A High-efficiency Optimized Detection Algorithm for Non-stationary Marine Acoustic Signals in the Time-frequency Domain

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ABSTRACT As the amount of data generated by marine acoustic observation signals grows, efficient information acquisition of non-stationary observation signals has become a major challenge in marine observation platform technology. In this paper, an optimized algorithm is proposed for the non-stationary marine acoustic signals. This algorithm can increase the effective data acquisition rate while lowering the observation platform's algorithm energy consumption. To constantly enhance the processing of the observation signal through the self-feedback, the optimized algorithm is based on the sign function, the adjustable coefficient, the adaptive step size, and the frequency domain threshold. This study shows the simulation verification experiment and the application experiment based on the optimized algorithm. The experimental results show that the optimized algorithm efficiency is 78.16% in the simulation conditions and reaches 89.89% in the application experiment. And the data compression rates for the simulation conditions and the application experiment are 74.65% and 69.32% respectively. Hence the performance of the optimized algorithm has been significantly improved.

INDEX TERMS Non-stationary marine acoustic signal, Self-feedback, Signal processing efficiency, Time-frequency data compression.

I. INTRODUCTION

Marine acoustic monitoring is one of the important technologies in marine observation [1], [2]. Marine acoustic monitoring equipment is used in many fields, such as observation of marine creatures’ sound [3], marine noise monitoring [4]–[6], marine military surveillance and tracking [7], [8], marine climate modeling and prediction [9], [10], etc. Despite these applications are different, they all suffer from similar issues in platform work, like limited electricity and management of growth data.

The marine observation environment is very harsh and special, and researchers cannot maintain the observation platform in time [9]. However, marine observation platforms such as buoys and submersible buoys require long-term deployment, and only a small number of nearshore buoys can be connected to shore power through cables [11]. Most of the other observation platforms are far away from the land, and there are problems such as rapid consumption of electricity and lack of effective supply [12], [13]. Also, they can only store energy through pre-installed lithium batteries. On the contrary, with the continuously increasing output of marine observations and numerical marine models [14], [15], the technical requirements of underwater acoustic monitoring are constantly increasing, such as signal range, signal duration, signal bandwidth, signal accuracy, and real-time signal processing capabilities, etc [2], [16], [17]. Therefore, the power consumption of the observation platform system also increases at the same time. The contradiction between the limited electricity reserves and a large amount of data collection and management is becoming increasingly prominent and has caused great pressure in all aspects [14], [18], [19]. These pressures mainly include data storage and quality control, efficient processing and visualization of the signals, system performance improvement, low power consumption, etc [14]. Hence the efficient use of electricity on marine observation platforms is a necessary research direction in ocean engineering.
In recent years, to make the marine observation platform work for a longer time, it is a feasible option to extract the marine energy from the local, which can charge the lithium batteries [13], [20]. A direct method to supply electricity is to install wind-solar complementary power generation equipment [21] or wave energy power generation devices [22] on the buoy platform, but these will also add additional operational and maintenance burdens to the platform. Nevertheless, the observation system can switch the working mode to improve the observation efficiency, thereby achieving low power consumption. Optimizing the length of the data transmission path is a good method to reduce the equipment energy consumption for the marine cluster monitoring platform [17], [23]. In the fixed cycle of marine observation, asynchronous power management is also an effective way to save electricity [24]. For long-term marine acoustic observation, the optimization of the observation signal processing algorithm can greatly reduce the signal processing time, the amount of data storage, and the average power consumption of the system.

In marine acoustic observation, the target signal of interest usually accounts for a relatively small proportion, and most acoustic signals only carry a large amount of energy in a very short time. Therefore, the time-frequency domain of the signal is very sparse. Generally, in the process of marine acoustic observation, the proportion of the interest signal is relatively small and the high energy only lasts for a short time. The useful information in the time-frequency domain of the observed signal is also very rare, most of which is noise in the background environment [25], [26]. Thereby, the target signal acquisition and effective data storage in the working process of the observation platform are inefficient. In other words, in the process of signal processing and analysis for marine acoustic observations, most of the time and electricity are dealing with background noise. The marine acoustic observation signal is a non-stationary signal with nonlinear, non-stationary, and non-Gaussian characteristics [27], [28]. The time-frequency domain processing and analysis of non-stationary signals have been studied in many fields [26], [29]. Such as compressed sensing (CS) in the field of wireless communication [30], short-time fractional order Fourier transformation (STFRFT) in the field of radar signal processing [31], and so on.

