Damage classification in concrete, mortar and cement-paste beams under bending by Acoustic Emission Technique (AET)

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Abstract. In concrete, AET has been used to characterize the different fracture modes in flexural beams by RA method (described in RILEM TC 212 ACD recommendation). In this study, three-point-bending tests have been conducted on cement-based specimens (concrete, mortar and cement-paste) to promote tensile mode and/or shear mode in these specimens. Acoustic Emission (AE) raw data were filtered to remove noise from signals. Then, $k$-means algorithm, as a Pattern Recognition Analysis (PRA) method, was used to identify the similarities within the recorded signals and to classify the filtered-signals into groups. Clustering results by $k$-means according to a proposed process have proven efficiency in providing information on RA, AF, Rise-time, Duration and Absolute Energy (ABEN) related to mode I and mode II. Then, two damage classification techniques were used, in which RA method was applied to filtered signals. By these techniques, the proportion of mode I and II was specified and the location of demarcation line also fixed.

1. Introduction
In recent decades, Acoustic Emission Technique (AET) is among of the Non-Destructive Testing (NDT) methods that have been implemented on cement-based engineering facilities (mortar, concrete, reinforcement concrete, pre-stressed concrete). The aims are to examine and to warn the clients or users on the condition of existing structures under gradual or sudden changes to their state of serviceability. AET can act as an accurately and cost-efficiently visual observation method to assess damages in building structures under corrosion, cracking, deformations and etc. AET can localize the position of developing fractures and determine the damage severity in the existing structures without discontinue their service functions and integrity.

There are two different approaches for AE data processing, including analysis of parameters extracted from the signals (Parameter-based) and direct analysis of the obtained signals (Signal-based). As a signal-based method, Moment Tensor Analysis, enables damage characterization by classifying the stresses into tensile, shear and mixed mode. In contrary, as a feature-based technique, RA method, a parameter-based one recommended in RILEM TC 212-ACD, would assist users to determine the tensile and shear occurring in damaged objects, but the proportion of these damage modes is not clarified. Some authors have proposed several classification techniques to calculate these damage proportions, but the results were not in good agreement [1].

In some recent bending tests, authors concluded that signals originated from damage mode I have higher AF value than those from mode II, while signals from mode II have higher RA than those from mode I [2]. And the increase of RA has been believed to be related to the shifting of damage modes from tensile to shear [2]. In addition, in the three-point-bending tests, the damage processes have simi-
lar trends as they began with mode I whereas mode II appears at final period and causes the complete failure of the samples [3]. Finally, the RA method has not addressed the effect of heterogeneity of the material and the propagation distances to the shape of waveforms as well as the signal’s parameters. These impactions could create signal modifications that will introduce wrong information to the damage classification results.

Finally, other limitation of RA method is that it is based on the four-point bending tests and the direct shear tests on concrete specimens. Thus, another tests on different damage mechanics (three-point-bending, indirect shear and tensile) with dissimilar materials (concrete, mortar and cement-paste) need to be performed to deeply characterize the shape of waveforms associated with specific crack modes.

In terms of research methodology, we applied filtering technique to eliminate the signals that are not associated with AE from the obtained raw data. The preserved data after filtering process was classified into groups which have similar parameters by applying k-means algorithm. The filtered data was then applied to crack classification by RA method.

2. Experimental setup and methodology

2.1 Materials used

The objective of the thesis is to characterize damage in cement-based specimens subjected to mechanical loading by means of AET. However, concrete is a very heterogeneous material compared with other materials such as steel, which has non-negligible consequences on ultrasonic wave propagation. For that, we decided to work separately on mortar (without coarse aggregate), on cement paste (without fine aggregate), on cobble stone (the aggregate phase only), to better understand AE in concrete. The CEM I Portland cement (taken from Lafarge factory, France) [1] with 28 days strength of 52.5 MPa was used. Coarse aggregates were composed of unconsolidated rock fragments that have rough surface with the maximum value of particle size of 16 mm. Crushed fine sand with maximum size less than 4 mm were used as fine aggregates. The mechanical properties of concrete were determined at 28 days after casting on six $\Phi118 \times 225$ mm$^2$ cylindrical specimens. Compressive strength ($f'_c$) of 51.0 MPa was obtained by direct compression tests on three specimens according to EN 12390-3 [4]. The Elastic modulus ($E$) of 37.5 GPa was determined based on RILEM CPC8 recommendation. In Mortar specimens, the aggregates were composed of 100% crushed fine sand with maximum size less than 4 mm. As for concrete, type I Portland cement was also used. The sand/cement and water/cement ratio were 3.0 and 0.5, respectively. A compressive strength ($f'_c$) of 48.2 MPa and an Elastic modulus of 28.1 GPa were obtained for the mortar.

