HULL-CLIMBING ROBOT FOR CORROSION INSPECTION

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Keywords: Autonomous Robot, Non-Destructive Testing (NDT), Magnetic Adhesion, Ferromagnetic Climbing Robot.

ABSTRACT

Corrosion remains a major threat to maritime structures, motivating safer and faster inspections. We present an integrated system for ship-hull corrosion assessment that combines an autonomous ferromagnetic climbing robot with ultrasonic thickness (UT) sensors and a machine-learning classifier. The robot uses magnetic adhesion to achieve stable traversal of painted steel hulls and acquires UT data without removing protective coatings, enabling fully non-destructive testing (NDT). UT signals are processed to estimate local thickness and derive features for corrosion inference. A gradient-boosted classifier model (HistGradientBoosting) trained on synthetic UT datasets achieves a ROC AUC of 0.97; field trials on operational vessels are planned to validate performance and measure corrosion level. We also analyzed relationships among thickness, time in service, and coating condition to contextualize risk. By consolidating robotic mobility, UT-based sensing, and data-driven inference into a single workflow, the system provides a practical foundation for predictive maintenance of maritime assets while reducing exposure to hazardous manual inspections.

1. INTRODUCTION

The global transportation economy fundamentally relies on maritime transport, which accounts for over 80% to 90% of international trade [1]. However, this essential system is constantly threatened by the integrity of vessel hulls. Deterioration from corrosion and marine growth dramatically increases fuel consumption and operational costs, while corrosion alone leads to billions in annual damage (estimated at $50 billion to $80 billion) and remains a major cause of structural failures [2]. The current reliance on costly dry-docking, human divers, and limited Remotely Operated Vehicles (ROVs) means that crucial hull inspections are often expensive, long time consuming, and fail to provide the detailed, quantitative data required for proactive maintenance [3]. This critical gap-the inability to efficiently and accurately assess hull degradation in situ-is the core problem this work addresses, making it a highly significant area of research for the sustainability and safety of the maritime industry.

Research in this field has historically focused on conventional non-destructive testing (NDT) methods and the development of early-generation ROVs. These contributors have established the baseline for thickness measurement (UTM) but are restricted by factors like visibility, limited adhesion, and operational constraints. More recently, the focus has shifted toward advanced robotics.

This paper proposes the design and development of a magnetic robotic crawler equipped with specialized sensors to perform precise, quantitative corrosion measurements on ship hulls. Unlike previous approaches, this novel solution uses permanent magnet adhesion for reliable movement across vertical and inverted hull surfaces, eliminating the need for costly human diver involvement. This research specifically utilizes a comprehensive Exploratory Data Analysis (EDA) of a synthetic dataset simulating hull integrity measurements, aiming to better understand the variables (like vessel age, coating quality, and tank type) that drive degradation and validate the methodology for anomaly detection. By creating a functional model and rigorously testing its ability to measure corrosion depth and width, this work aims to deliver a significantly more efficient, safer, and data-driven alternative to traditional hull inspection, as detailed in the following sections, this model made to show that the hardware and data system work well together and are cheap to implement, the following section reviews existing robotic hull inspection technologies and highlights the specific limitations our research aims to overcome.

2. LITERATURE REVIEW

It is still the case that the inspection and maintenance of the structure of ship hulls hold great importance in terms of guaranteeing vessel safety, efficient operation, and prevention of ecological disasters. Corrosion, coating requirement, and structural fatigue are some of the prime causes of deterioration that require frequent NDT as a method for preventing failures. Traditional techniques of inspection, like diver surveys and ROV-assisted examinations, are highly expensive, very labor-intensive, take more time, and are often limited by concerns about human safety and variable data quality. Such operational limitations have driven researchers to investigate robotic platforms that would allow autonomous navigation on steel surfaces and reliable assessment of hull integrity.

