

Research Article

A Novel Efficient Passive Spatial Orientation Detection Method of UMT Enabled by ISB

Zhengqiang Xiong,¹ Tao Sun ,¹ Zhengxing Wang,² Yuhao Wu,¹ and Jie Yin¹

¹The Department of Electrical and Information, Wuhan University, Wuhan 430072, China

²State Key Laboratory of Bridge Structure's Health and Safety, Wuhan 430034, China

Correspondence should be addressed to Tao Sun; suntao@whu.edu.cn

Received 15 June 2020; Revised 1 July 2020; Accepted 1 September 2020; Published 28 September 2020

Academic Editor: Chaoqun Duan

Copyright © 2020 Zhengqiang Xiong et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The passive detection and direction-of-arrival (DOA) estimation problem is of great importance in many underwater applications such as target reconnaissance and data collection. In this paper, an Efficient Correlation-based Orientation Detection (ECOD) method is proposed to achieve high efficiency. Without high computational complexity in any Transform Domain, the time consumption of ECOD is largely reduced, which is especially critical for underwater intrusion detection, territorial waters protection, and many other real-time underwater applications. To achieve good invisibility, we design an intelligent submerged buoy (ISB) structure, which consists of six embedded hydrophones and an in situ electronic control unit (IECU). As a supplement to solutions against complex underwater environments, a hybrid ECOD method is also developed by involving the cooperation from underwater distributed sensor networks. To be specific, when high SNR signals are not recorded by a single ISB node, other distributed sensors are scheduled to assist in cooperative sensing. Simulation experiments demonstrate the efficiency of the ECOD method in passive 3D spatial orientation of underwater acoustic target and show that the ECOD method has a better performance in time consumption compared with general DOA algorithms.

1. Introduction

Passive spatial detection and orientation estimation of a moving acoustic target is of great importance in many underwater applications [1, 2]. For example, tracking adversary targets, involving submarines and Autonomous Underwater Vehicles (AUV), are critical for security purposes [3, 4]. Also, with regard to biological research, it is beneficial to obtain the rough position and spatial behaviour features of marine creatures [5]. In addition, sensing underwater moving abnormal objects is potentially helpful to disaster forecast and relevant protection [6]. Hence, it is very important to develop effective underwater detection and spatial orientation technologies.

1.1. Motivations and Challenges. There are major considerations and challenges for underwater spatial orientation detection. Due to difficulties in deployment and maintenance,

the devices carrying out underwater detection should feature extremely low complexity and energy consumption, which may undermine the accuracy of detection results [7]. Additionally, it is widely proved that the underwater acoustic channel suffers from limited bandwidth, serious multipath effect, and high latency, which leads to packet loss and error bits, interfering the interdevice communications [8]. Furthermore, for homeland security applications, the deployed devices and interdevice communication signals can be possibly be exposed to adversary targets [9]. Therefore, the underwater passive detection and spatial orientation strategy is supposed to be extremely efficient, i.e., low complexity, energy saving, and stable with favorable invisibility.

Several research studies have been carried out in the fields of underwater detection and orientation. In [10], performances of well-known techniques implemented by a single acoustic vector sensor (AVS) are studied. Though the performance of practical AVS-based systems provides a

valuable insight, the cost of an acoustic vector sensor is still much higher than omnidirectional ones. Zou et al. [11] raises a two-step approach to reduce the complexity of AVS-based direction of arrival (DOA) estimation within a spatial sparse representation framework. In [12], the DOA estimation is achieved by a matrix-pencil pair derived from time-delayed signals collected from a single AVS. However, the very high computational payload significantly decreases the practicability of above methods. Disregarding the usage of AVS, the DOA and relevant techniques are common for precise localization. Shao et al. [13] develop efficient closed-form angle-of-arrival- (AOA-) based self-localization algorithms to improve the localization accuracy. In [14], the effectiveness of two novel positioning schemes based on n time-of-arrival (TOA) measurements is validated. A time difference of arrival (TDOA) algorithm for passive localization via estimating the delay of two correlated channels is proposed, which outperforms other TDOA algorithms [15]. However, most of AOA, TOA, and TDOA approaches are algorithms with high computational payload, which is a challenging difficulty to interdevice time synchronization. Moreover, both vector sensors and distributed sensors need to transmit recorded signals by wireless channel back to a control centre for decision, leading to more unreliability. In [16], the proposed trilateration algorithm achieves precise underwater target positioning by utilizing received signal strength indicator (RSSI) value, which is generally obtained by the signal transmission power. Nevertheless, due to lack of priori knowledge of noncooperative targets, we can hardly know the target's signal transmission power.

1.2. Contributions and Organization. Compared with existing research works, the specific contributions of this paper are given below:

An intelligent submerged buoy (ISB) structure is designed, which consists of an intelligent control board and three pairs of embedded hydrophones. Components of the ISB are integrated into a sphere structure, which contributes to receive signals from omnidirections and effectively reduce flow resistance for position stabilization.

An ECOD method is developed. Its efficient performance is achieved by a low-complexity crosscorrelation algorithm of input signals for each hydrophone pair. Without high computational complexity in any Transform Domain, the time consumption of the method is largely reduced, which is especially critical for some real-time applications including underwater intrusion detection and territorial waters protection.

