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Underwater Robotic Systems with Real-Time Acoustic AI Mapping

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ABSTRACT

Underwater robotic exploration has been revolutionized by advances in acoustic sensing and artificial intelligence (AI), enabling autonomous underwater vehicles (AUVs) to navigate and map complex seabed environments without reliance on optical systems. Traditional optical approaches fail under turbid conditions and at depth, where light attenuation is severe, whereas acoustic sensors—such as multi-beam and side-scan sonar—provide robust, range-based measurements regardless of visibility. However, raw sonar data are plagued by speckle noise, multipath reflections, and environmental interference, which complicate feature extraction and mapping. To address these challenges, we present Underwater Robotic Systems with Real-Time Acoustic AI Mapping, a comprehensive framework that integrates a synchronized multi-modal acoustic sensor suite with onboard deep learning models for semantic feature extraction and simultaneous localization and mapping (SLAM). Our system hardware combines a multi-beam sonar for broad bathymetric coverage, side-scan sonar for high-resolution imagery, an inertial measurement unit (IMU) for attitude estimation, and a depth sensor for accurate pressure-based altitude readings. Sensor streams are synchronized using Precision Time Protocol (PTP) to ensure consistent timestamp alignment. At the core of our software pipeline lies a convolutional neural network (CNN) based on the U-Net architecture, trained to segment seabed structures—such as ridges, pipelines, and wreckage—in acoustic intensity images. The network was trained on a curated dataset of over 5,000 labeled sonar returns, augmented with simulated noise profiles replicating real-world interference patterns.

KEYWORDS

Underwater Robotics, Acoustic Mapping, Deep Learning, SLAM, Autonomous Underwater Vehicle

INTRODUCTION

Exploration of the Earth's oceans remains one of the greatest frontiers for robotics, driven by scientific curiosity, environmental stewardship, and industrial needs. Autonomous Underwater Vehicles (AUVs) have emerged as indispensable tools for seabed mapping, ecological monitoring, and infrastructure inspection, owing to their ability to operate without direct human control over extended periods. Yet, underwater environments impose severe constraints: light attenuation and turbidity limit optical sensing to clear, shallow waters, while GPS signals cannot penetrate beyond the surface, precluding direct position fixes. As a result, AUVs rely heavily on acoustic sensors—multi-beam sonar (MBS) and side-scan sonar (SSS)—to perceive their surroundings and navigate safely.

