Wall-Climbing Robot for ShipCleanin

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Abstract: With the development of the global economy and the advancement of China's "Maritime Power" strategy, the ocean shipping industry has grown rapidly. However, the fouling on ship surfaces caused by seawater corrosion and marine organism attachment significantly increases fuel consumption and operational costs. To address this, this study combines cavitation jet technology, magnetic adsorption track structure, and a convolutional neural network (CNN) image recognition system to develop a new type of wall-climbing ship cleaning robot. This robot achieves precise positioning and efficient cleaning of hull surface attachments. Experiments show that its cleaning efficiency reaches 95 m²/h, a 300% improvement over traditional manual cleaning, and it can reduce fuel consumption by 12% to 15%, thereby significantly lowering greenhouse gas emissions. Therefore, this study provides an environmentally friendly and efficient solution, helping to optimize ship maintenance processes and enhance economic benefits.

Keywords: Hull Cleaning; Eco-Friendly Robot; Cavitation Jet; Magnetic Adsorption Track; CNN Image Recognition; Energy Saving and Emission Reduction

1. Introduction

Like many industrial machines, ships need to be taken out of service every four to five years for regular maintenance.[1] However, unlike other industrial machines, ships operate for long periods in the complex marine environment, leading to significant fouling on their surfaces. This fouling not only hinders surface inspections but also accelerates coating breakdown and corrosion processes, significantly increasing fuel consumption and impeding ship control. Vessel cleaning is a crucial step in optimizing ship performance and extending its service life. These operations are manually carried out in dry docks, with the cleaning process taking approximately 24 hours. After cleaning, inspectors visually examine the hull's condition and use ultrasonic probes to measure the thickness of the hull at various locations (selected by the inspectors). Due to the high costs of dry dock operations and downtime (including waiting for inspections, docking, and undocking the vessel), all of these factors contribute to significant financial expenditures[2].

It is noteworthy that marine fouling not only hinders the inspection of surface conditions but also accelerates coating breakdown and corrosion processes. Additionally, it significantly increases fuel consumption and impairs vessel control, among other adverse effects.

Therefore, high-quality, efficient, and cost-effective ship cleaning is both essential and necessary. It protects the hull's integrity, ensuring optimal sailing conditions. Maintaining a smooth hydrodynamic surface on the hull reduces fuel consumption, thereby minimizing atmospheric pollution. Consequently, the adoption of robotics to replace manual labor is an inevitable trend in the industry.

To address these issues, the European Commission supported a project that developed the AURORA underwater robot, which can clean marine fouling from ship hulls without dry-docking while inspecting the ship's floating condition. [3] Research on underwater robots has also been conducted domestically and internationally.

In developed countries such as the United States, Europe, and Japan, research on wall-climbing underwater cleaning robot operating systems has gradually matured and entered the marketization stage. Notable companies and research institutions include Flow and CHUKAR in the United States, KAMAT and HAMMELMANN in Germany, Cybernetix in France, the Jet Propulsion Laboratory (JPL) at the California Institute of Technology, the Robotics Institute at Carnegie Mellon University, and the University of Cartagena in Spain. [4] For example, in 2006, Flow introduced the Hydro-Cat ultra-high-pressure water jet ship rust remover. This device operates at a pressure of 255 MPa, with a rust removal width of 300 mm and an efficiency of up to 80 m²/h, but it is relatively expensive. HAMMELMANN developed a dual-wheel ship rust removal wall-climbing robot with excellent rust removal capabilities. Due to its wheeled structure, this robot can operate on ship walls with complex curvatures, but its adsorption capacity is limited.

Design concepts from underwater transport equipment, such as the French BK type, the Swedish Currer, and the Australian Australian type, allow the equipment to tightly adhere to the ship's side walls and move vertically or horizontally, with the control console located on a small operating boat for remote control. [5] The SCAMP underwater cleaner, developed by the British company BAE Systems, is cylindrical and uses turbine-generated suction to evenly spray cleaning agents onto surfaces, powered by a diver-driven binary hydraulic pump.