In Cement-paste specimens, the type I Portland cement was used with a water/cement ratio of 3.0. Similar to concrete, the mechanical properties were determined at 28 days after casting on six $\Phi118 \times 225$ mm$^2$ cylindrical specimens. In this material, $f'_c = 68.9$ MPa and $E = 23.6$ GPa were obtained.

2.2 AE data acquisition devices

AE signals acquisition was carried out using an eight-channel PCI–8 and a four-channel DISP-4 system device of the Physical Acoustic Corporation (PAC) series. AEwin for SAMOS software was used for data recording and data processing. Noesis 8.1 software was also used for further data analysis. R15-α sensors of PAC series, resonance frequency of 150 kHz, were used to detect AE signals. These sensors were mounted on the surface of the specimens with silicon grease as coupling agent.

Because electrical signals corresponding to the AE waves are generally very weak, PAC preamplifiers model 2/4/6 (selectable gain 20/40/60 dB + 5% dB) were employed to add a gain of 40 dB to increase the signal-to-noise ratio. Before each test, a standard source Pencil Lead Break (PLB) procedure called also Hsu-Nielsen test was carried out to check the coupling of the sensors. Besides, an Auto Sensor Test (AST) was also carried out, to check that there was no variation of sensor sensitivity before and after each test. The acoustic wave average velocity was estimated at around 4,000 m/s from AST test, knowing the position of the sensors and the time of propagation of the acoustic waves.
2.3 Specimens and AE setup description

2.3.1 Specimen setup

Three notched beams made with different cement-based materials (concrete, mortar and cement-paste) were tested. These specimens, designed by CB (for Concrete Beam), MB (for Mortar Beam) and CPB (for Cement-Paste Beam) had a length of 500 mm and a square cross section of \(100 \times 100 \text{ mm}^2\) (Figure 1). Notches 4 mm width and 10 mm in deep were created at mid-span of the beams to concentrate the potential crack in the central area of the beams. The flexural load was applied by a servo-hydraulic MTS testing machine with 100 kN capacity. The opening of crack at the notch was measured using a Crack Mouth Opening Displacement (CMOD) clip gauge which located across the notch. To ensure more stable conditions of crack propagation, particularly in the post-peak branch of the load-CMOD curve, the tests were conducted by applying a CMOD rate of 2.0 \(\mu\text{m/s}\) during loading and unloading processes. Finally, the mid-span deflection of the beams was measured using a Linear Variable Differential Transducer (LVDT).

2.3.2 Acoustic Emission setup

Six AE sensors were used during the tests and were fixed on the front and back of the samples as indicated in Figure 1. They were also placed close to and around the expected potential crack path to minimize errors in AE events localization. The three-dimensional Cartesian coordinates of the sensors are listed in Table 1.

![Figure 1. Sensors on CB, MB, CPB specimens: 1, 2 and 3 on front-view; 4, 5 and 6 on back-view](image)

| Sensor no. | X (cm) | Y (cm) | Z (cm) |
|------------|--------|--------|--------|
| 1          | 22     | 8      | 10     |
| 2          | 22     | 3      | 10     |
| 3          | 28     | 5      | 10     |
| 4          | 22     | 5      | 0      |
| 5          | 28     | 7      | 0      |
| 6          | 28     | 2      | 0      |

2.4 Presentation of some AE data processing used in the thesis

2.4.1 Filtering noise-related signals

Filtering process is necessary to distinguish AE signals from other interfering signals such as noise, friction between specimens and platen of testing machine and echo. In this thesis, signals with Count number less than 2 and Duration less than 10 \(\mu\text{s}\) were removed according to [5]. A typical AE waveform removed from AE raw data by the filtering process is presented in Figure 2.
Figure 2. Noise-related signal illustration (Duration = 9 μs; Count = 3)

