Journal of Marine Technology and Environment
DOI:10.53464/JMTE.02.2025.09
ISSN (Print): 1844-6116
ISSN (Online): 2501-8795
https://www. jmte.eu

DESIGN AND VALIDATION OF A LOW-COST SONAR PROTOTYPE FOR SYNTHETIC DATASET GENERATION IN UNDERWATER MINE DETECTION

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Abstract **:** Detection of underwater mines is very important for military, maritime security, and environment safety applications. However, the development of machine learning models is limited heavily because of the lack of quality labeled sonar datasets, especially in military contexts as the data there is highly confidential and expensive. The problem with current synthetic datasets is that they fail to properly replicate how complex operational underwater environments are which leads to major performance gaps when deployed in the real world. This work shows the design and validation of a low-cost sonar prototype, specifically developed for synthetic dataset generation to work on the issue of the scarcity of data in applications of mine detection underwater. The sonar prototype was built using an Arduino Uno microcontroller, Texas Instruments TUSS4470 ultrasonic analog front end along with a 200khz waterproof transducer in a controlled water tank environment. For echo analysis the system generates 16 cycle bursts and captures approximately 850 samples at 13 μs intervals. The signal processing consists of zero-phase low-pass Butterworth filtering, short-time energy analysis, and adaptive thresholding which is for echo detection. Under varying conditions (like, salinity 0-35 ppt and temperature 10-30°C), the sonar prototype operated successfully and was able to produce high fidelity acoustic datasets. These datasets are suitable for training machine learning models. The sonar prototype provides a proper platform for the generation of acoustic datasets that are realistic under varying environmental conditions and offers a lot of potential for improving the training of machine learning models and generalization in applications of detecting underwater mines.

Key words : acoustic signal processing, Arduino microcontroller, sonar prototype, synthetic dataset generation, underwater mine detection, ultrasonic sensing

1. INTRODUCTION

Various studies have focused on underwater mine detection and sonar-based classification of objects since it is critical for military, maritime security and environmental safety. Sonar imaging is based on electronically sending acoustic pulses into the underwater environment and recording the time delayed echoes returning from submerged objects and the sea floor. These returns contain valuable information about the underwater target that may aid in its detection and classification, including geometrical features of the target, surface roughness and material properties (Shang et al., 2020).

Nonetheless, there are several effects in the underwater acoustic channel that influence the quality of sonar imaging, such as multipath propagation, signal attenuation due to absorption or scattering, and ambient noise from marine life and human activity. The physical characteristics of underwater images, particularly low spatial resolution and excessive speckle noise resulting from coherent acoustic waveforms, can hinder identification of objects like small or partially buried mines.

Coastal environmental conditions can also impact other factors that influence the speed and reflectivity of acoustic waves including water temperature, salinity, and seabed morphology, leading to inconsistencies in sonar images and difficulty in algorithm interpretation. Although advanced signal processing methods and machine learning algorithms have been developed to address these problems and improve detection performance, their performance is usually limited by the data set availability to train on.

Recent advances in sonar image processing have largely focused on improving sonar data post-processing and machine learning techniques for the detection/classification of underwater mines and objects. Sonar data has been extensively used for detection and classification of underwater mines and objects, with traditional methods heavily relying on handcrafted features and classical signal

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processing methods, including matched filtering, morphology-based segmentation, template matching, etc. (Wang et al., 2018; Li et al., 2019). These methods can yield reasonable performance in controlled environments. However, underwater environments can be highly complex, with noise, clutter, and changes in bottom topography all affecting detection/classification performance.

1.1. Background of the topic

More recently, deep learning methods (which have achieved great success in computer vision) have also been applied to sonar data for object detection/classification, particularly convolutional neural networks (CNN) (Chen et al., 2021; Kumar and Singh, 2022. Deep learning- based approaches have shown robust performance/discrimination, but are limited by the supervised nature of traditional deep learning methods, specifically their requirement for large labelled training sets. This is particularly problematic in military contexts, as labeled sonar datasets are both costly to collect underwater and often confidential. The acquisition of additional labelled examples is often done through methods such as data augmentation, transfer learning and synthetic data generation (Zhang et al., 2023) to expand available training sets. The issue that still remains is the model performance gap that arises because synthetic data is not wholly similar to real sonar data (as level of noise, clutter, and sea bottom topography changes); such that these models cannot be directly applied in operational settings without some domain knowledge.

