Underwater Acoustic Signal Denoising Algorithms: A Survey of the State of the Art

Ruobin Gao, *Member, IEEE*, Maohan Liang, Heng Dong, *Member, IEEE*, Xuewen Luo, *Member, IEEE*, and Ponnuthurai N. Suganthan, *Fellow, IEEE*

***Abstract*— Underwater acoustic signal (UAS) denoising is crucial for enhancing the reliability of underwater communication and monitoring systems by mitigating the effects of noise and improving signal clarity. The complex and dynamic nature of underwater environments presents unique challenges that make effective denoising essential for accurate data interpretation and system performance. This article comprehensively reviews recent advances in UAS denoising, focusing on its critical role in improving these systems. The review begins by addressing the fundamental challenges in UAS processing, such as signal attenuation, noise variability, and environmental impacts. It then categorizes and analyzes various denoising algorithms, including conventional, decomposition-based, and learning-based approaches, discussing their applications, strengths, and limitations. Additionally, the article reviews evaluation metrics and experimental datasets used in the field. The conclusion highlights key open questions and suggests future research directions, emphasizing the development of more adaptive and robust denoising techniques for dynamic underwater environments.**

***Index Terms*— Deep learning (DL), denoising, marine engineering, signal decomposition, underwater acoustic signal (UAS).**

NOMENCLATURE

ADMMs	Alternating direction method of multipliers.
CEEMDAN	Complete ensemble EMD with adaptive selective noise.
CNN	Convolutional neural network.
DE	Dispersion entropy.
DL	Deep learning.
DWT	Discrete wavelet transform.
EMD	Empirical mode decomposition.
EEMD	Ensemble EMD.
EWT	Empirical wavelet transform.
FT	Fourier transform.
FFT	Fast FT.
GA	Genetic algorithm.
GANs	Generative adversarial networks.
IBM	Ideal binary mask.
ISTFT	Inverse short-time FT.
IMF	Intrinsic mode function.
LMSs	Least mean squares.
LWTD	Lift wavelet threshold.
MAE	Mean absolute error.
MFCC	Mel frequency cepstral coefficient.
MLP	Multilayer perceptron.
MRA	Multiresolution analysis.
MSE	Mean square error.
MSRU	Multiscale residual unit.
PE	Permutation entropy.
PSNR	Peak signal-to-noise ratio.
RMSE	Root mean square error.
RNN	Recurrent neural network.
SDR	Signal-to-distortion ratio.
SNR	Signal-to-noise ratio.
SSNR	Segment SNR.
STFT	Short-time FT.
VMD	Variational mode decomposition.
UAS	Underwater acoustic signal.
$x(t)$	Signal.
P_{signal}	Power of the signal.
P_{noise}	Power of the noise.
ω	Normalized frequency.
γ	Transitional bandwidth parameter.
$m(t)$	Mean of envelopes.
λ	Threshold.
K	Number of modes.

Received 21 August 2024; revised 28 November 2024; accepted 9 January 2025. Date of publication 20 March 2025; date of current version 27 March 2025. The Associate Editor coordinating the review process was Dr. Guglielmo Frigo. *(Corresponding author: Maohan Liang.)*

Ruobin Gao is with the School of Marine Science and Technology, Northwestern Polytechnical University, Xi'an 710072, China (e-mail: gaor0009@163.com).

Maohan Liang is with the Department of Civil and Environmental Engineering, National University of Singapore, Singapore 119077 (e-mail: mhliang@nus.edu.sg).

Heng Dong is with the School of Electronics and Information Engineering, Harbin Institute of Technology, Harbin 150001, China (e-mail: dongheng@stu.hit.edu.cn).

Xuewen Luo is with the School of Computer Science and Engineering, Northeastern University, Shenyang 110819, China (e-mail: luoxw@cse.neu.edu.cn).

Ponnuthurai N. Suganthan is with the KINDI Center for Computing Research, College of Engineering, Qatar University, Doha, Qatar (e-mail: p.n.suganthan@qu.edu.qa).

Digital Object Identifier 10.1109/TIM.2025.3551006

I. INTRODUCTION

UNDERWATER acoustic data are crucial for various applications [1], [2]. The efficient and intelligent processing of these data is vital for enhancing state-of-the-art underwater technologies. While numerous technologies have been developed specifically for terrestrial and aerial environments, the unique characteristics of the underwater environment make

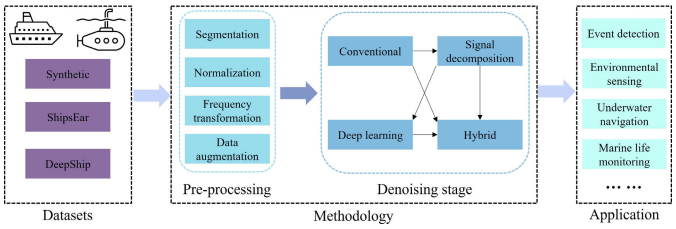


Fig. 1. Framework of UAS denoising.

acoustic signals particularly effective for capturing its conditions. However, severe noise interference presents significant challenges to receivers in underwater communications [3], [4], [5]. The complex underwater settings, unpredictable transmission channels, and varying motion states significantly affect real-world UASs, potentially obscuring the inherent features of targets [6], [7], [8]. Consequently, developing advanced technologies for UAS denoising has become a critical and burgeoning research area in underwater scenarios.

Since the UAS contains intensive noise, extracting noise-resistant features is essential for underwater recognition tasks [9]. The UAS denoising can be categorized into four groups: conventional approaches, decomposition-based framework, DL algorithm, and hybrid schemes. The overall framework for UAS denoising is illustrated in Fig. 1. The UAS denoising community evaluates algorithms using synthetic data, as well as the ShipsEar and DeepShip datasets, which are detailed in Section VII. A common preprocessing step involves segmenting UAS signals into windows, followed by normalization or frequency transformation to enhance the effectiveness of denoising algorithms. Additionally, data augmentation is frequently employed in DL approaches to improve robustness against noise. The preprocessed signals are then input into various denoising algorithms, including conventional techniques, decomposition-based methods, DL models, and hybrid approaches. Since denoising algorithms are foundational to subsequent tasks, they are critical in a broad spectrum of applications, including event detection, environmental monitoring, and underwater navigation.

Conventional UAS denoising is usually based on handcraft features [10] and linear filtering [11]. This article focuses on the most recent advancement in UAS denoising. We suggest readers refer to these survey studies for conventional signal processing and thresholding techniques [12], [13], [14]. Although these handcrafted features are interpretable, they may not effectively capture the high-level abstractions in underwater data that are essential for tasks involving complex patterns. Moreover, defining suitable handcrafted features for specific tasks requires extensive domain knowledge and offers limited flexibility.

Inspired by the *divide-and-conquer* strategy, the UAS denoising community has explored the decomposition of complex UAS into simpler components, which are then individually or collectively denoised. The family of signal decomposition algorithms in UAS denoising is extensive, including EMD [15], VMD [16], DWT [17], EWT [18], and their advanced variants [19]. Following decomposition, criteria are established and applied to classify components into signal-dominated, noise-dominated, and pure noise groups. Specific processing or denoising techniques are then tailored to each category. Noise components are discarded, while signal components are preserved. The final step involves aggregating these processed components to produce a denoised UAS.

In recent years, DL algorithms have succeeded across various fields due to their robust representation capabilities and minimal assumptions about the input data [20], [21]. The feature extraction prowess of DL algorithms has prompted researchers to explore their effectiveness in UAS denoising [22], [23], [24], [25]. DL-based frameworks for UAS denoising typically utilize different neural network architectures to reconstruct clean signals from noisy inputs and maximize the SNR. These models often employ an autoencoder architecture. The design of an efficient DL-based UAS denoising model depends on the choice of architectures and loss functions. The advantages of DL-based techniques include their consistency in denoising and applicability to subsequent tasks such as recognition or analysis based on UAS. Thus, the denoising process is task-oriented, ensuring satisfactory performance across these applications.

The underwater data mining and signal process community has been dedicated to imagery data [26], [27], [28]. Although there are some reviews about underwater sensing, they neglect a crucial role of UAS denoising [29], [30]. Meanwhile, a comprehensive review of the state-of-the-art UAS denoising research needs to be conducted. This article comprehensively reviews recent advances in UAS denoising and contributes to the literature from the following perspectives.

1) Despite the extensive research on UAS denoising algorithms, a comprehensive review systematically summarizing and discussing these diverse approaches is absent. This deficiency poses a significant challenge for researchers and practitioners in thoroughly understanding the landscape of UAS denoising techniques.
2) We systematically analyze UAS denoising algorithms, from conventional signal processing methods to advanced DL algorithms. Furthermore, we introduce a taxonomy of UAS denoising techniques, marking the first instance of such classification in the literature. This taxonomy meticulously delineates the current landscape of UAS research, revealing insightful connections among each category.
3) We outline the prevailing challenges encountered in UAS denoising and explore potential solutions. Spanning from methodological intricacies to real-world applications, these challenges offer valuable insights and point toward promising avenues for future research in UAS denoising.
4) We elucidate the diverse applications of UAS denoising techniques, underscoring their essential role in various underwater applications. This exploration holds significant interest for readers and practitioners alike, highlighting the critical importance of UAS denoising in underwater contexts.

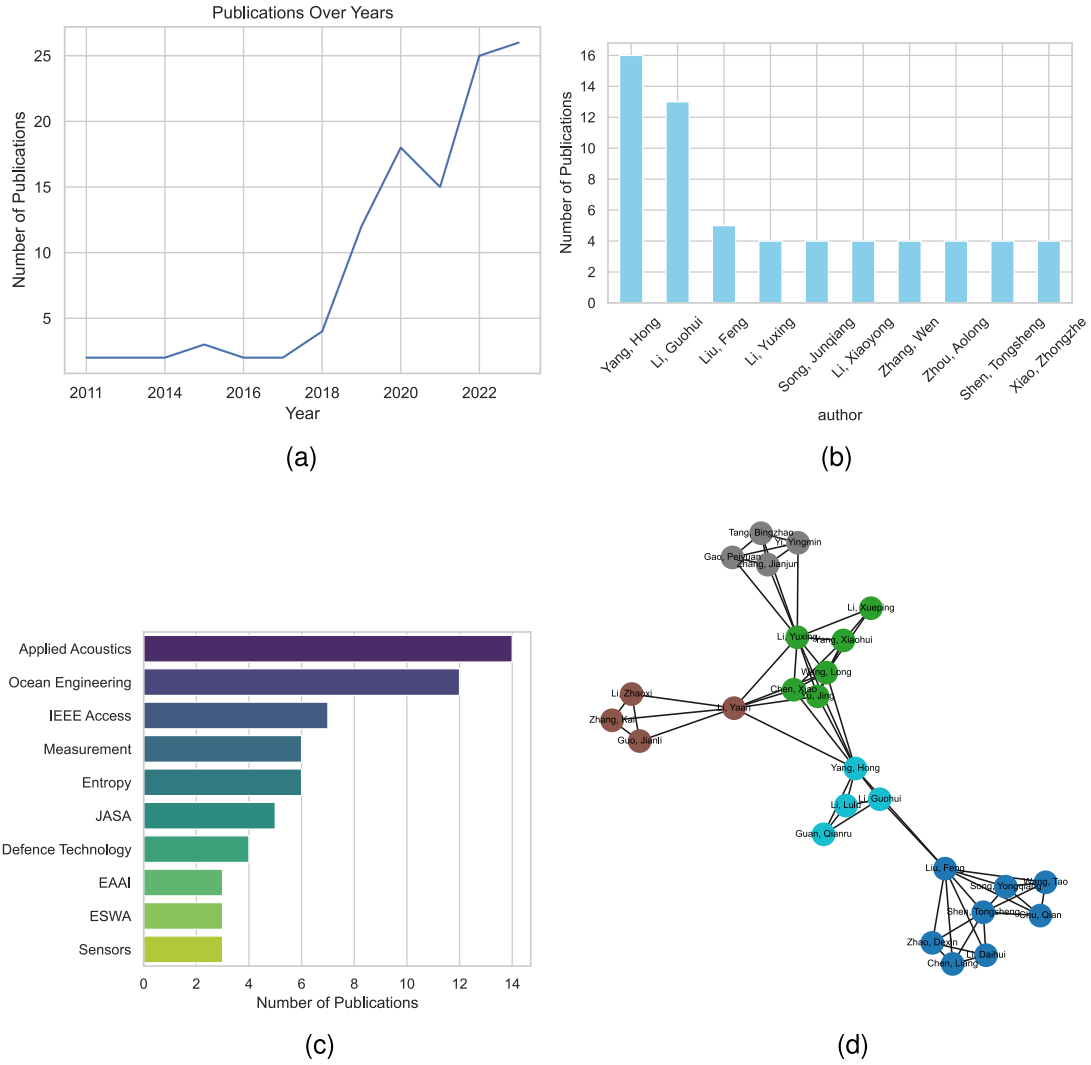


Fig. 2. Bibliometric analysis of UAS denoising from 2011 to 2023. (a) Annual distribution of recent publications. (b) Top ten authors by number of publications. (c) Top ten publication venues. (d) Network graph of coauthorship.

II. Overview of UAS Denoising Research

This section first conducts a bibliometric analysis of the reviewed UAS denoising literature. Then, we discuss the unique challenges in denoising UAS data.

