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Design and Development of an Automated Robotic Algorithm for Blasting, Painting, and Barnacle Cleaning of Offshore Structures

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Abstract

Marine surface maintenance tasks such as barnacle removal, abrasive blasting, and protective painting are traditionally carried out using manual methods that are labor-intensive, hazardous, and prone to variability in quality. These challenges are particularly significant for offshore structures, where harsh environmental conditions and restricted accessibility increase operational risks and maintenance costs. This paper presents the design and evaluation of an autonomous robotic system for automated surface preparation and coating of marine and offshore structures. The proposed system integrates vision-based surface inspection with deep learning–based barnacle detection to accurately identify biofouled regions requiring cleaning. A force-feedback control mechanism is employed to regulate tool–surface interaction, enabling effective barnacle removal while preventing substrate damage. To ensure complete and systematic coverage of complex structural surfaces, a grid-based coverage path planning strategy is implemented. Furthermore, closed-loop control algorithms are developed to dynamically regulate abrasive blasting pressure and paint deposition rate, thereby achieving uniform surface roughness and consistent coating thickness. The performance of the robotic system is experimentally evaluated using a set of quantitative metrics, including operational efficiency, surface roughness uniformity, coating thickness consistency, and task completion time. Comparative analysis with conventional manual maintenance methods demonstrates that the proposed autonomous system significantly improves worker safety, process repeatability, and overall maintenance efficiency. The results highlight the potential of intelligent robotic automation to enhance durability, corrosion protection, and lifecycle management of offshore structures, offering a viable solution for next-generation marine maintenance operations.

Keywords: Abrasive blasting, autonomous marine robotics, barnacle removal, offshore structure maintenance, protective coating

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INTRODUCTION

Marine structures, such as ship hulls, offshore platforms, and underwater pipelines, are continuously exposed to aggressive environmental conditions, resulting in biofouling, surface corrosion, and degradation of protective coatings.

Among these challenges, barnacle accumulation is particularly detrimental because it significantly increases hydrodynamic drag, fuel consumption, and long-term structural deterioration. Consequently, periodic surface maintenance operations, including barnacle removal, abrasive blasting, and repainting, are essential to ensure the operational efficiency, structural integrity, and safety of marine and offshore assets.

Conventional marine maintenance practices rely heavily on manual labor, requiring skilled personnel to operate in hazardous environments involving toxic coatings, high-pressure blasting equipment, and confined or submerged spaces. These manual procedures are time-consuming, costly, and inherently risky, and exhibit considerable variability in surface quality and coating thickness. Inconsistent execution often leads to premature coating failure and increased maintenance frequency, underscoring the need for automated and intelligent maintenance solutions capable of delivering higher precision, repeatability, and safety levels.

Recent advances in robotics, computer vision, and artificial intelligence have enabled the development of autonomous systems for industrial inspection and surface treatment applications. Vision-guided robotic platforms combined with force-feedback control facilitate accurate interactions with complex geometries, whereas deep learning–based techniques provide robust detection of biological growth and surface defects. However, most existing approaches are limited to isolated tasks, such as cleaning or painting, and lack an integrated end-to-end framework for comprehensive marine surface maintenance.

This study presents an autonomous robotic system designed to perform essential marine surface preparation tasks within a unified framework, including barnacle cleaning, abrasive blasting, and painting. The proposed system incorporates vision-based surface mapping, deep learning–based barnacle segmentation, and closed-loop control for autonomous detection, cleaning, surface preparation, and coating. A grid-based coverage path planning strategy ensures complete surface traversal, and an automated tool-switching mechanism enables seamless transitions between operational stages. The proposed framework aims to enhance the safety, efficiency, and consistency of marine maintenance operations, offering a viable solution for deployment in shipyards and offshore environments.