2.4.2 AE data classification by k-means algorithm

A clustering flow-chart in Figure 3 was proposed. The aim of this proposal is to group the similar-nature signals into some groups providing correlations of RA, AF, Rise-time, Duration and energy with damage mode I and mode II. In this study, an Unsupervised Pattern Recognition (UPR) algorithm namely k-means is applied to classify the data. To analyse, the users need to determine the input features as well as the number of pre-assign clusters. These two factors are chosen based on the user’s knowledge of physical phenomena, the expectation of different AE source mechanisms and the structure of the data [6]. In this paper, the pre-assigned number of clusters is achieved by calculating the Davies and Bouldin (DB) index whereas the input features are chosen from some AE parameters from the dendrogram.

Figure 3. Clustering process by k-means

In this study, the classification into clusters is achieved by minimizing the Davies and Bouldin (DB) index [7] which was chosen as features selection criterion. It is based on the ratio of the average distances within class to the distance between classes, as indicated in equation (1).

\[
DB = \frac{1}{k} \sum_{i=1}^{k} \max_{i \neq j} \left( \frac{d_i + d_j}{D_{ij}} \right)
\]  

(1)

where: \(d_i\) and \(d_j\) are the average within-class distances of clusters \(i\) and \(j\), respectively, and \(D_{ij}\) denotes the distance between the two clusters \(i\) and \(j\). DB index should be used in order to select the optimization cluster number or to evaluate feature subset partition. A lower value of DB index means a good concentration and a separation of dataset partition.

The input features were selected using a dendrogram exhibiting the correlation level among AE parameters to determine the efficiency ones. According to [8], the high number of clusters and AE features will result in higher error margins to the classification classes. Limitation input features are thus chosen. The dendrogram groups the feature set into pairs of correlated descriptors, if one pair has
highest degree of correlation (equal to 1.0), it is recommended using only one of them in the classification process. In this study, the following features are chosen: Rise-time (1-RISE), Count to peak (2-PCNT), Count (3-CNTS), Duration (4-DURA), Amplitude (5-AMPL), Average Frequency (6-AFRQ), and absolute energy (7-ABEN).

2.4.3 Damage classification by applying RA method to filtered AE data
In this thesis, an attempt to discriminate the damage modes (mode I or mode II damage) by means of a parametrical analysis (RA method) was made. According to the RILEM TC 212-ACD recommendation, the RA and AF values of the individual signal not eliminated after applying the noise filtering process are put on the same graph [9]. The maximum value on the RA and AF axis are A (ms/V) and B (kHz), respectively [1]. The transition from mode I (or tensile mode) to mode II (or shear mode) at the ratio of $K = A/B$ (ms/V×kHz$^{-1}$) is indicated by the diagonal line on the classification diagram. In this diagram, the signal with high RA is classified to shear mode, whereas the signal with low RA is classified to tensile mode. The proportion of damage modes can thus be obtained.

3. Characterization of damage in tested beams by AET

3.1 Damage quantification in the tested specimens
As discussed in the previous section, the global damage variable of a specimen can be estimated by measuring the relative variation of its stiffness during the entire load cycle. Loading and unloading loops are then defined to enable the stiffness to be measured and the damage variable of the specimen to be calculated after each loading-unloading step. The eight loading-unloading loops shown in Table 2 were performed. Loops L1 to L5 correspond to the pre-peak part and loops L6 to L8 correspond to the post-peak part of the load-CMOD curve.

