A solution for preprocessing to select discrete spectral features of propeller-equipped marine targets to enhance passive acoustic direction-finding accuracy

Nguyen Thanh Chinh*, Mac Duy Tuyen, Nguyen Van Sang, Nguyen Van Vuong

Naval Technical Institute, Vietnam People's Navy, 9 Mac Quyet, Hung Dao, Hai Phong, Vietnam.
*Corresponding author: thanhchinhvkthq@gmail.com

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ABSTRACT

The low-frequency discrete spectral components generated by the propeller system of marine targets play a crucial role in signal processing, particularly in the problem of underwater acoustic direction finding. The preprocessing step to select these spectral components helps enhance the signal-to-noise ratio (SNR) of the signal input to direction of arrival (DOA) algorithms. This paper proposes a novel solution to improve the selectivity and accumulation of low-frequency line spectral components, which are key features in the detection and parameter estimation of underwater targets. The proposed method combines several classical signal processing techniques, including low-frequency analysis and recording (LOFAR), detection of envelope modulation on noise (DEMON), and adaptive recursive comb filtering (AR-COMB). This combination enhances the input signal's SNR, providing improved quality for subsequent processing stages, especially DOA estimation. Simulation results demonstrate a significant improvement in the accuracy of the DOA algorithm, suggesting a new approach for detecting and characterizing this type of underwater target.

Keywords: Underwater; Passive sonar; Direction of arrival (DOA); Marine target; Propeller.

1. INTRODUCTION

Passive DOA is a complex problem in the field of signal processing. Solving this problem not only requires the implementation of sophisticated algorithms but also necessitates additional evaluations of noise models, useful signal models, and the impact of environmental acoustic propagation parameters [8, 14]. In recent years, numerous studies have been published in this field [3, 4, 6]. Accordingly, the foundations for constructing the spatial spectrum functions for DOA estimation have been investigated from various perspectives, including subspace decomposition, spatial-time-frequency distribution [11], and sparse representations [7]. In addition, AI-based solutions for the DOA problem have also been proposed [9, 10].

Preprocessing of underwater acoustic signals to enhance the SNR for DOA estimation is a widely used concept. Techniques such as LOFAR, DEMON, or a combination of both have been proposed and applied for a long time [5]. These techniques aim to isolate and select low-frequency bands containing the line spectra characteristic of the propeller system of marine targets, thereby enhancing target selection efficiency in signal processing systems. However, such signals are still significantly affected by noise, caused by mechanical inconsistencies of the propeller structure and operational disturbances. Nevertheless, the cyclic nature of signals from propeller-driven targets remains a stable and distinguishing feature of this type of source. Based on this property, comb filters can be applied to selectively extract useful signals, leading to significant performance improvements for LOFAR and DEMON. In [12], the authors proposed a solution that combines LOFAR, DEMON, and a comb filter (COMB) to detect shaft rotation frequencies in signal processing. However, this study was limited to deep learning networks using sample datasets, and the comb filter parameters, as well as their formulation and application mechanisms, were not thoroughly analyzed, lacking discussion on adaptability in real-world processing scenarios.

Building upon these analyses, this paper proposes a novel approach that combines the selection of discrete spectral features specific to propeller-driven marine targets with DOA algorithm based on spatial-time-frequency distribution (STFD). Furthermore, the use of AR-COMB in passive sonar systems is, for the first time, introduced as a solution in this line of research.

2. PROBLEM

2.1. Signal model

Radiated noise from marine targets has a complex structure, composed of various components with different characteristics and structures. Among these, the noise generated from propellers has many unique and important characteristics, often considered useful signals in sonar signal processing. The mathematical model of propeller noise is as follows [5, 14]:

$$s(t) = [s_D(t)] + [s_C(t)] \tag{1}$$

where $[s_D(t)]$ represents low-frequency discrete-spectrum noise, and $[s_C(t)]$ represents broadband continuous noise. Due to the hydrodynamic interaction between the propeller system and the water, especially the cavitation phenomenon, the envelope of $[s_C(t)]$ is modulated by the low-frequency components $[s_D(t)]$ to a certain extent. Whereas, $[s_D(t)]$ can be shown in detail form [14]:

$$s_D(t) = \sum_{l=1}^{LL} A_l \cos\left(2\pi l f_r t + \varphi_l\right) \tag{2}$$

