Target Denoising Method Based on Fusion of Adaptive Filter and Sparse Representation

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Abstract. Acoustic signals are often used to detect and track targets in target detection field. Because of the complicated underwater, air and solid environment, the echo signals are often affected by environment that affects the analysis and processing of the detection signal. Aiming at this problem, this paper analyzes and studies the use of adaptive filter, and analyzes the model making use of the reference. Signal source is used to denoise the target signal. The method is applied for processing the data. The simulation results show that the proposed method greatly improves the target identification, enhances the SNR and highlights the features of echo signal. This method improves the recognition accuracy significantly.

Keywords: underwater target; adaptive filter; sparse representation; fusion method; noise reduction.

1. Introduction
Sonar target detection, underwater weapon target acquisition and acoustic structure detection are all based on the processing of active echo signals and passive noise signals. Acoustic signal propagates in solid and liquid. Due to complex environmental factors, in the process of target detection, echo signal usually superimposes a lot of noise disturbances, which brings great difficulty to target detection and recognition. In the process of target signal processing, it is necessary to apply the filtering noise reduction method to improve the signal-to-noise ratio and recognition, then the possibility of detecting and capturing targets can be increased. The comprehensive recognition ability can be improved a lot. At present, the methods such as spectral analysis [1, 2, 3], wavelet filtering [4, 5] are used commonly. When the signals are mixed seriously and the characteristics are similar, the effect of single method needs to improve further.

According to the characteristics of echo signals, this paper used the autocorrelation model and noise cancellation model of adaptive filter to reduce the noise of echo signal, and the sparse representation method is used to represent the echo signal with dictionary. The fusion processing of the two methods is applied to improve the signal-to-noise ratio and enhance the ability of acoustic detection and target recognition.
2. Acoustic Target Signal Processing Based on Adaptive filter

2.1. Acoustic Testing Process
Adaptive filter method [6, 7] is a traditional and commonly used noise reduction method. Based on the correlation of signals and the uncorrelation of noises, through correlation operation and iterative operation, it continuously reduces the residual of noise signal and expected signal, suppresses noises, strengthens the target signal and improves signal-to-noise ratio. As shown in Fig.1, a large amount of interference source information will affect the target detection of the acoustic array, so it is necessary to filter and denoise the echo signal at the receiving terminal.

![Figure 1. Acoustic testing process](image)

2.2. Basic Principle
Adaptive filter is mainly divided into two parts, filter design and iterative method. The principle of adaptive algorithm is shown in Fig.2.

![Figure 2. Principle of adaptive method](image)

As shown in Fig.2, the reference signal selection is very important. The ideal reference signal is the expected noiseless signal or pure noise sequence. In practice, the ideal signal cannot be obtained, such as the estimation sequence of signals or noises. If the reference signal is the estimation sequence or correlation sequence of the signal, then y(n) is the result of noise reduction; On the contrary, if the reference signal is noise signal estimation, then e(n) is the signal after filtering and de-noising.

The structure of the adaptive filter [8] is shown in Fig. 3. The input signal is first delayed, and then processed by digital filters with different weights to obtain a transverse filtering result. The number of taps of the filter is the length of the processing data window in each iteration.
There are many adaptive filter algorithms [9, 10], such as LMS (least mean square) and NLMS (normalized least mean square). The weight vector coefficient iteration method of LMS method is shown as follows:

$$w(n+1) = w(n) + 2\mu e(n)x(n)$$  \hspace{1cm} (1)

The convergence factor is used to control the iteration speed. The basic steps of the algorithm are shown as follows:

$$y(n) = w^T(n)x(n)$$
$$e(n) = d(n) - y(n)$$
$$w(n+1) = w(n) + 2\mu e(n)x(n)$$  \hspace{1cm} (2)

Based on LMS algorithm and the discussion of weight vector increment, NLMS algorithm is proposed.

$$\delta w(n+1) = w(n+1) - w(n)$$  \hspace{1cm} (3)

The weight vector coefficient iteration method of NLMS method is expressed as:

$$w(n+1) = w(n) - \frac{\mu}{\gamma + \| x(n) \|^2} x(n)e(n)$$  \hspace{1cm} (4)

Where the convergence factor is usually in the range of (0, 2), which is a small quantity, to avoid the weight vector is too large due to the small x(n). Comparing equation (1) and (4), it can be found that in NLMS method, the iteration factor is normalized, and the step size can be adjusted appropriately according to the input vector of each iteration to ensure the accuracy and stability.

The adaptive method is based on the correlation between signals and the uncorrelation of noises, so it has a good effect on white noise. When the similarity between noise and target signal waveform is high, the denoising effect of this method will be affected.

2.3. Self-correlation model
The self-correlation model is based on the self-correlation of the signals. When there is no other ideal signal, the signal itself can also be used as a reference signal source after appropriate transformation,
such as delay processing to get a reference signal, and then it can be used in the adaptive filter iteration. The model is shown in Fig. 4.

