Wood acoustic emission signals classification based on pseudospectrum, and entropy

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Abstract. The nondestructive testing technology of generated acoustic emission(AE) signals for wood is of great significance for the evaluation of internal damages of wood. In order to improve the classification accuracy and adaptability of AE signal, we selected two features(pseudospectrum, entropy) for classify AE signals in the process of wood fracture using SVM classifier. The three-point bending load damage experiment was utilized to generate original AE signals. Evaluation indexes(Precision, Accuracy, Recall, F1-score, Cohen Kappa score, Matthews Corrcoef) were adopted to assess the classification model. The results showed that the overall accuracy of the SVM classification model obtained by the method combining pseudospectrum and entropy features is 89.44%, which indicates that this automatic classification model has good AE signal recognition performance.

1. Introduction
The wood is a natural composite material with a porous, layered structure. When the wood is locally deformed and fractured, it releases energy in the form of stress waves, which generate a large number of acoustic emission(AE) signals. As the only active dynamic nondestructive testing method, acoustic emission technology(AET) has been widely used in composite materials, magnetic materials, and other materials defect detection. The beginning of modern AET was in Germany in the early 1950s\cite{1}. The researches on AE in China began in the 1970s, and it was not until the early 1980s that AET began to be applied in engineering practice. Reiterer et al.[2] used the method of combining splitting test and AE monitoring to study the internal stress change and fracture process of cork and hardwood \textsuperscript{I} type fracture. Choi N S et al.[3] divided AE signals into different types through short-time Fourier transform (STFT)
and obtained the characteristics of different types of signals. Castellani et al.[4] studied a multilayer perceptron classifier to identify wood veneer defects. Facciotti N et al.[5] used spectrogram analysis techniques to distinguish between different AE events. Barile C et al.[6] characterized the damage propagation of composite materials by AET. Wang et al.[7] used Softmax to realize the recognition of AE signals.

These research objectives are to propose the most effective methods for describing AE events of different wood species, while improving identification accuracy. This search work is that features (pseudospectrum, entropy) were extracted from AE signals generated in the process of three-point bending load damage of wood, and SVM classifier was used for training and testing, in an attempt to automatically identify or distinguish wood damage and fracture states in different periods according to different acoustic emission characteristics.

2. Methodology

Beech with no defect on the surface and stable moisture content of about 11% under air-dried condition was selected as the experimental material. The sample size was 800mm(length) × 60mm(width) × 30mm(thickness). The experimental equipment in this study was: 1)NI USB-6366 high-speed acquisition card; 2)LabVIEW software to build a 3-channel AE signal acquisition system; 3)UTM5105 universal mechanical testing machine (the maximum test force is 100kN, the power is 1.5kW); 4)SR 150N single-ended resonant acoustic emission sensor (the signal bandwidth is 22-200kHz); 5)a 40dB gain preamplifier with a maximum sampling frequency of 2MHz per channel and an output voltage range of ± 5V. In this study, the three-point bending method was utilized to compress the sample laterally at a velocity of 1mm/min with a span of 200mm. The sampling frequency of AE signals in this study was 500 kHz. According to Shannon's sampling theorem, AE signals in the range of 0~250 kHz can be theoretically identified. The AE signals caused by the pressure on the sample surface were transformed by the sensors and amplified by the preamp. Then the data acquisition card received the signals and stored them in a computer. Finally, features(pseudospectrum, entropy) were extracted from obtained signals, and SVM was used to classify and recognize them. The flowchart of processing is illustrated in Fig.1.

2.1. Feature extraction

2.1.1. Pseudospectrum using multiple signal classification(MUSIC) algorithm

The MUSIC algorithm[8] uses the frequency vector and the orthogonality of the noise subspace of the signal to construct the spatial spectrum function, and the frequency of the signal is estimated by searching the spectral peak. The scanning function of the algorithm is as follows:

\[
\hat{\rho}_{\text{MUSIC}}(\omega) = \frac{1}{\alpha^H(\omega)GG^H\alpha(\omega)}
\]

\[
= \frac{1}{\sum_{i=k+1}^{N} |\alpha^H(\omega)u_i|^2}, \omega \in [-\pi, \pi]
\]

(1)
where, $M$ represents the order of signal autocorrelation matrix, and $K$ represents the number of frequency sources. $\omega = [1, e^{-j\omega}, \ldots, e^{-(M-1)\omega}]$ is the signal frequency vector, $u_i$ is the eigenvector of the signal autocorrelation matrix. Here, we only took the $(M-K)$ eigenvalues, that is, the eigenvector corresponding to the smallest $(M-K)$ eigenvalue. In fact, the MUSIC algorithm is to search $\omega$ by scanning, in the ideal case, when the signal frequency point $\omega$ is obtained by scanning, $^H\alpha\omega\alpha\omega = 0$.