where LL is the total number of harmonic components of $s_D(t)$, A_l and φ_l are the corresponding amplitude and random phase of the *l-th* harmonic component, $l = \overline{1, LL}$. Thus, the signal $s_D(t)$ will contain the harmonics of the shaft frequency f_r and the blade frequency f_b. If the propeller has N_r blades, the blade frequency f_b of the propeller is calculated as:

$$f_b = N_r f_r \tag{3}$$

The signal model of the sonar system is established as follows: suppose there are Q targets in the observation area located at angles $\left[\theta_1, \theta_2, ..., \theta_Q\right]$, each emitting noise that is received by a uniform linear array (ULA) (with M sensors). The antenna model is represented in figure 1.

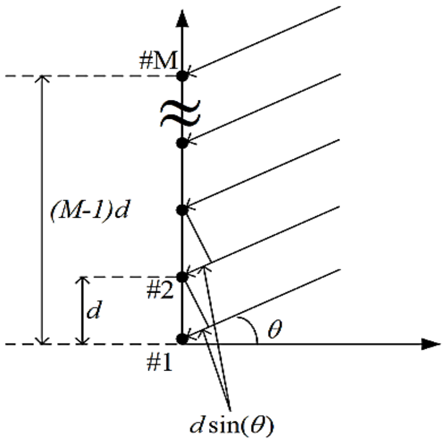

Figure 1. *ULA antenna model.*

The received signal can be expressed as:

$$f_b = N_r f_r \tag{4}$$

Here, $\mathbf{Y} = \left[\mathrm{y}_1(t), \ldots, \mathrm{y}_M(t) \right]^T$ is the matrix of received signals on the antenna array elements, $\mathrm{Y} \in \mathbb{C}^{M \times L}$ (where L is the number of processed snapshots); $\mathbf{S} = \left[\mathrm{s}_1(t), .., \mathrm{s}_Q(t) \right]^T$ is the matrix of source signals, $\mathrm{S} \in \mathbb{C}^{Q \times L}$ while assumes a total of Q sources; $\mathbf{A} = \left[\mathrm{a}(\theta_1), \ldots, \mathrm{a}(\theta_Q) \right]$ is the steering matrix representing the antenna array's response to the source signals, $\mathrm{A} \in \mathbb{C}^{M \times Q}$, where each column of $\mathbf{A}$ corresponds to a source signal; $\mathbf{N} = \left[\mathrm{n}_1(t), \ldots, \mathrm{n}_M(t) \right]^T$ is the matrix of additive noise affecting the system, with dimensions $\mathrm{N} \in \mathbb{C}^{M \times L}$.

2.2. Solution

2.2.1. Discrete spectral line characteristic of marine propeller targets selection based on combined techniques LOFAR, DEMON and AR-COMB

In typical situations, the received signal $s(t)$ may consist solely of background noise $[n(t)]$, or background noise combined with one of the other two components ($[s_D(t)]$ and $[s_C(t)]$), or all three components. When the components $[s_D(t)]$ dominate, the LOFAR algorithm is effective, whereas when $[s_C(t)]$ dominates, the DEMON algorithm is more commonly used [12]. However, in most cases, when there is no prior information about the dominant region in the noise spectrum, a combination of LOFAR and DEMON is common for signal processing. The functional block diagram of the combined LOFAR and DEMON algorithm (LDC) is shown in figure 2.