In China, underwater cleaning work began in 1983 in Xiamen, Tianjin, Qinhuangdao, Yantai, and Dalian. [6] Since 1991, the Harbin Institute of Technology research team has developed a tracked permanent magnetic climbing robot for inspecting coating thickness and applying anti-corrosion paint. Since 1992, Shanghai Jiao Tong University has been developing an underwater tracked permanent magnetic climbing robot for measuring oil tank capacity. [7] Today, the underwater ship surface cleaning robot designed by Harbin Engineering University is in use. This robot is fixed to the bottom of the ship via dual-track permanent magnetic adsorption and can clean rust and other attachments from the hull surface with steel brushes while the ship is sailing normally. [8] Other research institutions, such as Zhejiang University and the 716 Research Institute, are also actively exploring related technologies, but the stability and maturity of their designed robots still need improvement, [9] and their commercialization capabilities need enhancement, resulting in a significant gap compared to international leading technologies. To address these issues, this study integrates magnetic adsorption tracks, cavitation jets, and a CNN vision system to solve the above problems. The robot can clean ships while they are docked. We used Solidworks and other software to design and assemble the robot's structure. The STM32 microcontroller serves as the main control unit, remotely controlling the robot's cleaning and movement, GPS positioning, and image recognition for cleaning large ship hull attachments. This study introduces a CNN-based image recognition system to accurately identify different types of marine organisms and their attachments, effectively removing these pollutants through cavitation jet technology. Additionally, the designed magnetic adsorption track structure ensures stable operation on complex curved hulls. These technological innovations not only improve cleaning efficiency and reduce energy consumption but also lower operational costs, bringing revolutionary changes to the ship maintenance field.

2. Research Foundation

The research objectives include: adsorption force ≥500 N (meeting hull curvature radius ≥1.5 m); cleaning efficiency ≥90 m²/h; underwater command delay based on sonar communication ≤0.5s; image recognition accuracy ≥95% (F1-Score).

2.1 Adsorption Device

The robot uses a magnetic adsorption track structure, which can adapt to hull surfaces with different curvatures and ensure movement in all directions on the hull and cabin walls. The electromagnetic iron on the robot's belly is activated when cleaning begins. The magnetic adsorption force is calculated as:

$$F = \frac{B^2 A}{2\mu_0} \tag{1}$$

Among them, B is the magnetic induction intensity (1.2 T), A is the magnetic adsorption area (0.04 m²), and μ_0 is the vacuum permeability. Experiments show a maximum adsorption force of 800 N, capable of resisting water flow impacts ≤2 m/s, allowing the robot to withstand the reaction force from high-pressure jet cleaning and the water flow resistance during ship navigation, firmly adhering to the hull and cabin walls, [10] enabling stable cleaning operations.

2.2 Image Recognition Device

A high-definition camera mounted on the robot captures images of the hull bottom and transmits them to a database for processing, determining the location of attachments and areas that need cleaning [11]. Considering underwater light deficiency, noise, image blur, and color distortion, a convolutional neural network (CNN) is used for image recognition. The ResNet-34 network is employed, with an input image size of 640×480, and a training set containing 10,000 annotated underwater images (including hull debris, shellfish, rust layers, etc.). By using blue light compensation ($\lambda = 450$nm , attenuation coefficient $\alpha = 0.15m^{-1}$), the issue of red light attenuation is improved, resulting in a final classification F1-Score of 96.2%.

To achieve precise identification of hull surface attachments, we introduced a CNN-based image recognition system. The system's workflow consists of four steps:

1. Data preprocessing: First, noise reduction and enhancement are performed on the collected underwater images.
2. Feature extraction: Multiple convolutional layers capture local spatial information in the images, including edges, textures, and other basic features.
3. Feature selection: Pooling layers reduce data dimensionality while retaining key features, improving model robustness.
4. Classification prediction: Fully connected layers summarize the features, and the classifier outputs the recognition results.

