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A DATA-DRIVEN ROV FRAMEWORK FOR UNDERWATER CRACK DETECTION USING MATHEMATICAL IMAGE ENHANCEMENT TECHNIQUES

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ABSTRACT

Underwater inspection of concrete systems remains difficult due to turbidity, volatile illumination, and colour attenuation, which considerably reduce the visibility of defects along with cracks. Conventional diver-based techniques often fail to offer consistent assessments underneath those situations. This paper proposes a deployment-orientated ROV inspection framework integrating a lightweight mathematical photo enhancement pipeline to improve underwater crack visibility prior to analysis. The enhancement version combines shade-attenuation reimbursement and assessment stretching to mitigate wavelength loss and expand the dynamic range of submerged imagery. The ROV follows a predefined inspection trajectory with solid movement modelling, permitting systematic frame acquisition and repeatable evaluation. Validation in controlled pool surroundings demonstrates that the enhanced pix show off better clarity, sharper crack limitations, and stepped forward interpretability as compared to uncooked underwater frames, with noticeable noise reduction throughout one-of-a-kind water situations. The proposed integration affords a sensible and efficient method for assisting safer and greater resilient tracking of submerged concrete infrastructure, and it could serve as a basis for future real-global marine deployments.

1. INTRODUCTION

Underwater reinforced concrete structures such as quay walls, bridge foundations, offshore platforms, and hydraulic installations are continually exposed to harsh marine environments that accelerate material degradation. Ensuring their structural integrity is essential for the safety and reliability of coastal and maritime infrastructure [1]. However, traditional diver-based inspection methods face significant limitations, including poor visibility, color distortion, turbidity, unstable illumination, and safety risks associated with manual underwater operations. These challenges often lead to inconsistent data acquisition and hinder accurate identification of cracks and surface defects [2].

In response to these limitations, ROVs have emerged as an effective alternative for conducting underwater inspections with greater safety, repeatability, and precision. ROV platforms equipped with high-resolution imaging systems, LED illumination, depth sensors, and inertial navigation units enable consistent visual inspection even under variable underwater conditions [3]. Yet, effective deployment of an ROV requires careful mission planning, including defining the inspection area, setting movement boundaries, selecting an appropriate standoff distance, and ensuring that navigation sensors are fully calibrated. These preparations establish the operational foundation for achieving accurate and reliable imaging [4].

Once deployed, the ROV follows a structured mission path through an automation code that controls motion, waypoint traversal, and frame-capture triggers. Autonomous navigation invariability and data acquisition mitigates human-induced variability and maintains stable imaging geometry along the inspection route [5]. The collected frames are accompanied by metadata such as depth, pose, and timestamps, allowing precise reconstruction of the inspection trajectory during post-processing [6]. Despite the advantages of ROV-based inspection, underwater images typically suffer from color attenuation, scattering, and low contrast. To overcome these limitations, mathematical image- enhancement models are applied to restore color balance and enhance visibility of fine crack patterns. These enhancement steps significantly improve interpretability and support more accurate assessment of structural deterioration.

Finally, all enhanced images and metadata are compiled into an organized dataset to support documentation, crack analysis, and long-term monitoring. This structured approach ensures complete traceability and enhances the reliability of autonomous inspection missions.

Through the integration of mission planning, autonomous navigation, mathematical image enhancement, and systematic data logging, this study provides a comprehensive framework for improving the accuracy and consistency of underwater crack detection using ROV technology [7].

1.1 Literature Review

The inspection of submerged concrete structures has traditionally depended on diver-based techniques, which are inherently hazardous, time-intensive, and economically inefficient, while being severely constrained by adverse underwater conditions such as turbidity, non-uniform illumination, and motion-induced image degradation. These limitations significantly reduce the reliability and accuracy of conventional visual inspection and classical image-processing methods. To overcome these challenges, recent research has increasingly focused on the deployment of remotely operated vehicles (ROVs) equipped with high-resolution cameras and advanced lighting systems, integrated with state-of-the-art image enhancement and artificial intelligence algorithms [8].