In the research of this paper, the processing method of the non-stationary signal is considered to be optimized, and the method realizes the differential processing of the target signal and the background noise in the observation signal. This way can effectively reduce the time-frequency data generated by background noise, and at the same time improve the time-frequency processing efficiency of marine acoustic observation signals. The time-frequency domain of the non-stationary signal can be processed as a sparse model [32]. This model can realize self-feedback optimization of the marine observation signal processing process by introducing the sign function, the adjustable coefficient, and the frequency domain threshold. The optimized algorithm has adaptive signal classification processing capability. The optimized algorithm simplifies the processing of the background noise and improves the information acquisition rate of the observed signal without changing the time-frequency resolution of the original algorithm. Therefore, the amount of data in the time-frequency domain can be greatly reduced, and the effective data storage rate of the observation platform can be improved.

The organizational structure of this paper is as follows. Section 2 mainly analyzes the limitations of the original algorithm. Then it proposes the optimization method and implementation process of the algorithm. In Section 3, the optimized algorithm is verified by simulation, and the performance is analyzed and compared. In Section 4, a verification experiment was applied to the optimized algorithm for the acoustic observation of the Penaeus vannamei. Finally, the conclusions of the research contents are drawn in Section 5.

II. ALGORITHM ANALYSIS AND PROPOSAL

In marine acoustic observations, the information of acoustic signals is multi-dimensional, and time-frequency domain information is one of the most important information. This section mainly optimizes the time-frequency processing algorithm of non-stationary acoustic signals and realizes adaptive high-efficiency processing.

A. LIMITATION ANALYSIS

Short-time fractional order Fourier transformation (STFRFT) [31], Wavelet transform (WT), Hilbert-Huang transform (HHT), and short-time Fourier transform (STFT) are all non-stationary signal processing methods [32]. They are widely applied in marine acoustic observations [16]. Among them, STFT is one of the most commonly used in marine acoustic observation engineering [33]. In this paper, we take STFT as an example to study and analyze the optimization algorithm. As shown in (1), the fixed window function of STFT uniformly shifts on continuous time-domain signals, thereby realizing short-term stable processing of non-stationary signals, the schematic diagram is shown in Figure 1. In long-term marine acoustic observations, the target signals of interest appear mostly random and short-term, and other signals are mainly background environment noise [27]. Therefore, the window function mainly deals with the time-frequency domain information of the marine background environmental noise.

\[
\text{STFT}_{x}(\tau, f) = \int x(t) h^\ast(t - \tau) e^{-j2\pi ft} dt
\]  

(1)

where \(x(t)\) is the observation signal, \(t\) is the observation time, \(h(t - \tau)\) is the window function, \(\tau\) is the frameshift, \(f\) is the signal frequency.
The specific procedure of time-frequency domain processing is shown in Figure 1. First, the signal frame is intercepted in the time domain by the window function, the fast Fourier transform (FFT) is performed on the signal frame, and the frequency domain data frame can be obtained. Then, by moving the window function evenly, we can get every single signal frame performed by FFT. Although the increase of the signal frame length and interval can improve the processing efficiency of the observed signal, it affects the fineness of the spectrogram and lacks the detail resolution performance in the time-frequency domain. Therefore, it is an inefficient way for target signal processing and efficient information acquisition.

**B. OPTIMIZED ALGORITHM**

To improve the processing efficiency of the marine observation acoustic signal, this paper optimizes the signal processing flow of the original algorithm. The optimized algorithm retains the advantage of the signal frequency domain resolution and accuracy. The optimized process is to transform the uniform movement of the window function into a real-time self-feedback movement between the time domain and the frequency domain.

The self-feedback process introduces the decision threshold and the sign function \( \text{sgn}(\xi) \) in the frequency domain to realize the optimization of the original observation algorithm. The optimized algorithm can adaptively distinguish the target signal and the background noise in the observation, as in (2) and (3), the window function can adaptively select the moving step size based on self-feedback.

\[
\text{sgn}(\xi) = \begin{cases} 
1, & \xi \geq 0 \\
-1, & \xi < 0 
\end{cases} \tag{2}
\]

\[
\text{Optimized-STFT}_t(r, f) = \sum_{n=1}^{N} r(t) \cdot h(t - \tau_n) e^{-j2\pi f_n t} \
\xi = \text{THR} - \max(f_{\tau_1}) \cdot n \in \mathbb{N} \\
\tau_{n+1} = M^{n \cdot K}, \quad M \in [1, 2], n \in \mathbb{N} \\
\tau_1 = K \tag{3}
\]

where \( \xi \) is the frequency domain detection value, \( \tau_n \) is the adaptive step size of window function, \( f_{\tau_n} \) is the frequency of the window function at the current moment, \( \tau_1 \) is the starting step \( K, M \) is the adjustable coefficient, \( \text{THR} \) is the frequency domain threshold.

In the optimized algorithm, the maximum frequency \( \max(f_{\tau_n}) \) of each signal frame is subtracted from the frequency domain threshold \( \text{THR} \), and then the frequency domain detection value \( \xi \) can be obtained. The sign function \( \text{sgn}(\xi) \) acts on the adjustable coefficient \( M \) and the starting step \( \tau_1 \), after that the updated step size \( \tau_{n+1} \) of the window function is fed-back to the next signal frame.