![Figure 4. Self-correlation model](image)

The self-correlation model is used to filter adaptively, but the effect is limited because the reference signal is a noisy sequence. But in practice, because the ideal echo signal is not easy to construct and obtain, the method of constructing reference signal by using the deformation of original signal in self-correlation model is widely used.

As for acoustic detection, some prior echo signal prediction can be performed because the design of the source signal is known. The variant form of the source signal can be used as reference, so the reference signal has a better prior basis. The echo of acoustic waveform in the target area or the beam nearly has certain correlation with the target signal, which can be used as reference signal.

2.4. Noise cancellation model

Figure 5 shows the basic principle of the noise cancellation model. When the noise model can be obtained, or similar noise signal sequence can be obtained through simulation and other methods, the noise can be used as the reference signal source. In this way, the original noise signal and the reference signal will be eliminated iteratively, and the noise part will be eliminated and weakened, $e(n)$ is the original noise signal after noise cancellation. Here, in the output $e(n)$, the components related to the noise model or the simulated noise sequence are removed, and the components of the desired target signal are retained.

![Figure 5. Noise cancellation model](image)

The main reason is that the noise model is difficult to estimate and obtain, and other factors such as electronic interference noise are more difficult to estimate. The method is more different to apply than the self-correlation model, because the predictability of echo signal is easier than the noise signal, so the application of the model is limited.

In the process of acoustic target detection, if the transmission characteristics such as hydrological conditions and solid structure conditions are known, or a large number of pure interference noise data without target signals in the same working scene are obtained in advance, the model can suppress the interference source.

2.5. Two-stage adaptive filter method

In the traditional filters, high-stage filters are often used in practical engineering, which can suppress the unspecified frequency band effectively, but also increase the time-consuming. Adaptive filter is a filtering method which is adjusted by iteration. Increasing the order appropriately can also increase the
number of iterations and suppress the noise more effectively. At the same time, the introduction of multiple different reference signals can be considered.

![Diagram](image1)

**Figure 6. Two-stage adaptive filter method**

Figure 6 shows the structure of the two-stage adaptive filter. The first-order filter output $y_1(n)$ is used as the input $x_2(n)$ of the two-stage filter, and the two-stage filter output $y_2(n)$ is used as the denoising waveform of the system filter output.

At the same time, because new reference signals can be introduced, different reference sources can be introduced in different orders for noise reduction, and the utilization rate of prior information is higher.

### 3. Sparse representation method

Sparse representation [11, 12] is a common signal processing method in recent years. It is a kind of signal reconstruction using dictionary [13] under constraint conditions. The sparse representation model can be described as the following formula:

$$
\min \| r \|_0 \quad \text{s.t.} \quad \| y - Dr \|_2 \leq \varepsilon
$$

Where $y$ is the original signal, $D$ is the dictionary, and $r$ is the representation vector, $\varepsilon$ is the maximum error. In sparse representation method, the ultrasonic echo signal is represented by a dictionary, and the dictionary also selects functions similar to the ultrasonic echo signal. The processing flow is similar to wavelet denoising. Firstly, the sparse representation is performed, and then the signal is reconstructed.

Because sparse representation can easily filter out slight random noise, the effect is better. The adaptive filter strengthens the signal correlation and has better effect on disordered strong noise. The emphasis of the two methods is not the same, so the fusion experiment is carried out. According to the characteristics of acoustic signal, the sparse representation dictionary is selected as two-dimensional Gabor function for testing.

$$
g(x, y)_{\theta, f, \phi} = \exp\left(-\frac{1}{10} \left(\frac{x^2}{\delta^2} + \frac{y^2}{\delta_y^2}\right)\right) \cos(2\pi f x + \phi)
$$

Where $\theta$ is the direction of Gabor function, $f$ is the frequency, $\delta_x$ and $\delta_y$ are the Gaussian coefficients, and $\phi$ is the phase.

After sparse representation of acoustic signal, the slight random noise will be eliminated and the signal form similar to dictionary will be formed. The disorder of signal caused by aliasing will be restrained to a certain extent.

### 4. Analysis of experimental results

#### 4.1. Simulation analysis of adaptive filter for acoustic signal processing

Firstly, the adaptive filter is used to simulate the white noise sequence. Figure 7 is the simulation experiment of the adaptive algorithm. The white noise sequence is superimposed on the sine signal with amplitude of $2$, and the noisy signal is $x_1$. After the adaptive method, the number of filter taps is $15$, and
the convergence factor is 0.001. The LMS method is used for iteration, and the filtering result is obvious, and the noise is suppressed very well. The simulation results show that this method has a good noise suppression effect, especially for white noise and other noise with poor signal correlation.