A. Bibliometric Analysis

This survey reviews research in UAS denoising techniques, predominantly published in academic journals or conferences related to ocean engineering, measurement, signal processing, and artificial intelligence (AI). Notable venues include IEEE Transactions on Instrumentation and Measurement, *Ocean Engineering*, *IEEE Journal of Ocean Engineering*, *Journal of Marine Science and Engineering*, *Applied Acoustics*, *Applied Ocean Research*, *Measurement*, and *The Journal of the Acoustical Society of America*. Fig. 2 visualizes the scope of UAS denoising studies addressed in this survey. Fig. 2(a) illustrates a consistent upward trend from 2011 to 2023 in the number of studies within the UAS denoising field. There are around 17 publications in 2024, which only encompasses the first half of the year. Fig. 2(b) summarizes the top ten authors by the volume of their contributions to UAS denoising research. According to Fig. 2(c), the journals *Applied Acoustics* and *Ocean Engineering* publish the most research on UAS denoising, given their specific focus on acoustics and ocean engineering. Recently, with advancements in AI, AI-related journals such as *EAAI* and *ESWA* have also shown increased receptivity to UAS denoising research. Finally, Fig. 2(d) displays the network graph of coauthorship within the UAS denoising literature, highlighting five collaborative communities and the extent of their interactions.

B. Why UAS Denoising Is Challenging

The low SNR of the UAS presents significant challenges; moreover, the complexities of the underwater environment introduce unique difficulties that distinguish UAS denoising from typical signal denoising tasks [4], [31]. Various noise sources exist in underwater environments, as shown in Fig. 3. The noise sources vary in underwater settings and include natural and anthropogenic elements. Natural sources such

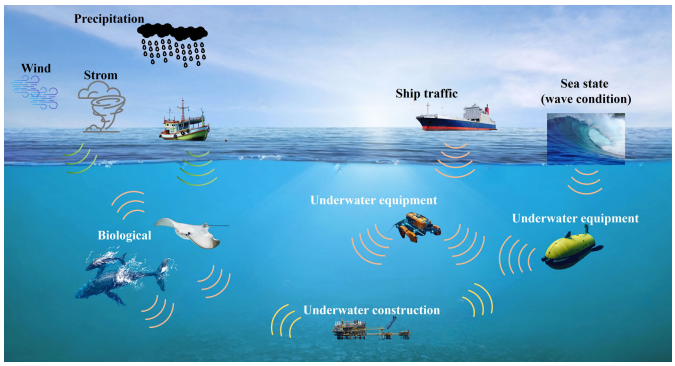


Fig. 3. Illustration of the complex noise sources in the underwater scenario.

as marine life activity, wind-driven waves, and precipitation contribute significantly to the background noise. On the other hand, anthropogenic sources include ship traffic, industrial activities, sonar systems, and other man activities, all adding complexity to the noise environment [32], [33]. These diverse noise sources necessitate specialized approaches in UAS denoising to effectively separate the signal from the noise, ensuring clarity and accuracy in data interpretation.

1) Complex Sources: In the underwater scenario, the noise sources contributing to the complexity of acoustic signals can be broadly categorized into natural, anthropogenic, and system-based sources, each adding layers of challenges to UAS denoising as follows.

a) Natural noise sources:

1) *Biological Noise:* This includes sounds from marine life, such as whales, dolphins, and fish [34]. These biological entities often produce sounds for communication, navigation, and foraging, which can overlap in frequency and time with the signals of interest.
2) *Geophysical Noise:* Geophysical noise arises from natural phenomena, including wind, rain, and sea state [35]. The term "sea state" refers specifically to the physical condition of the ocean surface, which depends on wave dynamics such as height, period, and direction. Noise contributions from sea state primarily result from wave turbulence, wave breaking, and interactions between water and the seabed during storms [36]. In contrast, wind and storm noise originates from the transfer of wind energy at the air–water interface, and precipitation noise is caused by the impact of raindrops on the water surface. These distinct mechanisms contribute to the overall geophysical noise profile.

b) Anthropogenic noise sources:

1) *Shipping Traffic:* Noise from commercial and recreational vessels is a dominant noise source in many oceanic environments. The sound from engines, propellers, and hull movement is pervasive at various frequencies and intensities [37], [38].
2) *Industrial Activities:* Underwater construction, oil drilling, and other marine operations involve heavy machinery that emits substantial acoustic signals [39], [40].
3) *Sonar and Naval Exercises:* Active sonar systems used by the military and some commercial ships emit powerful sound pulses that interfere with and mask natural acoustic signals [41].

c) System-based noise sources:

1) *Instrument Noise:* Noise inherent to the recording devices, such as electronic noise from sensors and recording equipment, can affect the data quality [42].
2) *Data Transmission Noise:* In wireless underwater communication, signals can be corrupted by noise introduced during transmission, including reflections and refractions from the water's surface or the seabed.

Each noise source interacts differently with the underwater environment, making it challenging to isolate and remove unwanted noise from valuable data. Effective denoising thus requires a deep understanding of both the characteristics of these noises and the acoustic properties of the environment. Advanced signal processing techniques, adaptive filtering, and machine learning models are typically employed to enhance the clarity and reliability of the extracted signals in such complex scenarios.

2) Energy Imbalance: In underwater environments, the fusion of multisource signals frequently results in an imbalanced energy distribution within the captured acoustic data. This imbalance complicates the signal processing tasks, particularly the denoising of UAS. Factors such as varying signal intensities, overlapping frequency ranges, and sporadic or persistent noise sources further exacerbate the challenge. These complexities necessitate sophisticated denoising techniques that effectively distinguish between noise and actual acoustic signals of interest. Moreover, the dynamic nature of underwater environments, including changes in water density, temperature, and movement, adds additional layers of variability that denoising algorithms must account for. Consequently, improving the accuracy of UAS denoising involves addressing the imbalance in signal fusion and adapting to the inherently noisy and unpredictable underwater acoustic landscape.

3) Disparate Optimization Objectives: Since UAS denoising is usually the first stage for underwater recognition tasks, recognition models must be developed. Most literature treats denoising and recognition as two independent stages [43]. When designing UAS denoising algorithms, researchers may not consider the requirements of recognition tasks. The denoising stage is unsupervised, and recognition labels are unavailable. The objectives of developing denoising and recognition models are different, and there are challenges in unifying these two stages.

III. Signal Decomposition

Signal decomposition techniques can decompose complex signals into various components or modes, carrying information of different frequencies. Individual modes are more accessible to analyze, process, and denoise [44]. The general framework of decomposition-based denoising methods is shown in Fig. 4. In summary, signal decomposition algorithms are utilized to extract various modes from the original signal. These modes are then categorized into groups based

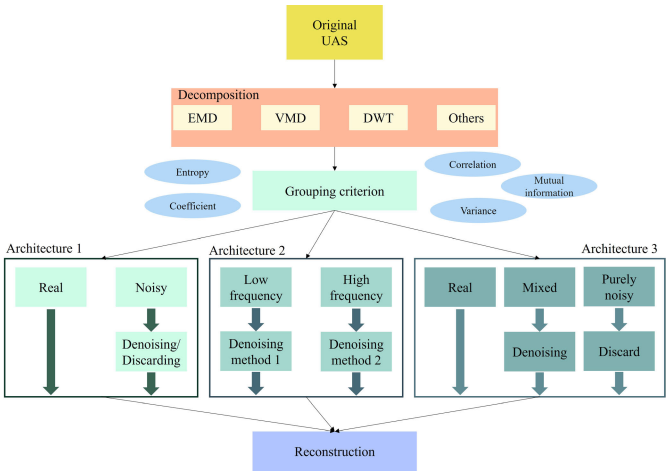


Fig. 4. Framework of decomposition-based UAS denoising.

TABLE I
SUMMARY OF REPRESENTATIVE DECOMPOSITION-BASED UAS DENOISING STUDIES

Literature	Signal decomposition	Denoising	Grouping	Hyper-parameters
[46]	DWT	Wavelet Thresholding	NA	Manually
[47]	EMD	Evolutionary filtering	Entropy	Sand cat swarm
[48]	EMD	Wavelet Thresholding	Entropy	Manually
[49]	VMD	Wavelet Thresholding	Correlation	Grey Wolf Optimisation
[50]	DWT, VMD	Wavelet Thresholding	NA	EMD's level
[51]	VMD	Discard noisy IMFs	Entropy	VMD's level
[52]	VMD	Grey relation analysis and thresholding	Frequency	Manually
[53]	EMD	Interval thresholding	Entropy	Manually
[54], [55]	VMD	Wavelet thresholding	Entropy	VMD's level
[56]	EMD	LMS filtering	Mean square variance	Manually
[57]	EMD	Interval thresholding	Entropy	Manually
[58]	VMD	Wavelet thresholding	Correlation and frequency	Manually
[59]	EWT	Discard noisy components	Energy intensity	Manually

on a predefined criterion that quantifies noise levels. Subsequently, three distinct architectures are designed to process these groups effectively for denoising purposes. Architecture 1 involves no further processing of the real signal obtained from decomposition; only the noisy components are denoised or discarded. Architecture 2 uses decomposition algorithms to separate the original signal into low-frequency and high-frequency components. Due to their distinct characteristics, different denoising methods (Denoising Method 1 and Denoising Method 2) are applied to the low-frequency and high-frequency components, respectively. Architecture 3 categorizes decomposed components into three groups: real, mixed, and purely noisy components. The purely noisy components are directly discarded, while the mixed components undergo further processing. After obtaining modes with the help of decomposition, suitable denoising algorithms are applied to these modes. Finally, denoised modes are aggregated to reconstruct the input signal. Table I summarizes the representative decomposition-based denoising studies.

A. Discrete Wavelet Transform

Classical wavelet threshold denoising techniques effectively suppress noise by leveraging thresholds derived from wavelet coefficients, thereby retaining stronger signals [45], [59], [60]. Thresholding within this context can be classified into hard, soft, and hybrid categories [45]. However, classical wavelet thresholding algorithms struggle with non-Gaussian, nonlinear, and nonstationary noise types. Moreover, selecting an appropriate threshold remains a significant challenge. To overcome these issues, some researchers have proposed using the posterior probability distribution of wavelet coefficients obtained from the DWT as the threshold to eliminate nondominant coefficients [49]. Additionally, integrating the lifting wavelet transform with soft thresholding has been investigated as a strategy to mitigate the shortcomings of the first-generation wavelet transform [54].

B. Empirical Wavelet Transform

The EWT represents an automated approach in signal processing, underpinned by robust theoretical foundations for decomposing nonstationary time series data [18]. Contrasting with DWT and EMD [61], EWT conducts a meticulous analysis of time series in the Fourier domain after the application of an FFT. This technique involves the segmentation of the spectrum through data-driven bandpass filtering. In the EWT, limited freedom is provided for selecting wavelets. The algorithm employs Littlewood–Paley and Meyer's wavelets because of the analytic accessibility of the Fourier domain's closed-form formulations [62].

Although EWT achieved tremendous success in other sequence tasks, the UAS community has not researched its denoising ability [44]. The EWT is employed to decompose the UAS into several subseries, where the subseries with the highest energy are utilized to train a recognition model [58]. Subseries with low energy, typically representing noise, are discarded for denoising purposes. This approach highlights the potential of EWT in enhancing signal quality for UAS applications.

C. Empirical Mode Decomposition

The EMD is a wholly data-driven approach for decomposing time-domain signals into distinct oscillatory modes and a residual component [15]. Each mode, defined as an IMF, must satisfy two specific criteria to be classified as such.

1) The number of extremums in the oscillation and the number of zero crossings must equal or differ by at most one.
2) The mean of the envelopes defined by the local maxima and the local minima shall equal zero.

The signal decomposed by EMD can be expressed as the sum of a finite number of IMFs and a residual value

$$x(t) = \sum_{m=1}^{k} \mathrm{IMF}_m(t) + r_k(t) \tag{1}$$

where k is the IMF number and $r_k(t)$ is the final residual value.

The set of IMFs constitutes a complete, adaptive, and nearly orthogonal basis for the original signal. The EMD method preserves the signal in the time domain. Each IMF encapsulates information on the variations in amplitude and frequency of the original signal over time. IMFs consist of a single or a narrow band of frequencies with no overlap. Furthermore, these functions or signals are orthogonal to the original signal [63].

EMD and its variants have achieved tremendous success in UAS denoising [64], [65]. For instance, Kannan and Latha [64]

decompose the acoustic signal into multiple IMFs and remove those with small correlations between the IMFs of similar classes. Instead of computing correlations between IMFs, Wang et al. [65] utilize dimensional reduction algorithms to maintain signal-dominated components, thereby reducing noise. The application of the EMD technique offers a novel approach to detecting and classifying marine mammal vocalizations in underwater acoustics, which traditionally requires extensive manual analysis by skilled acousticians. This method efficiently identifies and labels sound sources in a recording without prior knowledge or extensive preprocessing, streamlining the task through minimal postprocessing quality control [66]. The nonstationarity of each decomposition mode is utilized to select noise components obtained by the EEMD [67].

The CEEMD is employed to denoise the original signal first, and a bidirectional denoising autoencoder is developed to learn robust representations [68]. The CEEMDAN is adopted to decompose UAS into IMFs, and IMF with the minimum difference between the energy distribution ratio and average energy distribution ratio is selected [69]. While decomposing the acoustic target signal, the correlation coefficient between each IMF and the original signal is utilized as a threshold to determine signal-dominated IMFs. In addition to utilizing threshold to drop out noisy IMFs, the literature also employs denoising algorithms to denoise noisy IMFs [55]. A criterion determining noisy IMFs is designed, then noisy IMFs are denoised. Different criterion is proposed in the literature, such as minimum mean square variance [55] and energy concentration property [70]. For denoising IMFs, researchers have tried on least mean square filter [55]. Modified uniform EMD is employed to decompose the input into IMFs, and a double threshold is obtained according to hierarchical amplitude-aware PE. The threshold assists in dividing IMFs into clean, mixed, and noisy IMFs. Since mixed IMFs contain noisy information, an evolutionary improved wavelet threshold denoising method denoises mixed IMFs [46].