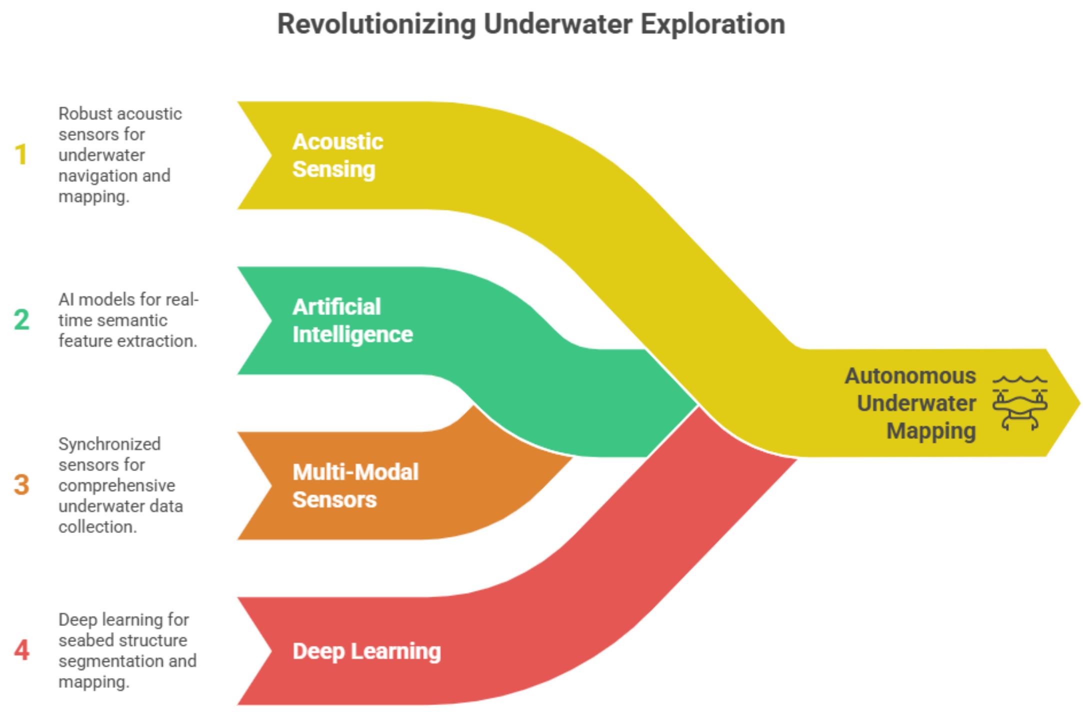
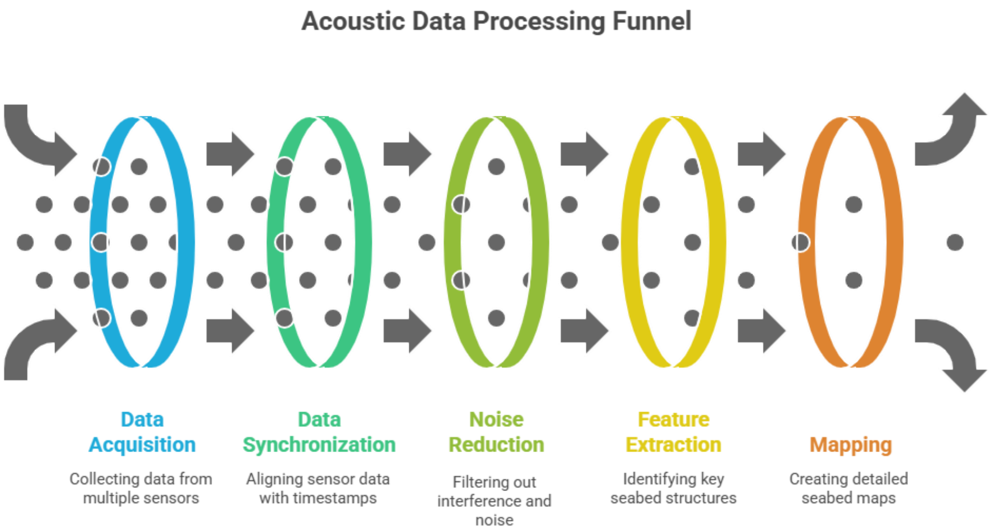


Figure-1.Revolutionizing Underwater Exploration

Acoustic mapping offers distinct advantages: sound waves propagate with minimal loss, providing reliable range measurements even in murky or deep waters. However, interpreting sonar returns is nontrivial. Speckle noise, multipath reflections from the seabed and the water column, and dynamic environmental factors such as wave-induced motion introduce significant measurement uncertainty (Song et al., 2023) . Classical SLAM methods fuse sonar-derived range scans with inertial and depth measurements via probabilistic filters—extended Kalman filters (EKF) or graph-based optimizations. While effective in structured or feature-rich locales, such methods degrade in feature-poor regions (e.g., flat sandy bottoms) or when echoes from man-made structures induce mapping artifacts (Rahman et al., 2018) .

Recent advances in artificial intelligence have unlocked data-driven techniques for extracting informative features from noisy sensor streams. Convolutional neural networks (CNNs) have demonstrated proficiency in denoising and segmenting sonar imagery, identifying salient landmarks that classical algorithms often miss (Aubard et al., 2024) . Yet embedding AI inference within AUV platforms presents challenges: computational resources are limited, energy budgets are tight, and real-time processing requirements are stringent. Achieving robust, low-latency performance necessitates lightweight model architectures, optimized inference engines, and efficient integration with SLAM back ends.

