-ARTBA-Bridge-Report.pdf`, accessed: 2023-05-09.
2. Nürnberger, U. and W. Beul. 1994. "Untersuchungen an Verkehrsbauten aus Spannbeton zur Abschätzung des Gefährdungspotenzials infolge Spannungsrisskorrosion der Spannstähle: Abschlussbericht zum BMV- Forschungsvorhaben: Teil 2 – Untersuchungen der FMPA." .
3. Xu, F., Z. Jiang, and Q. e. a. Jiang. 2022. "Damage Detection and Assessment of Broken Wires in Cables of a Bridge Based on Magnetic Flux Leakage," *Exp. Tech.*, doi:https://doi.org/10.1007/s40799-022-00605-1.
4. Käding, M., G. Schacht, and S. Marx. 2022. "Acoustic Emission analysis of a comprehensive database of wirebreaks in prestressed concrete girders," *Engineering Structures*, 270:114846, ISSN 0141-0296, doi:https://doi.org/10.1016/j.engstruct.2022.114846.
5. Käding, M., G. Schacht, and S. Marx. 2023. "Erfahrungen zum Dämpfungsverhalten impulsartiger, energiereicher Signale an Spannbetonkonstruktionen," .
6. Pirskawetz, S. M. and S. Schmidt. 2023. "Detection of wire breaks in prestressed concrete bridges by Acoustic Emission analysis," *Developments in the Built Environment*, 14:100151, ISSN 2666-1659, doi:https://doi.org/10.1016/j.dibe.2023.100151.
7. Käding, M., G. Schacht, and S. Marx. 2021. "Spanndrahtbruchdetektion mit Schallemissionsmonitoring," in *11. Symposium Experimentelle Untersuchungen von Baukonstruktionen; Schriftenreihe Konstruktiver Ingenieurbau Dresden*, pp. 96–104.
8. Sodeikat, C., R. Groschup, F. Knab, and P. Obermeier. "Acoustic Emission in der Bauwerksüberwachung zur Feststellung von Spannstahlbrüchen," *Beton- und Stahlbetonbau*, 114(10):707–723, doi:https://doi.org/10.1002/best.201900041.
9. Tra, V., J.-Y. Kim, I. Jeong, and J.-M. Kim. 2020. "An Acoustic Emission Technique for Crack Modes Classification in Concrete Structures," *Sustainability*, ISSN 2071-1050.
10. Richards, M. A. 2014. *Fundamentals of radar signal processing*, McGraw-Hill Education.
11. Solimine, J. and M. Inalpolat. 2022. "An unsupervised data-driven approach for wind turbine blade damage detection under passive acoustics-based excitation," *Wind Engineering*, 46(4):1311–1330, doi:10.1177/0309524X221080470.
12. Randall, R., "Cepstrum Analysis and Gearbox Fault Diagnosis," `https://www.bksv.com/media/doc/233-80.pdf`, accessed: 2023-05-29.
13. Breunig, M. M., H.-P. Kriegel, R. T. Ng, and J. Sander. 2000. "LOF: Identifying Density-Based Local Outliers," 29(2), doi:https://doi.org/10.1145/335191.335388.
14. Lange, A., M. Käding, R. Hinrichs, J. Ostermann, and S. Marx. 2023. "Wire Break Detection in Bridge Tendons Using Low-Frequency Acoustic Emissions," in P. Rizzo and A. Milazzo, eds., *European Workshop on Structural Health Monitoring*, Springer International Publishing, Cham, pp. 1024–1033.