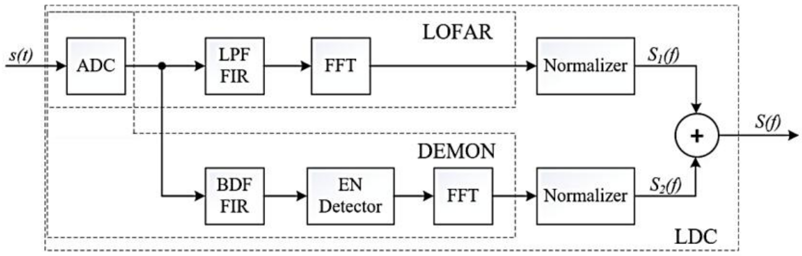

***Figure 2**. Functional block diagram of the LDC algorithm.*

This diagram includes the use of abbreviations as below. ADC: Analog to Digital Converter; LPF FIR: Lowpass Filter – Finite Impulse Response; BDF FIR: Bandpass Filter – Finite Impulse Response; FFT: Fast Fourier Transform; LDC: LOFAR - DEMON Composition; EN Detector: Envelope Detector. According to this, the LDC algorithm ensures an increased chance of selecting the low-frequency discrete spectral components of the signal. After the signal is processed and passed through normalizers, $S_1(f)$ is the normalized spectrum of the LOFAR branch, $S_2(f)$ is the normalized spectrum of the DEMON branch, and $S(f)$ is the synthesized spectrum of the output signal after LDC. If the input signal contains propeller noise components, this algorithm guarantees the separation of the low-frequency discrete spectrum without regard to which component, $s_D(t)$ or $s_C(t)$, is dominant.

2.2.2. Adaptive recursive comb filter in propeller noise signal processing

In passive sonar, when receiving noise signals from marine targets with propellers, the COMB can also be applied based on a similar principle to periodic cancellation used in active systems. In this case, the delay period is set equal to the rotation period of the detected target's propeller shaft, $T_r = 1/f_s$ [15]. The structural diagram, selection analysis of the filter type, and related coefficients of the COMB are presented below [13]. The chosen filter model is the recursive comb filter with the structural diagram shown in figure 3.

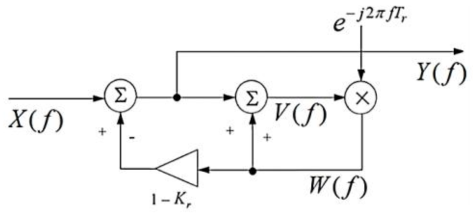

Figure 3. *The frequency domain structural diagram of recursive COMB.*

In this structure, instead of summing the input signal with its delayed version, a recursive process is proposed as a replacement to improve the filter's efficiency. Accordingly, the difference equation system of the filter is:

$$\begin{aligned} y(t) &= x(t) - (1-K_r)w(t) \\ v(t) &= y(t) + w(t) \\ w(t) &= v(t-T_r) \end{aligned} \tag{5}$$

where, K_r is the feedback ratio of R-COMB.

Apply the z-transform to the system of equations (5) and compute the transfer function $H(z) = Y(z)/X(z)$, then:

$$H(z) = \frac{1-z^{-1}}{1-K_r.z^{-1}} \tag{6}$$

The squared magnitude of the transfer function $H(z)$ and note that $z + z^{-1} = 2\cos(\omega T_r)$, will yield the squared amplitude–frequency response of the R-COMB filter:

$$\left|H(e^{j\omega T_r})\right|^2 = \frac{2(1-\cos(\omega T_r))}{\left(1+K_r^2\right) - 2K_r\cos(\omega T_r)} \tag{7}$$

Thus, in order to apply the filter in passive sonar, it is essential to have information about the shaft frequency f_s. This propeller's shaft frequency is detected based on the accumulated spectrum of the signal after LDC processing. The module that performs this function is called frequency bins selection and source number estimation (FBS&SNE) [16]. The combination of recursive COMB and FBS&SNE results in an adaptive recursive comb filter, referred to as AR-COMB. If $K_r = 0$, AR-COMB becomes typical COMB without feedback. Besides, K_r is chosen to be less than 1 to avoid oscillations caused by positive feedback in the filter. Normally, the value of $\left(1-K_r\right)^{-1}$ equal to the number of spectral lines to be selected in the received signal. For example, if 10 spectral lines are needed, then select $K_r = 0{,}9$.

2.2.3. A DOA estimation algorithm applied to signals with selected characteristic discrete spectral components

The combination of LDC, FBS&SNE, and AR-COMB forms an adaptive pre-processing method for selecting characteristic discrete spectra of marine propeller targets in passive sonar signal processing (bins selection: BS). The functional block diagram of the BS solution is shown in figure 4.

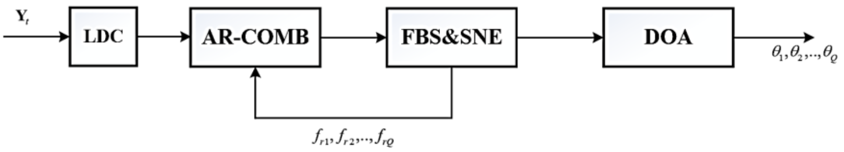

Figure 4. *The combination of BS solution and a DOA algorithm.*

Accordingly, the signal received at the output of the antenna array Y_t is digitized by ADC modules to obtain the digital signal Y_n. Next, the digital signal Y_n is passed through the LDC component to select the low-frequency region containing the characteristic discrete spectrum. The output of LDC is the frequency-domain signal Y_f. This signal Y_f is then passed through the AR-COMB filter to retain only the frequency components that are harmonics of the shaft and blade rotation frequencies $\left(f_s, f_b\right)$ of the propeller.