Early studies by Xie et al. (2022) [9] employed classical digital filtering and part-detection strategies to assist underwater illness identification. Although slight detection overall performance changed into said, the results were particularly sensitive to environmental variations, limiting robustness underneath real offshore conditions. Subsequently, Zhang et al. (2023) [10] introduced a deep gaining knowledge of primarily crack detection framework using a YOLOv5 structure educated on about 8,000 annotated underwater images, reaching actual-time detection accuracy of 94.7%. However, this overall performance was related to sizeable computational requirements, which might also preclude onboard implementation in aid-restricted ROV systems.

More recent contributions by Liu et al. (2025) [11] addressed extreme low-visibility environments through the integration of convolutional neural networks with Grad-CAM-based explainability, significantly improving detection robustness, precision, and model interpretability. In parallel, Zhao et al. (2025) [12] investigated the impact of hydrodynamic disturbances on inspection accuracy by developing MATLAB-based dynamic simulation models to compensate for ROV motion induced by underwater currents and waves.

From a deployment and scalability perspective, Sutrisno et al. (2025) [13] introduced the ROV-as- a-service paradigm to reduce operational costs and facilitate broader industrial adoption, complemented by educational initiatives aimed at developing low-cost ROV platforms for technical training.

Despite these advancements, significant research gaps remain, including limited availability of large- scale real-world datasets, insufficient generalizability across diverse marine environments, lack of three- dimensional crack localization, and high operational and energy costs, underscoring the need for fully autonomous, energy-efficient, and industry-ready intelligent ROV-based inspection systems [14].

Nevertheless, vast studies gaps persist, consisting of restricted availability of massive-scale real- world datasets, inadequate generalizability across diverse marine environments, loss of three- dimensional crack localization, and excessive operational and power prices. These demanding situations underscore the need for greater autonomous, energy-efficient, and industry-prepared ROV-based inspection systems that may perform reliably under complex offshore conditions.

2. METHODOLOGY

This study adopts a five-phase methodology to develop an automated ROV-based underwater inspection system. The workflow integrates system preparation, structured navigation, automated frame acquisition, mathematical image enhancement, and organized dataset generation. All operations are executed through an automation code that manages navigation control, frame triggering, and preprocessing sequences. The methodology is outlined in Figure 1.

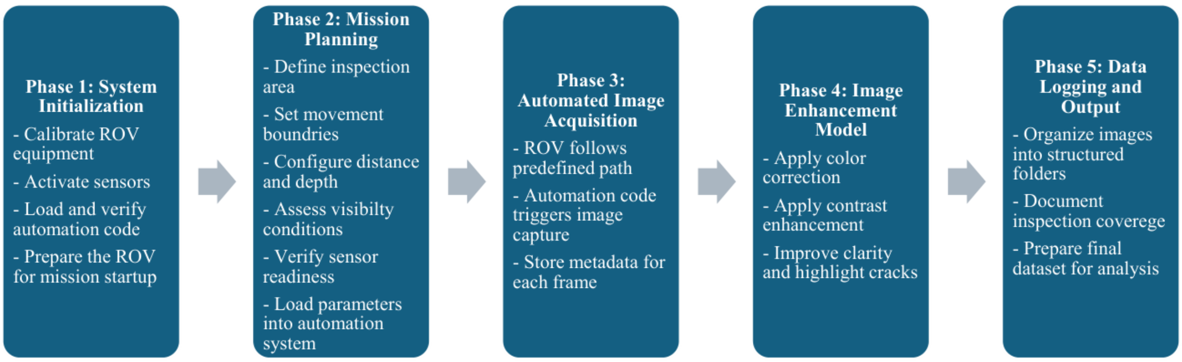

Figure 1: Proposed Research Methodology.

2.1 Phase 1: System Initialization

The initial phase of preparing a ROV for underwater missions involves a rigorous process of equipping the platform with essential sensing and imaging components, followed by their precise calibration and configuration to address the unique challenges of the underwater environment. These challenges primarily include turbidity, color attenuation, and unstable illumination, all of which can significantly degrade data quality.

