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R. Venkatesan
J. Preetha Roselyn
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Vijayan Sugumaran *Editors*

Artificial Intelligence for the Oceans

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Preface

With great pleasure and a profound sense of purpose, we lay before you the chapters of the peer-reviewed articles presented at the *International Conference on AI for the Oceans*—2025 at SRM Institute of Science and Technology, Kattankulathur. As the world faces growing environmental, ecological, and technological challenges, the role of artificial intelligence in understanding and preserving our marine ecosystems has never been more critical. This compilation represents the culmination of collaborative efforts from researchers, scientists, and practitioners across disciplines who are working at the cutting edge of artificial intelligence and marine science.

This conference brings together a global community of researchers, technologists, marine scientists, and policymakers to explore the vast potential of AI in oceanographic studies, climate modeling, marine biodiversity conservation, underwater robotics, and sustainable resource management. By bridging the gap between data science and ocean science, we hope to ignite meaningful collaborations and drive impactful innovations.

SRM Institute of Science and Technology is proud to serve as a hub for this interdisciplinary exchange, fostering knowledge that reaches beyond the shoreline into the depths of oceanic inquiry. We are honored to host thought leaders and emerging voices from around the world who are pushing the boundaries of what is possible at the intersection of technology and marine science.

Each paper included here has undergone a rigorous peer-review process, ensuring the quality, relevance, and originality of the contributions. We hope this volume will serve as a valuable reference for scholars, industry experts, and policymakers committed to leveraging AI for sustainable and impactful marine applications.

We extend our heartfelt thanks to all chief guests, special invitees, participants, keynote speakers, sponsors, reviewers, session chairs, and organizing members for their contributions and commitment to this pioneering effort. May the dialogues and discoveries from this conference resonate far beyond these sessions, inspiring action and insight for generations to come.

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Chennai, India	Dr. K. Vijayakumar
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About the Editors

R. Venkatesan having 42 years of experience in ocean science and technology. He is working as a Professor of Practice Anna University and Adjunct Professor UMass Dartmouth USA. He received his M.Tech. Degree from Karnataka Regional Engineering College and was awarded Ph.D. degree from the Indian Institute of Science, Bangalore, and continued his academic pursuit to complete courses in Marine Environmental Pollution and Management and International Business Management from IIFT New Delhi. He served in premier Indian Institutions (NIOT and NIO) including UNESCO-IOC-GOOS and UNEP Regional Seas. He has to his credit 190 papers edited three books and 10 products transferred to industry.

Dr. J. Preetha Roselyn is working as a Professor in the Department of Electrical and Electronics Engineering in SRM Institute of Science and Technology. She completed her B.E (EEE) from Madras University in the year 2002, M.S. (By Research) from Anna University in the year 2007, and Ph.D. from SRM University in the year 2015. She has published 55 international publications among which 54 are SCI indexed journals, four lecture notes, 58 conference publications, and 1 book. She has received DST-funded project in the topic Optimal energy management system in shipboard power system with solar PV for the period 2018–2021 and MODROB-funded project from AICTE, PI of MOES-funded project and Co-PI for MOES funded-project, Co-PI of four SATU projects, and three internally funded projects. She has completed Ph.D. for five research scholars, and currently, seven scholars are pursuing their Ph.D. under her guidance.

K. Vijayakumar received the B.E. degree in Electrical and Electronics Engineering and the M.E. degree in Power Systems from Annamalai University, India, and the Ph.D. degree from SRM Institute of Science and Technology. He is currently working as a professor in the Department of Electrical and Electronics Engineering, SRM Institute of Science and Technology, and holding the responsibilities of Dean, School of Electrical and Electronics Engineering. He has published more than 200 papers in various indexed journals. His research interest includes power electronics applications in power systems and renewable energy systems. He is also a member of

Analysis for SNR Reduction in Underwater Acoustic Communication Using Real and Complex Wavelets

B. Shiny, P. Vijayalakshmi, M. Monisha, and V. Rajendran

Abstract Underwater acoustic communication is vital for applications such as environmental monitoring, naval operations, and autonomous underwater vehicle networks. However, reliable data transmission underwater is severely impacted by ambient noise, originating from natural sources like surface waves and biological activity, as well as human activities such as shipping and construction. Effective noise reduction techniques are necessary to enhance signal quality. This study evaluates the performance of both real and complex wavelets in de-noising underwater acoustic signals affected by real wind noise. The sample noise data was collected from the acoustic group, National Institute of Ocean Technology (NIOT), covering frequencies from 100 Hz to 20 kHz. An input signal, modulated using a rectangular carrier, is used as the test signal. The noisy signal is processed using wavelet transform-based de-noising, with symlet and bi-orthogonal wavelets representing real wavelets, and gabor and bump wavelets representing complex wavelets. Performance is evaluated by comparing input and output signal-to-noise ratios (SNR).Results show that complex wavelets consistently outperform real wavelets in suppressing noise. The gabor wavelet achieves the highest output SNR of 17.54 dB for an input SNR of −15.87 dB. Among real wavelets, the symlet wavelet provides a peak output SNR of 14.58 dB. This analysis highlights the effectiveness of complex wavelets for improving underwater acoustic communication. Future work will explore hybrid de-noising approaches, combining wavelets with adaptive filtering techniques to further enhance signal quality in noisy underwater environments.

Keywords Underwater acoustic communication (UAC) wavelet transforms · Real and complex wavelets · SNR · Thresholding

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1 Introduction

Underwater acoustic communication refers to the process of transmitting information through acoustic waves in underwater environments. Compared to terrestrial wireless communication, underwater acoustic communication faces several significant challenges [1, 2], including high ambient noise, severe signal attenuation, multipath propagation, and dynamically varying channel conditions. These factors collectively make reliable data transmission in underwater environments particularly complex and demanding [3]. Recent advancements in underwater acoustic communication emphasize its critical importance in modern applications such as environmental monitoring, ocean sampling networks, disaster prevention and early warning systems, military surveillance, and ocean exploration [4, 5]. The integration of autonomous underwater vehicles (AUVs) with underwater communication networks, as well as the application of artificial intelligence for adaptive communication protocols, represents emerging trends aimed at enhancing performance.

However, effective communication in underwater environments remains limited by high noise levels and unpredictable channel dynamics. A primary factor affecting underwater acoustic signals is ambient noise, particularly in shallow water conditions, where surface activities, biological sources, and human activities contribute to high noise levels. The spectral characteristics of noise vary depending on location and environmental conditions, making it essential to develop flexible noise suppression algorithms adaptable to diverse underwater environments. Wavelet-based de-noising has emerged as a robust approach for underwater acoustic communication systems due to its inherent ability to perform multi-resolution analysis. Unlike traditional Fourier methods, wavelet transforms offer both time and frequency localization, making them particularly effective for analyzing non-stationary signals typically encountered underwater. By decomposing signals into multiple frequency bands, wavelets enable efficient noise removal through thresholding techniques applied to wavelet coefficients, effectively preserving important signal features. In addition to de-noising, wavelet transforms facilitate improved channel modeling and estimation by exploiting their multi-resolution properties. This capability enhances sparse channel estimation, aiding in the reconstruction of channel impulse responses under complex conditions. Compared to conventional OFDM-based approaches, wavelet-based systems have demonstrated superior accuracy under similar circumstances.