A Hybrid ECOD method is proposed. Other ISBs distributed in surrounding underwater sensor networks will join in to improve the spatial orientation estimation accuracy if some ISBs do not provide good sensing performance or fail to work, aiming to improve the stability of the ECOD method further. The remainder of this paper is organized as follows. Section 2 describes the underwater orientation detection system.

The ECOD method is proposed in Section 3, and Hybrid ECOD method, a cooperative detection, and orientation strategy are developed. Numerical experiment results are presented and discussed in Section 4. Section 5 draws a conclusion.

2. System Model

For traffic control in harbors or a homeland security sensitive sea area monitoring, a moving acoustic targets passive detection and spatial orientation system is designed for 3D underwater space, as shown in Figure 1. Several submerged buoys are anchored on the seabed, which are able to passively and continuously receive acoustic signals from underwater targets. Each submerged buoy is designed to be a compact sphere structure to provide stable connections with six embedded hydrophones.

Let equation (1) be the signal received by the m^{th} hydrophone in time domain:

$$y_n(t) = x_m(t) + n_m(t), \quad (1)$$

where $x_m(t)$ represented the received signal from the target and $n_m(t)$ denoted the additional noise. To simplify the calculation, continuous-time signals are truncated and discretely sampled. The acoustic signal monitored by the m^{th} sensor during $N\Delta t$ is then described as follows:

$$s_m = [y_m(1), \dots, y_m(n), \dots, y_m(N)], \quad (2)$$

where $y_m(n)$ is the n^{th} sample of the received signal and N is the sampling number.

In order to improve azimuth resolution and signal-noise ratio, the hydrophones are deployed as sensor arrays. The received signals are synchronously recorded by embedded hydrophones and processed simultaneously by the in situ control unit (IECU) on each submerged buoy. Because of varies noisy from marine animals, a prejudgment mechanism has also been developed to eliminate those incoherent signal, which is explained in Section 3.2. For energy conservation, orientation estimation is carried out on the basis of the above operation.

3. Intelligent Submerged Buoy-Enabled Target Orientation Detection

In this section, an efficient target orientation detection strategy enabled by intelligent submerged buoy (ISB) is proposed.

3.1. The Structure of the Intelligent Submerged Buoy. The basic idea for the submerged buoy enabled method is that the intelligent buoy is a relatively autonomous system to undertake the entire task during passive spatial detection and DOA detection independently. The control board sends commands to embedded hydrophones, as shown in Figure 1, makes decisions, and has wireless acoustic communications ability with the control centre on shore.

For high-effective signal sampling to analyze spatial orientation, an ISB consists of six embedded hydrophones

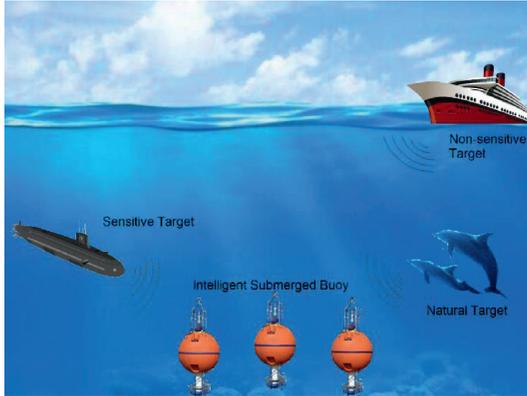


FIGURE 1: System model of the underwater acoustic detection system for moving target.

orthogonally distributed in 3D Cartesian coordinate, which is shown in Figure 2. The hydrophone array is divided into three pairs to be responsible for three dimensions, i.e., north-south (N-S), west-east (W-E), and up-down (U-D). Each pair of hydrophones collects the signal in one assigned dimension, which avoids redundancy in sensor deployment. Moreover, the invisibility of ISB is improved by aggregating IECU and hydrophones together into a sphere structure. The submerged buoy achieves independent low-complexity orientation computation enabled by the intelligent board and its received signals.

The structure design of the intelligent submerged buoy is inspired by the human auditory system. It is well known that the human auditory system consists of two ears and the auditory centre in the head, as shown in Figure 3. The sound source is localized by time delay estimation between each cochlea. Similarly, each pair of hydrophones receives acoustic signals transmitted from underwater targets and the in situ electronic control unit (IECU) functions as “auditory centre” by processing these received signals.

The shape of submerged buoy is approximately as a sphere, and the three pairs of hydrophones are exactly orthogonally distributed in three spatial dimensions, as illustrated in Figure 2. Each pair of hydrophones can judge that the target’s location lies in the same side of the positive axis or the negative one in the dimension where they are distributed as far as a 3D spatial coordinate is established with the ISB as its origin. On this basis, the IECU estimates the orientation of the underwater target through a synthesis processing of these three groups of signals, which contains direction information in their dimension, respectively.

