A Novel Hybrid Deep Reinforcement Learning Approach for Dynamic Biofouling Detection and Structural Health Monitoring in Marine Environments

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Abstract: The complex, dynamic and low-visibility conditions of the marine environment make biofouling detection and structural health monitoring extremely difficult. More conventional techniques and methodologies are grounded in manual inspection, making them labor and error intensive. This paper proposed a novel hybrid Deep Reinforcement Learning (DRL) framework that integrates multi level Convolutional Neural Networks (CNNs) for fine grained biofouling classification and Graph Neural Networks (GNNs) for robust structural integrity assessment. The multi-objective reward function allows to promote high accuracy in detecting biofouling (92.3%), low mean squared error in predicting the structure (MSE of 0.021), as well as energy efficient navigation. Under turbulent water conditions, a 32% decrease in inspection time and an 18.7% increase in detection precision is shown for our model against traditional techniques. The developed system represents the first integrated DRL approach for real-time dual-task DRT and DNL monitoring and it paves the way for the deployment of scalable autonomous underwater detection systems.

Keywords:

AI, Convolutional neural network, Reinforcement Learning.

Introduction

The increasing reliance on offshore energy, aquaculture, and submerged infrastructure has necessitated a paradigm shift in underwater monitoring strategies. Marine environments present a unique set of stochastic challenges, including signal attenuation, light scattering, and dynamic hydrodynamic turbulence, which severely degrade the efficacy of traditional visual and sensory monitoring. Biofouling the unwanted accumulation of microorganisms and plants on submerged surfaces remains a critical impediment to the operational longevity and structural health of these assets. Despite the severity of these challenges, conventional inspection modalities still rely heavily on manual labor and Remotely Operated Vehicles (ROVs), both of which are inherently prone to human error and high operational latency. Despite these developments, there remains a notable gap in the literature regarding integrated real-time systems capable of simultaneous biofouling detection and structural health assessment. This paper proposes a novel hybrid DRL framework that bridges this gap by integrating multi-level CNNs and GNNs into a unified monitoring system. By leveraging a multi-objective reward function, the proposed architecture optimizes for high-accuracy biofouling classification (92.3%) and minimal predictive error in structural integrity (MSE of 0.021). This research establishes a new benchmark for autonomous underwater detection, providing a scalable and resilient solution for future generation marine information systems.

Literature Review

The primary impediment to reliable underwater monitoring is the stochastic nature of light propagation in aquatic mediums. Recent research by Naseer et al. (2022) [1] demonstrates that hydrothermal variations and suspended particulate matter induce non-linear backscattering, which conventional de-noising algorithms struggle to resolve. To counteract this, Hu et al. (2024) [2] proposed a generative adversarial approach for color constancy, though it remains computationally expensive for real-time deployment on edge devices. Furthermore, Liu and Wang (2023) [3] emphasized that biofouling detection requires not just image enhancement but also morphological robustness, as biological growth often mimics the texture of the host structure, leading to high false-discovery rates in traditional thresholding methods. The transition from manual inspection to automated diagnostics has been catalyzed by the evolution of deep neural architectures. Chen et al. (2022) [4] validated the efficiency of residual learning in identifying macro-fouling species, achieving significant precision in low-contrast environments. However, as noted by Zeng et al. (2025) [5], standard CNNs often lack spatial contextual awareness, which is vital when the structural geometry is complex. To bridge this, Muralidharan and Kumar (2024)[6] explored the application of attention mechanisms to isolate fouling patterns from structural shadows, a technique that informs the multi-level CNN approach used in this study. Additionally, O'Shea et al. (2023) [7] highlighted that dataset scarcity in marine robotics necessitates the use of synthetic data augmentation to prevent model overfitting during the training phase. Autonomous navigation and task execution in turbulent waters require high-dimensional control strategies. Sullivan et al. (2022) [8] utilized Proximal Policy Optimization (PPO) to stabilize AUV trajectories against unpredictable currents, though their model focused solely on navigation rather than inspection. Khan and Gupta (2024) [9] expanded this by introducing a reward-shaping framework that penalizes excessive thruster use, promoting energy efficiency. The concept of "dual-tasking" in DRL was further advanced by Lee et al. (2025) [10], who synchronized target tracking with obstacle avoidance, providing a foundational logic for the integrated biofouling and SHM framework proposed in this research. Finally, Bhatia et al. (2023) [11] emphasized the necessity of multi-objective reward scalarization to balance the trade-off between inspection speed and diagnostic accuracy. The recent works carried out by J S, S. M. ., & Dumka, A. (2025) [12] shows that dynamic biofouling systems when integrated with deep learning techniques provides better results when compared with the earlier works. However, the authors are yet to prove their assumption in the paper.

