

Received May 6, 2022, accepted June 8, 2022, date of publication June 13, 2022, date of current version June 21, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3182701

A High-Efficiency Optimized Detection Algorithm for Non-Stationary Marine Acoustic Signals in the Time-Frequency Domain

TIANYU CAO^{ID}, MENGQI BIAN, YICHEN YANG, ZHONGWEI XU, AND XIAOQUN ZHAO^{ID}

Department of Information and Communication Engineering, College of Electronic and Information Engineering, Tongji University, Shanghai, Jiading 201804, China

Corresponding author: Xiaoqun Zhao (zhao_xiaoqun@tongji.edu.cn)

This work was supported by the Scientific Research Projects of Tongji University under Grant kh0080020203377 (Project name: XJH20200101) and Grant kh0080020212743 (Project name: XJH20210121).

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 decreasing 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. The simulation verification experiment and the application experiment based on the optimized algorithm are shown in this study. The experimental results indicate 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. As a result, the optimized algorithm's performance has 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 variety of applications, such as sound observation of marine creatures [3], marine noise monitoring [4]–[6], marine military surveillance and tracking [7], [8], marine climate modeling and prediction [9], [10], etc. Despite their differences, these applications all face similar platform issues, such as limited electricity and growth data management.

The marine observation environment is very extremely harsh and special, and researchers are unable to maintain the observation platform in time [9]. However, long-term deployment is required for marine observation platforms such as buoys and submersible buoys, and only a small number of nearshore buoys may be connected to shore electricity

The associate editor coordinating the review of this manuscript and approving it for publication was Bo Pu^{ID}.

via cables [11]. The majority of the other observation platforms are located far away from the land, and thus face issues such as rapid consumption of electricity and a lack of reliable power supply [12], [13]. Although, 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 rises concurrently. 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 area in ocean engineering.

In recent years, to make the marine observation platform work for a longer time, it has become 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. Nonetheless, the observation system can change the operating mode to improve the observation efficiency and thus achieve low power consumption. Optimizing the length of the data transmission path is an effective way 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 significantly 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 extremely 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, with the majority of it being background noise [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 regarded 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. Furthermore, 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. As a result, 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 remainder of this article is organized 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 performance of the optimized method is assessed and compared using simulation. 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, which can be expressed as

$$\text{STFT}_x(\tau, f) = \int x(t)h^*(t - \tau)e^{-j2\pi ft} dt \quad (1)$$

where $x(t)$ is the observation signal, t is the observation time, $h(t - \tau)$ is the window function, τ is the frameshift, f is the signal frequency. The fixed window function of STFT uniformly shifts on time-domain signals continuously, 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.

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

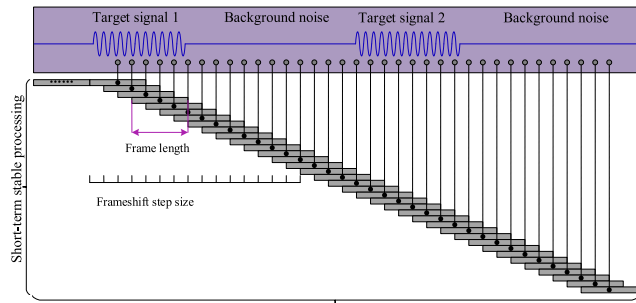


FIGURE 1. Schematic diagram of short-term stable processing of non-stationary signals.

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.

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

$$\text{Optimized-STFT}_x(\tau, f) = \begin{cases} \text{STFT}_x(\tau_n, f_{\tau_n}) = \int x(t)h^*(t - \tau_n)e^{-j2\pi f_{\tau_n}t} \\ \xi = \text{THR} - \text{Max}(f_{\tau_n}), n \in \mathbb{N} \\ \tau_{n+1} = M^{\text{sgn}(\xi)} \cdot \tau_1, M \in [1, 2], n \in \mathbb{N} \\ \tau_1 = K \end{cases} \quad (3)$$

where ξ is the frequency domain detection value, τ_n is the adaptive step size of window function, f_{τ_n} is the frequency of the window function at the current moment, τ_1 is the starting