Wavelets further offer advantages in compressing signals and extracting key features, supporting applications such as ship noise classification and source identification. These attributes make wavelet transform a highly versatile tool, contributing to enhanced de-noising, channel estimation, modulation, and feature extraction in underwater acoustic communication. Such advantages position wavelet-based methods as a viable and effective alternative to conventional Fourier-based techniques in challenging underwater environments.

1.1 Why Acoustic Waves?

Acoustic waves are used in underwater acoustic communication because they travel efficiently through water compared to other types of waves such as electromagnetic or optical waves. Acoustic waves have low attenuation and comparatively less absorption in water compared to EM waves so that they can travel over hundreds of kilometers with minimal loss in some cases. Optical waves suffer severe scattering loss compared to acoustic waves. Both EM waves and optical waves can travel only a few meters without much loss. But, Acoustic waves can navigate complex underwater environments better than light or radio waves. But they do have some challenges that have to be taken into consideration like Multipath Propagation, Absorption and scattering loss, Doppler spread, Environmental Noise and signal delay because of their low bandwidth, long wavelength and less speed. In case of applications with high frequency sound waves, water absorption is more and so the transmission range is limited to short to medium distances. When using low frequencies, there is a trade-off in data rates. The acoustic waves speed is usually 5 orders less than the speed of light and it escalates with increase in temperature, pressure and salinity [6].

1.2 Noises

The different noises and their frequency ranges is shown in Table 1 and Fig. 1.

Ambient Noise:

Biological Noise: Sounds from living organisms inside the ocean.
Oceanic Noise: Generated by ocean waves, wind, and precipitation.
Seismic Noise: Caused by underwater earthquakes and geological shifts.

Man-Made Noise:

Ship Noise: Noise from ship engines and propellers which is generally of low frequency range.
Construction noises: Noises from the construction, and underwater explosions.
Sonar Interference: Active sonar from naval and research vessels.

Table 1 Different noises and their frequency ranges

Frequency range	Causes of background—ambient noise
Below 10 Hz	Ocean turbulence and seismic activity
10–1 kHz	Distant shipping
100 Hz–20 kHz	Due to spray and bubbles associated with breaking waves varies with wind speed
Greater than 100 kHz	Electronics/thermal noise
100 Hz–10 kHz	Marine life

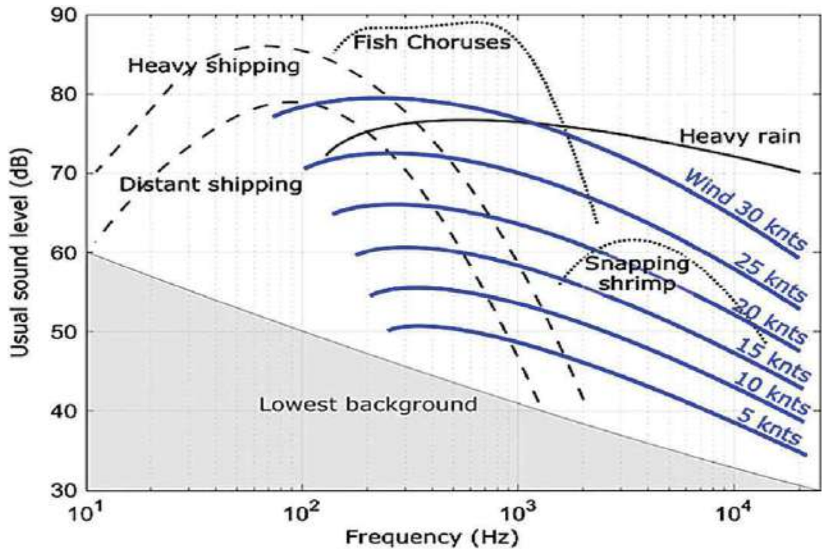


Fig. 1 Wenz diagram [7]

Self-Noise: Platform Movement: The movement of underwater equipment or vehicles according to the movement of water causes some noise.

Flow Noise: Noise created from the flow of water around the sensors or hydrophones.

Thermal Noise: Movement of water molecules randomly causes a high-frequency noise, customarily modeled as white Gaussian noise.

Multipath and Reverberation:

The acoustic signal travels in between the sea surface and the sea bed taking multiple paths from transmitter side to receiver side causing signal overlap and delays.

Electrical Noise:

Interference from Equipment generates additional noise. Thermal noise, Flicker noise, Quantization noise also comes under electrical noise. Low Signal to noise ratio and very high BER(Bit error rate) are the impacts of electrical noise.

2 Literature Survey

The noise interferences are severe in Underwater Acoustic Communication and this is the major challenge in the receiver side. De-noising of high frequency signals is carried out in ECG signals by transforming the signal from time to frequency domain using Fourier transform and Butterworth filter [8]. The linear frequency modulated input waveform is transformed to time frequency representation using Wavelet packet decomposition with Morlet wavelet as the basis function. MATLAB experiments are carried out to find the SNR using wavelet transform with Shannon and Gabor wavelets and it is found that Gabor wavelet gives an output of range 9 dB to15dB for some input SNR of range − 15 dB to 0 dB [9]. S-Transform is used for de-noising followed by soft thresholding with threshold assessed by universal threshold estimation. Complex wavelet reacts only to the positive frequencies of the signal. Since the modulus of the transform is less oscillatory compared to real wavelets, detecting instantaneous frequencies of the signal is a real benefit. Shannon and Gabor wavelets are used for wavelet packet decomposition and is found that Gabor filter gives improved SNR compared to Shannon in the order of 8 dB for an input SNR of − 15 dB to 0 Db [10]. The signal's basic characteristics are analyzed and highly similar waveform as a typical target waveform added with a noise is selected and de-noised using a candidate wavelet [11]. Then the evaluation indices (cross correlation coefficient, RMSE, smoothness, SNR) of de-noised signal are calculated and fused to get the optimal wavelet parameter [12]. Different types of wavelet transform include Discrete Wavelet Transform, Continuous Wavelet Transform, and the Discrete-Time Wavelet Transform (DTWT). A de-noising approach utilizing soft thresholding in conjunction with universal threshold estimation has been proposed and assessed using data collected through a broadband hydrophone array at Desaru Beach, located on the eastern coast of Johor, Malaysia. The evaluation is carried out on signal with fixed frequencies and time-varying characteristics. Results provides a notable improvement, yielding an increase of approximately 4 dB in signal-to-noise ratio (SNR) and a reduction of about 3 dB in root mean square error (RMSE) at the Nyquist sampling frequency [9]. For improved de-noising and more accurate reconstruction of signal, wavelet selection is very important. For specific phase and frequency response of the signal, specific wavelet should be used [13, 14].