Simultaneously, the FBS&SNE algorithm estimates the number of targets Q and selects a set of useful frequencies, along with the corresponding covariance matrix Ω of the selected spectral bins. In addition, the estimated shaft frequencies of the targets $f_{s1}, f_{s2}, .., f_{sQ}$ are fed back to the AR-COMB filter to adaptively tune the comb resonance frequencies. Selected signal leads to a DOA estimation to evaluate angles.

3. RESULTS AND DISCUSSION

3.1. Input data

The antenna array data is semi-simulated, generated by using a single acoustic sample and artificially assigning a simulated DOA. This acoustic sample is selected in one of two ways: either through simulation or by choosing audio samples from a database ASMD [1, 2]. The signal generation model for the ULA receiving array is based on the assumption that the target emits a sound signal $s(t)$ from direction θ. Under this assumption, the received signal of the array is formulated as follows:

$$y_m(t) = s\left(t-(m-1)\tau\right), \tag{8}$$

Where $y_m(t)$ is the signal received at the *m-th* antenna element, and $\tau = d\sin\theta / c$, with *c* is the speed of sound in water and *d* is the spacing between array elements.

3.2. Simulation results and comments

MATLAB R2022b software is used for data generation and result computation. Two audio files are used: file number 16 (#16) and file #30 from the ASMD database. The first sample is simulated with a target direction of -10°, and the second sample with a target direction of +30°. Along with the BS method, the characteristic energy region selection technique on the time–frequency plane (CSS) [17] is also employed to improve the accuracy of the STFD-DOA algorithm. The data samples have a sampling frequency of 16 kHz. However, since the characteristic discrete frequencies should only be considered within the $1 \div 100$ Hz band, the sampling frequency is reduced to 1 kHz for the simulation. In this simulation, the STFD window is set to $2^{10} \times 2^{10}$. Accordingly, the STFD representation of the mixed is shown in figure 5. The pseudo-spectrum of algorithms is presented in figure 6.

In the STFD representation, the characteristic energy regions are formed by discrete spectral components whose frequencies correspond to the shaft and propeller blade rotation frequencies. These appear as straight lines parallel to the time axis, distinguishable from the background level. The BS-CSS-STFD DOA algorithm selects these characteristic lines to construct the STFD matrix for processing. Thus, the main effect of the signal preprocessing step is to highlight the useful information of the target, specifically by making the energy corresponding to the shaft rotation frequency of the propeller and its harmonics stand out clearly from the background (thereby increasing the SNR). Utilizing the results of this preprocessing step for direction finding yields higher accuracy compared to conventional approaches.

With this semi-simulated signal, all methods perform well and provide accurate results based on the defined simulation parameters and the selected audio samples. Notably, the BS-CSS-STFD

DOA algorithm demonstrates superior peak-background-level (PBGL), achieving a PBGL of approximately 28 dB, along with narrower beamwidth and higher resolution. In contrast, the conventional STFD algorithm only achieves a PBGL of 8 dB.