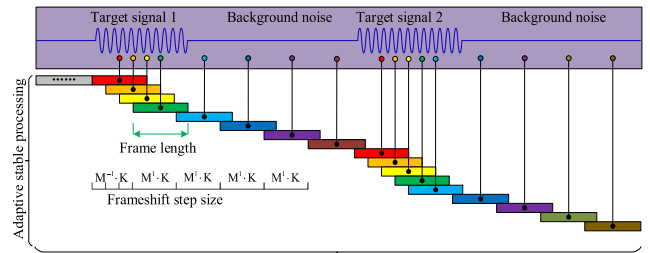


FIGURE 2. Schematic diagram of adaptive stable processing of non-stationary signals.

step K , M is the adjustable coefficient, THR is the frequency domain threshold.

In the optimized algorithm, the maximum frequency $\text{Max}(f_{\tau_n})$ of each signal frame is subtracted from the frequency domain threshold THR , and then the frequency domain detection value ξ can be obtained. The sign function $\text{sgn}(\xi)$ acts on the adjustable coefficient M and the starting step τ_1 , after that the updated step size τ_{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 τ_{P+1} becomes $M^{-1}K$ 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 τ_{P+1} is M^1K , and the step size of the window function is increased. Hence, the background noise can be processed sparsely and quickly.

As shown in Figure 2, the step size of the window function is $M^{-1}K$, when target signal 1 and target signal 2 appear, and the step size is M^1K during the background noise. In this signal processing process, the optimized algorithm realizes the adaptive classification of the marine acoustic observation signal.

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 F_s , the real-time

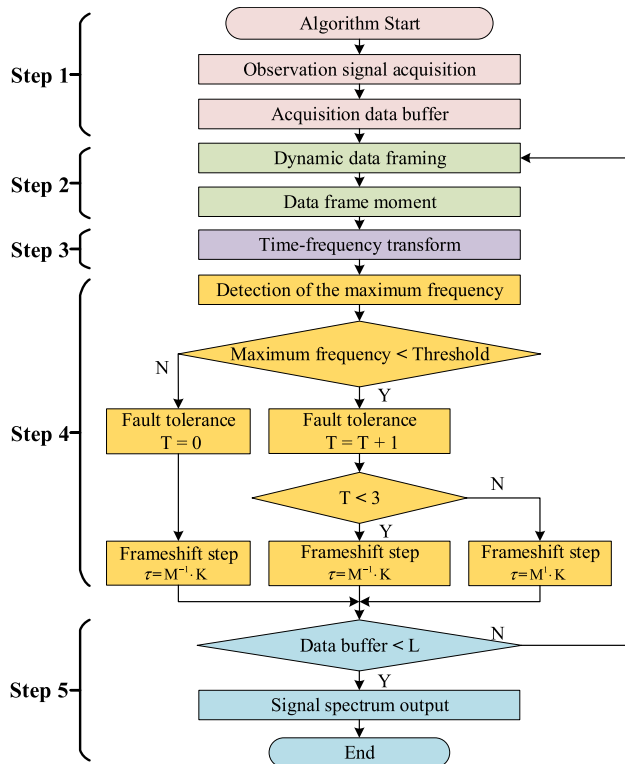


FIGURE 3. The structure of the optimized algorithm.

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/F_s , K/F_s , and $M^{sgn(\xi)}K/F_s$, 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 $\in T[2, 6]$ 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.

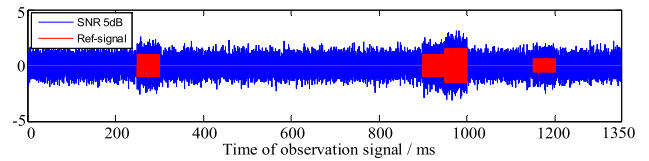


FIGURE 4. The simulation signal and the reference signal.