Instead of sinusoids in Fourier transform, wavelets are used in wavelet transform for transformation of the signal from time domain to time–frequency domain with variable window lengths and positions which makes it more intelligent comparatively. A wavelet transform-based smooth ordering (WTSO) for Hyper Spectral Image classification which includes extracting features using wavelet transform followed by similarity measurement based on spectral spatial, 1D embedding and construction of final classifier using interpolation scheme [15]. Wavelets frequency characteristics are analyzed by mathematical modeling and the ideal base function is carefully chosen hierarchically in regard to the ECG signal characteristics [16]. Based on the sensitivity of each scale, a rule is proposed to combine wavelet scales and appropriate wavelet combination is selected based on sequence combination analysis [17]. The performance of the wavelets is evaluated by Smoothness, mean square error, Signal to Noise Ratio (SNR), and correlation coefficient [18, 19]. Analysis of performance of adaptive algorithms such as adaptive filtering, normalized least mean square (NLMS), Least mean square (LMS), Kalman LMS (KLMS), Modified New LMS (MNLMS) is analyzed and then compared with the performance of measured characteristics such as mean square error (MSE) and signal to noise ratio [20]. The acoustic emissions characteristics of concrete signal can be solved by de-noising using wavelet transform [21]. For de-noising in underwater propeller signals based on CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise), the Wavelet Transform energy concentration property is used to separate noise and signal components

[22]. Based on CEEMDAN, Permutation Entropy (PE), Mutual Information (MI) and Wavelet thresholding, a new method of de-noising is adopted for underwater Acoustic signal communication [23]. The de-noising in underwater acoustic communication is carried out with wavelet transform using Gabor and Symlet Wavelet. New thresholding method and universal threshold value estimation method are used to find the appropriate threshold to de-noise the ambient noise present in underwater acoustic communication [24]. Image steganography Algorithm which enhances the safety is proposed with Particle Swarm Optimization and Integer wavelet transform for underwater acoustic communication [25].

3 Methodology

Since the acoustic signals are quasi–stationary, Fast Fourier transform (FFT) does not work well. Fourier transforms works well with the stationary signals that is the statistical properties of the signal (mean and variance) do not vary with time. The acoustic signals are quasi–stationary, that means they are stationary over a short range and for a longer duration, their statistical properties changes. Wavelets have gained its importance in the last decades since they work well with the quasi stationary and non–stationary signals. Before the introduction of wavelet transforms (WT), researchers used Short Time Fourier Transform (STFT) for non-stationary signals. The major disadvantages of STFT are that the window size cannot be changed which results in the dilemma of resolution. If the window is narrow, then the frequency resolution will be poor. If the window is wide, then it results in poor time resolution. Also, we cannot know what frequency exists at what time intervals. So, to overcome the disadvantages of STFT, wavelet transform is used. The translation parameters defines the mutual orthogonal set of wavelets which hints to a simple and efficient iterative system of Wavelet Transformation [26].

Wavelet transform offers variable window in turn provides multi-resolution analysis of signals. The time–frequency representation of signals makes the analysis easier. Wavelets are some mathematical tools which divides the actual signal into different frequency components [27]. Each components of the signal are then examined separately, and the basis functions of wavelet transform are scaled. Scaling and positioning by continuous wavelet transform is shown in Fig. 2.There are different types of wavelets such as real wavelets (Daubachies, Haar, Symlet, Coiflet, Mexican Hat, Morlet wavelets, etc.) and complex wavelets (Morse, Bump and Analytic Morlet). The wavelet transform is of two types: continuous wavelet Transform and discrete wavelet transform. The continuous wavelet transform is given by.

$$\mathrm{CWT}(a, b; x(t).\psi(t)) = \frac{1}{a}\int_{-\infty}^{\infty}\left[x(t)\psi^{*}\left(\frac{t-b}{a}\right)\right]\mathrm{dt} \tag{1}$$

where a denotes the scaling parameter and b denotes the translation parameter.

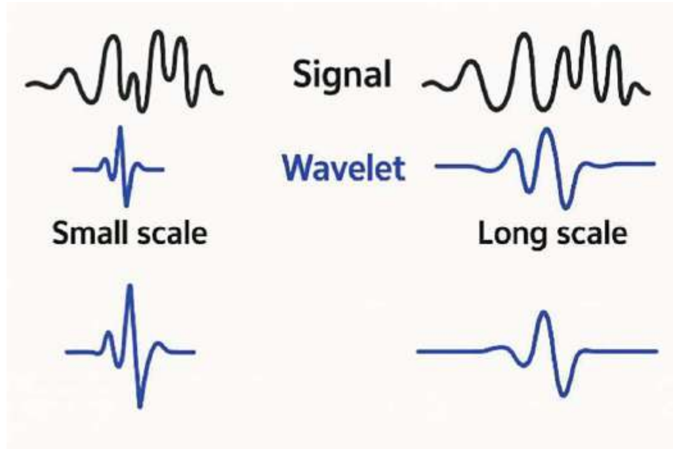


Fig. 2 Scaling and positioning by continuous wavelet transform

In continuous wavelet transform, the inner products of analyzing function and the original signal is used to determine the similarities by integration. CWT allows two operations: shifting, compression and expansion of mother wavelet to capture the frequency components at various positions. ψ(t) reacts as the impulse response of the band pass filter and so the bandwidth of the band pass varies with the scaling parameter.

The discrete wavelet transform is given by.

$$\mathrm{DWT}\left[n, a^j\right] = \sum_{m=0}^{N-1} x[m].\psi_j^*(-n) \tag{2}$$

where $\psi_j[n] = \frac{1}{\sqrt{a^j}}\psi\left(\frac{n}{a^j}\right)$, and ψ is the discretized mother wavelet, N is the signal length and n is the delay parameter. DWT involves the carefully chosen scaling parameter.

The threshold λ is dependent on resolution level and if $D^H(d|\lambda)$. denotes the wavelet coefficient, hard thresholding is given as.

$$\mathrm{D}^H(d|\lambda) = \begin{cases} 0, |d| \leq \lambda \\ d, |d| > \lambda \end{cases} \tag{3}$$

The real and complex wavelet is depicted in Figs. 3 and 4.

If $D^H(d|\lambda)$. denotes the Soft Thresholding and d_i. represents the wavelet coefficient of the noisy signal at index I, the soft thresholding equation is given as.

$$D^H(d|\lambda) = \mathrm{sign}(d_i).\max(|d_i| - \lambda.0) \tag{4}$$

Each coefficient d_i. contains contributions from both the true signal and the noise. After thresholding and removing some noise components, the decomposed cicients of wavelet transform are reconstructed. When $h(t)\,\varepsilon L^2(R)$, the Inverse wavelet transform

