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Analysis of acoustic emission signals for the characterization of cracking of reinforced concrete T-beams

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ABSTRACT Acoustic emission (EA) has proven to be very suitable for detecting and monitoring cracking of materials and structures. EA signals can be analyzed either based on physical considerations (geophysics/seismology) or using their temporal and frequency characteristics. However, the multitude of definitions related to the different parameters as well as the treatment methods make it necessary to develop a comparative analysis in the case of a heterogeneous material such as civil concrete. To this end, this contribution aims to study the microcracking of reinforced concrete T-beams subjected to quasi-static mechanical tests. To do this, four-point bending tests, carried out at different travel speeds, were carried out in the presence of a network of acoustic emission sensors. A comparison between the damage susceptibility of three definitions corresponding to the parameter b-value was carried out and supplemented by the evolution of the RA value and the mean frequency (AF) as a function of loading time. This work also shows the use of the support-vector machine (SVM) method to define different areas of damage in the load-displacement curve. This work shows the limitations of this approach and proposes the use of an unsupervised learning approach to group EA data according to physical parameters as well as time/frequency parameters. Finally, this work discusses the advantages and limitations of the different methods and parameters used in relation to the micro/macro mechanisms at the origin of concrete cracking.

Key-words Acoustic emission, concrete, RA value, b-value, average frequency

I. INTRODUCTION

The degradation in strength of concrete structures is very common, which is usually attributed to ageing, fatigue, corrosion, increase in service loading, environmental impacts, and so on (Prem et al., 2017). Acoustic Emission (AE) appeared to be highly promising to monitor various concrete structures through nondestructive means (Dzaye et al., 2018, Mandal *et al.*, 2022). AE techniques are based on the detection of the transient elastic waves from a source within the material (An et al., 2014). These AE signals are mainly burst type and can be attributed to various sources such as micro crack initiation, propagation of crack fronts, yielding of the reinforcement, bond failure, delamination, and so on (Meo et al., 2014). The major advantage of an AE based technique is its ability to perform a real time monitoring of a large volume of a structure (Tonolini et al., 1987). AE features can be analyzed by means of physical considerations to evaluate the predominant damage mechanisms. AE features such as rise time, amplitude and average frequency were considered to study the fractures created in various brick and mortar samples (Aggelis et al., 2011). The severity of a damage was evaluated using the seismology parameter called b-value. The seismology parameter b-value, being sensitive to the coalescence of micro-damage into macro-cracks, has been used in several studies for the detection and monitoring of damage development (Shiotani et al., 2000).

The classification of crack modes in concrete is one of the very important objectives since the crack modes depend on the state of degradation of concrete. AE based techniques were used to classify crack modes in reinforced concrete beams, subjected to bending (Aggelis et al., 2011, Soulioti et al., 2009, Aldahdooh et al., 2013). Gaussian mixture modelling (GMM) probabilistic method have been employed to classify cracks using AE data (Prem et al., 2017). Das et al. (2019) used a combined framework of Gaussian Mixture Models and SVM for classification of cracking modes in steel fiber reinforced concrete beam under bending and strain hardening cementitious composite samples under tension loading. The classification of crack mode shows that majority of AE events were caused by matrix cracking during strain hardening, however during the softening phase, more events were found to be created by fiber pull out. Soulioti et al. (2009) investigated the influence of fibre content on the fracture modes of concrete beams. It was observed that the dominating fracture mode is tensile for unreinforced concrete, however the dominating mode of fracture changes to shear with the increase in fibre content of reinforced concrete. Anay et al. (2018) identified three distinct crack behaviors, namely initiation of microcrack, crack extension, and unstable crack growth in cement-paste specimens subjected to compression loading. Research contributions have revealed that AE signals can also be used to study the nonlinear relaxation (slow dynamics) behaviors of concrete (Bentahar et al., 2020, Bentahar et al., 2006). Because of the huge volume of data usually obtained in the AE based monitoring, reduction of dimensionality of data, without losing much information, becomes extremely important for the meaningful interpretation of the AE data. Principal component analysis (PCA) is often employed to reduce the dimension of AE data obtained from concrete and composites (Anay et al., 2018). Tayfur et al. (2018) investigated micro cracking of steel fibers reinforced concrete beams under bending and clustering of the data revealed existence of two types of failures modes, namely matrix failure and steel fiber/matrix debonding. Sun et al. (2021) studied failure process of crumb rubber concrete under 4-point bending using various clustering methods, namely k-means, self-organizing mapping (SOM), Gaussian mixture model (GMM), hierarchical model, fuzzy c-means (FCM), and density peak clustering to find the best suited algorithm, and the density peak algorithm was found to be most suited for that scenario.

