ACOUSTIC SIGNAL DISCRIMINATION IN PRESTRESSED CONCRETE ELEMENTS BASED ON STATISTICAL CRITERIA

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One of the main issues concerning concrete structural integrity evaluation with Acoustic Emission (AE) technique is the signal interpretation.

The problem already arises at the level of acquisition because of the complexity of the considered structures i.e. bridges, and the inhomogeneity of reinforced concrete. The waveforms emitted from different sources corresponding to different destructive processes undergo modification processes when migrating through the source – sensor path. The waveform modification is subjective to material properties i.e. signal damping, geometric spreading as well as breaking up at boundaries i.e. reflections. The form of recorded signals reflects also the transducers' features. Moreover, major signal disturbance that should not be discounted is noise viz. electronic, electromagnetic or acoustic interference.

In this paper, signal discrimination criteria are proposed namely parameter-based analysis as well as signal pattern recognition. The main focus is on the recognition and classification of the limited number of records that contain representative waveforms and frequency spectrum magnitude. Additionally, extracted features from recorded waveforms are evaluated. The feature and vector discriminant i.e. class evaluation are studied based on the three statistical factors, namely Wilk's λ criterion corresponding to the feature and vector discrimination efficiency, along with Rij and Tou criteria that are based on the ratio of average within-class as well as between classes distances. For signal clustering, k-means algorithm is applied. The selected number of classes is verified based on the statistical criteria. Based on limited pre-processed data, the intensity of destructive processes' development is studied.

The procedure verification on two different full-scale laboratory tests is presented. The experimental prestressed concrete girders were loaded up to failure in four-point bending.

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ABSTRACT: In this paper, signal discrimination criteria are studied namely parameter-based statistical analysis and signal pattern recognition based on recorded waveforms. The main aim is to evaluate the recorded signals in order to discount records that appear to carry irrelevant information for the analysis. Following the accept/reject criteria, the pattern of representative waveforms together with their frequency spectrum magnitude is further analyzed. Clustering evaluation criteria are studied based on three statistical factors, namely Wilk's λ criterion corresponding to the feature and vector discrimination efficiency, along with Rij and Tou criteria that are based on the ratio of average within-class as well as between-classes distances. For signal clustering, k-means algorithm is applied.

1 INTRODUCTION

Continuous field monitoring of engineering structures, especially concrete bridges, delivers a large amount of recorded signals. Storage, but mainly analysis of the data is therefore demanding. It is highly required that data to be analyzed is appropriately pre-processed. Recorded signals contain relevant information regarding structural degradation as well as irrelevant information corresponding to the so-called noise. The main aim is to recognize and to separate signals that may relate to processes that may actuate failure mechanisms. For this purpose a parameter-based analysis is considered due to the large amount of recorded data and limited technical capabilities. The reason to consider the analysis of signal parameters is also related to monitoring efficiency that could serve as bases for automatic accept/reject criteria.

The aim of this study is to apply signal discrimination criteria for long term field monitoring of bridges with the acoustic emission technique. The acoustic emission is a passive non-destructive monitoring method that has proven to be successful in discovering internal destructive processes due to static loading in materials such as steel and composites. In case of concrete bridges, the situation is more complicated because of materials' inhomogeneity and structural complexity. A previous approach to signal analysis at Kielce University of Technology (KUT) in Poland was to create a database of representative clusters corresponding to possible destructive processes leading to

failure. For this purpose, experimental tests on samples have been performed at KUT laboratory in order to generate reference AE events e.g. Gołaski et al. (2006). The problem with such an approach is that the signal character and parameter values recorded from small experimental samples are significantly different in comparison with the results from field monitoring. Signal propagation depends very much on material properties as well as dimensions of considered tests' specimens.