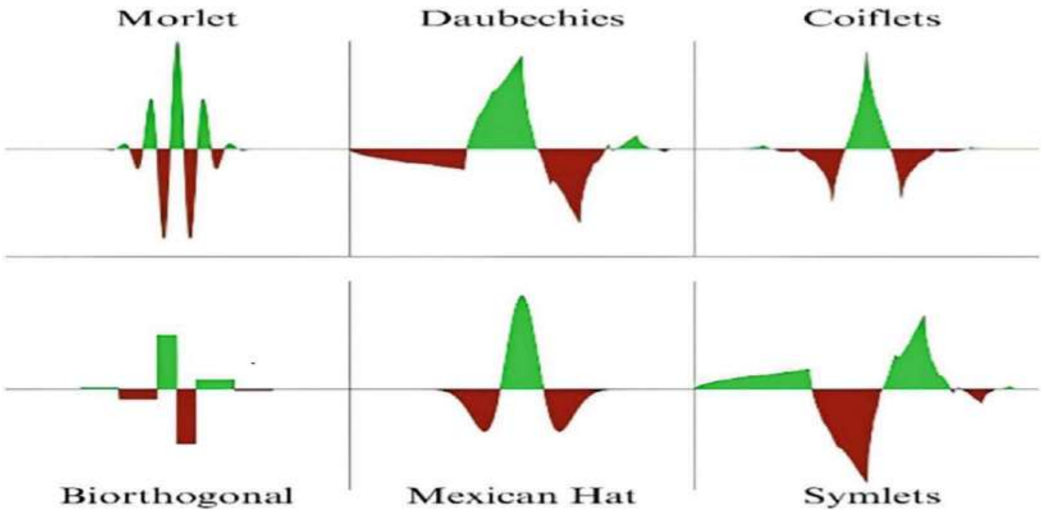
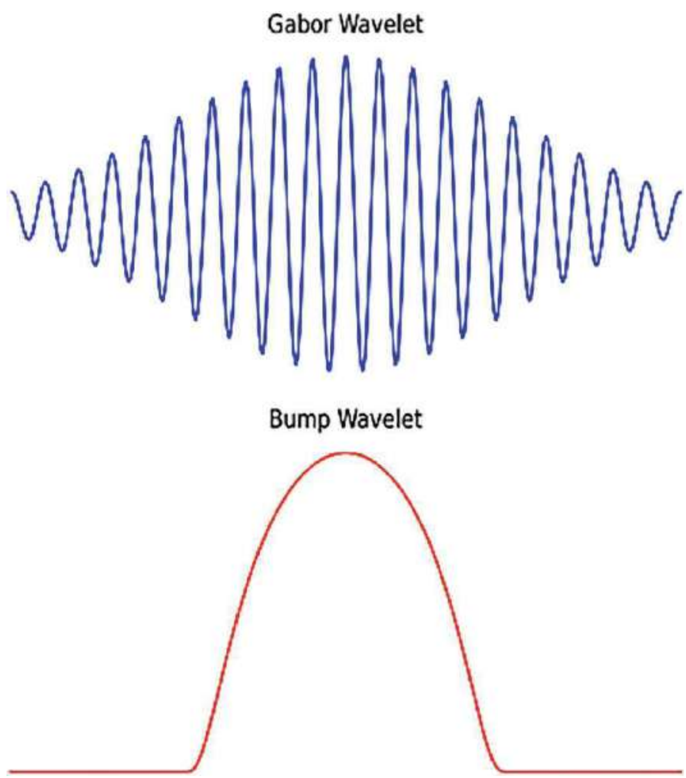


Fig. 3 Different types of real wavelets (Photo courtesy of MathWorks)

Fig. 4 Complex wavelets



[28] is given by

$$h(t) = \frac{1}{c_\psi} \int_{-\infty}^{\infty} \int W_\psi h(b, a) \psi_{(b,a)}(t) \frac{\mathrm{db}\,\mathrm{da}}{a^2} \tag{5}$$

where

$$c_{\psi} = \int_{-\infty}^{\infty} \frac{\left(\left|\hat{\psi}(\omega)\right|^{2}\right)}{|\omega|} d\omega. \tag{6}$$

Inverse wavelet transform involves the transformation from frequency to time domain and the SNR values are calculated using the formula,

$$\mathrm{SNR} = 10\log_{10}\left(\frac{P_{\text{signal}}}{P_{\text{Noise}}}\right) \tag{7}$$

where P_{signal} refers to the signal power and P_{Noise} refers to the noise power.

4 Results and Discussion

In this paper, a 1 kHz cosine wave serves as the input signal, which is modulated using a rectangular carrier signal through simple amplitude modulation (AM). A rectangular carrier is selected for its efficient bandwidth utilization, ease of generation, compatibility with pulse compression techniques, and its advantages in signal timing, synchronization, and energy concentration. To ensure realistic underwater noise conditions, real wind noise data collected from the NIOT acoustic group, is incorporated into all experiments. The wind noise, spanning frequencies from 500 Hz to 100 kHz, originates from sources such as surface turbulence caused by wind, bubble formation and spray from breaking waves, and bubble clouds generated by strong wave activity.

The modulated cosine signal is combined with the real-time noise data and processed through a band-pass FIR filter with an order of 100. The filtered signal is then transformed into the time–frequency domain using the Wavelet Transform, after sampling at 100 kHz. The wavelet decomposition level is set to 1. Both real and complex wavelets are explored: Symlet and Bi-orthogonal as real wavelets, and Gabor and Bump as complex wavelets. A thresholding step is applied prior to signal reconstruction to enhance noise suppression and signal recovery. Modulated input signal and the modulated signal with noise is displayed in Fig. 5.

A critical step in decomposition-based de-noising is the thresholding process, where noise components are suppressed based on a predefined threshold applied to the wavelet coefficients. There are two primary types of thresholding techniques: hard thresholding and soft thresholding. In this study, soft thresholding is employed in all cases due to its advantageous properties in handling real-world underwater noise. Hard thresholding operates by forcing all wavelet coefficients below the threshold to zero, while retaining coefficients above the threshold unchanged. Although simple to implement, hard thresholding often introduces discontinuities and artifacts in the reconstructed signal due to the abrupt transitions it creates in the coefficient values. This method tends to be less robust when applied to practical, non-ideal noise environments. Soft thresholding, in contrast, shrinks all coefficients toward zero by the