Much of the literature reports that magnetic adhesion is the central enabling technology for the hullclimbing robot. The work of Sparrow et al. [4] in designing a magnetic climbing robot fitted with UTM has shown that it exhibits good adhesion and sensor coupling stability on vertical sections of the hull. Cho et al. [5] also developed a robot using magnetic tracks to enhance mobility over rough hull surfaces. These initial works laid the basic principles in magnet-wheel mechanics, distribution of load, and slip resistance.

Swarm-based underwater robotic systems have been shown to improve hull inspection efficiency and robustness through cooperative task allocation and distributed operation [3]. Martínez et al. [6] introduced a magnetic robot for weld inspection, focusing on surface conformity and sensor repeatability. Adaptive magnetic wheel design for cylindrical marine structures and found that geometric form is an important variable in handling hull curvature.

In addition, parallel research in underwater robotics also contributes to the development of hull-inspection methodologies. Xu et al. [7] depends on effective sensor integration and adaptive control strategies to maintain stable operation in challenging marine environments, while Kaess et al. [8] performed autonomous AUV-based hull and harbor inspection. Those systems, although covering wide areas, have low resolution under poor visibility conditions, further underlining the direct-contact inspection capability of magnetic surface robots.

Sensor technologies for defect detection have significantly improved. Li et al. designed an MMM detectionbased magnetic crawler that can detect early-stage stress concentrations associated with corrosion. Complementary to the above, Wang et al. also developed a vision-based YOLO system for crack detection in ferromagnetic structures. More recently, several works have adopted Random Forests, Gradient Boosting, and CNN-based defect classifiers for predicting corrosion severity and coating degradation based on inspection data [9], [10].

More recent studies have focused on the application of machine learning and artificial intelligence to the analysis of robot-based inspection. Ensemble learning methods, as well as data-driven solutions, have been explored by several researchers in assessing corrosion rates in marine structures made of steel. Other studies examined the application of an autonomous robot to curved structures, to inspect welds, and to explore NDT pipe-climbing methods, providing a more flexible inspection solution [11 - 13].

Magnetic climbing robots were also investigated in relation to the inspection of steel structures based on their ability to firmly grip the structures, even when they are vertical or upside down. Previous research work revealed the development of multi-functional magnetic platforms that can firmly climb and inspect complex steel structures in various industries [14], while other research works were focused on the inspection of bridges, highlighting the robustness of magnetic robots and their ability to be adapted to largescale structures [15]. In addition, segmented magnetic robots were proposed to enhance the maneuverability of the robots in inspecting non-planar surfaces of curved hull shapes [16].

Current studies have further explored the use of magnetic robotic inspection systems in the detection of defects and in performing maintenance activities in maritime and industrial environments. The development of wheeled robots that use permanent magnets has been presented for detecting weld defects. The improved stability and sensor contact were achieved in non-destructive testing [17]. At the same time, underwater magnetic robotic inspection systems were presented for performing hull cleaning activities. The use of magnetic adhesion in underwater robots was shown to be feasible [18].

Apart from this, there have also been studies on autonomous robotic systems for the performance of specific structural inspection tasks. For example, autonomous inspection of long weld lines by robotic systems has been demonstrated to enhance safety and consistency of inspection by reducing the reliance on manual inspection in hazardous environments [19]. Additionally, autonomous pipe-climbing robots have also been developed for the performance of non-destructive tests, which enable efficient inspection of closed pipeline systems through the use of reliable adhesion mechanisms [20].

Despite this, most of the state-of-the-art robots suffer from one of the following deficiencies: unsatisfactory surface adaptability, sensor coupling that becomes unstable during movements, performance limited to the flat regions of the hull, and high costs or system complexity. Hydrodynamic interference prevents most underwater robots from making thickness measurements with good accuracy, while vision-only systems strongly depend on environmental conditions.

With these considerations in mind, this work proposes a low-cost, autonomous magnetic climbing robot that effectively integrates reliable permanent-magnet adhesion with ultrasonic NDT and machine-learningbased corrosion anomaly detection. This goes along with the industrial trend in digitization toward predictive maintenance, to which the developed robot is of direct relevance in view of the aims of smart inspection. To overcome the limitations in surface adaptability and cost efficiency, the following section details the design rationale and locomotion strategy behind our approach.