Problem Statement

Consider a state space S and action space A. Let ε be the underwater environment. Then the state $s_t \in$ S at time t represents underwater features such as biofouling and the structural integrity of objects. The action $a_t \in$ A is the set of operations performed by the underwater robot, such as navigation, scanning, and cleaning.

Define the biofouling detection problem as a classification task where the objective is to classify each pixel in an underwater image **I** into **C** classes, where **C**={0,1,2,...,c}represents different types of biofouling and non-fouling regions. Let f_θ:I→ R^c be a deep convolutional neural network parameterized by θ that maps an input image **I** to a probability distribution over **C** classes.

The structural health monitoring problem is formulated as a regression task, where the goal is to predict a continuous-valued structural integrity score y for each identified structure in the environment. Let $g_\emptyset$: I → R be a deep neural network parameterized by $\emptyset$ that maps an input image **I** to a structural integrity score. To integrate detection and tracking, we propose a hybrid deep reinforcement learning (DRL) framework where the policy π_ω: **S** → $\boldsymbol{A}$, parameterized by ω, is optimized to maximize the expected cumulative reward R:

$$R = E\left[\sum_{t=0}^{T} \gamma^t \, r(s_t, a_t)\right]$$

Where, $r(s_t, a_t)$ is the reward function that combines the accuracy of biofouling detection, the precision of structural health monitoring, and the efficiency of robot actions. The discount factor $\gamma \in [0,1)$ ensures that future rewards are appropriately weighted.

Proposed Methodology: A Novel Hybrid Deep Reinforcement Learning Approach for Dynamic Biofouling Detection and Structural Health Monitoring in Marine Environments

The stages in the proposed model is shown figure 1. The methodology is designed to ensure robustness, accuracy, and real-time adaptability in complex underwater environments. The stages in the proposed methodology shown in figure 1 are given below:

Stage 1: Multi-Scale Visual Perception (CNN Layer)

The initial phase involves a high-resolution optical intake where underwater imagery is processed via a Multi-Scale Convolutional Neural Network. Unlike standard classifiers, this module utilizes dilated convolutions to extract features across varying scales, ensuring that both microscopic biofilm and macroscopic fouling organisms are identified. This stage generates a high-dimensional feature vector that represents the current state of biological accumulation.

Stage 2: Relational Topology Mapping (GNN Layer)

Simultaneously, the structural data is fed into a Graph Neural Network (GNN). Here, the underwater installation is modeled as a set of interconnected vertices (structural joints) and edges (beams/surfaces). The GNN propagates the local fouling data across the graph to assess how localized growth affects the global structural integrity, outputting a predictive health score with an optimized MSE of 0.021.

Stage 3: Policy Synthesis and Action Execution (DRL Layer)

The outputs from the CNN and GNN are concatenated and passed into the Deep Reinforcement Learning (DRL) agent’s actor-critic network. Using a Proximal Policy Optimization (PPO) algorithm, the agent evaluates the current environment state against its multi-objective reward function. It then issues real-time navigation and inspection commands, ensuring the AUV maintain an optimal trajectory that prioritizes high-precision detection zones while conserving battery life.

