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CRACK CLASSIFICATION IN CONCRETE USING PARAMETER- AND SIGNAL-BASED ACOUSTIC EMISSION ANALYSIS

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Abstract

Acoustic emission (AE) is one of structural health monitoring techniques providing meaningful information about damages within the materials. To classify crack types in AE analysis, an optimal transition line between shear and tensile cracks has been still demanding. There exist numerous studies investigating this subject in the literature. The researchers have adopted the ratio of RA value and average frequency parameters of the signals for classification; however, it is concluded that the transition line is mostly based on the empirical conditions. In this study, parameter- and signal- based AE analyses were combined for crack classification of damage activities of concrete under flexure. After monitoring damage processes of the concrete simultaneously by AE, spectrum analysis was conducted on the AE signals and their weighted peak frequencies were obtained. By evaluating dominant frequency characteristics of the signals, they were classified as tensile or shear crack and the classification was verified by parameter-based analysis. Afterwards, AE signals were labelled using crack types obtained from signal-based analysis, RA and average frequency parameters were distributed and the optimal transition line was determined.

Keywords: acoustic emission; concrete; crack type; RA value; frequency

1 Introduction

Non-destructive testing methods are damage detection and evaluation methods that have been used frequently in different fields of application. Acoustic emission (AE) is also one of these methods and provides useful information about active cracks for damage assessment in materials. AE phenomenon is defined as propagation of elastic waves released from the damage that occurs in a stressed material. AE method has been developed to utilize this phenomenon with the aid of sensors placed on the surface. The elastic waves detected by the sensors are converted into electrical signals and features of these recorded electrical signals allow us to obtain information about the damage [1]. In this context, the most important information that can be obtained about a crack is its location and type. Although various algorithms can be used to determine the location and give acceptable results, crack classification vary depending on empirical conditions [2-7].

1.1 Crack classification

Different methods have been used for crack classification such as clustering algorithms, parameter- and signal- based methods. One of frequently used features of an AE signal is RA value and it is evaluated together with average frequency. According to JCMS-IIIB5706 standard [8], cracks can be divided into two classes as shear and tensile with the aid of distribution of RA values versus average frequencies. Activities with high average frequency

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and low RA value is defined as tensile, while the vice versa are defined as shear activity (Fig. 1). Definitions of the parameters are given in 2.2.

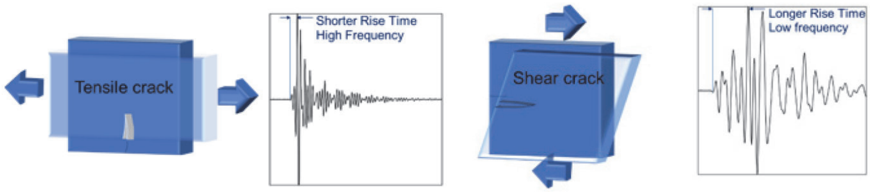


Figure 1 Representation of crack types and corresponding AE signals [9]

However, appropriate transition line separating the classes is still uncertain and it varies with empirical conditions (Fig. 2). In this study, to make a crack classification in concrete, parameter- and signal- based AE analyses were combined using different features of an AE signal and spectrum.

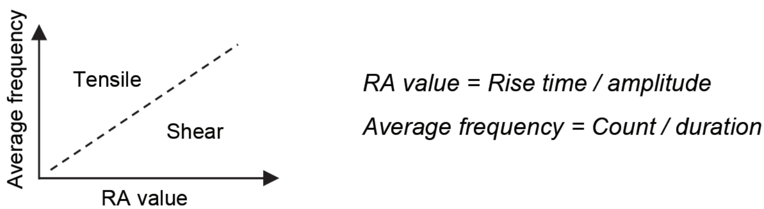


Figure 2 Crack classification according to JCMS-IIIB5706 standard [8]

1.2 Boundary decision with logistic regression

To separate RA values and average frequencies of the different types of cracks, this study used logistic regression model. Logistic regression has already been applied in processing acoustic emission data [8-10]. Logistic regression binary classification model uses input feature vector x and returns a probability of $\hat{y}$. The model is trained by the particular classes of x values as y(i) = 0 or 1 Decision boundary is found by the set of model parameters that minimizes the difference between $\hat{y}$(i) and y(i). The model parameters are vector of w and a constant b and they are related with a given feature of z. Here, z is associated with x whose class is y = 1 (Equations 1 and 2).