The overall structure of the CNN for image recognition is shown in **Figure 1**.

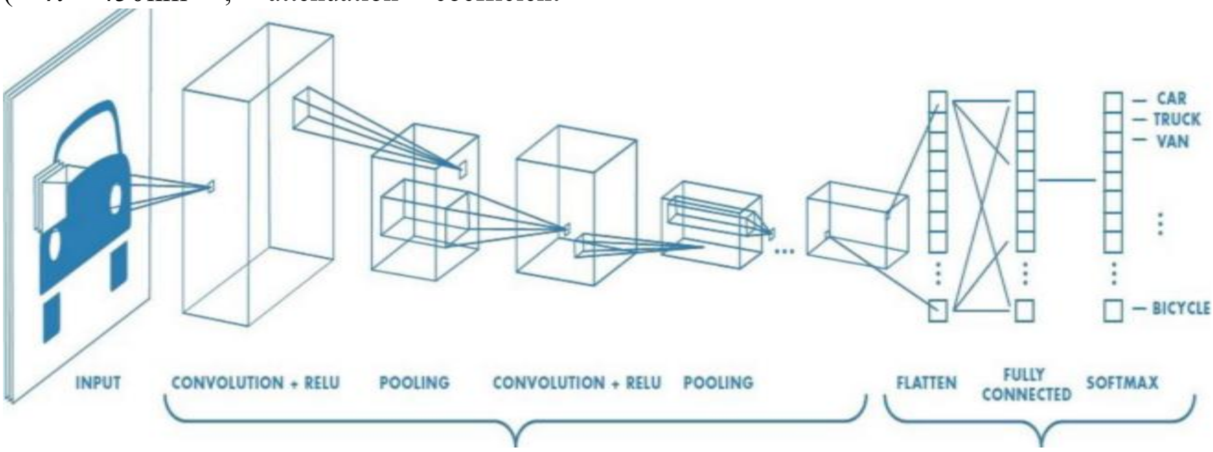

Figure 1. Overall Structure of the CNN for Image Recognition

In the CNN, convolutional layers use convolution kernels to perform convolution operations on input images, capturing local spatial information. This process helps detect edges, textures, and simple patterns in the images. By stacking multiple convolutional layers, the network gradually learns more abstract and high-level features, such as shapes, object parts, and overall structures. This hierarchical feature extraction enables the CNN to have strong expressive power in recognition tasks, effectively distinguishing different image categories.

Pooling layers are another key component, primarily extracting main features through downsampling operations. During pooling, max pooling or average pooling is typically used to extract the maximum or average value of local regions, reducing data dimensionality while retaining main information. Pooling layers help make the network more robust to spatial changes in input images and reduce computational burden. By reducing the resolution of feature maps, pooling layers retain key information in images, improving model generalization. This helps reduce overfitting, allowing the network to better adapt to features of different sizes and positions.

In CNNs, pooling layers are often alternated with convolutional layers, forming the deep structure of the network. Through successive convolution and pooling operations, the network effectively learns and extracts abstract features from input images, providing strong support for final classification or recognition tasks.

In fully connected layers, each neuron connects to all neurons in the previous layer, forming a fully connected weight network. The output of this layer corresponds to the network's understanding of the overall features of the input image. Fully connected layers learn weight parameters to capture complex relationships between various features, achieving high-level abstract representation of images. This allows the network to comprehensively understand image content, enabling more accurate classification or recognition. Fully connected layers effectively integrate local features into overall feature representations, providing strong input for the final output layer, completing global understanding and classification decisions of images.