The present research work focuses on the characterization of reinforced concrete T-beams subjected to four-point bending quasi-static tests, monitored with AE sensors to extract various AE signals, emitted during the creation and propagation of micro-cracks. The reinforcement steel bars prevent the beam from fragile catastrophic failure, hence improving the post-peak behavior (Soulioti et al., 2009). A comparative study on various physical parameters (e.g., b-values, RA- value, average frequency) has been done and the applicability of these parameters in the progressive damage assessment of concrete has been shown. Support vector machine (SVM) based classification has been adopted to separate the load-displacement curve into different zones, as per the involved

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damage mechanisms. However, it appears that assigning the classes becomes difficult if multiple damage mechanisms are present in a particular zone. Hence, an unsupervised machine learning scheme has been proposed for clustering AE data, which allowed to identify clusters based on the hidden pattern in the AE data.

II. THEORETICAL BACKGROUND

This section focuses on some algorithms, commonly used in AE based analysis, and the supervised and unsupervised learning approaches have also been presented.

A. Average frequency (AF) and RA value (RA)

Average frequency (AF) and RA value are the two most sought-after parameters used to identify crack modes in concrete structures (Ohtsu et al., 2010). AF is defined as the ratio between the number of threshold crossings (i.e., counts) and duration of an AE waveform. Whereas, RA value is defined as the ratio between the rise time and amplitude (Aggelis, 2011), as shown in Fig. 1.

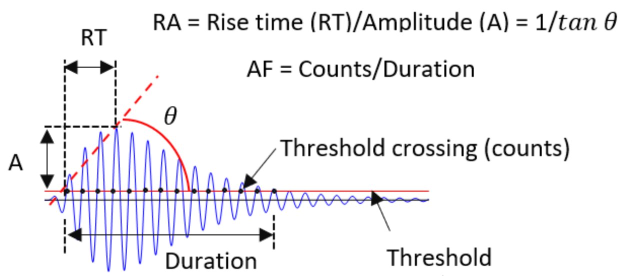

FIGURE 1. Schematic representation of an AE signal and definition of some important AE parameters

Many researchers have reported that AE waveforms which are generated due to tensile cracking have relatively shorter rise time. Hence, a tensile crack would generate AE signals with a lower RA value and higher AF. Whereas, in the case of a shear crack, AE waveforms have a longer rise time, which results in a relatively higher RA value and lower AF (Aggelis et al., 2013).

B. The three distinct b-values

According to the literature, there are three different b-values, namely b_1 *-value*, b_2 *-value* and b_3 *-value*, usually used in geophysics to investigate the fracture process in rocks (Niu et al., 2019).

b_1*– value:* The pioneer work using the b_1 *– value* was done by Shiotani et al. (1994) to study progressive failure. The expression of b_1 *– value* is given as:

$$b_1 = \frac{log_{10}N(\mu-\alpha_1\times\sigma)-log_{10}N(\mu+\alpha_2\times\sigma)}{(\alpha_1+\alpha_2)\sigma} \quad (1)$$

where N -number of recent AE events, μ - mean value of the amplitudes of those events, σ - standard deviation of those amplitudes, α_1 and α_2 are empirical constants, usually 0 and 1, respectively. Although b_1 *- value* was first employed to study fracture process in rocks, but later used to study fracture process in concrete (Aggelis et al., 2011). Researchers (Aggelis et al., 2011) have found that micro-cracks lead to relatively higher values of b_1–value and macro-cracks lead to lower b_1–value. Hence, a decrease in the b_1–value may indicate successive accumulation of stress associated with a propagating rupture front.