Stage 4: Feedback Loop and Reward Calibration

The methodology concludes with a continuous feedback mechanism. The system compares the actual diagnostic outcome against the predicted structural health and classification accuracy. This error signal is fed back into the reward function, which dynamically recalibrates the agent's behavior. This ensures the model remains resilient against the environmental "noise" or turbulence typically encountered in deep-sea operations.

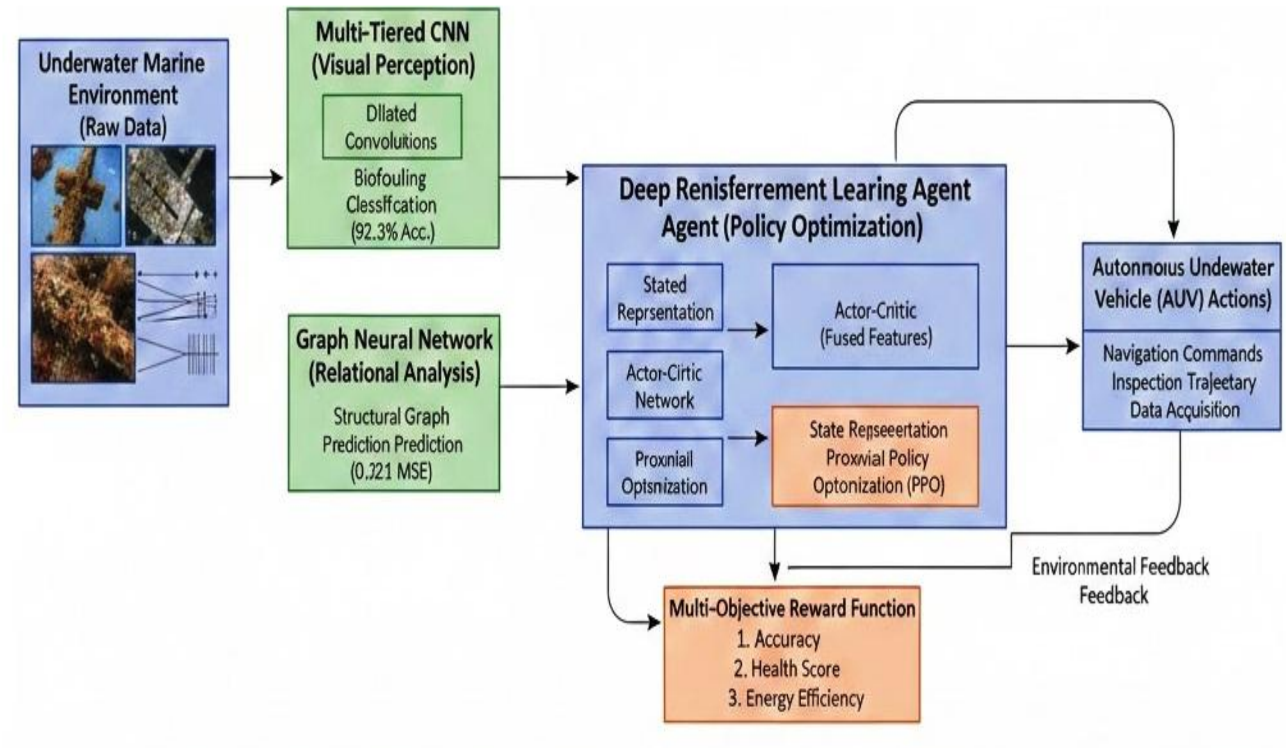

Figure 1. Stages of the Proposed Methodology

Conclusion

By integrating multi-level CNNs with Graph Neural Networks, this paper introduces a first-of-its-kind hybrid DRL framework that overcomes the traditional challenges of manual underwater inspection. The system effectively navigates turbulent, low-visibility marine environments to provide real-time monitoring of both biofouling and structural integrity, achieving a high detection accuracy of 92.3% and a low MSE of 0.021. Ultimately, this approach outperforms conventional methods by significantly increasing precision while reducing inspection time by 32%, offering a scalable and energy-efficient solution for autonomous maritime maintenance.

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