Analysis of Denoising Methods of Underwater Acoustic Pulse Signal Based on Wavelet and Wavelet Packet

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Abstract. Underwater acoustic countermeasures include active sonar countermeasures and passive sonar countermeasures. In order to achieve the best operational efficiency of jamming equipment, the generation of jamming signals must adapt to the development trend of underwater acoustic detection technology—nonlinear time-varying and broadband characteristics. Feature extraction is to map the high-dimensional original data to the low-dimensional transformation space through a certain mapping relationship, which can suppress a large amount of redundant information in the data and highlight the category information of the data. One of the applications of wavelet analysis in signal analysis and processing is to remove noise components from signals. In practical engineering applications, sampled signals are inevitably polluted by various noises and interferences. Through the analysis of noise characteristics, it can be seen that the wavelet denoising method is very effective in removing signal noise. In this paper, aiming at the signals with different spectrum distribution, we use various methods to de-noise in order to find the de-noising methods suitable for underwater acoustic pulse signals with different frequency characteristics, and thus find an effective means to detect signals.

Additional Keywords and Phrases: Wavelet analysis, pulse signal, spectrum, denoising.

1. Introduction
Underwater target recognition is a key technology in underwater acoustic field. When acoustic signal propagates in seawater, it is often non-stationary signal with very low signal-to-noise ratio collected by receiving system due to the influence of other targets, complex and changeable ocean environment and instruments [1]. Signal denoising is one of the important tasks of signal processing. Wavelet transform denoising is a denoising method based on time and frequency at the same time, which has its unique advantages [2]. One of the applications of wavelet analysis in signal analysis and processing is to remove noise components from signals [3]. Traditionally, Fourier transform is used for signal denoising, which separates the useful signal from the noise frequency band, and reconstructs the signal after eliminating the noise [4]. Because the short-time Fourier transform divides the frequency band of the signal linearly, its window size does not change with frequency, and it lacks discrete orthogonal basis [5]. Traditional underwater acoustic signal filtering usually adopts linear or statistical methods. The linear filtering method is put forward on the basis of analyzing the frequency spectrum of signal and noise. Its
assumption is that signal and noise occupy different frequency bands, so noise and signal can be separated by using band-pass filter [6]. Although wavelet transform can provide more effective time-frequency analysis for signals than short-time Fourier transform, its scale is binary, and its frequency resolution is poor in high frequency band, while its time resolution is poor in low frequency band [7].

Feature extraction is to map the high-dimensional original data to the low-dimensional transformation space through a certain mapping relationship, which can suppress a large amount of redundant information in the data and highlight the category information of the data [8]. When a signal with rich frequency components is used as input to excite the system, because the suppression and enhancement effects of this signal on each frequency component change, compared with the original signal, the energy of signals in the same frequency band will be quite different, which will reduce the energy of signals in some frequency bands and increase the energy of signals in other frequency bands [9]. Signal denoising is one of the important applications of wavelet. Because of the multi-resolution method, it can describe the non-stationary property of signal very well, so it can remove noise according to the distribution of signal and noise at different resolutions [10]. Wavelet packet transform further decomposes the non-subdivided parts of wavelet analysis, and divides the frequency bands of signals into multiple levels, thus providing a more detailed time-frequency analysis method for signals, and adaptively selecting the corresponding frequency bands according to the characteristics of the analyzed signals to match the signal spectrum and improve the time-frequency resolution [11]. In this paper, aiming at the signals with different spectrum distribution, we use various methods to de-noise in order to find the de-noising methods suitable for underwater acoustic pulse signals with different frequency characteristics, and thus find an effective means to detect signals.

2. The basic idea of wavelet packet transform
In practical engineering applications, the useful signals are usually low frequency signals or some relatively stable signals, while the noise signals are high frequency signals. The cost function can be defined as the real function m about the sequence Xi, which can be selected according to different signal analysis requirements. For example, if wavelet packet is used for band decomposition and then adaptive filtering, the cross-correlation function between input signal and reference input signal can be selected as the cost function. If we use wavelet packet to compress data, we can choose the cost function which can measure the concentration and has additivity. Wavelet packet decomposition constitutes a complete tree structure with good frequency domain resolution. In sonar countermeasures, it has obvious advantages in modulating interference signals with nonlinear time-varying structure [12]. The common methods to find the optimal wavelet packet basis are single tree algorithm and double tree algorithm. Single tree algorithm is a fast search from bottom to top according to the cost function.

For the multi-layer decomposition of wavelet transform, the noise part is usually contained in the high-frequency components. Therefore, the wavelet coefficients can be processed by means of threshold, and then the signal can be reconstructed to achieve the purpose of denoising. For the noisy signal, the proportion of noise energy is small in the low frequency region, while the proportion of noise energy is large in the high frequency region. Figure 1 shows the structure of the Internet of things image analysis system.