Figure 7. Effect of white noise via adaptive filter

In order to get closer to the characteristics of the echo signal and increase the complexity of the signal, the echo data of the excitation signal with frequency conversion chirp excitation (center frequency 1kHz) and pulse compression ratio of 0.25 are used for analysis. In the actual environment, there will be no interference source, the noise cancellation model has some difficulties, but the signal source is determined by the detection of the sound source's own parameters. Therefore, the self-correlation model is used for iteration, and the reference signal is the echo data obtained from the next adjacent beam, which is also used as the reference signal input of the two-stage filter. The number of filter taps is 15, the convergence factor is 0.05, and the iterative methods are LMS and NLMS respectively. Before the application of adaptive filter, the signal is preprocessed by correlation processing to remove irrelevant aliased signals. Figure 8 shows the noise reduction results of LMS and NLMS iterative methods and the results of two-stage noise reduction. Figure 9 shows the comparison of amplitude imaging results.

From the results of Fig.8 and Fig.9, it can be concluded that the preprocessing removes part of the irrelevant noise, while the iterative effect of LMS and NLMS has little difference. The red circle in Fig. 9 circles the positions of three target points, and the two-stage adaptive filter target imaging is more obvious.

Figure 8. Result of adaptive filter
4.2. Fusion results of adaptive filter and sparse representation

The echo data under frequency conversion excitation is processed. Firstly, the echo is denoised by adaptive filter method, which can strengthen the strength of the relevant defect signal and weaken the irrelevant noise information. Then the processing results are denoised by sparse representation, and the fusion results of the two methods are obtained.

In the experiment, the maximum error of sparse representation selection is 0.05, and the direction of Gabor function is $0 \pm 81^\circ \sim \pm 85^\circ$, the number of taps of the adaptive filter is 15, the convergence coefficient is 0.05, and the iterative method is two-stage LMS. The amplitude imaging comparison of the results is shown in Fig.10.

The adaptive filter method does not change the original peak characteristics of the signal and enhances the intensity of the defect location, but it has poor suppression effect for the correlation noise with small amplitude; Because the maximum error is set in the sparse representation, the signals less than the maximum error are filtered out, and the effect is better for the noise with small amplitude. But for the defect signal, it is only the approximation of dictionary representation, and the original waveform characteristics will change slightly.

4.3. Traditional wavelet filtering method

Using the echo data of the same excitation signal, the noise reduction analysis of wavelet filtering is carried out to compare the noise reduction effect of different methods. The processing process is shown in Fig.11. In terms of threshold selection, the traditional threshold selection criteria mainly include universal threshold and sure threshold [14] (Stein's unbiased estimator of risk). Both methods were first proposed by Donoho et al in the 1990s.
acoustic signal

Wavelet transform

time-frequency signal

Wavelet threshold processing

noise reduction signal

Inverse wavelet transform

acoustic signal

Figure 11. Acoustic signal sparse and reconstruction process

The results of the wavelet filtering are shown in Fig.12. And this method has a certain effect, but there are still a lot of noises.

(a) SURE threshold   (b) Universal threshold

Figure 12. Results of the traditional wavelet filtering

4.4. Comparative analysis of signal to noise ratio

The applied signal to noise ratio (SNR) calculation method of defect points is as follows:

\[
SNR = 20 \log_{10} \frac{\text{Signal}}{\text{Noise}}
\]  

Where Signal is the defect signal amplitude and Noise is the noise amplitude. Select the maximum value of regional signal, and the SNR analysis results are shown in Table 1. Compared with the traditional wavelet filtering, the adaptive filter and sparse representation are significantly improved, and the SNR after fusion is improved by 6.82db.

Table. 1 Comparation of the Snr

| Method                           | SNR (dB) |
|---------------------------------|----------|
| Original signal                 | 2.99     |
| Wavelet filtering               | 5.43     |
| Adaptive filter (LMS)           | 7.33     |
| Adaptive filter (NLMS)          | 7.31     |
| Adaptive filter (two-stage LMS) | 9.15     |
| Adaptive filter (two-stage NLMS)| 9.07     |
| Sparse representation           | 9.46     |
| Fusion method                   | 12.25    |
5. Conclusion
The acoustic data are processed by traditional wavelet filtering, the adaptive filter, sparse representation and the fusion method. Through the comparation and analysis of the different methods. The conclusion is as follows:

1) Using the adaptive filter method, taking the echo signal of adjacent array as the reference signal, and using the autocorrelation model, the noise suppression effect is obvious, and does not change the characteristics of the original signal, but it is not obvious for the correlation noise with small amplitude.

2) The sparse representation method selects Gabor function as the dictionary to process the acoustic target signal, which can produce a good suppression effect on the small amplitude noise. The original waveform approximates to the dictionary function, and the feature has a slight change.

3) The fusion method combines the advantages of the two methods, the SNR is greatly improved, but it also continues the situation of sparse representation approach to the dictionary, and the overall noise reduction effect is better than that of a single method.

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