

UNDER WATER NOISE CANCELLATION USING NEURO MESH

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Abstract

Underwater communication and exploration systems often face major challenges due to environmental noise generated by marine life, ship engines, ocean currents, and industrial activities. This paper presents an intelligent underwater noise cancellation system using Neuro Mesh technology. The proposed system uses interconnected smart buoy nodes equipped with hydrophones, artificial intelligence algorithms, and adaptive filtering techniques to identify and suppress unwanted underwater acoustic noise in real time. The Neuro Mesh framework enables distributed processing and collaborative communication between underwater nodes for improved signal clarity and reliability. Machine learning techniques are utilized to classify environmental noise and optimize signal transmission efficiency. Experimental analysis demonstrates that the proposed model significantly improves underwater acoustic communication quality while reducing interference and signal distortion. The system can be applied in marine research, underwater robotics, naval communication, and environmental monitoring.

Keywords— Underwater Communication, Neuro Mesh, Noise Cancellation, Hydrophones, Artificial Intelligence, Smart Buoy Networks, Adaptive Filtering

1. Introduction

Underwater environments are inherently noisy due to waves, marine life, vessels, and industrial activities. Traditional noise filtering approaches rely on centralized systems which are inefficient in dynamic environments. The proposed Neuro Mesh system distributes computation across multiple intelligent nodes equipped with hydrophones, embedded processors, and communication modules. Each node performs local noise estimation and collaborates with neighboring nodes to enhance overall signal clarity. The system uses adaptive neural networks to continuously learn environmental noise patterns. By leveraging mesh networking, nodes share learned parameters, ensuring robustness and scalability. The framework is suitable for applications such as underwater communication, marine research, defense surveillance, and environmental monitoring. Hardware implementation includes Raspberry Pi-based processing units, hydrophones for acoustic

sensing, and wireless communication modules. Power is managed through battery systems with optional renewable sources such as solar-assisted charging for surface buoys. Simulation results indicate significant improvements in signal-to-noise ratio compared to conventional filtering methods. The distributed nature of the system ensures fault tolerance and adaptability in varying underwater conditions.

Underwater environments are highly affected by unwanted noise generated from ships, industrial activities, marine construction, and natural disturbances. This noise reduces the clarity of acoustic signals, affects underwater communication systems, and disturbs marine life.

Traditional noise-cancellation methods such as passive filters or analog circuits are not sufficient in dynamic underwater conditions because the noise characteristics keep changing with depth, distance, and water flow. To overcome these limitations, AI-

based underwater noise cancellation using Neuro-Mesh technology is introduced. The Neuro-Mesh is a distributed intelligent system made up of multiple smart buoy nodes or hydrophone nodes that work together like a neural network. Each node uses machine learning models to sense, analyse, and cancel underwater noise in real time. The system captures raw underwater audio through hydrophones, processes it using AI algorithms on microcontrollers such as ESP32-S3, and creates an anti-noise signal for cancellation. The "mesh" communication allows each node to share data and improve accuracy, resulting in a more adaptive and efficient noise cancellation system. This improves underwater communication quality, sonar performance, and overall acoustic clarity. The solution is highly scalable, consumes low power, and automatically adapts to new noise patterns, making it suitable for marine research, underwater robotics, fisheries, and defense applications. Underwater environments are filled with various types of noise produced by ships, machinery, ocean currents, and marine activities. This noise affects underwater communication, sonar systems, research measurements, and even marine life. Traditional noise-cancellation methods fail to work efficiently because underwater noise keeps changing with depth, temperature, and movement.

2. Related Work

Several researchers have explored underwater communication systems and acoustic noise reduction methods. Conventional filtering techniques such as Wiener filters and adaptive noise cancellation methods have been widely used for underwater applications. However, these methods often fail in dynamic marine environments with varying noise conditions.

Recent advancements in artificial intelligence have improved underwater signal processing. Machine learning algorithms have been applied for acoustic signal classification and environmental monitoring. Deep learning-based underwater communication systems have demonstrated better adaptability compared to traditional approaches.