3.2. Predetection of Underwater Acoustic Targets. Table 1 shows the frequency range of acoustical signals generated by some typical underwater targets. Since the power spectrum of pure background noises differs a lot from that of a signal of underwater acoustic targets, the power spectrum of received signals for the in-device hydrophones is applied to target detection (judge an underwater acoustic target is out of detection range or not, through its energy distribution in the power spectrum). For each received signal of in-device

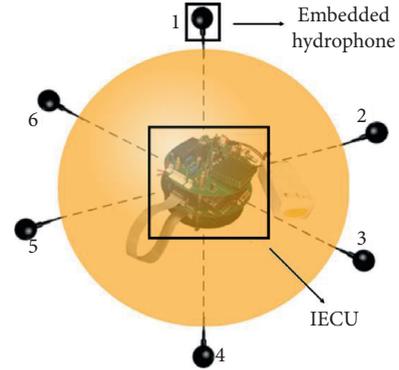


FIGURE 2: Components of an intelligent submerged buoy (ISB).

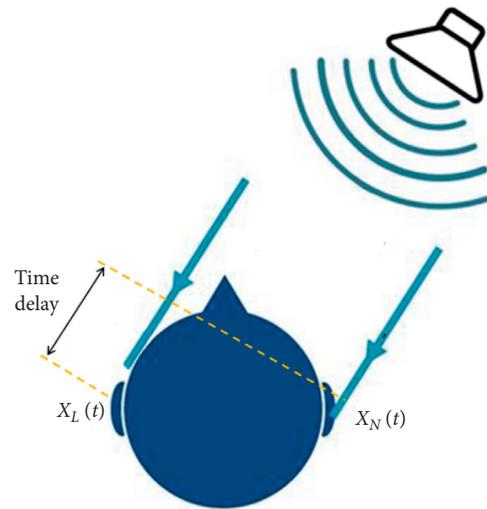


FIGURE 3: Orientation principle of the human auditory system.

TABLE 1: Frequency range of acoustical signals generated by some typical underwater targets.

Types of underwater target	Frequency range (Hz)
Whale	10–40
Toadfish	200–300
Ship	50–1000
Submarine	100–1000
Dolphin	7000–120000

hydrophone, the power spectrum can be obtained through Short-Time Fourier Transform (STFT):

$$\text{STFT}(n, \omega) = \sum_{m=-\infty}^{\infty} [y_i(m) \cdot w(n-m)] \cdot e^{-jm\omega}, \quad (3)$$

where $y_i(m)$ is the m^{th} sample of the signal received by the i^{th} hydrophone and $w(m)$ denotes the window function.

Considering the difficulty in battery replacement for the underwater system, several methods have been adopted for energy conservation. Since hydrophones receive only background noises without any available signal of target for most of the time, it is unnecessary for the IECU to keep

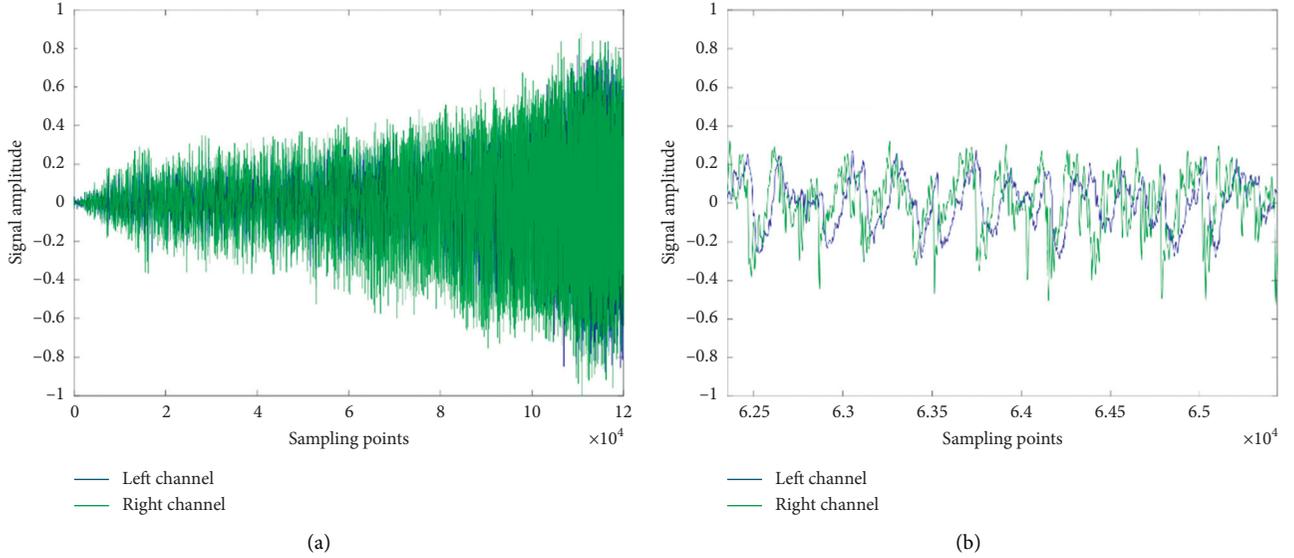


FIGURE 4: A dual-channel signal waveform of engine shipping noise recorded at East Sicily: (a) complete waveform and (b) a certain part of this signal.

working all the time. Accordingly, a threshold based on statistical characteristics of the overall spectrum is set to wake up the sense module. In this way, the central IECU is able to figure out potential threatens approaching the detection area in time, while ignoring some natural or cooperative targets to save energy.