If the maximum frequency of the \( P \)th time signal frame is greater than the frequency domain threshold, the frequency domain detection becomes a negative value. It also indicates that the target signal appears. Then the feedback value of \( \tau_{p+1} \) is \( M^{-1}K \) and the step size of the window function decreases. Hence, the target signal can be processed with high precision in the frequency domain during the marine acoustic observation. On the contrary, if the frequency domain detection is a positive value, it indicates that there is no target signal. The feedback value of \( \tau_{p+1} \) is \( M^{+1}K \), and the step size of the window function is increased. The background noise can be processed sparsely and quickly.

**C. STRUCTURE OF THE OPTIMIZED ALGORITHM**

The Equation derivation and analysis of the optimized algorithm demonstrate its feasibility theoretically. However, the theoretical research and the engineering application are not completely equivalent. This section implements the specific steps of the optimized algorithm based on the actual engineering requirements. This is also an important stage before engineering application. The structure of the optimized algorithm and the specific implementation process are shown in Figure 3.
The specific implementation procedure of the optimized algorithm is mainly divided into five parts, as follows.

Step 1: The initial basic parameters of the optimized algorithm including the sampling frequency Fs, the real-time acquisition data buffer L, and the observation signal x(t) is generated.

Step 2: Framing processing of the observation signal. On the one hand, the continuous observation signal is intercepted by the window function, and then the signal frames are obtained. On the other hand, the signal frame can be approximately regarded as the short-term stationary processing of the signal at this moment. Suppose the signal frame length is W, the starting step of the frame is K and the adjustable coefficient is M. Then the corresponding time lengths are W/Fs, K/Fs, and M*\text{sgn}(t)/K/Fs, respectively.

Step 3: Transform the time-domain signal frame into frequency-domain, then the frequency can be obtained at that moment. In this paper, STFT is taken as an example, which is widely used in non-stationary marine acoustic observation projects.

Step 4: Extract the maximum frequency from the frequency domain of the signal frame and then compare with the frequency domain threshold. Then the frequency domain detection value is calculated and the decision is made by the sign function. To improve the stability of the optimized algorithm application, the fault tolerance is recommended as T=[2, 6] and the value can be adjusted according to the actual conditions. The fault tolerance can prevent the influence of accidental factors. When the fault tolerance is greater than the threshold, it means that there are invalid frequency components in the signal frame after multiple confirmations, and then the background noise is quickly processed.

Step 5: If the data buffer is greater than or equal to L, repeat Step 2. Contrarily, it means that there is no enough data length for framing, then we output the spectrogram and end the algorithm.

III. SIMULATION AND VALIDATION

A. SIMULATION AND VERIFICATION OF THE OPTIMIZED ALGORITHM

This section uses MATLAB software for simulation and verification. The specific parameters of the simulation are set as follows. The observation signal is a non-stationary signal, the signal-to-noise ratio (SNR) of the signal is 5dB, and the total duration is 1350ms, as shown in Figure 4. The target signal is 4 linear frequency modulation (LFM) signals. The LFM ranges are 10kHz ~ 13kHz, 10kHz ~ 13kHz, 13kHz ~ 6kHz, and 10kHz ~ 13kHz, respectively. The signal energy ratio is 1: 1: 2: 0.5. The duration of each target signal is 50ms and appears in 250ms ~ 300ms, 900ms ~ 950ms, 950ms ~ 1000ms, and 1150ms ~ 1200ms, respectively.

We processed the observation signal on both the original algorithm and the optimized algorithm respectively. From the spectrogram of the observation signal, we verified and compared these two algorithms intuitively. The parameters of the optimized algorithm are as follows. The signal frame length is 256 points, the starting step is 256 points, the step size adjustable coefficient is 2 and the fault tolerance is 3. The results of the algorithms are compared and shown in Figure 5.
Two points can be clearly contrasted in Figure 5. The first point is that the optimized algorithm can identify the target signals and the background noise, and adjust the frame step size adaptively. It can achieve ordered high-resolution processing and sparse processing. The second point is that the amount of data generated in the time-frequency domain is greatly reduced. Both illustrate that the performance of the optimized algorithm has been significantly improved.

B. EFFICIENCY OF THE OPTIMIZED ALGORITHM

Algorithm efficiency is a key metric to evaluate performance. Under the same computer simulation conditions and same length of duration, we can get the processing time of the two different algorithms. Then the time consumed by the algorithm processing can indirectly represent the efficiency of the algorithm. During the same observation time, the percentage of background noise is changed for comparative analysis. The observation signal duration is 1350ms, and the percentage of the background noise ranges from 0 to 100%. The processing time of the original algorithm is \( t_1 \) and the optimized algorithm is \( t_2 \). To prevent the influence of accidental factors, the algorithm processes each observation signal three times in the experimental analysis. The average processing time of the two algorithms are \( t_1 \) and \( t_2 \), respectively. The efficiency of the algorithm is \( \eta \), as shown in (4).

\[
\eta = \frac{t_1 - t_2}{t_1} \times 100\%
\]  (4)

The time-consuming comparison and analysis of the two algorithms are shown in Figure 6 (Please refer to Appendix-I for the specific data). Since the original algorithm processing process each frame of the observation signal at equal intervals, the percentage of background noise has little effect on the algorithm’s time-consuming. The original algorithm takes about 100ms each time, as shown by the red line in Figure 6 (a).