$$z = \boldsymbol{w}^T \boldsymbol{x} + b \tag{1}$$

$$z = w_1 x_1 + w_2 x_2 + b \tag{2}$$

2 Method

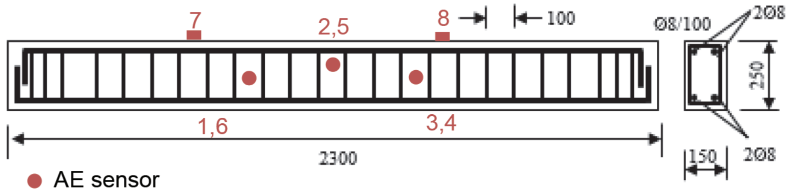
2.1 Experimental work

Within the scope of the experimental study, a reinforced concrete beam was tested under three-point-bending. The specimen was in dimensions of 2350x250x150 mm and its concrete mix design (W/C = 0.66 and C25/30) is presented in Table 1. S420 steel bars were used as reinforcement. Monotonic concentrated load was applied at the mid-span of the specimen with a rate of 30 N/s by a hydraulic pump to observe crack developments clearly.

Eight AE sensors of 150 kHz were placed on to the test specimen by silicon grease and an 8-channel DiSP AE system was used to monitor damage processes. AE waves were amplified with 40 dB gain by pre-amplifiers and threshold was set as 40 dB. Reinforcement details of the test specimen and AE sensor locations are given in Fig. 3.

Table 1 Concrete mix design (kg/m^3)

Cement CEM I 42.5R	Aggregate 0-3 mm	Aggregate 5-15 mm	Aggregate 15-25 mm	Water	Fly ash	Plasticizer
255	934	429	485	167	84	4.24



Unit: mm	1	2	3	4	5	6	7	8
X	800	1150	1500	1500	1150	800	750	1550
Y	125	200	125	125	200	125	250	250
Z	0	0	0	150	150	150	75	75

Figure 3 Reinforcement details of the test specimen and AE sensor locations

2.2 Crack classification procedure

In order to classify cracks with respect to their RA (rise time/amplitude) values and average frequencies, firstly some other parameter- and signal-based analyses were conducted. The basic AE parameters are shown in Fig. 4. In this study, weighted peak frequency (WPF) and RA values of the signals were used to estimate the classes of the signals and were verified with energy and amplitude relations.

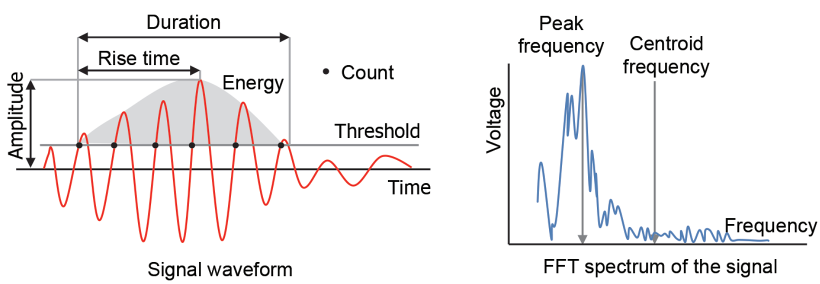


Figure 4 AE signal features

Peak frequency (frequency of the peak magnitude of the spectrum) and frequency centroid (the center frequency value of the spectrum) in Fast Fourier Transform (FFT) of a signal are also characteristics showing the type of a damage. To combine these features, weighted peak frequency (WPF) was used in this study as its calculation was given in Eq. 3.

$$Weighted\,peak\,frequency\,(WPF) = \sqrt{f_{center} \cdot f_{peak}} \tag{3}$$

3 Results

Totally 21703 AE hits were recorded from all sensors during the flexure test. In order to eliminate attenuation effects and make a clearer classification, only the data recorded by the 2nd sensor (2811 hits), which was located at the mid-span of the beam, were analysed (Reason for using multiple sensors in the study was other analyses such as source localization as part of other studies). Fig. 5 presents RA values of the activities with respect to their WPFs. As can be seen, the activities could be mainly clustered in three different classes according to their frequencies. While inverse relation between the RA and WPF provides a classification, activities with both low- or high- RA and WPFs define mixed-mode type. To observe a clear distinction, activities defined within rectangles, which are thought to be pure tension and shear, were examined instead of all data. A typical tensile crack waveform is expected to have a lower RA value compared to the shear crack. For this reason, since high-RA (higher than 27 µs/V) and low-WPF (lower than 100 kHz) activities can be associated with shear crack, Class-1 can be attributed as shear. Accordingly, low-RA (lower than 5 µs/V) and high-WPF (higher than 200 kHz) activities Class-2 can be associated with tensile.