Recently, secondary decomposition outperforms one-time approaches [50]. Implementing a secondary decomposition assists in extracting high-level features and further denoising IMFs containing indistinguishable noise [71]. Furthermore, secondary decomposition techniques can be employed to enhance the denoising performance of noisy IMFs. In [50], the noisy IMFs obtained from the initial decomposition can undergo further decomposition, followed by denoising using Architecture 2, as illustrated in Fig. 4. Another method involves initially applying EMD to the signal and subsequently processing the low-frequency components with CEEMDAN to address the mode mixing problem [72]. Adaptive chirp mode decomposition, an advanced extension of EMD, is recently explored in [73].

D. Variational Mode Decomposition

VMD can decompose the nonstationary signals into several subseries called modes [16]. To overcome the theoretical limitations of EMD, Dragomiretskiy and Zosso [16] propose the VMD algorithm with solid theoretical development. VMD has successfully handled noisy UAS [57]. For instance, VMD is initially applied, and the center frequency and correlation coefficient of each IMF are analyzed to classify it as noisy, pure noise, or a pure signal [57]. Subsequently, Architecture 3 is utilized to process the IMFs further. Yang et al. [54] employ VMD to decompose the input signal. Then, the authors apply the Savitzky–Golay filter and LWTD algorithms to denoise low-frequency and high-frequency components, respectively. Finally, all components are aggregated for reconstruction. Another principle of denoising IMFs is to classify noise-dominated and signal-dominated IMFs. Different denoising algorithms can be applied to noise-dominated and signal-dominated IMFs [53]. For instance, wavelet-thresholding algorithm and Savitzky–Golay filtering are employed to denoise noise-dominated and signal-dominated IMFs, respectively [53]. Their results demonstrate the superiority of VMD over EMD for UAS denoising tasks. The hyperparameters of VMD, particularly the decomposition level, significantly influence its denoising performance. In [48], Grey wolf optimization (GWO) is utilized to optimize the penalty factor and decomposition level, ensuring optimal performance of the VMD. A similar study utilizes the black widow optimization algorithm to obtain VMD's penalty factor and decomposition level [74]. Unlike the above methods dividing IMFs into two groups (clean and noise, low-frequency and high-frequency), some studies divide IMFS into three groups—pure, mixed, and noisy signals—for fine-gained denoising [46]. VMD decomposes signals denoised by wavelet thresholding further [49]. Then, the IMFs of high mutual information are selected for the following recognition tasks.

E. Other Decompositions

The improved symplectic geometry modal decomposition generates IMFs in [75]. Unlike most literature, which utilizes some criterion to group IMFs into clean signal and noisy parts, spectral clustering is employed to cluster IMFs into mixed and noise clusters. Finally, wavelet thresholding techniques filter out noise in mixed clusters. The authors employ intrinsic time-scale decomposition and correlation coefficients to denoise UAS data [76].

F. Thresholding

Thresholding is a fundamental step in the decomposition-based denoising framework. It eliminates noisy information from all decomposed components based on a predefined threshold [46]. This technique comprises two main stages: threshold determination and the thresholding function application. The first stage, threshold determination, primarily involves calculating threshold values using an appropriate criterion. The second stage, the thresholding function, involves removing noise components while preserving the significant signal elements according to the established threshold.

1) Threshold Determination: When decomposing signals, distinguishing between meaningful components and noise is crucial. Noise components typically have little to no informational overlap with the original signal. The first stage of thresholding is to determine the threshold value. A good threshold value should assist in retaining signal-dominated information and eliminating noise as much as possible. Researchers have utilized a variety of criteria to compute the threshold value. For instance, correlation coefficients between IMFs and original signals are employed to determine the threshold [77]. Signal-dominated components should show a much higher correlation than noise-dominated components. However, correlation coefficients cannot measure the nonlinear dependency between decomposed components and original UAS, which is essential in complex signal environments.

In addition to linear criterion, the entropy is an essential indicator to reflect information in each IMF [78]. Hence, the literature has explored various entropy-based metrics to compute the threshold, such as PE [79], [80], [81], [82], [83], amplitude-aware PE [46], [78], DE [55], [56], [84], fluctuation-based DE [74], [85], slope entropy [82], weighted PE [86], and neural network estimation time entropy [52].

Mutual information quantifies the amount of information obtained about one random variable through another random variable. In the context of signals, it measures how much information the presence of one signal can tell about another signal. This is particularly useful when determining how much of one signal (such as the original) is present in another (like a decomposed signal component). In [79], mutual information is utilized as a criterion to evaluate whether the IMFs produced by CEEMDAN are dominated by noise or represent meaningful signal components.

In addition to the above thresholding technique based on single threshold, dual thresholds are researched in the literature [56]. For instance, an interval thresholding is employed in [56].

2) Thresholding Function: Thresholding functions aim at eliminating noisy components while retaining strong signals. Table II summarizes essential thresholding functions and baselines for advanced thresholding functions in the literature [45]. For instance, in [87], a new adaptive thresholding function considering the continuity of input-output curves is defined as follows:

$$\hat{w}_{j,k} = \begin{cases} \operatorname{sgn}\left(w_{j,k}\right)\left(\left|w_{j,k}\right| - \left|w_{j,k}\right|^{\eta}\left(\lambda_j - \left|w_{j,k}\right|\right) * \lambda_j\right), \\ \qquad \left|w_{j,k}\right| \geq \lambda_j \\ 0, \quad \left|w_{j,k}\right| < \lambda_j. \end{cases} \tag{2}$$

Although advanced adaptive or semisoft thresholding functions have been proposed and demonstrated outstanding performance, they often necessitate the optimization of additional hyperparameters. This requirement can complicate their practical implementation and demand extensive computational resources or domain expertise to achieve optimal results. Such complexities can be a barrier, especially in applications with critical real-time processing or limited computational resources. Moreover, tuning these hyperparameters can be sensitive to the specific characteristics of the data, making these methods less robust across diverse datasets unless carefully adjusted.

TABLE II
SUMMARY OF CONVENTIONAL THRESHOLDING FUNCTIONS

Technique	Formula	Characteristic
Hard thresholding [46]	$f(x) = \begin{cases} x_i, & \lvert x\rvert > \lambda \\ 0, & \lvert x\rvert \leq 0 \end{cases}$	Simplicity and efficiency Non-Adaptivity
Soft thresholding [46]	$f(x) = \begin{cases} \operatorname{sgn}(\lvert x\rvert - \lambda), & \lvert x\rvert > \lambda \\ 0, & \lvert x\rvert \leq \lambda \end{cases}$	Smoothness in the Reconstructed Signal Over-Smoothing
Semi-soft thresholding [46]	$f(x) = \begin{cases} \operatorname{sgn}(x)(\lvert x\rvert - m\lambda), & \lvert x\rvert > \lambda \\ 0, & \lvert x\rvert \leq \lambda \end{cases}$	Flexible transfer between hard and soft schemes. More hyper-parameters

G. Hyperparameters of Signal Decomposition

A practical issue of the decomposition-based denoising framework is determining the hyperparameters of decomposition algorithms [49]. Signal decomposition algorithms share an essential hyperparameter, the decomposition level. Smaller decomposition levels lead to significant mode mixing issues. However, high decomposition levels may generate components of fake frequencies and deteriorate the denoising performance. Meanwhile, each additional level of decomposition increases the computational burden.

Researchers attempted to directly apply the decomposition level of EMD to VMD to retain the advantages of VMD while incorporating the adaptive capabilities of EMD [49]. Spearman correlation coefficients are utilized as a threshold to determine significant decomposed components. Measuring correlations between reconstructed and original UAS can also guide the selection of decomposition level [88]. Evolutionary optimization successfully determines hyperparameters of signal decomposition algorithms in the UAS denoising literature [77]. Researchers employ various evolutionary algorithms to search for threshold, decomposition, and other crucial parameters [87].

IV. DEEP LEARNING

DL algorithms employ a deep neural network to reconstruct clean signals from noisy input [89], [90], [91], [92]. Most literature has followed the framework of autoencoder for reconstruction [93]. Designing suitable architectures and novel loss functions to extract noise-resistant features efficiently is crucial [94], [95], [96], [97]. Table III summarizes representative DL-based UAS denoising in recent years.

A. DL-Based UAS Denoising Methodology

Unlike traditional denoising algorithms and signal decomposition techniques, neural networks operate without preset assumptions about the noise characteristics [97]. Various DL architectures have demonstrated efficacy in UAS denoising, including CNNs [22], [23], [24], [25], [110], [111], RNNs [98], and attention-based neural networks [99]. The reconstruction-based DL denoising algorithms pipeline is visualized in Fig. 5. Time–frequency transformation is optional

TABLE III
SUMMARY OF REPRESENTATIVE DL-BASED UAS DENOISING STUDIES

Literature	Architecture	Input	Training logic	Hyper-parameters tuning
[89]	MLP and CNN	Original UAS	Unsupervised reconstruction	Manually
[24]	CNN	Original UAS	Supervised recognition	Manually
[100]	CNN and RNN	Original UAS	Unsupervised reconstruction	Manually
[101]	RNN and Transformer	STFT	Unsupervised reconstruction Supervised recognition	Manually
[70]	MLP	Mel-frequency cepstral coefficients	Unsupervised reconstruction	Manually
[102]	CNN and GAN	Original signal	Unsupervised reconstruction	Manually
[103], [104]	GAN	STFT	Unsupervised reconstruction	Manually
[105]	Attention	STFT	Unsupervised reconstruction	Manually
[106]	Attention	STFT	Unsupervised reconstruction	Manually
[107]	Attention	Original UAS	Unsupervised	Manually
[108]	Attention	Mel spectrum	Recognition	Manually
[109]	Attention	Time-frequency spectrum	Self-supervised	Manually
[110]	CNN and attention	Mel spectrum	Supervised	Manually
[111]	CNN	FFT	Supervised	Manually

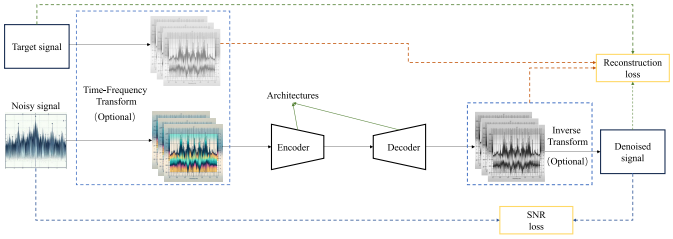


Fig. 5. Framework of DL-based autoencoder UAS denoising algorithms.

because the DL model can directly process the original UAS. This framework trains a denoising DL model based on reconstruction loss and SNR-related loss. Reconstruction loss can be computed based on the spectrum when any time–frequency transform is adopted.

An IBM is initially estimated using features derived from clean and noisy signals, followed by training a deep MLP to predict the IBM for effective denoising [112]. In [112], the Wiener filtering method struggles to retain essential characteristics when the premixed SIR drops below −12 dB. In contrast, the IBM-based DNN method consistently achieves a 7 dB advantage in denoising, preserving a more complete waveform in low-SIR conditions. To reconstruct the noisy input, a stacked convolutional sparse denoising autoencoder is employed, leveraging sparse representations [113]. The proposed stacked convolutional sparse denoising autoencoder effectively reduces noise while preserving valuable features. However, traditional methods destroy feature structures. Furthermore, an MSRU incorporating various convolutional kernels has been proposed to extract robust noise-resistant features [24]. Experimental results demonstrate an improvement of up to 6.99% over networks without the MSRU module. Additionally, CNN features can be enhanced through a dual-path RNN, significantly improving the denoising performance for UAS [98]. Considering the high dimensionality of the original time series, MFCCs are extracted as training samples from both the original and denoised UAS using CEEMDAN [68]. Comparative studies reveal that the DL method surpasses baseline approaches using only CEEMDAN for denoising, improving detection accuracy by 14.35%.

Researchers have investigated the denoising capabilities of GANs for UAS [100], [102]. Specifically, the GAN algorithm has been employed to mitigate underwater ambient noise [102]. Initially, the STFT is applied, using magnitude and phase features as inputs for the GAN. Clean signals are then reconstructed from the GAN's output using the ISTFT. Compared to Wiener filtering, GAN demonstrates superior performance, achieving 45.1% and 61.1% improvements in SNR and RMSE, respectively. In another approach, a GAN is utilized to generate clean signals, with the discriminator designed to distinguish between real noisy signals and the combination of clean signals with ambient noise [101]. This denoising model incorporates a 1-D convolutional layer for feature extraction. Experimental results demonstrate that the GAN model achieves significantly better performance, surpassing Wavelet denoising by 227%, EMD by 247%, and the Wiener technique by 65%.

Recently, the attention mechanism has been integrated into denoising UAS. Zhou et al. [103] developed a dual-branch attention-based neural network to reconstruct clean signals from noisy complex spectra. The proposed attention network achieves an average SDR improvement of 14.41 dB and SSNR improvement of 13.12 dB. Meanwhile, comparative studies have demonstrated that this DL approach surpasses traditional Wavelet-based and EMD-based denoising algorithms. Additionally, Zhou et al. [104] proposed a DL model incorporating residual (Res) blocks and attention modules to effectively separate a noisy waveform into noise and a denoised waveform. Furthermore, a Transformer model, trained to maximize the SNR, has been utilized for acoustic signal denoising [105]. Another innovative DL model, featuring channel, frequency, and time attention modules, has been introduced to extract robust noise-resistant features across multiple domains [106]. On the DeepShip dataset, the recognition accuracy exceeds that of previous state-of-the-art methods by 7.06%.

Another significant challenge involves the disparate optimization objectives between denoising and recognition tasks in UAS processing [43]. To address this, a joint training framework utilizing a modified Transformer neural network has been proposed, which successfully achieves both denoising and recognition [43]. The loss function in this framework is dual-part; it includes a denoising component where the mean squared error between the noisy and the clean signal is minimized. The proposed DL method achieves significant gains of 22.66 dB in SDR, 22.44 dB in SI-SNR, and 22.51 dB in SSNR.

