Crack Classification of Concrete under Uniaxial Compression using Acoustic Emission Monitoring Technique

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***Abstract*—Monitoring the crack modes in concrete is of importance because the performance of the entire structural system is revealed. The cause and location of cracks is crucial to determine which type of crack is predominant. Assessment of failure or structural monitoring by non-destructive methods is desirable. Acoustic Emission (AE) method shows promising outcomes for monitoring cracks in concrete at real-time using some AE parameters like Rise Angle (RA) and Average Frequency (AF). This paper introduces a probabilistic approach based on Gaussian Mixture Modeling (GMM) to classify the crack modes based on the AE signals. The crack classification is checked for accuracy using Support Vector Machine (SVM) method. The algorithms are validated by an experimental study on concrete cylinders subjected to uniaxial compression.**

Keywords—Acoustic emission; concrete; crack classification; Gaussian Mixture Modeling; Support Vector Machine

I. INTRODUCTION

It is known that the mechanical behavior of reinforced concrete (RC) structures is influenced by the materials used for their construction. A quasi-brittle material like cement concrete and rock is characterized by a gradually decreasing stress after the peak stress. When a reinforced concrete (RC) is subjected to flexural loads, concrete will be subjected to compression after reaching the maximum strain in steel. Therefore, it is required to study the fracture process in concrete under compression. Fracture mechanics is the study of the response and failure of structures as a consequence of crack initiation and propagation [12]. It is important to understand the initiation of internal cracks in quasi-brittle materials and their propagation with increasing load.

Deterioration of concrete structures due to aging or natural events yields the need for rehabilitation of these structures. Non-Destructive Testing (NDT) techniques are often used to assess the safety and performance of the present condition of concrete structures. Recent studies have been focused on using Acoustic Emission (AE) technique which helps in monitoring the real-time damage without affecting the workability of structures. At the time of fracture, cracking takes place with the release of stored strain energy in the form of elastic waves called acoustic emission, which propagate through concrete. This can be detected by AE sensors mounted on the surface. A schematic representation of a typical AE signal and corresponding AE parameters is shown in Figure.1.

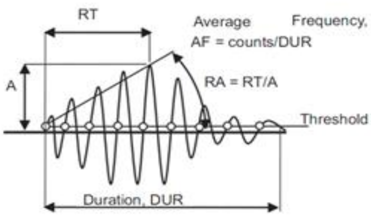

Figure 1-Schematic representation of AE signal

To study the damage and crack classification in RC shear wall Alireza et al. Has conducted AE testing and concluded that GMM algorithm can be adopted to classify the cracks into tensile or shear from the AE signals recorded [4]. The present experimental study on concrete cylinders implements a probabilistic approach based on Gaussian mixture modeling (GMM) algorithm to classify the cracks based on the recorded AE signals. Two parameters extracted from the AE signals i.e., rise angle (RA) and average frequency (AF) are divided into two clusters, namely tensile and shear using the GMM algorithm. Support vector machine (SVM) method is useful to cross verify the classification of the data which is previously clustered using GMM algorithm. The rise angle (RA) and the average frequency (AF) are defined as [11],

RA = (Rise time) / (Peak Amplitude)
AF = (Counts) / (Duration)

The Japan Construction and Material Standard (JCMS-III) proposed a technique to monitor crack propagation in concrete structures based on AE signal parameters as shown in Figure. 2.

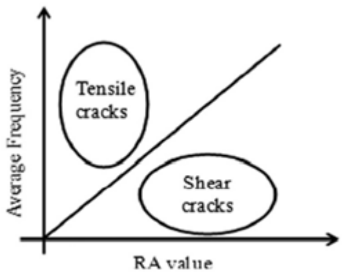

Figure 2-Crack Classification based on JCMS-IIIB5706

According to JCMS-III method, the cracks are classified as tensile cracks and shear cracks based on RA and AF values without any confirmation on the proportions of these parameters [7]. The understanding of physical mechanisms that influence the fracture process in concrete structures motivates to implement a probabilistic analysis of the recorded AE signals to classify the cracking process occurring during compression of concrete specimens. To this end, a probabilistic method is used to study the effect of the AE characteristics for crack classification in reinforced concrete. GMM and SVM methods are explained in detail in Appendix A and Appendix B.