Table 2. Loading processes according to CMOD and LVDT

| Loop | Loading            | Un-loading | CB     | MB     | CPB    |
|------|--------------------|------------|--------|--------|--------|
|      |                    |            | CMOD (µm) | LVDT (µm) | CMOD (µm) | LVDT (µm) | CMOD (µm) | LVDT (µm) |
| L1   | 0 to 20% $P_{\text{max}}$ | 20% $P_{\text{max}}$ to 10% | 2       | 14.6   | 1.0     | 42       | 2.0     | 39       |
| L2   | 10% $P_{\text{max}}$ to 40% | 40% $P_{\text{max}}$ to 10% | 3.1     | 15.8   | 2.5     | 71       | 4.8     | 81       |
| L3   | 10% $P_{\text{max}}$ to 60% | 60% $P_{\text{max}}$ to 10% | 5.3     | 18.3   | 5.7     | 103      | 7.8     | 118      |
| L4   | 10% $P_{\text{max}}$ to 80% | 80% $P_{\text{max}}$ to 10% | 7.9     | 21.2   | 10.6    | 139      | 12.3    | 149      |
| L5   | 10% $P_{\text{max}}$ to 100% | 100% $P_{\text{max}}$ to 40% | 23.6    | 39     | 50.2    | 191      | 16.4    | 158      |
| L6   | 40% $P_{\text{max}}$ to 80% | 80% $P_{\text{max}}$ to 20% | 44.1    | 62.2   | 79.8    | 210      | 20.4    | 161      |
| L7   | 20% $P_{\text{max}}$ to 60% | 60% $P_{\text{max}}$ to 10% | 75.1    | 97.2   | 105.7   | 236      | 23.0    | 164      |
| Final| 10% $P_{\text{max}}$ to 40% | 40% $P_{\text{max}}$ to the | 102     | 127.7  | -       | -        | 32.4    | 168      |

3.2 Damage quantification by means of AET
During the CB test, AE activities matched the loading and unloading cycles very well, as can be seen in Figure 4. The figures represent the evolution of the amplitude (dB) and the loading (kN) versus time. The total number of AE signals recorded by the six sensors was 28,287 at the end of the test. Figure 4 also indicates that AE activities started from cycle L1, with some signals having amplitudes reaching 95 dB. Such a high level of amplitude cannot be associated with background noise and must be due to damage occurrence inside the beams. This was also confirmed by inspection of the waveforms associated with the signals. The load was maintained for a few minutes at the end of each loading step and before each unloading step in order to check for AE activities during this phase (due to sustained loading). It can be observed that AE activity falls. This effect is clearly seen for loops L1 to...
L4, which correspond to the pre-peak phase before the localization of a main crack. However, AE activities still occur in the post-peak phase due to the unstable propagation of a localized crack, even when the load is decreased. This should be considered in relation with the hysteresis loops observed in Figure 4.

![Figure 4. Loading (kN) and AE amplitude (dB) versus time (s) in CB](image)

In MB test, the process was finished at P = 2.25 kN corresponding to CMOD = 236 μm and the total number of AE signals recorded is 28,965. During CPB testing, it was stopped at loading of P = 958 N corresponding to CMOD = 168 μm, and cracks have grown up to 60% of the height of the beam. The total number of AE recorded by the four sensors is 2,272 signals.

3.3 Damage classification by means of AET

3.3.1 Filtering noise-related signals

On the raw data of the three beams has been applied a filtering process as introduced in section 2.4.1 before performing the damage classification by RA method. The results are indicated in Table 3 with up to 50% of the filtered signals have been removed. It is clear that this filtering technique plays an important role in eliminating the non-consistent signals that will supply wrong information for the damage classification results.

| Beam | Number of Raw signal | Number of preserved signal | Proportion of filtered signals (%) |
|------|-----------------------|---------------------------|-----------------------------------|
| CB   | 28,287                | 19,124                    | 32.4%                             |
| MB   | 28,965                | 16,447                    | 43.2%                             |
| CPB  | 2,272                 | 987                       | 56.6%                             |

3.3.2 AE data classification by k-means

3.3.2.1 Clustering results in CB specimen

After signal filtering in CB, the preserved signals (19,124) are classified according to the k-means algorithm into 5 classes. The summary of characterisations of AE signals in these classes, 0 to 4, is indicated in Table 4. In CB, Class 0 has the lowest number of signals (0.8%) but the signals in this class have highest Amplitude (from 80-95 dB) and highest range of Duration as well as Absolute Energy (ABEN). On the contrary, the most extended Class 2 (occupied up to 78.8% total signals) has a
The classification results are presented in the following graphs. The Figure 5 indicates the evolution of Amplitude throughout time in CB. Accordingly, the signals are divided into 5 groups with different range of Amplitude values. In this plot, the images of the classes from 0 to 4 are clearly visible, the data in every class is compacted with a good separation.