A self-supervised, dual-channel self-attention encoder has been proposed to learn robust, noise-resistant features of UAS [107]. This self-supervised learning approach compels the UAS model to identify and retain the most informative and stable patterns for succeeding in the pretext task. Additionally, this method inherently encourages the model to learn features invariant to minor perturbations or variations (i.e., noise) in the input data, focusing on attributes crucial for distinguishing between fundamentally different classes or scenarios. Furthermore, data augmentation has been demonstrated to enhance the accuracy and noise robustness of the UAS model [108], [114].

Diversity in architectures is crucial for DL-based approaches in UAS processing. For example, multiple classifiers are constructed to handle different types of noise [109]. The pivotal

principle in designing DL models for UAS-related tasks lies in extracting robust and noise-resistant features. A diverse set of feature extractors facilitates the extraction of multiscale features, ultimately enhancing noise resistance. The literature demonstrates using convolutional filters with diverse kernel sizes to capture these multiscale features [99], [115], [116], [117]. Different convolutional kernels aid in automatically learning features across various frequencies. Moreover, Tian et al. [117] propose a parallel architecture to jointly learn from UAS data, optimizing feature extraction for enhanced performance.

Designing suitable loss functions is essential for deep-learning denoising methods. Generally, DL-based UAS denoising algorithms employ reconstruction-based loss [22], [68], [118]. They train a DL model to reconstruct clean signal-dominated components from noisy UAS [103]. For recognition-based DL models, supervised classification losses are employed [24]. Besides reconstruction-based and recognition-based terms, other terms assisting in enhancing noise-resistance representations and generalizations are designed and employed [22]. For instance, the distance between learned features and feature centroid is minimized to enhance the noise resistance of features [115]. Correspondingly, a passive attention loss is defined. Some studies train the neural network to maximize SNR [43], [98].

B. Input Formulation

Appropriate formulations of the input for UAS are critical for the performance of DL denoising methods [23]. Although directly processing raw UAS data is a straightforward choice, a meaningful formulation significantly aids in training DL models. Typically, the UAS community utilizes time–frequency transformations of the raw signal, such as the STFT [119], Mel spectrum [106], Bark spectrum [108], and handcrafted features [9], [120]. Experimental studies have demonstrated that features like the magnitude STFT spectrum, complex-valued STFT spectrum, and log-mel spectrum notably enhance the performance of deep CNNs in underwater recognition tasks [23]. Additionally, MFCCs are employed as inputs for a deep CNN to improve recognition accuracy further [111].

C. Data Augmentation

Data augmentation is a critical technique in improving the noise resistance of DL models and achieved significant success in sequential tasks [114], [121]. Data augmentation artificially expands the training dataset by creating modified versions of the existing UAS. These modifications might include adding noise, cropping, or changing lighting conditions. This variety assists in training denoising and recognition models based on diverse samples. By training on a more diverse dataset, data augmentation acts as a form of regularization. It effectively prevents the model from memorizing the training UAS (overfitting), encouraging more robust generalization abilities.

UAS denoising models are usually developed based on the time–frequency transformation of the original UAS [99]. Data augmentations can be directly applied to the original UAS in the time domain by adding noise [99]. Adding noise is naturally advantageous for underwater tasks due to the noisy and complex characteristics of the underwater environment [114]. After transforming the original UAS into time–frequency representations, masking is a common and straightforward augmentation strategy [108]. For instance, time masking and frequency masking are implemented on representations obtained from Mel filter bank [99].

Conventional data augmentation strategies in UAS processing involve training denoising or recognition models using both raw and augmented samples. However, the direct contribution of augmented samples to training losses may lead to performance degradation [108]. To address this issue, a smoothness-inducing regularization technique has been proposed to minimize the distance between representations of raw and augmented samples, thereby improving the consistency and effectiveness of the training process [108]. Additionally, a local masking and replicating technique has been developed, which randomly selects two samples, applies local masking, and mixes them to create a new augmented sample [108]. Experimental results indicate that these proposed augmentation techniques outperform GAN-based algorithms in terms of enhancing model robustness and recognition accuracy [122], [123].

V. Hybrid Methods

Hybrid methods for UAS denoising combine the strengths of multiple algorithmic categories, leveraging their complementary capabilities to address the unique challenges underwater environments pose. These methods integrate approaches such as signal decomposition techniques, machine learning algorithms, and advanced statistical models to enhance the robustness and accuracy of denoising performance. By combining the interpretability and domain-specific efficacy of classical approaches with the data-driven adaptability of modern techniques, hybrid methods effectively tackle issues like nonstationary noise, signal sparsity, and variability in acoustic environments [84]. Such integrative strategies are particularly beneficial for improving signal processing quality in complex underwater conditions, where standalone methods often fall short.

DL models are flexible to be hybridized with other approaches that focus on input transformation [68]. Hybrid frameworks might utilize wavelet transform methods for initial noise reduction, followed by DL-based algorithms for adaptive filtering and signal reconstruction. Transformation of the original UAS assists in extracting low-level features and providing prior knowledge to train the following DL denoising model. For instance, the CEEMDAN is employed to decompose the UAS into different modes denoised by bidirectional autoencoder [68]. Implementing signal decomposition before developing the DL model assists in filtering out some dominant noise and extracting signal-dominated components.

Another branch of hybrid methods combines optimization algorithms, such as evolutionary optimization, with UAS denoising methods [77], [87]. These hybrid methods utilize evolutionary algorithms to automatically search for the best hyperparameters for the combined UAS denoising methods.

With the help of optimization methods, UAS denoising methods can be objectively and optimally designed. For instance, the GA is developed to obtain the optimal threshold value for the shrinking of wavelet coefficients [124]. The GA is employed to dynamically optimize the filter vector to denoise each mode generated from the signal decomposition module [47]. Similarly, GA is utilized to dynamically adjust Kalman filter's parameters [125].

VI. Evaluation Metrics

Performance evaluation is crucial for assessing the effectiveness of UAS denoising techniques [118]. Various metrics are utilized in the literature to evaluate UAS denoising performance. Predominantly, these metrics are based on the SNR, which quantifies the desired signal level relative to the background noise. Additionally, some studies employ recognition accuracy as a direct measure of performance, primarily when denoising is intended to improve the accuracy of subsequent recognition tasks. This section summarizes the evaluation metrics commonly used in UAS denoising research.

A. Signal Quality Metrics

1) Signal-to-Noise Ratio: The SNR quantifies the proportion of signal power to noise power. Higher SNR values indicate lower noise content in the signal, whereas lower SNR values suggest higher noise content. The SNR is defined as follows:

$$\mathrm{SNR} = 10\log_{10}\left(\frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}}\right) \tag{3}$$

where P_{signal} and P_{noise} represent the power of pure UAS and noisy signals, respectively. SNR is a necessary and popular evaluation metric for UAS denoising [54].

2) Peak SNR: The PSNR is a significant metric for evaluating UAS denoising quality. For the UAS, PSNR measures the ratio of the maximum possible power of a signal to the power of corrupting noise that affects the fidelity of its representation [97]. The PSNR can be computed by

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}}\right) \tag{4}$$

where MSE is the mean squared error between the original and the denoised signal. A higher PSNR value indicates that the denoised signal is of higher quality than the noise level. The denoising process effectively reduces the noise while preserving the integrity and strength of the original signal.

3) Signal-to-Distortion Ratio: The SDR specifically focuses on the distortion between the original signal and the estimated signal [103]. The SDR is defined as follows:

$$\mathrm{SDR} = 10\log_{10}\left(\frac{P_{\mathrm{signal}}}{P_{\mathrm{distortion}}}\right). \tag{5}$$

4) Signal-to-Distortion Ratio Improvement: The signal-to-distortion ratio improvement (SDRi) measures the improvement in SDR due to some processing or alteration of a signal. The SDRi is calculated by comparing the SDR before and after the processing [103]

$$\mathrm{SDRi} = \mathrm{SDR}_{\mathrm{after}} - \mathrm{SDR}_{\mathrm{before}}. \tag{6}$$

TABLE IV
Reconstruction Error in the UAS Denoising Literature

Metric	Definition	Literature
Mean square error (MSE)	$\frac{1}{L}\sum_{n=1}^{L}(\hat{x_n} - x_n)^2$	[76], [108], [128]
Root Mean square error (RMSE)	$\sqrt{\frac{1}{L}\sum_{n=1}^{L}(\hat{x_n} - x_n)^2}$	[11], [55], [56], [80], [128]
Mean absolute error (MAE)	$\frac{1}{L}\sum_{j=1}^{L}\lvert\hat{x_n} - x_n\rvert$	[129]

5) Scale-Invariant SNR Improvement: The scale-invariant SNR improvement (SI-SNRi) is a measure often used in audio and speech processing to evaluate the effectiveness of enhancement algorithms, particularly when the absolute scale of the signal may not be consistent or important. This metric adjusts for scaling differences between the processed and original signals, providing a more robust comparison

$$\text{SI-SNRi} = \text{SI-SNR}_{\mathrm{after}} - \text{SI-SNR}_{\mathrm{before}}. \tag{7}$$

The scale-invariant SNR is calculated differently from the traditional SNR to account for scaling factors between the target and estimated signals. It involves normalizing the signal relative to a reference before computing the power ratio

$$\text{SI-SNR} = 10\log_{10}\left(\frac{\|\alpha \cdot x(n)\|^2}{\left\|\hat{x}(n) - \alpha \cdot x(n)\right\|^2}\right) \tag{8}$$

where $\alpha = (\langle \text{estimate, target}\rangle)/(\|\text{target}\|^2)$ scales the target signal to best fit the estimate in a least-squares sense. This normalization allows the SI-SNR to be independent of the signal's scale, focusing solely on the noise and distortion relative to the target's shape and structure [103].

6) Segment SNR: The SSNR averages the SNR values computed for each segment, giving a more detailed measure of signal quality across different parts of the signal, which is especially useful in cases where signal characteristics vary over time [103]. The SSNR can be computed by

$$\mathrm{SSNR} = \frac{10}{M}\sum_{m=1}^{M}\log_{10}\left(\frac{P_{\mathrm{signal}}^m}{P_{\mathrm{noise}}^m}\right) \tag{9}$$

where P_{signal}^m and P_{noise}^m represent the power of the mth segment of the signal and noise, respectively.

B. Reconstruction Error

Reconstruction error measures the deviations between the pure signal and noise reduction signal. An outstanding denoising algorithm should precisely reconstruct the pure signal and achieve a small reconstruction error. There are various reconstruction errors in the literature [54]. Table IV summarizes popular reconstruction errors employed in the UAS denoising literature.

VII. Experimental Dataset

The literature on UAS denoising algorithms has been evaluated using a variety of datasets due to the challenges inherent in the underwater environment and the difficulties associated with real-world data collection. Consequently, many studies have utilized synthetic data and artificial noise to test their algorithms. On the other hand, some studies have conducted

TABLE V
SUMMARY OF SYNTHETIC PURE SIGNALS

Signal	Formula	Literature
Lorenz signal	$\begin{cases}\dot{x}=-r(x-y)\\ \dot{y}=-xz+gy-y\\ \dot{z}=xy-kz\end{cases}$	[51], [53], [54], [78], [80], [81] [47], [48], [52], [76]
Chen signal	$\begin{cases}\dot{x}=-r(x-y)\\ \dot{y}=(k-r)x-xz+ky\\ \dot{z}=xy-gz\end{cases}$	[47], [48], [54], [76], [78]
Rossler signal	$\begin{cases}\dot{x}=-y-z\\ \dot{y}=x+ry\\ \dot{z}=g+z(x-k)\end{cases}$	[47], [48], [52], [76]
Duffing signal	$\begin{cases}\dot{x}=y\\ \dot{y}=-\rho y+\alpha x(1-x^2)+\mu\cos(\omega t)\\ \dot{z}=\delta\end{cases}$	[47], [52], [78]
Rossler signal	$\begin{cases}\dot{x}=-y-z\\ \dot{y}=x+ry\\ \dot{z}=g+z(x-k)\end{cases}$	[47], [48], [52], [76]
Mackey Glass signal	$\begin{cases}\frac{dx(t)}{dt}=\beta\frac{x(t-\tau)}{1+x(t-\tau)^n}-\gamma x(t) & \text{for } x(t-\tau)>0,\\ z=\theta & \text{otherwise.}\end{cases}$	[52]
Ikeda signal	$x_{n+1}=1+u\left(x_n\cos(t_n)-y_n\sin(t_n)\right),$ $y_{n+1}=u\left(x_n\sin(t_n)+y_n\cos(t_n)\right),$ $t_n=\kappa-\frac{\alpha}{1+x_n^2+y_n^2},$	[52]

TABLE VI
SUMMARY OF REAL-WORLD DATASET

Dataset	Access	Literature
ShipsEar	https://underwaternoise.atlanttic.uvigo.es/ [130]	[101], [108], [110], [131] [70], [100], [103], [105], [106], [109], [116]
DeepShip	https://github.com/irfankamboh/DeepShip [132]	[111], [131] [101], [108], [110], [131]
Cooperative-project Dataset	Confidential	[109]
Ocean Networks Canada	https://oceannetworks.ca	[109]
Dataset of two type of vessels	Confidential	[110], [133]
Ship radiated noise	https://aigei.com/	[47]
Department of the Interior of National Parks	https://www.nps.gov/glba/learn/nature/soundclips.htm	[48]
National Park Administration	https://www.nps.gov/glba/learn/nature/soundclips.html	[54]

experiments with real-world UAS datasets. The table below provides a summary of popular datasets used in UAS denoising research.