LITERATURE REVIEW

Marine surface maintenance has received considerable research attention because of its direct influence on vessel performance, structural integrity, safety, and lifecycle costs [1–3]. Early studies predominantly investigated manual and semi-automated approaches for hull cleaning, abrasive blasting, and painting, emphasizing issues related to worker safety, environmental pollution, high operational costs, and inconsistent surface quality. [4–6]. These studies collectively highlight the limitations of human-dependent maintenance practices in harsh marine and offshore environments.

Several researchers have proposed robotic systems for hull inspection and biofouling removal, employing mechanisms such as magnetic adhesion, tracked or wheeled crawlers, and remotely operated vehicles (ROVs) [7–9]. These platforms significantly reduce human exposure to hazardous conditions and improve operational safety. However, many of these systems rely on predefined trajectories and open-loop control, limiting their adaptability to varying surface geometries and fouling conditions. [10]. Furthermore, early barnacle detection methods commonly use rule-based image processing and handcrafted features, which are highly sensitive to changes in illumination, occlusions, and complex surface textures typical of marine environments.

Recent advances in computer vision and artificial intelligence have enabled the application of machine learning and deep learning techniques for marine biofouling detection. Convolutional neural networks and segmentation-based models have shown superior performance in identifying barnacle-covered regions under diverse environmental conditions. Despite these advancements, most studies have evaluated detection algorithms independently, with limited integration into robotic actuation and control systems for fully automated maintenance operations.

Research on robotic abrasive blasting and painting has largely focused on terrestrial infrastructure, such as bridges, pipelines, and storage tanks. These systems employ coverage path planning, trajectory optimization, and process parameter control to achieve uniform surface preparation and coatings. However, their applicability to marine and offshore structures remains constrained by challenges, including complex curved geometries, variable surface conditions, and biological growth. Moreover, existing approaches typically treat blasting and painting as isolated tasks rather than components of an integrated maintenance workflow.

In summary, the existing literature reveals a lack of end-to-end autonomous systems that seamlessly integrate barnacle detection, adaptive cleaning, abrasive blasting, and painting into a single robotic framework. This study addresses this gap by proposing a unified vision-guided robotic system with closed-loop control, enabling consistent, safe, and fully automated marine surface maintenance.

SYSTEM ARCHITECTURE AND DESIGN

The proposed system is designed as an autonomous robotic platform capable of performing barnacle cleaning, abrasive blasting, and painting in a unified and sequential manner. The architecture follows a modular design approach, enabling flexibility, scalability, and ease of maintenance while operating in complex marine environments (Figure 1 and Table 1).

The system consists of four primary modules:

1. Perception Module
2. Planning and Control Module
3. Robotic Actuation Module
4. Tool and End-Effector Module

The perception module acquires real-time visual and sensor data from the surface, which are then processed to generate surface maps and detect regions covered with barnacles. The planning and control module uses this information to generate navigation paths and task-specific motion plans for the robot.

The robotic actuation module executes the planned motions, whereas the tool module performs cleaning, blasting, or painting based on the current operational stage.

