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A Novel Adaptive Weighted Feature Combination Method for Pile Classification

Kang Weixin[1*] and Zhao Tianwei[2]

[1,2]College of Information and Communication Engineering, Harbin Engineering University, Harbin, Heilongjiang Province, 150000, China
*[*1]kangweixin@hrbeu.edu.cn, [2]zhaotianwei@hrbeu.edu.cn*

Abstract

Adaptive weighted combination is a intelligent method. To automatically set proper weights is the most important key of adaptive weighted combination. In this paper a suited adaptive weighted feature combination method is proposed for pile classification, which is a blend of energy-damage method, wavelet fractal method, and wavelet entropy method and automatically determines optimal weights based on maximum entropy. The proposed method uses wavelet entropy to improve the anti-noise performance in keeping the energy-damage algorithm and wavelet fractal method for well description ability of feature information. Though the proposed method is simple and easy to implement, it can obtain better anti-noise performance than previous methods, and it can make up the shortcoming of single classification method. Result shows that the classification accuracy can reach 95%. It can be widely applied to the field of damage identification.

***Keywords**: Maximum entropy, Adaptive weighted, Feature combination, Pile classification*

1. Introduction

Pile foundation is a typical one-dimensional rod bearing geotechnical engineering such as bridges and houses. How to accurately and efficiently extract features including the damage information from the pile stress wave reflection signals is a key issue to ensure the engineering quality and the pile foundation of structural health monitoring in service in the field of damage identification[1~4]. To extract good feature whether or not directly affects the accuracy of damage identification. At present, pile foundation damage feature extraction method is mostly local energy change method based on the wavelet packet transform. It could obtain the corresponding frequency band energy as the damage feature vector through the wavelet packet transform and reconstruction of torsional stress wave signal. Then the feature would be regarded as input vector of the classified recognition by using pattern recognition method. Energy-damage (ED) method had better recognition accuracy. However, it could be prone to false features and small submerged damage features under the noise interference, which caused the false identification or miss discrimination.

In addition to ED feature extraction method, some scholars also put forward using wavelet combined with fractal theory and wavelet entropy feature extraction methods[5]. Wavelet fractal dimension (WFD) theory is widely used in structural damage identification and heart sound identification, etc, that is used to identify the damage through the signal self-similarity feature extraction of fractal box-dimension after the signal wavelet decomposition. While wavelet entropy (WE) used wavelet energy distribution of each scale to replace the probability distribution of the signal, that did not depend on scale choice, and had the insensitivity characteristics to noise.

Aiming at the shortcomings of the existing single detection method in the field of pile damage identification, the paper introduces the mean value of power spectrum, the fractal

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box-dimension, and the entropy as a damage identification combination features based on the wavelet transform respectively. Meanwhile adaptive weighted damage detection is put forward, that is based on maximum entropy theory. Anti-noise performance and reliability are performed to investigate the feasibility of the method.

2. Feature Extraction Methods

Energy-damage, wavelet fractal dimension and wavelet entropy method are based on the wavelet transform. These methods describe the stress wave from different levels, that can avoid the limitations of single method. Thus the paper choose the three mentioned methods above for feature combination.

2.1. Energy-damage

Wavelet packet transform can further decompose high frequency without being subdivided in wavelet transform, and it can adaptively select frequency band to match the signal spectrum according to the signal features. Thus, it is a more extensive application method of the wavelet decomposition [6]. Energy-damage method is one of the most commonly used methods for pile damage identification, whose core is the frequency band energy to represent the original signal energy distribution. For the energy of the wavelet packet transform and the original signal has the equivalent relation, and the decomposition of wavelet packet transform can adaptively adjust scale parameter according to the change of the signal itself, so it is especially suitable for non-stationary signal representation and processing. The paper uses the mean power spectrum to reflect node energy distribution in wavelet packet transform, the extracted eigenvalues can constitute feature vector to reflect the damage information[7], Basic flow diagram is shown in Figure 1.

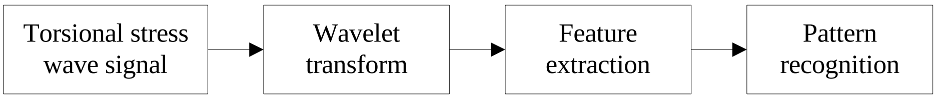


Figure 1. Basic Flow Diagram of ED Method

2.2. Wavelet fractal Dimension

Wavelet fractal method is mainly used in the field of structural damage identification[8-10]. The fractal method mainly includes box-dimension, information dimension, correlation dimension and generalized dimension, etc. Fractal dimension is a quantitative value obtained from scaling relations in fractal meaning. It can represent the irregular and complexity degree of fractal sets, which is one of the important parameters describing fractal characteristics. The box-dimension is widely used in that its calculation is simple and easy to empirical estimates[11]. For pile signal under wavelet decomposition satisfies self-affine, the paper selects one box-dimension of each frequency as combination feature vector.