II. LITERATURE REVIEW

Aggelis et al. (2009) studied the AE released during the fracture of cementitious materials subjected to four point bending and compared the results with ultrasonic techniques. It was concluded that results obtained using AE technique and tomography based on pulse velocity were in good agreement and can be used to study failure progress of concrete [2].

Farhidzadeh et al. (2013) studied crack classification in shear wall tested in laboratory under displacement controlled quasi-static reversed cyclic loading. Using GMM approach, the recorded AE data was analyzed and it was concluded that this method was capable of identifying three stages, namely, the dominance of tensile crack stage, the transition stage and the dominance of shear crack stage [4].

Farhidzadeh et al. (2014) applied Support Vector Machine method on pairs of AE features and interrogated the performance on classification. Results indicated that the boundaries between tensile and shear signals translated according to the distance between the sensor and the cracking source. It was also found that several pairs of descriptors perform well in classification error regardless of the data set; the lowest rate error is reached by the pair AF-RA [5].

A review on the AE technique and fatigue of RC structures has been carried out by Noorsuhada (2016). It was found that the AE parameter analysis such as intensity analysis, average frequency and RA value analysis are based on channel basis and the fatigue test is based on constant amplitude [8].

Ohno and Ohtsu (2010) studied the classification of cracking based on the AE parameter based analysis using RA and AF to compare the results with AE signal based analysis (SiGMA). It was concluded that the two analysis methods showed similar results and the parameters of the first arrival of AE signal have more important information on crack generation than other AE signals [9].

III. EXPERIMENTAL PROGRAM

Three cylindrical concrete specimens (150 mm diameter X 300 mm height) subjected to uniaxial compression are tested using AE at 28th day. The load-time plots for the specimens at 7th day, 20th day and 28th day are as shown in Figure.3.

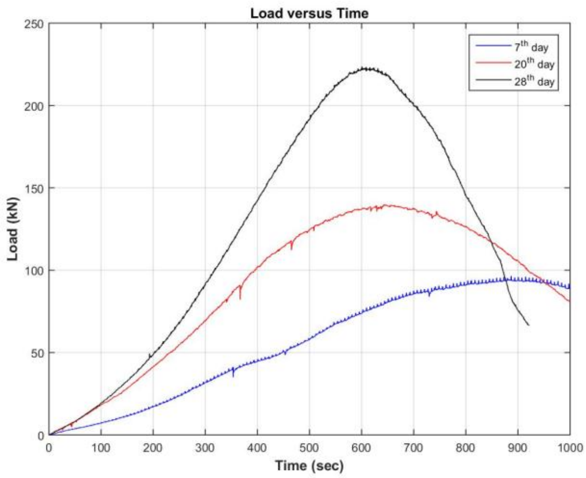

Figure 1-Load-time plot for specimens

Grade of cement used is 53 grade. Concrete mixture ratio of 1:2.54:3.14 is used. The water cement ratio is 0.54. The 28th day compressive strength of concrete is 25MPa. The tests were conducted using servo controlled hydraulic testing machine of capacity 1200 kN. AE released were recorded using an 8 channel AE monitoring system in which 6 sensors are activated. The AE parameters were obtained by AEwin SAMOS software. The test setup is shown in Figure.4.