In CNNs, the classifier is the final layer of the network structure, responsible for mapping abstract features extracted by previous layers to specific categories. This layer is typically a fully connected layer, with outputs transformed into category probability distributions via the softmax activation function. The classifier's weight parameters are continuously adjusted during training, enabling the network to accurately classify images of different categories. During prediction, input images are forward-propagated to obtain outputs, i. e., probability values for each category. Finally, the category with the highest probability is selected as the network's predicted label for the image. This process enables CNNs to achieve excellent performance in image recognition tasks, efficiently classifying and recognizing complex image data.

Light attenuation in water follows the Lambert-Beer law. This law states that the amount of light attenuation is related to the transmission distance, with the light attenuation model formula as follows:

$$I = I0 * e^{\wedge} (-\alpha x) \tag{2}$$

Where I0 represents the original light source's radiation intensity, x represents the distance traveled by the light, and I represents the light radiation intensity after traveling distance x. α represents the attenuation coefficient during transmission, with different wavelengths having different attenuation coefficients. Typically, red light attenuates faster than blue light in water. Light attenuation in water is mainly caused by medium scattering and absorption, with the attenuation coefficient α being the sum of the light absorption coefficient and the light scattering coefficient. The underwater image classification evaluation metrics are shown in **Figure 2**.

	Precision	Recall	Specificity	F1 - Score
human	0. 932	0. 935	0. 977	0. 933
fish	0. 933	0. 939	0. 977	0. 936
diving machine	0. 957	0. 950	0. 985	0. 953
bottom-of -ship trash	0. 754	0. 766	0. 785	0. 768

Figure 2. Underwater Image Classification Evaluation Metric

2.3 Cleaning Device

The robot uses interchangeable and retractable blades and cavitation nozzles (**Figure 3**) for cleaning. By controlling pressure and flow rate, the water jet generates a large number of cavitation bubbles as it passes through the cavitation nozzle. The collapse of these bubbles in narrow areas on the hull surface produces micro-jet impacts, effectively cleaning hull surface attachments and fouling layers [12].The cavitation nozzle has a diameter of 2 mm, with a target distance adjustable between 10-30 mm. At a pressure of 80 MPa, the cavitation bubble density reaches 1.2×10^5 bubbles/cm^3, with an impact strength ≥50 MPa (**Figure 3**). The blades are made of tungsten carbide (hardness 92 HRC) and can clean fouling with adhesion ≤20 MPa. The rotary blades can clean attachments of different hardness and adhesion levels and adapt to hull curvatures. The spiral roller is driven by a DC motor and controlled by a microcontroller [13].

2.4 Drive and Control Devices

The robot uses efficient brushless motors to drive adjustable-angle propellers, with precise speed and direction control via electronic speed controllers [14]. This design provides high flexibility and maneuverability during task execution, with sensors continuously monitoring and feeding back the robot's status to adapt to complex underwater environments and cleaning task requirements.

Control System: Integrates brushless motors (500 W, 10 N·m torque), sonar communication modules (LoRa protocol, 20 kHz bandwidth), and an STM32 main controller, achieving command delay ≤0.3 s and positioning accuracy ±5 cm.

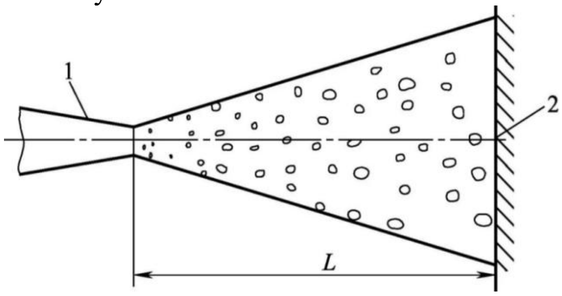

Figure 3. Cavitation Nozzle Schematic
1- Cavitation Nozzle 2- Hul

A dedicated remote control software is developed, allowing operators to send commands to the underwater robot via a computer. An underwater communication protocol is designed and implemented to ensure reliable command transmission and data reception in underwater environments. Considering the complexity of underwater environments, the remote control program is designed with sufficient safety and stability to prevent accidents [15]. Operators use a remote controller to precisely control the robot's forward, backward, and other operations [1].