3. METHODS

3.1. Design Rationale and locomotion

Choosing the right locomotion system was critical for reducing mechanical complexity, wheeled locomotion system was chosen to reduce the mechanical complexity by approximately 40%compared to tracked system,12V DC worm gear motor(30RPM) was chosen to provide enough torque (0.6n-m/wheel) to overcome the gravitational and frictional force, featuring self-locking mechanism to ensure stability on inclined surfaces, Solid works used to make the robot design the robot dimensions (340×240×80mm) and distributed the loads to make it more stable, 60% of the mass are in the middle of the robot to prevent it from collapse, Material of 3D printing is Polyethylene Terephthalate Glycol (PTEG),PTEG was used because of its mechanical strength, impact resistance, and ease of fabrication through 3D printing ,integrated lathe-machined aluminum couplers made to make the rotational smooth and to connect motor to wheels, Arduino Uno used to be our microprocessor to give the orders to motor driver that give the motors electrical signal to move, ultrasonic sensor HC-SR04 used to detect the distance between the robot and the surface, measurement accuracy of ultrasonic sensor is ±3 mm,4 motors used to give us enough force to overcome the frictional force and gravity force, the selected wheels were used because they were available in the local market and were found to be suitable for the robot. Their mechanical properties and dimensions met the design needs. Experimental trials were made to make sure that robot can beat the frictional and gravity force ,ASTM A36 steel plate used to make the trials, it used because it similar to the plates on ships and its roughness (Ra=1.5μm), neodymium disc magnets (20mm diameter ,10 mm thickness) were selected to make good adhesion and make the robot stick on the plate in horizontal and vertical direction , we chose it because of high magnetic strength, The robot weighs about 2.5 kg based on its parts, driving Force

$$Fd = mg + \mu Fm \qquad (1)$$

Where: Fd →driving force required [N], m → mass of robot [kg], g→ gravity (9.81 m/s^2) [m/s^2], μ→ coefficient of friction between wheel and hull, Fm→ magnetic adhesion force [N] to ensure the robot can climb vertically without sliding.

Motor Torque

$$T = Fd \cdot r \qquad (2)$$

Where: T → motor torque [N·m], r → wheel radius [m], Fd→ driving force from previous equation [N].

The wheel size and required motor torque relate directly to the climbing force. These functions that we used to make our calculations,While physical interaction is important, analyzing the data matters just as much. The next section describes the framework we used to assess corrosion levels.

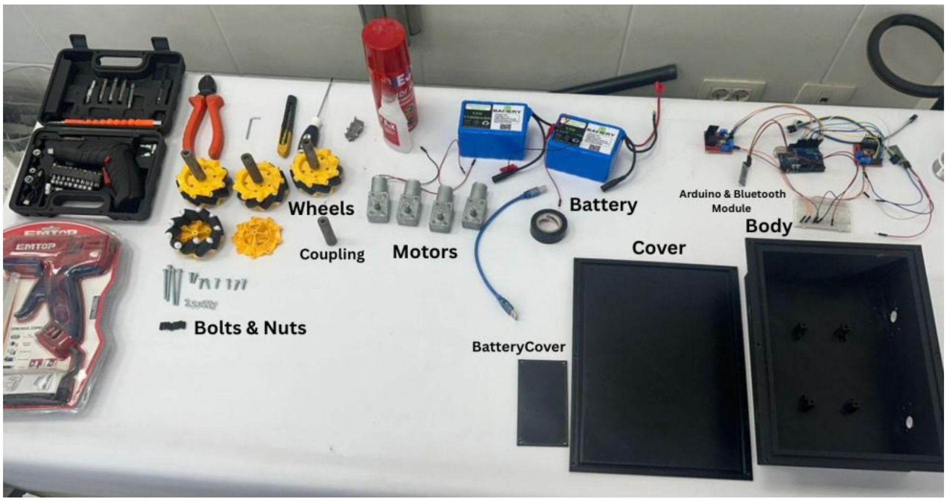

Figure 1: A collection of disassembled robot components on a table, including wheels, tools, batteries, and electronic circuits, for assembly