3.3. The Efficient Correlation-Based Orientation Detection (ECOD) Method. Sound source localization algorithms mainly consist of two key components: azimuth and distance estimation. The range estimation is generally achieved by power attenuation calculation. However, it is arduous to figure out the signal strength of acoustic source due to the passive listening mechanism taken in our method. Hence, this work focuses on the orientation detection problem.

The spatial behaviour features (relative position, moving direction, etc.) of the underwater acoustic target are acquired by a dual-channel signal and its associated waveform time delay analysis. Considering that a target's relative position varied over time in realistic applications, the input signal is segmented into frame sequences. Let $y_L(n)$ and $y_R(n)$ be the time sequence of left and right channels, respectively; then, the crosscorrelation function of them is formulated as

$$R_{LR} = \frac{1}{N} \sum_{k=n}^{n+N-1} y_L(k) \cdot y_R(k-m), \quad (4)$$

where N is frame length and m represents the amount of displacement of $y_L(n)$ and $y_R(n)$.

In order to extract features of realistic underwater acoustic signals, some measured data are adopted in this paper. A part of engine shipping noise was recorded at East Sicily by the observatory NEMO set by the Laboratory of Applied Bioacoustics (LAB) of the Technical University of Catalonia (Barcelona Tech, UPC). Figure 4 shows the waveform of this dual-channel signal.

We can see that the amplitudes of both the left and right channels grow gradually for the whole process. This indicates the target is getting closer to the ISB as time goes by. Moreover, the green curve corresponding to the right channel stays ahead of the blue one, which demonstrates that the target approaches the ISB from the right side.

Since structures of acoustic signal waveform of both channels are similar to each other except a slight time delay between them, the maximal crosscorrelation coefficient can be determined via time delay estimation (TDE). Due to their approximate waveforms, the displaced right channel signal is approximated as copy of left channel signal. That is to say $y_R(n-D) \approx y_L(n)$. Then, the corresponding cross-correlation coefficient can be presented as follows:

$$R_{LR} = \frac{1}{N} \sum_{k=n}^{n+N-1} [y_L(k)]^2 = \frac{E_n}{N}, \quad (5)$$

where E_n denotes short-time energy.

The next step is to figure out the maximal cross-correlation coefficient M and corresponding TDOA (Time Difference of Arrival) D of left and right channels. Since the received signals from each pair of hydrophone are similar in time domain, the crosscorrelation coefficient reaches the maximum as time delay from corresponding channels is zero. According to the analysis above, M can be employed to estimate the distance between the ISB and target. This operation is illustrated in Figure 5. Let D be the time delay between acoustic signals of discrete time received by the right and left channels. To acquire the maximal crosscorrelation coefficient, signals from the right channel are translated to eliminate the time delay. Afterwards, D can also be defined as the TDOA via this operation, which contributes to identify the target bearing. We can see from Figure 5 that the target is on the left side of the observation point.

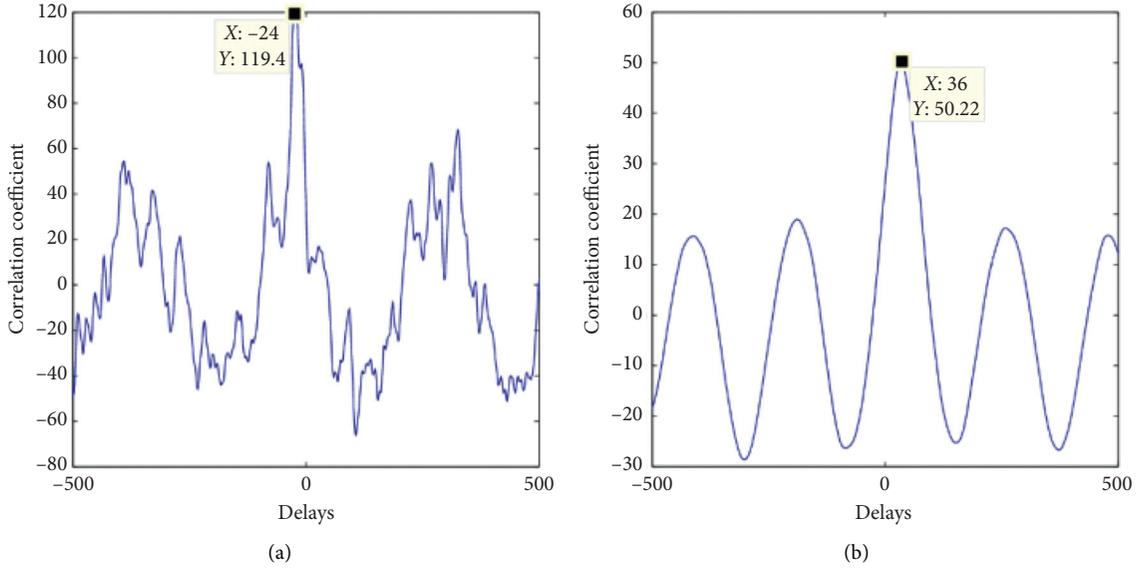


FIGURE 5: Peak search of the crosscorrelation coefficient: (a) the time delay of the maximal crosscorrelation $D > 0$ and (b) the time delay of the maximal crosscorrelation $D < 0$.