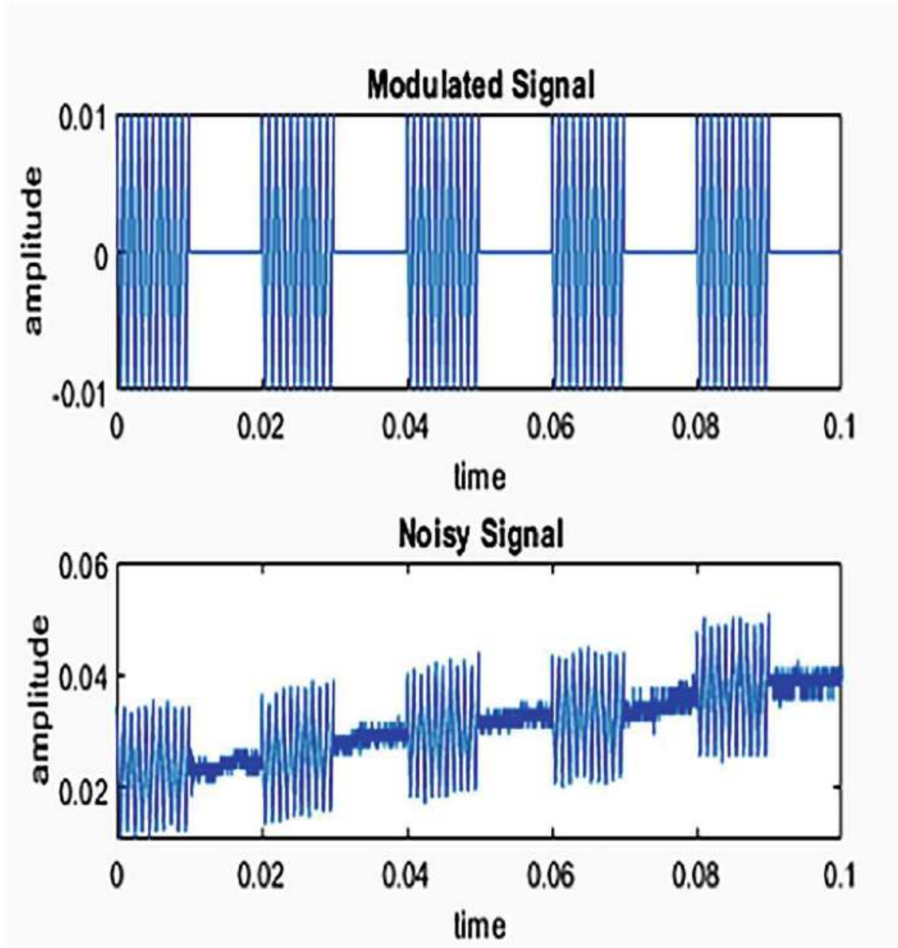


Fig. 5 Modulated input signal and noisy signal

threshold amount, rather than simply truncating them. This smooth shrinkage minimizes the occurrence of sharp cutoffs and significantly reduces reconstruction artifacts. As a result, soft thresholding provides smoother and more natural signal reconstructions, making it better suited for real-world noise suppression. To determine the optimal threshold, Stein's Unbiased Risk Estimate (SURE) method is used, as it is a widely accepted, data-driven technique that adapts the threshold based on the statistical properties of the observed noisy signal. Following the thresholding process, the de-noised signal is reconstructed using the inverse wavelet transform.

Figure 6 depicts the reconstructed signal using Bi-orthogonal and Symlet wavelets. The input and output Signal-to-Noise Ratios (SNR) are computed by varying the signal amplitude from 0.01 to 0.3. These calculations are performed for both real wavelets—Symlet and Bi-orthogonal, and the results are summarized in Table 2. In this context, sym4 refers to the Symlet wavelet with a scaling factor of 4, while bior3.5 denotes the Bi-orthogonal wavelet with three vanishing moments in the synthesis wavelet and five vanishing moments in the analysis wavelet.

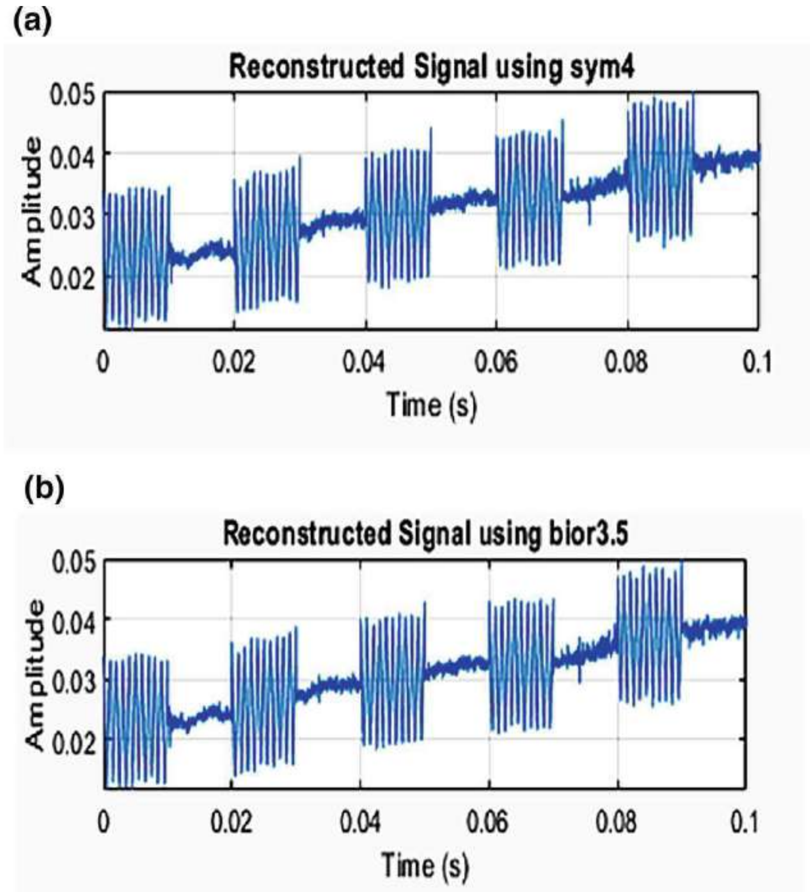


Fig. 6 Reconstructed signal after discrete wavelet transform using different real wavelets. **a** Symlet wavelet, **b** Bi-orthogonal wavelet

Table 2 Input and output SNR for real wavelets

Real wavelets		bior3.5	sym4
Amplitude	Input SNR(dB)	Output SNR(dB)	Output SNR(dB)
0.01	− 15.87	14.34	14.58
0.02	− 9.84	20.32	20.39
0.03	− 6.32	23.85	23.9
0.04	− 3.82	26.34	26.35
0.05	− 1.89	28.28	28.29
0.06	− 0.3	29.87	29.87
0.07	1.04	31.21	31.19
0.08	2.2	32.36	32.33
0.09	3.22	33.39	33.46
0.1	4.13	34.3	34.37
0.2	10.16	40.32	40.46
0.3	13.68	43.85	43.98

Discrete wavelet transform is applied for real wavelets and continuous wavelet transform is used for complex wavelets. The corresponding input versus output SNR characteristics for both wavelets are illustrated in Fig. 7, providing a comparative evaluation of their denoising performance under varying input signal amplitudes.

Comparing the results of input and output SNR of real wavelets such as Symlet, and Bi-orthogonal, the Symlet wavelets gives a little better output SNR of 14.58 for an input SNR of − 15.87.