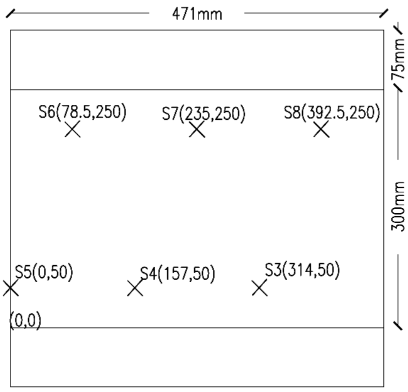

Figure 4-Schematic representation of sensor layout

IV. RESULTS AND DISSCUSIONS

The compressive load was applied monotonically on the concrete cylinders. The total duration of testing was divided into 9 time intervals. In other words, the load-time plot was divided into 9 load steps. Each load step is for an interval of 120 sec. For each load step, the RA and AF were calculated from each AE signal detected. By using these parameters, cracks are classified into tensile cracks and shear cracks by implementing GMM analysis and this classification was validated using SVM method. Tensile cracks started in the initial load steps and were followed by shear cracks. The shear crack started to develop near the peak load. The shear cracks became dominant at the final load steps. Shear cracks exhibited lower AF and higher RA than tensile ones. It was observed that in the first load step, the AF is higher when compared to that of the last load step which shows lesser AF values and higher RA values. This indicates that during the first loading stages, tensile cracks dominate and at the last loading stages, shear cracks dominate.

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The graphical representation of the percentages of each data cluster is shown in Figure.5.

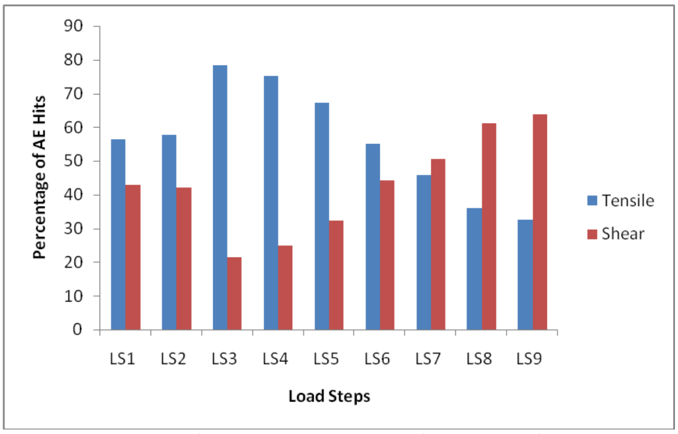

Figure 5-Estimation of crack mode propagation for specimen failing in shear

The GMM feature vectors for the first, intermediate and the last load step is shown in Figure 6. This result is in accordance with the classification of cracks according to JCMS-III [7]. The first load step shows that the vector is dominant in the tensile region and the last load step shows that the vector completely occupies the shear region indicating failure of the specimen by shear cracks.

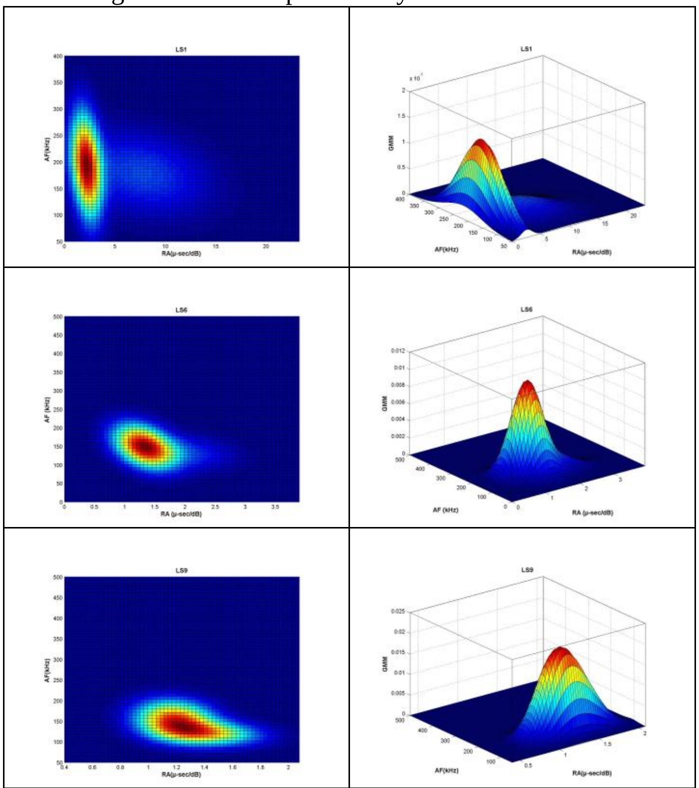
Figure 6 – GMM feature vectors at LS1, LS6 and LS9