Since ISBs are fixed to the seabed, the possible location areas of underwater acoustic targets can be divided into 4 quadrants (quadrant I–quadrant IV in Figure 6). In far field applications, both the target and the ISB can be assumed to be a point source, since its dimensions are much smaller compared with the acoustic wavelength. Thus, the wavefront incident on the ISB can be considered as planar wave [10]. As shown in Figure 7, the 3D spatial orientation of an underwater target relative to the ISB is described by a direction vector, which can be expressed with azimuth angle θ and elevation angle α .

Elevation angle α is able to be acquired once the angle between target direction vector and Z-axis is calculated, as shown in Figure 8. Assume that ΔL_{14} denotes the transmission distance difference of the planar wave between 1st hydrophone and 4th hydrophone (set in Z-axis), as demonstrated in Figure 8. The elevation angle α is given by

$$\alpha = \arcsin\left(\frac{\Delta L_{14}}{\Phi}\right) = \arcsin\left(\frac{V_w \Delta T_{14}}{\Phi}\right), \quad (6)$$

where V_w denotes the velocity of sound traveling underwater, ΔT_{14} denotes time difference of arrival between the 1st hydrophone and the 4th hydrophone, and Φ is the diameter of an ISB.

In order to estimate the azimuth angle θ , both angles with X-axis and Y-axis are needed. Let θ_i ($i = x, y$) be the angle between target direction vector and axis, as shown in Figure 9, when the target locates in area I, the azimuth angle θ is

$$\theta = \arctan\left(\frac{\cos \theta_y}{\cos \theta_x}\right) = \arctan\left(\frac{\Delta T_{25}}{\Delta T_{36}}\right). \quad (7)$$

Finally, the azimuth angle θ is described as follows:

$$\theta = \begin{cases} \arctan\left(\frac{\Delta T_{25}}{\Delta T_{36}}\right), & \text{in area I,} \\ 180^\circ - \arctan\left(\frac{\Delta T_{25}}{\Delta T_{36}}\right), & \text{in area II,} \\ \arctan\left(\frac{\Delta T_{25}}{\Delta T_{36}}\right) - 180^\circ, & \text{in area III,} \\ -\arctan\left(\frac{\Delta T_{25}}{\Delta T_{36}}\right), & \text{in area IV,} \end{cases} \quad (8)$$

where ΔT_{ij} denotes time difference of arrival between the i^{th} hydrophone and the j^{th} hydrophone. Target can also be approximated, combining with short-time energy analysis of the signal in different time periods. Although the exact transition energy intensity is unknown, our method is still able to efficiently identify the direction and movement trajectory relative to ISB. As it has been widely proved that the amplitude of crosscorrelation coefficient has a positive correlation with the target signal, the received signal power at each time is normalized. By this, the relative position can be determined.

3.4. A Hybrid ECOD Method. The proposed ECOD method is potentially vulnerable when the time delay between two channels is too short to be distinguished. To solve this, a robust orientation detection strategy enabled by cooperative sensing of underwater intersensor-network is developed. There are minor limitations for ECOD method enabled by a single ISB. Firstly, the time delay D would be too small to be distinguished when the target moves just in one of the three axis directions in the 3D Cartesian coordinate with an ISB

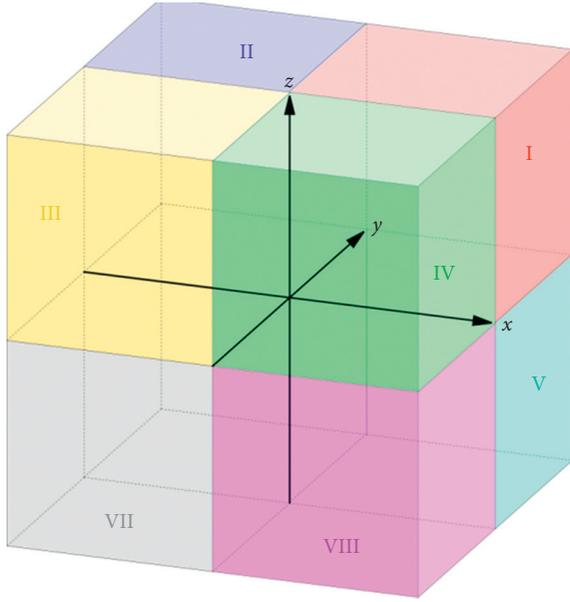


FIGURE 6: Preparatory division of underwater acoustic target's location areas.

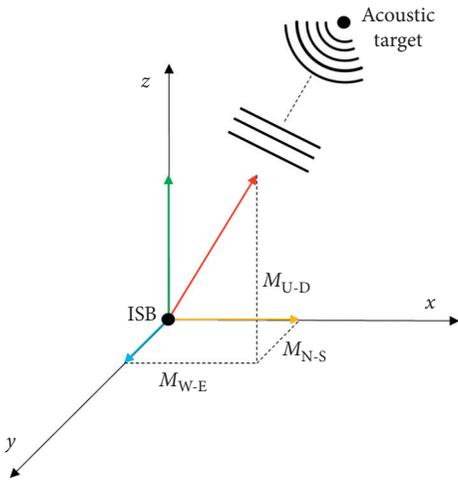


FIGURE 7: Explanation of a spatial direction vector.

located at the origin point. In the case of low SNR, the sign of D could even be the opposite from its real value. Furthermore, Method 1 for the comprehensive orientation detection would fail when one hydrophone in the submerged buoy is broken down. Hence, it is dispensable to take some assistant measures.