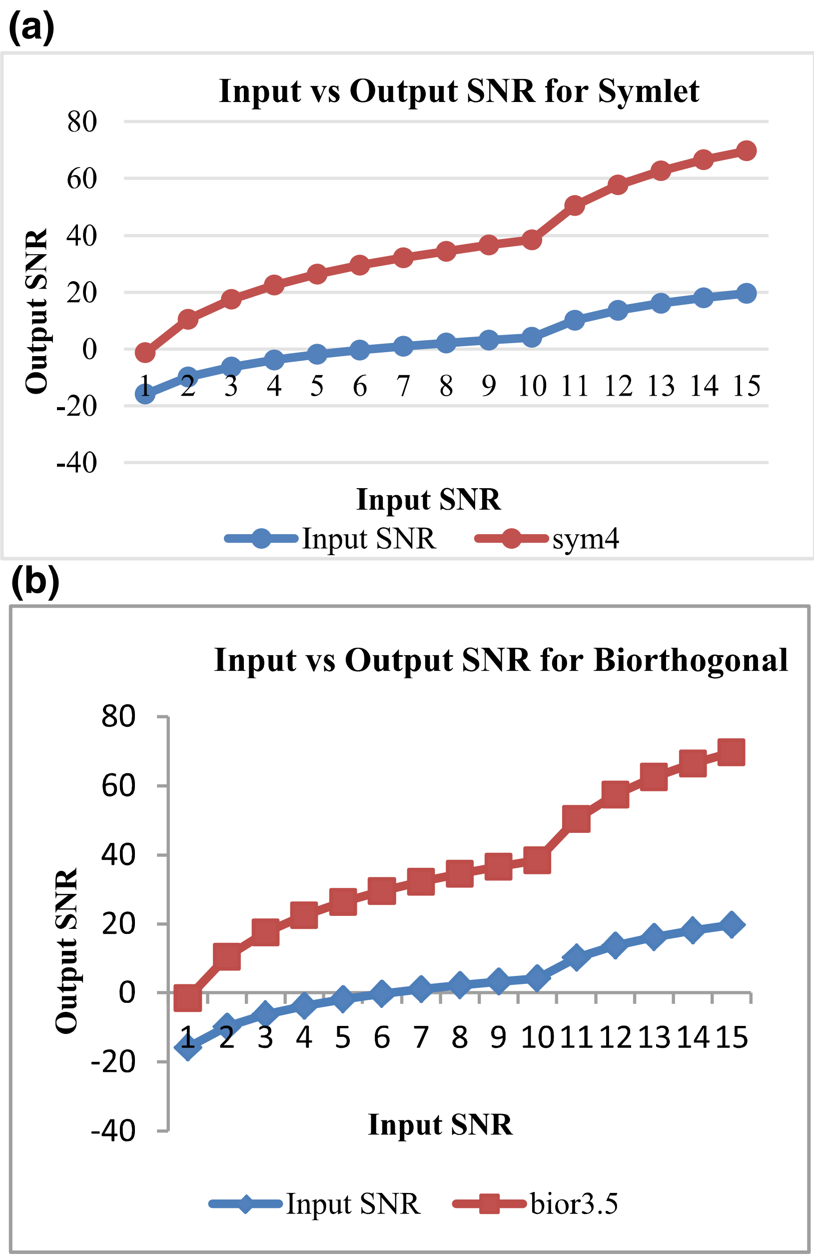


Fig. 7 Input versus output SNR graphs of real wavelet-Symlet and Bi-orthogonal wavelets. **a** Symlet wavelet, **b** Bi-orthogonal wavelet

The reconstructed signals obtained using complex wavelets, specifically Gabor and Bump wavelets, are presented in Fig. 8. The optimal choice of decomposition level and wavelet scaling depends on the characteristics of the input signal and the nature of the noise introduced. It is important to note that increasing the decomposition level does not necessarily guarantee an improvement in SNR. In certain cases, higher decomposition levels can lead to a reduction in SNR, as some critical components of the original signal may be suppressed or lost during decomposition and reconstruction. Table 3 and Fig. 9 present the input versus output SNR values and the corresponding graphs for the complex wavelets—Analytic Morlet (Gabor) and Bump wavelets.

The Gabor wavelet achieves a higher output SNR of 17.54 dB for an input SNR of − 15.87 dB, indicating its superior performance in this scenario. Furthermore, when comparing the performance of real wavelets (Symlet and Bi-orthogonal) with

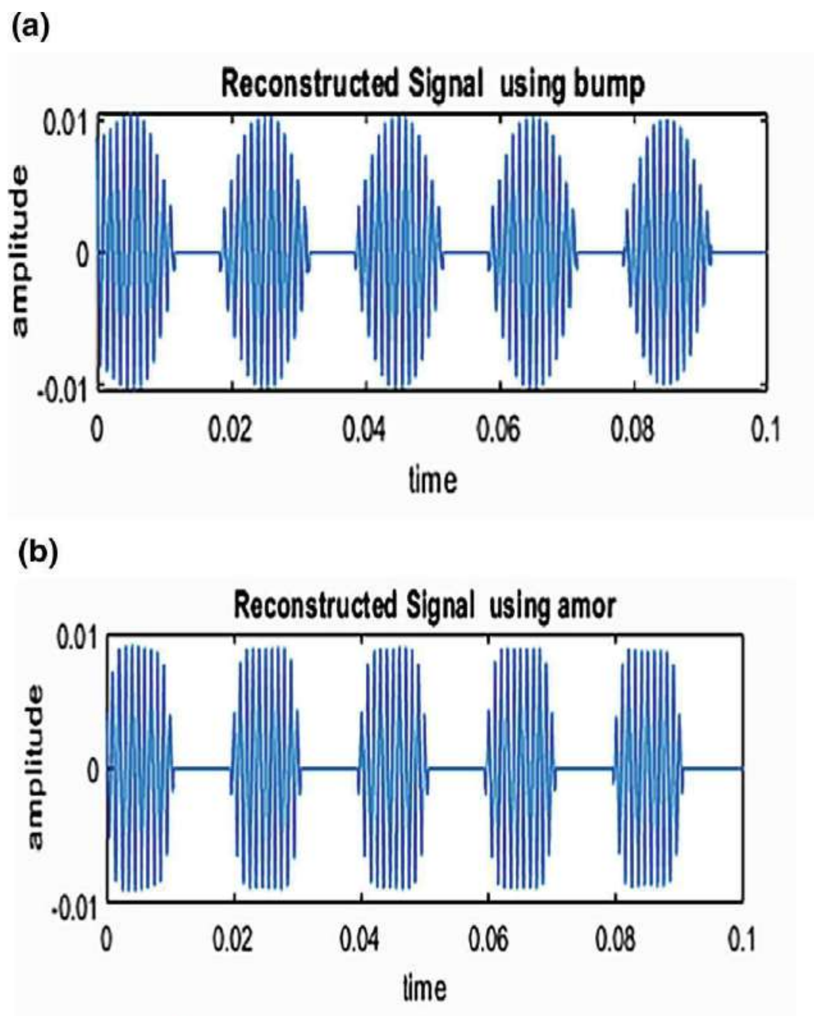


Fig. 8 Reconstructed signal after wavelet transform using different complex wavelets. **a** Bump wavelet, **b** Analytic Morlet (Gabor) wavelet

Table 3 Input and output SNR for complex wavelets

Complex wavelets		Bump	Gabor
Amplitude	Input SNR(dB)	Output SNR(dB)	Output SNR(dB)
0.01	− 15.87	17.04	17.54
0.02	− 9.84	17.48	17.94
0.03	− 6.32	17.59	18.11
0.04	− 3.82	17.66	18.15
0.05	− 1.89	17.67	18.19
0.06	− 0.3	17.68	18.22
0.07	1.04	17.69	18.23
0.08	2.2	17.69	18.22
0.09	3.22	17.69	18.23
0.1	4.13	17.69	18.24
0.2	10.16	17.69	18.29
0.3	13.68	17.69	18.31

