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Damage Mode Identification of CFRP-Strengthened Beam Based on Acoustic Emission Technique

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Abstract. Externally bonded (EB) carbon fiber reinforced polymer (CFRP) is widely used in structural strengthening and retrofitting. Premature debonding of the FRP severely limits the efficiency of CFRP utilization. The application of CRRP anchorage system offers a solution to the debonding problem. However, the understanding of damage mode identification of this combined system still remains elusive. Acoustic emission (AE) technique is employed to identify the damage mode of this CFRP anchorage system, due to its high sensitivity and the ability to detect damage in real-time. The objective of the current study is to identify the failure mechanisms of CFRP-strengthened beam by applying advanced pattern recognition techniques to the collected AE data. Firstly, four-point test of CFRP-strengthened beam was carried out until failure with simultaneous recording of AE signals. Then, correlation analysis was adopted to select the AE characteristic parameters, and principal component analysis (PCA) was used for dimensionality reduction. Lastly, the AE signals of the CFRP-strengthened beam was clustered to track the evolutionary behavior of the different damage modes by Gaussian mixture model (GMM) algorithm. Three main damage modes of CFRP-strengthened beam were identified by GMM clustering: concrete cracking, debonding of CFRP sheet and fracture of CFRP sheet. This study explores the damage evolution mechanism of combined system and provides a basis for achieving health monitoring of CFRP-strengthened structures.

Keywords: Acoustic emission · CFRP anchorage system · Damage mode identification · Gaussian mixed model clustering · Principal component analysis

1 Introduction

The use of fiber-reinforced polymer (FRP) as a strengthening material of existing concrete structures has become widespread in recent years, with strengthening possible in both flexural and shear modes [1, 2]. Among the various materials available for strengthening, carbon-fiber-reinforced polymer (CFRP) is unique in terms of its strength-to-weight ratio [3, 4]. Although CFRP-strengthened concrete structures are known to offer significant advantages, there is still a need to develop monitoring techniques to mitigate failure modes under sustained loading.

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This is where acoustic emission (AE) monitoring techniques come into play. AE is a non-destructive testing method that is used to monitor material integrity and detect sources of failure. By measuring the acoustic signature of an acoustic emission source before, during, and after the CFRP-strengthening process, the AE technique can be used to detect localized stress concentrations, micro-cracking, and changes in the structural stiffness of the CFRP-strengthened concrete structure [5, 6]. The use of AE can provide a better understanding of the behavior of FRP-strengthened concrete structures, and can even be used to develop predictive models for failure. For instance, an AE-based monitoring system can be used to detect the onset of fatigue failure in CFRP-strengthened concrete beams and slabs, and can indicate the onset of local damage before a catastrophic failure occurs [7]. With the emergence of miniaturized AE sensors, the potential for AE-based monitoring systems to detect the onset of fatigue failure in CFRP-strengthened concrete structures is even greater.

With the rapid development of artificial intelligence technologies, the application of pattern recognition methods in AE signal analysis has gradually emerged [7]. Pattern recognition methods can be divided into two categories: unsupervised and supervised, depending on whether the object classification of study is known or not. Cluster analysis is a representative of unsupervised pattern recognition methods, which classify patterns based on pattern characteristics and similarity measures. Several studies have used pattern recognition algorithms to group AE signals with similar characteristics and use these groupings to distinguish between damage states [8]. Johnson et al. [9] analyzed the AE transients in composite laminate tensile test specimens by principal component analysis (PCA). The unsupervised cluster analysis results showed that AE damage features from matrix cracking and local delamination can be separated in different clusters. Pei et al. [10] used the fuzzy c-means clustering algorithm to classify the AE events into three clusters which correspond to three damage modes of carbon/glass fiber-reinforced hybrid laminate composite specimens with different structure and indentation. Guo et al. [11] performed principal component analysis and K-means clustering analysis using relevant AE characteristic parameters (including energy, amplitude and duration) to identify various fatigue damage modes of carbon fiber/epoxy composite laminates with symmetrical architecture. Sause et al. [12] applied the validity analysis of clustering to determine the optimal number of clusters for the AE data, and the number of clusters obtained was consistent with the number of damage types of the CFRP samples. It can be found that pattern recognition technology represented by cluster analysis shows a powerful signal analysis capability with high recognition rate and intelligence, which has become an effective means for composite structure damage pattern recognition and damage mechanism exploration. Nevertheless, there is a lack of corresponding experimental studies on damage mode identification and monitoring of FRP-reinforced structures.