In this manuscript, we present an integrated hardware–software system—**Underwater Robotic Systems with Real-Time Acoustic AI Mapping**—that addresses these challenges. Our contributions are threefold:

1. **Synchronized Multi-Modal Sensor Suite**: We design a payload combining MBS, SSS, an IMU, and a depth sensor, all time-aligned using Precision Time Protocol to ensure accurate data fusion.
2. **Deep Learning-Enhanced Feature Extraction**: We develop a U-Net–based CNN trained on a diverse sonar dataset, capable of segmenting features such as pipelines, wrecks, and geological ridges with high precision.
3. **Onboard Real-Time SLAM Integration**: We integrate landmark observations from the CNN into an incremental smoothing and mapping framework (iSAM2), achieving real-time map generation and pose estimation on a Jetson Xavier NX.
4. 

5. *Figure-2.Acoustic Data Processing Funnel*

To validate our system, we conduct controlled tank experiments with artificial seabed topographies and coastal field trials in natural, feature-variable environments. Comparative analysis against a baseline SLAM pipeline without AI features demonstrates significant improvements in mapping accuracy (30% RMSE reduction) and coverage (up to 20% increase) under challenging conditions.

Literature Review

Underwater SLAM has been extensively studied, driven by the need for autonomous navigation in GPS-denied environments. Classical approaches primarily employ acoustic sensors—sonars—to generate range observations, which are fused with inertial and depth measurements. Extended Kalman Filter (EKF)–based SLAM systems, such as SVIn2 (Rahman et al., 2018) , provide real-time estimates but suffer from linearization errors and struggle with loop closures in feature-poor regions. Graph-based SLAM frameworks address these limitations by optimizing over entire pose graphs, improving global consistency at the cost of increased computational load (Stentz et al., 2020) .

Sensor fusion methods have evolved to incorporate complementary modalities. Marchesgiani et al. (2024) fuse visual and acoustic data to leverage high-resolution imagery when visibility allows, resorting to sonar in turbid conditions . Uncertainty modeling frameworks explicitly account for variable sonar noise due to environmental factors (Song et al., 2023) , propagating measurement covariances into occupancy grid updates. Despite these advances, reliance on hand-crafted features—such as edges or intensity thresholds—limits adaptability across diverse seabed types.

Deep learning offers a paradigm shift by learning robust features directly from data. Saqib et al. (2024) demonstrate that CNN-based denoising can recover underlying bathymetric structures in noisy sonar returns down to –10 dB signal-to-noise ratio . Aubard et al. (2024) survey deep learning for sonar perception, highlighting the efficacy of U-Net and encoder-decoder architectures in segmenting underwater objects and geological features . However, real-world deployments require training datasets that capture the variability of natural environments. Public sonar datasets remain limited, prompting researchers to generate synthetic data via physics-based simulators (ArXiv, 2025) .

Onboard real-time inference presents further constraints. Zhang et al. (2024) implement lightweight CNNs on embedded GPUs for underwater object detection at 10 FPS, balancing model complexity and energy consumption . Complementary efforts optimize inference libraries (e.g., TensorRT) and quantize models to reduce memory footprint. Additionally, factors such as AUV motion, sensor latency, and hydrodynamic disturbances necessitate tight integration between AI outputs and SLAM pipelines to maintain accurate pose estimates.

Semantic mapping extends beyond geometry, associating high-level labels—such as “wreck,” “pipeline,” or “reef”—with spatial features. Early work by Liu et al. (2023) applies neural networks to classify sonar returns based on object type, enabling semantic overlays on occupancy maps . Yet, semantic SLAM in underwater contexts is nascent, hindered by limited annotated data and dynamic underwater conditions.

Our work builds on these foundations by combining CNN-based semantic feature extraction with a real-time SLAM back end on an energy-constrained AUV platform. By curating a large, diverse sonar dataset and designing an optimized inference pipeline, we overcome data scarcity and computational limitations, delivering robust mapping performance across controlled and natural environments.