![Figure 5. Evolution of Amplitude vs. Time in CB specimen](image)

There are significant differences in Amplitude, Count, Rise-time and ABEN ranges between the five classes. On the one hand, these differences are possible resulting from the different sources of damages, because tensile or shear mode will create different waveforms. On the other hand, variation of the distances from the sensors to the location of the cracks could affect the wave transmission due to the heterogeneity of the material. In addition, the influence of the other sources, for example noise, vibration of the testing system, also affect the magnitude and shape of waveforms. Therefore, by selecting AE signals for damage classification, it is necessary to combine with their shape of waveforms.

### 3.3.2.2 Clustering results in MB specimen

The summarization of AE parameters in five Classes is indicated in

Table 5. In MB, Class 0 contributes the lowest proportion (0.5%), while the most common proportion is Class 2 with 89.2% of the whole population.

| Class no. | (%) | Amplitude (dB) | Duration (µs) | ABEN (µJ) | Rise-time (µs) | AF (kHz) | RA (ms/V) |
|-----------|-----|----------------|---------------|------------|----------------|----------|-----------|
| 0         | 0.8 | 80-95          | 800-1,400     | 180,000-2,490,597 | 2-480         | 65-140   | 0-0.45    |
| 1         | 4.0 | 70-80          | 300-3,600     | 12,500-933,000  | 6-540         | 62-183   | 0-2.25    |
| 2         | 78.8| 40-60          | 11-1,400      | 12-750      | 0-530         | 7-414    | 0-31      |
| 3         | 10.6| 45-65          | 90-1,900      | 600-2,500   | 0-530         | 36-287   | 0-13.92   |
| 4         | 5.8 | 60-70          | 160-1,750     | 2,500-12,500 | 1-560         | 57-310   | 0-6.62    |

The classification results are presented in the following graphs. The Figure 5 indicates the evolution of Amplitude throughout time in CB. Accordingly, the signals are divided into 5 groups with different range of Amplitude values. In this plot, the images of the classes from 0 to 4 are clearly visible, the data in every class is compacted with a good separation.
and AF can be appreciably affected by the nature of source of the increasing AF trends assessing the tension result is indicated in CPB specimen.

In terms of Amplitude, the five clusters correspond to 5 clear groups with different Amplitude ranges. As the largest population, Class 2 has the lowest Amplitude range (from 40 to 60 dB). Following, Class 4 has relatively low Amplitude range (from 55 to 70 dB). The next is the Medium-Amplitude groups, Class 3 with Amplitude in the range of 60 to 70 dB, and Class 1 from 65 to 75 dB Amplitude. Finally, the Class 0 contains all the highest Amplitude signals (from 75 to 90 dB).

3.3.2.3 Clustering results in CPB specimen

In CPB, due to a low number of received signals, the data have been classified to 4 classes. The clustering result is indicated in Table 6, in which the “weak” signals are classified to Class 3 (89.8% of total population) and the “strong” ones are in Class 0 (3.6%).

| Class no. | Percentage (%) | Amplitude (dB) | Duration (µs) | ABEN (aJ) | Rise-time (µs) | AF (kHz) | RA (ms/V) |
|-----------|----------------|----------------|---------------|------------|----------------|----------|-----------|
| 0         | 0.5            | 75-90          | 600-1,300     | 45,900-490,000 | 10-95         | 88-151   | 0-0.19    |
| 1         | 1.7            | 65-75          | 270-1,100     | 6,650-43,650 | 6-260         | 80-178   | 0-1.01    |
| 2         | 89.2           | 40-60          | 11-700        | 10-780     | 0-420         | 11-545   | 0-30.3    |
| 3         | 2.0            | 60-70          | 180-980       | 2,750-6,600 | 2-250         | 70-210   | 0-1.79    |
| 4         | 6.6            | 55-70          | 90-800        | 700-2,750  | 2-320         | 48-258   | 0-6.22    |

In Amplitude classification, Class 3 has lowest Amplitude (from 40 to 60 dB) and Class 0 has highest Amplitude (80 to 100 dB).