The optimized algorithm can adaptively identify the target signals and the background noise, so the time-consuming of each time is related to the percentage of the background noise in the observation signal, as shown by the blue line in Figure 6 (a). In an extreme case, the percentage of the background noise is 0%, then the target signal is 100%. The two algorithms are equivalent at this moment. However, as the percentage of background noise gradually increases, the optimized algorithm’s time-consuming keeps decreasing. The efficiency of the optimized algorithm continues to improve, as shown in Figure 6 (b). The optimized algorithm takes the shortest time of 22.15ms and improves the maximum efficiency of 78.16% when the percentage of background noise is 100%. In actual marine acoustic observations, the proportion of background noise is generally large, so the optimized algorithm can be executed high-efficiently.

C. DATA PROCESSING PERFORMANCE COMPARISON

The optimized observation algorithm can adaptively distinguish the target signals and the background noise according to the frequency domain threshold. The impact on the data generated in the time-frequency domain is one of the main achievements of the optimized algorithm.

In order to analyze the performance of the data generated in the time-frequency domain, it is assumed that the data length of the observation signal is \( L_N \). Two extreme conditions are used for analysis, combining (3) and the flow of Figure 3. When the proportion of the target signals in the observation signal is 100%, the feedback value \( \tau_{n+1} \) is always \( M^{-1}K \) and the number of data frames is the less than \( L_N/M^{-1}K \). When the SNR of the observation signal is low and the proportion of the background noise is 100%, the feedback value \( \tau_{n+1} \) is always \( M^4K \) and the number of data frames is the less than \( L_N/M^4K \). To analyze the relationship between the adjustable coefficient and the window function adaptive step size, the starting step \( \tau_{n+1} \) is set as \( K = 256 \), as shown in Figure 7.

As the adjustable coefficient \( M \) increases, the feedback value of \( \tau_{n+1} \) is divergent. It can be clearly seen that \( M \) is negatively correlated with \( M^{-1}K \) and positively correlated with \( M^4K \). To ensure the stability and robustness of the optimized algorithm performance, the adjustable coefficient...
value is \( M \in [1,2] \). In this paper, \( M \) takes the value 2. When the percentage of the target signals is 100%, the number of data frames is \( 2^{-3}K \). And when the background noise percentage is 100%, the number of data frames is \( 2K \). The information of the observation signal is very rare when the SNR is low. As shown in (5), the percentage reduction in the number of data frames for the background noise is \( \sigma \), and the theoretical value of the data frames reduction is up to 75%.

\[
\frac{L_{m}-L_{n}}{2^{3}K} \times \frac{L_{m}}{2^{3}K} \times 100\% \tag{5}
\]

Further, the stability of \( \sigma \), in the process of the background noise by the optimized algorithm is discussed and analyzed. The key parameters of the simulation are as follows. The observation signal duration is 1350ms, the signal sampling frequency is 48kHz and the data length is 64800 points. The percentage reduction of the data frames keep pace with the theoretical analysis by changing the value of K. And the signal data processing performance of the optimized algorithm has been greatly improved, the performance data are shown in Table I.

| K-value | Original algorithm data frames | Optimized algorithm data frames | Percentage reduction of the data frames % |
|---------|--------------------------------|--------------------------------|-----------------------------------------|
| 32      | 2018                           | 508                            | 74.83                                   |
| 64      | 1009                           | 255                            | 74.73                                   |
| 128     | 505                            | 128                            | 74.65                                   |

**IV. APPLICATION EXPERIMENT**

The application experiment of the optimized algorithm is the link between theoretical research and engineering application. In this paper, the acoustic observation signal of the Penaeus vannamei was used in the application experiment. The experimental address is located in the Penaeus vannamei breeding base in Fengxian District, Shanghai, China. And the passive acoustic hydrophone model was Brüel&Kjær-8103 with high sensitivity \(-211\text{dB re } 1V/\mu \text{Pa} \). The key parameters of the application experiment were as follows. The hydrophone was placed at 2m depth underwater, the duration of the observation signal was the 90s, the signal sampling frequency was 48kHz, and the data width was 16bit.