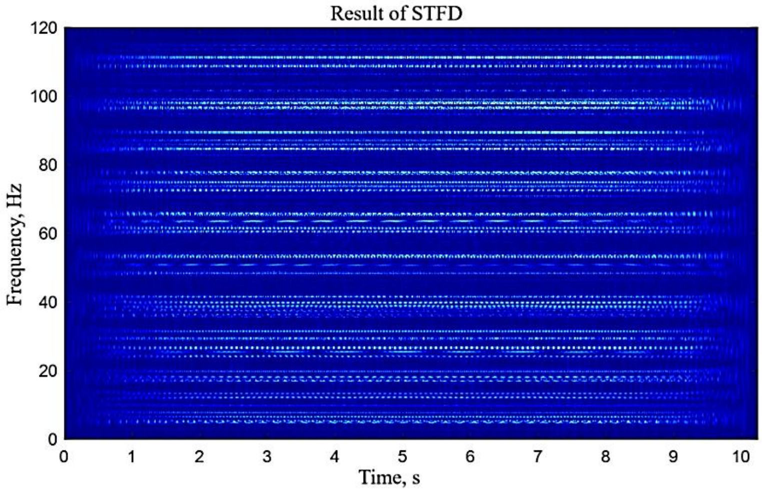

Figure 5. *STFD result of input data.*

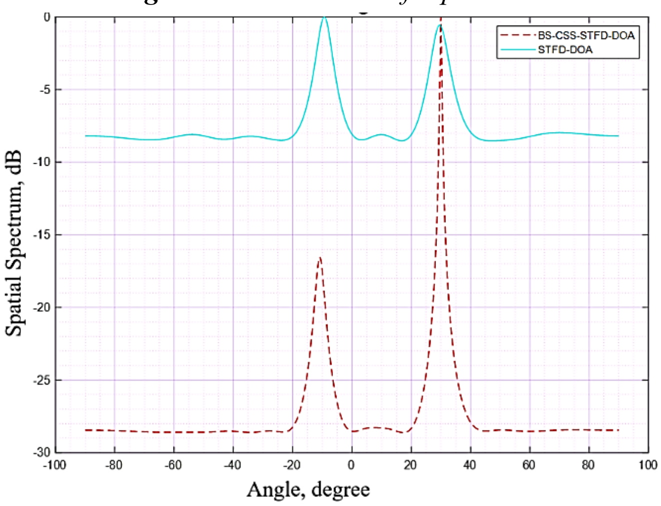

Figure 6. *Result of the new DOA method compared to traditional STFD DOA.*

3.3. Accuracy assessment of the proposed solution

In the case of normal propagation (there is only one propagation path from the target to the antenna), the root mean square error (RMSE) evaluation results are shown in figure 7.

The analysis results show that in the low-noise region (when SNR is high in dB), both algorithms perform equally well. This can be explained by the fact that the signal energy significantly surpasses the noise energy, ($SNR > 0$ dB). Therefore, whether selecting only the signal energy region or both signal and noise regions, the signal still dominates. However, in the high-noise scenario (low SNR in dB), selecting the energy region corresponding to the true useful signal source significantly improves performance compared to averaging all points across the time-frequency (t-f) plane. Strong noise leads to increased RMSE, with varying degrees across different algorithms. At an $SNR = -10$ dB, the BS-CSS-STFD approach achieves an RMSE of approximately 0.45°, while the standard STFD algorithm yields an RMSE of 1.4°, more than three times higher than the proposed method.

Assuming multipath propagation in the case of target 2: Only target No. 2, simulated by acoustic sample #30, is considered. The signal propagates to the antenna via three paths: the direct path; the path reflected once from the sea surface with 65% energy loss; and the path reflected once from the seabed with 60% energy loss. The sea depth is 100 m, the sea surface has 30 cm waves, and the seabed consists of sand–mud material. The RMSE evaluation results are shown in figure 8.

