Research on Acoustic Emission Signal Denoising Based on Autoencoder

Jun Zhou¹, mei Yang¹, yue Yin¹*

¹Chongqing Business Vocational College, Chongqing,401331, China
²Chongqing Institute of Commerce and Economy, Chongqing,401331, China
*Corresponding author’s e-mail: hgzhou2008@dingtalk.com

Abstract. Acoustic emission signal denoising is the premise of acoustic emission signal identification. The traditional filter and wavelet analysis have the problems of relying on prior information and poor adaptability in acoustic emission signal denoising. Therefore, a noise denoising model of acoustic emission signal based on noise reduction autoencoder is proposed. By unsupervised learning training, the noise reduction autoencoder has more stable invariant characteristics, so that the error between the reconstructed signal and the original signal converges to a minimum, thus achieving the purpose of denoising. The denoising experiments are carried out on the basis of processing 3000 corrosive acoustic emission signal samples. The experimental results show that the model has better denoising effect when the number of hidden layer neurons is 400. The proposed DAE model has better performance and robustness than Donoho wavelet threshold denoising method.

1. Introduction

The collected acoustic emission signals have complex components and contain a large amount of mechanical noise and electromagnetic noise[1]. It is the premise of eliminating noise from acoustic emission signals for identifying acoustic emission signals. Early acoustic emission signal denoising technologies include traditional filtering denoising and Fourier transform methods[2], which have the problem of loss of useful signals caused by smoothing the instantaneous transformation of original signals. In the later period, the wavelet analysis method is applied to acoustic emission signal denoising and some achievements have been made. Donoho [3] set a fixed threshold value according to the variance and length of the noise signal, and carried out threshold processing on all high-frequency coefficients after wavelet decomposition. Tang [4] used Morlet wavelet transform and continuous wavelet transform method to denoise the vibration signals of gearbox and rolling bearing of wind power equipment respectively, and achieved certain denoising effect. Although wavelet transform has the characteristic of multi-resolution, there are some problems such as wavelet basis function selection, stationarity assumption and parameter sensitivity [5]. It is a typical nonlinear pattern recognition problem to analyze the collected AE signals in engineering survey to infer the types and degrees of defects and damages in the structure, which is difficult to complete through traditional threshold setting and AE characteristic parameter correlation analysis method [6].

A method base on the denoising autoencoder (DAE) acoustic emission signal can extract deep-level representation features from noisy emission signals by encoder. The decoder is used to reconstruct the extracted features. DAE can make the network learn more robust invariant features and obtain more effective expression of the input through unsupervised learning training, so that the error...
between the reconstructed signal and the original signal converges to a minimum, thus achieving the purpose of denoising. The denoising experiments are carried out on the basis of processing 3011 corrosive acoustic emission signal samples. The experimental results show that the denoising model has better effect when the number of hidden layer neurons is 400. The proposed DAE denoising model has better performance and robustness than Donoho wavelet threshold denoising method. DAE denoising model is applied to acoustic emission signal denoising, which can effectively remove noise and is of great significance for subsequent acoustic emission signal identification and processing.

2. Acoustic Emission Signal Denoising Model Based on DAE

The principle of DAE-based acoustic emission signal denoising model is shown in Figure 1. Generally, the number of hidden layer neuron is less than the number of input neurons.

\[ P(X = k) = \binom{n}{k} p^k (1 - p)^{n-k} \]  \hspace{1cm} (1) \\
\[ E(X) = np \] \hspace{1cm} (2)

Binomial distribution depends on parameters \( n \) and \( p \). Through the distribution, a one-dimensional data sequence with the same number of sampling points as the input acoustic emission signals is generated, and the 0 element index in the sequence is taken as the basis for setting the corresponding input data of acoustic emission signals to zero, so as to ensure the generation of certain zero elements. In the paper, \( n = 10, p = 0.1 \).

3. Acquisition and Processing of Acoustic Emission Signals

Corrosion Acoustic Emission Signal collected a total of 3011 corrosion acoustic emission signal samples through the previous 5% brine corrosion simulation test, with 8192 sampling points. Corrosion acoustic emission signal samples are shown in Figure 2. In order to eliminate the difference between signal data and improve the accurate recognition rate and convergence speed of DAE model, z-score standardization processing is adopted for each acquired acoustic emission signal, which is calculated according to formula (3).
\[ x' = \frac{x - m}{s} \]  

(3)

\(x'\) is the standardized data of acoustic emission signals, \(\mu\) is the average value of acoustic emission signals, \(\sigma\) is the standard deviation of acoustic emission signals, and \(x\) is the original data of acoustic emission signals. The sample of acoustic emission signal after z-score standardization is shown in Figure 3. In order to facilitate subsequent experiments to check the denoising performance, Gaussian white noise is added to the standardized acoustic emission signal, with a noise power of 10dBW. The acoustic emission signal with Gaussian white noise is shown in Figure 4. Before adding Gaussian white noise to the acoustic emission signal and inputting it into DAE, the acoustic emission signal needs to be damaged by adding noise, i.e. the input data is set to zero according to the binomial distribution probability, and the binomial distribution related parameters \(n=10\), \(p=0.1\). The acoustic emission signal sample after noise addition and damage is shown in Figure 5.

