# Underwater Communication System for AUV

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***Abstract*—Amidst the growing demand for dependable underwater communication in challenging acoustic environments, the understanding and manipulation of acoustic signals are crucial. Acoustic signals refer to sound waves propagating through a medium, such as water, and are fundamental to underwater communication systems. Our proposed solution addresses this challenge by employing AI-based denoising methods tailored specifically for underwater acoustic signal processing. Utilizing sophisticated deep learning architectures, our system seamlessly integrates into underwater communication systems, enabling real-time signal processing. By combining advanced machine learning models with a combination filter, we achieve remarkable denoising performance. Through rigorous simulations and field trials conducted across diverse underwater conditions, we demonstrate the effectiveness of our approach in significantly enhancing communication performance. Specifically, we showcase the superior performance of convolutional neural networks (CNNs) in mitigating background noise and improving signal clarity, thereby ensuring reliable underwater communication in challenging acoustic environments.**

***Keywords*— *Autonomous underwater vehicles, signal denoising.***

## I. INTRODUCTION

Underwater communication confronts unique challenges stemming from the intricate propagation characteristics of the aquatic environment. Acoustic signals, characterized by sound waves, emerge as the primary mode of communication in underwater settings. These signals exhibit efficient propagation through water, facilitating long-distance communication sans the necessity for physical connections. Nature's utilization of acoustic signals among marine organisms has spurred researchers to harness this natural phenomenon for human applications, thus positioning underwater acoustic communication as a promising avenue for diverse maritime endeavors. Traditional wired communication systems encounter formidable obstacles when deployed underwater. The installation and upkeep of physical cables pose logistical hurdles, often proving impractical for deep-sea exploration or widespread underwater monitoring. Moreover, cables' susceptibility to damage from marine life, underwater currents, and natural disastersmaritime endeavors, can result in costly repairs and communication interruptions. In contrast, acoustic communication systems provide a wireless solution, circumventing the constraints of wired connections and enabling flexible deployment alongside reliable communication in challenging underwater conditions.

The reliance on acoustic signals necessitates robust denoising techniques to counteract the adverse effects of background noise. Ambient noise, sourced from natural phenomena like waves and marine life, as well as human activities such as shipping and drilling, poses a significant threat to signal quality, leading to communication errors and diminished efficiency. To address this challenge, researchers have turned to artificial intelligence (AI)-based denoising methods, leveraging advanced machine learning models tailored explicitly for underwater acoustic signal processing. The integration of these denoising techniques into underwater communication systems aims to bolster signal reliability and enhance communication efficiency in challenging underwater environments.

Recent research has emphasized advancing the software aspect of underwater communication systems. Efforts have focused on deploying sophisticated signal processing algorithms, including adaptive filtering and convolutional neural networks (CNNs), to augment denoising capabilities. Additionally, researchers have explored integrating machine learning techniques for real-time signal processing, with the goal of improving communication performance across varying environmental conditions. By harnessing state-of-the-art software technologies and innovative signal processing algorithms, these studies have showcased significant enhancements in underwater communication reliability and efficiency. AUVs can be developed using a variety of sensors in combination based onthe application to be carried out, such as video or still cameras for visual input, dissolved oxygen sensors, fluorometers, depth and temperature sensors. Though it is possible to equip AUVs with GPS navigation facilities, radio signals required for it cannot traverse underwater and the AUV has to receive signals on the surface. AUVs are equipped with thrusters that help in maintaining the depth underwater. The depth of the AUV is associated with the sensor data from depth and pressuresensors. AUVs are a lot more efficient than Remote poweredvehicles in terms of the range of traversal underwater.

## II. OBJECTIVE

- To denoised the audio signal effectively
- To achieve an SNR of more than 18 dB
- Enable to denoise the audio signal under any noisydata