Based on the assumption that X is non-empty bounded subset and $N(X,\varepsilon)$ represents the minimum number of the maximum diameter ε and covering the X set, the box-dimension of X can be defined as:

$$\dim_B X = \lim_{\varepsilon \to 0} \frac{\ln N(X,\varepsilon)}{\ln(1/\varepsilon)} \tag{1}$$

Where R^n is divided by ε grid as little as possible, and N_ε is grid counting of X set. When calculating the fractal box dimension, approximation is generally adopted. The grid is gradually enlarged from ε to $k\varepsilon$, where k is positive integer. Thus, supposing that $N_{k\varepsilon}$ is grid counting of X set in discrete space, the space that time sequence takes up can be divided into dense grids in order to getting amount of square with its side as ε. Next, $N_{k\varepsilon}$ can be found by counting the squares that time sequence X takes up. Therefore, the approximate box-dimension of X can be calculated as:

$$D_B \approx \frac{\ln N_{k\varepsilon}}{\ln(1/\varepsilon)} \tag{2}$$

In the $\ln N(\varepsilon) - \ln(1/\varepsilon)$ diagram the good linearity is a scale-free area for the signal. The slope of fitting line is the corresponding fractal box-dimension.

2.3. Wavelet Entropy

Wavelet entropy theory is widely applied in the fault diagnosis of non-stationary signals and damage detection [12] such as ERPs (Event Related Potentials), which is proposed upon based on the good resolution and local characteristics of wavelet transform and combined the entropy to measure overall information of the signal. Torsional stress wave is non-stationary and nonlinear signal. Therefore the paper adopts the method dividing the signal window to calculate each window's wavelet entropy respectively in order to realize the damage feature extraction.

Specific steps about feature extraction of wavelet entropy are as follows:

W_j is the coefficient of j-th scale wavelet decomposition, that is obtained by N-resolution wavelet decomposition of torsional stress wave in m-th window. where j is scale parameter， w_{j_i} is wavelet decomposition.

$$W_j = \left(w_{j_1}, w_{j_2}, \cdots, w_{j_n}\right)$$

The following E_j is the definition of energy in j-th scale.

$$E_j = \left\|W_j\right\|^2 = \sum_{i=1}^{n}\left|w_{j_i}\right|^2, \quad i = 1, 2, \cdots, n, \quad j = 1, 2, \cdots, N \tag{3}$$

Then the normalized energy sequence under each scale is as Equation (4).

$$p_j = E_j / E, \quad E = \sum_{j=1}^{N} E_j, \quad j = 1, 2, \cdots, N \tag{4}$$

The final step is to calculate wavelet entropy in each window. the wavelet entropy value in m-th window is as followed:

$$H_{we_m} = \sum_{j=1}^{N} p_j \log p_j, \quad j = 1, 2, \cdots, N \tag{5}$$

Therefore, wavelet entropy feature vector can be expressed as H_{we}.

$$\mathrm{H}_{we} = \{H_{we_1}, H_{we_2}, \cdots, H_{we_M}\}$$

3. Feature Combination Algorithm and Improvement

As is known from 1-th section, ED has well multi-resolution and local characteristic, WFD can reflect the complexity degree of the signal, while WE is whole measurement of the signal. It is difficult for damage identification to artificially determine which extraction method contribution is bigger. Therefore, the paper puts forward the adaptive weighted combination algorithm to extract damage features based on maximum entropy theory.

3.1. Adaptive Weighted Feature Fusion Algorithm

Adaptive weighted feature fusion(AWFF) algorithm is mainly applied to multi-sensor intelligent detection system[13-14]. In recent years, this method is adopted to fuse multi-feature for the purpose of a higher precision value in the field of the heart sound identification and structural damage identification, etc. The basic process of the combination feature extraction is shown in the Figure 2, that uses several feature extraction methods for a certain object. Each feature extraction method has the corresponding weighting. In the case of minimum total mean square error(MSE), AWFF finds the eigenvector corresponding weight by adaptive way in each used method so that the combined eigenvector can be optimal.