The proposed analysis considers processing recorded events using parameter-based statistical analysis instead of reference signal's data base of "clear" processes. The verification of the proposed procedure has been performed with results from experiments on full scale prestressed concrete girders. Two types of girders were loaded up to failure in a number of cycles: non-symmetrical I-type of length 18.8 m and T-type of length 26.5 m. Both were tested in the laboratory at the Road and Bridge Research Institute (IBDiM) in Kielce in Poland. The acoustic emission monitoring was performed by the research team of KUT supervised by Prof. Gołaski e.g. Świt (2008). The aim of the experiments was to study the correspondence of the AE signals with the failure mechanisms including reference data base verification. The number of sensors applied varied between 11 and 12, which was adjusted to the length of the girders based on the measured signal attenuation. The mounted AE sensors were of the resonant type with a frequency peak sensitivity of 55 kHz. The analysis results in comparison to the KUT procedure are presented.

2 AE PARAMETERS AND DISCRIMINATION CRITERIA

Generally two approaches for data analysis are commonly applied e.g. Grosse & Ohtsu (2008) namely parameter-based analysis and signal-based analysis. Parameter-based analysis i.e. classical analysis is limited to the evaluation of values recorded directly from waveforms during an acquisition. In early applications of acoustic emission, the acquisition was limited to recording signal parameters due to poor technical possibilities. Nowadays due to advancing technology, commercially available monitoring equipment can record both, parameters as well as corresponding waveforms.

Currently, research on acoustic emission is concentrating more on signal-based analysis that emphases the evaluation of waveform patterns. It has been confirmed that analysis of waveforms provides more detailed information about the character and localization of the signal source e.g. Grosse & Ohtsu (2008). Problematic in field applications considering this approach are more technical aspects i.e. demanding sufficient acquisition and storage capabilities as well as high costs of equipment.

Acoustic Emission parameters are recorded based on the pre-set threshold that is selected based on the external noise measurements. Key burst AE parameters that are acknowledged in the standards are: rise time, peak amplitude, time, signal duration, ring down counts, energy (aka signal strength), and first threshold crossing e.g. CEN standards (2009) & ASTM standard (2010). The same parameters have been used in the presented procedure. Parameters like frequency, peak amplitude, and energy give an important indication of acoustic emission intensity as well as activity e.g. Stone & Dingwall (1977). In case of monitoring large structures, it is important to have at first an indication of more active zones. For this purpose, the detailed information about the character of the signals is less important, especially when considering the size of involved structure and technical limitations.

The study covered by this paper focuses on parameter-based analysis with addition of signal-based waveform pattern recognition. Feature and class discrimination is performed based on statistical criteria. For this purpose the following statistical tools are applied, namely Wilk's λ criterion, along with Rij and Tou criteria. These criteria are based on the calculation of event distribution of within-class scatter matrix, the between-class scatter matrix and the total scatter matrix. Wilk's λ (also known as the trace criteria e.g. Duda (2001)) corresponds to the feature and vector discrimination efficiency and is defined as the ratio of within-class to the total scatter matrix. In terms of statistics, Wilk's λ distribution is a probability distribution used in multivariate hypothesis testing e.g. Wikipedia (2011). A low value of Wilk's λ criterion is an indication of a high discrimination efficiency of the selected features' set. The Rij and Tou criteria are based on the ratio of within-class as well as between-classes average distances. The Rij criterion (also known as the determinant criteria e.g. Duda (2001)) is an average ratio that is calculated using all different pairs of classes. The Tou criterion (also known as the invariant criteria e.g. Duda (2001)) corresponds to the ratio of the minimum distance between any pair of classes, to the maximum of the average within-class distances. Consequently, the lower the value of the Rij criterion (or alternatively the higher the Tou criterion), the higher is the discrimination efficiency of the selected features' set e.g. NOESIS Manual (2010).

3 PARAMETER-BASED ANALYSIS

3.1 Signal classification

To be able to perform the feature and vector discrimination based on Wilk's λ, Rij and Tou, it is necessary to perform a pre-clustering that is the k-means algorithm in the presented approach. K-means is an iterative algorithm that aims at minimizing the square error for a specified number of clusters. The sum-of-squared-error criterion (see Eq. 1) is appropriate when analyzing the clusters that form compact clouds. It minimizes the sum of the squared lengths of the vectors: data samples $\boldsymbol{x}$ and cluster centers $\boldsymbol{m}_i$e.g. Duda et al. (2001).

$$J_e = \sum_{i=1}^{k} \sum_{x \in D_i} \|x - m_i\|^2 \tag{1}$$

The k-means algorithm, starting with the initial clusters specified, assigns the remaining points to one of the predefined clusters by nearest neighbor classification. The cluster centers are updated and the process continues until none of the patterns changes class membership e.g. NOESIS Manual (2010).