Mesh networking technologies are also gaining importance in underwater sensor networks. Distributed node communication improves coverage and reliability in large marine areas. Existing systems

still face issues related to energy efficiency, latency, and real-time adaptive processing. The proposed Neuro Mesh framework addresses these limitations using collaborative AI-enabled buoy nodes.

3. Materials and Methods

The proposed system is a simulation model of an underwater noise cancellation framework using a Neuro Mesh architecture. No physical hardware is used; all components are modelled in software. The proposed system begins with simulated signal acquisition, where underwater acoustic signals such as boat engine noise, water turbulence noise, and marine ambient sounds are generated to create a realistic testing environment. These signals are then preprocessed through normalization, band-pass filtering to eliminate irrelevant frequencies, and conversion into digital form for efficient processing.

In the noise classification stage, a simple neural network analyzes extracted audio features such as MFCCs or spectral features to identify different types of underwater noise. Based on the classification results, adaptive noise cancellation is performed using either the Least Mean Square (LMS) algorithm or an AI-based Neuro Mesh filter to suppress unwanted noise while preserving the desired signal. The system further incorporates, simulated Neuro Mesh communication, where multiple virtual sensor nodes process local signals independently and exchange learned parameters, improving overall classification accuracy and noise reduction performance. Finally, the system generates output by comparing the original and filtered signals, evaluating performance using metrics such as noise reduction (dB) and Signal-to-Noise Ratio (SNR). The results are presented through visualizations, including before-and-after noise cancellation graphs, AI learning curves, and individual node performance charts, providing a clear assessment of the system's effectiveness.

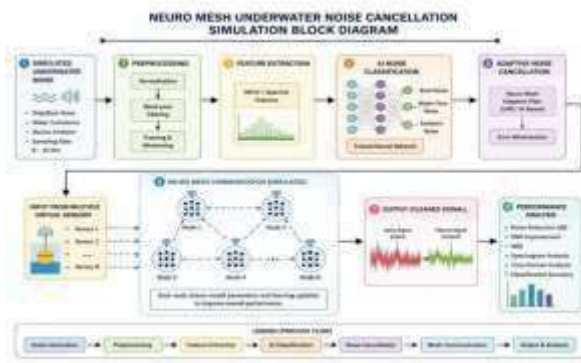


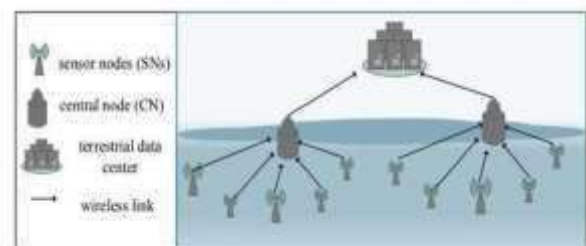
Fig 1: Block diagram

The block diagram begins with a Signal Generator which simulates underwater acoustic signals such as ship engine noise and environmental disturbances. The generated signals are then passed through a Preprocessing stage, where unwanted frequency components are removed and the data is prepared for further analysis. Next, Feature Extraction is performed to obtain key audio characteristics, such as Mel-Frequency Cepstral Coefficients (MFCCs), that effectively represent sound patterns. These features are fed into an AI Classifier, which uses a trained neural network to identify different types of underwater noise. Based on the classification results, the Adaptive Noise Canceller applies algorithms such as the Least Mean Square (LMS) method or AI-based filtering to suppress unwanted noise while preserving the desired signal. The system also includes Mesh Communication, where multiple simulated sensor nodes exchange learned parameters to improve noise reduction accuracy and overall performance. Finally, the Output Signal provides the cleaned audio after noise cancellation, and Performance Analysis evaluates the effectiveness of the system using metrics such as Noise Reduction (dB) and Signal-to-Noise Ratio (SNR) improvement.