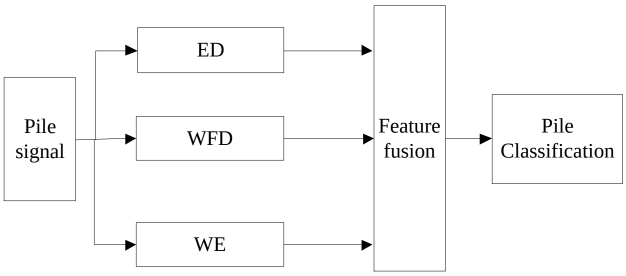


Figure 2. Basic Flow Diagram of Pile Damage Classification Based on Feature Combination

After the introduction of the weighted factor, the fused eigenvalue should be:

$$\hat{X}=\sum_{i=1}^{n}W_i X_i \tag{6}$$

where

$$\sum_{i=1}^{n}W_i=1 \tag{7}$$

Total mean square error is σ^2.

$$\sigma^2=\sum_{i=1}^{n}W_i^2\sigma_i^2 \tag{8}$$

where σ^2 is the pluralistic quadratic function of each weighted factor W_i in Equation 8. According to the theory of multi-function of seeking extreme, σ^2 is the minimum value when the weighting factor W_i' is calculated by Equation (9). The σ^2 minimum can be expressed as followed Equation (10).

$$W_i'=\frac{1}{\sigma_i^2\sum_{i=1}^{n}\frac{1}{\sigma_i^2}} \tag{9}$$

$$\sigma_{\min}^2 = \frac{1}{\sum_{i=1}^{n} \frac{1}{\sigma_i^2}} \tag{10}$$

On account that the fused eigenvalue is a objective constant, it can be estimated through arithmetic mean of the existing feature data. The arithmetic mean can be defined as:

$$\bar{X}_i\left(k\right) = \frac{1}{k}\sum_{q=1}^{k} X_q, \quad i=1,2,\cdots,n \tag{11}$$

Estimate value $\hat{\bar{X}}$ can be expressed as:

$$\hat{\bar{X}}=\sum_{i=1}^{n} W_{\text{i}} \bar{X}_i\left(k\right) \tag{12}$$

Total MSE $\bar{\sigma}^2$ can be derived from Equation 10 and Equation 12

$$\bar{\sigma}^2 = \frac{\sigma_{\min}^2}{k} \tag{13}$$

3.2. Maximum Entropy

The more significant the feature difference is, the bigger amount of information is, namely the greater its contribution is. The existing adaptive weighted fusion algorithm focus on the weights under the condition of the minimum total variance. As a result, in case of the unbiased weights, the maximum entropy theory [15] is proposed to calculate the combination weights. The method can make the feature contain the biggest uncertainty amount of information. Then the ability to describe the pile signal is most close to the real condition. And damage features difference is more significant.

Based on the assumption that each feature extraction method has m eigenvalues, n kinds of feature extraction method. The constituted feature vector matrix can be written as:

$$D=\begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \tag{14}$$

The entropy that used j-th kind of feature extraction method can be expressed as:

$$E_j=\text{-K}\sum_{i=1}^{m} p_{ij} \ln p_{ij}, \quad j=1,2,\cdots,n \tag{15}$$

where $\text{K}=\left(\ln m\right)^{-1}$, and $p_{ij} = \frac{d_{ij}}{\sum_{i=1}^{m} d_{ij}}, \quad \left(i=1,2,\cdots,m; \quad j=1,2,\cdots,n\right)$.

Under the condition that the weights of each feature extraction method is unbiased, the weights can be rewritten as:

