

(ChatGPT helped write this) Underwater acoustics forms an intriguing area of study with multi-faceted implications in diverse disciplines, including marine engineering, environmental conservation, and naval warfare. The evolution of sound profiles or 'acoustic footprints' owing to the activity of underwater propellers has invoked extensive research interest, offering avenues for enhanced maritime surveillance and submarine warfare tactics. Notwithstanding the developments, a conspicuous knowledge gap prevails in terms of a comprehensive approach that spans across varying environmental conditions and different propeller types, as is real world scenarios.

I present a proposal that expands the narrow contours of traditional methods, encompassing Fourier Transforms and Spectral Analysis, and integrates them with advanced techniques like Mel-frequency Cepstral coefficients (MFCC), Constant-Q transforms (CQT), Gammatone Filter Cepstral Coefficients GFCC (GFCC), and Wavelet Packets. Here I want to show that by applying these techniques to a set of controlled experiments with a range of 3D-printed propellers under distinct simulated conditions, I can improve the precision of propeller identification significantly.

The proposed approach is expected to outperform previous research efforts, which have achieved an accuracy rate of approximately 70% under optimal conditions. The incremental improvements aim to broaden the capability of existing systems to identify attributes of underwater propellers accurately, including blade count and speed. If results are promising, the system might also identify multiple propellers simultaneously.

In the wider context of maritime surveillance and submarine warfare, these advancements have the potential to revolutionize current methodologies by providing increased precision and range in acoustic identification capabilities.

In a quest to advance underwater acoustics, several researchers have made significant strides in respect to data collection and processing. The DeepShip dataset, a key resource in my background research, encompasses over 47 hours of real-world data procured from the Strait of Georgia near Vancouver [1]. The researchers who worked on this project also provide their best attempts to classify and predict data using the DeepShip dataset, with the most accurate instances recording a success rate of around 70% [1]. These practices involved the application of highly sophisticated data processing methods, which implies a substantial scope for improvement and innovation.

Shedding light on one of processing techniques, a resource on Medium outlines the significance and working of Mel Spectrogram in audio signal processing. In essence, the article elaborates on the conversion of sound signals into visual representations to deduce patterns and notes. A profound understanding of such techniques may serve as a stepping stone to develop a path-breaking methodology in my research [3]. This article

provided insight into one of the mathematical operations that are used in the data processing.

The creators of the DeepShip dataset also presented the architecture of their most effective model, revealing the incorporation of the Xception model components it. Venturing into a deeper understanding of these special Convolutional Neural Network (CNN) structures, I referred to an articulate exposition by Maël Fabien, which detailed the inception, evolution, and application of Xception models [4].

For my own data, I aim to emulate the methodologies employed by the authors of the DES-Pat study [2]. During their data collection they set up a tank with their propeller and microphone contained in water. For my data collection I am envisioning adapting the researchers methods with a variety of propeller types including the 5 given in the original research done plus additional creations to simulate a variety of vessel types ranging from outboard motors to nuclear aircraft carriers. If time permits there will also be an additional level of difficulty added to discern between multiple propellers and identify them.

The environment conditions will contain a variety of conditions to simulate many environments. Some variables that will be changed are: Ambient Noise Levels to simulate real world environments such as like marine traffic, wave noise, and animals in the water, Temperature to see what effect that will have on the variance of sounds waves, Flow velocities ranging in speed and direction, Water composition comparing different values of sediments in the water in addition to salt vs freshwater, The Propeller Running conditions including speed, load, damage, and other types of wear, and finally distance to the object.

The networks will be evaluated on their accuracy, precision and recall in addition to more advanced metrics such as: signal-to-noise ratio, computational efficiency. These metrics will be compared against the results found by the authors of the DES-Pat study [2]

The end presentation will show a result a live demonstration of a propeller being identified live in the water. In addition to the live demonstration graphs will show a comparison in the metrics of the differences in the models and how that effected their performance. The data collected from this research will be made publicly available so that others can replicated or improve this research.

There is a chance that I might be doing more than I can handle with the amount of time left in semester. If that ends up being the case, I was planning that I would work on the DeepShip data set and see what improvements I could make.

References:

1. C. C. Lo, H. T. Lu, "DeepShip: An underwater acoustic benchmark dataset and a modulated autoencoder-based baseline for ship classification," *Expert Systems with Applications*, vol. 188, p. 115270, November 15, 2021. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0957417421007016>.
2. X. Niu, H. Li, "DES-Pat: A novel DES pattern-based propeller recognition method," *Applied Acoustics*, vol. 172, p. 107859, November 01, 2020. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0003682X20309646>.
3. L. Roberts, "Understanding the Mel Spectrogram," Medium, March 5, 2020. [Online]. Available: <https://medium.com/analytics-vidhya/understanding-the-mel-spectrogram-fca2afa2ce53>.
4. M. Fabien, "Understanding Xception model," Dec. 15, 2019. [Online]. Available: <https://maelfabien.github.io/deeplearning/xception/>

Criteria	Rating	Good Score	Points
Quality of data	Based on amount of data, different conditions, accuracy of the collection, labels	Extensive amount of data covering a wide range of conditions, collected and labeled accurately	10
Quality of data collection method	Procedures defined, accuracy of equipment, data managed well, reproducibility	Well-defined, consistently-applied procedures, high-accuracy equipment, effective data management, and reproducible methodology	10
Clear description for NN model	Model created in a logical manner	Model is logically created and meticulously explained providing comprehensive understanding of its design, operation, and outcome interpretation	30
Correlation to researchers previous data	Able to compare results to researchers, able to present what went wrong, right, and what could lead to improvement	Able to meaningfully compare current results to previous researchers' data, clearly interpret discrepancies and similarities, and suggest informed improvements	10

Live Demonstration/Presentation	Quality of graphs and live demonstration, clear and understandable to a wide audience	High-quality graphical representations and live demonstration, presented clearly and understandably to a wide audience, with effective communication of project aims, processes, results, and implications.	25
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