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AI-Driven Multi-Sensor Fusion for 3D Motion Tracking of a Subsea Steel Catenary Riser Using an AUV

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ABSTRACT

Steel Catenary Risers (SCRs) transport hydrocarbons from subsea wells to floating production systems in deep-water environments. SCRs are prone to material degradation and fatigue damage over time, particularly in the touchdown zone (TDZ), where the riser is exposed to cyclic contacts with the seabed under the environmental and operational loads. The cyclic riser-seabed interaction results in seabed soil remoulding and a gradual trench formation 3 to 5 riser diameters deep within the first few years after SCR installation. It is publicly accepted that the trench formation and the non-linear hysteretic riser-seabed interaction may have a significant impact on fatigue life in the TDZ. The assessment of the trench impact on SCR fatigue requires an accurate understanding of the trench profile. This, in turn, needs costly and time-consuming subsea surveys using remote operating vehicles (ROVs). Autonomous Underwater Vehicles (AUVs) can be a cost effective alternative if they can effectively track the SCR catenary profile during the autonomous navigation. This paper explores, in a simulated environment, the utilization of virtual sensors such as an echosounder, camera, and sonar to develop an image processing pipeline incorporating bilateral denoising, Canny edge detection, Hough transform, and K-means clustering for SCR autonomous tracking. Due to the inherent noise causing asymmetric edge detection, the algorithms focused on stabilizing and refining the image processing results. A torpedo-shaped AUV was chosen for its efficiency in maintaining stability during operations. The simulations were performed in the UUV Simulator, and the generated images were analyzed to evaluate the computer vision performance. The developed SCR tracking solution by AUV, can be used for getting autonomous access to the touchdown zone and scan the seabed trench profile that can be implemented into the numerical simulations and contribute to the SCR integrity assessment studies by incorporation of vital riser-seabed interaction effects.

KEYWORDS: Steel Catenary Risers; Autonomous Underwater Vehicles; Computer Vision; Sensor-Based Tracking; Fatigue analysis.

1. INTRODUCTION

The global energy supply heavily relies on the transfer of oil and gas from underwater sources. Steel Catenary Risers (SCRs) are commonly used in offshore fields to transport hydrocarbons from the seabed to the floating platform, where they experience cyclic stress from environmental factors like waves, currents, and the movement of the host vessel (Janbazi & Shiri, 2023), especially in the touchdown zone (TDZ). The interaction between the riser and seabed under cyclic loading leads to remoulding of the seabed soil and the gradual development of a trench, typically reaching a depth of 3 to 5 riser diameters within a few years after SCR installation. It is widely acknowledged that both trench formation and the non-linear, hysteretic nature of riser-seabed interaction can significantly influence fatigue life in the Touchdown Zone (TDZ). Accurately assessing the trench's impact on SCR fatigue requires a detailed understanding of its profile, which generally demands expensive and time-consuming subsea surveys using remotely operated vehicles (ROVs). However, Autonomous Underwater Vehicles (AUVs) may offer a more cost-effective solution, provided they can reliably follow the SCR's catenary profile during autonomous navigation. Traditional methods, particularly those relying on remotely operated vehicles (ROVs), can be costly, time-consuming, and limited in scalability. Nevertheless, robotic technologies, particularly autonomous underwater vehicles (AUVs), have revolutionized subsea operations. With sonar, optical cameras, and environmental sensors, they can autonomously navigate and inspect underground pipelines and cables (Monterroso Muñoz et al., 2023).

Because of the high dangers associated with exploring the maritime environment, Unmanned Underwater Vehicles (UUVs) are a necessary tool for improving operating efficiency and safety. Autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) are two examples of UUVs that are becoming indispensable in marine technology. While AUVs function autonomously and are therefore perfect for sophisticated, independent operations, particularly in situations where manned vessels are impractical, ROVs are attached to a Surface Control Unit (SCU) and are flexible in carrying out a variety of duties (Zalewski, J. et al., 2024).