The k-means algorithm has been chosen for this study based on its simplicity. Since the measured results originate from unknown sources, it is necessary to distinguish the desired clusters in an unsupervised manner. However, this algorithm classifies data with a specified number of clusters; therefore it is necessary to assume this number. Following the clustering, the number of clusters is adjusted and verified accordingly to the feature and vector statistical criteria.

3.2 Normalization

Before simulating the clustering, it is important to normalize the scale of the AE features. The parameters' scales range between 10^1 and 10^{10}. Considering non-

normalized data, the clustering algorithm gives cluster center priority to signals with high values (see Figure 1).

There are different normalization algorithms available. One that has been applied in this study is normalization 0-1 that repositions the considered data between values 0 and 1. As a consequence, the weight of the features is more uniform (see Figure 2).

During pre-processing, it is also advisable to look closer at the features namely to delete correlated features based on feature statistics' discrimination as well as to delete signals that do not match any waveforms.

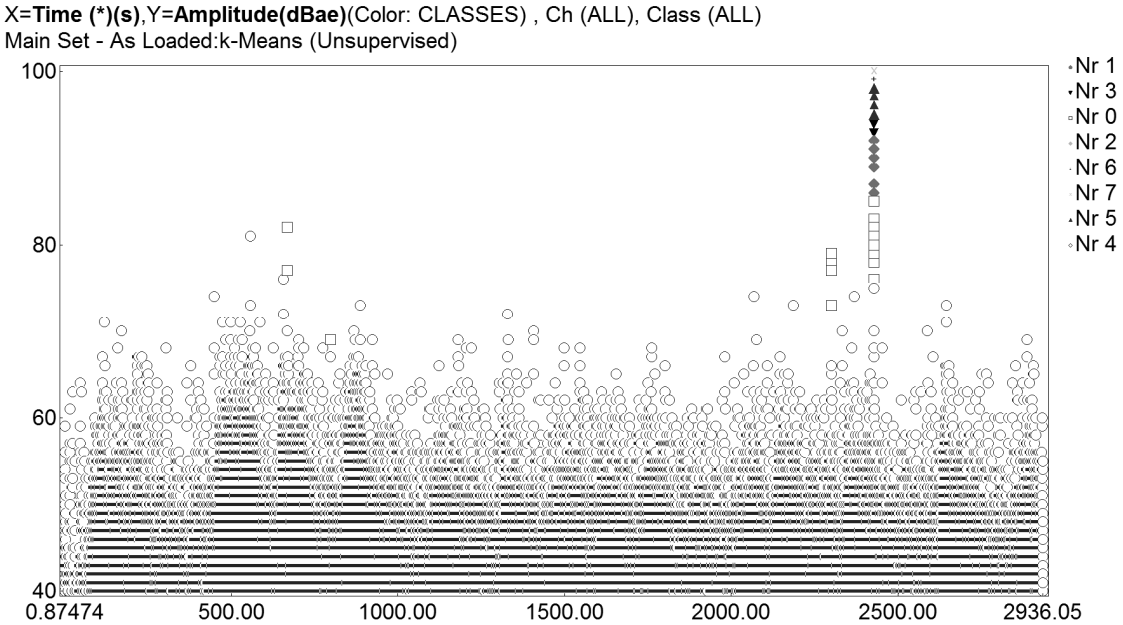


Figure 1. I-18-type girder. Last loading cycle. Failure at 681.2 kN. Amplitude vs. time point diagram. Non-normalized data. K-means clustering with 8 classes.