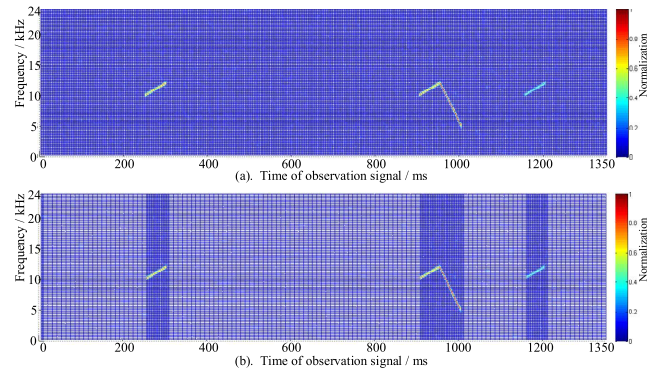


FIGURE 5. Simulation verification and comparison of the original algorithm and the optimized algorithm. (a). The original algorithm. (b). The optimized algorithm.

Step 5: If the data buffer is greater than or equal to L , repeat Step 2. Contrarily, it means that there is not 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 set 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

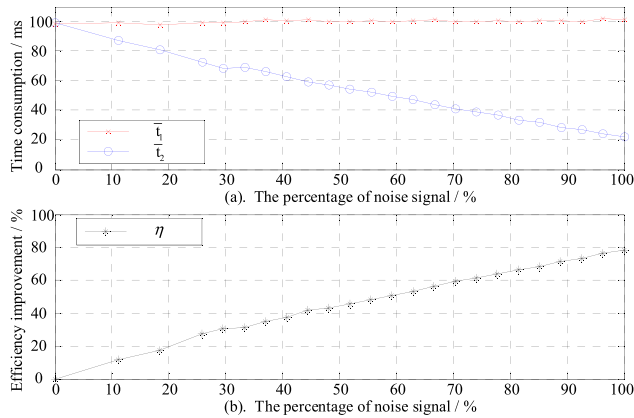


FIGURE 6. The performance of the algorithms. (a) The time-consuming comparison of the two algorithms. (b) The efficiency improvement of the optimized algorithm.

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 varies 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 \bar{t}_1 and \bar{t}_2 , respectively. The efficiency of the algorithm is η , as shown in (4).

$$\eta = \frac{\bar{t}_1 - \bar{t}_2}{\bar{t}_1} \times 100\% \tag{4}$$

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 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 in every simulation, 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 every simulation 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, when the percentage of the background noise is 0%, then the target signal is 100%.

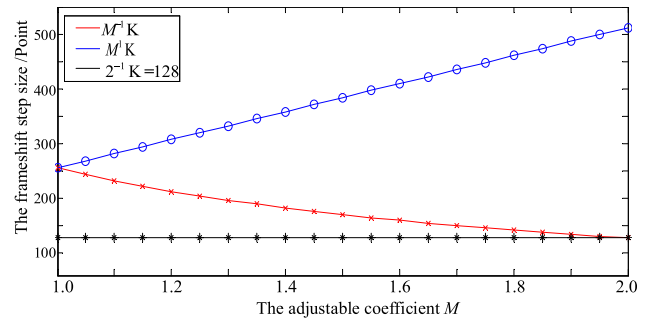


FIGURE 7. The relationship between the adjustable coefficient and the window function adaptive step size.

The performance of these 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 quantity of data generation 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 τ_{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 τ_{n+1} is always M^1K and the number of data frames is the less than L_N/M^1K . To analyze the relationship between the adjustable coefficient and the window function adaptive step size, the starting step τ_1 is set as $K = 256$, as shown in Figure 7.

As the adjustable coefficient M increases, the feedback value of τ_{n+1} is divergent. It can be clearly seen that M is negatively correlated with $M^{-1}K$ and positively correlated with M^1K . 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 $2^{-1}K$. 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), σ is the percentage reduction in

TABLE 1. The percentage reduction of the data frames.

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

the number of data frames for the background noise, and the theoretical value of the data frames reduction is up to 75%.

$$\sigma = \frac{\left(\frac{L_N}{2^{-1}K} - \frac{L_N}{2^1K}\right)}{\frac{L_N}{2^{-1}K}} \times 100\% \quad (5)$$

Further, we discussed and analyzed the influence on the stability of σ introduced by the optimized algorithm in the process of the background noise. 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 1.