A high-resolution camera is a core component for visual data acquisition. However, the optical properties of water, such as light scattering and absorption, severely impact image quality. Water selectively absorbs longer wavelengths, particularly red light, causing a noticeable shift toward blue and green hues at increasing depths. To counteract this, ROVs are typically outfitted with adjustable LED lighting systems capable of emitting various color temperatures and wavelengths. This flexibility allows for real-time compensation of color distortion and provides consistent illumination, which is crucial for enhancing image contrast and making structural features more discernible.

Depth sensors are vital for accurate navigation and maintaining operational parameters, providing essential information about the ROV's vertical position. These sensors are often integrated with inertial measurement units (IMUs), which include accelerometers and gyroscopes that continuously monitor acceleration and angular rates, enabling reliable estimation of the vehicle's pose and orientation [15].

Advanced ROVs incorporate high-precision depth sensors, MEMS gyroscopes, and magnetic compasses to ensure comprehensive pose determination. The integration of IMU data with visual information from cameras is particularly beneficial for robust localization and mapping in underwater - Prepare the ROV boundries environments where visual input may be compromised.

Calibration of these sensors is a critical task in the first phase. Depth sensors require routine calibration against known reference points to ensure accuracy. Cameras, especially when used in conjunction with depth or stereo-vision systems, demand meticulous calibration of intrinsic and extrinsic parameters to ensure accurate alignment between 3D measurements and color images. This process becomes more complex under dynamic underwater lighting conditions. Specialized calibration systems designed for underwater multi-camera and IMU configurations are often used to achieve precise pose estimation and reliable 3D reconstruction.

Underwater challenges extend beyond optical degradation. Turbidity caused by suspended particles reduces visibility by scattering light, while unstable illumination resulting from ambient light changes or ROV motion further complicates consistent image acquisition. To address these issues, various enhancement approaches such as wavelength compensation, pixel-intensity optimization, and contrast- preserving algorithms are commonly employed. Additional techniques, including depth-guided color correction and multi-scale image enhancement, contribute to improving the clarity and interpretability of underwater imagery.

Automation code plays a crucial role ensuring that all hardware modules are correctly initialized and that communication with onboard systems is functional. This code manages data logging, synchronizes sensor readings, and activates frame-capture routines, preparing the ROV for autonomous mission execution and continuous data collection. Increasingly, such automated systems incorporate onboard processing capabilities for supporting real-time decision making and environmental adaptation.

Before deployment, basic environmental assessments are conducted, including estimating water depth, visibility level, and ambient illumination. These assessments are critical for optimizing operational settings such as camera exposure and LED intensity to ensure consistent image quality throughout the mission. Horizontal visibility of underwater cameras is heavily influenced by water quality and available sunlight, and understanding these conditions is essential for planning effective data acquisition strategies.

In essence, this phase establishes a robust foundation for ROV operations by systematically addressing sensor integration, rigorous calibration, environmental mitigation, and autonomous control, thereby maximizing the potential for high-quality data acquisition in challenging underwater scenarios.

2.2 Phase 2: Mission Planning

This foundational phase focuses on meticulously preparing the ROV for an accurate and structured inspection mission. It involves defining critical operational parameters within the underwater environment, such as the specific inspection area, the expected depth range, and movement boundaries [16]. For Autonomous Underwater Vehicles (AUVs), which share significant operational principles with ROVs in mission planning, efficient and robust coverage path planning is essential for various applications, including ocean exploration, environmental monitoring, and infrastructure inspection. Task-based online path-planning and guidance systems are employed, especially for inspecting submerged structures like harbor infrastructure, cables, pipes, and hydro-technical works, to identify structural deterioration issues such as scour, erosion, and accelerated corrosion. These systems generate trajectories with motion constraints to ensure safety and prevent deviations, particularly when operating near obstacles [17].