Maintaining a precise alignment along the whole length of the pipe while keeping a set distance between the robot and the object is necessary for tracking an underwater object, especially a pipeline. The robot's lateral movement must be carefully navigated to keep the pipe in the center of the field of view during this operation. Many studies have been carried out to address these issues within the last 20 years. Sonar sensors and visual cameras, which are essential for tracking in low-visibility situations and provide high-resolution visual information, are the subjects of the majority of investigations. To improve the navigation and placement of Autonomous Underwater Vehicles (AUVs), additional techniques have been developed that make use of depth sensors, Inertial Measurement Units (IMU), and Doppler Velocity Logs (DVL). To provide efficient and dependable tracking in challenging underwater settings, these sensors cooperate to maintain precise distance and direction concerning the pipeline. A vision-based autonomous robotic fish was shown by Hu et al. (2009), proving that dynamic target following in submerged situations is feasible. Their technique uses a digital camera and a modified continuously adaptive mean shift (Camshift) algorithm to maintain a visual lock on a target. It was inspired by the steadiness and mobility of the boxfish. The Camshift algorithm operates on a probability distribution image derived from the object's color histogram, utilizing the Cr and Cb components from YCrCb color space to enhance robustness in varying lighting conditions while minimizing computational resources. As the target moves in the image plane or changes distance from the camera, the search window adapts accordingly, enabling the robotic fish to actively adjust its position and maintain consistent tracking. Further contributions to the field include the work of Jacobi and Karimanzira (2014), who developed a multi-sensor fusion approach for underwater pipeline tracking using AUVs. Their method combined data from cameras, multibeam echo sounders (MBES), sub-bottom profilers, and magnetic sensors to create probability maps for pipeline detection, improving the accuracy and efficiency of inspections. Fatan, M. et al. (2016) presented an image processing technique for underwater cable detection utilizing edge classification. Their method combines Multilayer Perceptron neural networks and Support Vector Machines with texture analysis to enhance the precision of Automated Underwater Vehicle (AUV) tracking systems. This approach refines edge detection and employs morphological operations and the Hough transform to accurately identify underwater cables. Chen, Chuang, and Wang (2015) developed a specialized algorithm to improve the detection of yellow guide ropes in turbid underwater environments, crucial for guiding ROVs during breakwater inspections. Their approach incorporates a three-stage process involving target enhancement, edge detection, and line detection, utilizing the YCbCr color space, Otsu's method for adaptive thresholding, and the probabilistic Hough transform.

Lu, Y., & Song, D. (2015) used a vision-based technique to provide real-time target identification and location in aquatic environments. The artificial landmarks are made with color patches placed in a certain way. The technique differs between two detection modes: strong detection uses the topological links between colors to pinpoint the landmark center precisely, whereas weak detection recognizes individual colors. To accomplish effective real-time two-dimensional target tracking, Yu, J. et al. (2020) progressed the development of a camera-stabilizing system for robotic fish by utilizing a deep reinforcement learning (DRL) technique. This system incorporates a small camera for capturing underwater images, utilizing the Kernelized Correlation Filter (KCF) algorithm, known for its high performance and low computational cost, to visually track the target. Akram and Casavola (2021) presented a visual control scheme for AUVs to track underwater pipelines via camera-based image processing. Their method converts camera images into HSV format for segmentation, efficiently detecting pipelines through image resizing and HSV thresholding within ROS and OpenCV environments. This approach, validated through simulations, significantly enhances the robustness and accuracy of underwater pipeline tracking. Da Silva et al. (2022) explore the combination of cutting-edge image processing and machine learning techniques to enhance the autonomous navigation of Unmanned Aerial Systems (UAS) in onshore unburied pipeline inspections. They implemented a Convolutional Neural Network (CNN), specifically the You Only Look Once (YOLO) architecture, to effectively detect pipelines. This system combines YOLO's real-time object detection with traditional image processing methods like Canny edge detection and Hough Transform to refine the tracking of pipeline routes. Yang et al. (2021) introduce an enhanced algorithm for detecting curved line shapes, crucial for aiding Autonomous Underwater Vehicles (AUVs) in underwater cable inspection tasks. Their approach, the Crossline Correction Non-linear RANSAC (CCNL-RANSAC), innovates by incorporating adaptive Canny edge detection and an improved RANSAC method tailored for nonlinear environments. The integration of advanced visual processing methods in underwater inspections has evolved with the introduction of structured light vision (SLV) and stereo-image processing techniques. A dual-line laser SLV system was created by Fan, J. et al. (2023) for underwater pipeline tracking and three-dimensional reconstruction. Using adaptive threshold segmentation and a second-order difference operator, the method locates laser stripe regions on the pipeline. In parallel, Bobkov et al. (2023) enhanced the accuracy of AUV inspections using stereo images by developing algorithms that combine 2D and 3D video data processing. Their approach focused on identifying underwater pipeline (UP) boundaries against the seabed background through vectorized images, allowing for both tracking and initial recognition of the pipeline. While the recognition mode depends on matching contours in stereo-pair images, the tracking mode uses a continuity-based algorithm to estimate the position of the current segment based on historical data. Feng et al. (2023), which proposed an automatic cable-tracking method (ACTM) based on side-scan sonar (SSS). The method developed by Feng et al. enables rapid localization and stable tracking of submarine cables despite environmental uncertainties due to autonomous decision-making and dynamic replanning.