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 $-211\text{dB re } 1\text{V}/\mu\text{Pa}$. 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 $2^{-1}K = 128$ points. The parameters of the

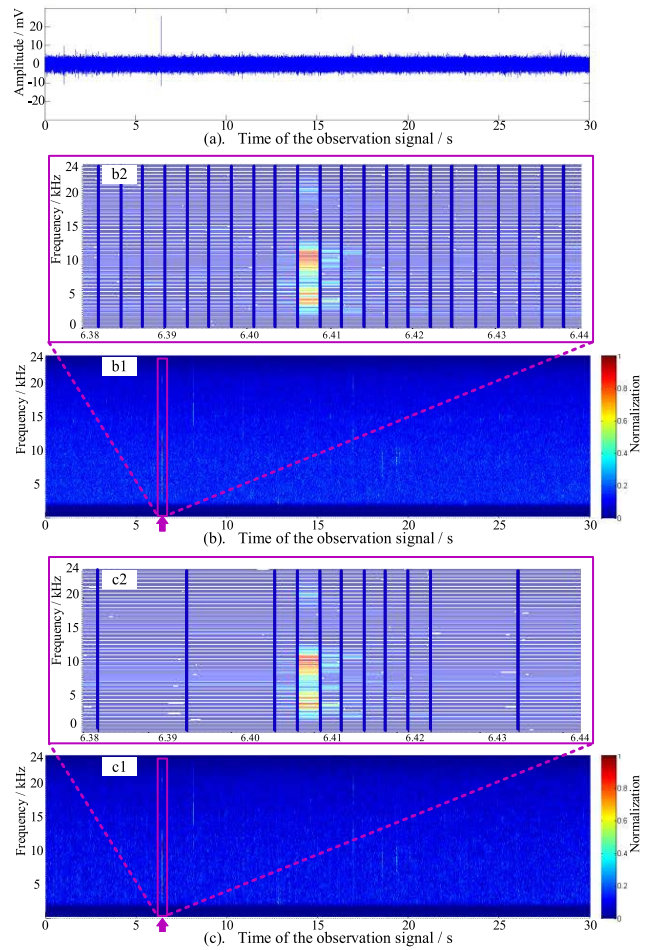


FIGURE 8. Comparison of the time-frequency domain effects of the two algorithms. (a) The time-domain observation signal. (b) The processing result of the original algorithm. (c) The processing result of the optimized algorithm.

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 $M^1K = 512$ 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 (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

TABLE 2. 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 3. Data compression rate comparison of the two algorithms.

Category	Acoustic observation signal duration			Total 0 ~ 90 s
	0 ~ 30 s	30 ~ 60 s	60 ~ 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

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 starts from 6.38s to 6.44s in the time-frequency domain.

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. These 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 2 (Please refer to Appendix-II for the detailed data), and the data compression rate is shown in Table 3.

The processed data in Tables 2 and 3 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 includes the simulation, verification, and application, which proves the better performance of the optimized algorithm. Hence, we draw 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

TABLE 4. 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	26.540	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	52.2027	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

TABLE 5. 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	30.150559	29.213490	29.081958	88.446007	2.872506	2.937114	2.977616	8.787236	90.0649
2nd	28.940506	30.057200	29.480295	88.478001	3.008547	3.005014	2.948964	8.962525	89.8703
3rd	29.038111	29.027625	29.688262	87.753998	3.023134	2.962411	2.976494	8.962039	89.7873
4th	28.859264	29.514088	29.417542	87.790894	2.884933	2.943212	3.050728	8.878873	89.8863
5th	29.099001	29.109368	29.288815	87.497184	2.927417	2.912528	3.042961	8.882906	89.8478
Average	29.217488	29.384354	29.391374	87.993217	2.943307	2.952056	2.999353	8.894716	89.8916

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*. As mentioned above, 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 a promising 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

See Tables 4 and 5.

ACKNOWLEDGMENT

The authors would like to thank the *Penaeus vannamei* breeding base in Fengxian District, Shanghai, China.