A. Synthetic Data

Due to the limited availability of UAS datasets, researchers have purposefully simulated synthetic pure and noise signals to test denoising algorithms. Table V summarizes that synthetic pure signals are popular in the UAS denoising literature. The literature may generate different pure signals with different initial states. Then, various synthetic noise signals are added to pure signals to simulate the noisy UAS. According to Table V, Lorenz signal is the most popular, whereas Ikeda and Mackey Glass signals are much less popular.

B. Real-World Data

In addition to the synthesized data discussed earlier, the literature also examines UAS denoising algorithms using real-world datasets. Table VI provides a summary of studies that utilize these real-world datasets. Unfortunately, most datasets gathered by respective authors are not publicly accessible. Among the publicly available datasets, ShipsEar and DeepShip are the most notable. The ShipsEar dataset comprises underwater acoustic recordings of ships and boats, featuring 90 recordings across 11 vessel types, totaling 6189 s of audio. In contrast, the DeepShip dataset includes 47 h and 4 min of real-world underwater recordings, capturing 265 different ships categorized into four classes. These recordings were made throughout various seasons, featuring diverse sea states and noise levels. The DeepShip dataset contains nearly seven times more recordings and is approximately 25 times longer in total duration than the ShipsEar dataset. Usually, each record is segmented into small windows to train denoising algorithms [68].

VIII. DISCUSSION ON ACOUSTIC SENSOR PROPERTIES

The design and operation of UAS denoising algorithms are intricately linked to the properties of the acoustic sensors used to capture the data [131]. Key factors such as accuracy, repeatability, temperature drift, and the feasibility of regular calibration significantly influence the performance of denoising methods, especially in challenging environments like the deep ocean [132].

The accuracy of acoustic sensors determines the quality of raw data, directly affecting the input to denoising algorithms [59]. High-accuracy sensors produce cleaner signals with less intrinsic noise, enabling more straightforward denoising methods to perform effectively. Conversely, low-accuracy sensors introduce additional noise components that require more sophisticated algorithms to disentangle signals from noise.

Repeatability refers to the sensor's ability to produce consistent measurements under the same conditions [133]. Inconsistent sensor behavior complicates denoising, as the algorithms may struggle to differentiate between actual signal variations and sensor-induced noise. Algorithms designed for such cases must incorporate adaptive learning or real-time calibration mechanisms to account for sensor performance variability.

Temperature drift, a common issue in acoustic sensors, becomes particularly significant in deep-ocean environments, where extreme and varying temperatures can alter sensor sensitivity [134]. This drift can introduce systematic errors that mimic or obscure acoustic signals. To address this, denoising algorithms must include compensation strategies, such as incorporating temperature data as an auxiliary input or designing filters to counteract temperature-induced noise.

In deep-ocean scenarios, regular calibration of sensors is often impractical due to the remote and harsh conditions [135]. This lack of calibration can lead to gradual degradation in sensor performance over time, increasing the noise levels and bias in the data. To mitigate this, denoising algorithms must be robust to uncalibrated data, employing self-calibration techniques or leveraging redundancy in multisensor systems. For example, algorithms can compare data from multiple sensors to identify and correct anomalies caused by sensor drift.

Given the challenges posed by sensor properties, denoising algorithms for underwater applications must be designed with the following considerations. Algorithms should account for sensor-specific characteristics and adapt to changes over time without requiring frequent recalibration. Multisensor setups

can provide complementary data to enhance denoising accuracy, even in the presence of faulty or degraded sensors. Incorporating auxiliary information, such as temperature or pressure data, can help algorithms compensate for environmental factors affecting sensor performance. Advanced DL methods can leverage large datasets to learn general noise characteristics, enabling effective denoising even with uncalibrated or degraded sensors.

IX. Applications

UAS denoising is a critical component for a wide range of underwater applications, enabling clearer signal processing and enhancing the performance of various technologies in challenging acoustic environments. This section highlights some major roles of UAS denoising technologies in real-world applications, emphasizing their significance across diverse fields.

A. Maritime Navigation and Safety

Accurate denoising techniques improve the detection and interpretation of acoustic signals used for identifying obstacles, vessels, and navigational aids [136], [137]. These improvements are particularly critical in conditions with limited visibility, such as during storms or in turbid waters, significantly reducing the risk of collisions and groundings. For instance, enhanced signal clarity can aid autonomous underwater vehicles (AUVs) in route optimization and hazard avoidance [138], [139]. The integration of denoised acoustic signals into advanced sonar systems further improves situational awareness in complex maritime environments.

B. Submarine Communications

In underwater environments where electromagnetic waves are highly attenuated, acoustic signals serve as the primary medium for communication. Denoising these signals is essential to mitigate the impact of ambient noise and signal distortions, ensuring reliable data transfer among submarines, surface vessels, and underwater stations [140]. This is especially critical for military operations and deep-sea exploration, where clear and uninterrupted communication can be a matter of safety and mission success.

C. Marine Life Monitoring

UAS denoising is pivotal in acoustic-based ecological studies, where accurate identification and classification of marine species are crucial. By removing ambient and anthropogenic noise, denoising enables precise detection of species-specific vocalizations, contributing to biodiversity assessments and conservation initiatives [34], [141]. For instance, denoising enhances the monitoring of marine mammals such as dolphins and whales, facilitating behavioral analysis and population tracking. Moreover, it helps differentiate biological sounds from geophysical and vessel noises, improving the reliability of marine soundscapes [36].

D. Shoreline Surveillance

Shoreline surveillance involves monitoring coastal regions for security, safety, and environmental protection [30]. UAS denoising technologies are vital in reducing interference from natural and anthropogenic noises, improving the detection of unauthorized activities, vessel movements, and environmental anomalies such as oil spills [30]. Denoised signals are also used in automated systems to classify sounds for efficient threat identification, aiding in enforcing maritime regulations and preserving coastal ecosystems.

E. Environmental Monitoring and Disaster Management

Denoising acoustic signals is crucial for effectively monitoring underwater environments and detecting signs of ecological changes or natural disasters [142]. For instance, denoised data from acoustic sensors enhance the detection of seismic activities [143], [144], tsunamis [145], and underwater landslides [146], enabling faster and more accurate responses. These techniques also support the tracking of ocean currents, temperature variations, and other oceanographic parameters through improved acoustic propagation analysis. Such insights are vital for understanding climate dynamics, developing early warning systems, and preparing for potential disasters, ensuring both environmental and human safety.

F. Resource Exploration and Exploitation

Denoising plays a critical role in resource exploration, including oil, gas, and mineral extraction, by enhancing the clarity and accuracy of seismic and acoustic survey data [147]. This improvement facilitates more precise subsurface imaging, reducing exploration errors and optimizing resource identification [148]. Additionally, in underwater mining operations, denoised signals are crucial for monitoring machinery performance, detecting faults, and minimizing operational risks. By ensuring high-quality data, denoising techniques also improve resource recovery efficiency and support sustainable extraction practices [149], [150].

G. Aquaculture Management

UAS denoising technologies are integral to monitoring and managing fish farms by isolating and interpreting acoustic signals generated within aquaculture systems [151], [152]. These signals provide critical insights into fish behavior, such as feeding activity, stress responses, and movement patterns [153]. By effectively denoising these signals, aquaculture operators can implement precision management practices, optimize feeding schedules, monitor water quality, and detect early signs of disease or environmental stress. This enhances productivity, reduces feed waste, and contributes to sustainable aquaculture practices by minimizing environmental impact and ensuring healthier stock. Furthermore, advanced denoising improves the accuracy of automated monitoring systems, enabling real-time decision-making and reducing reliance on manual observation. Denoising enhances the accuracy of sonar-based fish stock and biomass estimation by filtering out ambient and anthropogenic noise [154]. This improved signal

clarity enables precise assessments of fish abundance, distribution, and species composition, even in noisy environments. By supporting sustainable fisheries management, denoising helps set appropriate quotas, monitor overfishing, and ensure regulatory compliance [155]. Furthermore, it facilitates using advanced acoustic technologies and machine learning models for species identification and behavioral prediction, contributing to long-term ecosystem preservation and resource management [156].

H. Fault Diagnosis of Underwater Equipment

UAS denoising techniques are essential for isolating and removing noisy components, enabling the accurate preparation of signal-relevant parts for fault diagnosis in underwater equipment [157]. For example, in underwater pump systems, these techniques enhance the detection of anomalies such as cavitation, bearing wear, or flow disruptions [26]. By providing cleaner data for analysis, denoising improves the performance of diagnostic methods, ensuring timely maintenance and reducing the risk of equipment failure in critical operations [8].

X. Open Questions and Future Directions

The UAS community has delved into advanced decomposition frameworks, thresholding techniques, and DL algorithms. Nevertheless, numerous unexplored avenues remain, warranting further extensive research and exploration.

1) Signal decomposition is widely used to denoise the UAS, yet identifying the optimal decomposition level continues to pose a significant challenge. While the sensitivity analysis of decomposition levels across different algorithms has been explored, it remains largely cursory. Treating the decomposition level as a hyperparameter and applying hyperparameter optimization algorithms could be a promising strategy. However, this approach is often too time-consuming and impractical for underwater applications, which demand real-time processing capabilities.
2) There is no consensus in the literature regarding the most effective signal decomposition algorithm for denoising the UAS. Benchmarking studies comparing different signal decomposition algorithms are notably absent. While some studies claim the superiority of specific algorithms based on outcomes from signal decomposition research, UAS presents unique challenges that necessitate further specialized investigation.
3) The literature employs different steps and parameters, such as normalization, sampling rate, and window length, to preprocess the UAS data before establishing the following denoising model. Differences in preprocessing lead to different conclusions and findings regarding the performance of denoising and recognition models. A specific UAS denoising model may obtain outstanding performance on a small window and become much worse on long windows. Therefore, the standard framework to identify preprocessing schemes for any UAS dataset needs to be well-researched.
4) Although researchers have explored various advanced DL architectures, underwater applications require extremely high computing speed. When deploying the technology in underwater scenarios, the denoising model must adapt to new contexts quickly. Therefore, gradient-based DL models may fail to satisfy these requirements. However, deep randomized neural networks are suitable candidates due to their strong nonlinear feature extraction ability and fast training speed [158].
5) Automated learning is imperative, encompassing the fine-tuning of hyperparameters and training of learning-based UAS denoising algorithms. The varied applications of UAS denoising techniques necessitate an automated framework, enabling practitioners to employ these methods across diverse applications seamlessly. Regrettably, current research overlooks the critical need for and significance of automated learning. Manual selection of hyperparameters and training algorithms diminishes the flexibility and practicality of UAS denoising techniques. Therefore, developing an environment-agnostic automatic learning framework for UAS denoising techniques is worth exploring.
6) Advanced ensemble learning techniques have demonstrated their efficacy in enhancing model robustness by creating a diverse array of base models [159]. In UAS-related tasks, extracting noise-resistant features and developing robust models are imperative. However, the existing literature largely neglects the significance of an ensemble UAS denoising framework. Such a framework holds the potential to mitigate the weaknesses inherent in individual UAS denoising models, thereby enhancing overall denoising performance. Given the diversity and complexity of underwater environments, a single UAS denoising technique may struggle to achieve optimal performance across all scenarios. Nevertheless, various base models can collectively address different types of noisy signals through ensemble learning, thus culminating in improved accuracy.
7) Efficient exploration of the marine environment and accurate detection of underwater events necessitate deploying diverse data collection systems, including unmanned underwater vehicle (UUV) swarms and acoustic sensor networks. Each UUV and sensor unit can gather acoustic signals from distinct spatial coordinates. However, integrating these disparate UUV systems and developing a denoising algorithm based on the amalgamated data remains an uncharted territory. The potential schemes for dynamically fusing these data sources and denoising the resulting signal hold significant promise and merit further exploration.
8) Many UAS denoising algorithms operate within an offline framework, assuming all UAS data are available for model establishment. However, online processing is essential as UAS data is inherently sequential, and underwater applications often occur in real-time scenarios. The denoising step of UAS data typically precedes control or detection systems, which operate continuously in real-world applications. Thus, there is a

need to extend decomposition-based and DL-based UAS denoising techniques to online variants. These online algorithms can incorporate online signal decomposition methods, real-time training algorithms for DL models, and online adaptation of DL architectures, among other considerations.

9) While many UAS denoising algorithms rely on unsupervised reconstruction, a few pioneering studies have delved into the potential of self-supervised learning for UAS denoising. However, a plethora of advanced self-supervised learning techniques remain unexplored and under-investigated. Crafting appropriate pretext tasks is crucial for the efficacy of self-supervised learning algorithms, especially given the unique challenges UAS data poses. Moreover, there is ample opportunity to design pretext tasks tailored to UAS characteristics. Furthermore, integrating self-supervised learning with existing decomposition-based denoising algorithms holds promise. Developing a self-supervised decomposition-based denoising scheme is a promising avenue for future research.

XI. Conclusion

UASs are the most commonly collected data in underwater environments and play a pivotal role in various applications. However, the inherent complexity of these environments poses significant challenges for the transmission, recognition, feature extraction, and interpretation of UAS. As a result, denoising UAS is a critical technological step that is essential for various applications. This review article provides an overview of the developments in UAS denoising, from theoretical underpinnings to practical applications. Denoising involves the removal of extraneous noise and extracting signal-dominated information, which is then utilized for tasks such as target recognition. Traditional methods typically rely on signal processing and wavelet thresholding algorithms for noise removal. The majority of UAS denoising solutions employ signal decomposition techniques, which facilitate the separation of the complex original UAS into multiple modes. Subsequently, specific denoising algorithms are applied to each mode to eliminate noise. Finally, all denoised modes are recombined to produce the cleaned UAS.