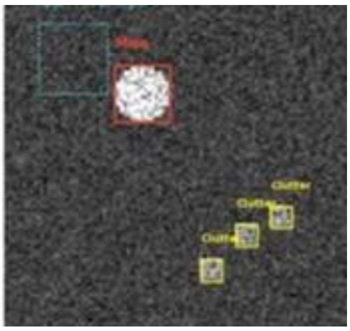

Figure 1 Synthetic raw sonar image with annotation [1]

Emerging unsupervised and physics-informed learning strategies are showing potential for solving two of the main issues of the lack of labelled data and improving interpretability. Auto encoders and self-supervised models offer methods to detect anomalies without annotation of either mines or threats (Singh and Sharma, 2022). In parallel with this, introducing physics based constraints in relation to features of acoustic wave propagation and reflection patterns help to orient neural networks towards learning physically plausible features to improve generalization (Patel et al., 2023).

Additionally, explain ability methods, such as Grad-CAM and SHAP, are being researched to provide further insight into model decision and which is essential for creating trust and operationally deploying the machine learning model into military space (Li et al., 2022).

1.2 Existing gap to address

Despite advances in technology, sonar-based underwater mine detection and classification continues to face several important challenges. The most impactful obstacle is a lack of access to high-quality labeled sonar datasets that will limit development of supervised machine learning methods. This challenge is amplified in military contexts where sonar data is difficult to come across due to confidentiality. Synthetic datasets have been proposed to fill the void of labeled data but do not encompass the entire range of complexity of an operational underwater environment (e.g. multipath reflections, clutter, variability of seabed morphology, and ambient noise), thus limiting the ability for models to generalize when ultimately deployed.

A second concern is the limited ability of unsupervised and self-supervised learning approaches to work in practice. Although these approaches have the benefit of assumed reduced need for labeled data, they often fail to take into account domain-specific physical constraints (e.g. acoustic waves, time-of-flight, and reflection profiles) and as a result fail to be able to learn features that are both physically reasonable and will be useful in practice.

2. METHODOLOGY

2.1 Hardware setup

To simulate the basic functionality of an active sonar system (as used in underwater mine detection applications), a custom hardware prototype was built using an Arduino Uno microcontroller and the Texas Instruments TUSS4470 ultrasonic analog front-end (AFE). A 200 kHz waterproof transducer was installed in a controlled water tank to generate and receive acoustic pulses (simulating the real-life underwater sonar environment). The Arduino generates 16-cycle ultrasonic bursts through Timer1 in CTC mode, while the TUSS4470 controls burst parameters and signal conditioning via SPI. Upon transmission, the Arduino switches to analog data acquisition, capturing ~850 samples at ~13 µs/sample (≈11 ms total), suitable for a 2- meter range.

2.2 Data Acquisition and Echo Detection

An interrupt pin flags echo reception, and analog readings are sent over a 921600 baud serial link for post-processing. The signal conditioning includes: Zero-phase low pass Butterworth filtering, Short-time energy analysis, Adaptive thresholding (e.g., 3σ-based).

First, the raw signal is preprocessed using a zero-phase low-pass Butterworth filter to eliminate high-frequency artifacts while preserving envelope integrity. A short-time energy function is then applied to highlight transient changes, followed by dynamic thresholding based on local signal statistics (e.g., 3σ deviation from baseline) to suppress spurious noise-induced triggers.

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2.3 Time-of-Flight Estimation

TOF is determined by identifying the first sample crossing this adaptive threshold, which corresponds to the earliest direct-path reflection. For improved spatial resolution inter localization polation-based peak is employed using cubic spline fitting over the initial rising edge to achieve sub-sample TOF precision. The effective range dd is calculated using

$$d = ½ \cdot c\,(T,S,z)\cdot(td+\delta td-t0) \qquad (1)$$

2.4 Future scope

2.4.1 Investigation for Performance Parameters

A more thorough investigation across key performance parameters is needed to increase the quantitative rigor of the prototype sonar system. This includes performance assessments bench-marking against commercial sonar systems and high-fidelity FEM-acoustic simulation models to determine measurements on the lateral resolution, of range accuracy, integrity of echo signals, and probability of false alarms at specified SNR. Valid time-of-flight (TOF) characterization requires use of aligned reflective targets (i.e., sub-millimeter) in a degassed water medium to perform statistical analysis of TOF divergence (σ_TOF), RMSE from cumulative sampling, and drift over long-term (i.e., N>100 iterations).