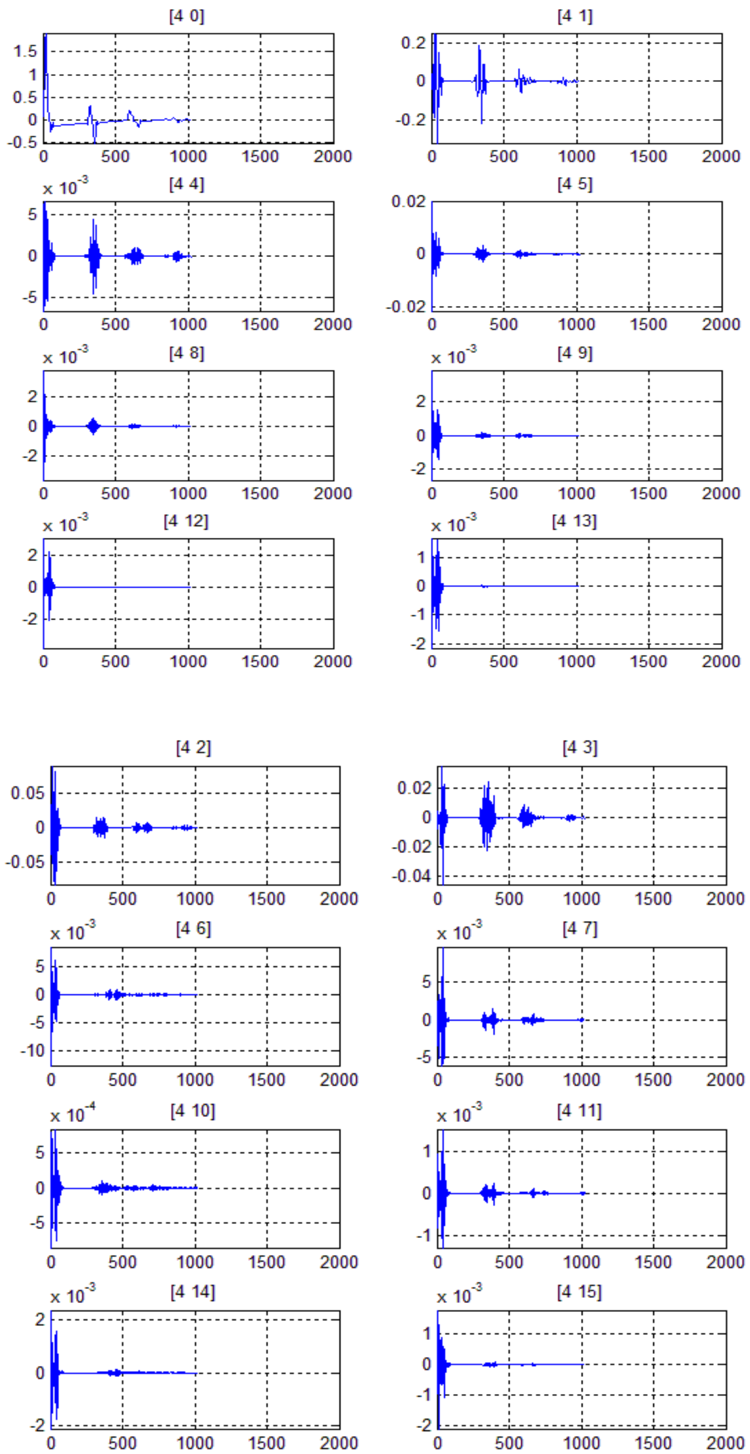
$$W_j=\frac{1-E_j}{\sum_{j=1}^{n}\left(1-E_j\right)}, \quad j=1,2,\cdots,n \tag{16}$$

According to AWFF and maximum entropy, the combination feature can be defined as:

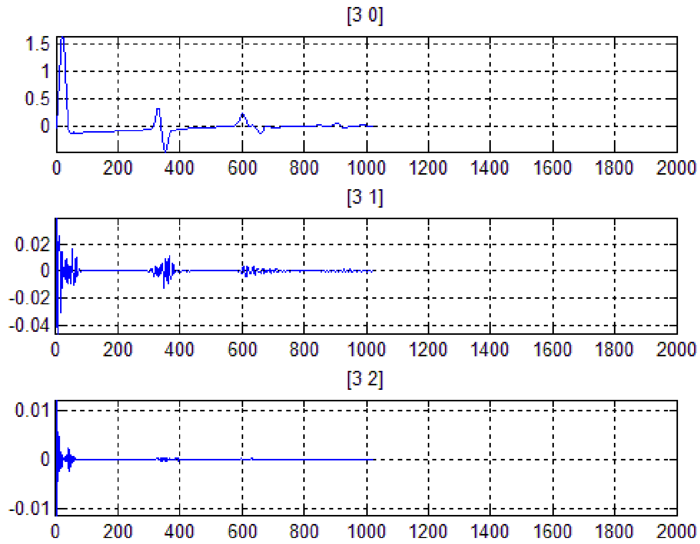
$$\hat{\mathbf{X}}=\left\{W_1X_{11}, W_1X_{12}, \cdots, W_1X_{1m}, W_2X_{21}\cdots, W_2X_{2m}, \cdots W_nX_{nm}\right\}$$

4. Performance Study and Discussion

In this section, wavelet decomposition level of is discussed by the experiment and evaluating the quality of combination feature, and anti-noise and reliability of the combination method are verified through comparing with the single algorithm of pile damage detection method.