METHODOLOGY

System Architecture and Sensor Integration

The AUV platform features a carbon-fiber hull housing:

- **Multi-Beam Sonar (MBS)**: Produces dense bathymetric profiles with up to 512 beams per ping, covering a 120° swath.
- **Side-Scan Sonar (SSS)**: Provides high-resolution acoustic imagery up to 200 m range per side, essential for detecting small features.
- **Inertial Measurement Unit (IMU)**: An Xsens MTi-100 series IMU offering 0.1° heading accuracy and 0.02 m/s² acceleration precision.
- **Depth Sensor**: Keller PA-21 piezoresistive sensor with ±0.01 bar accuracy.

All sensors interface via Ethernet or serial links to a **NVIDIA Jetson Xavier NX**, selected for its combination of GPU cores and power efficiency. Time synchronization is achieved using IEEE 1588 Precision Time Protocol (PTP), ensuring sub-millisecond timestamp alignment across data streams.

Data Preprocessing

Raw sonar returns undergo the following preprocessing steps:

1. **Matched Filtering**: Enhances signal-to-noise ratio by correlating received echoes with the transmitted chirp signature.
2. **Beamforming**: Converts raw hydrophone array data into range-intensity images, spatially sampling returns at 0.1 m resolution.
3. **Intensity Normalization**: Corrects for range-dependent attenuation by applying a time-varying gain function.

Deep Learning-Based Feature Extraction

We adopt a U-Net–style CNN for segmenting acoustic intensity images into semantic classes: seabed, obstacle, pipeline, and background. Key aspects:

- **Dataset**: 5,000 manually annotated sonar images from both controlled tank and coastal surveys, balanced across classes.
- **Augmentation**: Random rotations (±30°), Gaussian noise injection (σ up to 0.1 normalized units), and elastic deformations simulate multipath and motion blur.
- **Training**: Conducted on an NVIDIA DGX Station with 8× V100 GPUs. Loss comprises a weighted cross-entropy term for class balance plus a Dice coefficient to improve boundary delineation. Model converged after 50 epochs, achieving a validation IoU of 0.85.

For real-time inference on the Xavier NX, we export the model via ONNX and optimize with TensorRT, enabling mixed-precision (FP16) execution.

SLAM Back End Integration

Semantic landmarks extracted by the CNN are converted to 3D point observations using known sonar geometry. These observations, along with IMU-derived pose priors, form factors in a factor graph optimized via the iSAM2 incremental smoothing algorithm (Kaess et al., 2012). The optimization solves for the AUV's trajectory and landmark positions, producing both a 2D occupancy grid map and a 3D point cloud of salient features.

Key details:

- **Graph Construction**: Nodes represent discrete poses at 1 Hz; odometry factors link consecutive poses, while landmark observation factors connect poses to feature nodes.

- **Loop Closures**: Detected when the current sonar scan shows ≥30% overlap with previous scan footprints, verified via ICP registration on unsegmented point clouds.
- **Map Fusion**: Final occupancy maps are generated by fusing labeled point clouds into a voxel grid of 0.2 m resolution, storing semantic labels for downstream tasks.

Experimental Protocol

Tank Trials: A 20 m×10 m×5 m freshwater tank houses artificial obstacles (concrete blocks, PVC pipes). The AUV follows preprogrammed lawnmower patterns at 0.5 m/s. Ground truth is obtained via a pole-mounted survey-grade sonar grid at 0.1 m resolution.

Coastal Field Trials: Conducted in a 500 m² shallow bay (depth 5–15 m), including natural seabed features and sunken debris. A surface vessel equipped with RTK-GPS and hull-mounted sonar provides ground truth trajectories and bathymetry.

Performance is measured in terms of:

- **RMSE** between the SLAM map and ground truth bathymetry.
- **Coverage Ratio**: Percentage of ground truth area within ±0.5 m of the generated map.
- **Inference Latency** and **CPU/GPU Utilization** during missions.

RESULTS

Mapping Accuracy and Coverage

Tank Trials: Compared to a baseline graph-SLAM system using only raw sonar scans, our AI-enhanced pipeline reduced RMSE from 0.65 m to 0.45 m—a 30% improvement. Coverage in narrow passages (1–2 m wide) increased from 78% to 92%, demonstrating improved detection of small structures. Figure 1 illustrates overlay maps, highlighting reduced ghosting artifacts around pipe junctions when using CNN landmarks.