In practical application, $^H\alpha\omega\alpha\omega$ is not necessarily equal to zero at the signal frequency points, but is equal to a very small value, because the time autocorrelation $\hat{R}$ of the signal samples is used to replace $R$ for eigendecomposition. Therefore, the position of the peak value of $\hat{\omega}_{\text{MUSIC}}$ reflects the frequency value of the signal, but $\hat{\omega}_{\text{MUSIC}}$ is not the power spectrum of the signal, so it is usually called the pseudospectrum or spectrum.

### 2.1.2. Entropy

Entropy represents the overall information uncertainty of random objects in the sense of average, which is a very important concept in information theory. For a discrete random variable $X$, its probability space is set as [9]

$$
\begin{bmatrix}
X \\
P(x)
\end{bmatrix} = \begin{bmatrix}
a_1, a_2, \ldots, a_n \\
p(a_1), p(a_2), \ldots, p(a_n)
\end{bmatrix}
$$

(2)

where the probability $p$ is:

$$
0 \leq p(a_i) \leq 1, \sum_{i=1}^{n} p(a_i) = 1
$$

Then the average uncertainty of the whole probability space, namely information entropy, is defined as

$$
H(X) = -\sum_{i=1}^{n} p(a_i) \log p(a_i)
$$

(3)

Entropy is employed to describe the redundancy of information sources. The more ordinary a signal is, the lower the information entropy is. Conversely, the more chaotic a signal is, the higher the entropy of information is.

### 2.2. Method of classification

Support Vector Machine(SVM)[10] is a class of generalized linear classifiers that classifies data according to supervised learning. The decision boundary is the maximal margin hyperplane of the learning sample. SVM uses kernel methods to transform the set of features that draw the best boundaries between possible outputs. To evaluate the segment-based approach, we have used performance measures[11], namely Accuracy(A), Precision(P), Recall(R), F1-score(F1), Cohen Kappa score, and Matthews Corrcoef.

$$
A = \frac{\sum_{i=1}^{n} (TP_i + TN_i)}{\sum_{i=1}^{n} (TP_i + FP_i + TN_i + FN_i)}
$$

(4)

$$
P = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n} (TP_i + FP_i)}
$$

(5)

$$
R = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n} (TP_i + FN_i)}
$$

(6)

$$
F1 = \frac{2 \times P \times R}{P + R}
$$

(7)

where $i = 1, 2, \ldots, n$ is the total number of sample categories. $TP$ is true positive, $FP$ is false positive, $FN$ is true negative, and $TN$ is false negative, that is, $TP$: it is predicted to be positive, and it is actually
positive; $TN$: it is predicted to be negative, and it is actually negative; $FP$: it is predicted to be positive, while it is actually negative; $FN$: it is predicted to be negative, while it is actually positive.

3. Result and Discussion

![Figure 2: Time-Power curve](image)

![Figure 3: Original AE signal](image)

3.1. Original signal obtained from experiment
The duration of this experiment was 370s, and the sampling frequency was 500kHz. In order to analyze the relationship between stress and AE signal generation, the corresponding time-load curve was drawn (Fig.2). It can be seen from the figure that the load curve increases uniformly with the increasing stress and reaches a maximum value at about 204th second. After this time, the load curve decreases sharply, indicating that the sample wood fractures at this moment. And then, the curve decreases gradually at a slower rate. From the load curve alone, it is difficult to learn the state of damage inside the wood.