![Figure 1. The structure of the Internet of Things image analysis system](image-url)
Wavelet packet analysis provides a more complex and flexible analysis method than wavelet analysis. It subdivides the low-frequency part and the high-frequency part of the upper layer signal at the same time, and has more accurate local analysis ability. In order to optimize the approximation of nonlinear signals, wavelet packet bases can be adaptively selected according to signals and some criteria to determine the best tree structure, which can be characterized by cost function. If the useful signal has a wide bandwidth and is distributed in a wide range from low frequency to high frequency, it is possible to suppress the useful signal and distort the reconstructed signal while suppressing the high frequency noise by using wavelet de-noising. The properties of some signals are time-varying, and different optimal wavelet packet decomposition schemes can be obtained in different time periods by using the dual-tree algorithm. The method is as follows: firstly, wavelet packet decomposition is used according to the single-tree algorithm to obtain the optimal frequency domain decomposition scheme; Then calculate the optimal subspace decomposition scheme when each segment is combined as different segments; Then, the total cost function calculated by each section constitutes a time tree, and the bottom-up search algorithm is implemented to obtain the optimal time period division; Finally, the time-varying optimal wavelet packet basis is formed by the optimal spatial solutions of each segment.

After selecting a kind of wavelet, the signal is decomposed by wavelet packet, and then an interpretation value of each layer coefficient obtained by decomposition is selected for soft threshold processing, which can effectively avoid discontinuity. Finally, the processed coefficients are reconstructed by wavelet packet to restore the original signal, so as to realize signal denoising. Figure 2 shows the flow chart of the measurement system.

![Figure 2. Measurement system flow](image-url)

The goal of impulse signal noise control is to minimize the following error function:

$$E(k) = \sum_{i=1}^{N_e} e_i^2(k) = \sum_{i=1}^{N_e} \left( p_i(k) + c_i(k) \right)^2$$

(1)

where $N_e$ is the number of error sensors in the system, and $p_i(k)$ and $c_i(k)$ are the disturbance and control at time $k$ at the i-th sensor, respectively. The goal can be achieved by adjusting the weights of the neural network through the following gradient descent algorithm:

$$w(k+1) = w(k) - \frac{\partial E(k)}{\partial w(k)}$$

(2)
Where $\mu$ is the convergence coefficient. The control quantity $c_i(k)$ at the i-th error sensor is:

$$c_i(k) = \sum_{j=1}^{N_o} x_{ij}(k)^* \quad TF_{ij} = \sum_{j=1}^{N_h} \left(\sum_{l=1}^{N_h} x_{il}(k)w_{jl}\right)^* TF_{ij}$$

(3)

Where $N_o$ is the number of drives, $N_h$ is the number of hidden layer nodes, $*$ is the convolution operator, and $TF_{ij}$ is the transfer function between the j-th drive and the i-th sensor.

The training algorithm of the output layer is:

$$w_{ij}(k+1) = w_{ij}(k) - 2\sum_{i=1}^{N_o} e_i(k)g_{ij}(k)$$

(4)

Where $g_{ij}(k)$ is the output signal of the hidden layer after filtering:

$$g_{ij}(k) = x_{ij}(k)^* \quad TF_{ij} = TF_{ij} * f\left(\sum_{q=1}^{N_h} x_{iq}(k)w_{iq}\right)$$

(5)

Wavelet packet analysis can provide a more detailed analysis method for signals. It divides the frequency band into multiple levels, further decomposes the high-frequency part of multi-resolution analysis, and adaptively selects the corresponding frequency band according to the characteristics of the analyzed signal to match the signal spectrum, thus improving the time-frequency resolution and making the wavelet packet have wider application value. In the case of high noise level or colored noise, when searching the best matching wavelet packet base adaptively, the searching process may be adaptive to the noise structure. The threshold method commonly used in wavelet packet denoising is similar to wavelet denoising. According to the characteristics that the signal has large amplitude at small scale and the noise tends to zero with the increase of scale, a threshold is set for the wavelet packet coefficient of the signal at each scale. If the coefficient on a certain scale is larger than the threshold, it is considered to correspond to the signal, otherwise it corresponds to the noise signal.

### 3. Wavelet denoising

For soft threshold processing, the absolute value of the signal is compared with the threshold, and the point less than or equal to the threshold becomes 0, and the point greater than the threshold becomes the difference between the point value and the threshold value. The selection of threshold is mainly divided into hard threshold, soft threshold and improved threshold processing. Hard threshold processing is to compare the absolute value of the signal with the threshold, and the points less than or equal to the threshold become zero, while the points greater than the threshold remain unchanged. Soft threshold processing is to compare the absolute value of the signal with the threshold. When the absolute value of the data is less than or equal to the threshold, it will be zero, and the data point larger than the threshold will shrink to zero, becoming the difference between the point value and the threshold value. Each coefficient in wavelet transform is determined by the inner product between the input function and one of the signal basis functions. These coefficients represent the similarity between the input function and a specific basis function. If the basis functions are orthogonal, then the inner product between any basis functions is zero, indicating that they are completely dissimilar.