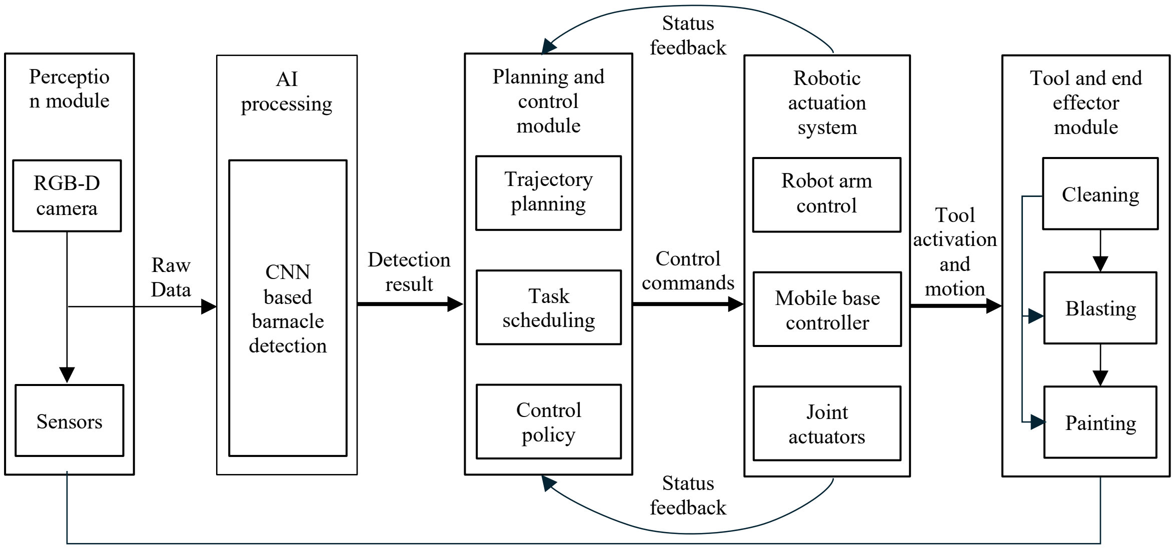
Perception Module

The perception module is responsible for surface inspection and environmental awareness of the surroundings. It comprises RGB or RGB-D cameras and distance sensors mounted on a robotic platform. The captured images were pre-processed to enhance the contrast and reduce the noise, improving the robustness under varying lighting and surface conditions.

A deep learning–based segmentation model was employed to identify and localize barnacle clusters on the surface. The output of this module includes spatial coordinates, size estimates, and confidence scores for the detected barnacle regions, which are forwarded to the planning module for targeted cleaning operations.

Table 1. Major system components and their functions.

Module	Component	Core function
Perception	Camera / Force Sensor	Sensory feedback & data capture
AI Processing	CNN Model	Barnacle detection
Control	Planner / Controller	Path & command generation
Actuation	Robotic Arm	Physical task execution
Tooling	Tool Changer	Automated tool switching



Thin arrow: data flow
Thick Arrow: control flow
Curve arrow: feedback loop

Figure 1. Autonomous robotic Hull maintenance system architecture.

Planning and Control Module

The planning and control module coordinates the overall system operation. A grid-based surface decomposition strategy was used to divide the target area into smaller work zones to ensure complete coverage. Coverage path planning algorithms generate optimized traversal paths to minimize redundancy and operational time.

For interaction tasks, closed-loop control was implemented using force and distance feedback. During barnacle cleaning, the force-feedback control regulates the applied pressure to prevent surface damage. During blasting and painting, the sensor feedback dynamically adjusts the nozzle distance, pressure, and spray parameters to maintain a uniform surface quality and coating thickness.

Robotic Actuation Module

The robotic actuation module consists of a multi-degree-of-freedom robotic arm mounted on a mobile or fixed platform. The arm provides precise positioning and orientation control, allowing it to adapt to curved and irregular marine surfaces. The motion trajectories are continuously updated based on sensor feedback to account for surface variations and alignment errors.

Tool and End-effector Module

To support multistage maintenance operations, the system incorporates an automated tool-switching mechanism. Interchangeable end-effectors include:

- A rotary brush or high-pressure water jet for barnacle removal
- An abrasive blasting nozzle for surface preparation
- A paint spray nozzle for coating application

Tool selection is performed automatically based on task requirements, enabling seamless transitions between cleaning, blasting, and painting, without human intervention.

System Workflow Integration

All the modules operate within a unified control framework that synchronizes perception, planning, and actuation. Task completion is verified through post-operative inspection, and zones failing the quality thresholds are automatically reprocessed. This integrated design enables reliable, repeatable, and efficient marine surface maintenance (Figure 2).