b_2- *value:* In seismology, C. F. Richter and B. Gutenberg proposed an empirical relationship between the frequency of occurrence of earthquakes and their magnitudes, as given in eq. (2). The exponent of the expression is known as *b-value* (Burud et al., 2019).

$$\mathrm{N}(\geq \mathrm{M}) = 10^{a-b*M} \quad or, \quad \log(N) = a - b*M \tag{2}$$

where N - number of earthquakes whose magnitude is $\geq M$. a and b are constants for an area over a span of time (Sagar et al., 2014). Because of the difference in measurement unit between AE amplitude and earthquake, it has been suggested to use the following equation for estimation of b_2-value in concrete (Niu et al., 2019).

$$\log(N) = a_2 - b_2 * \left(\frac{A_{dB}}{20}\right) \tag{3}$$

N - number of acoustic emission hits of amplitude $\geq A_{dB}$, a_2 -a constant which depends on background noise.

b_3 *– value:* It was introduced by K. Aki (Aki, 1965). The expression to find b_3–value is (Niu et al., 2019):

$$b_3 = \frac{20 \log_{10} e}{a_{avg.} - a_c} \tag{4}$$

where, a_{avg} - average amplitude, and a_c - threshold magnitude (Aki, 1965).

C. Machine learning approaches

The present research work encompasses both the supervised and unsupervised learning for the interpretation of AE data. The fundamental difference between these two approaches is that in supervised learning technique a model is first trained with labelled data to predict future outputs, whereas, an unsupervised learning technique finds the hidden patterns in the input data, hence no need of labelled data. The supervised and unsupervised schemes used in the present study are presented in the subsequent section.

Support-vector machine (SVM): Support-vector machine (SVM) is a supervised learning tool, often used for classification. SVM tries to find an optimal separation boundary (i.e., hyperplane) between classes, which results in an efficient classification of data (Hastie et al., 2009). An important feature of SVM is its various kernel functions, such as Gaussian radial basis function (RBF), Polynomial, Sigmoid (i.e., neural network), and Linear.

Unsupervised learning scheme: The unsupervised learning scheme adopted here involves three steps- feature selection, optimization, and clustering. The important features are first identified using Laplacian score (He et al., 2004) and then these features are optimized using principal component analysis (PCA). Finally, clustering of optimized data is performed by k-means algorithm (Likas et al., 2003), which partitions data into k-number of mutually exclusive clusters. The point to be noted that the optimal number of clusters k is determined with the help of Davies-Bouldin (DB) index (Davies et al., 1979) and Silhouette coefficient (SC) (Rousseeuw et al., 1987).

III. AE MONITORED MECHANICAL TESTS

The four-point quasi-static bending tests have been carried out on 3.50m long reinforced concrete T-beams using the Universal Testing Machine (INSTRON 8801), as given in Fig. 2. The details of the cross section of the beam have also been shown there. The characteristic strength of concrete and steel of the beams are given in Table 1. The distance between the upper loading points is 1m and distance between supports at the bottom is 3m. The displacement rates applied are 1 mm/min, 2 mm/min, and 4 mm/min for the three identical samples, namely sample 1, sample 2, and sample 3, respectively. The mechanical tests were monitored by four AE sensors, which are broad band type PAC (MICRO-80). The threshold and pre-amplifier gain were assigned as 45 dB and 40 dB, respectively.

TABLE 1. Mechanical properties of the reinforced concrete T-beams, provided by the manufacturer RECTOR®

Ingredients	Characteristics
Concrete	Compressive strength = 50 MPa
Steel	Ultimate tensile strength = 525 MPa Yield strength in tension = 500 MPa