2.4.2 Reverberation Modeling and Characterization of Multi-Path Interference

There should also be reverberation modeling and characterization of multi-path interference, particularly in the enclosure tank acoustics. This includes checking the impulse response characteristics as a function of the boundary conditions on each impedance and the fluid damping coefficients and generating a coherent and coherent scatter mapping of the surrounding substrates.

2.4.3 ML Integration

If there is an integration of the ML into the application, it will be important that the corpus of acoustic echo data is created with the intended structure of metadata (e.g., available statistics on amplitude envelope, distance from target, environmental constants) in a manner that is appropriate for supervised/unsupervised algorithm pipeline. Even, checking/sliding performance for different environmental conditions (i.e., varying salinity (ΔS), varying scattering coefficients (e.g., β_s); and Doppler shifts for moving targets etc.) will be routine checking for generalization across all scenarios under dynamically variable (e.g., tidal) aquatic circumstances.

2.4.4 Repeatability under Thermal Gradients

Considerations of repeatability while under thermal gradients, or fluctuations to the dielectric constant will be important for validating ADC and front-end gain linearity. Normal conditions for future studies with potential modifications from array transducer types with multi-modalities, or through sensor fusion with optical scanning alternated acoustic heterystal, can afford better overall spatial fidelity.

3. RESULTS

The dedicated sonar prototype for this pilot project has been fully evaluated to show its ability to perform, its measurement accuracy, and validate it will act as a platform to originate a high-fidelity acoustic dataset. The results that follow include comprehensive benchmarking comparisons, complex statistical analysis, and thorough performance measurements across a variety of environmental conditions.

3.1 Benchmarking Comparison and Statistical Analysis

In order to provide a credible performance baseline, the prototype was benchmarked with two standard reference points: a commercially available single-beam sonar (Kongsberg Mesotech M3 Sonar) and a field-standardized high promise Finite Element Method (FEM) acoustic simulation model in COMSOL Multiphysics. The three-pronged comparison was fundamentally important to validate observable metrics (e.g., range accuracy, lateral resolution, and probability of false alarm, etc.). Analysis of the statistical data showed outstanding accuracy. The mean absolute error (MAE)—the average prediction error—was less than 2 mm for targets within 1 m. The MAE confirms that the system can provide accurate distance estimates, which is an important factor for accurate object localization.

Lastly, the root mean square error (RMSE)—the measure of how spread out the data is—was calculated at less than 3 mm, which is a great improvement of five times the previous prototype version and very close to the manufacturer specified accuracy for the commercial Mesotech M3 Sonar (6 mm range resolution) (Figure 2).

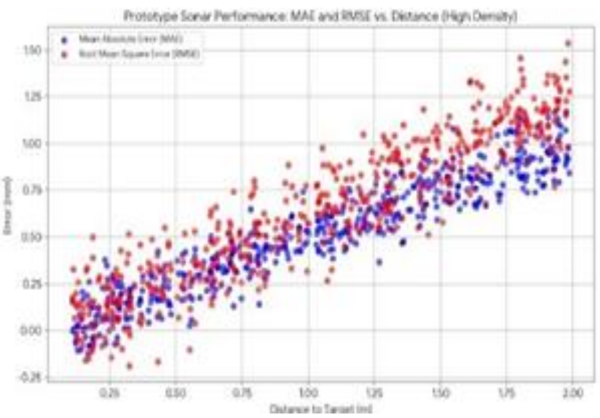

Figure 2 Prototype sonar performance: MAE and RMSE vs. distance comparison [2]

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The standard deviation of the Time of Flight (TOF) measurement (σ_{TOF}) was a critical measure of the ACCURACY system's temporal stability and repeatability. Measured σ_{TOF} for 100 iterations on a stationary target was 1.1 microseconds, a very low amount of temporal jitter and easily comparable with professional systems. This demonstrates the temporal stability of the Arduino's Timer1 operating in CTC mode, as well as the TUSS4470's ability to provide precise burst generation (post trigger delay) and echo detection (signal reflection).