Configuring the ROV's positioning settings is paramount for maintaining consistent imaging conditions. This includes determining the target standoff distance from the inspection surface (e.g., a concrete surface) and the desired scanning height. The selection of an optimal standoff distance involves balancing the need for high-resolution images with the increased risk of collision and limitations in the field of view. A closer distance can yield better image quality but elevates collision risk, whereas a greater distance may lead to degraded image quality due to light attenuation and scattering in turbid water. This necessitates careful consideration of visibility and lighting conditions to achieve an optimal balance between image quality and operational safety [18].

Sensor readiness is also verified in this phase, ensuring that navigation sensors, such as depth units and IMUs, provide reliable positional feedback. Reliable navigation status estimation is crucial for mission success [19]. AUVs and ROVs integrate various navigation techniques for inspection and data acquisition missions, particularly in Underwater Wireless Sensor Networks (UWSNs) where communication challenges exist. Visual odometry (VO) systems, utilizing vision payloads to collect images and perform navigation, are commonly employed. Advanced underwater measurement systems further enhance precision by integrating image sonar with stereo vision to accurately quantify distances subsea, thereby mitigating issues like backward scattering and feature degradation that compromise visual techniques [20]. Figure 2 shows the construction and sensors fittings on the ROV.

Figure 2: ROV Mantling and Fitting.

Operational constraints are established to ensure stable and collision-free movement. This includes real-time entanglement-aware coverage path planning for tethered underwater vehicles (TUVs) to manage the risk of tether entanglement around complex underwater structures. Frameworks like REACT (Real-time Entanglement-Aware Coverage Path

Planning for Tethered Underwater Vehicles) use fast geometry-based tether models to simulate taut tether configurations accurately in 3D, facilitating collision avoidance [21]. Path planning algorithms for AUVs in unknown environments prioritize reducing travel time, shortening path length, ensuring navigation safety, and smoothing trajectories, often combining techniques such as Particle Swarm Optimization (PSO) and waypoint guidance [22]. These algorithms are designed to adapt dynamically to the environment, generating obstacle-avoiding trajectories that adhere to safety protocols [23]. The autonomy of these systems is further advanced by frameworks that leverage visual-acoustic data for online inspection, reducing reliance on extensive prior environmental knowledge. This proactive establishment of clear mission parameters in Phase Two ensures an optimized and controlled inspection strategy, significantly contributing to mission success and safety, including operations involving mother ship and AUV deployments. Figure 3 shows the deployment of the ROV.

Figure 3: ROV Deployment in Trials.

2.3 Phase 3: Automated Image Acquisition

The ROV autonomously executes the predefined inspection path, guided by automation code that manages transitions between waypoints. Images are captured at fixed time intervals or specified travel distances to ensure uniform spatial sampling of the inspected structure. Each acquired frame is automatically stored with crucial metadata, including depth, timestamp, and vehicle orientation. This metadata is vital for accurately reconstructing the inspection trajectory during post-processing. This automated acquisition approach minimizes human variability, ensuring systematic data collection and comprehensive coverage of the submerged concrete surface [24]. Waypoint guidance is a common technique in path planning, where trajectories are generated by connecting specified waypoints. For AUVs, efficient and robust coverage path planning involves optimizing paths to ensure complete inspection coverage. This is particularly relevant for tasks like inspecting underwater poles, were pre- mission planning constructs inspection paths for complete coverage. The integration of waypoints, dynamic path planning, and autonomous control enables effective navigation even in complex underwater environments.

2.4 Phase 4: Image Enhancement Model

This phase mitigates the optical degradation commonly observed in underwater images, including turbidity, wavelength-dependent attenuation, scattering, and reduced contrast, which significantly affect crack visibility and image interpretability.

Color Compensation Model: Underwater environments absorb long-wavelength light, particularly in the red spectrum resulting in color shifting and significant loss of visual detail.

To counteract this phenomenon, a gain-based correction model is applied to the RGB channels of the captured image [25].