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*, E. Sheppard, Ed. New York, NY, USA: Academic, 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," *Frontiers Mar. Sci.*, vol. 6, pp. 1–22, Jul. 2019, doi: [10.3389/fmars.2019.00426](https://doi.org/10.3389/fmars.2019.00426).
- [3] G. Pavan and F. Speziale, "Continuous real-time monitoring with a deep underwater acoustic station. Noise spectra and biological sounds from the NEMO test site," in *Proc. 58 Conf. IWC Sci. Committee*, Saint Kitts and Nevis, West Indies, Jun. 2016, pp. 1–4.
- [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," in *Proc. OCEANS, May 2015*, pp. 1–8, doi: [10.1109/OCEANS-Genova.2015.7271421](https://doi.org/10.1109/OCEANS-Genova.2015.7271421).
- [5] I. F. Enguix, M. S. Egea, A. G. González, and D. A. Serrano, "Underwater acoustic impulsive noise monitoring in port facilities: Case study of the port of cartagena," *Sensors*, vol. 19, no. 21, p. 4672, Oct. 2019, doi: [10.3390/s19214672](https://doi.org/10.3390/s19214672).
- [6] T. Cao, X. Zhao, Y. Yang, C. Zhu, and Z. Xu, "Adaptive recognition of bioacoustic signals in smart aquaculture engineering based on R-sigmoid and higher-order cumulants," *Sensors*, vol. 22, no. 6, p. 2277, Mar. 2022, doi: [10.3390/s22062277](https://doi.org/10.3390/s22062277).
- [7] I. F. Akyildiz, D. Pompili, and T. Melodia, "Underwater acoustic sensor networks: Research challenges," *Ad Hoc Netw.*, vol. 3, no. 3, pp. 257–279, Mar. 2005, doi: [10.1016/j.adhoc.2005.01.004](https://doi.org/10.1016/j.adhoc.2005.01.004).
- [8] Y. B. Kaya and M. Ranjbar, "A review on methods and approaches in underwater acoustics," *CRPASE Trans. Appl. Sci. J.*, vol. 6, no. 3, pp. 220–227, 2020.
- [9] P. Wang, X. Tian, T. Peng, and Y. Luo, "A review of the state-of-the-art developments in the field monitoring of offshore structures," *Ocean Eng.*, vol. 147, pp. 148–164, Jan. 2018, doi: [10.1016/j.oceaneng.2017.10.014](https://doi.org/10.1016/j.oceaneng.2017.10.014).
- [10] K. Tadokoro, N. Kinugasa, T. Kato, Y. Terada, and K. Matsuhiro, "A marine-buoy-mounted system for continuous and real-time measurement of seafloor crustal deformation," *Frontiers Earth Sci.*, vol. 8, pp. 1–12, Apr. 2020, doi: [10.3389/feart.2020.00123](https://doi.org/10.3389/feart.2020.00123).
- [11] R. Venkatesan, A. Tandon, E. D'Asaro, and M. A. Atmanand, *Recent Trends in Ocean Observations*. Cham, Switzerland: Springer, 2018.
- [12] S. Oliveira-Pinto, P. Rosa-Santos, and F. Taveira-Pinto, "Electricity supply to offshore oil and gas platforms from renewable ocean wave energy: Overview and case study analysis," *Energy Convers. Manage.*, vol. 186, pp. 556–569, Apr. 2019, doi: [10.1016/j.enconman.2019.02.050](https://doi.org/10.1016/j.enconman.2019.02.050).
- [13] A. E. Copping, R. E. Green, R. J. Cavagnaro, D. S. Jenne, D. Greene, J. J. Martinez, and Y. Yang, "Powering the blue economy-ocean observing use cases report," Pacific Northwest Nat. Lab., Washington, DC, USA, Tech. Rep. PNNL-29585, Feb. 2020, doi: [10.2172/1700536](https://doi.org/10.2172/1700536).
- [14] T. C. Vance, M. Wengren, E. Burger, D. Hernandez, T. Kearns, E. Medina-Lopez, N. Merati, K. O'Brien, J. O'Neil, J. T. Potemra, R. P. Signell, and K. Wilcox, "From the oceans to the cloud: Opportunities and challenges for data, models, computation and workflows," *Frontiers Mar. Sci.*, vol. 6, pp. 1–18, May 2019, doi: [10.3389/fmars.2019.00211](https://doi.org/10.3389/fmars.2019.00211).
- [15] C. Qian, B. Huang, X. Yang, and G. Chen, "Data science for oceanography: From small data to big data," *Big Earth Data*, pp. 1–15, May 2021, doi: [10.1080/20964471.2021.1902080](https://doi.org/10.1080/20964471.2021.1902080).
- [16] R. J. Vaccaro, "The past, present, and the future of underwater acoustic signal processing," *IEEE Signal Process. Mag.*, vol. 15, no. 4, pp. 21–51, Jul. 1998, doi: [10.1109/79.689583](https://doi.org/10.1109/79.689583).