For any autonomous SCR monitoring system, a critical prerequisite is the ability to accurately capture the real 3D profile of the riser. This is essential for fatigue analysis, which depends on the actual riser shape under dynamic environmental conditions. However, a clear gap exists in the current literature regarding autonomous tracking of SCR profiles in such subsea environments. This study directly addresses that gap by focusing on reliable, real-time tracking as a foundational step for generating updated riser profiles required for fatigue assessment.

We propose a multi-sensor fusion approach, where an AUV equipped with a stereo camera and a multibeam echosounder autonomously tracks the SCR in real time. The system is validated through dynamic simulations that include environmental disturbances, sensor noise, and riser motion, demonstrating its effectiveness in maintaining a stable trajectory and capturing the riser’s time-varying shape with high fidelity.

In this study, we prioritize efficiency in terms of computing load and cost and concentrate on real-time detection and tracking of a steel catenary riser inside a 3D space. An AUV equipped with a stereo camera for lateral movement tracking and a multibeam echosounder to determine the distance from the riser processes sensor data to adjust its position and maintain continuous tracking with the approach presented in Figure 1.

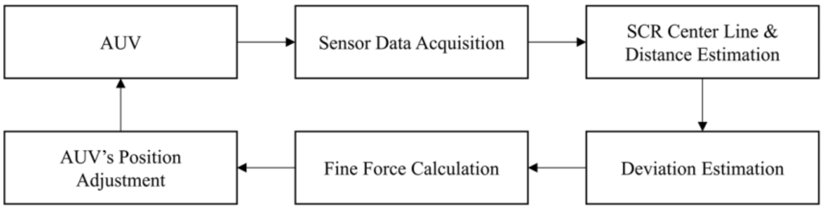

Figure 1. Autonomous Riser Tracking Loop – The AUV collects sensor data, detects the riser centerline and distance, calculates deviation, adjusts fin forces, updates position, and repeats the process for continuous tracking.

The developed SCR tracking solution by AUV, can be used for getting autonomous access to the touchdown zone and scan the seabed trench profile that can be implemented into the numerical simulations and contribute to the SCR integrity assessment studies by incorporation of vital riser-seabed interaction effects.

2. SIMULATION AND ENVIRONMENT SETUP

An effective underwater simulation platform in the marine environment must accommodate diverse vehicles, manipulators, and sensors while accurately simulating complex environments, including hydrodynamic and hydrostatic forces. Among the most popular simulators in this domain are UWSim (M. Prats et al., 2012) and UUV Simulator (M. M. M.

Manhaes. et al., 2016), both widely recognized for their capabilities in handling such requirements (Collins et al., 2021). We used the UUV Simulator, a powerful underwater simulation tool based on Gazebo and ROS, which provides a range of sensors like sonar, cameras, DVL, and IMU, along with hydrodynamic models and actuators such as fins and propellers. In this work, we focused on simulating three key aspects: the sea environment, the AUV model, and its motion control, to effectively evaluate the riser tracking scenario.

1.1. Environment

To establish the foundation for our work, we modified the UUV simulator's world files, described in the SDF (Simulation Description Format), an XML-based format used to define objects, environments, and interactions for robot simulation, visualization, and control. We incorporated a steel catenary riser (SCR) model as shown in Figure 2 designed in SolidWorks, the global geometry based on its real-world placement in the Gulf of Mexico, with a total curve length of 2,333 m from the hang-off point to the anchor point and a depth of 1,600 m and the angle from the hang-off point 78 degrees (Janbazi, H., Shiri, H., 2023). The SCR model was exported in STL format and then converted into SDF format for integration into the simulation environment.

The motion of the riser was simulated based on a time frame of 20 seconds, accounting for vertical and lateral movements of the spar floating facility. The SCR was set to sinusoidal oscillate with a range of ±0.5 m due to these forces, effectively simulating the motion of the riser in an underwater environment.

The hydrodynamics of the sea were simulated using the default underwater world settings of the UUV simulator. These enhancements ensured the environment accurately represented the operational conditions of SCRs in offshore locations, enabling precise testing and evaluation. Additionally, we introduced environmental noise and adjusted the sea color to create a more realistic setting, as our research is vision-based. The seabed, a critical element in the context of steel catenary risers, was also included to enhance the overall accuracy of the simulation.