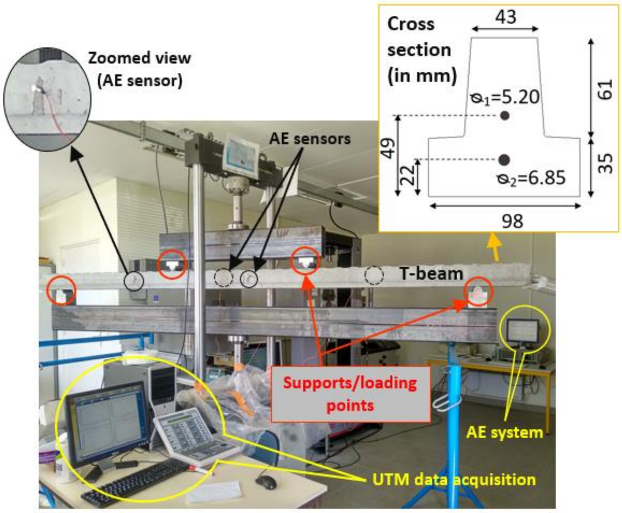

FIGURE 2. Experimental set-up: UTM, AE-setup, and sample beam ($\varnothing_1$, $\varnothing_2$ -are diameters of longitudinal steel).

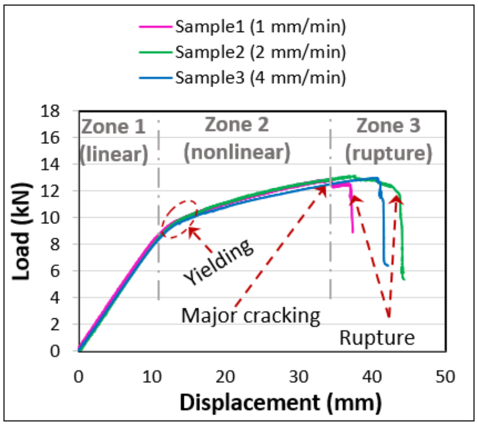

FIGURE 3. Load-displacement curves of the tree samples obtained from the test

IV. RESULTS AND DISCUSSION

Since the study considers many algorithms which normally produce many results. However, due to the limitation in page, only some representative results have been presented.

A. Global analysis

The results of quasi-static bending tests on three different samples are found to be very similar (Fig. 3), although the loading rate was not the same for the three samples. A point to be noted that a sudden drop in the load-displacement curve indicates formation of a major crack in the sample during the test. We also noted that the loading rate has a clear effect on the duration of the tests, since rupture of sample 1, sample 2 and sample 3 were found to happen at 650s, 1300s, and 2300s, approximately. The AE data shows that the AE activity evolves as a function of the applied load, in

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other words, for major cracks the AE amplitude gets higher values and a significant jump have been observed in cumulative AE hits (Fig. 4).

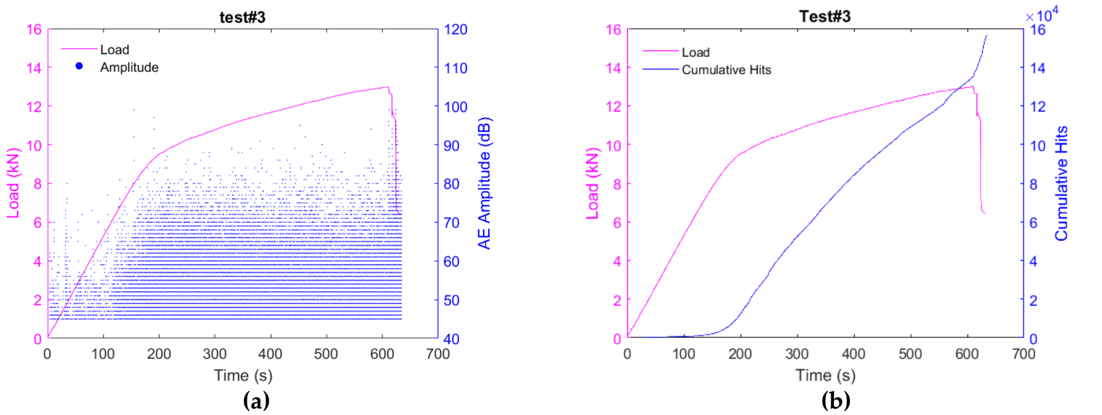

FIGURE 4. (a) Variation of load and AE amplitude with time, (b) variation in cumulative AE hits with time (sample 3)