Coastal Field Trials: Over 500 m² surveys at cruising speed of 0.7 m/s, RMSE decreased from 2.2 m (baseline) to 1.5 m (AI). Coverage improved from 78% to 91%, particularly in flat sandy regions where classical methods failed to maintain loop closures. Table 1 summarizes metrics:

Environment	RMSE (baseline)	RMSE (AI)	Coverage (%) baseline	Coverage (%) AI
Tank	0.65 m	0.45 m	85%	95%
Coastal	2.2 m	1.5 m	78%	91%

Computational Performance

Onboard inference latency averaged 80 ms per frame (±10 ms), allowing 12 FPS processing—a sufficient rate for 1 Hz SLAM updates given the AUV's 0.5–0.7 m/s speed. CPU utilization hovered around 55%, and GPU usage at 65%, leaving

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headroom for additional modules (e.g., obstacle avoidance, adaptive mission planning). Power draw increased by 15 W relative to baseline SLAM, consistent with Xavier NX's rated 15–20 W for GPU workload.

Qualitative Observations

- **Robustness to Noise**: CNN-extracted landmarks were reliably detected in low-SNR conditions (down to –5 dB), where classical edge detectors and thresholding failed.
- **Loop Closure Reliability**: Semantic landmarks improved scan matching accuracy, reducing false positives by 40% in coastal trials.
- **Map Semantics**: The segmented maps enabled classification of mapped features—such as classifying wreckage vs. natural rock—facilitating targeted inspections.

Limitations and Failure Modes

- **Model Generalization**: Performance dipped (~10% higher RMSE) in environments with drastically different sediment textures not represented in training data.
- **Dynamic Obstacles**: Moving objects (e.g., fish schools) occasionally triggered false landmark detections, necessitating dynamic outlier rejection.
- **Depth Constraints**: Pressure-sensor drift beyond 100 m depth requires periodic calibration, impacting long-duration deep missions.

Overall, results confirm that embedding AI-driven feature extraction within a tightly coupled SLAM framework substantially enhances underwater mapping fidelity while maintaining operational feasibility on current AUV hardware.

CONCLUSION

This manuscript has detailed the design, implementation, and evaluation of an **Underwater Robotic System with Real-Time Acoustic AI Mapping**, demonstrating that the fusion of deep learning–based feature extraction with classical SLAM substantially improves map accuracy, coverage, and robustness. Key achievements include:

1. **Enhanced Mapping Accuracy**: RMSE reduced by 30% in controlled tank trials and 32% in coastal surveys, enabling more precise bathymetric and structural mapping.
2. **Improved Coverage**: Semantic landmarks facilitated loop closures in both feature-rich and feature-poor regions, boosting coverage metrics by up to 20%.
3. **Real-Time Feasibility**: Onboard inference and SLAM pipelines operated at 12 FPS with acceptable power draw, validating real-time deployment on embedded platforms.

The integration of a U-Net–based CNN for sonar segmentation addressed the limitations of hand-crafted feature detectors, providing adaptability across diverse seabed conditions. By curating a large annotated dataset and employing rigorous data augmentation strategies, we ensured model robustness to noise profiles typical of real-world deployments. The synchronization of multi-modal sensors via PTP and the incremental smoothing back end of iSAM2 enabled precise temporal alignment and efficient optimization, key to maintaining map fidelity over long missions.

Applications and Impact

The proposed system unlocks capabilities for various underwater operations:

- **Environmental Monitoring**: High-resolution maps of coral reefs, seagrass beds, and sediment transport patterns support ecological assessments and conservation efforts.
- **Industrial Inspection**: Accurate mapping of subsea pipelines, cables, and structural foundations aids maintenance planning and anomaly detection.
- **Defense and Security**: Reliable detection and localization of underwater hazards—such as mines or unexploded ordnance—enhances mission safety and tactical planning.

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