

AI Based Underwater Noise Cancellation to Reduce Ship-induced Marine Noise Pollution

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Abstract: In recent years, the impact of human activities on marine environments has drawn increasing attention, particularly concerning the detrimental effects of marine noise pollution. This anthropogenic noise in oceans has disrupted marine ecosystems, especially marine mammals that rely on sound waves for vital life processes. Commercial shipping is a primary contributor to this issue, prompting increased efforts to develop technologies that mitigate vessel noise. This paper introduces an AI-driven device that leverages machine learning algorithms to detect and locate sources of ship-generated noise. The device employs hydrophones to capture the noise, and uses an AI system to determine the frequency of the sound waves. The AI system then computes an anti-signal that is 180 degrees out of phase with the original noise. This anti-noise is emitted through an Active Noise Cancellation (ANC) speaker thereby providing a real-time solution that surpasses the existing traditional methods.

Keywords—Active Noise Cancellation, Artificial Intelligence (AI), Machine Learning, Hydrophones, Noise Reduction

I. INTRODUCTION

In the past decade, advancements in artificial intelligence (AI) and machine learning (ML) have brought significant innovations across various fields, including environmental conservation. Among the numerous environmental challenges, underwater

noise pollution has emerged as a critical issue due to its negative impact on marine life. Marine mammals, such as whales and dolphins, rely heavily on sound for essential activities such as communication, navigation, foraging, and predator avoidance. The increasing levels of human-made noise, primarily originating from shipping activities, have disrupted these essential functions, leading to serious consequences for marine ecosystems.

Continuous exposure to elevated underwater noise can cause physical harm and induce chronic stress in marine animals. Moreover, behavioral alterations such as disrupted migration routes, reduced reproductive success, and heightened susceptibility to predators have been observed. In ecologically sensitive regions like coral reefs and seagrass beds, heightened noise levels can disturb the balance of biodiversity, resulting in long-term ecological degradation. Addressing this issue has become imperative, as anthropogenic noise is now recognized as a major threat to the health and sustainability of marine ecosystems.

In response to this challenge, a novel AI-based device is proposed, which leverages machine learning algorithms to detect and locate noise sources on ships. This device is equipped with hydrophones to capture underwater noise and an AI system to analyze

the acoustic data. By determining the type and frequency of noise, the AI system can generate an anti-signal that is 180 degrees out of phase with the original noise, effectively canceling it out. This solution not only aims to mitigate the harmful effects of noise pollution on marine life but also offers a more efficient and scalable approach compared to existing noise reduction methods. The integration of advanced AI technologies into environmental conservation efforts represents a significant step forward in protecting marine biodiversity from the adverse effects of human activities.

II. BACKGROUND

To address the adverse effects of underwater noise pollution on marine ecosystems, the proposed device integrates various advanced technologies for effective noise detection, analysis, and mitigation. These technologies work together to ensure precise identification and effective counteraction of harmful noise frequencies, representing a significant advancement in marine environmental protection efforts.

Fast Fourier Transform (FFT)

FFT is a mathematical algorithm widely used for analyzing the frequency components of signals. In the context of the proposed device, FFT is employed to decompose complex noise signals into their constituent frequencies, enabling a precise analysis of the noise emitted by the ship's machinery. This frequency domain analysis is crucial for identifying the specific characteristics of the noise that needs to be canceled.

Wiener Filter

The Wiener filter is a technique used in signal processing to remove noise from a signal. In this device, it is utilized to enhance the clarity of the detected noise signals by filtering out irrelevant background noise and enhancing the primary noise components generated by the ship. This pre-processing step ensures that the subsequent noise cancellation is highly accurate and effective.

Destructive Interference

The principle of destructive interference is central to the noise cancellation process. By generating an anti-

signal that is 180 degrees out of phase with the original noise, the device can effectively cancel out the unwanted noise. This approach is inspired by the fundamental physics of wave interference, where two waves of equal amplitude and opposite phase can nullify each other when they overlap.

Time Distance of Arrival (TDOA)

TDOA is a method used to estimate the location of a sound source by measuring the time differences in the arrival of the sound at multiple sensors (in this case, hydrophones). By analyzing these time differences, the device can accurately determine the position of the noise source within the ship. This spatial information is essential for targeting the noise-canceling signals precisely where they are needed most.

III. METHODOLOGY

The proposed AI-driven device for mitigating marine noise pollution integrates advanced signal processing techniques and real-time AI algorithms. The system architecture, as illustrated in the block diagram, comprises several key components:

A. AI Processing Unit

The system's central component, the AI processing unit, is in charge of carrying out machine learning algorithms that examine the recorded acoustic data. This device analyzes the noise signals to pinpoint the precise traits and frequencies that need to be canceled.

B. Signal Processing Unit

This unit employs Digital Signal Processors (DSPs) to perform real-time analysis of the noise signals. Techniques such as Fast Fourier Transform (FFT) and Wiener filtering are applied here to decompose the noise into its frequency components and enhance the clarity of the signals by filtering out irrelevant noise.