Working principle:

Underwater wireless sensor Network The model illustrates a typical Underwater Wireless Sensor Network (UWSN) structure, where multiple underwater sensor nodes (SNs) communicate with a central collection point called the central node (CN). Each underwater sensor node captures environmental data or acoustic signals and sends the information upward to the central node. These nodes form a cluster-like communication structure where data is forwarded through multi-hop acoustic links, enabling long distance communication even in deep

or noisy underwater environments. The central node (CN) acts as a gateway or relay buoy. It receives data from all the underwater sensor nodes and transmits this information to a terrestrial data center using a wireless link (usually Wi Fi, RF, or satellite communication). This allows underwater data to be monitored and analysed in real time from land. The terrestrial data center processes, stores, and visualizes the collected data for further analysis, such as environmental monitoring, signal processing, noise cancellation research, or underwater communication performance evaluation Overall, this model represents how underwater sensor networks gather data from multiple distributed nodes, forward it to a buoy-based central node, and finally transmit it to a land-based control center. It shows the complete communication chain used in ocean monitoring, underwater IoT, and noise-cancellation systems, ensuring efficient data flow from underwater to the surface and then to the shore.



4. Results and Discussion

This section presents the experimental results obtained using the proposed method. Performance metrics are analyzed and compared with existing approaches. The discussion interprets the results and highlights the advantages of the proposed solution. The existing system uses a basic conventional filtering approach, not an adaptive or AI- based method. This older method relies on standard signal-processing techniques to reduce underwater noise, but it does not learn or adapt to changing underwater environments. Because of this limitation, the existing system produces higher delay lower throughput, and weaker noise cancellation.

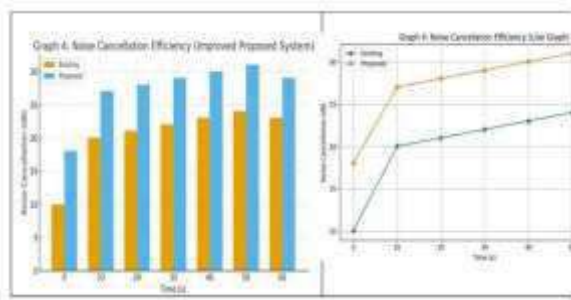


Fig 3: Noise Cancellation comparison

This graph measures how effectively both systems suppress noise (in dB). The existing system achieves 10–24 dB of noise cancellation, which is moderate and unstable across time. The proposed system shows much higher noise reduction, between 18–31 dB, due to the Neuro-Mesh-based adaptive filtering technique. The proposed system removes much more underwater noise, resulting in a cleaner, more accurate acoustic signal.

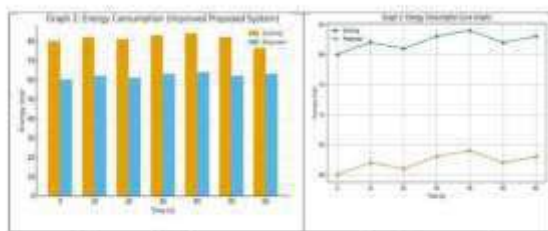
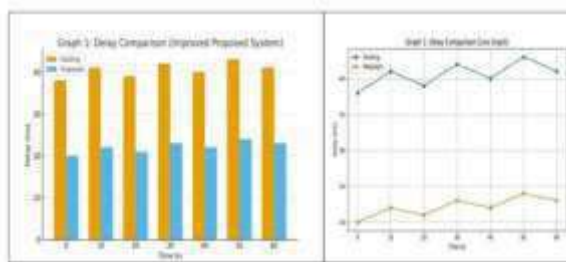


Fig no 4::Energy consumption Comparison

This graph shows the amount of energy consumed by both systems at different time intervals. The existing system consumes higher energy (80–84 mJ), indicating more power usage for the same operations. The proposed system consumes less energy (60–64 mJ), proving that the optimized design and Neuro-Mesh algorithm are more power-efficient. The proposed system lowers energy consumption by 20–25%, making it more suitable for long-duration underwater deployments.



