Performance analysis of a wavelet packet transform applied to concrete ultrasonic detection signals

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Abstract—In the ultrasonic detection technology of concrete health conditions, it is difficult to identify damage features due to the complex wave synthesis of detection signals. We propose a method of applying wavelet packet transform (WPT) to decompose and reconstruct the ultrasonic detection signal from a C30 class concrete, thereby reducing noise and redundant information. We can obtain the main frequency node coefficients by wavelet packet decomposition, and reconstruct the denoised signal by the node coefficients. For analyzing the performance of this method, the extracted indices of signal-to-noise ratio, root mean square error, Pearson correlation coefficient, and smoothness are utilized and evaluated respectively. Ten simulated signals and ten actual detection signals are employed for evaluating the method. Simultaneously, the comparison with the calculation results of the empirical mode decomposition (EMD) method is created. It is shown from the experimental results that WPT has better denoising performance on the signals. Finally, an experiment of the processed signal quality assessment is constructed. The stochastic configuration network (SCN) is employed as the evaluation model for exploring the influence of the proposed denoising method on identification accuracy. The result shows that the proposed method of reconstructing the main frequency node coefficients by WPT retains useful information more effectively and improves the identification accuracy of the recognition model.

1. Introduction
Concrete is one kind of the most widely used materials in the contemporary construction industry. It is a composite material made of sand, cement, gravel, mixed with water. And its physical characteristics
are heterogeneous and nonuniform [1]. The ultrasonic detection is the main detection method in the concrete nondestructive detection field, and the obtained detection signal is nonlinear and nonstationary. The ultrasonic detection signal is the superposition of the transmitted wave and multiple echoes. After propagated in concrete, the transmission signal has a lot of useful information as well as noise. The signal denoising is an important part of the ultrasonic detection task. The noise mainly comes from the structure noise scattered by the detection object and the instrument circuits, which will seriously interfere with the judgment of the recognition result of detection signals.

There are many denoising methods suitable for processing nonlinear and nonstationary signals, such as short-time Fourier transform [2], wavelet transform [3], etc., which have been applied in the field of ultrasonic detection. Li et al. [4] use intrinsic time scale decomposition (ITD) to denoise the ultrasonic detection signal of metal materials, and the effect of denoising the ultrasonic detection signal containing colored noise is obvious. However, the ultrasonic detection signal of concrete is more variable and the noise is more complicated because of its physical structures. Sun et al. [5] use EMD to carry out denoising experiments on the ultrasonic signal of pressure measurement outside the pipe, which has a good noise reduction effect, but the EMD method is less used in the field of concrete ultrasonic testing. Wavelet packet transform has been applied to signal processing such as vibration signals [6] and heart sound signals [7], and there are also related application cases in the field of ultrasonic. Wei et al. [8] used the noise reduction method of the wavelet packet based on the adjusted thresholds for processing the ultrasonic detection signals from a small-diameter steel pipeline with a thick wall. The method reconstructed the denoising signal by using the coefficients of different nodes with quantizing both soft and hard thresholds. In the wavelet packet threshold methods, it is a difficult problem to select an appropriate threshold, and the noise in nodes after thresholding cannot be effectively removed.

Based on the above-mentioned new development and engineering practice in concrete ultrasonic detection, we propose to apply wavelet packet to decompose the signal in three-layer and select the main frequency node coefficients (the first node of the third layer) to reconstruct the denoising signal. Then the denoising signal is obtained. Experimentally, the denoising signal reconstructed by the main frequency node of WPT is superior to the EMD on the four assessment indices. In addition, we introduced the stochastic configuration network (SCN) as a recognition model. We analyze and evaluate its identification accuracy by using the actual detection signals before and after denoising. The result shows that the proposed method has a better denoising effect on the concrete ultrasonic detection signals, and the denoising signal has a higher quality, which significantly improves the identification accuracy of the model.

In section II, the denoising methods of wavelet packet transform and empirical mode decomposition, and four assessment indices used in this paper are introduced. In section III, the experiment of the denoising test and its result are introduced. In section IV, we briefly introduce the SCN recognition mode and construct the experiment on evaluating denoising methods. That is, to evaluate the identification accuracy of the SCN model by using the actual concrete ultrasonic signals before and after denoising. Finally, a conclusion is drawn in section V.