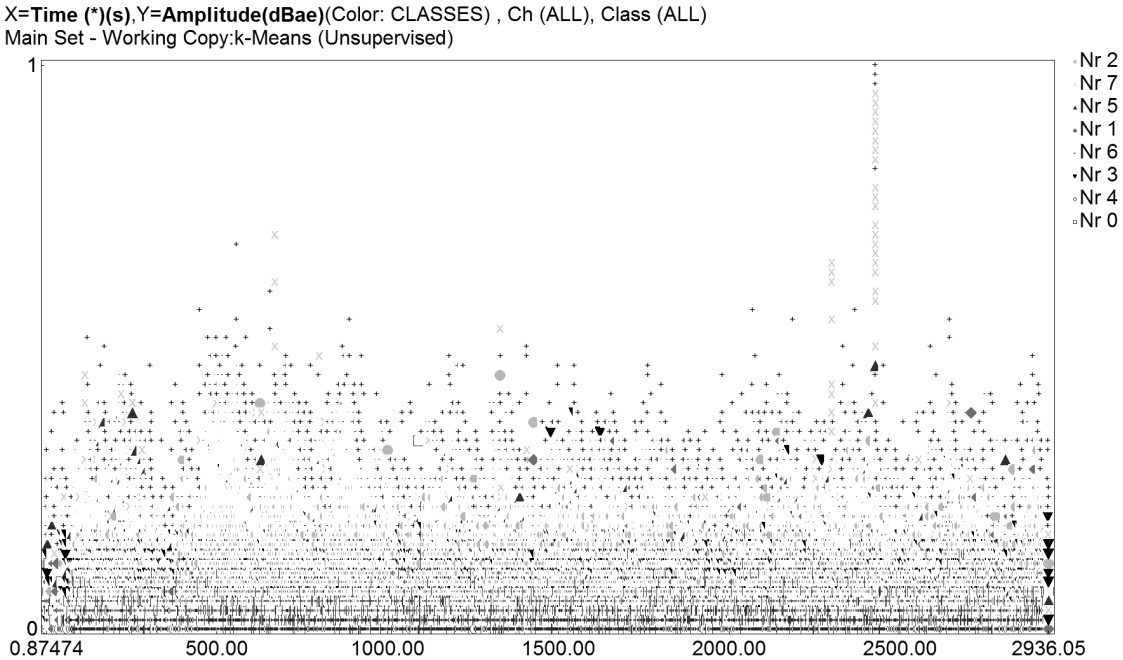


Figure 2. I-18-type girder. Last loading cycle. Failure at 681.2 kN. Amplitude vs. time point diagram. Normalized data. K-means clustering with 8 classes.

The alterations between non-normalized and normalized data are also reflected in the values of the statistical criteria (see Table 1). The desired values are: minimum of Wilk's λ and Rij criteria as well as maximum of Tou criterion. In presented examples of the non-normalized and normalized data, the Wilk's λ criterion tends to lower values by a higher number of clusters for both presented types of girders. What should be remarked, are the disagreements between different discrimination criteria in case of non-normalized and normalized data. The low value of Rij together with high value of Tou criteria do not agree with the high value of Wilk's λ criterion for non-normalized data. These variations are limited or disqualified in case of normalized data. In comparison with the KUT reference data base, the results from the girder T-27 agree for normalized data e.g. Gołaski (2006).

Table 1. Statistical criteria values for different numbers of clusters. I-18 and T-27 girders at the failure loading cycle.

No of clusters	I-18 girder			T-27 girder		
	Wilk's λ	Rij	Tou	Wilk's λ	Rij	Tou
Non-normalized data						
5 clusters	0.00162	**0.42519**	**0.17822**	0.00497	0.69289	**0.087801**
6 clusters	0.0009	0.48447	0.074473	0.00127	**0.506**	0.058378
7 clusters	0.00065	0.51676	0.048012	0.00056	0.54216	0.02724
8 clusters	0.00048	0.53825	0.020421	0.00037	0.57173	0.025108
9 clusters	0.00028	0.67621	0.0007939	0.00022	0.58041	0.019509
10 clusters	**0.00021**	0.63344	0.00055524	**0.00011**	0.59317	0.011756
Normalized data						
5 clusters	0.00762	1.9277	0.83395	0.00674	1.7619	0.84191
6 clusters	0.00346	1.8119	0.7915	0.00128	1.6805	0.89733
7 clusters	0.00183	1.7695	0.80451	0.00054	**1.6602**	**0.94095**
8 clusters	0.00091	1.6941	0.82377	0.00022	1.733	0.90124
9 clusters	0.00055	1.6454	0.84189	**0.00005**	1.7346	0.85078
10 clusters	**0.00041**	**1.5479**	**0.83731**	0.00009	1.7267	0.78318