C. Hydrophones

Hydrophones positioned strategically record the sounds made underwater by the ship. Because of their exceptional sensitivity across a broad frequency range, these acoustic sensors allow for the accurate identification of dangerous noise levels that interfere with marine life.

D. Micro Camera

The micro camera provides visual data to complement the acoustic analysis. This component is particularly useful for validating the noise sources identified by the system and ensuring accurate targeting of the noise cancellation process.

E. ANC (Active Noise Cancellation) Speaker

The ANC speaker generates an anti-noise signal that is 180 degrees out of phase with the detected noise. This signal is emitted in real-time, effectively canceling out the unwanted noise through the principle of destructive interference. This procedure aids in reducing the noise pollution caused by ships to the marine environment.

F. Feedback System

The feedback system continuously monitors the effectiveness of the noise cancellation process. It captures real-time data on the residual noise and feeds it back to the AI processing unit, allowing the system to adapt and optimize the cancellation algorithms dynamically.

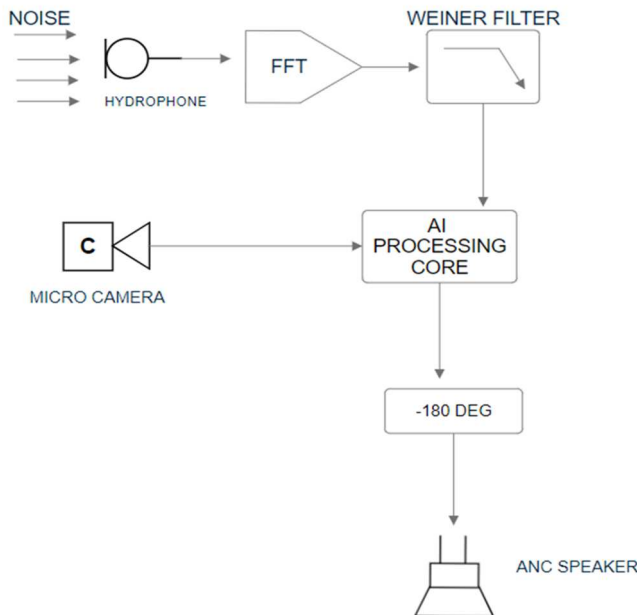


Fig.1. Block diagram of the system

IV. SETUP

The implementation involves processing and analyzing two critical datasets to achieve higher accuracy in mitigating marine noise pollution. These datasets include:

i. Acoustic Data

This dataset includes spectrograms, frequencies, and sound pressure levels, among other audio properties. The acoustic data is essential for understanding the characteristics of noise generated by maritime vessels and serves as the foundation for generating anti-noise signals.

ii. AIS (Automatic Identification System) Data

This dataset includes Maritime Mobile Service Identity (MMSI), navigation status, speed over ground, course over ground, and other attributes related to ship movements.

A. Acoustic Data Processing

The software implementation begins by focusing on the acoustic dataset. To make sure the data is suitable for additional analysis, the initial step entails cleaning and visualizing the information. Using a sample audio file from the Australian Antarctic Data Center, the following steps are undertaken:

a. Waveform Visualization

The audio file is imported into the Google Colaboratory environment for its interactive and collaborative features. Utilizing the Librosa library, the raw audio waveform is visualized to observe the overall structure and amplitude variations over time. This provides initial insight into the characteristics of the acoustic data, highlighting regions of interest corresponding to significant noise events.

b. Time-Frequency Representation

The Short Time Fourier Transform (STFT) transforms the time domain into a time-frequency representation. This method separates the complex noise signals into their constituent frequency components. Finding the particular frequency ranges that are mostly responsible for the noise pollution requires a thorough visual depiction of the noise's hanging frequency content over time, which is provided by the resulting spectrogram.

c. Data Type Verification and Conversion

The spectrogram data is ensured to be complex-valued, as required for precise frequency domain analysis. The amplitude values are converted to a decibel scale, providing a more intuitive representation of the signal strength across frequencies. This normalized spectrogram, expressed in decibels, offers a clearer view of the acoustic environment, aiding in the accurate identification of noise sources.

d. Feature Extraction and Reshaping

The spectrogram data is reshaped to prepare it for feature extraction, adjusting the format to facilitate processing by machine learning algorithms. Negative values in the spectrogram are set to zero to ensure numerical stability. An essential input to the AI system for extracting significant elements from the audio data is the reshaped and pre-processed spectrogram.

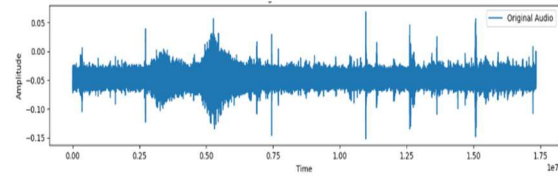
e. Phase Inversion Calculation

After identifying the key noise frequencies, phase inversion is calculated as a crucial step in generating the anti-noise signal. The anti-noise signal is produced by 180-degree phase inversion of the detected noise signal. When this signal is coupled with the original noise, it causes destructive interference. This interference effectively cancels out the noise, significantly reducing its impact.