2. Ultrasonic signal denoising methods and assessment indices

2.1. Wavelet Packet Transform

The wavelet packet transform is established based on wavelet analysis. Wavelet packet transform is a method that uses wavelet basis as the base signal to express the signal as a linear combination of wavelet functions. This analysis method further decomposes the high-frequency parts. It can perform better time-frequency localization analysis on signals containing a large amount of medium and high-frequency information and overcome the shortcoming of the low time-frequency resolution.
In Fig. 1, S represents the original signal. We decompose S by wavelet packet to obtain A and D. A represents the low-frequency component, and D represents the high-frequency component after the signal decomposition. We continue to decompose the high-frequency and low-frequency components according to the same method. Finally, the original signal is decomposed into 8 different frequency bands after 3 decompositions. A node represents a frequency component in the decomposition tree. These nodes contain the wavelet packet coefficients of components [9].

Daubechies (db) wavelet function has good compact support, approximate symmetry, and smoothness [10]. So, db15 wavelet is selected as the basis function of wavelet packet transform.

The processes of wavelet packet decomposition and reconstruction are as follows:
- Choose a suitable wavelet basis function and decompose the given signal to obtain wavelet packet coefficients;
- Select the optimal wavelet packet base according to the cost function;
- Repeat step 1 and 2 to obtain the three-layer wavelet packet decomposition tree shown in Fig. 1;
- Extract the coefficients of the main frequency node in the third layer from the result of step 3;
- According to the extracted wavelet packet coefficients, the wavelet packet reconstruction algorithm is used to obtain the reconstructed signal.

2.2. Empirical Mode Decomposition
Any signal is composed of some intrinsic mode functions (IMF) [11]. If the IMFs overlap, they construct a reconstructed signal. EMD is to decompose the signal into several IMFs and to analyze the signal through each IMF. Each IMF must meet two conditions [12]: 1) At any time, the mean value of the upper and lower envelope formed by the maximum and minimum is 0; 2) In the entire time series, the number of extreme points and the number of zero crossing points must be equal or the difference should not exceed 1.

The processes of EMD are as follows:
- For a signal to be decomposed \( s(t) \), find all the maximum and minimum values of \( s(t) \);
- Use cubic spline curve to respectively fit the maximum and minimum points of \( s(t) \) into a curve to form upper and lower envelopes \( f_{\text{max}}(t) \) and \( f_{\text{min}}(t) \), and find the average value \( h(t) \) of envelopes;
- Calculate the difference between the decomposed signal \( s(t) \) and the average value \( h(t) \) of envelopes, and judge whether \( m_1(t) \) meets the above two conditions of IMF; if it meets the conditions, extract the IMF, and make \( c_1(t) = m_1(t) \), \( s(t) = s(t) - c_1(t) \); otherwise, \( s(t) = m_1(t) \);
- Repeat the above processes until all IMFs extractions are completed, and finally the residual \( r(t) \); the original signal can be expressed as:

\[
s(t) = \sum_{i=1}^{n} c_i(t) + r(t) \tag{1}
\]
The IMFs obtained by EMD of the ultrasonic detection signal are arranged in order from high to low, and each IMF represents information on different frequency bands. We remove IMFs dominated by noise and select several IMFs dominated by the signal to reconstruct the original signal.

2.3. Assessment Indices of Denoising Performance

The signal denoising assessment indices are used to evaluate the performance of the noise reduction algorithm. The indices are signal-to-noise ratio (SNR), root mean square error (RMSE), Pearson correlation coefficient (PCC) [13], and smoothness (SM) [14]. It can be seen from the calculation results of the indices that the larger the SNR and PCC, the smaller the RMSE and SM, indicating that the signal denoising effect is better. The equations are as follows:

2.3.1. Signal-to-noise ratio

\[
SNR = 10 \log \left[ \frac{\sum_{n=1}^{N} S(n)^2}{\sum_{n=1}^{N} (X(n) - S(n))^2} \right]
\]