Wavelet packet analysis can provide a more detailed analysis method for signals. It divides the frequency band into multiple levels, further decomposes the high frequency part of multi-resolution analysis, and adaptively selects the corresponding frequency band according to the characteristics of the analyzed signal to match the signal spectrum, thus improving the time-frequency resolution. In order to make up for the deficiency of the existing contraction function, a new curve contraction function is constructed. The contraction trend of adaptive nonlinear curve is shown in Figure 3.
The basis of wavelet de-noising lies in using the different characteristics of wavelet transform coefficients distribution between signal and noise, referring to the threshold de-noising method proposed by Donoho, which holds that the wavelet coefficients corresponding to signal contain important information of signal, with large amplitude but few numbers, while the wavelet coefficients corresponding to noise are uniformly distributed. Except for the components similar to one or several basis functions, the other coefficients will be very small. Because the square of wavelet coefficients indicates the energy of each point at a certain scale, the energy values of different components are quite different, which can be used as the eigenvalue of the original data. The neighborhood selection of the traditional local projection denoising algorithm is determined according to the noise intensity of the signal, but its relationship has not been well quantified, which is often compensated by observation or empirical formula [13]. However, without visualization tools in high-dimensional phase space, observation method is not feasible, and empirical formula is only a reference. In most cases, the noise intensity is unknown, so it is not applicable. Wavelet packet denoising also needs to get the closed value of wavelet packet decomposition. Of course, after the threshold is obtained, we can observe the denoising effect by manually modifying the threshold according to the simulation results.

The selection of threshold depends on the prior knowledge of noise. For the estimation of noise level, when passive sonar countermeasure records the radiated noise of warship, if a better marine environment is chosen, the noise environment can be considered as stationary Gaussian white noise. Most of the useful parts of one signal are distributed in low frequency band, while the useful parts of the other signal are distributed in a wide range from low frequency to high frequency. Through simulation, the application range, advantages and disadvantages of these methods are compared. From the simulation results, it can be seen that the direct low-frequency reconstruction and the forced denoising method play a good role in denoising by discarding the high-frequency part. In fact, these two methods are equivalent in this example. When using local projection algorithm to denoise chaotic signals, the selection of some parameters has a direct impact on the denoising effect. These parameters mainly include embedding dimension, neighborhood radius and division of signal space and noise space. For embedding dimension, choosing larger embedding dimension will have better noise suppression effect. The fault features extracted by noise reduction self-coding neural network are shown in Figure 4. The fault features extracted by wavelet packet analysis are shown in Figure 5.

Figure 3. Adaptive nonlinear curve shrinking trend
Figure 4. Fault features extracted by noise reduction self-encoding neural network

Figure 5. Fault features extracted by wavelet packet analysis

Wavelet packet denoising subdivides the high-frequency part and obtains the threshold value, but it cannot effectively filter the high-frequency noise, so the denoising effect is average, but we get an ideal denoising effect by manually increasing the threshold value. If the neighborhood radius is too small to make the number of neighbors sparse, then both linear approximation and local projection will be disturbed by noise, resulting in sharp oscillation of the filtered waveform. If the radius of the neighborhood is too large, the effect of piecewise linear approximation is not obvious, and some subtle structures are not reflected, and the effect of local linear approximation cannot be achieved [14]. Since wavelet decomposition pays more attention to the low-frequency part, it can be seen that the high-frequency part of the signal gradually attenuates with the increase of frequency after denoising by using the default threshold wavelet. It can be seen that the effect of wavelet denoising is obviously worse than that of wavelet packet denoising. Wavelet transform inherits and develops the localization idea of windowed Fourier transform, and makes up for the shortcoming that its window is not adjustable. Its essence is multi-resolution or multi-scale analysis. The multisresolution decomposition of orthogonal wavelet transform is only decomposed in scale space, but not in wavelet space. The principle of local projection noise reduction is to reconstruct nonlinear time series by phase, decompose background
signal, characteristic signal and noise into different subspaces by local projection algorithm in high-dimensional phase space, and separate background signal and characteristic signal by subspace reconstruction, and suppress random noise component in time series at the same time, so as to highlight and eliminate noise and decompose background signal and characteristic signal.

4. Conclusions

Noise reduction is a key issue in the field of underwater acoustic signal processing. The quality of noise reduction plays a very important role in underwater target detection and recognition and underwater acoustic communication quality. For signal recognition, one of the criteria to measure the advantages and disadvantages of an algorithm is the recognition rate. Wavelet packet decomposition can divide low frequency band and high frequency band at multiple levels, which can effectively filter out noise interference. Wavelet packets can be composed of many different orthogonal basis decomposition results. Different orthogonal basis decomposition results of wavelet packets have different properties and reflect different signal characteristics. The method of wavelet denoising is not static. We should choose the appropriate wavelet denoising method by analyzing the frequency characteristics of signal and noise, and choose the appropriate wavelet function, so as to achieve good denoising effect. The full-frequency wavelet and wavelet packet energy method, which is commonly used in signal recognition, usually has a good recognition rate for signals with high signal-to-noise ratio, but has a poor recognition effect for ship signals with low signal-to-noise ratio. Under the condition that the traditional linear filtering effect is not ideal, aiming at the characteristics of nonlinear components in underwater target radiated noise, the nonlinear time series denoising method can effectively filter out the noise. In the actual signal denoising problem, only by choosing an optimal decomposition result from numerous orthogonal basis decomposition results of wavelet packets can a better signal denoising effect be obtained.

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