2.5 Algorithms and Operation Process

The system's operation relies on a series of algorithms, including:

Path planning algorithm: Determines the optimal cleaning path to maximize coverage while minimizing redundant work.

Adaptive control algorithm: Adjusts cleaning parameters such as pressure and speed based on real-time feedback to handle different types of fouling.

Fault detection and recovery mechanism: Ensures the robot can automatically diagnose issues and attempt to recover in case of unexpected events [16].

3. Applications

(1) Operational Flexibility and Reduced Unplanned Downtime

This cleaning robot provides comprehensive operational flexibility for ships, ensuring optimal performance regardless of how long they are out of service. Regular proactive cleaning significantly reduces unplanned downtime caused by sudden inspections and cleaning. **Figure 4** shows the robot in action during actual operations. This continuous maintenance strategy helps keep the hull surface in good condition, avoiding severe fouling issues from prolonged neglect, thereby reducing unnecessary maintenance and cleaning work that causes operational interruptions.

Figure 4. Ship Cleaning Robot in Operation

(2) Reduced Fuel Consumption and Greenhouse Gas Emissions

Keeping the hull clean not only optimizes sailing performance but also effectively reduces fuel consumption, thereby lowering greenhouse gas (GHG) emissions. For example, a reference bulk carrier using this cleaning robot can reduce CO2 emissions by up to 17,600 tons (about 12.5%) over 60 months. This demonstrates that efficient hull cleaning technology can save fuel costs and contribute positively to environmental protection.

(3) Preventing Invasive Species Spread

To minimize the transfer of invasive aquatic species, the International Maritime Organization (IMO) has issued guidelines specifically for ship biofouling control and management. Timely removal of mild biofouling on hulls, especially at departure ports, can significantly reduce the risk of foreign species being introduced to new marine areas, protecting marine ecosystems from invasive species.

(4) Economic Benefits and Market Competitiveness

By adopting proactive cleaning strategies, ships can maintain better overall performance, achieving lower-than-average market emissions and fuel costs. Specifically, a reference bulk carrier using this cleaning robot can save approximately $2.83 million over 60 months compared to the market average. This economic advantage not only enhances the economic efficiency of ship operations but also strengthens the company's market competitiveness.

(5) To verify the robot's actual effectiveness, we conducted multiple field tests, with results shown in **Figure 5**. The figure presents key metrics such as cleaning efficiency, fuel savings, and greenhouse gas emission reductions under different conditions.

Test ID	Cleaning area(m^2)	cleaning time(h)	cleaning efficiency(m^2/h)	conserve fuel(%)
1	475	5	95	12.5
2	950	10	95	13.0
3	1425	15	95	14.5

Figure 5. Cleaning Efficiency and Environmental Benefits under Different Test Conditions

The data proves that the robot significantly improves cleaning efficiency while reducing fuel consumption and greenhouse gas emissions, offering important economic and environmental benefits.

4. Conclusion

In summary, the ship cleaning robot provides an effective and environmentally friendly solution for marine ship maintenance. The cleaning robot described in this paper can clean ship hulls without affecting normal ship operations. Extensive experiments show that such robots can effectively reduce biofouling, improve ship fuel efficiency, and lower operational costs and environmental pollution.

However, despite significant technological advancements, ship cleaning robots still face many challenges in practical applications. For example, navigation accuracy, cleaning effectiveness, and the complexity of the operating environment are issues that require further research. Additionally, improving cleaning efficiency, expanding application scope, and reducing production and operational costs are important directions for future research.

Therefore, future research should focus on solving these problems through technological innovation and optimization to enable broader application of ship cleaning robots. Meanwhile, policymakers and regulators should provide appropriate policy environments and regulatory frameworks to promote healthy development in this field.

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