# Classification of acoustic emission sources produced by carbon/epoxy composite based on support vector machine

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**Abstract.** Carbon/epoxy specimens were made and stretched to fracture. In the process, acoustic emission (AE) signals were collected and their parameters were set as the input parameters of the neural network. Results show that using support vector machine (SVM) network can recognize the difference of AE sources more accurately than using the BP neural network. In addition, the accuracy of the SVM increases when the number of the training set increases. It is proved that using AE signal parameters and SVM network can recognize the AE sources' pattern well.

## 1. Introduction

Carbon fiber reinforced composites (CFRP) have been widely used in fields of civil aviation, medical care as well as architecture because of their excellent properties such as high strength, light quality, corrosion resistant and high temperature resistant [1]. However, due to the high price of CFRP, it is quite necessary to find ways to discover and prevent the defects as early as possible. Acoustic emission (AE) testing is a novel non-destructive testing method which can be used online, and support vector machine (SVM) is a general feedforward network which can be used for pattern recognition [2]. Therefore, combining AE and SVM can well solve the pattern recognition problems of CFRP and prevent the loss.

## 2. Basic theories

### *2.1. Acoustic emission*

AE is defined as "the class of phenomena whereby transient elastic waves are generated by the rapid release of energy from localized sources within a material or the transient waves so generated" [3, 4]. AE is generated by the material itself. In material, AE sources can be from dislocation movement, cracks, fractures, and even corrosion. The waveform of the AE sources is shown in figure 1 and the features of the waveform are presented as below.

In figure 1, amplitude means the peak voltage of the largest excursion attained by the signal waveform from an emission event. In other words, peak amplitude is the highest point of the signal. Counts means the number of times the AE signal exceed a preset threshold during any selected portion

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of a test. Rise time is defined as the time between the start of the AE signal (Time of Hit) and its peak amplitude. Duration is the time from the start to the end of the AE signal. The energy is contained in a detected AE burst signal, with units usually reported in joules and values which can be expressed in logarithmic from (dB) [5]. Energy is defined as:

$$E = \frac{1}{2}\int_{t_1}^{t_2} f_+^2(t)dt - f_-^2(t)dt$$

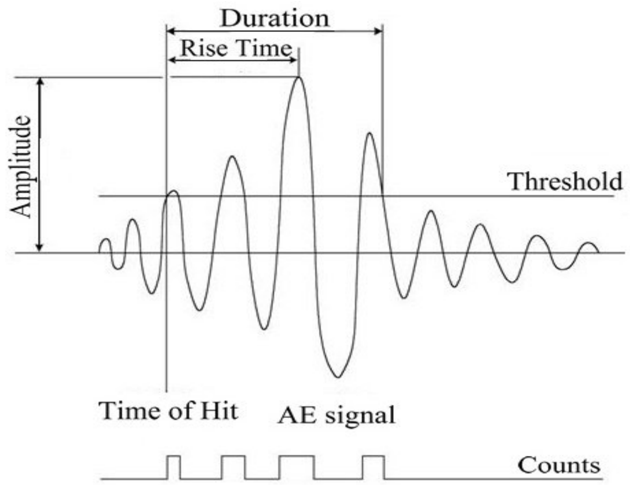


**Figure 1.** Signal features of the AE source.

*2.2. Support vector machine*

SVM, first proposed by Vapnik, is a typical neural network based on study algorithm [6-8]. The algorithm of SVM is as follows:

Firstly, the input vectors are mapped into high dimensional feature space through a nonlinear transform Φ.

Secondly, the maximal $\alpha_{0p}$ of the objectives of equation (1) is solved under the constraint condition $\sum_{p=1}^{P} \alpha_p d^p = 0$, $0 \le \alpha_p \le C$(or$\alpha_p \ge 0$), p=1, 2, …, P.

$$Q(\alpha) = \sum_{p=1}^{P} \alpha_p - \frac{1}{2}\sum_{p=1}^{P}\sum_{j=1}^{P} \alpha_p \alpha_j d^p d^j \Phi^T(X^p)\Phi(X^j) \quad (1)$$

Thirdly, the optical weight can be calculated through equation (2):

$$W_0 = \sum_{p=1}^{P} \alpha_0 d^p \Phi(X^p) \quad (2)$$

Fourthly, given an unclassified model X, the classification discriminant function is obtained through equation (3):

$$f(X) = \mathrm{sgn}[\sum_{p=1}^{P} \alpha_{0p} d^p \Phi^T(X^p)\Phi(X) + b_0] \quad (3)$$

The X’s classification is judged from the value of f(x).