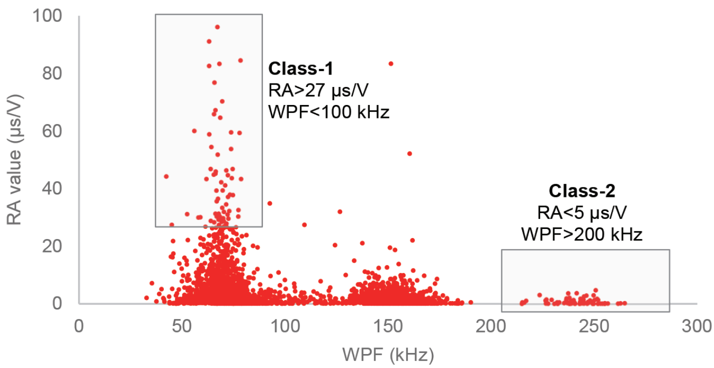


Figure 5 Selection of the dataset for classification using WPF vs. RA value relations

To assess the precision of this distinction, amplitudes of the activities correlated with their energies were evaluated, yielding compatible findings (Fig. 6): As expected, the energies associated with Class-1 exhibit higher levels for the same amplitude level, in contrast to lower energies observed for Class-2. This situation is also caused by the duration of the waveform, thus compatible with classified crack types.

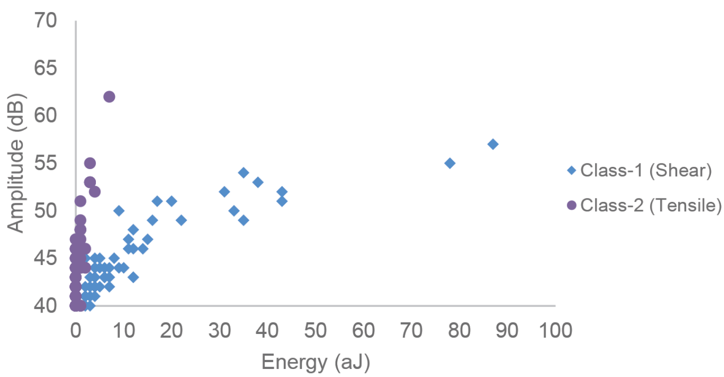


Figure 6 Energy - amplitude relations of the classified activities

To classify the activities using RA value vs. average frequency relations, Fig. 7 was constructed. As expected, average frequencies of the activities were inversely affected by their RA values. To classify any AE activity using average frequency and RA value, this distribution was separated using logistic regression model. Equation 2 was utilized on this dataset to separate activities and define the decision boundary. Accordingly, following logistic regression model coefficients were calculated as given in Table 2 and transition line equation between shear and tensile cracks was calculated as AF(kHz) = 75.18RA(μs/V)-1340. In the other words, activities placed at the left side of this boundary are associated with tensile cracks, and vice versa.

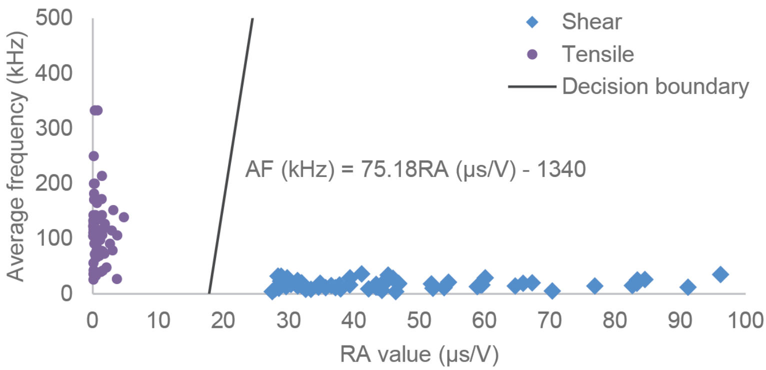


Figure 7 RA value – average frequency relations of the AE activities and decision boundary of the logistic regression model

Table 2 Logistic regression model coefficients of decision boundary

Coefficient	b	c	m	w_1	w_2
Value	85.05	-1340	75.19	-4.77	0.063

4 Conclusion

In this study, parameter- and signal- based AE analyses were combined for crack classification of damage activities of concrete under flexure. A reinforced concrete simple beam was tested under flexure and simultaneously monitored by AE. Spectrum analysis was utilized on the AE signals and their weighted peak frequencies were obtained. By evaluating dominant frequency characteristics of the signals and their RA values, they were classified into two classes. Accuracy of this distinction was verified with energy-amplitude relations. Accordingly, the activities were labelled and RA value and average frequency distributions were evaluated. To identify decision boundary between these two classes, a logistic regression model was generated. The results of the model showed that the classified tensile and shear activities can be separated by a transition line. Under these experimental conditions, equation of this line was determined as AF(kHz) = 75.18RA(μs/V)-1340. The results show that when they are evaluated together; WPF, amplitude, energy, RA value and average frequency are useful indicators for crack classification.

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