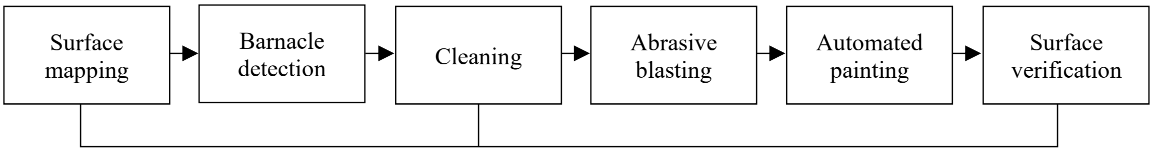


Figure 2. Integrated workflow of surface mapping, barnacle detection, cleaning, blasting, and painting.

METHODOLOGY

The proposed system follows a sequential yet adaptive methodology that enables the autonomous surface preparation and coating of marine structures. The methodology integrates perception, decision-making, and actuation modules to ensure efficient barnacle removal and uniform painting while minimizing hull surface damage. The overall workflow consists of surface mapping, barnacle detection, adaptive cleaning, abrasive blasting, and automated painting, all of which are governed by a centralized control framework.

Surface Mapping and Navigation

Accurate surface mapping is essential for autonomous navigation and precise task execution on complex hull geometry. The robotic system employs a combination of depth sensors and visual cameras to acquire spatial information of the target surface. The collected data was used to generate a three-dimensional representation of the hull, capturing the curvature, edges, and structural irregularities.

Simultaneous Localization and Mapping (SLAM) techniques were used to continuously update the robot's position relative to the surface. Based on the reconstructed surface model, an optimal traversal path was planned to ensure full coverage while avoiding obstacles such as weld joints, protrusions, and appendages. The navigation algorithm dynamically adjusts the robot trajectory to maintain a consistent standoff distance from the hull, ensuring stability during cleaning and painting operations.

Barnacle Detection Using Deep Learning

Barnacle detection was performed using a deep learning–based vision module. High-resolution images of the hull surface are captured using underwater or surface-grade industrial cameras, depending on the operating environment. These images undergo preprocessing steps, such as contrast enhancement, noise reduction, and color correction, to mitigate the effects of uneven lighting and surface discoloration.

A convolutional neural network (CNN)-based object detection or segmentation model was employed to identify barnacle clusters on the hull surface. The model outputs spatial coordinates or segmentation masks that indicate the exact location and extent of biological fouling. This information is mapped onto the surface model generated during the mapping phase, enabling the precise localization of areas requiring cleaning. The detection module operates in near real time, allowing the system to adapt to varying barnacle densities and surface conditions (Figures 3 and 4).

Force-Feedback Cleaning Mechanism

To prevent damage to the hull surface while ensuring effective barnacle removal, the system incorporates a force-feedback-based cleaning mechanism. Force sensors mounted on the cleaning end-effector continuously measured the contact pressure between the tool and hull surface.

A closed-loop control strategy was implemented to regulate the applied force within predefined safety thresholds. When excessive resistance is detected, the controller reduces the tool pressure or alters the cleaning angle to prevent surface abrasion.