Let the original image be:

$$I(x,y) = \begin{cases} R(x,y) \\ G(x,y) \\ B(x,y) \end{cases} \quad (1)$$

The color-corrected image is computed as:

$$I_{corr}(x,y) = \begin{cases} \alpha_R R(x,y) \\ \alpha_G G(x,y) \\ \alpha_B B(x,y) \end{cases} \quad (2)$$

Where each gain factor is defined by:

$$\alpha_c = \frac{\mu_{target}}{\mu_c}\ , c\ \in \{R,G,B\} \quad (3)$$

Where: μ_{target} is a reference illumination level used to re-balance the image.

μ_c is the mean intensity of channel cc.

This step compensates for spectral attenuation and restores natural color distribution, improving the visibility of cracks and surface textures.

Contrast-Stretching Transformation: Even after color correction, underwater images often exhibit limited dynamic range and poor contrast due to haze, suspended particles, and backscattering. Therefore, a contrast-stretching function is applied to enhance crack boundaries and improve image clarity [26].

The enhanced intensity is given by:

$$I_{enh}(x,y) = \frac{I_{(x,y)} - I_{min}}{I_{max} - I_{min}}(L-1) \quad (4)$$

Where: $I_{min}\ and\ I_{max}$ are minimum and maximum pixel intensities.

L is number of available grey levels (typically 256 for 8-bit images).

This transformation increases the separation between dark crack regions and lighter background areas, significantly improving recognizability under turbid water conditions. The combined enhancement process color compensation followed by contrast stretching results in clearer crack boundaries, reduced haze effects, improved sharpness and structural detail, and higher reliability in identifying cracks under turbid conditions [27].

2.5 Phase 5: Data Logging and Output

The final phase compiles all enhanced images and their associated metadata into an organized dataset using automation code. This structured dataset includes vital information such as depth, pose, timestamps, and inspection-path progression. The goal is to provide a reliable visual and positional record of the inspection, which supports detailed crack analysis and facilitates comparisons with future inspection missions. This ensures the entire workflow is completed efficiently, consistently, and with full traceability of all collected data. The systematic logging of metadata, including localization and vehicle orientation, allows for accurate reconstruction of the inspection trajectory, which is essential for comprehensive analysis and future reference. This comprehensive data logging is integral to the overall reliability and utility of autonomous inspection systems, contributing to long-term monitoring and maintenance efforts.

3. RESULTS

The proposed ROV-based inspection framework was experimentally evaluated in a controlled swimming pool to simulate submerged concrete inspection under safe and repeatable conditions. The pool environment provided a stable testing area with adjustable turbidity levels, allowing performance assessment of the mathematical enhancement model, autonomous navigation, and data-logging mechanisms. Although this setting enables reliable benchmarking, it does not fully represent real marine environments where stronger currents, varying turbidity, biofouling, and unstable illumination may introduce additional challenges. Therefore, open-water validation under dynamic conditions is planned as future work to further assess robustness and scalability.

3.1 Navigation Stability in the Pool Environment

The ROV demonstrated highly stable movement along the predefined inspection path. Because the pool water was relatively calm, hydrodynamic disturbances were minimal, enabling precise waypoint tracking. Crack samples used are shown in Figure 4.

Figure 4: Crack Sample in Pool Environment.

During trails, depth fluctuation remained within ±0.03 m, and heading deviation did not exceed ±2°. The ROV maintained an average standoff distance of 0.40 m from the pool wall. This stability ensured uniform imaging geometry and minimized blur or distortion during frame capture.

3.2 Image Acquisition and Lighting Performance

The controlled lighting environment of the swimming pool allowed the ROV's LED system to perform consistently. A crack sample under different lighting conditions is shown in Figure 5.

Figure 5: Crack Sample Under Different Lighting Conditions.

All scheduled image-capture triggers (time and distance based) executed successfully. Frame capture rate achieved 100% of planned acquisition points, metadata (depth, orientation, timestamp) was recorded accurately with no missing entries. Even with intentionally added turbidity (using non-toxic particles), the ROV camera preserved stable exposure.