Recently, the rapid advancement of DL algorithms has spurred the UAS community to develop sophisticated DL-based denoising methods. These algorithms are typically trained to reconstruct signal-dominated information and maximize the SNR. Since a DL model's loss function can comprise multiple terms, researchers can combine denoising and recognition objectives within a single loss function. Consequently, DL-based denoising is task-oriented and highly flexible, adapting to specific application needs with greater efficacy.

References

[1] Y. Wu, X. Ta, R. Xiao, Y. Wei, D. An, and D. Li, "Survey of underwater robot positioning navigation," *Appl. Ocean Res.*, vol. 90, Sep. 2019, Art. no. 101845.

[2] W. Zhang, W. Wu, Y. Teng, Z. Li, and Z. Yan, "An underwater docking system based on UUV and recovery mother ship: Design and experiment," *Ocean Eng.*, vol. 281, Aug. 2023, Art. no. 114767.

[3] W. Zhang, X. Yang, C. Leng, J. Wang, and S. Mao, "Modulation recognition of underwater acoustic signals using deep hybrid neural networks," *IEEE Trans. Wireless Commun.*, vol. 21, no. 8, pp. 5977–5988, Aug. 2022.

[4] A. C. Singer, J. K. Nelson, and S. S. Kozat, "Signal processing for underwater acoustic communications," *IEEE Commun. Mag.*, vol. 47, no. 1, pp. 90–96, Jan. 2009.

[5] Y. Zhu, B. Wang, Y. Zhang, J. Li, and C. Wu, "Convolutional neural network based filter bank multicarrier system for underwater acoustic communications," *Appl. Acoust.*, vol. 177, Jun. 2021, Art. no. 107920.

[6] Y. Xie, J. Ren, and J. Xu, "Unraveling complex data diversity in underwater acoustic target recognition through convolution-based mixture of experts," *Expert Syst. Appl.*, vol. 249, Sep. 2024, Art. no. 123431.

[7] J. Jiang, Z. Wu, M. Huang, and Z. Xiao, "Detection of underwater acoustic target using beamforming and neural network in shallow water," *Appl. Acoust.*, vol. 189, Feb. 2022, Art. no. 108626.

[8] F. Liu, H. Tang, Y. Qin, C. Duan, J. Luo, and H. Pu, "Review on fault diagnosis of unmanned underwater vehicles," *Ocean Eng.*, vol. 243, Jan. 2022, Art. no. 110290.

[9] J. Jiang, Z. Wu, J. Lu, M. Huang, and Z. Xiao, "Interpretable features for underwater acoustic target recognition," *Measurement*, vol. 173, Mar. 2021, Art. no. 108586.

[10] J. Jiang, T. Shi, M. Huang, and Z. Xiao, "Multi-scale spectral feature extraction for underwater acoustic target recognition," *Measurement*, vol. 166, Dec. 2020, Art. no. 108227.

[11] Y. Yousif Al-Aboosi and A. Zuri Sha'ameri, "Improved underwater signal detection using efficient time–frequency de-noising technique and pre-whitening filter," *Appl. Acoust.*, vol. 123, pp. 93–106, Aug. 2017.

[12] D. Middleton, "Channel modeling and threshold signal processing in underwater acoustics: An analytical overview," *IEEE J. Ocean. Eng.*, vol. OE-12, no. 1, pp. 4–28, Jan. 1987.

[13] G. M. Wenz, "Review of underwater acoustics research: Noise," *J. Acoust. Soc. Amer.*, vol. 51, no. 3B, pp. 1010–1024, Mar. 1972.

[14] K. M. Awan, P. A. Shah, K. Iqbal, S. Gillani, W. Ahmad, and Y. Nam, "Underwater wireless sensor networks: A review of recent issues and challenges," *Wireless Commun. Mobile Comput.*, vol. 2019, pp. 1–20, Jan. 2019.

[15] N. E. Huang et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. Roy. Soc. Lond. Ser. Math. Phys. Eng. Sci.*, vol. 454, no. 1971, pp. 903–995, Mar. 1998.

[16] K. Dragomiretskiy and D. Zosso, "Variational mode decomposition," *IEEE Trans. Signal Process.*, vol. 62, no. 3, pp. 531–544, Feb. 2013.

[17] M. J. Shensa, "The discrete wavelet transform: Wedding the a trous and Mallat algorithms," *IEEE Trans. Signal Process.*, vol. 40, no. 10, pp. 2464–2482, Oct. 1992.

[18] J. Gilles, "Empirical wavelet transform," *IEEE Trans. Signal Process.*, vol. 61, no. 16, pp. 3999–4010, Aug. 2013.

[19] Z. Wu and N. E. Huang, "Ensemble empirical mode decomposition: A noise-assisted data analysis method," *Adv. Adapt. Data Anal.*, vol. 1, pp. 1–41, Jan. 2009.

[20] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[21] P. Singh and A. Sharma, "Attention-based convolutional denoising autoencoder for two-lead ECG denoising and arrhythmia classification," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–10, 2022.

[22] X. Zhou and K. Yang, "A denoising representation framework for underwater acoustic signal recognition," *J. Acoust. Soc. Amer.*, vol. 147, no. 4, pp. EL377–EL383, Apr. 2020.

[23] Q. Sun and K. Wang, "Underwater single-channel acoustic signal multitarget recognition using convolutional neural networks," *J. Acoust. Soc. Amer.*, vol. 151, no. 3, pp. 2245–2254, Mar. 2022.

[24] S. Tian, D. Chen, H. Wang, and J. Liu, "Deep convolution stack for waveform in underwater acoustic target recognition," *Sci. Rep.*, vol. 11, no. 1, p. 9614, May 2021.

[25] S. Wang and X. Zeng, "Robust underwater noise targets classification using auditory inspired time–frequency analysis," *Appl. Acoust.*, vol. 78, pp. 68–76, Apr. 2014.

[26] Q. Jiang, Y. Chen, G. Wang, and T. Ji, "A novel deep neural network for noise removal from underwater image," *Signal Process., Image Commun.*, vol. 87, Sep. 2020, Art. no. 115921.

[27] J. Zhou, T. Yang, and W. Zhang, "Underwater vision enhancement technologies: A comprehensive review, challenges, and recent trends," *Int. J. Speech Technol.*, vol. 53, no. 3, pp. 3594–3621, Feb. 2023.

[28] J. Zhou, L. Pang, D. Zhang, and W. Zhang, "Underwater image enhancement method via multi-interval subhistogram perspective equalization," *IEEE J. Ocean. Eng.*, vol. 48, no. 2, pp. 474–488, Apr. 2023.

[29] X. Lin, R. Dong, and Z. Lv, "Deep learning-based classification of raw hydroacoustic signal: A review," *J. Mar. Sci. Eng.*, vol. 11, no. 1, p. 3, Dec. 2022.

[30] L. C. F. Domingos, P. E. Santos, P. S. M. Skelton, R. S. A. Brinkworth, and K. Sammut, "A survey of underwater acoustic data classification methods using deep learning for shoreline surveillance," *Sensors*, vol. 22, no. 6, p. 2081, Mar. 2022.

[31] S. Sendra, J. Lloret, J. M. Jimenez, and L. Parra, "Underwater acoustic modems," *IEEE Sensors J.*, vol. 16, no. 11, pp. 4063–4071, Jun. 2016.

[32] C. M. Duarte et al., "The soundscape of the anthropocene ocean," *Science*, vol. 371, no. 6529, p. 4658, Feb. 2021.

[33] J. Butler, E. R. Anderson, and M. J. Butler, "Habitat restoration restores underwater soundscapes and larval recruitment," *Frontiers Ecology Evol.*, vol. 10, Mar. 2022, Art. no. 785986.

[34] N. Pieretti, M. L. Martire, C. Corinaldesi, L. Musco, A. Dell'Anno, and R. Danovaro, "Anthropogenic noise and biological sounds in a heavily industrialized coastal area (Gulf of naples, Mediterranean Sea)," *Mar. Environ. Res.*, vol. 159, Jul. 2020, Art. no. 105002.

[35] R. Hilmo and W. S. D. Wilcock, "Physical sources of high-frequency seismic noise on cascadia initiative ocean bottom seismometers," *Geochemistry, Geophys., Geosystems*, vol. 21, no. 10, p. 2020, Oct. 2020.

[36] X. Zhang, R. Simons, J. Zheng, and C. Zhang, "A review of the state of research on wave-current interaction in nearshore areas," *Ocean Eng.*, vol. 243, Jan. 2022, Art. no. 110202.

[37] S. Cominelli et al., "Vessel noise in spatially constricted areas: Modeling acoustic footprints of large vessels in the cabot strait, eastern Canada," *Ocean Coastal Manage.*, vol. 194, Aug. 2020, Art. no. 105255.

[38] J.-P. Jalkanen, L. Johansson, M. H. Andersson, E. Majamäki, and P. Sigray, "Underwater noise emissions from ships during 2014–2020," *Environ. Pollut.*, vol. 311, Oct. 2022, Art. no. 119766.

[39] E. Chou, B. L. Southall, M. Robards, and H. C. Rosenbaum, "International policy, recommendations, actions and mitigation efforts of anthropogenic underwater noise," *Ocean Coastal Manage.*, vol. 202, Mar. 2021, Art. no. 105427.

[40] W. D. Halliday, M. K. Pine, and S. J. Insley, "Underwater noise and Arctic marine mammals: Review and policy recommendations," *Environ. Rev.*, vol. 28, no. 4, pp. 438–448, Dec. 2020.

[41] S. Isojunno et al., "When the noise goes on: Received sound energy predicts sperm whale responses to both intermittent and continuous navy sonar," *J. Experim. Biol.*, vol. 223, no. 7, Jan. 2020, Art. no. 219741.

[42] S. Cope, E. Hines, R. Bland, J. D. Davis, B. Tougher, and V. Zetterlind, "Multi-sensor integration for an assessment of underwater radiated noise from common vessels in san Francisco bay," *J. Acoust. Soc. Amer.*, vol. 149, no. 4, pp. 2451–2464, Apr. 2021.

[43] A. Zhou et al., "A novel cross-attention fusion-based joint training framework for robust underwater acoustic signal recognition," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023, Art. no. 4209516.

[44] R. Gao, R. Li, M. Hu, P. N. Suganthan, and K. F. Yuen, "Online dynamic ensemble deep random vector functional link neural network for forecasting," *Neural Netw.*, vol. 166, pp. 51–69, Sep. 2023.

[45] K. M. Raj, S. S. Murugan, V. Natarajan, and S. Radha, "Denoising algorithm using wavelet for underwater signal affected by wind driven ambient noise," in *Proc. Int. Conf. Recent Trends Inf. Technol. (ICRTIT)*, Jun. 2011, pp. 943–946.

[46] G. Li, Y. Han, and H. Yang, "A new underwater acoustic signal denoising method based on modified uniform phase empirical mode decomposition, hierarchical amplitude-aware permutation entropy, and optimized improved wavelet threshold denoising," *Ocean Eng.*, vol. 293, Feb. 2024, Art. no. 116629.

[47] G. Li, W. Bu, and H. Yang, "Noise reduction method for ship radiated noise signal based on modified uniform phase empirical mode decomposition," *Measurement*, vol. 227, Mar. 2024, Art. no. 114193.

[48] H. Li, S. Li, J. Sun, B. Huang, J. Zhang, and M. Gao, "Ultrasound signal processing based on joint GWO-VMD wavelet threshold functions," *Measurement*, vol. 226, Feb. 2024, Art. no. 114143.

[49] F. Liu, G. Li, and H. Yang, "Application of multi-algorithm mixed feature extraction model in underwater acoustic signal," *Ocean Eng.*, vol. 296, Mar. 2024, Art. no. 116959.

[50] G. Li, W. Bu, and H. Yang, "Research on noise reduction method for ship radiate noise based on secondary decomposition," *Ocean Eng.*, vol. 268, Jan. 2023, Art. no. 113412.

[51] H. Yang, X. Yang, and G. Li, "Dual feature extraction system for ship-radiated noise and its application extension," *Ocean Eng.*, vol. 285, Oct. 2023, Art. no. 115352.

[52] G. Li, F. Liu, and H. Yang, "Research on feature extraction method of ship radiated noise with K-nearest neighbor mutual information variational mode decomposition, neural network estimation time entropy and self-organizing map neural network," *Measurement*, vol. 199, Aug. 2022, Art. no. 111446.

[53] H. Yang, Y. Cheng, and G. Li, "A denoising method for ship radiated noise based on Spearman variational mode decomposition, spatial-dependence recurrence sample entropy, improved wavelet threshold denoising, and savitzky-golay filter," *Alexandria Eng. J.*, vol. 60, no. 3, pp. 3379–3400, Jun. 2021.

[54] H. Yang, L. Li, and G. Li, "A new denoising method for underwater acoustic signal," *IEEE Access*, vol. 8, pp. 201874–201888, 2020.

[55] Y.-X. Li and L. Wang, "A novel noise reduction technique for underwater acoustic signals based on complete ensemble empirical mode decomposition with adaptive noise, minimum mean square variance criterion and least mean square adaptive filter," *Defence Technol.*, vol. 16, no. 3, pp. 543–554, Jun. 2020.

[56] G. Li, Z. Yang, and H. Yang, "A denoising method of ship radiated noise signal based on modified CEEMDAN, dispersion entropy, and interval thresholding," *Electronics*, vol. 8, no. 6, p. 597, May 2019.

[57] H. Hu, L. Zhang, H. Yan, Y. Bai, and P. Wang, "Denoising and baseline drift removal method of MEMS hydrophone signal based on VMD and wavelet threshold processing," *IEEE Access*, vol. 7, pp. 59913–59922, 2019.

[58] Y.-X. Li, S.-B. Jiao, and X. Gao, "A novel signal feature extraction technology based on empirical wavelet transform and reverse dispersion entropy," *Defence Technol.*, vol. 17, no. 5, pp. 1625–1635, Oct. 2021.