The distributed ISB nodes in underwater sensor networks provide critical assistance. Although it is highly costly for the distributed sensors to undertake all orientation detection tasks, it is reasonable to “ask” one or two sensor nodes for cooperation when necessary. When $|D| < \delta$, it indicates the target is nearly equally distant to those associated hydrophones in the submerged buoy. In this case, the ISB communicates with other ISB nodes distributed in the nearby underwater sensor network for cooperative sensing. In this way, the accuracy of orientation detection in corresponding dimension is significantly improved. This

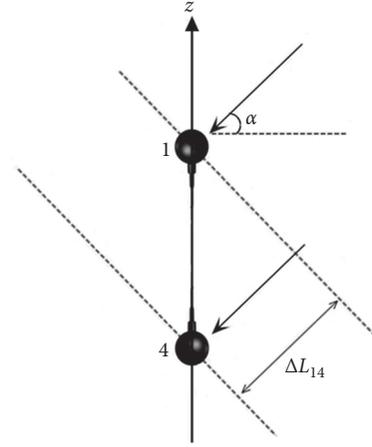


FIGURE 8: Estimation of elevation angle for spatial direction vector.

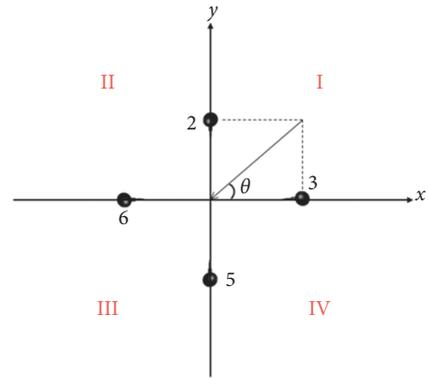


FIGURE 9: Estimation of azimuth angle for spatial direction vector.

Strategy can also be applied in the situation that one ISB breaks down. To be specific, the principle of Hybrid ECOD method is depicted in Figure 10.

4. Experiments and Analysis

4.1. The Efficiency Validation. To evaluate the performance of the proposed algorithm, simulated experiments were carried out to locate a moving target. To demonstrate the superiority of the proposed algorithm, typical azimuth estimation method including MUSIC was compared with the proposed algorithm.

Since targets are expected to be detected online, the real-time performance should be firstly to be considered. Thus, the average time consumption is counted for both algorithms. With the length increment of the input signal, the time consumption of each method becomes longer accordingly. Figure 11 shows the average time consumption of each method. It can be seen that ECOD keeps 50% average time consumption less than that of MUSIC. The result shows that ECOD is still more suitable for underwater detection and monitoring.

4.2. Target Tracking Simulation. Besides orientation, the ECOD method is also able to obtain the spatial behaviour of the underwater acoustic target. As demonstrated in Section

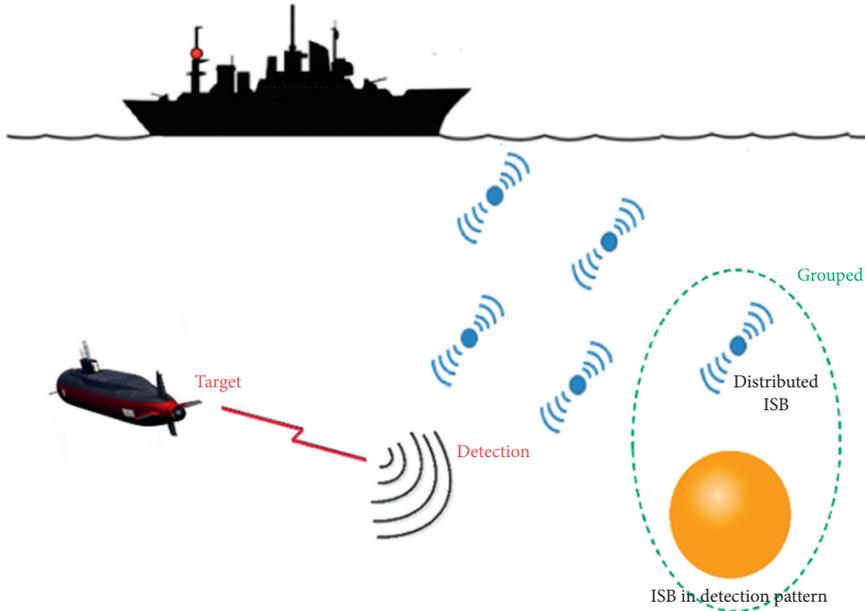


FIGURE 10: An application scenario of the Hybrid ECOD Method.