3.3 Feature extraction (FX)

Additional AE parameters can also be extracted directly from the recorded waveforms that are mainly form and frequency related. Most significant are rise angle, decay angle, peak frequency, frequency centroids and others. The information they provide about the shape and character of the waveforms are substantial in the process of signal discrimination. The main goal is to seek for distinguishing features that are invariant to irrelevant transformations of the recorded data e.g. Duda et al. (2001).

In order to better understand the pattern of the multidimensional signals' network, examples of different parameter combinations in cross plots are presented (see Figure 3). Based on the parameter combinations, irrelevant signals may be selected, for example signals, of which the Fast Fourier Transform Peak Frequency equals zero (see Figure 3 right). The rise and decay angle features express well the form of signals i.e. for example low rise angle together with low decay angle indicates continuous type emission e.g. CEN standards (2009), which could be for example background noise.

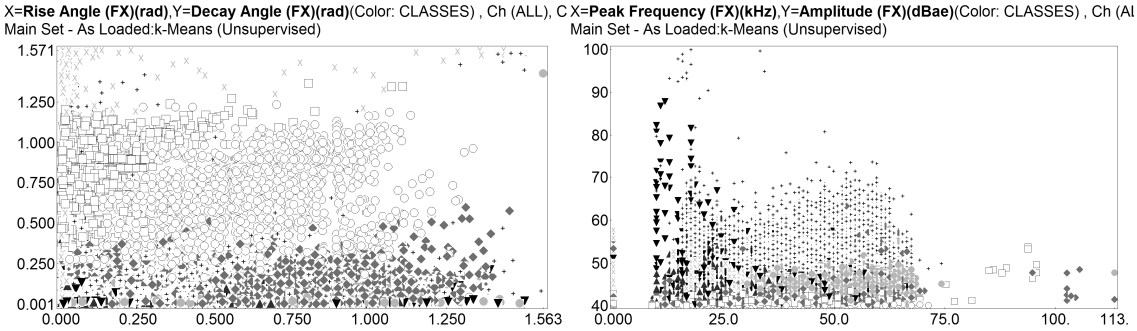
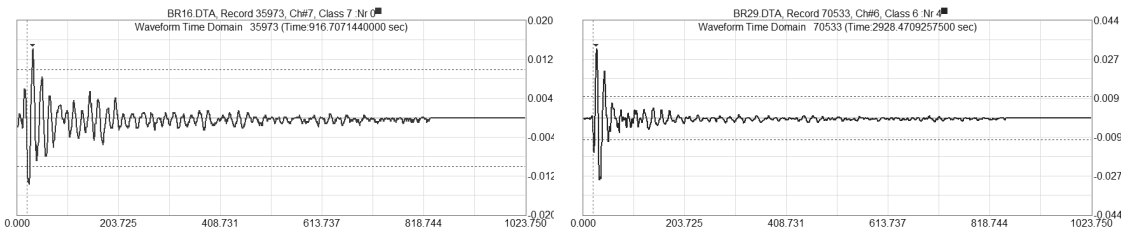


Figure 3. I-18 girder. Last loading cycle. Failure at 681.2 kN. Normalized data. K-means clustering with 8 classes. Diagrams: (left) decay angle vs. rise angle, (right) amplitude vs. peak frequency. Cluster numbers correspond to the Figure 2.

4 SIGNAL PATTERN RECOGNITION

To complement the parameter-based statistical analysis, it is necessary to look closer at the pattern of recorded waveforms. The propagating elastic waves carry energy along with significant information about the character and magnitude of emission sources. Based on the waveform propagation theory, recorded signals by the piezoelectric resonant transducers comprise information about the source, material properties, sensor's properties as well as acquisition equipment's properties e.g. Grosse & Ohtsu (2008). Considering these dependencies, it is obvious that the recorded outcome signals are very much distorted, which has to be taken into account throughout the acquisition set up as well as the analysis. The higher the distance between source and sensor is, the more distorted the signals are.