In this paper, a Gaussian mixture model will be used to cluster and analyze the AE signals, so as to classify the various types of information contained in the acoustic emission signals. First, a data set from the collected acoustic emission data sample parameters were constructed to build a database of AE signals of CFRP anchor nail reinforced beams; Then, the acoustic emission data are pre-processed, including removal of abnormal acoustic emission data, dimensionality reduction, correlation matrix analysis and principal component analysis; Lastly, the AE signals of the CFRP-strengthened beam was clustered to track the evolutionary behavior of the different damage modes by Gaussian mixture model (GMM) algorithm.

2 Experimental Investigations

2.1 Materials and Specimen

In this experiment, a CFRP-reinforced beam will be built and tested. The beam will be constructed of steel members, with CFRP strips used as reinforcement. The size and material attributes of the experimental beam are as follows. The RC beam will have a rectangular cross section of 150 mm × 250 mm and a length of 1.6 m. The concrete protection layer has a thickness of 25 mm. The bottom of the beam is reinforced with HRB400 ribbed steel bars of 14 mm diameter, which have a total length of 1800 mm. Upright steel bars of 8 mm diameter and 1800 mm length are also used. Additionally, two-arm hoop steel bars of 6 mm diameter HPB235 round steel bars with 80 mm spacing are used. To prevent corrosion of the hoop steel bars, epoxy resin is applied at the contact locations of the hoop and pulled steel bars.

The RC beam was cast with ordinary concrete mixture with equivalent compressive strength. The compressive strength of the concrete column is 42.5 MPa with a standard deviation of 3.6 MPa. The yield strength and ultimate strength of longitudinal bars are 462.2 MPa (standard deviation of 15.2 MPa) and 408.9 MPa (standard deviation of 5.5 MPa) respectively, and 615.7 MPa (standard deviation of 16.2 MPa) and 611.3 MPa (standard deviation of 4.5 MPa) respectively. The material properties of the CFRP sheet are provided by the manufacturer, with a thickness of 1.02 mm, a tensile strength of 3000 MPa, an ultimate tensile strain of 1.66%, and a tensile modulus of 230 GPa. The adhesive carbon fiber cloth adopts a chenglu brand building structure glue, whose composition is mainly epoxy resin (Fig. 1).

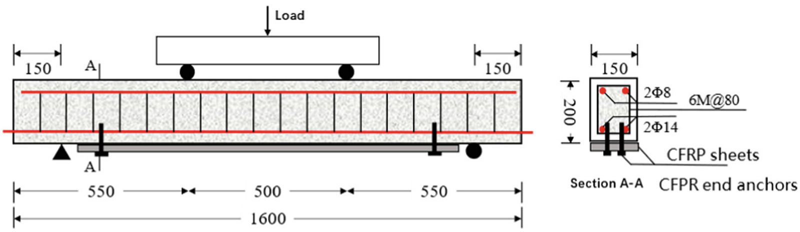

Fig. 1. Dimensions and reinforcement details of RC beams.

2.2 CFRP Anchorage System Strengthening

The construction of CFRP anchors is shown in Fig. 2. Carbon fiber anchors were carbon fiber bundles with a diameter of 8 mm made by cutting CFRP sheet according to 80 mm length and 150 mm width and rolling it in the vertical direction along the texture of CFRP sheet. The CFRP sheet connecting wire in the direction of the texture was withdrawn and tied at the end and at the anchorage depth of 35 mm. The carbon fiber bundles were sufficiently impregnated to the anchoring depth with epoxy resin, waiting for its initial setting and then impregnated again. A completed carbon fiber anchor can be got through the above process.

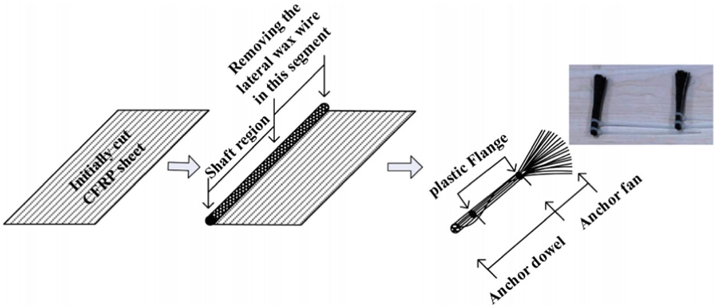

Fig. 2. Construction of CFRP anchors.