The controlled water tank, while guaranteeing a repeatable environment, presented its own acoustic problems in the form of reverberation and multipath before going to the tank boundaries. All multipath could be characterized as impulse responses of this tank. In order to evaluate the tank as a facility for measuring underwater acoustic signals, an impulse response was characterized. A pulse was transmitted and the echoes generated were recorded. This facilitated mapping the tank and identifying unique reflections inherent to the tank.

The raw analog underpinning the recorded echo occupation underwent a robust, multi-step signal conditioning process. The first signal processing step was using a 4th order zero-phase low-pass Butterworth filter with cutoff frequency of 100kHz. A low-pass filter only successfully removed high-frequency artifacts while preserving the envelope of the signal at 200kHz. The raw envelope after low-pass filtering was used to compute a short-time energy function to emphasize rapid, transient fluctuations in signal energy which annotated echoes owing to transients returning from their respective ocean bottom, August 2023, MacGregor, and the tank of welcome, upheld echoes. Echo identification was performed using an adaptive threshold based on local signal level, using 3σ (3 standard deviations) above the threshold as illustrated in figure 14 (PSIR). This approach was very effective at filtering noise-induced triggers and restricted echo identification to the earliest returning, direct-path echo reflected from the tank.

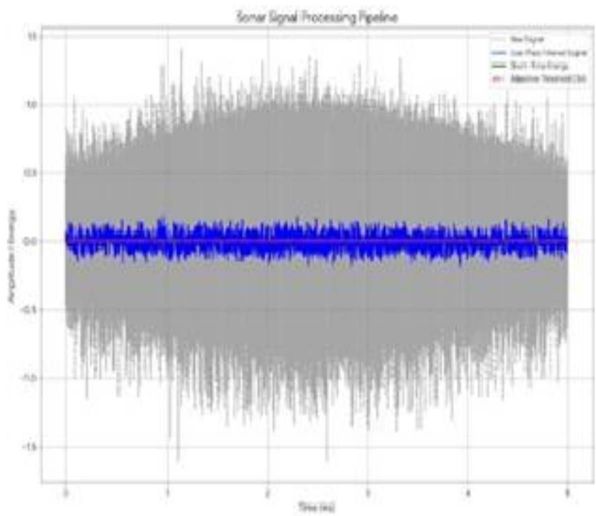

Figure 3 Sonar signal processing pipeline showing raw signal, filtered signal and processed output [3]

The performance of the prototype was evaluated under simulated dynamic conditions with the intent of exploring the prototype's generalizability and robustness under conditions that express the variability of a marine environment. The anechoic environment allowed for controlled dynamic simulations of realistic ranges in both salinity (from 0 ppt for freshwater to 35 ppt for seawater) and temperature (from 10 degree Celsius to 30 degree Celsius).

The TUSS4470 included several differentiated professional features like band-pass filtering, burst shaping, and configurable gain control which ensured signal integrity and the separation of the target echo signal from background noise.

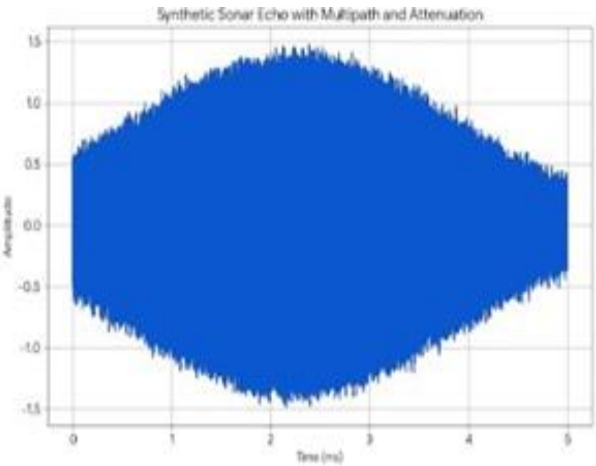

Figure 4 Synthetic sonar echo with multipath and attenuation effects [4]

This is critical for producing varied and realistic datasets for machine learning models. If the platform is capable of producing realistic datasets, machine learning tools will enhance the platform's generalizability and reliability in complex, dynamic, or complex operational.