[59] B. M. Gur and C. Niezrecki, "Autocorrelation based denoising of manatee vocalizations using the undecimated discrete wavelet transform," *J. Acoust. Soc. Amer.*, vol. 122, no. 1, pp. 188–199, Jul. 2007.

[60] S. Ganapathi, S. M. Kumar, and D. Meganathan, "Noise reduction in underwater acoustic signals for tropical and subtropical coastal waters," in *Proc. IEEE/OES China Ocean Acoust. (COA)*, Jan. 2016, pp. 1–6.

[61] P. Flandrin, G. Rilling, and P. Goncalves, "Empirical mode decomposition as a filter bank," *IEEE Signal Process. Lett.*, vol. 11, no. 2, pp. 112–114, Feb. 2004.

[62] J. Spencer, *Ten Lectures on the Probabilistic Method*, vol. 64. Philadelphia, PA, USA: SIAM, 1994.

[63] L. Zão, R. Coelho, and P. Flandrin, "Speech enhancement with EMD and hurst-based mode selection," *IEEE/ACM Trans. Audio, Speech, Language Process.*, vol. 22, no. 5, pp. 899–911, May 2014.

[64] R. Kannan and G. Latha, "Acoustic toning of marine species vocalization by empirical mode decomposition," in *Proc. IEEE Underwater Technol. (UT)*, Feb. 2015, pp. 1–4.

[65] X. Wang, A. Liu, Y. Zhang, and F. Xue, "Underwater acoustic target recognition: A combination of multi-dimensional fusion features and modified deep neural network," *Remote Sens.*, vol. 11, no. 16, p. 1888, Aug. 2019.

[66] K. D. Seger, M. H. Al-Badrawi, J. L. Miksis-Olds, N. J. Kirsch, and A. P. Lyons, "An empirical mode decomposition-based detection and classification approach for marine mammal vocal signals," *J. Acoust. Soc. Amer.*, vol. 144, no. 6, pp. 3181–3190, Dec. 2018.

[67] A. Caldeira and R. Coelho, "EEMD-IF based method for underwater noisy acoustic signals enhancement in time-domain," *IEEE Signal Process. Lett.*, vol. 30, pp. 294–298, 2023.

[68] Y. Dong, X. Shen, and H. Wang, "Bidirectional denoising autoencoders-based robust representation learning for underwater acoustic target signal denoising," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–8, 2022.

[69] H. Yang, L.-L. Li, G.-H. Li, and Q.-R. Guan, "A novel feature extraction method for ship-radiated noise," *Defence Technol.*, vol. 18, no. 4, pp. 604–617, Apr. 2022.

[70] W. Chengkun, Z. Zhifeng, C. Bohua, and Y. Yong, "Denoise for propeller acoustic signals based on the improved wavelet thresholding algorithm of CEEMDAN," *Cogent Eng.*, vol. 11, no. 1, Dec. 2024, Art. no. 2327570.

[71] X. Qiu, P. N. Suganthan, and G. A. J. Amaratunga, "Ensemble incremental learning random vector functional link network for short-term electric load forecasting," *Knowl.-Based Syst.*, vol. 145, pp. 182–196, Apr. 2018.

[72] Y. Tian, M. Liu, S. Zhang, and T. Zhou, "Underwater multi-target passive detection based on transient signals using adaptive empirical mode decomposition," *Appl. Acoust.*, vol. 190, Mar. 2022, Art. no. 108641.

[73] Z. Li, K. Yang, X. Zhou, and S. Duan, "A novel underwater acoustic target identification method based on spectral characteristic extraction via modified adaptive chirp mode decomposition," *Entropy*, vol. 25, no. 4, p. 669, Apr. 2023.

[74] H. Yang, W.-S. Shi, and G.-H. Li, "Underwater acoustic signal denoising model based on secondary variational mode decomposition," *Defence Technol.*, vol. 28, pp. 87–110, Oct. 2023.

[75] T. Xing, X. Wang, K. Ni, and Q. Zhou, "A novel joint denoising method for hydrophone signal based on improved SGMD and WT," *Sensors*, vol. 24, no. 4, p. 1340, Feb. 2024.

[76] Z.-X. Li, Y.-A. Li, and K. Zhang, "A feature extraction method of ship-radiated noise based on mathematical morphological filtering," *J. Vib. Control*, vol. 28, nos. 23–24, pp. 3664–3675, Dec. 2022.

[77] H. Yan, T. Xu, P. Wang, L. Zhang, H. Hu, and Y. Bai, "MEMS hydrophone signal denoising and baseline drift removal algorithm based on parameter-optimized variational mode decomposition and correlation coefficient," *Sensors*, vol. 19, no. 21, p. 4622, Oct. 2019.

[78] G. Li, Z. Yang, and H. Yang, "Noise reduction method of underwater acoustic signals based on uniform phase empirical mode decomposition, amplitude-aware permutation entropy, and Pearson correlation coefficient," *Entropy*, vol. 20, no. 12, p. 918, Nov. 2018.

[79] 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.

[80] Y. Zhang, Z. Yang, X. Du, and X. Luo, "A new method for denoising underwater acoustic signals based on EEMD, correlation coefficient, permutation entropy, and wavelet threshold denoising," *J. Mar. Sci. Appl.*, vol. 23, no. 1, pp. 222–237, Mar. 2024.

[81] Y. Li, X. Chen, J. Yu, and X. Yang, "A fusion frequency feature extraction method for underwater acoustic signal based on variational mode decomposition, duffing chaotic oscillator and a kind of permutation entropy," *Electronics*, vol. 8, no. 1, p. 61, Jan. 2019.

[82] Y. Li, P. Gao, B. Tang, Y. Yi, and J. Zhang, "Double feature extraction method of ship-radiated noise signal based on slope entropy and permutation entropy," *Entropy*, vol. 24, no. 1, p. 22, Dec. 2021.

[83] D. Xie, S. Hong, and C. Yao, "Optimized variational mode decomposition and permutation entropy with their application in feature extraction of ship-radiated noise," *Entropy*, vol. 23, no. 5, p. 503, Apr. 2021.

[84] G. Li, W. Chang, and H. Yang, "A new hybrid model for underwater acoustic signal prediction," *Complexity*, vol. 2020, pp. 1–19, Jul. 2020.

[85] Z. Li, Y. Li, K. Zhang, and J. Guo, "Hierarchical refined composite multiscale fluctuation-based dispersion entropy: Application to feature extraction of underwater target signal," *Nonlinear Dyn.*, vol. 111, no. 24, pp. 22399–22417, Dec. 2023.

[86] Y. Li, L. Wang, X. Li, and X. Yang, "A novel linear spectrum frequency feature extraction technique for warship radio noise based on complete ensemble empirical mode decomposition with adaptive noise, duffing chaotic oscillator, and weighted-permutation entropy," *Entropy*, vol. 21, no. 5, p. 507, May 2019.

[87] J. Wang et al., "A novel underwater acoustic signal denoising algorithm for Gaussian/non-Gaussian impulsive noise," *IEEE Trans. Veh. Technol.*, vol. 70, no. 1, pp. 429–445, Jan. 2021.

[88] H. Yang, L. Gao, and G. Li, "Underwater acoustic signal prediction based on correlation variational mode decomposition and error compensation," *IEEE Access*, vol. 8, pp. 103941–103955, 2020.

[89] S. Koh, C. S. Chia, and B. A. Tan, "Underwater signal denoising using deep learning approach," in *Proc. Global Oceans, Singap. U.S. Gulf Coast*, Oct. 2020, pp. 1–6.

[90] A. Testolin and R. Diamant, "Underwater acoustic detection and localization with a convolutional denoising autoencoder," in *Proc. IEEE 8th Int. Workshop Comput. Adv. Multi-Sensor Adapt. Process. (CAMSAP)*, Dec. 2019, pp. 281–285.

[91] P. Kumar and K. Nathwani, "Self-noise cancellation in underwater acoustics using deep neural network-based eigencomponent transformation," *IEEE Sensors Lett.*, vol. 7, no. 11, pp. 1–4, Nov. 2023.

[92] G. Xie, J. Yang, and Y. Yang, "An improved sparse autoencoder and multilevel denoising strategy for diagnosing early multiple intermittent faults," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 52, no. 2, pp. 869–880, Feb. 2022.

[93] Y. Song, Q. Chu, F. Liu, T. Wang, and T. Shen, "Underwater acoustic signal noise reduction based on a fully convolutional encoder–decoder neural network," *J. Ocean Univ. China*, vol. 22, no. 6, pp. 1487–1496, Dec. 2023.

[94] W. Mallik, R. K. Jaiman, and J. Jelovica, "Predicting transmission loss in underwater acoustics using convolutional recurrent autoencoder network," *J. Acoust. Soc. Amer.*, vol. 152, no. 3, pp. 1627–1638, Sep. 2022.

[95] F. Ji, G. Li, S. Lu, and J. Ni, "Research on a feature enhancement extraction method for underwater targets based on deep autoencoder networks," *Appl. Sci.*, vol. 14, no. 4, p. 1341, Feb. 2024.

[96] R. Song, X. Feng, J. Wang, H. Sun, M. Zhou, and H. Esmaiel, "Underwater acoustic nonlinear blind ship noise separation using recurrent attention neural networks," *Remote Sens.*, vol. 16, no. 4, p. 653, Feb. 2024.

[97] T. Ma, S. Yan, and W. Wang, "An underwater acoustic signal denoising algorithm based on U-Net," in *Proc. IEEE Int. Conf. Signal Process., Commun. Comput. (ICSPCC)*, Nov. 2023, pp. 1–6.

[98] Y. Song, F. Liu, and T. Shen, "A novel noise reduction technique for underwater acoustic signals based on dual-path recurrent neural network," *IET Commun.*, vol. 17, no. 2, pp. 135–144, Jan. 2023.

[99] A. Zhou et al., "An attention-based multi-scale convolution network for intelligent underwater acoustic signal recognition," *Ocean Eng.*, vol. 287, Nov. 2023, Art. no. 115784.

[100] M. Zhou, J. Wang, X. Feng, H. Sun, J. Li, and X. Kuai, "On generative-adversarial-network-based underwater acoustic noise modeling," *IEEE Trans. Veh. Technol.*, vol. 70, no. 9, pp. 9555–9559, Sep. 2021.

[101] H. Ashraf, B. Shah, A. M. Soomro, Q.-U.-A. Safdar, Z. Halim, and S. K. Shah, "Ambient-noise free generation of clean underwater ship engine audios from hydrophones using generative adversarial networks," *Comput. Electr. Eng.*, vol. 100, May 2022, Art. no. 107970.

[102] H. Ashraf, Y. Jeong, and C. H. Lee, "Underwater ambient-noise removing GAN based on magnitude and phase spectra," *IEEE Access*, vol. 9, pp. 24513–24530, 2021.

[103] A. Zhou, W. Zhang, G. Xu, X. Li, K. Deng, and J. Song, "DBSA-Net: Dual branch self-attention network for underwater acoustic signal denoising," *IEEE/ACM Trans. Audio, Speech, Language Process.*, vol. 31, pp. 1851–1865, 2023.

[104] A. Zhou et al., "A novel noise-aware deep learning model for underwater acoustic denoising," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023, Art. no. 4202813.

[105] Y. Song, F. Liur, and T. Shen, "Method of underwater acoustic signal denoising based on dual-path transformer network," *IEEE Access*, vol. 12, pp. 81483–81494, 2022.

[106] S. Yang, A. Jin, X. Zeng, H. Wang, X. Hong, and M. Lei, "Underwater acoustic target recognition based on sub-band concatenated mel spectrogram and multidomain attention mechanism," *Eng. Appl. Artif. Intell.*, vol. 133, Jul. 2024, Art. no. 107983.

[107] X. Wang, P. Wu, B. Li, G. Zhan, J. Liu, and Z. Liu, "A self-supervised dual-channel self-attention acoustic encoder for underwater acoustic target recognition," *Ocean Eng.*, vol. 299, May 2024, Art. no. 117305.

[108] J. Xu, Y. Xie, and W. Wang, "Underwater acoustic target recognition based on smoothness-inducing regularization and spectrogram-based data augmentation," *Ocean Eng.*, vol. 281, Aug. 2023, Art. no. 114926.

[109] P. Zhu, Y. Zhang, Y. Huang, C. Zhao, K. Zhao, and F. Zhou, "Underwater acoustic target recognition based on spectrum component analysis of ship radiated noise," *Appl. Acoust.*, vol. 211, Aug. 2023, Art. no. 109552.

[110] H. Chu et al., "A deep-learning based high-gain method for underwater acoustic signal detection in intensity fluctuation environments," *Appl. Acoust.*, vol. 211, Aug. 2023, Art. no. 109513.

[111] C. Lyu, X. Hu, Z. Niu, B. Yang, J. Jin, and C. Ge, "A light-weight neural network for marine acoustic signal recognition suitable for fiber-optic hydrophones," *Expert Syst. Appl.*, vol. 235, Jan. 2024, Art. no. 121235.

[112] L. Cao, Z. Lei, Z. Zhou, J. Sun, and Y. Shi, "An underwater acoustic signal denoising method for broadband interference from underwater platforms based on the deep neural network model," in *Proc. 6th Int. Conf. Inf. Commun. Signal Process. (ICICSP)*, Sep. 2023, pp. 439–444.

[113] X. Wang, Y. Zhao, X. Teng, and W. Sun, "A stacked convolutional sparse denoising autoencoder model for underwater heterogeneous information data," *Appl. Acoust.*, vol. 167, Oct. 2020, Art. no. 107391.

[114] D. Li, F. Liu, T. Shen, L. Chen, and D. Zhao, "Data augmentation method for underwater acoustic target recognition based on underwater acoustic channel modeling and transfer learning," *Appl. Acoust.*, vol. 208, Jun. 2023, Art. no. 109344.