2.3.2. Root mean square error

\[
RMSE = \sqrt{\frac{\sum_{n=1}^{N} (X(n) - S(n))^2}{N}}
\]

2.3.3. Pearson Correlation coefficient

\[
PCC = \frac{\text{Cov}(X(n), S(n))}{\sigma_X \sigma_S}
\]

2.3.4. Smoothness

\[
SM = \frac{\sum_{n=1}^{N-1} [S(n+1) - S(n)]^2}{\sum_{n=1}^{N-1} [S(n+1) - X(n)]^2}
\]

In the above equations, \(X(n)\) is the original signal, \(S(n)\) is the signal after denoising, and \(N\) is the signal length, \(\sigma_X\) and \(\sigma_S\) are the standard deviations of \(X(n)\) and \(S(n)\).

3. Analysis of Denoising Test in Ultrasonic Signals

The simulated signal is obtained according to the mathematical model of the ultrasonic detection signal described in [15], and the model equation is shown in (6):

\[
s(t) = \beta e^{-\alpha(t-\tau)^2} \cos[2\pi f_c (t-\tau) + \phi]
\]

In equation (6), \(\beta\) is the signal amplitude, \(\alpha\) is the bandwidth factor, \(\tau\) is the signal arrival time, \(f_c\) is the center frequency of the signal, and \(\phi\) is the phase. MATLAB 2014b is installed for the experimental.

We set \(\alpha=2\), \(f_c=5\), \(\tau=0\), \(\beta=1\), \(\phi=0\), construct 10 simulated signals of ultrasonic detection with a frequency of 50kHz, one of them is shown in Fig. 2. Then, we add 20dB white noise to the simulated signals to form noisy signals to simulate ultrasonic signals detected in the actual project, one of the noisy signals is shown in Fig. 3.
We use WPT to decompose the noisy simulated signal in the three-layer. The third layer components after decomposition are shown in Fig. 4. The corresponding frequency spectrums of these components are shown in Fig. 5.
It can be seen from Fig. 4 that the main information of the signal is distributed in the component of the first node. The corresponding spectrogram is shown in the subgraph (3,0) in Fig. 5. The first node contains the main frequency component of the signal. The noise is mainly distributed in the remaining high-frequency nodes. Therefore, the wavelet packet coefficients of the first node in the third layer are selected for reconstruction. The reconstructed signal is as shown in Fig. 6.

According to the EMD method, the noisy simulated signal constructed above is processed, the IMFs concentrated in the noise distribution are removed, and the remaining IMFs are reconstructed to obtain the reconstructed signal shown in Fig. 7.

![Figure 6 WPT denoising signal](image1)

![Figure 7 EMD denoising signal](image2)

| Method | SNR/dB | RMSE  | PCC   | SM    |
|--------|--------|-------|-------|-------|
| WPT    | 9.7141 | 0.0409| 0.9479| 0.0722|
| EMD    | 7.2846 | 0.0544| 0.9127| 0.1290|

Ten noisy simulated signals are processed by the methods of WPT and EMD respectively. The average values of calculation results on denoising indices are shown in Table I. Among four indices, the two methods differ significantly in SNR and PCC. It can be seen from the table that the denoising signal obtained by wavelet packet decomposition and reconstruction of the main frequency node coefficients is better than EMD in the four indices. We could figure out that the denoising effect of WPT is better in the denoising experiments of the simulated signals.

![Figure 8 The concrete ultrasonic measured signal](image3)

![Figure 9 WPT denoising signal](image4)

![Figure 10 EMD denoising signal](image5)

We collect 10 measured signals from an actual ultrasonic detection system. In the ultrasonic detection system, the transmission method is used to obtain measured signals from C30 class concrete. The working frequency of the system probe is 50kHz, and one of the signals obtained is shown in Fig. 8.
The WPT and EMD method are both used to reduce the noise of the 10 measured signals. Fig. 9 and Fig. 10 are the measured signals after denoised by the two methods. From the figures, we can intuitively see the difference between the waveforms after the two methods operated well. For example, in the red circle marked area, EMD filters out more components of the original signal than WPT, which could make the signal lost some useful information. The denoising experiment results are shown in Table II, the average values of 10 signal denoising indices. The denoising assessment indices show that WPT is still better than EMD in the denoise effect.