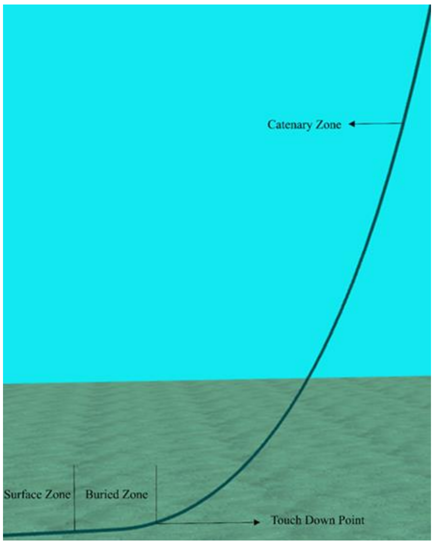

Figure 2 Simulated environment in SDF format, depicting the Steel Catenary Riser (SCR) with its key regions: the catenary region from the sea surface to the Touch Down Point (TDP), the buried zone, and the surface zone where the riser lies on the seabed.

As shown in Figure 2, the steel catenary riser consists of distinct regions from the sea surface to the touchdown point, known as the catenary region, where the riser follows a suspended curve due to its weight and hydrodynamic forces. Beyond the touchdown point, the riser transitions into the buried region, where it descends into the seabed before eventually resting and laying along the seabed surface.

1.2. AUV Model

We used the ECA A9 fin-based AUV in this scenario because it is effective and fits our goals nicely. Furthermore, the UUV simulator already contains URDF (Unified Robot Description Format) files. As shown in Figure 3, we adjusted the positions and angles of the sensors, such as the camera and echosounder, to 45 degrees to ensure effective detection of the riser at all stages, including both the horizontal and vertical sections of the catenary. Furthermore, the camera resolution and field of view, along with the echosounder settings, were optimized to balance accuracy and processing efficiency. The camera's horizontal field of view (HFOV) was set to 0.45 radians, with a resolution of 400x300. For the echosounder, the field of view was configured to 0.523 radians with 60 samples, and a Gaussian noise of 0.1 was added to both sensors.

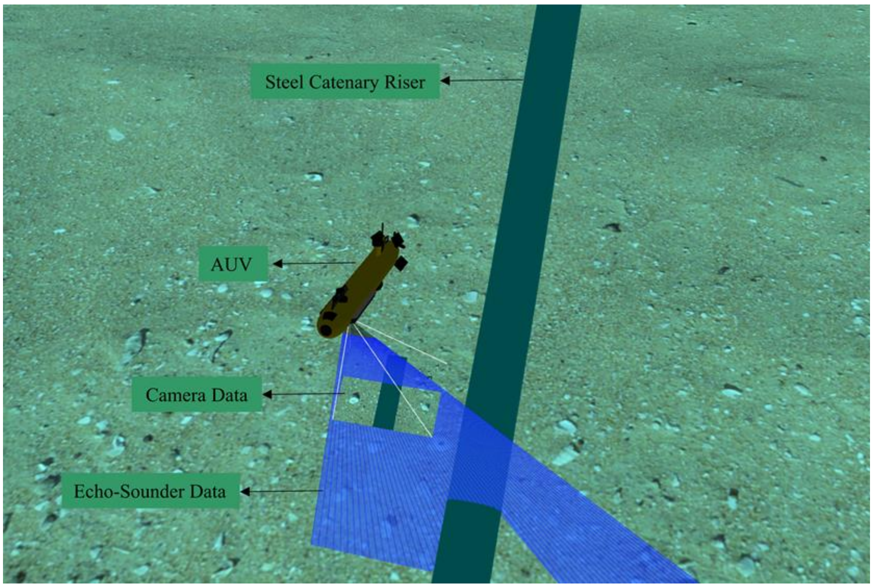

Figure 3 AUV equipped with sensors collecting real-time data to detect and estimate deviation from the steel catenary riser for precise tracking and navigation.

3. SENSOR FUSION AND DATA INTERPRETATION

The core of the work involves a continuous loop of receiving sensor data and processing it to determine the AUV's position relative to the riser in 3D space. The camera data is converted from ROS format to OpenCV using the cv_bridge library. The communication occurs via a rospy subscriber, where the Image module from the sensor_msgs library is used for receiving camera sensor data. For echosounder data, the Range module from the same library is utilized. Both the camera and echosounder data are handled in a Python 2.7 ROS node.

1.3. Vision-Based Processing

To ensure accurate detection of the steel catenary riser (SCR), multiple image processing techniques were applied, as shown in Figure 4 including bilateral filtering, Canny edge detection, Hough Transform, and K-means clustering. These steps refined the visual data, reducing noise, enhancing pipeline edge visibility, and finding the center of the riser.