The application of CFRP anchor is done in the following steps, as shown in Fig. 3. First, the concrete surface should be cleaned with an angle grinder and kept flat and dry. Then, the holes were drilled in the RC beams according to the location of the carbon fiber anchor holes arrangement, and the debris and powder in the holes were removed in time. After that, the CFRP anchor is inserted into the drilled hole. The predrilled hole was filled with epoxy resin and the dowel end of the anchor was placed inside it to make them fully bonded. The ends of the anchor were then fanned over the CFRP sheet to fully impregnate the epoxy resin.

(a) Carbon fiber anchors inserted into concrete (b) Finished carbon fiber anchor reinforcement. (c) Finished RC beams reinforcement.

Fig. 3. CFRP anchorage installation procedure.

2.3 Experimental Setups

The schematic diagram of the loading device is shown in Fig. 4. The loading test was conducted by an electro-hydraulic servo testing machine with a maximum load capacity of

2,000 kN. Two pre-loading was performed before the formal loading, and the pre-loading value was 5% of the theoretical calculated ultimate load of the beam to ensure close contact between the loading device and the RC beam. Thereafter, a displacement-controlled loading scheme with a loading rate of 1 mm/min was utilized until the specimen failed.

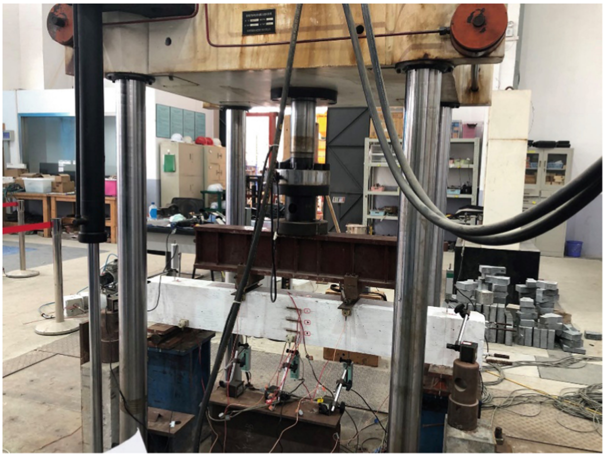

Fig. 4. Diagram of the loading device

The main device of the monitoring system is shown in Fig. 5. Five sensors were attached to the surface of each reinforced beam and glued with iron and epoxy adhesive to increase the sensing of the AE sensors as shown in Fig. 6. In addition, a pencil break test was used to check the sensitivity of the AE sensors. The threshold is initially set to 40 dB and the input preamplifier gain is 10 dB. The hit lock time and hit definition time are 300 us and 1000 us respectively.

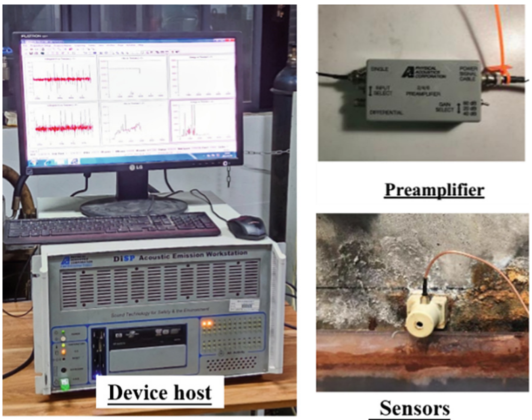

Fig. 5. AE monitoring system

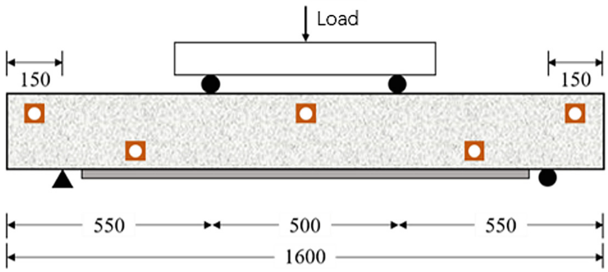

Fig. 6. Layout of the AE sensors.