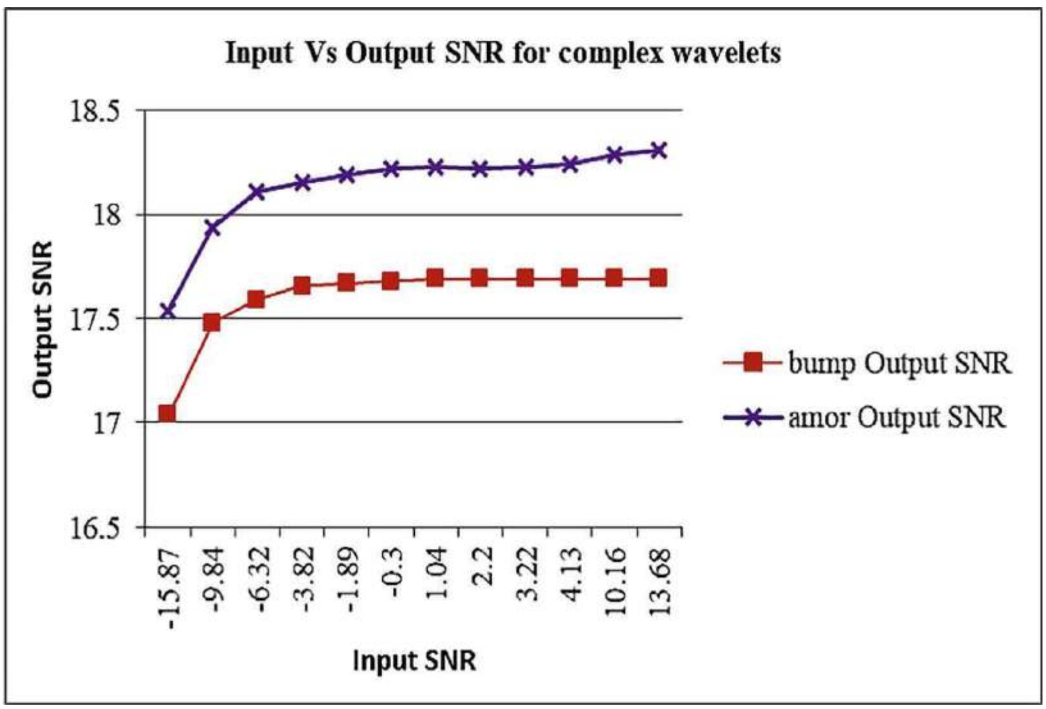


Fig. 9 Input versus output SNR graphs of complex wavelets

complex wavelets, it is observed that complex wavelets consistently achieve higher output SNR, demonstrating their greater effectiveness in de-noising underwater acoustic signals contaminated with wind noise.

The comparative analysis presented in Table 4 highlights the performance of various existing de-noising techniques applied to different types of signals, including block signals, fixed frequency signals, speech signals with noise, and real ambient noise data collected from the Bay of Bengal. The performance is evaluated in terms of improvement in Signal-to-Noise Ratio (SNR), which serves as a key metric for assessing the effectiveness of de-noising approaches. It is observed that empirical mode decomposition (EMD) and its variants (EEMD, CEEMDAN, CEEMDAN-MI-PE), which are widely used for non-stationary signal analysis, provide only moderate improvements in output SNR, typically around 2–2.5 dB when applied to block signals. This indicates that while these methods are useful for signal decomposition, they show limitations in effectively handling low SNR data under strong noise interference. On the other hand, wavelet-based techniques, particularly wavelet thresholding (WT) using Gabor wavelets combined with statistical noise estimation, demonstrate significantly better performance on real ambient noise data collected from the Bay of Bengal. This highlights the effectiveness of wavelet transforms in capturing transient features in environmental noise and applying appropriate thresholding for noise suppression. The S-transform-based approaches, when applied to synthetic fixed-frequency signals (400 Hz), achieve output SNR improvements of approximately 7 dB. This shows that S-transform methods are effective for narrowband signals, with the inclusion of pre-whitening offering a slight additional improvement. This emphasizes the importance of preprocessing techniques in enhancing de-noising performance, especially for stationary signals. Among the examined techniques, the balanced wavelet thresholding (BWT) applied to simulated underwater propeller acoustic signals achieves a relatively high output SNR of 14.22 dB. This demonstrates that combining wavelet decomposition with balanced thresholding strategies can lead to effective noise reduction, especially for complex underwater acoustic signals.

The proposed method, wavelet transform (WT) with SURE (Stein's Unbiased Risk Estimation) soft thresholding technique, applied to real wind noise data collected from the NIOT, achieves the highest output SNR across all techniques evaluated. The proposed approach delivers output SNR values as high as 17.54 dB when using Gabor wavelets. This performance underscores the advantages of adaptive threshold selection using SURE, which dynamically optimizes the noise suppression process. Such capability makes the proposed method particularly suitable for challenging real-world applications, including underwater ambient noise monitoring.

5 Conclusion

This paper presented a comprehensive study on wavelet transform-based de-noising techniques for enhancing the SNR of underwater acoustic communication signals affected by wind-driven ambient noise. The real noise data provides a realistic test scenario for evaluating de-noising performance. Through simulations in MATLAB, both real wavelets (Symlet and Bi-orthogonal) and complex wavelets (Gabor and

Table 4 Comparison with the existing de-noising techniques versus proposed

S. No.	Method/technique	Frequency/signal type	Input SNR(dB)	Output SNR(dB)
1	EMD-MI	Blocks signal	− 10	1.8632
2	EEMD-MI	Blocks signal	− 10	2.0988
3	CEEMDAN-MI	Blocks signal	− 10	2.2803
4	CEEMDAN-MI-PE	Blocks signal	− 10	2.5588
5	Gabor wavelet-WT + matched filter	Real ambient noise data collected at Bay of Bengal using broadband hydrophones	− 10	20 kHz: 9 66 kHz: 15 86 kHz: 14
6	WT using Gabor and noise threshold estimation performed using high-order statistics	Real ambient noise data collected at Bay of Bengal using broadband hydrophones	− 15	8
7	S Transform-Soft Thresholding with Universal Threshold Estimation	Fixed time signals(400 Hz)	3	6.8
8	S-transform with pre-whitening	Fixed time signals(400 Hz)	3	7.2
9	CEEMDAN-BWT (Balanced Wavelet Thresholding), Sym4, 5 decomposition levels, balanced threshold	Underwater propeller acoustic signals (measured and simulated using CFD software, covering cavitation wake noise)	Not explicitly specified	14.22
10	DWT with universal soft thresholding technique under db4 of level 3 decomposition	Speech with keyboard noise	0–5	13.828
11	**Proposed**: WT with SURE threshold estimation and soft thresholding technique	Wind noise data from National Institute of Ocean Technology (Bay of Bengal)	− 15.87	bior3.5-14.34 sym4- 14.5 Bump-17.04 Gabor-17.54

Bump) were employed to filter noise from a modulated signal. The analysis demonstrated that complex wavelets outperformed real wavelets in terms of output SNR, with Gabor wavelet achieving an SNR improvement of 17.54 dB for an input SNR of − 15.87 dB. In contrast, Symlet wavelet achieved a maximum output SNR of 14.58 dB under similar conditions. These findings emphasize that complex wavelets are more effective in preserving signal integrity while suppressing noise, due to their ability to capture both amplitude and phase information. The study also highlights the importance of carefully selecting wavelet type, decomposition level, and thresholding method to optimize de-noising performance. Future work will focus on developing adaptive and hybrid de-noising techniques that incorporate matched filtering and adaptive thresholding further improving the robustness and reliability of underwater acoustic communication systems in highly noisy environments.