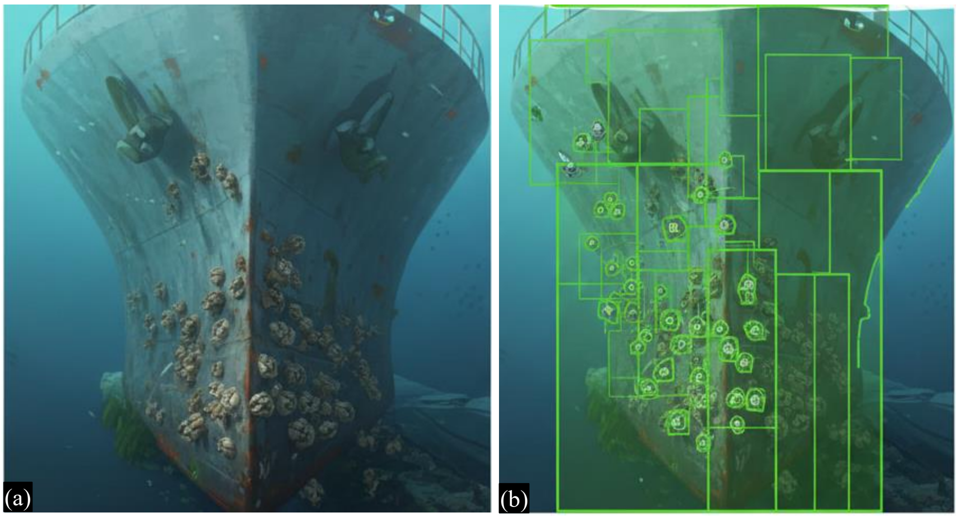


Figure 3. Sample barnacle detection results on marine surface images using deep learning. (a) Original hull surface; (b) AI detection output (conceptual).

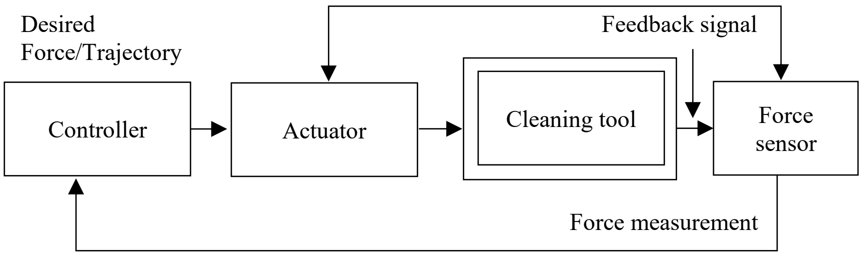


Figure 4. Closed-loop force-feedback control for adaptive barnacle cleaning.

Conversely, insufficient force triggers an increase in the contact pressure to ensure complete removal of the fouling. This adaptive mechanism allows the robot to handle variations in barnacle hardness and adhesion strength while maintaining surface integrity, as shown in Figure 4.

Abrasive Blasting Strategy

Following mechanical cleaning, abrasive blasting is selectively applied to the residual fouling and corrosion-prone areas. The blasting process was controlled by adjusting parameters such as the nozzle distance, abrasive flow rate, and impact angle. These parameters were dynamically tuned based on the surface condition data obtained from the detection and force-feedback modules.

Targeted blasting minimizes material wastage and reduces environmental impact by confining abrasive action to the required regions. The integration of vision-based feedback ensures that blasting is terminated once the desired surface cleanliness level is achieved, preventing the over-processing of the hull surface.

Automated Painting Process

Once the surface preparation phase is completed, the system transitions to an automated painting stage. Prior to painting, the surface was inspected to verify cleanliness and readiness. The painting module uses pre-computed spray paths aligned with the surface geometry to ensure uniform coverage.

The paint flow rate, spray angle, and traversal speed were controlled to maintain a consistent paint thickness across the hull surface. Overlapping spray patterns were optimized to reduce streaking and uneven deposition. The system also accounts for the drying intervals between successive coats, enabling efficient multilayer application without manual intervention.

ALGORITHM AND WORKFLOW

This section describes the operational logic of the autonomous robotic system. The algorithm integrates perception, decision-making, and actuation modules to ensure the coordinated execution of surface mapping, barnacle removal, abrasive blasting, and painting tasks. The workflow was designed to be modular, allowing each subsystem to operate independently while remaining synchronized through a centralized control framework.

High-Level Operational Algorithm

The system operates sequentially yet adaptively. Initially, the robot performs surface mapping and localization to establish a geometric understanding of the target's hull. Navigation paths were planned based on the generated surface model to ensure complete surface coverage.

Once navigation is initialized, the vision module continuously scans the surface to detect barnacle formation. The detected regions were prioritized and queued for cleaning. The system then executes mechanical cleaning using force-regulated control to remove loosely adhered foulants. Abrasive blasting is selectively applied if residual deposits or corrosion are detected.

After the surface preparation is verified, the robot switches to the painting module. Automated spray paths were followed to achieve a uniform coating thickness. Throughout the operation, sensor feedback was used to monitor the task completion, surface quality, and system safety. The process terminates once the entire designated surface area is cleaned and painted, as shown in Figure 5.