(a)



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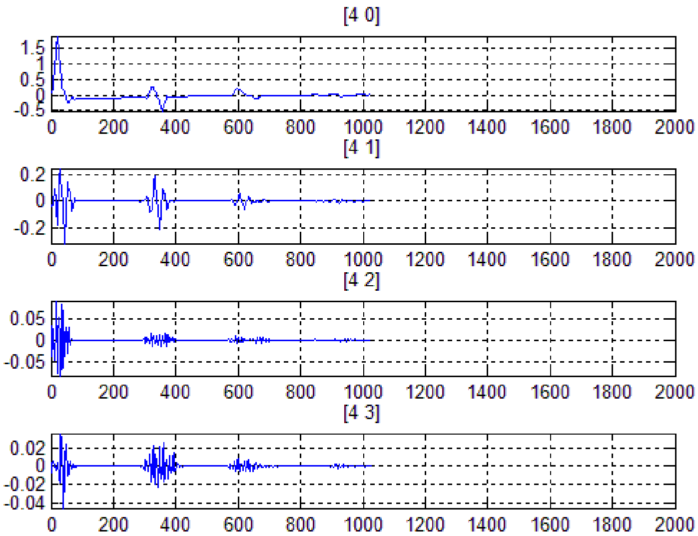

(c)

Figure 3. Wavelet Packet Decomposition of Pile Torsional Stress Wave

4.1. Choice of Wavelet Decomposition Level

The purpose of wavelet decomposition is to choose suitable wavelet basis in that it can describe some characteristics of the signal. And then time-frequency characteristic is analyzed by decomposing the signal under the given wavelet basis. In 1-th section, it is kwon that all the selected combination method are based on wavelet decomposition. So it is more significant how many levels of wavelet decomposition can describe the damage feature.

The experimental signal is torsional stress wave. Daubechies wavelet db6 is used as wavelet basis function. And the optimal wavelet packet decomposition with Shannon criterion is obtained. The result of 4 levels wavelet packet decomposition is shown in Figure 2. When the signal is decomposed to 4-th levels, the damage reflection of its each node is obvious. Therefore, 4 levels of wavelet packet decomposition is used to extract the energy-damage and fractal feature vector.

In the issue of choosing the wavelet decomposition scales about WE method, the scale is 3, 4, 5, 6 and 7 respectively to calculate the wavelet entropy value of the pile torsional stress signal. Figure 3 shows the feature curve move towards consistently in different level. It is verified that the wavelet entropy is not dependent on the scale of the wavelet decomposition.