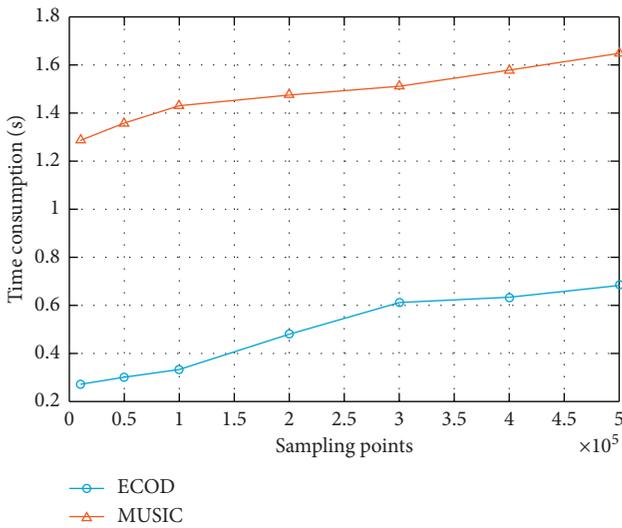


FIGURE 11: The time consumption comparison between the ECOD method and MUSIC method.

3, the maximal crosscorrelation coefficient M is approximately equal to the average power of each signal frame. Thus, the ECOD method can obtain the motion state of underwater acoustic target.

In order to test the performance of proposed ISB in underwater monitoring and tracking, the target is assumed to approach our underwater sensor networks from a distance, as described in Figure 12. Some measured dual-channel data are applied and processed to demonstrate the observed data received by three pairs of hydrophones in an ISB: dual-channel signal is developed into three groups of input signals corresponding to the three pairs of hydrophones, respectively, distributed in 3D space, by adjusting the time delay of the two channels. The three groups of input

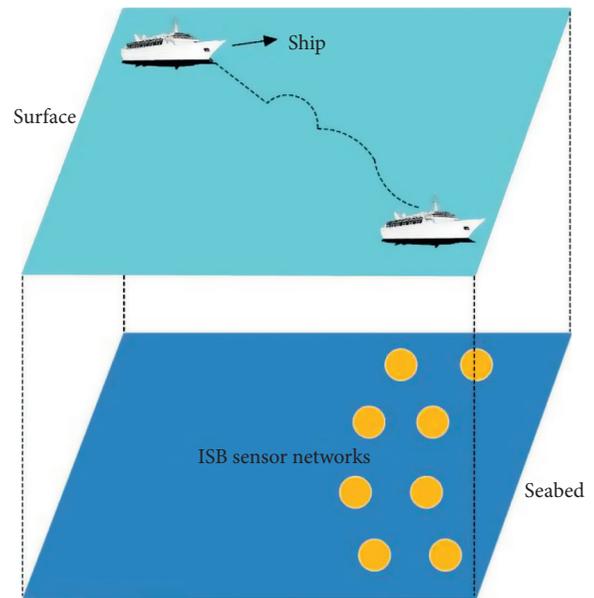


FIGURE 12: Simulation scenario: a ship is approaching to the ISB from a distance.

signals are segmented into 40 frames with a smooth window. The IECU obtains 40 groups of direction vectors using the ECOD method and assigns these vectors' relative values based on the maximal crosscorrelation coefficient M of each frame. 40 spatial location points in the coordinate system will be arranged according to time sequences, which is the target orientation information and its trajectory.

As described in Section 3, spatial feature parameters of the target are represented by 3D coordinates after simple vector synthesis computation. To achieve this, the 40 points in the coordinate system which represent the current orientation are connected together one by one

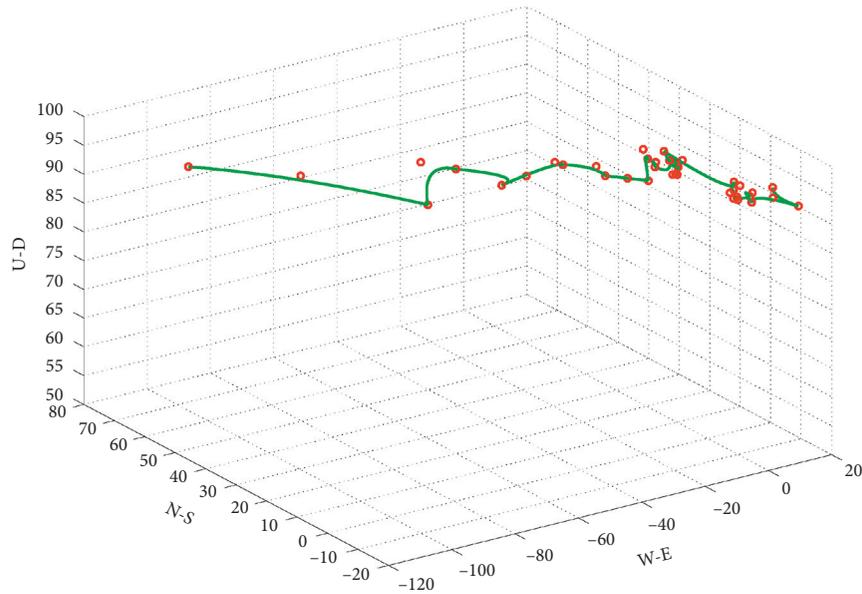


FIGURE 13: The 3D trajectory generated by the proposed ECOD method.

according to time sequences. In this way, the trajectory of the target is derived through Bezier curve fitting, as shown in Figure 13. The direction of the target in a particular time as well as its moving behaviour is then obtained in this relative trajectory.