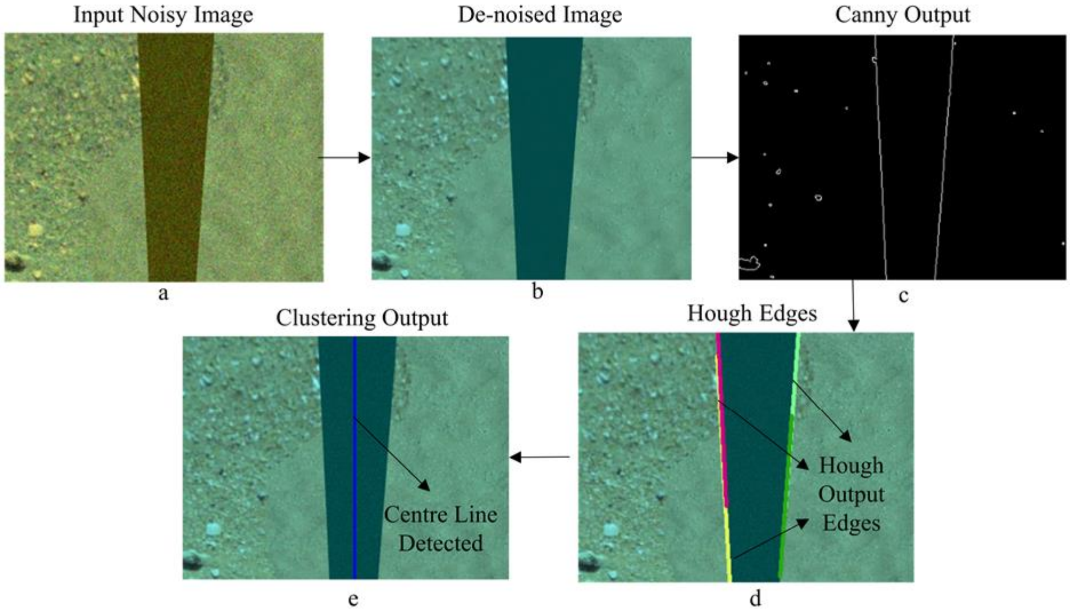

Figure 4 Image processing pipeline for riser detection: (a) Input image, (b) Denoising using bilateral filtering, (c) Edge detection with Canny, (d) Line detection in different colors using Hough transform, and (e) Identified clusters center which is located at the center of riser.

Bilateral filtering was used as a preprocessing step to smooth the image while preserving critical edges. The intensity distribution before filtering showed high fluctuations, with abrupt changes between neighboring pixels, leading to false edge detections. After applying a bilateral filter with parameters d = 15, σ_{color} = 75, and σ_{space} = 75, the intensity variations were significantly reduced while retaining key structural details. This resulted in a smoother image where the edges remained sharp, as illustrated in Figure 5.

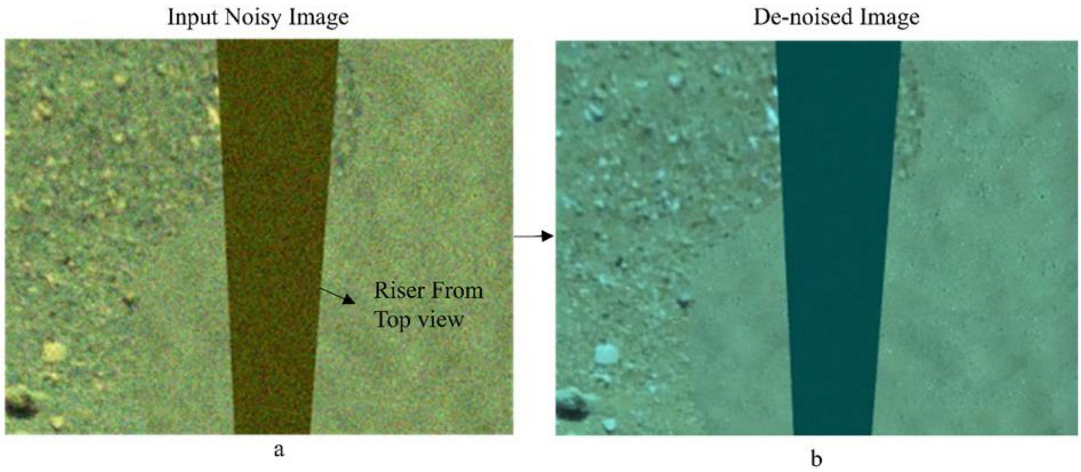

Figure 5 Comparison of input and denoised images: The left side shows the noisy input image, while the right side presents the result after bilateral filtering, where noise is removed while preserving edges.

Following noise reduction, Canny edge detection was applied to extract pipeline edges. The algorithm was set with low and high thresholds of 50 and 200, ensuring that strong edges were detected while suppressing weak ones. This step produced a clear segmentation of pipeline boundaries, reducing false positives from background textures. The resulting emphasizes the riser contours edges shown in Figure 6.