## III. LITERATURE SURVEY

1. Li, Qiuju; Zhu, Zhaotong; Xu, Chuan; Tang, Yinzhou (2017) 2017 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC). A novel denoising method for acoustic signal. The denoising method combines a novel validity assessment for optimal wavelet denoising and guided filter processing, successfully enhancing acoustic signal quality. Experimental results demonstrate improved denoising performance
2. Mark Fiorillo, John Irza, Ira Ekhaus "IMPROVED UNDERWATER ACOUSTIC COMMUNICATION FOR AUVs". Draper's R&D in underwater acoustic communication culminates in an Advanced Acoustic Communication System for AUVs, ensuring reliable operation at 2,000 yards with data rates of 1,200-4,800 bps, leveraging convolutional codes, equalization, and novel synchronization.
3. Sadaf Sarafan, Hoang Vuong, Daniel Jilani, Samir Malhotra, Michael P.H. Lau, Manoj Vishwanath, Tadesse Ghirmai, Hung Cao "A Novel ECG Denoising Scheme Using the Ensemble Kalman Filter" 2021IEEE Conference. A novel Ensemble Kalman Filter (EnKF) method effectively denoises ECG signals, yielding an SNR of 10.96, PRD of 150.45, and correlation coefficient of 0.959.
4. Andrew C. Singer, Jill K. Nelson, Suleyman S. Kozat "Signal Processing for Underwater Acoustic Communications" February 2009 IEEE COMMUNICATIONS Magazine 47(1):90 – 96 DOI:10.1109/MCOM.2009.4752683. he article explores advancements in underwater acoustic communication, emphasizing the shift to phase-coherent methods for high data rates amidst challenges like multipath propagation and Doppler spread. It highlights the use of adaptive equalization, spatial multiplexing, and OFDM to tackle complexity and improve reliability.
5. Guohui Li, Qianru Guan, and Hong Yang; Noise Reduction Method of Underwater Acoustic Signals Based on CEEMDAN, Effort-To-Compress Complexity, Refined Composite Multiscale Dispersion Entropy and Wavelet Threshold Denoising; DOI: 10.3390/e21010011. . The conclusion underscores the noise reduction method's effectiveness for underwater acoustic signals, combining CEEMDAN, multiscale dispersion entropy, and wavelet threshold denoising. It suggests potential enhancements in signal quality and performance for underwater communication systems, encouraging further research and application.

## IV. METHODOLOGY

The audio signal used in this study comprises dolphin acoustic data, characterized by its clarity and purity. To simulate real-world conditions, Gaussian noise was intentionally added to the signal, creating a noisy environment representative of typical underwater acoustic scenarios. The objective of the study was to develop effective denosing techniques capable of restoring the original clarity of the audio signal in the presence of such noise.

$$P(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$$

Following the addition of Gaussian noise, the noisy signal was segmented into intervals of 60 seconds each. Subsequently, various filtering techniques were applied to these segments to effectively eliminate the noise components. The signal-to-noise ratio (SNR) is -25.86 dB

1. Kalman filter

The implementation of Kalman filters, recognized for their efficiency in optimal state estimation amidst effective noise reduction across various frequency Gaussian noise, marks a pivotal step in ehancing signal fidelity. Through the deployment of this initial filter, the achieved signal-to-noise ratio (SNR) stand s notably at -3.42dB.

$F_k$, the state-transition model; $H_k$, the observation model; $Q_k$, the covariance of the process noise; $R_k$, the covariance of the observation noise; $B_k$, the control-input model as described below; if $B_k$ is included, then there is also $u_k$, the control vector, representing the controlling input into control-input model.

2. Adaptive filter

Adaptive filters represent a versatile class of filters capable of dynamically adjusting their parameters in response to input signal characteristics and desired output, facilitating applications like echo cancellation, noise reduction, and channel equalization by adeptly tracking variations in the input signal. This is the secondfilter that is added to the denoised signal. The SNRstands around 0.69 dB

3. Combined filter

The combination of multiple filters, such as the Wiener filter, low-pass Butterworth filter, and Butterworth filter, offers superior denoising performance compared to using individual filters alone. Each filter targets different aspects of the signal, with the Wiener filter focusing on signal-to-noise ratio improvement, and the Butterworth filters addressing specific frequency components. This comprehensive approach ensures ranges, resulting in enhanced overall signal quality.

