Underwater Acoustic Channel Denoising Algorithm Based on Least Mean Square Algorithm

Yuan Cheng*, Hui Gao*

School of Software Engineering State Key Laboratory of Networking and Switching Technology Beijing University of Posts and Telecommunications, China

*Corresponding author e-mail: sunyisse@bupt.edu.cn, acy1818cy@bupt.edu.cn

Abstract. In order to decrease the high transmission error rate caused by background noise and impulse noise during underwater acoustic communication, this paper considers the influence of noise during the communication process based on the frequency division multiplexing system model. A filter is carried out to estimate the real-time noise, which is implemented by the least mean square error algorithm and is improved according to the characteristics of short duration and high energy of impulse noise. Finally, the effectiveness of the algorithm is verified by computer simulation.

1. Introduction

For the underwater acoustic communication process, a key issue is that the transmission error rate is high in comparison to radio communication. Background noise and impulse noise interfere with the transmission process of sound waves in the ocean, resulting in a high bit error rate. Therefore, a denoising algorithm can greatly improve the quality of underwater acoustic communication.

Traditional impulse noise suppression method mainly determines the time domain signal of the receiving end by setting a threshold value, and if the amplitude value of the received signal exceeds the threshold value, it is judged as a signal interfered by the impulse noise. The application of this method in underwater acoustic communication is studied in a paper [1]. Another paper [2] gave out an impulsive noise mitigation based on iteration adaptive approach. By utilizing the orthogonality of the subcarriers in OFDM system, both the impulsive noise and background noise were separated from the signals. The main advantage of this method is that it does not require statistical models and sparsity of the impulse noise, so it has better adaptability.

The paper is divided into two parts. The first part summarized the model of the underwater frequency division multiplexing system based on the characteristics of the underwater acoustic channel and shallow sea noise distribution. The second part proposed an algorithm for constructing an adaptive filter, and then performed a computer simulation.

2. Network System Model

2.1. Acoustic network characteristics

Since the special medium of seawater is not conducive to the long-distance propagation of signals such as radio and laser, the use of acoustic signals is almost the only means of communication for underwater sensor networks. The high transmission error rate is one of the main problems in the use of acoustic
signal communication. The underwater acoustic channel is highly dynamic due to fluctuations in sea level, internal waves, sea background noise, channel multipath propagation, shadow areas, dynamic changes in delay, and Doppler dispersion caused by node movement. The signal is intermittent and unstable.

Piggot has made statistical measurements on the shallow sea noise spectrum [3].

2.2. Noise evaluation model
Assume that the signal duration is T, the subcarrier spacing is \( \Delta f = \frac{1}{T} \), the total number of subcarriers is \( N \), and the data subcarrier set is \( C_D \). Then the complex expression of the signal transmitted on the baseband is: [2]

\[
S_t = \sum_{k \in C_D} s(k)e^{j2\pi \Delta f t}
\]

Where \( s(k) \) represents the digital signal in the \( k \)th channel.

The effective signal strength that still falls within the observation window after passing the demodulator is

\[
S = \left| \sum_{i=1}^{r} (1 - \frac{v_i}{T_i}) s_i \right|
\]

Where \( T_i \) is the duration of each symbol of the transmitted signal, \( r \) is the number of multipath interferences, i.e. the number of paths over which the multipath delay does not exceed, and \( v_i \) is the normalized value of the \( i \)th path relative to the direct path.

According to the Shannon formula, when the effective bandwidth of the signal is \( B \) and the signal-to-noise ratio is \( S/N \), the maximum capacity \( C \) of the channel is

\[
C = B \log_2 \left( 1 + \frac{S}{N} \right)
\]

According to (2) and (3),

\[
C = B \log_2 \left( 1 + \operatorname{abs} \left\{ \sum_{i=1}^{r} \left( 1 - \frac{v_i}{T_i} \right) \sum_{k \in C_D} s(k) e^{j2\pi \Delta f t} \right\} \right)
\]

This formula gives the upper limit of the underwater acoustic channel capacity. It can be seen that in the case of fixed environmental noise, the better the processing algorithm for noise, the larger the capacity of the channel, and the smaller the bandwidth required for the unit channel.

3. Denoising algorithm
3.1. Least mean square algorithm
The least mean square algorithm, known as the LMS algorithm, makes appropriate adjustments to the objective function to simplify the calculation of the gradient vector, and its computational complexity is low.