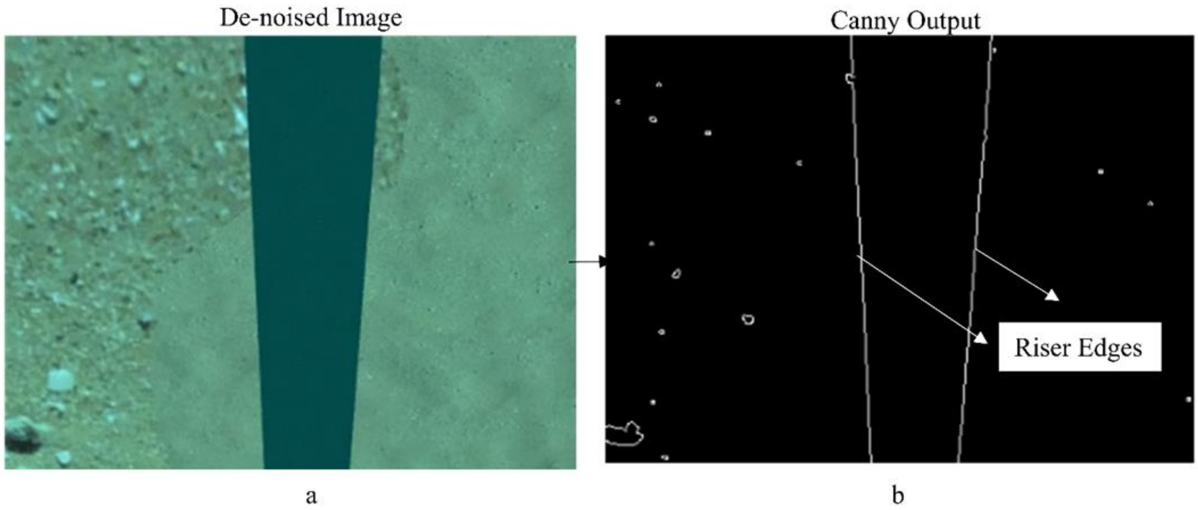

Figure 6 Denoised image (left) and Canny edge detection output (right), highlighting riser edges extracted from the background.

The left side of Figure 6 presents the input image, displaying the original scene before edge extraction. On the right, the extracted edges using the Canny algorithm are highlighted in white, effectively distinguishing the riser contours from the seabed. All pixels classified as edges are shown in white, ensuring a clear contrast against the background for accurate boundary detection.

To further refine edge detection, the Hough Transform was used to identify structured line segments corresponding to the riser. Since parameter selection significantly affects performance, multiple configurations were tested. Threshold values (50, 100), minimum line lengths (20, 30, 50), and maximum gaps (5, 10, 20) were evaluated to optimize line detection. Table 1 presents the performance results for different settings, using the F1 Score as the primary metric. The best configuration was Threshold = 100, Min Length = 20, and Max Gap = 20, which maximized Precision and Recall while reducing false detections. The final detected edges using this optimized configuration are shown in Figure 7. As shown in the figure, the Hough Transform successfully detected edges from the Canny output, with identified line candidates displayed in different colors.

Table 1 Hough Transform Parameter Tuning and Performance Metrics – Comparison of threshold, max gap, and min line length settings with corresponding precision, recall, and F1 score.

Threshold	Min Length	Max Gap	Precision	Recall	F1 Score
50	20	5	1.00	0.70	0.83
50	20	10	1.00	0.82	0.90
50	20	20	1.00	0.97	0.98
50	30	5	1.00	0.70	0.83
50	30	10	1.00	0.82	0.90
50	30	20	1.00	0.97	0.98
50	50	5	1.00	0.70	0.83
50	50	10	1.00	0.82	0.90
50	50	20	1.00	0.97	0.98
100	20	5	1.00	0.34	0.51
100	20	10	0.99	0.69	0.81

100	20	20	0.99	0.99	0.99
100	30	5	1.00	0.30	0.46
100	30	10	0.99	0.69	0.81
100	30	20	0.99	0.99	0.99
100	50	5	1.00	0.47	0.64
100	50	10	0.99	0.69	0.81
100	50	20	0.99	0.99	0.99