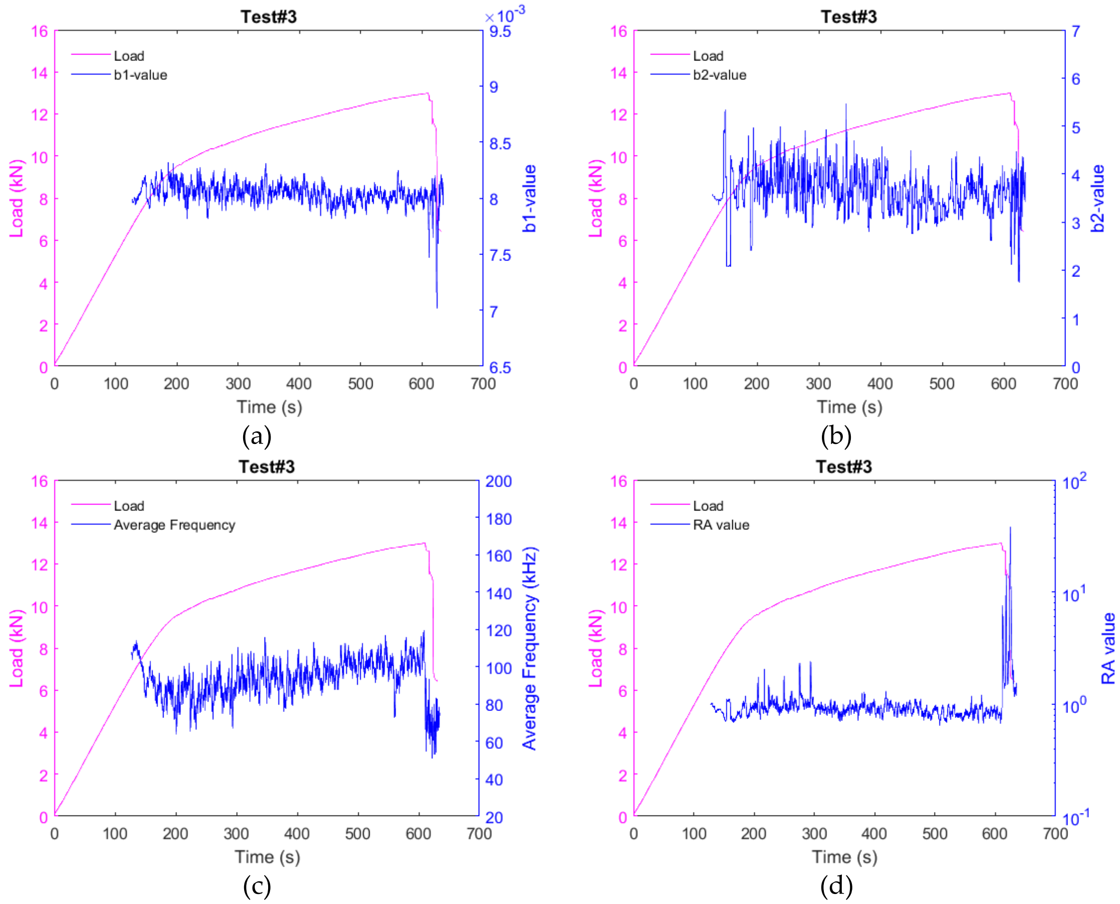

FIGURE 5. Evolution of (a) b1-value, (b) b2-value, (c) Average frequency, and (d) RA-value (sample 3)

B. Physical parameters-based analysis of damage

In this section, some representative results on b-value, AF, and RA-value analysis have been shown. The results obtained using different b-value definitions show that these parameters sharply decrease in case of macro-crackings (Fig. 5 (a, b)). These results are in line with studies performed on geomaterials (Niu et al., 2019). The fracture modes can be monitored using the evaluation of average frequency (AF) and RA-value. It has been observed that AF is higher, and RA-value is lower if the fracture mode is dominated by tension cracking. On the contrary, a sudden drop in AF and a sharp increase in RA-value occur if the fracture mode is strongly shear (Fig.5 (c, d)). This observation is in line with many studies (Aldahdooh et al., 2013)

C. Machine learning schemes

SVM based analysis (supervised): In this method, initially three different classes (i.e., zone 1, zone 2, and zone 3 (Fig. 3)) were assigned. However, in the case of three labels it has been observed that zone 1 comes within zone 2 (Fig 6(a)). This could only possible when the data of zone 1 has similarity with some data of zone 2. Therefore, zone 1 and zone 2 are combined to a single class (zone 1 + zone 2) and then SVM was applied. A very good separation boundary was obtained (Fig 6(b)). The Gaussian kernel trick of SVM has been found to be very efficient in the classification of AE data. However, the existence of multiple damage mechanisms poses difficulty to label. Hence, there is a need of an unsupervised learning approach, without needing labelled data for the classification.