In aquaculture engineering, power frequency interference and noise crosstalk of auxiliary aquaculture equipment are serious. First, the acoustic observation signal was processed by high-pass filtering to remove the low-frequency interference of the underwater environment. Then, the original algorithm and the optimized algorithm were applied respectively, and the performance was analyzed from the operational efficiency and the data compression rate. To facilitate signal processing, the 90s duration of the observation signal was equally divided into 3 signal segments, each with a duration of 30s. The process of each signal segment was repeated 5 times to reduce the impact of accidental factors.

The original algorithm parameters were set as that the data frame length was \( K = 256 \) points and the frameshift step size was \( 2^{-3}K = 128 \) points. The parameters of the optimized algorithm were set as follows. The starting step was \( K = 256 \) points, the adjustable coefficient was \( M = 2 \), the target signal frameshift step size was \( M^{-1}K = 128 \) points and the background noise frameshift step size was \( M^{-1}K = 512 \) points. The duration of the acoustic observation signal was long and the target signal was relatively sparse. Therefore, this paper only shows the processing effect of the 0 ~ 30s observation signal in the time-frequency domain, as shown in Figure 8. And the processing effect of the 30s ~ 90s observation signal is similar and it was not displayed.

**Figure 8.** Comparison of the time-frequency domain effects of the two algorithms. (a) The time-domain observation signal. (b) The processing result of the original algorithm. (c) The processing result of the optimized algorithm.

Figure 8 (a) illustrates the time domain observation signal, and it is relatively intuitive to see some small burrs, but it is difficult to obtain useful information. Figure 8 (b) shows the time-frequency domain processing result of the original
algorithm for the non-stationary acoustic observation signal, which is also a widely used method. It can be seen that there are sparse target signals in the time-frequency domain. Figure 8 (c) shows the processing result of the optimized algorithm. Figure 8 (b1) and (c1) are preliminary identical in comparison. The details cannot be shown because the observation signal duration is too long. And Figure 8 (b2) and (c2) are the partial magnified effect of Figure 8 (b1) and (c1), the magnified area is the time-frequency domain of 6.38s ~ 6.44s.

From the comparison of Figures 8 (b2) and (c2), it can be seen that the optimized algorithm can also adaptively adjust the signal frame length in application experiment processing.

Also, the results verified that the optimized algorithm can realize the autonomous identification of target signal and sparse processing of background noise.

Then, the performance of the acoustic observation algorithm is studied, and the operation efficiency and data compression rate of the two algorithms under the same conditions were compared in the application experiment. The two algorithms respectively processed the acoustic observation signal of Penaeus vannamei with a duration of 90s. The comparison data of the algorithm operation efficiency is shown in Table II (Please refer to Appendix-II for the detailed data), and the data compression rate is shown in Table III.

### Table II: Operation Efficiency Comparison of the Two Algorithms

| Test times | Original algorithm processing time / s | Optimized algorithm processing time / s | Operation efficiency / % |
|------------|----------------------------------------|---------------------------------------|--------------------------|
|            | 0~30 s  | 30~60 s  | 60~90 s  | Total  | 0~30 s  | 30~60 s  | 60~90 s  | Total  |                      |
| 1st        | 30.15   | 29.21    | 29.08    | 88.44  | 2.87    | 2.94     | 2.98     | 8.79   | 90.06       |
| 2nd        | 28.94   | 30.06    | 29.48    | 88.48  | 3.01    | 3.01     | 2.95     | 8.97   | 89.86       |
| 3rd        | 29.04   | 29.03    | 29.69    | 87.76  | 3.02    | 2.96     | 2.98     | 8.96   | 89.79       |
| 4th        | 28.86   | 29.51    | 29.42    | 87.79  | 2.88    | 2.94     | 3.05     | 8.87   | 89.90       |
| 5th        | 29.10   | 29.11    | 29.29    | 87.50  | 2.93    | 2.91     | 3.04     | 8.88   | 89.85       |
| Average    | 29.22   | 29.38    | 29.39    | 87.99  | 2.94    | 2.95     | 3.00     | 8.89   | 89.89       |

### Table III: Data Compression Rate Comparison of the Two Algorithms

| Category                  | Acoustic observation signal duration | Total         |
|---------------------------|-------------------------------------|---------------|
|                           | 0 ~ 30 s  | 30 ~ 60 s | 60 ~ 90 s | 0 ~ 90 s |
| Optimized algorithm / Data frame | 3428      | 3434      | 3492      | 10354   |
| Original algorithm / Data frame | 11249     | 11249     | 11249     | 33747   |
| Data compression rate / %  | 69.53     | 69.47     | 68.96     | 69.32   |

The processed data in Tables II and III can be analyzed to obtain several following results. The performance of the original algorithm are relatively stable in all aspects. The average processing time of each signal segment is about 29.3s, and the number of data frames is 11249. However, the performance of the optimized algorithm has been significantly improved. The average processing time of each signal segment is only about 2.9s, and the number of data frames is only about 3450. In other words, the operation efficiency of the optimized algorithm is improved by about 89.89% compared with the original algorithm. In terms of data processing, the average data frame is reduced by about 69.32%.