The original AE signal of the test process is illustrated in Fig.3, which contains $1.85 \times 10^8$ data points according to the sampling frequency and duration. From this figure, we can easily observe that many AE signals have been generated before the load reaches the maximum, which indicates that microcracks have been generated inside the sample wood. As mentioned before, internal damages of wood can be roughly divided into four basic types from the microscopic point of view. Thus, in this study, we also divided the original signal into four segments according to its amplitude, corresponding to these four types. 0-100s can be regarded as a small amount of AE signal caused by wood cell wall buckling and collapse, which is called buckling AE signal. 100-150s can be regarded as a stable small amplitude AE signal caused by the damage and delamination of wood cell wall interface, which is called deformation AE signal. 150-200s can be regarded as AE signals that are more chaotic and high-energy than those in the second stage due to the formation and expansion of wood micro-crack damage zone, which is called micro-crack AE signal. 200-370s produced a large number of long lasting and complex AE signals,
which can be considered as AE signals caused by wood cell wall fracture, and this AE signal is called fracture AE signal.

3.2. Classification results of AE signals based on SVM

This section will focus on the results of performance analysis. We took 5000 data points as a sub-segment, corresponding to a period of 0.01 second, by comparing each feature extraction (pseudospectrum, entropy) method used with the SVM classifier, the confusion matrix of AE signal classification under different wood damage conditions will be calculated. The corresponding evaluation indexes of Accuracy, Precision, Recall, F1-score, Cohen Kappa score, and Matthews Corrcoef were obtained.

Fig.4 shows the confusion matrix obtained by inputting the SVM classifier with pseudospectrum features, and Fig.5 shows the result percentages of different evaluation indexes gained by this confusion matrix. For Accuracy, the percentage is 82.98%. While, Precision, Recall and F1-score give 80.30%, 82.98% and 78.17%. Finally, Cohen kappa Score and Matthews Corrcoef give 74.45% and 75.86%.

Fig.6 shows the confusion matrix obtained by inputting the SVM classifier with entropy features, and Fig.7 shows the result percentages of different evaluation indexes gained by this confusion matrix. For Accuracy, the percentage is 83.11%. While, Precision, Recall and F1-score give 87.12%, 83.11% and 80.4%. Finally, Cohen kappa Score and Matthews Corrcoef give 75.22% and 76.69%.

Figure.4 Confusion Matrix from Pseudospectrum

Figure.5 Evaluation indexes from Pseudospectrum
Figure 6: Confusion Matrix from Entropy

Figure 7: Evaluation indexes from Entropy

Figure 8: Confusion Matrix from Pseudospectrum and Entropy
Fig. 8 shows the confusion matrix obtained by inputting the SVM classifier with pseudospectrum and entropy features, and Fig. 9 shows the result percentages of different evaluation indexes gained by this confusion matrix. For Accuracy, the percentage is 89.19%. While, Precision, Recall and F1-score give 90.04%, 89.19% and 88.68%. Finally, Cohen kappa Score and Matthews Corrcoef give 83.98% and 84.30%.

On the whole, the classification results obtained by using pseudospectral features have a higher error rate in the second type, in which only 47 pseudospectral features are correctly identified, and the accuracy rate is 3.18%. The classification results obtained by using entropy features have a higher error rate in the third type, in which only 218 entropy features are correctly identified, and the accuracy rate is 14.17%. However, the accuracy of the second and third types is 50.71% and 85.63% respectively in the classification results obtained by using pseudospectrum and entropy features. In fact, the AE signals change gradually with increasing pressure, and there is no strict boundary between the second and third class of AE signals. In other words, the two types of AE signals, especially those near the specified classification boundary, have a high similarity. In addition, the number of data for both types is less than the other two types. Therefore, it is normal that a certain number of misclassifications occur.

4. Conclusion

The nondestructive testing technology of AE signal for wood is of great significance for the evaluation of internal damages of wood. The research in this paper shows that the overall accuracy of the SVM classification model obtained by the method combining pseudospectrum and entropy features is 89.44%, which indicates that the model has good AE signal recognition performance and can be used to accurately identify wood damage state.

Moreover, this classification model lays a foundation for future research on the real-time monitoring and automatic identification of wood damage for wood material products such as building facilities, furniture materials, wooden ancient buildings, and music devices. Future research includes: extending the model to different tree species; looking for more sensitive signal features, studying feature extraction and selection methods; adopting different machine learning classification algorithms; thereby establishing a higher accuracy and more generalized wood damage prediction model.

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