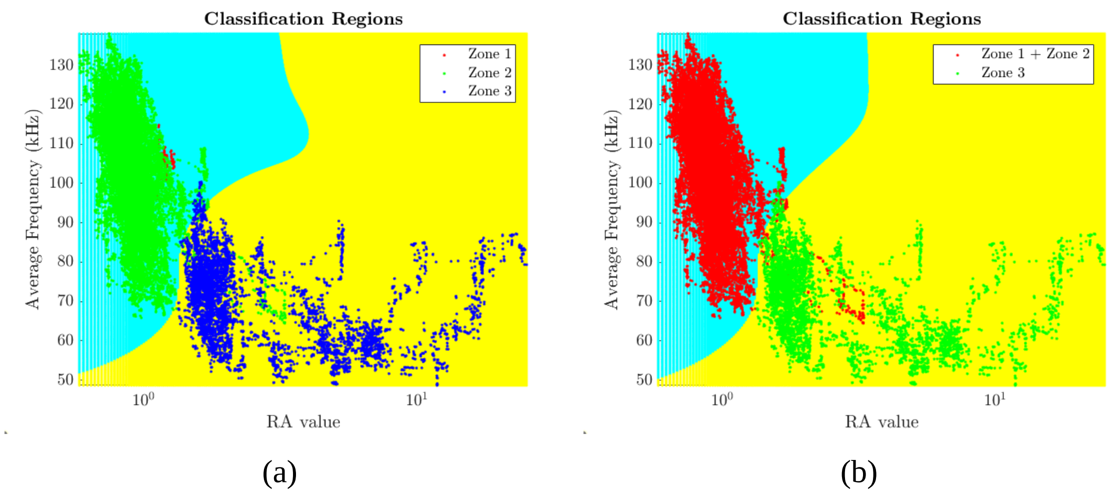

FIGURE 6. SVM classification using Gauss kernel: (a) three labels, (b) two labels (sample 2)

Unsupervised machine learning scheme: In this section a large number of features were considered. Following the steps, as described in the theory section, clustering has been done. A representative result has been shown in Fig. 7. The AE signals of the three clusters do not possess the same characteristics. For example, cluster 1 is found to possess the highest frequency signals, on the other hand, cluster 3 consists of lowest frequency signals, while cluster 2 consists signals of intermediate frequency components, as shown in Fig. 8. It should be noted that due to shear, more friction at shear cracking is expected, and the resulting shear waves filter out higher-frequency components significantly (Zhang et al., 2022). In considering these aspects, the results obtained suggest that cluster 3, which consists of weakest frequency signals (around ~50 kHz) is related to friction, while cluster 1 indicates tensile cracking (around ~350 kHz). On the other hand, cluster 2, i.e., signals with intermediate frequency components (around ~150 kHz), represents combination of both shear and tensile cracking (Yang et al., 2014).