V. RESULT

This paper analyzed the simulation, verification, and application, which proved the better performance of the optimized algorithm. Hence, we formed following results.

1) The optimized algorithm is an adaptive non-stationary signal processing method. It can be introduced into marine acoustic observations for the efficient processing of non-stationary signals. Meanwhile, non-stationary signals in other fields can also refer to this method.

2) The operation efficiency of the observation signal is significantly improved. Under the same operating conditions, the percentage of the target signal in the observation signal determines the degree of efficiency improvement. The simulation parameters set in this paper could improve the efficiency by 78.16%. In the application experiment, the efficiency could be improved by 89.89%. This can save the electrical energy of the marine observation platform or extend the working time of the non-stationary signal observation system, which is very important and meaningful.

3) The data processing quantity of the non-stationary acoustic signal in the time-frequency domain is greatly compressed. The compression performance is closely related to the adjustable coefficient. The theoretical maximum data compression rate can reach 75%. In this paper, the data compression rate of the simulation conditions was 74.65%, and the data compression rate in the application experiment was 69.32%. Hence the storage proportion of effective data is greatly improved.
VI. CONCLUSION
This paper proposed an optimized observation signal processing algorithm, which can realize the adaptive processing of the non-stationary signals in marine acoustic observation. The optimization process introduces the sign function, the frequency domain threshold, and the adjustable coefficient for self-feedback. It realized the differential processing of the target signals and background noise. In this paper, the STFT method was taken as an example to carry out the simulation and verification of the optimized algorithm, and then some good results were obtained. Finally, the optimized algorithm was applied to the acoustic observation of the Penaeus vannamei. The proposed algorithm was more efficient than previous methods.

The optimized algorithm improved the operation efficiency and data compression rate of the non-stationary signal, which could be extended to the non-stationary signal processing methods such as Short-time fractional order Fourier transformation (STFRFT), Wavelet transform (WT), Hilbert-Huang transform (HHT) and Wigner-Ville distribution (WVD). It could balance the deficiency of some algorithms which cannot be popularized and applied in marine observation platforms due to the complexity of calculation.

As future research, the generalization of the optimized algorithm is an important direction. Also, the optimized algorithm can be applied to the acoustic observation of underwater animals, monitoring of underwater non-cooperative targets, marine seismic signal monitoring, and so on. It shows that the optimized algorithm can be widely popularized and applied to buoys, submarine buoys, and other marine non-stationary signal observation platforms.

APPENDIX

APPENDIX - I
THE TIME-CONSUMING COMPARISON OF THE TWO ALGORITHMS

| Target signal duration /ms | Original algorithm processing time /ms | Optimized algorithm processing time /ms | Operation efficiency /% |
|----------------------------|---------------------------------------|---------------------------------------|------------------------|
|                            | The 1st time | The 2nd time | The 3rd time | Average | The 1st time | The 2nd time | The 3rd time | Average | |
| 0                          | 100.465      | 102.055      | 101.750      | 101.4233 | 22.194       | 22.040       | 22.206       | 22.1467 | 78.16 |
| 50                         | 101.435      | 101.484      | 103.455      | 102.1247 | 24.625       | 23.969       | 24.351       | 24.3150 | 76.19 |
| 100                        | 100.274      | 99.277       | 99.534       | 99.6950  | 26.788       | 26.260       | 26.682       | 26.6700 | 73.25 |
| 150                        | 100.372      | 98.663       | 101.574      | 100.2030 | 29.050       | 28.211       | 28.744       | 28.6683 | 71.39 |
| 200                        | 99.419       | 101.398      | 100.046      | 100.2877 | 31.484       | 31.765       | 31.395       | 31.5480 | 68.54 |
| 250                        | 99.759       | 99.224       | 100.641      | 99.8747  | 34.135       | 33.466       | 33.121       | 33.5740 | 66.38 |
| 300                        | 100.231      | 99.209       | 102.245      | 100.5617 | 37.015       | 35.635       | 36.844       | 36.4980 | 63.71 |
| 350                        | 99.876       | 99.954       | 100.685      | 100.1717 | 37.992       | 38.871       | 38.926       | 38.5963 | 61.47 |
| 400                        | 101.877      | 98.952       | 99.681       | 100.1700 | 40.264       | 40.917       | 41.011       | 40.7307 | 59.34 |
| 450                        | 100.424      | 103.007      | 99.621       | 101.0173 | 43.888       | 44.192       | 43.957       | 44.0123 | 56.43 |
| 500                        | 100.188      | 100.648      | 101.762      | 100.8660 | 47.715       | 47.523       | 47.095       | 47.4443 | 52.96 |
| 550                        | 99.126       | 99.626       | 100.155      | 99.6357  | 49.647       | 49.190       | 49.335       | 49.3907 | 50.43 |
| 600                        | 101.117      | 100.901      | 99.416       | 100.4780 | 51.893       | 52.921       | 51.794       | 52.2072 | 48.05 |
| 650                        | 99.358       | 100.250      | 99.309       | 99.6390  | 53.907       | 53.912       | 54.288       | 54.0357 | 45.77 |
| 700                        | 98.925       | 99.456       | 101.937      | 100.1060 | 57.483       | 56.903       | 57.189       | 57.1917 | 42.87 |
| 750                        | 101.958      | 103.013      | 99.105       | 101.3587 | 58.774       | 59.327       | 59.113       | 59.0713 | 41.72 |
| 800                        | 99.966       | 99.902       | 100.730      | 100.1993 | 62.549       | 62.516       | 63.316       | 62.7937 | 37.33 |
| 850                        | 104.016      | 99.953       | 100.273      | 101.4140 | 67.147       | 65.517       | 65.477       | 66.0470 | 34.87 |
| 900                        | 99.496       | 97.269       | 102.216      | 99.6603  | 69.126       | 67.986       | 69.202       | 68.7713 | 30.99 |
| 950                        | 99.605       | 98.949       | 97.959       | 98.8377  | 68.199       | 69.112       | 68.210       | 68.5070 | 30.69 |
| 1000                       | 99.138       | 101.259      | 96.609       | 99.0020  | 71.542       | 72.210       | 72.764       | 72.1720 | 27.10 |
| 1100                       | 98.644       | 96.140       | 97.638       | 97.4740  | 80.450       | 79.678       | 81.801       | 80.6430 | 17.27 |
| 1200                       | 100.202      | 97.706       | 98.842       | 98.9167  | 87.572       | 86.996       | 87.163       | 87.2437 | 11.80 |
| 1350                       | 98.415       | 99.985       | 97.258       | 98.5527  | 98.537       | 98.672       | 100.148      | 99.1190 | -0.57 |