The GMM classification of shear and tensile clusters in the first and last load steps are shown in Figure 7. The blue points on the GMM plot are the shear clusters.Load step 1 to load step 5 show lesser shear cracks when compared to other load steps. This indicates that tensile cracks occur in load step 1 to 5 and shear cracks dominate in the other load steps. Load step 6 is the transition stage where the percentage of shear clusters exceeds the tensile clusters. The last few load steps showed dominance of shear clusters indicating that the specimen has reached its ultimate strength with more of shear cracks.

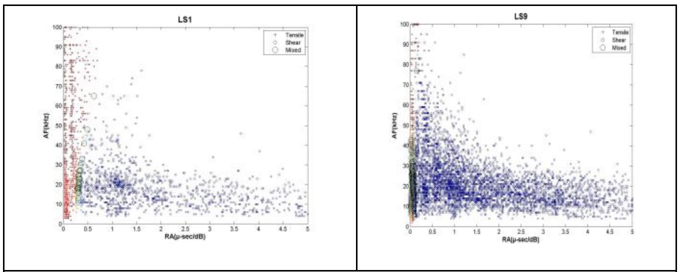
Figure 7 - Variation of RA and AF during GMM analysis for specimen failing in shear at LS1 and LS9

SVM method has indicated similar results in comparison to GMM. The SVM classified data points for the first and the last load step is shown in Figure 8. The red dots indicate the tensile clusters and the green dots indicate the shear clusters. Here also it was observed that the number of shear clusters increase as the load increases leading to failure of specimen in shear. The black clusters in the plots are the support vectors and the straight line passing through the cluster is the decision boundary or the hyperplane. The slope of the decision boundary increases as the load increases. To study the robustness of SVM for classification, out of the total number of the data set, 20% of the data set was considered for testing set and the remaining for training set.

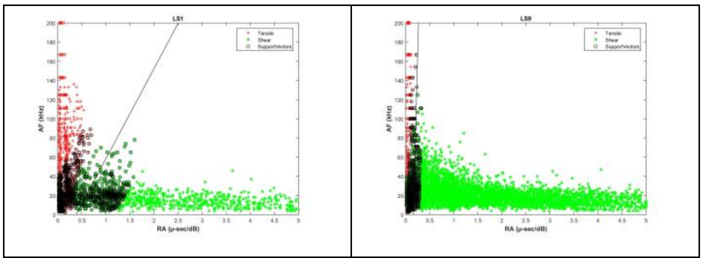
Figure 8 - Variation of RA and AF during SVM analysis for specimen failing in shear at LS1 and LS9

The results did not vary when the percentage of testing data was changed. Table 1 shows the comparison of percentage of AE activity for tensile and shear cluster for both GMM and SVM. The percentage error indicated in the last column of Table 1 shows that the crack classification by both the methods is approximately equal.

The results obtained by these analysis methods are in confirmation with the real-time testing of the concrete girders.

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Table 1. Comparison of percentage of tensile and shear clusters obtained from GMM and SVM analysis for the cylindrical concrete specimen

Load Step	No. of hits	GMM		SVM		Error
		Tensile(%)	Shear(%)	Tensile (%)	Shear(%)	
LS1	3840	56.27	42.91	56.5	42.4	1.1
LS2	8807	57.63	42.06	57.5	42.2	0.3
LS3	9915	78.39	21.47	78.4	21.5	0.1
LS4	11847	75.07	24.90	74.8	25	0.2
LS5	12774	67.14	32.24	67.1	32.3	0.6
LS6	9414	44.10	55.05	44.1	55.1	0.8
LS7	7315	45.67	50.67	45.3	51.1	3.6
LS8	7891	36.12	61.10	36.2	33.5	2.7
LS9	8385	32.43	63.82	34.6	61.4	4