Pseudocode Representation

```
  Initialize system parameters
  Load task configuration and safety thresholds

Perform surface mapping
Generate 3D surface model
Plan navigation path

FOR each surface segment in planned path DO
 Navigate to segment
 Capture surface image

 IF barnacle detected THEN
 Activate cleaning tool
 WHILE barnacle present DO
 Apply force-controlled cleaning
 Update force feedback
 END WHILE

 IF residual fouling detected THEN
 Activate abrasive blasting
 Perform localized blasting
 END IF
 END IF

 Verify surface cleanliness
```



```
END FOR
IF surface preparation completes THEN
  Activate painting module
  FOR each painting path segment DO
  Apply paint with controlled flow rate
  Maintain uniform spray distance
  END FOR
END IF

Shutdown system safely
```

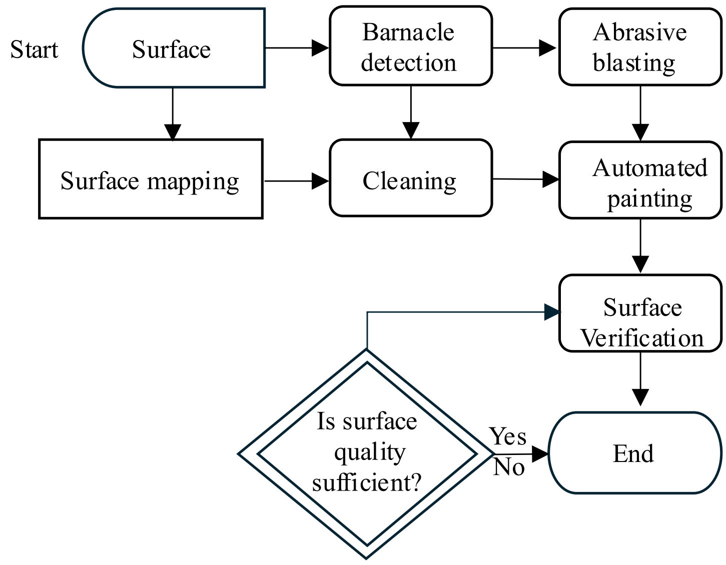


Figure 5. High-level operational flow of the autonomous surface treatment algorithm.

This abstract representation highlights the decision-making flow without binding the implementation to a specific programming language or a robotics framework.

Tool-Switching Strategy

Efficient tool switching is critical for minimizing the operation time and ensuring process continuity. The robotic system is equipped with a multitool end-effector or an automated tool-changing mechanism that allows seamless transitions between cleaning, blasting, and painting tools.

Tool selection is governed by the task state and the sensor feedback. Mechanical cleaning is prioritized for initial barnacle removal, followed by abrasive blasting only when necessary. Upon completion of the surface preparation, the system transitioned to the painting tool. Safety interlocks ensure that tool switching occurs only when the robot is in a stable configuration and sufficient clearance from the surface is maintained.

This strategy reduces unnecessary tool usage, minimizes wear, and optimizes the overall system efficiency.

EXPERIMENTAL SETUP AND EVALUATION METRICS

The performance of the proposed autonomous robotic system was evaluated from an end-to-end operational perspective, with an emphasis on its ability to reliably execute the complete surface treatment workflow. Rather than assessing individual modules in isolation, the evaluation focused on how effectively the integrated system performed barnacle detection, surface preparation, and automated painting under controlled conditions.

Table 2. Experimental setup parameters.

Parameter	Value	Description
Surface Type	Steel panel	Representative marine-grade surface
Area Size	Fixed test region	Controlled cleaning area
Sensor Type	RGB-D, Force Sensor	Used for perception and feedback
Detection Model	CNN-based	AI-driven barnacle detection module
Control Mode	Closed loop	Force-adaptive operation for cleaning

The system performance was first assessed based on task completion reliability. This includes the system's ability to autonomously navigate the target surface, identify fouled regions, execute appropriate cleaning and blasting actions, and transition to the painting phase without manual intervention. The completion time per unit surface area was recorded to evaluate the operational efficiency and repeatability across multiple trials.