3 Results and Discussion

3.1 Data Preprocessing

The AE signals collected by the AE acquisition system were represented by a set of characteristic parameters, involving rise time, ring count, energy, duration, amplitude, average frequency, signal strength, center frequency, and peak frequency. The calculation of coefficients base on the assumption that all AE characteristic parameters above exhibit Gaussian distribution, and use Gaussian algorithm to realize the cluster analysis of AE signals in the follow-up work. In order to optimize the clustering procedure, a subset of uncorrelated features must be selected. The preprocessing and standardization process of most AE data in this experiment were carried out in IBM SPSS Statistics 24 software.

Among the mentioned AE parameters, some parameters varieties are strongly related to the damage of reinforced concrete beams in the process of failure. In this experiment, the coupling effect of CFRP reinforcement and corrosion beams should also be considered, which will make it more complex to use all parameters to identify the failure process. Therefore, principal components were extracted from the parameters, the damage process of CFRP anchorage system is identified by the extracted principal components. Principal Component Analysis (PCA) is a multivariate statistical method that convert a set of variable data that may have correlation into a set of linearly unrelated variables through orthogonal transformation, and the converted variables are called principal components.

In this experiment, five parameters including rise time, ring count, average frequency, absolute energy, and peak frequency were selected for dimensionality reduction clustering. The parameters selection is not unique and the clustering results are not unique, either. In fact, there is no indisputable standard to determine a most appropriate and accurate clustering result that best represents the actual failure mechanism. The main purpose of selecting the above parameters is to better divide the AE data and show the characteristics it represented.

Conduct correlation analysis on the above five parameters. The new correlation matrix is shown in Table 1. It can be seen that the correlation coefficients between the five parameters were all less than 0.8. Table 2 shows the principal components of the five characteristic parameters. Parameters with characteristic value greater than 1 or cumulative variance contribution rate more than 85% could be used as new comprehensive parameter, namely the principal component. So the first two principal components were extracted for Gaussian cluster analysis in the experiment.

Table 1. The new correlation matrix

	Ring counts	Rise time	Average frequency	Absolute Energy	Peak frequency
Ring counts	1.000	0.269	0.397	0.182	0.118
Rise time	0.269	1.000	−0.214	0.042	−0.258
Average frequency	0.397	−0.214	1.000	−0.019	0.630
Absolute Energy	0.182	0.042	−0.019	1.000	−0.016
Peak frequency	0.118	−0.258	0.630	−0.016	1.000

Table 2. The principal components of the five characteristic parameters

Components	Total	Initial eigenvalue variance percentage	Cumulative percentage
1	1.852	37.032	50.032
2	1.365	27.296	88.328
3	0.951	19.025	90.353
4	0.551	11.017	95.37
5	0.281	5.63	100

3.2 Clustering Analysis of AE Signals Based on Gaussian Algorithm

Gaussian mixture model (GMM) is a probability model [13]. It assumed that the existing data is the weighted sum of finite Gaussian densities with unknown parameters. The GMM can be expressed as Eq. (1–4):

$$\mathrm{p}(x) = \sum_{k=1}^{K} w_k g(A|\mu_k,\ \Sigma_k) \tag{1}$$

$$g(A|\mu_k,\ \Sigma_k) = \frac{1}{\sqrt{(2\pi)^k|\Sigma_k|}} exp\left[\frac{-\frac{1}{2}(A-\mu_k)^T}{\Sigma_k(A-\mu_k)}\right] \tag{2}$$

$$\sum_{k=1}^{K} w_k = 1 \tag{3}$$

where A are the data, w_k is the mixed weight function, g is a Gaussian density function with a mean vector μ_k and the covariance matrix Σ_k.

The GMM algorithm involve three steps:

1. Make an initial estimation of mean vector μ_k and the covariance matrix Σ_k, and then calculate the density function involve all data.
2. Using membership and data to calculate the new parameters, defined $\mathrm{Nk} = \Sigma_k$, and express the new blending weight w_k^{new} as Eq. (4):

$$w_k^{new} = \frac{N_k}{N};\ 1 \le k \le K \tag{4}$$

And the new mean vector μ_k^{new} and new covariance matrix Σ_k^{new} will be update as Eq. (5–6).

$$\mu_k^{new} = \left(\frac{1}{N_k}\right)\sum_{i=1}^{n} w_{ik} \cdot A_i;\ 1 \le k \le K \tag{5}$$

$$\Sigma_k^{new} = \left(\frac{1}{N_k}\right)\sum_{i=1}^{n} w_{ik} \cdot \left(A_i - \mu_k^{new}\right)\left(A_i - \mu_k^{new}\right)^T;\ 1 \le k \le K \tag{6}$$

3. Repeat step 1 and step 2 until it meet the stopping criteria.

Generally, AE data clustering in FRP corresponds to actual different failure patterns of composite materials: matrix cracking, matrix/fiber interface layer delamination, fiber pull-out and fiber rupture. Thus, AE parameters were separated into four (or three) clusters in most studies, which can correspond each cluster directly to different failure patterns.