## 3. AE signals acquisition

CFRP specimens respectively with 0, 1, 5, 9 bundles of carbon fiber and carbon-cloth/epoxy specimens were made and drawn to fracture at a speed of 2 mm/min. PCI-2 AE system was used to collect AE signals in the process. The sampling rate of the AE system was set at 2 MHz while the hit length was 1k. The threshold was set at 30 dB in order to remove the environmental noise and mechanical noise. The preamplifier gain was set at 20 dB and the analog filter was 2 kHz-3 MHz. The sensor was R15α with Vaseline as couplant. The construction and the geometry size of the specimen were shown in figure 2.

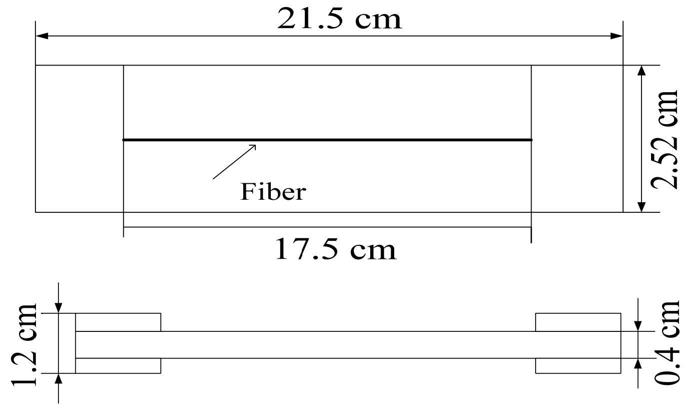


**Figure 2.** Construction and geometry of specimen.

**Table 1.** Input data of the neural network.

| | | | **Rise Time (μs)** | **Counts** | **Energy ($mV^2$)** | **Duration (μs)** | **Amplitude (dB)** |
|---|---|---|---|---|---|---|---|
| **Matrix Crack** | **Training (10 data)** | **Sum** | 547 | 165 | 128 | 2779 | 584 |
| | | **Average** | 54.7 | 16.5 | 12.8 | 277.9 | 58.4 |
| | **Testing (20 data)** | **Sum** | 398 | 280 | 126 | 3142 | 1145 |
| | | **Average** | 19.9 | 14 | 6.3 | 157.1 | 57.25 |
| **Delaminations** | **Training (10 data)** | **Sum** | 531 | 621 | 1566 | 9670 | 791 |
| | | **Average** | 53.1 | 62.1 | 156.6 | 967 | 79.1 |
| | **Testing (20 data)** | **Sum** | 7819 | 1705 | 6182 | 23826 | 1574 |
| | | **Average** | 390.9 | 85.25 | 309.1 | 1191.3 | 78.7 |
| **Fiber Breakage** | **Training (10 data)** | **Sum** | 205 | 2241 | 1154 | 3910 | 783 |
| | | **Average** | 20.5 | 224.1 | 115.4 | 391 | 78.3 |
| | **Testing (20data)** | **Sum** | 461 | 3772 | 7188 | 7241 | 1537 |
| | | **Average** | 23.05 | 188.6 | 359.4 | 362.05 | 76.85 |

## 4. Result and discussion

In this tensile experiment, the AE signals were divided into three main groups through the waveform and frequency spectrum, that is, matrix crack, delaminations and fiber breakage. It is revealed that the rise time, duration, amplitude and energy of matrix crack signals are low while those of delaminations are high, the rise time and duration of fiber breakage are low and amplitude and energy of fiber breakage are high. Rise time, counts, energy, duration and amplitude were set as the input of the neural network. Besides, 30 data of these AE signal features were chosen for each group of the AE signals, 10 for training and 20 for testing. Sum and average of these signals features of the three groups were shown in table 1.

After the training data were respectively trained for the BP neural network and SVM network, the testing data were put into the two neural networks to test the veracity of the two neural networks. Their classification results were shown in figures 3 and 4, respectively.

The details of the contrast between BP neural network and SVM network were shown in table 2.