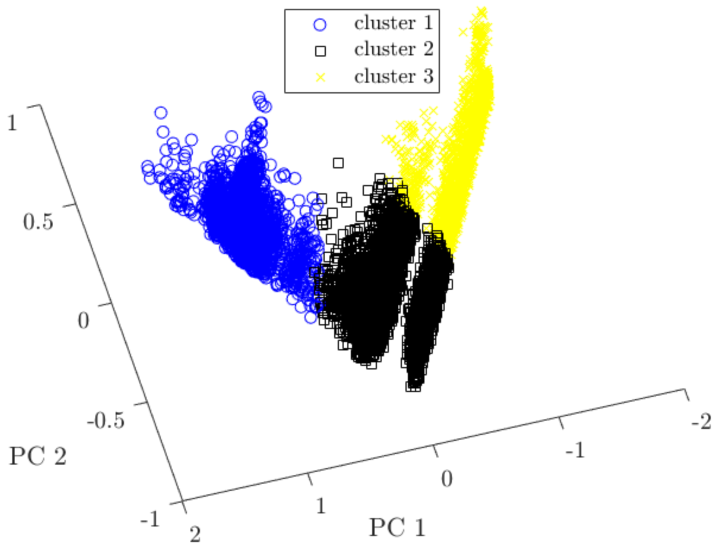

FIGURE 7. **Clustering using k-means**

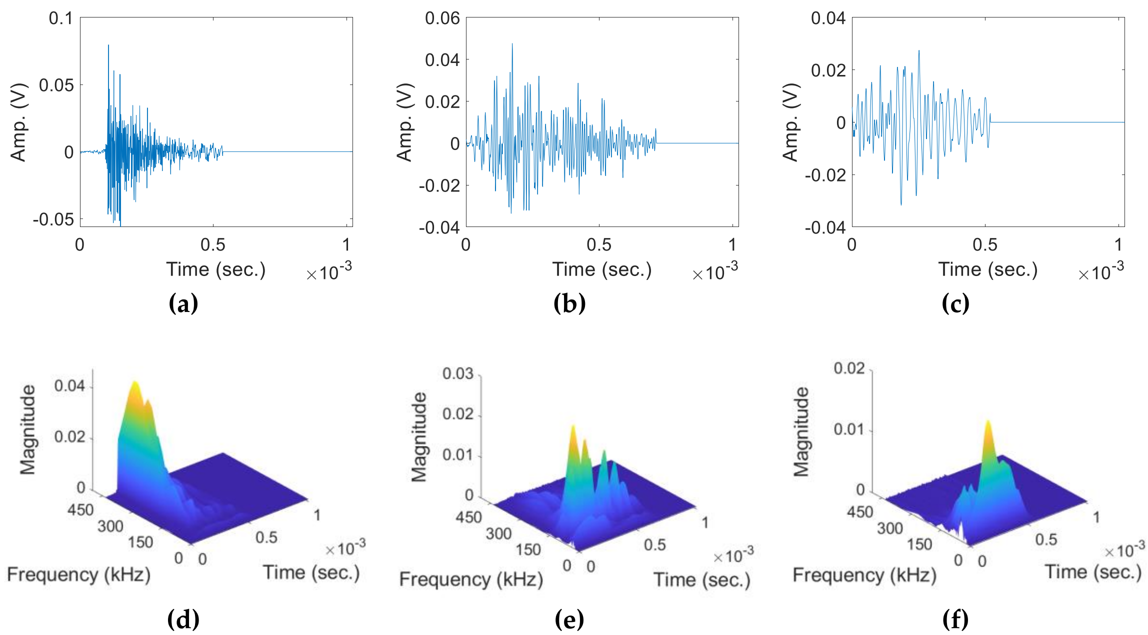

FIGURE 8. **Representative signals in time and integrated time-frequency domain: (a, d) cluster 1, (b, e) cluster 2, (c, f) cluster 3**

V. CONCLUSIONS

Acoustic emission (AE) monitored four-point test has been performed on three identical reinforced concrete T-beams to study the evolving damage mechanisms during the test. The load-displacement curves of the three samples are found to be very similar, hence repeatable. The physical parameter-based algorithms, i.e., three different b-values, average frequency (AF), and RA-value, all are found to be very sensitive to the evolving damage mechanisms, although the individual algorithms may use different AE feature/s. For example, in the case of tensile cracks, b-values and AF are found to have higher values, while for shear cracks these parameters get lower values. RA -value is found to be extremely sensitive to the evolving damage mechanisms and follows the reverse trend to the formers. In case of classification using SVM, two classes were successfully made considering only the AF and RA value. The Gaussian kernel of SVM has been found to be very efficient to classify AE data. Although SVM worked well in classification, however it becomes difficult to classify the data if multiple mechanisms are present in a particular zone of load-displacement curve. Hence there is a need of an unsupervised scheme. The adopted unsupervised method is based on k-means. Three clusters were obtained, which have been identified as tensile cracking (cluster 1: high frequency signals), both shear and tensile cracking (cluster 2: intermediate frequency signals), and friction (cluster 3: low frequency signals).

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