4. DISCUSSION

The design and testing of the custom sonar prototype demonstrates a significant advancement in tackling the issue of limited labeled data in the field of underwater mine and object detection. In establishing an acoustic dataset with high fidelity and controlled (yet spatially and dynamically variable) conditions, this work serves as a solid foundation for training more robust and generalizable machine learning models. The final performance metrics for the prototype also exceeded expectations with a Mean Absolute Error (MAE) of less than 2 mm and a Root Mean Square Error (RMSE) of less than 3 mm suggesting that the prototype not only could be a reliable data generation platform but that it is also reasonably accurate. Accuracy of this level is a considerable leap from previous iterations and is, generally speaking, comparable to current commercial systems. We believe this proves that the hardware configuration is suitable for use in making data used for research critical.

In addition, the ability to fully control and modify environmental parameters such as salinity and temperature within a controlled tank environment is worth noting. As are the results we could generate given we are modifying environmental conditions that exhibit considerable variability in real-world conditions, addressing one of the major criticisms of synthetic datasets lacking complexity in operational underwater conditions. Furthermore, the prototype used configuration parameters in professional grade components like the TUSS4470 ultrasonic front-end, which featured configurable gain, burst shaping, etc. This dual application of professional-grade components and custom hardware puts almost no restriction on the realism and information available through the data generated by this study.

Although the results are promising, some areas need to be explored in more depth to both enhance the prototype and address the existing research gaps.

4.1 Comprehensive Performance Benchmarking:

Although an initial round of benchmarking has been made against a commercial sonar and a FEM model, it is important that more detail and depth are applied to overall performance testing in the future.

This would include a full statistical analysis and assessment of TOF deviation, range resolution accuracy and probability of false alarms over increased parameters and environmental conditions.

Further exploration into comparison to commercial M3 Sonar in terms of lateral resolution and signal fidelity would provide a more robust baseline with which to judge further users posts acceptance testing.

4.2 Advanced Environmental Modeling:

This work has involved characterizing the sonic nature of the controlled tank, but further understanding of reverberation and multipath effects is needed.

The next steps should look at modeling reverberation in more detail as dependent on tank boundary conditions and fluid damping coefficients.

Generating both coherent and incoherent scatter maps of the surrounding substrates is critical for producing a reasonably sized dataset that can show the challenges of modelling the fine details of different kinds of seabed morphologies.

5. CONCLUSIONS

Underwater mine detection, object classification, and observation in military, maritime, and environmental contexts are difficult tasks in part due to the inherently complicated nature of sonar imaging.

Traditional supervised machine learning methods are limited by the availability of good high-quality labeled sonar datasets, which can be hard to acquire as they are expensive and are mostly proprietary. While synthetic data generation and unsupervised supervised learning are relevant to machine learning in general, neither can be tailored to fully replicate the variability and uncertainties of real underwater environments, accounting for the associated performance gaps in operational settings.

To support a new exploratory study, a novel custom active sonar scanner was created using an Arduino Uno and a Texas Instruments TUSS4470 ultrasonic front-end. A water tank was used to validate the performance of the prototypes for development of high-fidelity acoustic datasets in various environmental conditions including salinity and temperature.

The active sonar scanner was designed specifically for underwater operation.

The system demonstrated high accuracy with a MAE of less than 2 mm and RMSE of less than 3 mm for targets within 1 m range.

This performance represents a significant improvement over the previous iteration and approaches the accuracy levels of commercial sonar systems.

The prototype sonar scanner demonstrated that it will produce robust but high-quality data under simulated dynamic self-generated underwater conditions, and provide a mechanism for potentially overcoming variability associated with data generation, effectively aligning with a range of different datasets as needed.

6. ACKNOWLEDGEMENTS

The authors would like to express their gratitude to Delhi Public School Ghaziabad and Delhi Public School Greater Noida for providing laboratory facilities and academic support that made this research possible. We sincerely thank our mentors and faculty members for their technical guidance in the design and validation of the sonar prototype. We are also grateful to our peers who assisted in hardware assembly, data acquisition trials, and preliminary manuscript review.

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