References

1. P.C. Kishore Kumar, P. Sathish Kumar, S. Jerritta, V. Rajendran, De-noising algorithm for SNR improvement of underwater acoustic signals using CWT based on fourier transform, underwater technology. Int. J. Soc. Underw. **35**(1), 23–30 (2018) https://doi.org/10.3723/ut.35.023
2. G. Kalpana, V. Rajendran, Development of adaptive de-noising algorithm using wavelet technique for a linear FM acoustic signal. Indian J. Sci. Technol. **8**(35) (2015). https://doi.org/10.17485/ijst/2015/v8i35/82273
3. P. Vijayalakshmi, N. Noorunnisa, V. Rajendran, Performance analysis of VBF protocol for position tracking of moving nodes in underwater communications, in *Proceeding of International Conference on Communication and Signal Processing* (IEEE Xplore, 2018), pp. 1813–1817. https://doi.org/10.1109/ICCSP.2017.8286708
4. P. Vijayalakshmi, V. Rajendran, Performance analysis of VBF protocol in underwater communication for anchoring nodes and moving nodes. ARPN J. Eng. Appl. Sci. **12**(8) (2017). ISSN 1819-6608
5. R.S. Deepak Ram, P. Vijayalakshmi, P. Venkataraman, T. Jaya, V. Rajendran, Channel modelling of underwater communication network with AUVS. Int. J. Innov. Technol. Explor. Eng. **9**(1) (2019). https://doi.org/10.35940/ijitee.a9126.119119
6. T.T. Manikandan, S. Rajeev, M.R. Christu Raj, M. Saravanan, Routing strategies for underwater wireless communication: a taxonomy. Int. J. Commun. Netw. Distrib. Syst. 147–177 (2021)
7. https://www.researchgate.net/figure/Spectra-of-the-typical-contributions-to-underwater-ambient-noise-in-the-open-ocean-from_fig1_327256014
8. X. Zhang, S. Jiang, Application of fourier transform and butterworth filter in signal de-noising, in *IEEE 6th International Conference on Intelligent Computing and Signal Processing (ICSP)* (2021), pp. 1277–1281
9. Y.Y. Al-Aboosi, A.Z. Sha'ameri, Improved signal de-noising in underwater acoustic noise using S-transform: a performance evaluation and comparison with the wavelet transform. J. Ocean. Eng. Sci. **2** 172–185 (2017)
10. S.M. Santhanam, V. Rajendran, Study of de-noising techniques for SNR improvement for underwater acoustic communication, proceedings of the institute of marine engineering, science, and technology. J. Mar. Eng. Technol. **13**(3) Part A (2014)
11. X. Zhang, B. Lu1, L. Qiao, A wavelet selection scheme in underwater discharge signal analysis. EURASIP J. Adv. Signal Process. **2023**, 106 (2023). https://doi.org/10.1186/s13634-023-01065-4
12. R.C. Guido, F. Pedroso, A. Furlan, R.C. Contreras, L.G. Caobianco, J.S. Neto, Cwt $\times$ dwt $\times$ dtwt $\times$ sdtwt: clarifying terminologies and roles of different types of wavelet transforms. Int. J. Wavel. Multiresolut. Inf. Process. **18**(06), 2030001 (2020). https://doi.org/10.1142/S0219691320300017
13. R.C. Guido, Wavelets behind the scenes: practical aspects, insights, and perspectives. Phys. Rep. **985**, 1–23 (2009). https://doi.org/10.1016/j.physr ep.2022.08.001
14. L. Yang, H. Su, C. Zhong, Z. Meng, H. Luo, X. Li, Y.Y. Tang, Y. Lu, Hyperspectral image classification using wavelet transform based smooth ordering. Multiresolut. Inf. Process. **17**(06), 1950050 (2019). https://doi.org/10.1142/S0219691319500504

15. D. ZhaoHeng, L. ShangHe, W. Lei, Selection of the optimal wavelet bases for wavelet denoising of partial discharge signal, in *2nd International Conference on Signal Processing Systems*, vol. 3 (2010), pp. 3–4003404. https://doi.org/10.1109/ICSPS.2010.5555675
16. K. Wang, X. Zhang, J. Ota, Y. Huang, Estimation of handgrip force from SEMG based on wavelet scale selection. Sensors **18**, 663 (2018). https://doi.org/10.3390/s18020663
17. R.C. Guido, F. Pedroso, R.C. Contreras, L.C. Rodrigues, E. Guariglia, J.S. Neto, Introducing the discrete path transform (DPT) and its applications in signal analysis, artefact removal, and spoken word recognition. Digit. Sign. Process. **117**, 103158 (2021). https://doi.org/10.1016/j.dsp.2021.103158
18. L. Yang, H. Su, C. Zhong, Z. Meng, H. Luo, X. Li, Y.Y. Tang, Y. Lu, Hyperspectral image classification using wavelet transformbased smooth ordering. Multiresolut. Inf. Process. **17**(06), 1950050 (2019). https://doi.org/10.1142/S0219691319500504
19. S. Sakthivel Murugan, V. Natarajan, S. Radha, Analysis of MNLMS and KLMS algorithm for underwater acoustic communication. Fluct. Noise Lett. **11**(4) 1250023 (2012). https://doi.org/10.1142/S021947751250023X
20. Y. Wanga, S.J. Chena, L. Gea, H.X. Hua, Y. Wangb, L. Zhou, The optimal wavelet threshold denosing method for acoustic emission signals during the medium strain rate damage process of concrete. Nondestruct. Test. Eval. **32**(4), 400–417 (2017). https://doi.org/10.1080/10589759.2016.1241252
21. W. Chengkuna, Z. Zhifenga, C. Bohuab, Y. Yong, Denoise for propeller acoustic signals based on the improved wavelet thresholding algorithm of CEEMDAN. Cognent Eng. **11**(1), 2327570 (2024). https://doi.org/10.1080/23311916.2024.2327570
22. Y. Li, Y. Li, X. Chen, J. Yu, H. Yang, L. Wang, A new underwater acoustic signal denoising technique based on CEEMDAN, mutual information, permutation entropy, and wavelet threshold denoising. Entropy **20**, 563 (2018). https://doi.org/10.3390/e20080563
23. K. Mathan Raj, S. Sakthivel Murugan, V. Natarajan, S. Radha, Denoising algorithm using wavelet for underwater signal affected by wind driven ambient noise, in *2011 International Conference on Recent Trends in Information Technology (ICRTIT)* (Chennai, India, 2011), pp. 943–946. https://doi.org/10.1109/ICRTIT.2011.5972413
24. W. Wang, Q. Li, An image steganography algorithm based on PSO and IWT for underwater acoustic communication. Digit. Object Identifier (2022). https://doi.org/10.1109/ACCESS.2022.3212691
25. F. Alejandro, K. Guillermo, Robust phase recovery in temporal speckle pattern interferometry using a 3D directional wavelet transform. Opt. Lett. **34**, 2336–2338 (2009). https://doi.org/10.1364/OL.34.002336
26. M. Misiti, Y. Misiti, G. Oppenheim, J. Poggi, Wavelets and their applications. Lecture notes (2007). https://doi.org/10.1002/9780470612491
27. Ç.P. Dautov, M.S. Özerdem, Wavelet transform and signal denoising using Wavelet method, in *26th Signal Processing and Communications Applications Conference (SIU)* (Izmir, Turkey, 2018), pp. 1–4, https://doi.org/10.1109/SIU.2018.8404418
28. Dr. P. Yadav, A brief description of wavelet and wavelet transforms and their applications. Int. J. Stat. Appl. Math. **3**(1), 266–271 (2018)