APPENDIX - II
OPERATION EFFICIENCY COMPARISON OF THE TWO ALGORITHMS

| Test times | Original algorithm processing time /s | Optimized algorithm processing time /s | Operation efficiency /% |
|------------|---------------------------------------|---------------------------------------|------------------------|
| 0 ~30 s    | 30.150559                            | 0.57                                  | 90.0649                |
| 30 ~60 s   | 28.940506                            | 28.940295                             | 89.8703                |
| 60 ~90 s   | 29.038111                            | 29.038262                             | 89.7873                |
| Total      | 88.440075                            | 88.478005                             | 88.8863                |
| 3rd        | 28.859264                            | 28.859472                             | 89.7873                |
| 0 ~30 s    | 29.193685                            | 29.193582                             | 89.8478                |
| 3rd        | 29.099001                            | 29.099185                             | 89.8478                |
| Total      | 88.8478                              | 88.8478                               | 88.8478                |
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REFERENCES

[1] D. T. I. Bayley and A. O. M. Mogg, “Chapter 6 - New Advances in Benthic Monitoring Technology and Methodology,” in World Seas: An Environmental Evaluation, C. B. T-W., S. an E. E. (Second E. Sheppard, Ed. Academic Press, 2019, pp. 121–132.

[2] B. M. Howe, J. Miksis-Olds, E. Rehm, H. Sagen, P. F. Worcester, and G. Haralabus, “Observing the oceans acoustically,” Front. Mar. Sci., vol. 6, no. JUL, pp. 1–22, 2019, doi:10.3389/fmars.2019.00426.

[3] G. Pavan, T. H. E. N. Collaboration, G. Cosentino, and M. M. and F. Spezia., “Continuous real-time monitoring with a deep underwater acoustic station. Noise spectra and biological sounds from the NEMO Test Site,” Unpubl. Pop. to IWC Sci. Committee, 4 pp. St Kitts Nevis, West Indies, June 2006., no. January 2016, p. 4, 2006.

[4] G. McIntyre, C. Loadman, J. F. Bousquet, and S. Blouin, “Low power beamforming for underwater acoustic sensing using a 5-element circular hydrophone array,” MTSS/IEEE Ocean. 2015 - Genova Discov. Sustain. Ocean Energy A New World, no. 2, 2015, doi: 10.1109/OCEANS-Genova.2015.7271421.

[5] I. F. Akyildiz, D. Pompili, and T. Melodia, “Underwater acoustic sensor networks: Research challenges,” Ad Hoc Networks, vol. 3, no. 3, pp. 257–279, 2005, doi: 10.1016/j.adhoc.2005.01.004.

[6] Y. B. K and M. Ranjbar, “A Review on Methods and Approaches in Underwater Acoustics,” CRPASE Trans. Appl. Sci. J., vol. 22, no. 6, 2022, doi:10.3390/22062277.