V. CONCLUSION

An experimental study was carried out on concrete cylinders subjected to uniaxial compression. 8 channel AE monitoring system with 6 active sensors was used for the acquisition of AE parameters. Two features i.e., RA and AF values were calculated from the recorded AE data to classify the cracks into tensile and shear mode based on GMM algorithm. Shear cracks exhibit longer rise time with lower frequency and tensile cracks exhibit shorter rise time and higher frequency [3]. Three stages of cracking were observed; (a) dominance of tensile cracks during initial load steps; (b) transition stage during intermediate load steps; (c) dominance of shear cracks in the final load steps. It was also observed that as the loading progressed, the percentage of shear clusters increased. The results obtained by GMM analysis was verified by importing the clustered data into SVM algorithm. SVM analysis yielded results similar to the results obtained from GMM analysis. SVM analysis showed minimum error percentage for the classification. Hence, it can be concluded that the classification of cracks by GMM analysis is accurate. These results were also validated by visual inspection during the time of testing.

VI. ACKNOWLEDGMENT

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VIII. APPENDICES

Appendix A-Gaussian Mixture Modeling [10]

GMM is a parametric probability density function represented as a weighted sum of Gaussian component densities. It is useful to sort large quantity of data into different clusters using the expected maximum (EM) algorithm. Gaussian mixture modelling is useful to classify these AE signals into two clusters i.e., is tensile and shear. The general equation of a P-variate Gaussian distribution is given in Eq. (1)

$$P(X|\mu,\Sigma) = F(x_1, x_2, \dots \dots . x_p) = \frac{-1}{(2\pi)^{P/2}|\Sigma|^{1/2}} e^{\frac{-1}{2}[(X-\mu)^T \Sigma^{-1}(X-\mu)]} \quad (1)$$

To apply GMM model to classify crack mode in concrete specimens under compression, the input data is a 2D-vector i.e., RA and AF and sequence of T training vectors,

$$X = \{\vec{x_1} = (RA_1, AF_1), \dots, \vec{x_t} = (RA_t, AF_t), \dots, \vec{x_T} = (RA_T, AF_T)\} \quad (2)$$

And the hidden classes are i = {1, 2} which represent tensile and shear mode.

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Appendix B-Support Vector Machine [1,6]

Support vector machine (SVM) is a discriminative classifier defined by a separating hyper plane. Support vector machines can separate of a given data into two categories by a hyper-plane or decision boundary using a suitable mapping function. Support vectors are those points which do not belong to either of the two categories and lie on the maximum margin hyperplane in the featured space.

The goal in training a SVM is to find the separating hyper-plane with the largest margin. To minimize the magnitude of the weight vector, method of Lagrange multiplier is adopted. Lagrange multiplier is given by λ≠0 Lagrangian function for one constraint is given by]

$$L(x,\{\lambda_j\},\{\mu_k\}) = f(x) + \Sigma\, \lambda_j g_j(x) + \Sigma\, \mu_k h_k(x) \qquad (3)$$

subjected to $\mu_k \geq 0$ and $\mu_k h_k(x) = 0$ for k= 1,…….., K.

To solve equation (3) with the constraint b||a|| = 1, the Lagrange function constructed is,

$$L(\mathbf{a}, \alpha) = \frac{1}{2}||\mathbf{a}||^2 - \sum_{k=1}^{n} \alpha_k [z_k \mathbf{a}^t \mathbf{y}_k - 1]. \qquad (4)$$

This seeks to minimize the function L() with respect to weight vector '*a*' and maximize it with respect to the Lagrange Multiplier. The last term expresses the goal of classifying the points correctly.

GMM is a way of combining probability distributions to use in clustering of the data and then it classifies the data into different groups. However, SVM method depends on the distance of a data point from another point/plane of the previously clustered data and then classifies the data based on the decision boundary.