- [17] O. Kravchick, D. S. L. Wei, and X. Zhang, "Delay-sensitive data gathering in wireless sensor networks," in *Proc. IEEE Int. Symp. Personal Indoor Mob. Radio Commun. (PIMRC)*, vol. 25, no. 1, Sep. 2013, pp. 2479–2483, doi: [10.1109/PIMRC.2013.6666563](https://doi.org/10.1109/PIMRC.2013.6666563).
- [18] S. M. Wiggins and J. A. Hildebrand, "High-frequency acoustic recording package (HARP) for broad-band, long-term marine mammal monitoring," in *Proc. Symp. Underwater Technol. Workshop Sci. Use Submarine Cables Rel. Technol.*, Apr. 2007, pp. 551–557, doi: [10.1109/UT.2007.370760](https://doi.org/10.1109/UT.2007.370760).
- [19] 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, Jan./Mar. 2019, doi: [10.1109/TSUSC.2018.2830704](https://doi.org/10.1109/TSUSC.2018.2830704).
- [20] J. M. Ayers and K. Richter, "The potential of small-scale turbines and microbial fuel cells to support persistent oceanographic sensors," in *Proc. OCEANS*, Sep. 2016, pp. 1–6, doi: [10.1109/OCEANS.2016.7761015](https://doi.org/10.1109/OCEANS.2016.7761015).
- [21] S. Guo, Y. Zheng, and L. Gan, "The design and application of intelligent buoys in polar water," in *Proc. 7th Int. Conf. Energy, Environ. Sustain. Develop. (ICEESD)*, vol. 163, 2018, pp. 1419–1424, doi: [10.2991/iceesd-18.2018.258](https://doi.org/10.2991/iceesd-18.2018.258).
- [22] 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. 5, Jan. 2013, Art. no. 105072, doi: [10.1155/2013/105072](https://doi.org/10.1155/2013/105072).
- [23] L. Xia, Z. Jiandao, and W. Huafeng, "A Lora buoy network coverage optimization algorithm based on virtual force," in *Proc. IEEE 2nd Int. Conf. Inf. Commun. Signal Process. (ICICSP)*, Sep. 2019, pp. 204–209, doi: [10.1109/ICICSP48821.2019.8958591](https://doi.org/10.1109/ICICSP48821.2019.8958591).
- [24] A. F. Harris, M. Stojanovic, and M. Zorzi, "Idle-time energy savings through wake-up modes in underwater acoustic networks," *Ad Hoc Netw.*, vol. 7, no. 4, pp. 770–777, Jun. 2009, doi: [10.1016/j.adhoc.2008.07.014](https://doi.org/10.1016/j.adhoc.2008.07.014).
- [25] L. Zhang, C. Meng, and J. Na, "Modeling of high background noise in large area ocean based on measured data," in *Proc. IEEE Int. Conf. Signal Process., Commun. Comput. (ICSPCC)*, Sep. 2018, pp. 1–4, doi: [10.1109/ICSPCC.2018.8567802](https://doi.org/10.1109/ICSPCC.2018.8567802).
- [26] S. Siddagangaiah, Y. Li, X. Guo, and K. Yang, "On the dynamics of ocean ambient noise: Two decades later," *Chaos, Interdiscipl. J. Nonlinear Sci.*, vol. 25, no. 10, Oct. 2015, Art. no. 103117, doi: [10.1063/1.4932561](https://doi.org/10.1063/1.4932561).
- [27] 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, p. 563, Jul. 2018, doi: [10.3390/e20080563](https://doi.org/10.3390/e20080563).
- [28] B. Boashash and J. Imberger, "Signal processing in oceanography," in *Proc. 1st Int. Symp. Signal Process. Appl. (IASTED)*, Jan. 1987, pp. 1–2.
- [29] L. Cohen, "Time-frequency distributions—a review," *Proc. IEEE*, vol. 77, no. 7, pp. 941–981, Jul. 1989, doi: [10.1109/5.30749](https://doi.org/10.1109/5.30749).
- [30] T. Xifilidis and K. E. Psannis, "Wireless fading channels performance based on Taylor expansion and compressed sensing: A comparative approach," *Int. J. Commun. Syst.*, vol. 34, no. 8, May 2021, doi: [10.1002/dac.4794](https://doi.org/10.1002/dac.4794).
- [31] C. Pang, Y. Han, H. Hou, S. Liu, and N. Zhang, "Micro-doppler signal time-frequency algorithm based on STFRFT," *Sensors*, vol. 16, no. 10, pp. 10–18, 2016, doi: [10.3390/s16101559](https://doi.org/10.3390/s16101559).
- [32] H. Zhang, T. Shan, S. Liu, and R. Tao, "Optimized sparse fractional Fourier transform: Principle and performance analysis," *Signal Process.*, vol. 174, Sep. 2020, Art. no. 107646, doi: [10.1016/j.sigpro.2020.107646](https://doi.org/10.1016/j.sigpro.2020.107646).
- [33] 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*, F. Hu, Ed., 1st ed. Boca Raton, FL, USA: CRC Press, Feb. 2019, pp. 189–208.