[7] G. Haralabus, “Observing the oceans acoustically,” EE Signal Process. Mag., vol. 36, no. 5, pp. 77–84, 2019, doi:10.1109/MSP.2019.8783677.

[8] O. Kravchick, D. S. L. Wei, and X. Zhang, “Delay-sensitive data gathering in wireless sensor networks,” IEEE Int. Symp. Pers. Indoor Mob. Radio Commun. PMRC, vol. 25, no. 1, pp. 479–483, 2013, doi:10.1109/PMRC.2013.666563.

[9] S. M. Wiggins and J. A. Hildebrand, “High-frequency Acoustic Recording Package (HARP) for broad-band, long-term marine mammal monitoring,” Int. Symp. Underw. Technol. UT 2007 - Int. Work. Use Submar. Cables Relat. Techn. 2007, pp. 551–557, 2007, doi:10.1109/UT.2007.370760.

[10] I. Kakalou and K. E. Psannis, “Sustainable and Efficient Data Collection in Cognitive Radio Sensor Networks,” IEEE Trans. Sustain. Comput., vol. 4, no. 1, pp. 29–38, 2019, doi:10.1109/TSC.2018.2830704.

[11] J. M. Ayers and K. Richter, “The potential of small-scale turbines and microbial fuel cells to support persistent oceanographic sensors,” in OCEANS 2016 MTS/IEEE Monterey, 2016, pp. 1–6, doi:10.1109/OCEANS.2016.7761015.

[12] S. Guo, Y. Zheng, and L. Gan, “The Design and Application of Intelligent Buoy in Polar Water,” vol. 163, no. iceesd, pp. 1419–1424, 2018, doi:10.2991/iceesd-18.2018.258.

[13] D. Li, D. Li, F. Li, J. Shi, and W. Zhang, “Analysis of floating buoy of a wave power generating jack-up platform Haiyuan 1,” Adv. Mech. Eng., vol. 2013, 2013, doi:10.1155/2013/105072.

[14] L. Xia, Z. Jiandao, and W. Huafeng, “A LoRa Buoy Network Coverage Optimization Algorithm Based on Virtual Force,” in 2019 IEEE 2nd International Conference on Information Communication and Signal Processing (ICS2P), 2019, pp. 204–209, doi: 10.1109/ICSP48821.2019.8958591.

[15] A. F. Harris, M. Stojanovic, and M. Zorzi, “Idle-time energy savings through wake-up modes in underwater acoustic networks,” Ad Hoc Networks, vol. 7, no. 4, pp. 770–777, 2009, doi:10.1016/jadhoc.2008.07.014.

[16] L. Zhang, C. Meng, and J. Na, “Modeling of High Background Noise in large area Ocean Based on Measured Data,” in 2018 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC), 2018, pp. 1–4, doi:10.1109/ICSPCC.2018.8567802.

[17] S. Siddagangaiah, Y. Li, X. Guo, and K. Yang, “On the dynamics of ocean ambient noise: Two decades later,” Chaos, vol. 25, no. 10, 2015, doi:10.1063/1.4932561.

[18] Y. Li, Y. Li, X. Chen, J. Yu, H. Yang, and L. Wang, “A New Underwater Acoustic Signal Denoising Technique Based on CEEMDAN, Mutual Information, Permutation Entropy, and Wavelet Threshold Denoising,” Entropy, vol. 20, no. 8, 2018, doi:10.3390/entropy20080565.

[19] B. Boushabsh and J. Imberger, “Signal processing in oceanography,” 1st IASTED Int. Symp. Signal Process. Its Appl., no. January, 1987.

[20] L. Cohen, “Time-frequency distributions—a review,” Proc. IEEE, vol. 77, no. 7, pp. 941–981, 1989, doi:10.1109/5.30749.

[21] T. Xiflidis and Kostas E. Psannis, “Wireless fading channels performance based on Taylor expansion and compressed sensing: A comparative approach,” Int. J. Commun. Syst., vol. 34, no. 8, pp. 4621–4639, 2021, doi:10.1002/dac.4794.

[22] C. Pang, Y. Han, H. Hou, S. Liu, and N. Zhang, “Micro-doppler signal time-frequency algorithm based on STFRFT,” Sensors (Switzerland), vol. 16, no. 10, pp. 10–18, 2016, doi:10.3390/s16101559.

[23] H. Zhang, T. Shan, S. Liu, and R. Tao, “Optimized sparse fractional Fourier transform: Principle and performance analysis,” Signal Processing, vol. 174, pp. 107646, 2020, doi:10.1016/j.sigpro.2020.107646.

[24] M. Shadloo-Jahromi, M. R. Khosravi, and H. Rostami, “Signal Classification Using Feature Extraction Techniques and Artificial Neural Network in Underwater Acoustic Environment,” in Magnetic Communications: From Theory to Practice, 1st Edition., no. February 2019, F. Hu, Ed. CRC Press, 2019, pp. 189–208.

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