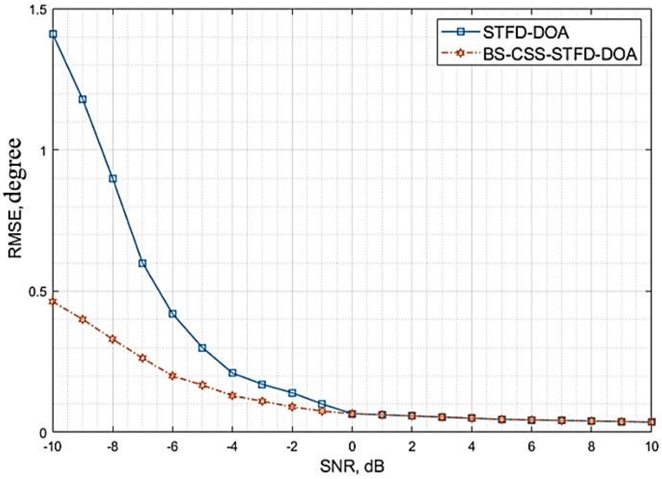

Figure 7. *RMSE of BS-CSS-STFD and STFD in normal conditions.*

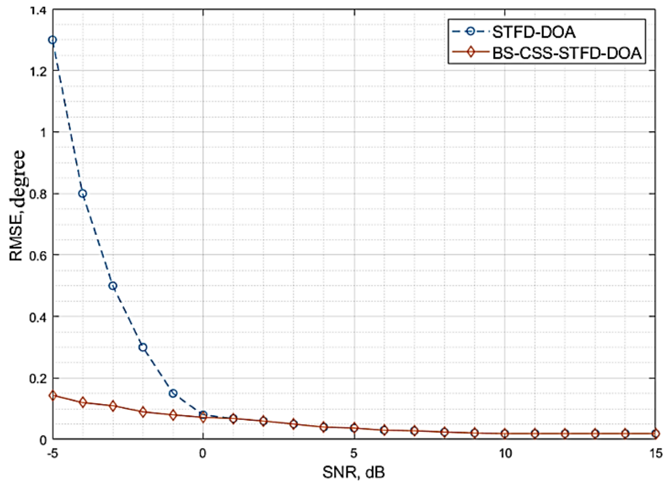

Figure 8. *RMSE of BS-CSS-STFD and STFD in the case of multipaths*

The results show that when the SNR is high $(SNR > 0 \text{ dB})$, both algorithms yield the same level of accuracy. However, as the noise power increases, the error of the traditional STFD method rises sharply, reaching an error of over 1.30° at $SNR = -5$ dB. In contrast, the proposed BS-CSS-STFD method still maintains an acceptable error level of 0.15°.

In addition, the BS-CSS-STFD DOA method is capable of multi-target direction finding when the targets are distinguishable in terms of characteristic frequency, direction, range, or any combination of these factors. The degree of discrimination depends on several factors, such as SNR, antenna structure and sensitivity, and the processing window size. However, if the targets have characteristic discrete frequencies differing by more than 0.2 Hz, or are located at azimuth angles differing by more than 0.5°, and the signal quality is sufficiently good, the BS-CSS-STFD DOA method can determine that they are distinct targets.

4. CONCLUSIONS

In conclusion, the proposed solution exhibits higher accuracy compared to conventional direction-finding algorithms built upon similar theoretical foundations. By selectively extracting the characteristic discrete spectral components associated with propeller-driven marine targets, the method effectively enhances SNR. This improvement contributes to an increase in PGBL and significantly refines the accuracy of the direction-of-arrival estimation.

To ensure realism and reliability, the simulations were conducted using a semi-synthetic array data generation approach, which integrates real-world acoustic recordings. This not only validates the robustness of the proposed method under practical conditions but also provides a promising pathway for further advancements in passive sonar system development, particularly in complex and noisy underwater environments.

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TÓM TẮT

Một giải pháp tiền xử lý để lựa chọn các đặc trưng phổ rời rạc của mục tiêu biển có chân vịt nhằm nâng cao độ chính xác của định hướng thủy âm thụ động

Các thành phần phổ rời rạc tần số thấp do hệ thống chân vịt của các mục tiêu trên biển tạo ra đóng vai trò quan trọng trong xử lý tín hiệu, đặc biệt trong bài toán định hướng âm thanh dưới nước. Bước tiền xử lý để chọn lọc các thành phần phổ này giúp nâng cao tỷ số tín hiệu trên nhiễu (SNR) của tín hiệu đầu vào cho các thuật toán ước lượng hướng đến (DOA). Bài báo này đề xuất một giải pháp mới nhằm cải thiện khả năng chọn lọc và tích lũy các thành phần phổ đường tần số thấp, vốn là những đặc trưng then chốt trong phát hiện và ước lượng tham số của mục tiêu dưới nước. Phương pháp được đề xuất kết hợp một số kỹ thuật xử lý tín hiệu kinh điển, bao gồm phân tích và ghi tần số thấp (LOFAR), phát hiện điều biên trên nhiễu (DEMON), và lọc lược thích nghi hồi quy (AR-COMB). Sự kết hợp này giúp tăng SNR của tín hiệu đầu vào, nâng cao chất lượng cho các bước xử lý tiếp theo, đặc biệt là ước lượng DOA. Kết quả mô phỏng cho thấy độ chính xác của thuật toán DOA được cải thiện đáng kể, gợi mở một hướng tiếp cận mới trong phát hiện và đặc trưng hóa loại mục tiêu dưới nước này.

Từ khoá: Ngầm; Sonar thụ động; Định hướng (DOA); Mục tiêu biển có chân vịt.