Logically, recorded waveforms with least disturbed pattern represent best the source mechanisms. From the example results from the I-18 girder, representative signals for chosen clusters are shown (see Figure 4). Within 8 selected clusters based on the statistical criteria, only 4 contain similar waveforms' patterns, these are cluster numbers 0, 4, 6 and 7. This is a positive indication that signals have been assigned to appropriate clusters representing different source mechanisms. Signals assigned with the cluster numbers 1, 2, 3 and 5 do not display a representative waveform pattern. It is assumed that these represent a product of signal overlapping and reflections.



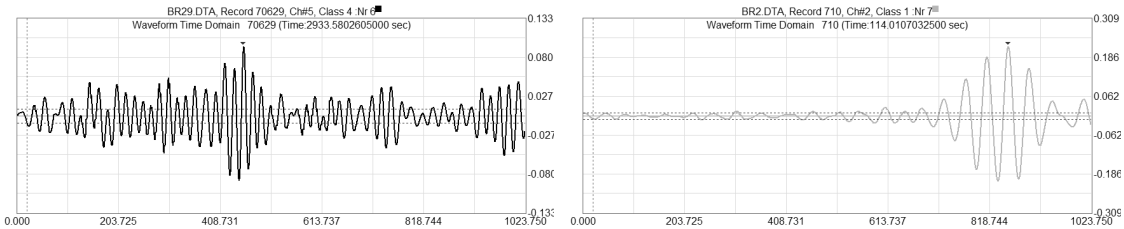


Figure 4. I-18 girder. Representative waveforms from cluster number: 0, 4, 6 and 7.

Based on representative waveform patterns, signal triggering might be considered. The character of the signals' clusters is represented by the parameters that are presented in the table below (see Table 2). Triggering filtering is established based on known parameter values.

The presented examples represent possible destructive processes. In case of signal duration, the low values designate cracking processes, while high values indicate friction processes. Considering signal amplitude – wire breaking or electromagnetic noise emits very high amplitudes, while mechanical friction causes very low amplitude.

Table 2. I-18 girder. Max-min AE parameters' values of the representative clusters.

Cluster	Amplitude (dBae)		Duration (s)		FX Peak Freq. (kHz)		FX Counts (-)	
	max	min	max	min	max	min	max	min
Nr 0	45-60	40	400-620	5	41-48	23-34	3-15	1
Nr 4	42-58	40	6-74	0	41-45	25-32	2-4	1
Nr 6	80-99	45	1024	560-850	55-99	42	47-60	16-21
Nr 7	52-99	40	1024	470-600	50-92	32-39	20-41	1

5 DISCUSSION AND CONCLUSIONS

In this paper, signal discrimination criteria are proposed. These are parameter-based statistical analysis and signal-based pattern recognition analysis. Clustering evaluation criteria are based on three statistical factors, namely Wilk's λ, Rij and Tou criteria.

Following conclusions to the signal discrimination analysis are listed:

1. The proposed criteria demonstrate significant differences between normalized and non-normalized features. A normalization algorithm allows discounting great parameter scale ranges that affect clustering by prioritizing higher values.

2. For signal clustering, the k-means algorithm was applied. The number of clusters was chosen. The verification has been performed using the feature and vector statistics. For this purpose the clustering algorithm was run several times with different numbers of classes. Based on statistical data, 8 clusters have been chosen that corresponds to the results from KUT data base.

3. Analysis of the corresponding waveforms' patterns has been performed in order to visualize the classified data. Similarities in the pattern of some clusters have been observed, which expresses possible undistorted representations of origins of destructive processes.

4. Based on the representative clusters, boundary values for accept/reject criteria have been distinguished and presented.

The proposed pre-processing criteria should be used as a first step to processing and understanding the character of considered data. Since unsupervised clustering method is applied, a priori data is not required.

Further verification of the procedure on field monitoring results is planned.

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