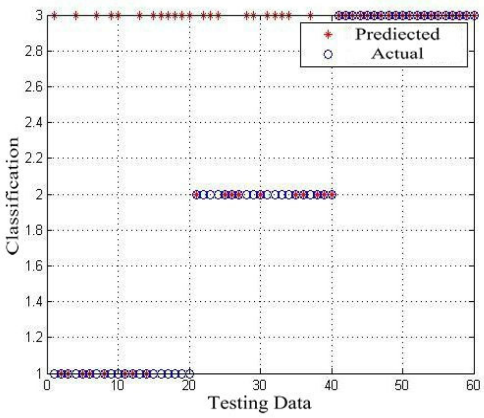


**Figure 3.** Classification of BP neural network.

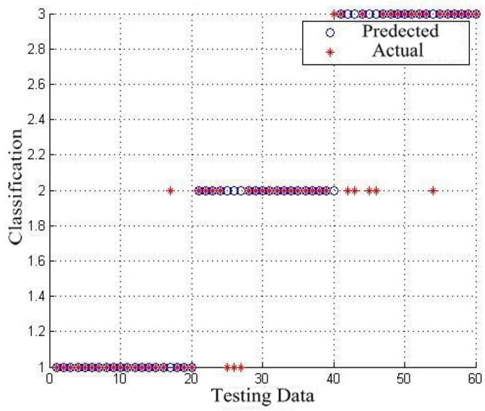


**Figure 4.** Classification of SVM network.

**Table 2.** Result of the neural network.

| | | Matrix Crack | Delaminations | Fiber Breakage | Total Accuracy |
|---|---|---|---|---|---|
| **BP** | **Accurate number** | 8 | 10 | 20 | 63.33% |
| | **Accurate rate** | 40% | 50% | 100% | |
| **SVM** | **Accurate number** | 19 | 16 | 15 | 83.33% |
| | **Accurate rate** | 95% | 80% | 75% | |

It reveals that classification of the AE signals based on SVM network is more accurate than that based on BP neural network from figures 1 and 2 and table 1, except for classification of the fiber breakage signals. When the training data of SVM neural network increased to 15 from 10 and the testing data remained 15, the classification result was shown in figure 5.

It can be concluded that the classification result is more accurate when then training increases to 15 as demonstrated by figures 4 and 5. Table 3 shows the results contrast of the SVM network with 15 and 10 training data.

From figures 4 and 5 and table 3, it is revealed that when the training data increase the accuracy of the SVM network also increases dramatically. It can be concluded from table 3 that the accurate number and rate of matrix crack, delaminations, fiber breakage all increase much, especially the accurate rate of fiber breakage.

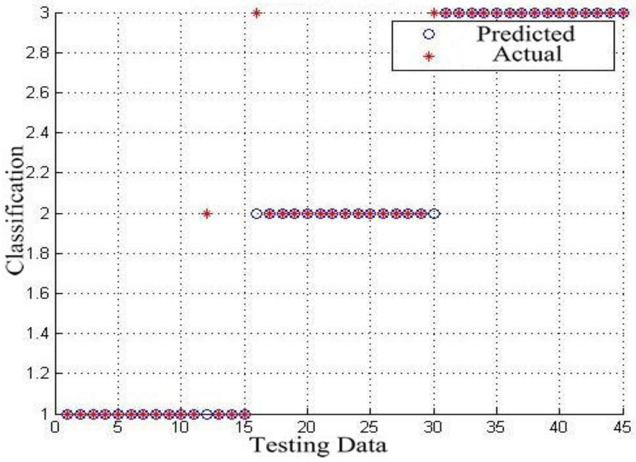


**Figure 5** Classification of the SVM training data increased

**Table 3.** Result of the SVM with different training data.

| | | **Matrix Crack** | **Delaminations** | **Fiber Breakage** | **Total Accuracy** |
|---|---|---|---|---|---|
| **15 Training data** | **Accurate number** | 14 | 13 | 15 | 93.33% |
| | **Accurate rate** | 93.33% | 86.67% | 100% | |
| **10 Training data** | **Accurate number** | 19 | 16 | 15 | 83.33% |
| | **Accurate rate** | 95% | 80% | 75% | |

## 5. Conclusion

It is concluded from this paper that the AE signal features and SVM network can be used for pattern recognition of the AE sources. The AE sources' pattern recognition based on AE signal features and SVM network is more accurate than that based on BP neural network. What's more, with the increase of the training data, the accuracy of pattern recognition based on SVM also increases. Therefore, adding the training data without impacting the arithmetic speed can improve the effect of SVM network on the AE signal sources' recognition.

## Acknowledgments

This work is supported by the Graduate Innovation Base of Jiangxi Province. We also gratefully acknowledge the National Natural Science Foundation of China (Nos. 61062010) and Aviation Science Foundation (Nos. 2007ZF56013) for their support of this work.

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