5. Conclusion

An ECOD method of efficient 3D spatial orientation and motion estimation of an underwater target based on a novel intelligent submerged buoy structure is proposed. The high efficiency is achieved by low-complexity crosscorrelation algorithm and independent signal processing in the in situ electronic control unit of the intelligent submerged buoy. To achieve robustness, a distributed hybrid ECOD method featuring the cooperative sensing of underwater sensor networks is developed. Other distributed sensors are scheduled to provide cooperation for sensing when a separate pair of embedded hydrophones is unable to obtain highly distinguishable signals. Numerical simulations show that our ECOD method obtains the spatial behaviour features of the simulated underwater target and has better performance on efficiency than MUSIC algorithm. Because of passive detection pattern and real-time capability, the ECOD method is much more suitable for underwater detection and monitoring with low cost.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

The work presented here was carried out in collaboration among all authors.

Conflicts of Interest

The authors declare that there are conflicts of interest.

Authors' Contributions

All authors have contributed to, seen, and approved the manuscript.

Acknowledgments

This work was supported by Project of Technical Innovation of Hubei Province (2018AAA029).

References

- [1] S. Zhang, D. Li, and J. Chen, "A link-state based adaptive feedback routing for underwater acoustic sensor networks," *IEEE Sensors Journal*, vol. 13, no. 11, pp. 4402–4412, 2013.
- [2] H. Ramezani, H. Jamali-Rad, and G. Leus, "Target localization and tracking for an isograd sound speed profile," *IEEE Transactions on Signal Processing*, vol. 61, no. 6, pp. 1434–1446, 2013.
- [3] K. A. C. Baumgartner, S. Ferrari, and T. A. Wettergren, "Robust deployment of dynamic sensor networks for cooperative track detection," *IEEE Sensors Journal*, vol. 9, no. 9, pp. 1029–1048, 2009.
- [4] Y. Zeng, J. Cao, J. Hong, S. Zhang, and L. Xie, "Secure localization and location verification in wireless sensor networks: a survey," *The Journal of Supercomputing*, vol. 64, no. 3, pp. 685–701, 2013.
- [5] Y. Pailhas, C. Capus, and K. Brown, "Dolphin-inspired sonar system and its performance," *IET Radar, Sonar & Navigation*, vol. 6, no. 8, pp. 753–763, 2012.
- [6] C. R. Krishna and P. S. Yadav, "A hybrid localization scheme for underwater wireless sensor networks," in *Proceedings of the IEEE 2016 International Conference on Inventive Computation Technologies (ICICT)*, pp. 1–4, Ghaziabad, India, February 2014.

- [7] S. Sendra, J. Lloret, J. M. Jimenez, and L. Parra, "Underwater acoustic modems," *IEEE Sensors Journal*, vol. 16, no. 11, pp. 4063–4071, 2016.
- [8] E. Lattanzi, V. Freschi, M. Dromedari, and A. Bogliolo, "An acoustic complexity index sensor for underwater applications," *IEEE Sensors Journal*, vol. 16, no. 11, pp. 4043–4050, 2016.
- [9] V. Vadori, M. Scalabrin, A. V. Guglielmi, and L. Badia, "Jamming in underwater sensor networks as a Bayesian zero-sum game with position uncertainty," in *Proceedings of the IEEE GLOBECOM*, pp. 1–6, San Diego, CA, USA, December 2015.
- [10] A. Bereketli, M. B. Guldogan, T. Kolcak, T. Gudu, and A. L. Avsar, "Experimental results for direction of arrival estimation with a single acoustic vector sensor in shallow water," *Journal of Sensors*, vol. 2015, Article ID 401353, 10 pages, 2015.
- [11] Y.-X. Zou, B. Li, and C. H. Ritz, "Multi-source DOA estimation using an acoustic vector sensor array under a spatial sparse representation framework," *Circuits, Systems, and Signal Processing*, vol. 35, no. 3, pp. 993–1020, 2015.
- [12] X. Yuan and J. Huang, "Polynomial-phase signal direction-finding and source-tracking with a single acoustic vector sensor," in *Proceedings of the International Conference on Acoustics, Speech, and Signal Processing*, pp. 2559–2563, Brisbane, Australia, August 2015.
- [13] H. Shao, X. Zhang, and Z. Wang, "Efficient closed-form algorithms for AOA based self-localization of sensor nodes using auxiliary variables," *IEEE Sensors Journal*, vol. 62, no. 10, pp. 2580–2594, 2014.
- [14] H. Chen, B. Liu, P. Huang, J. Liang, and Y. Gu, "Mobility-assisted node localization based on TOA measurements without time synchronization in wireless sensor networks," *Mobile Networks and Applications*, vol. 17, no. 1, pp. 90–99, 2012.
- [15] Q. Liang, B. Zhang, C. Zhao, and Y. Pi, "TDoA for passive localization: underwater versus terrestrial Environment," *IEEE Transactions on Parallel and Distributed Systems*, vol. 24, no. 10, pp. 2100–2108, 2013.
- [16] C. Klungmontri, I. Nilkhamhang, W. Covanich, and T. Isshiki, "Underwater positioning systems for underwater robots using trilateration algorithm," in *Proceedings of the IEEE Information and Communication Technology for Embedded Systems (IC-ICTES)*, pp. 1–5, Hua-Hin, Thailand, May 2015.