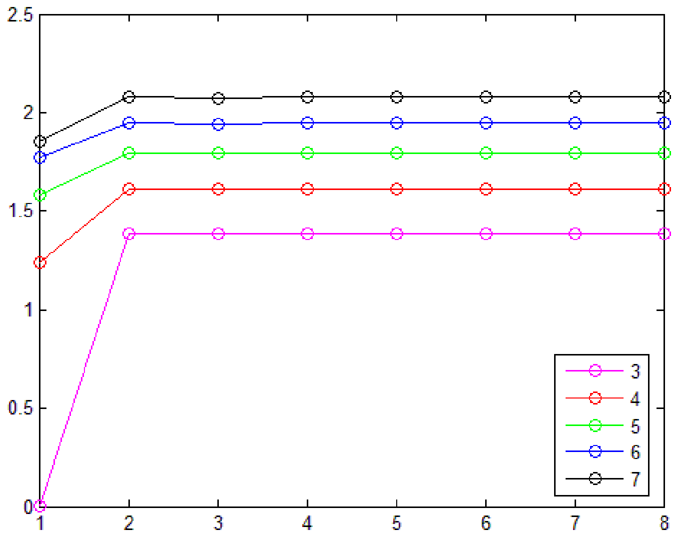

Figure 4. The Wavelet Entropy of Different Scales

4.2. Comparison of Different Feature Extraction Method

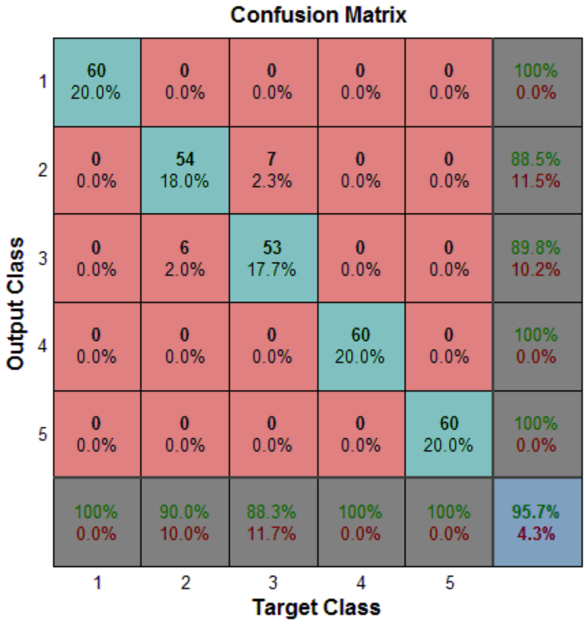

Figure 5. Classification Result of Combination Feature Method

In condition of numerical simulation, the damage pile stress wave accords with practical application. 300 groups of pile torsion wave signal data including 5 damage types are obtained by finite difference numerical simulation method[16], where fifteen percent of the data are forecast samples. The proposed method is applied to feature extraction, and the BP Neural Networks predicts classification [17]. The result is shown in Figure 4, where 1 to 5 represent no damage, shrinking-diameter, broaching, separation, break respectively. The classification error of the adaptive weighted combination algorithm based on maximum entropy is 4.3%. In contrast, the error of ED, WFD and WE are 19.7%, 6.7% and 6% respectively as shown in Table1. The proposed method is better than the other three methods. It is confirmed that the proposed feature extraction method is effective.

Table 1. The Classification Error of Feature Extraction Methods

Feature extraction method	Combination	ED	WFD	WE
Classification error（%）	4.3	19.7	6.7	6

4.3. Analysis of Anti-noise Performance and Reliability

Noise or interference among pile detection environment can impact the results. Whereas, the signal is nearly pure in damage identification as before. The paper considers classification accuracy under the condition of different signal to noise ratio (SNR). And the proposed algorithm has carried on the comparative error analysis with other three methods. When SNR is 20, the classification error of combination feature extraction is 32%, and the error of ED, WFD, and WE are 55.3%, 64%, 45.7% respectively. The error of each method becomes smaller and smaller with the increase of signal-to-noise ratio. As it is seen in Table 2, the error of feature combination method are lower than other three methods. Furthermore, the reliability[18]can be calculated by the error ratio of different SNR as shown in Table3. Reliability index of the method is much more than others. It illustrates that the method is more reliable than ED ,WFD and WE method for the damage identification. Therefore, the proposed feature extraction method has a good anti-noise performance, has also good detection performance under complex noise environment, and is reliable.

Table 2. The Classification Error of Feature Extraction Methods with Different SNR

SNR	Combination Feature(%)	ED(%)	WFD(%)	WE(%)
None	4.3	19.7	6.7	6
20	32	55.3	64	45.7
30	37.7	42	39.3	32
40	21	19.7	33	11.3
50	13.7	35	51.7	6.3

Table 3. Reliability index of feature extraction methods

Method	Combination	ED	WFD	WE
Reliability index	0.9942	0.7327	0.5135	0.7625

5. Conclusion

The paper puts forward adaptive weighted feature combination method based on maximum entropy. The experiments have been carried on in a typical one-dimensional rod. In comparison with the existing ED, WFD and WE detection method, the method is superior in noiseless environment. Even more it has well damage recognition accuracy, and has great advantages in anti-noise performance under a complex noise environment. It is important that the proposed method is reliable.

This method increases the redundancy in the process of signal feature extraction, but it can avoid the limitations of single algorithm detection. While the method uses adaptive weighted based on maximum entropy to determine the feature weights, which has good application value in the one-dimensional structural health detection, pattern recognition and other related fields.

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Authors

Kang Wei-xin, received his B.Sc. degree in 1991 from Harbin Institute of Technology, received his M.Sc. degree in 2001 from Harbin Institute of Technology, received his Ph.D. degree in 2010 from Harbin Institute of Technology, now he is a professor in Harbin Engineering University. His main research interests include information intelligent detection theory and technology, modern sensing & inspection technologies, Modern digital communication system and communication technology.

Zhao Tian-wei, received her B.Sc. degree in 2012 from Heilongjiang Institute of Science and Technology, now she is a master student in Harbin Engineering University. Her main research interests is Signal detection and processing.