4. Experimental Results and Analysis

DAE is a single hidden layer neural network. The number of hidden layer neurons should be set according to DAE and actual denoising application scenarios. The signal-to-noise ratio (SNR) is used to measure the denoising performance, The DAE training algorithm is the scaled conjugate gradient method, which can train any network as long as its weight, net input, encoding activation function is the Logistic sigmoid function, the decoding activation function is the Positive saturating linear transfer function. 30% of the processed 3000 etching acoustic emission signal samples are extracted as DAE train and test data, 70% is taken as DAE training data, and the maximum number of training rounds \(\text{Max epochs}\) is 30. After the DAE denoising model training converges, 900 samples of 30% of the
extracted acoustic emission signal test data are denoised. The training process of DAE model is shown in the figure 6, the Mean Squared Error is 0.018809.

Fig 6. The training process of DAE model

The denoising performance of DAE denoising model of acoustic emission signals is compared with Wavelet threshold denoising method. The AE signal is decomposed by Daubechies 2 wavelet, and the number of decomposition layers is 5. The soft threshold method is used to remove the noise from AE signal. The mean SNR of 1100 acoustic emission signal samples denoised by DAE is 6.22, and the corresponding variance is 0.15. The mean SNR after denoising by wavelet threshold denoising method is 4.73, and the corresponding variance is 0.35. In terms of acoustic emission signal denoising performance, DAE denoising model is generally better than wavelet threshold denoising method, with smaller variance and better robustness.

5. Conclusions

A denoising model of acoustic emission signals based on DAE is proposed. The DAE is trained based on unsupervised learning to reconstruct the noisy emission signals so as to achieve the purpose. The experimental results show that the DAE denoising model has advantages in effect and convergence speed when the number of hidden layer neurons is 400. The proposed DAE denoising model has better denoising performance and robustness than Wavelet threshold denoising method. DAE denoising model is applied to acoustic emission signal denoising, which can effectively remove noise and is of great significance for subsequent acoustic emission signal identification and processing. In order to improve the performance of the DAE, the size of the data set of the AE signal will be increased, and the DAE model will be further trained and tested. The proposed method provides a new idea and direction for nondestructive testing.

Acknowledgements

The authors also would like to thank the financial supported by the Science and Technology Research Program of Chongqing Municipal Education Commission (Grants No.KJZD-K201904401). (Grants No.KJZD-K202004401). Supported by the Science and Technology Research Program of Chongqing Municipal Education Commission (Grants No.2020-GX-414). Artificial Intelligence Application Collaborative Innovation Center of Chongqing Business Vocational College.
References

[1] Zhou F, Min H, Kun Z, et al. (2019) Review of on-line monitoring of oil and gas pipe corrosion in acidic environment by acoustic emission [J]. Surface Technology, 48 (04): 245-252.

[2] Da Zhao C, Congcheng Q. (2018) Introduction of research on acoustic nondestructive testing of welding defects in China [J]. Precision Forming Engineering, 10 (01): 74-81.

[3] D.L. Donoho, I.M. Johnstone, (1995) Wavelet Shrinkage: Asymptopia [J]. Journal of the Royal Statistical Society. 57: 301-369.

[4] Tang, B, P, Liu, W, Y, SONG, T. (2010) Wind turbine fault diagnosis based on morlet wavelet transformation and wigner-villedistribution [J]. Renewable Energy, 35: 2862-2866.

[5] Zhang R, Deng A, Xiaodong S, Dongying L, Jing L. (2018) A new method of acoustic emission signal denoising and fault diagnosis [J]. Vibration and Shock, 37 (04): 75-81.

[6] Zhichun Y, Zhefeng Y. (2004) Research progress of damage detection technology in structural health monitoring [J] Progress in Mechanics. 34 (2): 215-223.

[7] Vincent P, Larochelle H, Bengio Y, et al. (2008) Extracting and composing robust features with DAEs[C]/Proceedings of the 25th International Conference on Machine Learning. Helsinki, Finland, pp.1096-1103.