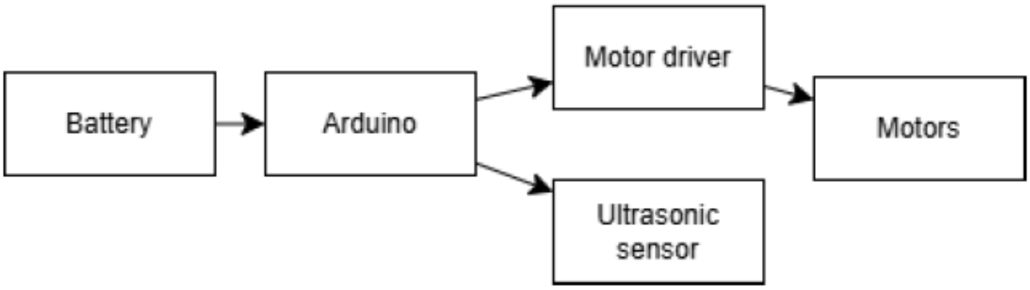

Figure 2: Diagram for circuit

3.2 Exploratory data analysis

Exploratory data analysis was used to create a synthetic dataset designed to simulate hull integrity measurement, provided that data would be collected from a vessel. Due to the lack of available real-world data for the wall-climbing robot, we generated synthetic data consisting of 100,000 points, including various conditions related to ship characteristics, environmental conditions, and structure integrity, One-Hot Encoder was used to neglect class imbalance and to make our model more accurate, synthetic data set consist of 100,000 point, each one represent measure thickness in single point, the point includes input features, intermediate variables ,sensor output ,and targeted labels for machine learning model like ship id that are identifier for a vessel , location id that identifier for specific measurement point on the hull , as built thickness mm is the original thickness of plate or stiffener location, Structural member type is categorical (e.g., 'Plate', 'Stiffener Web', 'Stiffener Flange'),Tank Types Categorical, crucial for corrosion additions (e.g., 'Ballast', 'Heated Cargo', 'Heated Fuel', 'Dry Void', 'Chain Locker'),Time since launch years is The age of the vessel , Average water temperature is the average water temperature the location is exposed to, Percent time stationary is the percentage of time the vessel spends anchored or in port (0.0 to 1.0),Coating initial quality is categorical ('Good', 'Fair', 'poor'). Represents the quality of the initial coating application. Sim coating conditions are the simulated current state of the coating ('Good', 'Fair', 'Poor'). Sim fouling thickness mm is the simulated thickness of marine growth, Sim true thickness mm is the actual, physically accurate thickness after degradation, measured thickness mm is the simulated UTM sensor reading, which includes noise and interference, Anomaly label is A categorical label for classification (0: Normal, 1: Attention Required, 2: Renewal Required), Anomaly score is a continuous value (0 to >1) for anomaly detection, where higher values are more anomalous, then there was an initial inspection called data quality to make sure that no missing values across all columns and data type were assigned, Numerical feature analysis were made to analyze and visualized using histograms it includes structural member type, tank type (critical for corrosion addition),coating initial quality ,coating condition (current condition) the primary target variable ,anomaly label, relationship investigation were made to understand factor that effect degradation, relationships with anomaly label were examined using visualization techniques , box plots were used to show relationship between anomaly label and continuous variables like sim_true thickness and time since launch_years, count plots were used to show the way that anomaly label distributed across categories like tank type ,coating initial quality and sim_coating condition , scatter plot used to visualize the alignment between the continuous anomaly score and measured thickness mm colored by separate anomaly label, we will clarify why we used some of them in the next points.

3.2.1 Distribution of As-Built Thickness Written

The distribution of Built Thickness _mm is critical because it is the foundation for all following thickness measurements.