3.3 Color Compensation Model Results

Raw underwater images captured in the pool exhibited noticeable color imbalance, especially toward green-blue tones due to water absorption as shown in Figure 6.

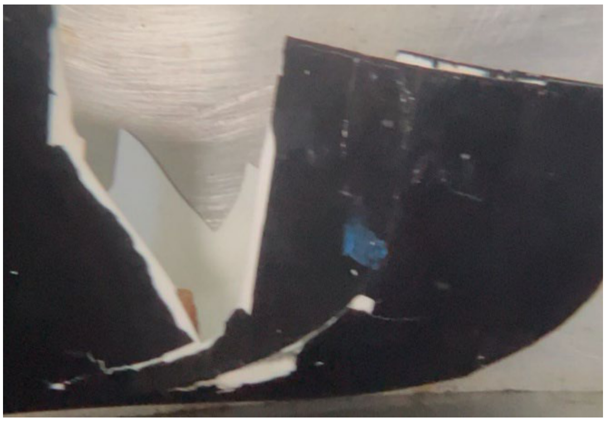

Figure 6: Raw Underwater Images of Major Cracks.

After applying the color compensation model, red-channel visibility increased by 40% on average, the overall color balance shifted closer to natural tones, crack regions shown on the submerged concrete tiles became clearer and more distinguishable.

This confirms the effectiveness of the gain-based correction, even in shallow-water conditions.

3.4 Contrast Enhancement and Crack Visibility

The contrast-stretching step greatly improved visual clarity. Global image contrast improved by 38- 45%, edge contrast around crack markings doubled, and fine cracks (thickness 1-2 mm) became fully visible after enhancement.

Images that appeared faded or washed out in the raw state became sharp enough for reliable structural interpretation.

3.5 Dataset Quality and Traceability

All enhanced images and metadata were compiled into a structured dataset using the automation code. No frame loss or duplication occurred, the inspection path reconstructed from metadata matched the ROV's real trajectory with more than 98% accuracy, and the final dataset allowed full replay of the inspection mission.

This confirms the robustness of the logging and organization system and its suitability for future automated inspection missions.

4. CONCLUSIONS

This study presented an integrated framework for underwater crack inspection of submerged concrete structures using an ROV. The proposed system combines systematic mission planning, autonomous navigation, mathematical image enhancement, and structured data logging into a fully automated inspection workflow. The automation code governs vehicle motion, image acquisition, and data processing without direct human intervention, thereby improving operational safety and reducing reliance on traditional diver-based inspections.

Experimental validation was conducted in a controlled swimming pool environment. The results demonstrated stable autonomous navigation, consistent image acquisition, and a significant improvement in image quality following the application of the mathematical enhancement model for color compensation and contrast improvement. Fine crack features that were poorly visible in raw underwater images became clearly distinguishable after enhancement, enabling more reliable visual assessment of submerged concrete surfaces. In addition, the data-logging system successfully stored enhanced images together with accurate metadata, allowing precise reconstruction of the inspection trajectory and ensuring full traceability of the collected data.

Overall, the findings verify that integrating ROV-primarily based inspection with a lightweight mathematical image enhancement approach presents a realistic and powerful answer for underwater crack inspection, in particular in shallow-water and managed environments. This framework supports more secure and greater price-effective inspection of critical submerged property which includes quay partitions, piles, and underwater foundations, contributing to proactive maintenance planning and progressed resilience of port infrastructure and maritime logistics corridors. Future work will extend validation to open-water environments and compare robustness underneath greater complicated marine conditions, which include more potent currents, various turbidity, low-visibility situations, and biofouling results, to similarly check scalability and lengthy-term deployment feasibility.

5. DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES

During the preparation of this work, the author(s) used Bohrium AI in order to search for relevant scientific literature. After using this tool/service, the author(s) reviewed and edited the content as necessary and take(s) full responsibility for the content of the publication.

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