The surface preparation quality was evaluated following the cleaning and abrasive blasting stages. The effectiveness of barnacle removal was verified through visual inspection and sensor feedback to confirm the absence of residual fouling. In addition, the surface uniformity after treatment was assessed to ensure that the preparation process produces a consistent substrate suitable for coating without excessive material removal or surface damage.

The automated painting process was evaluated based on the coating consistency and coverage. Paint thickness is measured at multiple locations across the treated surface to assess uniformity, and visual inspection is used to identify coating defects such as streaking, uneven deposition, or overspray. These measurements provide insights into the system's ability to maintain stable spray parameters and a consistent standoff distance during painting.

Finally, the overall system performance was evaluated using aggregate measures, such as total operation time, repeatability of results across trials, and operational stability under varying surface conditions. Together, these evaluation metrics provide a comprehensive assessment of the effectiveness, reliability, and practical applicability of the proposed autonomous blasting and painting system (Table 2).

RESULTS AND DISCUSSION

This section presents the experimental results obtained by evaluating the proposed autonomous robotic blasting and painting system and discusses its performance across the complete surface treatment pipeline. The results were analyzed with respect to task completion reliability, surface preparation quality, and coating consistency, reflecting the effectiveness of the system as an integrated solution.

Barnacle Removal Performance

The experimental results indicate that the system can reliably detect and remove barnacle-like deposits across both flat and curved surface regions. The vision-guided cleaning process successfully identified and prioritized fouled areas for treatment, enabling targeted cleaning actions. Mechanical cleaning was effective for loosely adhered deposits, whereas abrasive blasting was selectively applied to regions with stronger adhesion or residual fouling.

Through multiple trials, the system demonstrated consistent barnacle removal without causing observable damage to the underlying surface. The adaptive force-feedback mechanism plays a critical role in maintaining controlled contact pressure, preventing excessive abrasion, while ensuring effective removal. These results validate the effectiveness of combining vision-based detection with feedback-driven cleaning strategies for removing litter.

Surface Roughness Analysis

Surface roughness measurements taken before and after the cleaning and blasting stages showed a noticeable improvement in surface uniformity. The controlled abrasive blasting process reduced surface irregularities and produced a consistent finish suitable for coating applications. Importantly, the variation in the surface roughness across the treated regions remained within acceptable limits, indicating uniform surface preparation.

The results suggest that the localized blasting strategy successfully balances the material removal and surface conditioning. By restricting blasting to necessary regions, the system avoids excessive surface degradation, which is critical for maintaining structural integrity and extending the coating lifespan.

Paint Thickness Uniformity

The automated painting process resulted in uniform paint deposition on the treated surface. Measurements taken at multiple locations indicated consistent coating thickness with minimal variation between adjacent regions. The predefined spray paths and controlled painting parameters ensured a stable standoff distance and overlap, reducing common defects such as streaking and uneven coverage.

Visual inspection further confirmed the absence of significant coating defects, demonstrating the ability of the system to maintain steady motion and spray control during operation. These results highlight the effectiveness of integrating surface geometry information into painting path planning.

Comparative Analysis

To contextualize the system performance, the results were qualitatively compared with conventional manual or semi-automated surface treatment processes. Compared with manual operations, the proposed system offers improved consistency in cleaning and painting outcomes, reduced dependency on operator skill, and enhanced safety by minimizing human exposure to hazardous environments.

While manual methods may offer flexibility in highly irregular conditions, autonomous systems demonstrate superior repeatability and precision for structured maintenance tasks. This comparative assessment underscores the potential of robotic automation for marine maintenance applications.