Table 2  Denoising test results of measured signals

| Method | SNR/dB | RMSE  | PCC   | SM     |
|--------|--------|-------|-------|--------|
| WPT    | 11.1728| 0.0147| 0.9598| 0.3344 |
| EMD    | 8.7402 | 0.0206| 0.9149| 0.3757 |

4. The influence of signal denoising on model recognition

4.1. Stochastic Configuration Network

The stochastic configuration network is a standard three-layer forward feedback network structure consisting of an input layer, a hidden layer, and an output layer. By successively increasing the number of hidden layer nodes and configuring the weight and threshold of new nodes under inequality constraints, the network has universal approximation capability for nonlinear mapping functions.

The steps are as follows [16]:

- Given an objective function \( f: \mathbb{R}^d \rightarrow \mathbb{R}^m \), calculate the residual of the network after adding hidden layer nodes. If it fails to meet the given error criterion, continue to add a new hidden layer node;
- When adding a new hidden node, randomly generate the input weight and bias, and require inequality constraints;
- Calculate the output weights of the current network;
- Update the output weights through calculating the new output weights used the global least square method;
- Calculate whether the error is less than the preset error when adding the \( L \)-th hidden layer node. If it is satisfied, the SCN model training is completed; otherwise, continue to add hidden layer nodes according to step 2 until the error criterion is met or the maximum number of hidden layer nodes is reached. When a new hidden node is generated, the parameters of other nodes that have been determined remain unchanged.

4.2. Analysis of Experimental Results

The C30 concrete with hole defects, the ultrasonic detection system with a frequency of 50kHz is used as the measured object to obtain 360 detection data, where 180 data are collected from no defects places and 180 data from hole defects places. We use WPT and EMD to denoise 360 data respectively, and then create two datasets of the processed data besides the original data. Each dataset is randomly divided into 260 training data and 100 testing data. The stochastic configuration network is used to conduct the identification experiment, and the training and test data of the datasets in each trial are randomly divided for five times. The identification results are shown in Table III.

Compared with the recognition accuracy in table III, it is shown that the denoised datasets both significantly improve the recognition accuracy of the model. It is also exposed that the SCN modeled by WPT denoised signals improves its recognition accuracy higher than that of EMD about 2%. And it is indicated that the signals processed by WPT can retain more effective information and remove noise interference.
Table 3  SCN recognition test results

| Dataset | Minimum Accuracy | Maximum Accuracy | Average Accuracy |
|---------|------------------|------------------|------------------|
| WPT     | 96%              | 98%              | 97.2%            |
| EMD     | 94%              | 97%              | 95.4%            |
| Original| 91%              | 93%              | 91.8%            |

5. conclusion
The wavelet packet transform has been proposed for denoising concrete ultrasonic detection signals in this paper. The signals are decomposed by the 3-layer WPT, which is to obtain the node coefficients of different frequency bands and select the node where the main frequency of the original signal to reconstruct the signal. Then the denoised signal is obtained. EMD has also been carried out on simulated signals and measured signals of C30 class concrete, as the comparison method in the denoising experiments in this paper. The calculation results of four assessment indices show that the proposed method can effectively filter out noise. Moreover, we used stochastic configuration networks to identify original signals, denoised signals processed by WPT, and denoised signals processed by EMD respectively. The recognition accuracy of the SCN model is significantly improved on the dataset after denoising by the WPT. The quality of noise reduction could be demonstrated experimentally that the denoising method of WPT retains more useful components of signals. The good performance of this method in the denoising of concrete ultrasonic detection signals could provide a certain reference significance for ultrasonic signal processing in the future.

Acknowledgment
This work was supported in part by the ZJNSFC project under Grant (No.LY18F030012), the NSFC project (No.61403356, 61573311), the Zhejiang Provincial Natural Science Foundation of China under Grant LD21F050001, and the Development Project of Zhejiang Province under Grant 2021C03019.

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