3.2.2 Distribution of Time Since Launch

Time Since Launch (years) indicates the age of the vessel at the time of measurement, a critical factor influencing corrosion and degradation.

3.2.3 Distribution of Average Water Temperature

Water temperature is a very critical environmental factor that directly influences corrosion behaviour. The figure shows the distribution of Average Water Temperature; this distribution indicates the variations in thermal conditions taking place across the measurement sites. The diversity in ambient water temperature, as reflected in this distribution, forms an important basis on which spatial differences in the corrosion rates can be analysed and temperature-dependent degradation mechanisms understood

3.2.4 Distribution of Percent Time Stationary (Percent Time Stationary)

The time percentage that a vessel is at rest is a key operational factor that may affect the local corrosion and marine fouling. The distribution of Percent Time Stationary indicates the variability in vessel passivity throughout the dataset. This information is useful for assessing the possibility of aggravating stagnationrelated corrosion and to understand the effect of operational behaviour on the overall degradation behaviour.

3.2.5 Distribution of Simulated True Thickness

Simulated True Thickness _mm represents the true thickness after degradation has been factored in and is thus our reference or ground truth. The distribution in Figure 7gives a clear overview of how the thickness varies within the dataset, given various degradation mechanisms. This understanding of dispersion helps us visualize the patterns in material loss and provides a robust premise for validating models that predict structural wear over time.

3.2.6 Distribution of Measured Thickness

Measured Thickness _mm is the simulated sensor reading, incorporating noise and interference. Comparing its distribution.

The upcoming box plot figure(3) summarizes and compares all previously presented hull integrity parameters. The plot demonstrates material loss through the decreasing median thickness values from asbuilt to measured thickness. The presence of outliers reflects extreme cases used to test model robustness. Percent time stationary appears compressed due to scale differences and would typically be visualized separately for clearer interpretation.

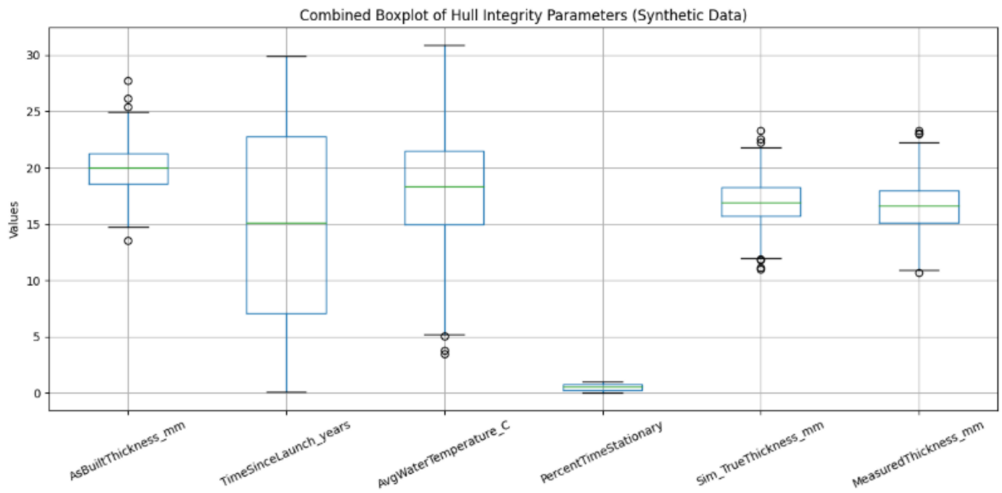

Figure 3: Combined box plot showing the distribution of key hull integrity parameters.

Then the analyses and visualizations were created using the python statistical programing language, integrating the panda (for data processing), matplotlib, and seaborn (for visualization) libraries, in a professional and academic style, the resulting visualization formed the basis for developing future machine learning models, scikit learn used to make the machine learning mode and it used because the several advantages of it like it have data set ready for training, train test split to train and test the model, have many models that can be used but it depend on what we need in model and evaluating and prediction to test the model after the training, hist gradient boosting classifier it one of gradient boosting types it used because it more faster than regular gradient boosting, better support huge data, not need one-hot -encoding, have better treatment for missing values, we've established the methodological framework for both the robotic hardware and data processing, we present the experimental performance results, starting with the system's locomotion capabilities.