DISCUSSION

The experimental results demonstrate that the proposed system can autonomously execute a complete surface treatment workflow with a high degree of reliability and consistency. The integration of perception, adaptive control, and task-level decision-making enables effective handling of surface variability and fouling conditions (Table 3).

Table 3. Performance metrics used for system evaluation.

Metric	Description	Key objective
Detection accuracy	Correct identification of barnacle regions	High precision to avoid missing biofouling
Surface roughness (R_a)	Average roughness after cleaning/blasting	Ensure optimal profile for paint adhesion
Paint thickness uniformity	Consistency of the applied coating layer	Avoid sag or thin spots that lead to corrosion
Task completion time	Total time required per square meter (m^2)	Maximize operational throughput
Reprocessing rate	Frequency of required re-cleaning/repainting	Minimize "Surface Verification" failure loops

LIMITATIONS AND FUTURE WORK

Although the proposed autonomous system demonstrated effective performance in automated barnacle removal and painting, several limitations remain at the perception, control, and system integration levels. The current implementation primarily relies on vision-based sensing for surface mapping and fouling detection. Variations in lighting conditions, surface reflectivity, or underwater visibility can affect detection reliability and mapping accuracy, which in turn influences downstream cleaning and painting decisions.

The barnacle detection model was trained in a limited set of fouling patterns and surface conditions. Although it performs reliably within the experimental setup, its generalization to unseen barnacle morphologies, extreme fouling densities, and degraded visual conditions remains a challenge. Additionally, the current control framework assumes fixed operational ranges for cleaning and blasting. While effective for moderate fouling, these assumptions may limit adaptability when encountering highly irregular or hardened biological growths.

From a system-level perspective, the present implementation does not explicitly model long-term factors, such as actuation variability, tool wear, or energy constraints, which may affect performance during extended deployments. Furthermore, experimental validation is currently restricted to controlled environments, and real-world marine conditions may introduce additional uncertainties that are not captured in the present evaluation.

Future work will focus on improving robustness and autonomy through enhanced sensor fusion by incorporating depth, force, and visual data for more reliable perception under challenging conditions. Extending the detection framework using continual or online learning techniques could improve adaptability to diverse fouling patterns. Additional improvements include adaptive control strategies for the dynamic adjustment of cleaning and blasting actions, optimized task scheduling for energy efficiency, and real-time quality monitoring during painting. Large-scale validation in real marine environments is a critical step toward practical deployment.

CONCLUSION

This study presents an autonomous robotic system for integrated barnacle removal, abrasive blasting, and automated painting of marine and offshore surfaces. The proposed framework combines vision-based surface mapping, deep learning–based biofouling detection, force- and feedback-driven control, and automated coating mechanisms to achieve end-to-end surface maintenance with minimal human intervention. By unifying multiple maintenance stages within a single robotic platform, the system addresses the key limitations of conventional manual and semi-automated approaches.

Experimental evaluation demonstrated that the proposed system can reliably execute the complete maintenance workflow while maintaining consistent surface preparation quality and uniform coating thickness. The results indicate improved process repeatability, reduced operator dependency, and enhanced safety compared with traditional methods. Rather than focusing on isolated component-level optimization, this study emphasizes system-level decision-making, closed-loop control, and adaptive operation in response to real-time surface conditions, which are critical for deployment in dynamic marine environments.

Overall, this study contributes a scalable, software-driven robotic framework for autonomous marine surface treatment. The proposed approach provides a foundation for future research on advanced robotic perception, adaptive control strategies, and intelligent maintenance systems for shipyards and offshore infrastructure. Further developments may include large-scale field validation, improved multisensor fusion, and enhanced autonomy to support long-term offshore asset integrity management.

Nomenclature

AI	Artificial intelligence
CNN	Convolutional neural network
SLAM	Simultaneous localization and mapping
RGB	Red–green–blue
RGB-D	RGB with depth information
IoU	Intersection over union
DOF	Degree of freedom
FSM	Finite state machine
Ra	Average surface roughness
FPS	Frames per second

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