For the instantaneous values \( R(n) \) and \( p(n) \) of the matrix \( R \) and the vector \( p \), an estimate of the gradient vector can be given by:

\[
\hat{g}_w(n) = -2d(n)x(n) + 2x(n)x^T(n)w(n)
\]

Where \( x(n) \) and \( d(n) \) are deducted from

\[
\hat{R}(n) = x(n)x^T(n) \\
\hat{p}(n) = d(n)x(n)
\]
Since the communication process requires high real-time performance, it is considered to use an adaptive filter to process the gradient vector. Assume that the step size parameter is set to $\mu$, the update equation of the filter matrix $w(n)$ of the LMS algorithm is:

$$w(n + 1) = w(n) + \mu(d(n) - w^Tn)x(n)$$

3.2. Dynamic Step expansion

In the underwater acoustic noise reduction model, since the impulse noise has the characteristics of short duration and high energy, the filter requires a large step size to recursively obtain the corresponding gradient vector when the impulse noise occurs. Meanwhile, a long time background noise requires a shorter step size. This makes it difficult to balance the traditional LMS algorithm, so it is considered to introduce dynamic step sizes. The size of the step is expressed by $\mu(n)$, and it obeys the recursive relationship with respect to the parameters $\alpha, \beta$:

$$\mu(n + 1) = \alpha\mu(n) + \beta e(n) + \gamma v(n)$$

$\alpha$ is the step size genetic factor, and $1 - \alpha \ll 1$; $\beta$ is the weight of the instantaneous error energy, and $\gamma$ is the weight of the Gaussian noise energy. In addition, in order to ensure that the algorithm does not explode exponentially, the maximum and minimum values of the step size should be set in the recursive formula, namely:

$$\mu(n + 1) = \begin{cases} 
\mu_{\min} & \mu(n) < \mu_{\min} \\
\mu_{\max} & \mu(n) > \mu_{\max} \\
\alpha\mu(n) + \beta e(n) + \gamma v(n) & \text{otherwise}
\end{cases}$$

In the startup phase, a larger step size should be set to speed up the convergence:

$$\mu_0 = \mu_{\max}$$

In the convergence phase, a smaller step size should be set to reduce the impact on the signal:

$$\lim_{n \to \infty} \mu(n) = \mu_{\min}$$

Overall, the update equation of the filter matrix $w(n)$ is

$$w(n + 1) = w(n) + (d(n) - w^Tn)x(n)\mu(n)$$

The algorithm can be described by pseudocode as follow:

1. $n = 0$ // Initialize the counter
2. $w = F^H$
3. $\mu = \mu_{\max}$ // Initialize the step
4. Repeat
5. $y_{\text{pre}} = y$ // Restore previous $y$
6. Fetch $y = DF^H\Lambda y_s + e + v$ from the sensor
7. $y_{\text{now}} = y$ // Restore now $y$
8. $y = wy^T$ // $y$ is passed through the filter
9. Calculate $y_{\text{now}}$ according Eq. ()
10. $e = y - y_{\text{now}}, v = y - y_{\text{pre}}$ // Calculate the gradient vector
11. $\mu = \alpha\mu + \beta e + \gamma v$ // Update the step
12. $w = w + (d - wy^T)y\mu$
13. End repeat
4. Simulation
In order to test the reliability and effectiveness of the algorithm, a computer simulation was used to simulate the acoustic signal transmission process between two sensors. We simulated an environment with both background noise and impulse noise, and the algorithm described above is used to reduce these noise. It is calculated that how much the noise can be reduced.

The environmental noise and the noise calculated from the received signal are compared as shown in figure 1. The blue line at the bottom is the original environment noise, and the red line at the top is the calculated noise.

![Comparison of simulated and calculated noise](image)

Figure 1. Comparison of simulated and calculated noise

5. Conclusion
Based on the existing noise evaluation model and underwater acoustic system model, this paper proposes a new implementation method of noise reduction process for underwater acoustic communication from the perspective of constructing adaptive filter, and uses the extended minimum mean square error algorithm. Filters for impulse noise and background noise. The main advantage of this algorithm is that it is simple to implement, low in complexity, and adaptive to changing environments. It is not necessary to perform statistics on the frequency of impulse noise. However, how to adjust the parameters in the algorithm to ensure the trade-off between the stability and efficiency of the algorithm remains to be studied.

References
[1] Çivicioğlu, Pınar. Using a Neuro-Fuzzy Network for Impulsive Noise Suppression from Highly Distorted Images of WEB-TVs. Advances in Web Intelligence. Springer Berlin Heidelberg, 2005: 107-113.
[2] Zhou Guili, etc. Impulsive noise mitigation based on iteration approach in underwater acoustic communication. Telecommunications science. 33.11 (2017): 66-72.
[3] Piggott, C. L. "Ambient Sea Noise at Low Frequencies in Shallow Water of the Scotian Shelf." Journal of the Acoustical Society of America. 36.11 (1964): 2152.
[4] Goodwin, Graham C., D. J. Hill, and X. Xie. "Stochastic adaptive control for exponentially convergent time-varying systems." Decision and Control, 1984. the, IEEE Conference on IEEE, 1984: 39-44.
[5] Stojanovic, Milica. "Recent advances in high-speed underwater acoustic communications." IEEE Journal of Oceanic Engineering 21.2 (1996): 125-136.
[6] Kingsley, Peter B. "Introduction to diffusion tensor imaging mathematics: Part III. Tensor calculation, noise, simulations, and optimization." Concepts in Magnetic Resonance Part A28A.2 (2010): 155-179.