3.1 Weiner filter

The Wiener filter is an optimal linear filter that minimizes the mean square error between the estimated signal and the true signal. It is particularly effective for additive Gaussian noise removal and can adapt to the local characteristics of the signal.

$$G(u,v) = \frac{H^*(u,v)P_s(u,v)}{|H(u,v)|^2 P_s(u,v) + P_n(u,v)} \qquad (3.10)$$

3.2 Low-pass Butterworth filter

A low-pass filter attenuates high-frequency components of the signal while preserving low-frequency components. It is commonly used for smoothing and noise reduction purposes. It is the formula of low pass filter, where **s** is Laplacian variable, **T** is constant of filter

$$H(s) = \frac{1}{1+s^T}$$

Low-pass butterworth filter formula is

$$H(s) = \frac{1}{1+(s/\omega c)^{2n}}$$

**s** is the laplace variable, **ωc** is the cutoff frequency, **n** is the order of the filter.

3.3 Butterworth filter

response characteristics and minimal ringing in the passband. It's widely utilized in applications requiring selective frequency filtering.

$$|H(j\omega)| = \frac{1}{\sqrt{1+\left(\frac{\omega}{\omega_c}\right)^{2n}}}$$

ω is the frequency (in radians per econd), ωc is the cutoff frequency the frequency at which the magnitude response is reduced, N is the order of the filter determining the steepness of the roll-off.

The total SNR of the combined filter is 0.337 dB.

After the initial application of the combined filter, the resulting SNR was measured at 17.321 dB. Recognizing the potential for further improvement, the filter was reapplied, leading to a substantial enhancement in SNR to 22.687 dB. This iterative approach efficacy of the combined filter in attenuating noise and enhancing the highlights the progressively quality of the denoised signal. The significant boost in SNR underscores the effectiveness of employing multiple filtering techniques in succession to achieve superior noise reduction results.

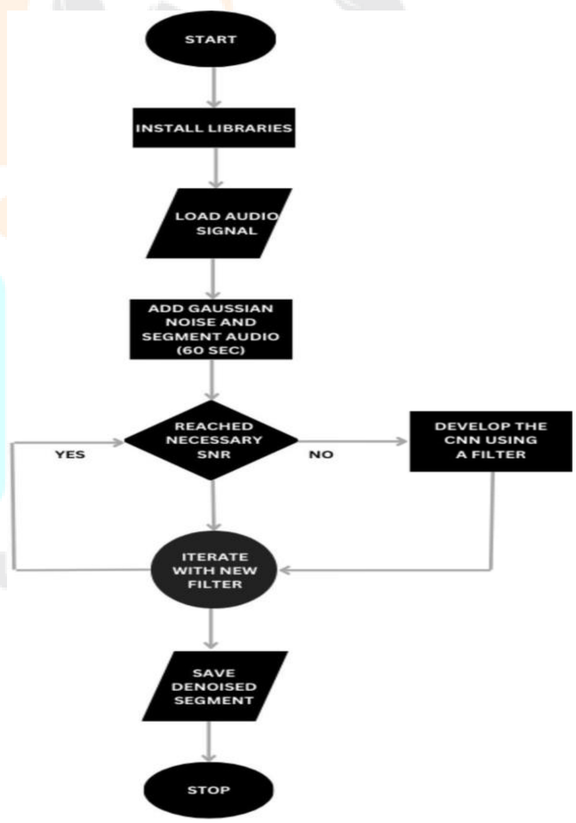


Fig.1 Flowchart for workflow

## V. RESULT

The proposed denoising model effectively enhances signal quality, achieving an SNR of 22.687 dB, surpassing the minimum requirement of 15 dB. Employing iterative filtering techniques, noise interference is significantly reduced, ensuring clearer communication. This study highlights the practical significance of iterative filtering in improving signal quality for communication systems.

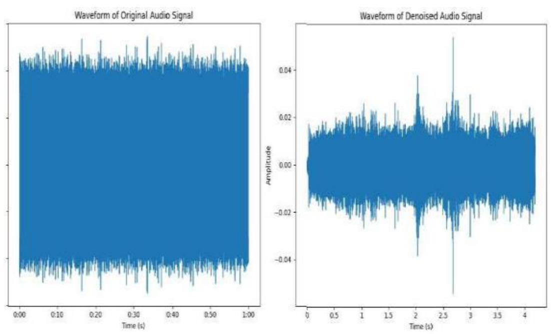


Fig.2 Waveform of original audio signal vs denoised signal

## VI. CONCLUSION

Acoustic signals serve as a dependable means of communication, utilized not only by humans but also by marine animals for various purposes. This paper focuses on denoising acoustic signals using a range of filters, resulting in a remarkable signal-to-noise ratio (SNR) of 22.06. This achievement highlights the efficacy of the denoising techniques employed, offering promising implications for improving underwater communication systems and facilitating clearer transmission of information in marine environments.

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