TIANYU CAO received the B.E. and M.E. degrees in information and communication engineering from the College of Underwater Acoustic Engineering, Harbin Engineering University, China, in 2015 and 2018, respectively. He is currently pursuing the Ph.D. degree with the School of Electronics and Information Engineering, Tongji University, China. His research interests include intelligent signal and information perception, non-stationary signal processing, and marine acoustic signal analysis.



MENGQI BIAN received the B.E. degree in electronics information engineering from Southwest Jiao Tong University, China, in 2020. He is currently pursuing the Ph.D. degree in information and communication engineering with the School of Electronics and Information Engineering, Tongji University, China. His research interests include target sensing and localization, reconfigurable intelligent surface, and signal processing.



YICHEN YANG received the B.S. degree from Harbin Engineering University, China, in 2016, and the M.S. degree from the Huazhong University of Science and Technology, China, in 2018. He is currently pursuing the Ph.D. degree with the Department of Information and Communication Engineering, College of Electronic and Information Engineering, Tongji University, China. His research interests include control of connected vehicles and signal processing.



ZHONGWEI XU received the B.S. and M.S. degrees from the College of Information Science and Engineering, Ocean University of China, Qingdao, China, in 2007 and 2010, respectively. He is currently pursuing the Ph.D. degree with the School of Electronics and Information Engineering, Tongji University, China. From 2010 to 2022, he was an Engineer with CSSC Haiying Enterprise Group Company Ltd., Wuxi, China. His research interests include sonar equipment development and remote sensing image processing.



XIAOQUN ZHAO was born in Heilongjiang, China, in March 1962. He received the B.E., M.E., and Dr.E. degrees from the Harbin Institute of Technology, Harbin, China, in 1982, 1985, and 1998, respectively. Since 2003, he has been a member of Tongji University, where he is currently a Professor with the Department of Information and Communication Engineering, College of Electronic and Information Engineering. He is a member of the *Journal of Electronics & Information Technology* (China), *Journal of Electronics* (China), and Chinese Institute of Electronics. His research interests include communication networks, information theory, speech signal processing and analysis, and complex signal processing.

...