3.3.3 Damage classification by applying RA method to AE signals after filtering

The RA and AF values of the remaining signals after applying the noise filtering process were shown on the same graph. Accordingly, the maximum value on the RA and AF axis are A (ms/V) and B (kHz), respectively. The transition from mode I to mode II at the ratio $K = RA/AF = A/B$ (ms/V×kHz$^{-1}$) is indicated by a diagonal line on the classification diagram. If we accept the damage classification under RILEM TC 212-ACD as well as the diagonal position under this proposal, the following proportion of damage modes in tested beams can be obtained.

Distinct transmission of the fracture progress in specimens, from tensile to shear, could be observed by assessing the variation of RA and AF value. Accordingly, the simultaneous increasing RA and decreasing AF trends before the specimen is completely failed has been recorded. As also concluded, RA and AF can be appreciably affected by the nature of source of the imposed structural damage [10].
With $K = 50/500 = 1/10$ (ms/V×kHz$^{-1}$), the crack mode in CB specimen from beginning to final failure is almost a tensile mode (99.4%) as introduced in Figure 6. In particular, the high Amplitude, Duration and ABEN classes produce 100% of damage mode I (Class 0, 1 and 4 with Amplitude from 60 to 100 dB). The other classes, 2 and 3, have low Amplitude (from 40 to 65 dB) which results in almost of mode I and 0.6% mode II. Mode II occurring in these two groups is due to some signals with high RT and low Amplitude, producing high RA. However, at the end of the test, because the CB sample was not completely destroyed, the RA value was low and mode II could be negligible.

![Figure 6. Damage classification in CB specimen ($K = 1/10$), mode I: 99.4%](image)

Similar to CB, by applying $K = 1/10$ (ms/V×kHz$^{-1}$) for the MB specimen, mode I occupies 99.1% of the damage modes during the test. Classes with high Amplitude and large energies, in order as 0, 1, 3 and 4, result in 100% mode I. The lowest energy group, class 2, mostly results in mode I and only 0.9% in mode II. Thus, the damage of the MB specimen can be considered as fully mode I because the number of Mode II is very low. The phenomenon is similar to CB specimen except that at the end of the test, the specimens are not completely broken.

In the CPB test, by applying $K = 50/250 = 1/5$ (ms/V×kHz$^{-1}$), the crack modes in specimen from beginning to end correspond to both tensile and shear mode. The noticeable of the CPB classification is that the AF value of 250 kHz is significantly lower than for CB and MB (500 kHz). In addition, because of RA values of a large amount of signals in class 3 were highest among the four classes (Class 3 has lowest Amplitude and ABEN), the number of Mode II in this class is quite significant, accounting for 9.9% of the receiving signals. Thus, the damage progress in CPB is similar to CB and MB, because the CPB has not been completely destroyed, either; however, mode II has appeared in a remarkable proportion (comparing with those in CB and MB).

The interesting, in all three specimens (CB, MB and CPB) mode I damage is generated from signals which have higher Amplitude and ABEN than these in mode II. And, in the three tests, the number of mode II is relatively low and they belonging to Class 2 (CB and MB) and Class 3 (CPB) which consists of the lowest Amplitude as well as ABEN signals. This is in contrast to the results in [74], in which authors concluded that the S-wave or shear waves, which excited from shear damage mode, embraces higher amplitude and larger amount of energy than the P-wave (excited from tensile damage); this means that, amplitude and ABEN of shear mode are higher than these in tensile mode.
4. Conclusions
The purpose of this study is to contribute knowledge on the degradation mechanisms of concrete, mortar and cement-paste beams subjected to mechanical loading by using AET. For that target, three-point-bending tests controlled with CMOD were conducted on three notched beams which the same shape and dimensions. The following conclusions can be drawn:

- Background noise-related filtering technique applied to raw AE data plays an important role in the applications of RA method. Filtering processes preserved burst emission signals as suggested in [11], thus resulting more accurately to damage classification. The technique has been eliminated 32.4% (CB), 43.2% (MB) and 56.6% (CPB) of noise-related signals in the specimens.
- Clustering technique by applying k-means provided some information on RA, AF, Rise-time, Duration and energy related to Mode I and Mode II. Interestingly, while 100% high-amplitude signals (above 60 dB) are classified to mode I, the low-amplitude ones (40-60 dB) are classified to both damage modes. Damage classification by applying RA and AF calculated from individual signals shows, while in CB and MB mode I is dominant with 99% of total filtered signals, the proportion of mode I in CPB is 90.1%.

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