[115] J. Li and H. Yang, "Deep learning method with auditory passive attention for underwater acoustic target recognition under the condition of ship interference," *Ocean Eng.*, vol. 302, Jun. 2024, Art. no. 117674.

[116] J. Li and H. Yang, "The underwater acoustic target timbre perception and recognition based on the auditory inspired deep convolutional neural network," *Appl. Acoust.*, vol. 182, Nov. 2021, Art. no. 108210.

[117] S.-Z. Tian, D.-B. Chen, Y. Fu, and J.-L. Zhou, "Joint learning model for underwater acoustic target recognition," *Knowledge-Based Syst.*, vol. 260, Jan. 2023, Art. no. 110119.

[118] Y. Xu, X. Kong, and Z. Cai, "Cross-validation strategy for performance evaluation of machine learning algorithms in underwater acoustic target recognition," *Ocean Eng.*, vol. 299, May 2024, Art. no. 117236.

[119] H. Yang, K. Zheng, and J. Li, "Open set recognition of underwater acoustic targets based on GRU-CAE collaborative deep learning network," *Appl. Acoust.*, vol. 193, May 2022, Art. no. 108774.

[120] X. Wang, Y. Zhang, Z. Xiao, and M. Huang, "HIDR: A hierarchical independent detection and recognition strategy for underwater acoustic multi-target recognition," *Appl. Acoust.*, vol. 211, Aug. 2023, Art. no. 109503.

[121] R. Li, L. Wang, P. N. Suganthan, and O. Sourina, "Sample-based data augmentation based on electroencephalogram intrinsic characteristics," *IEEE J. Biomed. Health Informat.*, vol. 26, no. 10, pp. 4996–5003, Oct. 2022.

[122] Y. Gao, Y. Chen, F. Wang, and Y. He, "Recognition method for underwater acoustic target based on DCGAN and DenseNet," in *Proc. IEEE 5th Int. Conf. Image, Vis. Comput. (ICIVC)*, Jul. 2020, pp. 215–221.

[123] H. Yang, H. Gu, J. Yin, and J. Yang, "GAN-based sample expansion for underwater acoustic signal," *J. Phys., Conf. Ser.*, vol. 1544, no. 1, May 2020, Art. no. 012104.

[124] C.-K. Tu and Y.-Y. Jiang, "Development of noise reduction algorithm for underwater signals," in *Proc. Int. Symp. Underwater Technol.*, Apr. 2004, pp. 175–179.

[125] J. S. Saravanan, U. S. R. Nithish, R. G. Prasath, B. Balaji, V. A. Narayanan, and T. Sudhakar, "Enhancing autonomous underwater vehicle sensor precision with adaptive genetic algorithm aided Kalman filtering," in *Proc. 15th Int. Conf. Comput. Commun. Netw. Technol. (ICCCNT)*, Jun. 2024, pp. 1–6.

[126] V. Vijayabaskar, V. Rajendran, and E. Logashanmugam, "Study of different denoising methods for underwater acoustic signal," *J. Mar. Sci. Technol.*, vol. 23, no. 4, pp. 414–419, Aug. 2015.

[127] D. Santos-Domínguez, S. Torres-Guijarro, A. Cardenal-López, and A. Pena-Gimenez, "ShipsEar: An underwater vessel noise database," *Appl. Acoust.*, vol. 113, pp. 64–69, Dec. 2016.

[128] L. Chen, X. Luo, and H. Zhou, "A ship-radiated noise classification method based on domain knowledge embedding and attention mechanism," *Eng. Appl. Artif. Intell.*, vol. 127, Jan. 2024, Art. no. 107320.

[129] M. Irfan, Z. Jiangbin, S. Ali, M. Iqbal, Z. Masood, and U. Hamid, "DeepShip: An underwater acoustic benchmark dataset and a separable convolution based autoencoder for classification," *Expert Syst. Appl.*, vol. 183, Nov. 2021, Art. no. 115270.

[130] J. Ren, Z. Huang, C. Li, X. Guo, and J. Xu, "Feature analysis of passive underwater targets recognition based on deep neural network," in *Proc. OCEANS-Marseille*, Jun. 2019, pp. 1–5.

[131] A. Boukerche and P. Sun, "Design of algorithms and protocols for underwater acoustic wireless sensor networks," *ACM Comput. Surveys*, vol. 53, no. 6, pp. 1–34, Nov. 2021.

[132] M. Erol-Kantarci, H. T. Mouftah, and S. Oktug, "A survey of architectures and localization techniques for underwater acoustic sensor networks," *IEEE Commun. Surveys Tuts.*, vol. 13, no. 3, pp. 487–502, 3rd Quart., 2011.

[133] K. J. Listewnik and J. Mindykowski, "Study on the ensuring of reliability and repeatability of research in the area of marine ecology through calibration of underwater acoustics devices," *Appl. Sci.*, vol. 14, no. 17, p. 7725, Sep. 2024.

[134] I. F. Akyildiz, D. Pompili, and T. Melodia, "Underwater acoustic sensor networks: research challenges," *Ad Hoc Netw.*, vol. 3, no. 3, pp. 257–279, 2005.

[135] X. Huang, R. W. Pascal, K. Chamberlain, C. J. Banks, M. Mowlem, and H. Morgan, "A miniature, high precision conductivity and temperature sensor system for ocean monitoring," *IEEE Sensors J.*, vol. 11, no. 12, pp. 3246–3252, Dec. 2011.

[136] Y. Yu, J. Zhao, C. Huang, and X. Zhao, "Treat noise as domain shift: Noise feature disentanglement for underwater perception and maritime surveys in side-scan sonar images," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023, Art. no. 4208115.

[137] M.-E. Fernández-García, J. Larrey-Ruiz, and J.-L. Sancho-Gómez, "Reducing the noise introduced by the engine of a moving autonomous vehicle for recording underwater sounds," *Appl. Acoust.*, vol. 155, pp. 250–259, Dec. 2019.

[138] T. C. Austin, "The application of spread spectrum signaling techniques to underwater acoustic navigation," in *Proc. IEEE Symp. Auto. Underwater Vehicle Technol. (AUV)*, Jul. 1994, pp. 443–449.

[139] A. Alcocer, P. Oliveira, and A. Pascoal, "Underwater acoustic positioning systems based on buoys with GPS," in *Proc. 8th Eur. Conf. Underwater Acoust.*, vol. 8, 2006, pp. 1–8.

[140] A. Song, M. Stojanovic, and M. Chitre, "Editorial underwater acoustic communications: Where we stand and what is next?" *IEEE J. Ocean. Eng.*, vol. 44, no. 1, pp. 1–6, Jan. 2019.

[141] N. Rako-Gospić and M. Picciulin, "Underwater noise: Sources and effects on marine life," in *World Seas: An Environmental Evaluation*. Amsterdam, The Netherlands: Elsevier, 2019, pp. 367–389.

[142] Y.-H. Cho and H.-L. Ko, "Channel estimation based on adaptive denoising for underwater acoustic OFDM systems," *IEEE Access*, vol. 8, pp. 157197–157210, 2020.

[143] M. van den Ende, I. Lior, J.-P. Ampuero, A. Sladen, A. Ferrari, and C. Richard, "A self-supervised deep learning approach for blind denoising and waveform coherence enhancement in distributed acoustic sensing data," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 7, pp. 3371–3384, Jul. 2021.

[144] T. Chang et al., "Shallow seafloor seismic wave monitoring using 3-component fiber optic interferometric accelerometer," *Meas. Sci. Technol.*, vol. 33, no. 1, Jan. 2022, Art. no. 015101.

[145] D. Tang and H. Liu, "Estimation of the water level variations in the 2022 tonga tsunami event based on multiple machine learning models," *Ocean Eng.*, vol. 312, Nov. 2024, Art. no. 119240.

[146] H. Dong et al., "Enhanced infrasound denoising for debris flow analysis: Integrating empirical mode decomposition with an improved wavelet threshold algorithm," *Measurement*, vol. 235, Aug. 2024, Art. no. 114961.

[147] W. Xi, Z. Li, Z. Tian, and Z. Duan, "A feature extraction and visualization method for fault detection of marine diesel engines," *Measurement*, vol. 116, pp. 429–437, Feb. 2018.

[148] M. Shao, W. Song, and X. Zhao, "Polymetallic nodule resource assessment of seabed photography based on denoising diffusion probabilistic models," *J. Mar. Sci. Eng.*, vol. 11, no. 8, p. 1494, Jul. 2023.

[149] Z. Sha et al., "Interference cancellation and wavelet denoising for magnetometers in electric work-class ROVs," *IEEE Sensors J.*, vol. 23, no. 22, pp. 27438–27449, Nov. 2023.

[150] C. Ma et al., "Visual information processing for deep-sea visual monitoring system," *Cognit. Robot.*, vol. 1, pp. 3–11, Jan. 2021.

[151] D. Li, Z. Du, Q. Wang, J. Wang, and L. Du, "Recent advances in acoustic technology for aquaculture: A review," *Rev. Aquaculture*, vol. 16, no. 1, pp. 357–381, Jan. 2024.

[152] X. Mouy et al., "Automatic detection of unidentified fish sounds: A comparison of traditional machine learning with deep learning," *Frontiers Remote Sens.*, vol. 5, Aug. 2024, Art. no. 1439995.

[153] Y. Zeng et al., "Fish school feeding behavior quantification using acoustic signal and improved Swin transformer," *Comput. Electron. Agricult.*, vol. 204, Jan. 2023, Art. no. 107580.

[154] A. V. Lindseth and P. S. Lobel, "Underwater soundscape monitoring and fish bioacoustics: A review," *Fishes*, vol. 3, no. 3, p. 36, Sep. 2018.

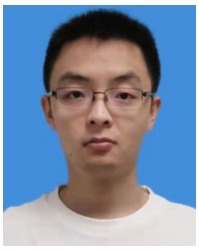
[155] M. Rezzouki and G. Ferré, "Sustainable fishing: Chirp-based signals for underwater acoustic communication and localization," *IEEE Trans. AgriFood Electron.*, vol. 2, no. 2, pp. 527–535, Oct. 2024.

[156] A. S. Abangan, D. Kopp, and R. Faillettaz, "Artificial intelligence for fish behavior recognition may unlock fishing gear selectivity," *Frontiers Mar. Sci.*, vol. 10, Feb. 2023, Art. no. 1010761.

[157] S. Gao, Y. Wang, Z. Zhang, B. Wang, B. He, and E. Zio, "Hybrid fault diagnosis method for underwater thrusters based on the common features of multi-source signals," *Mech. Syst. Signal Process.*, vol. 222, Jan. 2025, Art. no. 111740.

[158] A. K. Malik, R. Gao, M. A. Ganaie, M. Tanveer, and P. N. Suganthan, "Random vector functional link network: Recent developments, applications, and future directions," *Appl. Soft Comput.*, vol. 143, Aug. 2023, Art. no. 110377.

[159] M. A. Ganaie, M. Hu, A. Malik, M. Tanveer, and P. Suganthan, "Ensemble deep learning: A review," *Eng. Appl. Artif. Intell.*, vol. 115, Sep. 2022, p. 105151.



Ruobin Gao (Member, IEEE) received the B.Eng. degree from Jilin University, Changchun, China, in 2017, the M.Sc. degree from the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore, in 2018, and the Ph.D. degree from the School of Civil and Environmental Engineering, Nanyang Technological University, in 2022.

His research interests include machine learning, randomized neural networks, and time series forecasting.

Dr. Gao is an Associate Editor of *Computers and Electrical Engineering*.

Maohan Liang received the M.S. and Ph.D. degrees from the School of Navigation, Wuhan University of Technology, Wuhan, China, in 2018 and 2023, respectively.

He was an Exchange Student with Nanyang Technological University, Singapore, in 2021. He is currently a Research Fellow with the Department of Civil and Environmental Engineering, National University of Singapore, Singapore. His research interests include trajectory data mining, deep learning, and intelligent transportation systems.

Heng Dong (Member, IEEE) received the B.S. degree in communication engineering from Jilin University, Changchun, China, in 2017, and the M.S. degree in electronics and communication engineering and the Ph.D. degree in information and communication engineering from Harbin Institute of Technology, Harbin, China, in 2019 and 2024, respectively.

From 2023 to 2024, he was a Visiting Scholar with the Computer Networks and Communications Laboratory (CNCL), School of Computer Science and Engineering, Nanyang Technological University (NTU), Singapore. His current research interests include physical layer security, signal processing techniques in communication systems, and human–computer interaction intelligent systems.

Xuewen Luo (Member, IEEE) received the B.E. degree in communications engineering from Jilin University, Changchun, China, in 2017, and the Ph.D. degree from the School of Electronics and Information Engineering, Harbin Institute of Technology, Harbin, China, in 2024.

He is currently an Associate Professor with the School of Computer Science and Engineering, Northeastern University, Shenyang, China. His research interests include physical layer security, intelligently connected vehicle networks, mobile edge computing, and semantic communications.

Ponnuthurai N. Suganthan (Fellow, IEEE) received the B.A. and M.A. degrees in electrical and information engineering from the University of Cambridge, Cambridge, U.K., in 1990, 1992, and 1994, respectively, and the Honorary Ph.D. (Doctor Honoris Causa) degree from the University of Maribor, Maribor, Slovenia, in 2020.

He was a Predoctoral Research Assistant with the Department of Electrical Engineering, The University of Sydney, Sydney, NSW, Australia, from 1995 to 1996, and a Lecturer with the Department of Computer Science and Electrical Engineering, The University of Queensland, Brisbane, QLD, Australia, from 1996 to 1999. Since August 2022, he has been a Research Professor with the KINDI Computing Research Center, College of Engineering, Qatar University, Doha, Qatar.