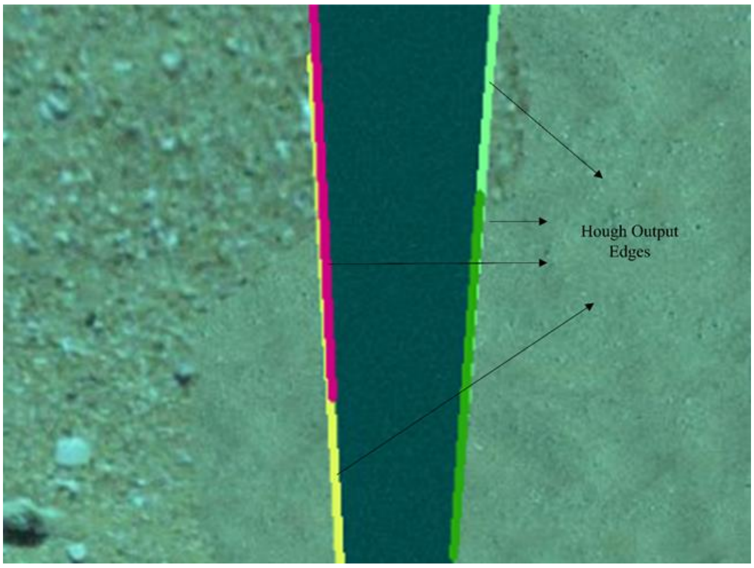

Figure 7 Probabilistic Hough Line Transform applied to extract riser edges, with detected line segments shown in different colors. Some edges are discontinuous, highlighting the potential for detecting additional edges on each side of the riser.

Finally, K-means clustering was applied to separate pipeline edges from background artifacts. With K = 2, the largest clusters were assumed to represent the pipeline edges, allowing a centerline estimation for tracking. This approach reduced variations caused by outlier pixels, leading to a more stable detection of the riser's centerline to adjust the position of AUV based on that.

1.4. Echo-Sounder Data Interpretation

The echosounder provides distance measurements between the AUV and the riser. A field of view (FOV) of 0.52 radians ensures optimal signal reception in subsea conditions where electromagnetic signals fail. The shortest range detected in the sonar beams determines the riser's depth and proximity, allowing dynamic AUV positioning adjustments.

1.5. Motion Control

The East-North-Up (ENU) coordinate system is employed in this simulation and is commonly used for underwater navigation and mapping. ENU system defines the x-axis as pointing east, the y-axis as pointing north, and the z-axis as pointing upward. Figure 8 illustrates how this system ensures that all positional and motion data is aligned with geographic directions, simplifying the interpretation of the AUV's movements and interactions with its environment.

In the highly nonlinear environment caused by the motion of the riser and the significant coupling effects of hydrodynamic forces, developing a robust mathematical model to continuously and effectively control the AUV's position is crucial for this research. Fossen's equations, as shown in equation (1) (Fossen, T. I., 2011), of motion, the default hydrodynamic model in the simulation package, are employed to compute the necessary forces.

$$M\dot{\upsilon}_r + C(\upsilon_r)\upsilon_r + D(\upsilon_r)\upsilon_r + g(\eta) + g_0 = \tau + \tau_{wind} + \tau_{wave} \tag{1}$$

Where M is the system inertia matrix (MRB + MA), C (υ_r) is Coriolis matrix (CRB (υ_r) + CA (υ_r)), D (υ_r) is the damping matrix, g (η) vector of gravitational/buoyancy forces and moments, g_o is the vector used for pre-trimming, τ is a vector of control inputs, τ_{wind} is a vector of wind forces, and τ_{wave} is the vector of wave forces.

Once the desired motion (left, right, up, or down) is determined for tracking the riser, the PID controller calculates the required pitch, yaw angles, and thrust force to achieve the desired position. These control inputs are used to adjust the fin angles of the AUV's four fins and the angular velocity of the propeller. Appropriate forces, as defined by equations (2) and (3), are generated to control the AUV's movement in 3D space.

$$F_D = 0.5\,\rho\, v^2 C_D\, A \tag{2}$$

$$F_L = 0.5\,\rho\, v^2 C_L\, A \tag{3}$$

Where ρ is the fluid density, v is the velocity, CL/CD is the lift and drag coefficient which depends on the shape and the flow regime, and A is the reference area.