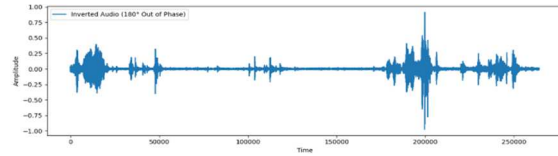
The phase inversion process involves detailed calculations to ensure the accuracy of the inverted signal. The resulting inverted phase is then applied to the anti-noise signal, which is tested and validated against the original noise to confirm the effectiveness of the cancellation.

f. Noise Source Localization

Using the combined datasets, algorithms are implemented to precisely locate noise sources. The Time Distance of Arrival (TDOA) technique analyzes the variations in sound arrival times from hydrophone to determine the location of noise sources. This spatial information is crucial for targeting the emission of anti-noise signals effectively.



(a)



(b)

Fig.2. Visualizations of the audio signal analysis

(a) Original Audio Waveform.

(b) Inverted Audio Waveform (180° Out of Phase)

V. CONCLUSION

In conclusion, the implementation of AI-based technology to mitigate ship-generated noise in oceans presents a promising and practical solution. By employing sophisticated algorithms to detect, analyze, and counteract noise, this approach holds the potential to significantly reduce the adverse impact on marine life. This not only aligns with the imperative to address the escalating challenges posed by human activities but also underscores a proactive step towards harmonizing maritime operations with the preservation of marine ecosystems. Ultimately, the integration of AI in noise reduction offers a pathway towards a more sustainable coexistence between human activities and the well-being of marine environments.

VI. REFERENCES

- [1] A. N. Kawade, V. M. Shinde, R. K. Shastri and A. Das, "Analysis of ship noise from underwater ambient noise," 2016 Conference on Advances in Signal Processing (CASP), Pune, India 2018.
- [2] L. Liu, K. Kuo and S. M. Kuo, "Infant cry classification integrated ANC system for infant incubators," 2013 10th IEEE INTERNATIONAL CONFERENCE ON NETWORKING, SENSING AND CONTROL (ICNSC), Evry, France 2023.
- [3] S. Sun, C. Zhao, C. Zheng, C. Zhao and Y. Wang, "High-Precision Underwater Acoustical Localization

of the Black Box Based on an Improved TDOA Algorithm," in *IEEE Geoscience and Remote Sensing Letters*, Aug. 2021

[4] C. Zhu, T. Cao, L. Chen, X. Dai, Q. Ge and X. Zhao, "High-Order Domain Feature Extraction Technology for Ocean Acoustic Observation Signals: A Review," in *IEEE Access*

[5] O. Axelsson and C. Rhén, "Neural-Network-Based Classification of Commercial Ships From Multi-Influence Passive Signatures," in *IEEE Journal of Oceanic Engineering*

[6] M. Chunxia, L. Xiaoyuan, M. Zhongcheng, C. Feng and S. Hang, "Construction of Acoustic Dipole and Its Performance Verification Test in Shallow Water," *2021 OES China Ocean Acoustics (COA)*

[7] A. M. Rodríguez, R. S. Mullor, P. Beltrán Palomo, E. Baudin and V. Lamaison, "New European underwater noise measurement standard developed in the AQUO project," *OCEANS 2015*.

[8] K. Wei, Z. Liu and X. Zhang, "Research of underwater acoustic confrontation technology based on warship radiated noise modeling," *2014 IEEE International Conference on Signal Processing, Communications and Computing*.

[9] A. M. Patterson, J. H. Spence and R. W. Fischer, "Evaluation of underwater noise from vessels and marine activities," *2013 IEEE/OES Acoustics in Underwater Geosciences Symposium*, Rio de Janeiro, Brazil, 2013.

[10] S. Che, C. Meng, J. Bai and W. Wu, "Mapping underwater sound noise and assessing its characteristic based on AIS," *2016 IEEE/OES China Ocean Acoustics (COA)*, Harbin, China, 2016.

[11] F. Traverso, T. Gaggero, G. Tani, E. Rizzuto, A. Trucco and M. Viviani, "Parametric Analysis of Ship Noise Spectra," in *IEEE Journal of Oceanic Engineering*, April 2017.

[12] M. A. Kishk and A. M. Alaa, "On the capacity of the underwater acoustic channel with dominant noise sources," *2014 IEEE 2nd International Symposium on Telecommunication Technologies (ISTT)*, Langkawi, 2014.

[13] L. Fillinger *et al.*, "Towards a passive acoustic underwater system for protecting harbours against intruders," *2010 International Waterside Security Conference*, Carrara, Italy, 2010.

[14] A. Sutin *et al.*, "Stevens Passive Acoustic System for underwater surveillance," *2010 International WaterSide Security Conference*, Carrara, Italy, 2010.