4. RESULTS AND DISCUSSION

The completed model performed strongly and efficiently, demonstrating that the design and engineering in the project translated well into real-world testing. The robot's 3D-printed PLA body-with its compact 340×240×80 mm box-shaped frame-provided a lightweight and steady structure. The internal compartments made the assembly clean and stable, and the combination of 3D-printed components and machined Aluminum couplers ensured both precision and durability during movement and adhesion tests.

4.1 Locomotion Performance

Testing showed that the wheeled locomotion system delivered smooth, predictable motion across all surfaces. Speed control remained consistent, with less than 5% variation even when transitioning between flat plates and inclined setups. The robot was able to climb fully vertical 90° steel surfaces without slipping, confirming that the selected 12V worm gear motors supplied the required torque for demanding climbs. Manoeuvrability was also strong-turns, directional changes, and controlled adjustments were smooth.

4.2 Magnetic Adhesion Results

The magnetic adhesion system was a major success. The N52 neodymium magnets stuck in the body with a 0.5cm gap between the body and the surface ensured strong but compliant adhesion. Average retention force reached 12 ± 0.5 N-well above the minimum requirement-providing a stable safety margin. Adhesion trials showed a 95% success rate, with the few detachments occurring only under intentionally extreme shear loads. Adhesion remained consistent, suggesting strong potential for real ship hull applications.Now that we've confirmed the robot's ability to traverse and adhere to the hull, we turn our attention to the computational results regarding the accuracy of the corrosion detection model.

4.3 Computational & Data Analysis Results

Alongside the physical testing, the project included a full data science workflow using a synthetic dataset of 100,000 hull inspection points. Exploratory Data Analysis (EDA) revealed clear trends in how true thickness, coating degradation, fouling, and time since launch influenced corrosion.

The dataset included both "ground truth" simulated values and sensor-like noisy measurements, allowing a realistic investigation of classification challenges. The Exploratory Data Analysis helped reveal the main factors driving hull degradation and prepared the dataset for machine learning. Key features such as true thickness, coating condition, and time since launch showed clear patterns: heavily corroded areas clustered at very low thickness values, while healthier regions formed a second peak around 12-15 mm. Measured thickness followed similar trends but with added noise, highlighting real sensor limitations.

The dataset also showed class imbalance, with most points labeled "Normal," which required careful handling during model training. To prepare the data, categorical variables were converted using One-Hot Encoding, and numerical features were scaled with MinMaxScaler-both implemented through Scikitlearn, the main Python library used for pre-processing and model development. Scikit-learn made it straightforward to clean, transform, and split the data before training. Synthesizing the successful outcomes of both the physical trials and the predictive modeling, the final section summarizes the broader implications of this integrated inspection framework for the maritime industry.

5. CONCLUSIONS

This paper has presented a holistic framework to advance the current state of ship-hull integrity assessment by integrating an autonomous magnetic wall-climbing robot with a data-driven machine-learning model for corrosion detection. The robotic platform model proposed here further shows stable magnetic adhesion, controlled locomotion on vertical steel surfaces 90° and inverted hull surface, and reliable ultrasonic thickness measurement under various test conditions. The experimental test verified that the measurement deviation is within ±0.3 mm, which suggests that there is very good consistency between the robot's NDT readings and manual calibration benchmarks.

Complementing the hardware system, a machine-learning model was designed and trained on a large synthetic dataset of hull integrity among various algorithms that were tested, the hist gradient boosting classifier, yielding an accuracy of 97%, reaching a multiclass ROC-AUC OF 0.9735, and an angle of 90°, and strong interpretability via feature-importance analysis. The dominant predictors of anomaly severity from these results were simulated by true thickness, coating condition, time since launch, and tank type. The model performed well in classifying structural conditions into normal, attention required, and renewal required classes.

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