The two extracted principal components (PCA1 and PCA2) were used to cluster by Gaussian algorithm, as shown in Fig. 7. It can be found that the Gaussian algorithm successfully separated all data into three clusters, named them cluster 0, cluster 1 and cluster 2 respectively.

3.3 Failure Pattern Identification Using Clustered AE Signals

As introduced in Sect. 3.2, all AE data of RC beam were dimensionality reduced into three clusters by IBM SPSS Statistics 24, the results of the mean value of each characteristic parameter of three clusters are shown in Table 3, respectively.

The above tables listed the value of rise time, ring count, amplitude, absolute energy, duration and peak frequency of three clusters. The peak frequency showed a decreasing trend from cluster 0 to cluster 2, whereas other parameters showed an increase trend. Among them, the absolute energy showed a magnitude increase trend, and the amplitude, ring count also showed a large increase trend. It is very obvious that cluster 0 showed the characteristics of low frequency and high energy, while cluster 2 showed the characteristics of high frequency and low energy.

The damage situations and mechanisms are complex in the process of loading and failure of CFRP anchorage reinforcement system. Including original damage, plastic

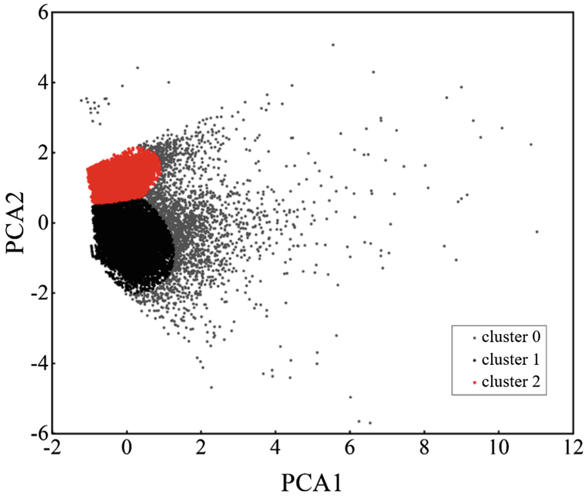

Fig. 7. The results of Gaussian clustering

Table 3. The mean value of each characteristic parameter of three clusters

	Rise time	Counts	Duration	Amplitude	Absolute Energy	Peak frequency
Cluster 1	100	21	461	48	1889	96
Cluster 2	235	66	1601	60	279888	76
Cluster 3	298	198	16414	94	40679667	37

deformation of concrete, micro-crack initiation, propagation and connection inside the beam, interface failure between concrete and reinforcement, slip of reinforcement, partially concrete crushing between reinforcement ribs, macro crack development, stripping between CFRP and the beam, CFRP breakage. The main damage patterns in different damage periods are different, and multiple damage patterns occur in a same damage period. Due to the lack of prior knowledge of signal characteristics related to each failure mechanism, and the lack of microscopic evidence to confirm the existence of specific damage patterns, the principal component clustering realized the data separation of the three damage patterns represented by AE characteristic parameters. The results of the three clusters can correspond to the three damage patterns of concrete matrix damage, CFRP peeling, and CFRP tearing in order, providing a solid data basis for subsequent analysis.

4 Conclusions

(1) The dimension of AE data was reduced using principal component analysis, five AE parameters including ring count, rise time, absolute energy, peak frequency and average frequency were selected for cluster analysis. The basic principle of

Gaussian clustering algorithm was introduced and used to cluster the five above AE parameters. The clustering results showed that the optimal solution is to separate in to three clusters.

(2) By analyzing the characteristics of the three clusters, corresponding cluster 0, cluster 1, cluster 2 to three damage patterns including concrete matrix damage, CFRP peeling and CFRP tearing, respectively. Provide a data basis for subsequent pattern identification.

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