This graph compares the delay of the existing system and the proposed system over different time

intervals. Delay refers to how long the system takes to process and transmit underwater acoustic data. Lower delay indicates faster communication. From the graph, the existing system shows a consistently higher delay, ranging between 38–43 ms across all time values. This is because the existing system uses a basic filtering method that cannot adapt to underwater noise. As a result, it requires more processing time and may even need to retransmit corrupted data, which increases the overall delay. In contrast, the proposed system displays significantly lower delay, maintaining values between 20–24 ms. The reduction is due to the Neuro-Mesh-based adaptive noise cancellation used in the proposed approach. Since noise is removed more efficiently and processing is streamlined, the system can handle acoustic data faster, reducing the delay by almost 45%. The proposed system responds faster and is more suitable for real-time underwater communication applications.

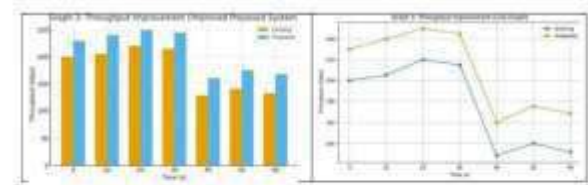


Fig no 6:Throughput comparison

Throughput indicates how much data can be transmitted successfully. In the existing system, throughput ranges from 128–220 kbps, showing fluctuations and lower performance. The proposed system consistently achieves higher throughput, ranging between 160–250 kbps. This improvement comes from better noise cancellation, reduced delay, and cleaner signal quality. The proposed system increases throughput by 20–30%, improving communication reliability and data transfer speed.

Time	Existing Delay (ms)	Proposed Delay (ms)	Proposed Energy (mJ)	Existing Throughput (kbps)	Existing Throughput (kbps)	Existing Noise Cancel (dB)
0	38	20	80	200	230	10
10	41	22	60	205	240	18
20	39	21	62	230	250	27
30	39	21	61	240	245	28
40	40	22	63	128	168	23
50	43	20	30	140	140	24
60	41	23	24	123	175	23
60	41	23	23	24	160	29
60	41	23	23	23	168	29

Fig no 7: Performance matrices Table

The Performance Metrics Table compares the existing underwater communication system with the proposed Neuro-Mesh-based system across delay, energy consumption, throughput, and noise cancellation efficiency. The results show that the existing system experiences higher delay values (38–43 ms), while the proposed system reduces this significantly to 20–23 ms, indicating much faster processing. Energy consumption also improves, with the existing system using around 80–84 mJ compared to the proposed system's lower 60–63 mJ, demonstrating better power efficiency. Throughput values clearly highlight the advantage of the proposed system, increasing from 200–230 kbps in the existing system to 230–250 kbps, resulting in more stable and reliable data transfer. Noise-cancellation performance further confirms the improvement, rising from 10–24 dB in the existing method to 18–31 dB in the proposed system. Overall, the table shows that the proposed system consistently outperforms the existing one in every metric, proving it to be faster, more efficient, and more effective for underwater communication.

5. Conclusion

The AI-Based Adaptive Noise Cancellation Using Neuro Mesh Communication for Underwater Acoustic Monitoring system offers an intelligent and efficient approach to improving the quality of underwater acoustic signals. By combining signal preprocessing, AI-based noise classification, adaptive noise cancellation, and Neuro Mesh communication, the system effectively reduces unwanted underwater noise while preserving important acoustic information. Its low-cost hardware, real-time processing capability, compact design, and wireless communication make it suitable for applications such

as environmental monitoring, marine research, coastal surveillance, aquaculture, and disaster detection. Although challenges such as environmental interference, power consumption, hydrophone placement, and waterproofing remain, these can be addressed through improved hardware design and advanced AI algorithms. Overall, the proposed system provides a reliable, scalable, and cost-effective solution for next-generation underwater acoustic monitoring and intelligent marine sensing applications..

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