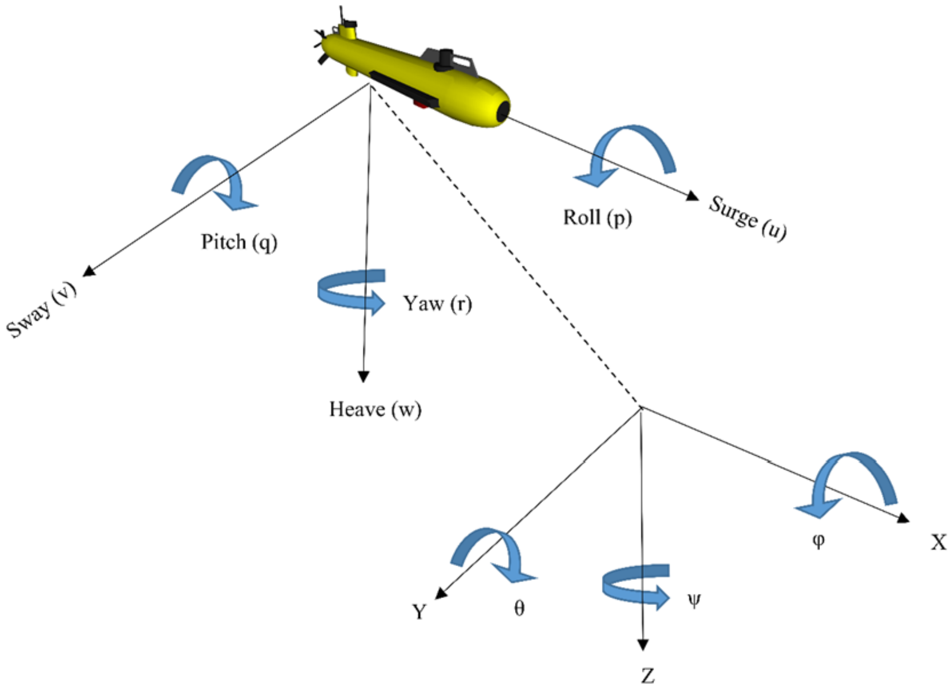

Figure 8 AUV's six degrees of freedom (roll, pitch, yaw, surge, sway, heave) compared to the Earth-fixed coordinates (X, Y, Z).

In order to determine nonlinear control inputs based on the riser's vertical and horizontal deviations, sensor data is evaluated at each instant. The thrust force and computed pitch and yaw angles are subsequently transmitted to the AUV's actuators. Therefore, the AUV provides the required lift, drag, and thrust forces to achieve the desired motion by adjusting its fins and propeller.

4. PERFORMANCE EVALUATION

1.6. Success Rate

In this study, 20 images were selected along the entire length of the steel catenary riser (SCR) to evaluate the performance of the detection method under varying environmental conditions, as shown in Figure 9. These images capture different background transitions, ranging from a uniform blue water column to complex seabed structures that introduce additional noise and variations in illumination. The selection process ensures that the dataset includes a diverse range of scenarios, allowing a comprehensive assessment of the method's robustness.

To quantitatively measure detection accuracy, F1 scores were computed for each selected image by comparing Hough-detected edges with ground truth edge pixels, as reported in Figure 10. These scores provide insight into the method's reliability across different sections of the SCR, highlighting performance variations due to changes in background complexity, visibility, and riser curvature. The results demonstrate how well the proposed approach maintains consistent detection performance along the riser, despite environmental challenges.

As shown in Figure 10, the F1 scores range from 0.75 to 1.0, reflecting varying detection accuracy across different images (a–t). Higher scores indicate precise edge detection, while lower scores suggest cases where background noise or complex seabed features impacted performance.

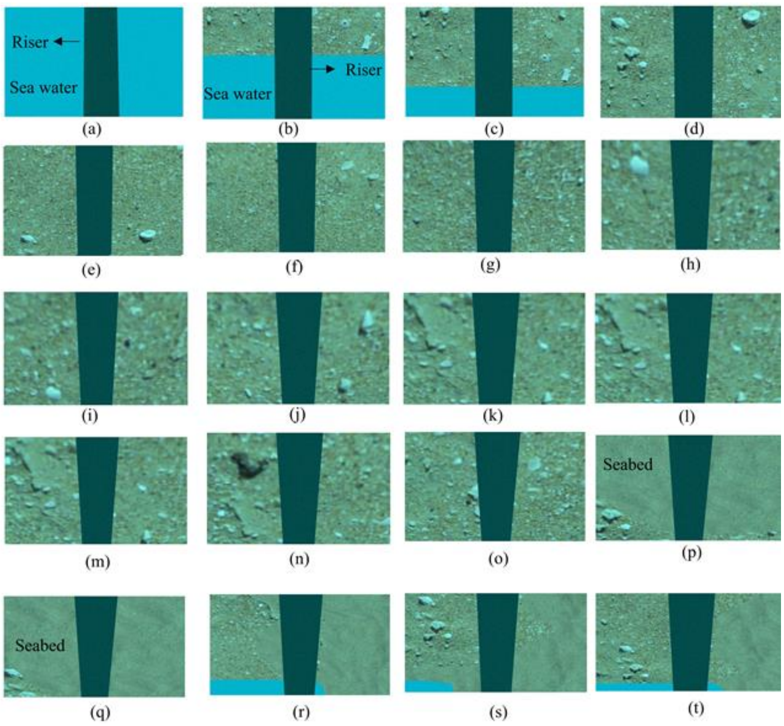

Figure 9 Set of 20 selected images (labeled a-t) for performance evaluation along the length of the Steel Catenary Riser, transitioning from a blue background (representing seawater) to seabed. The gray regions depict the riser, while the brown areas indicate the seabed

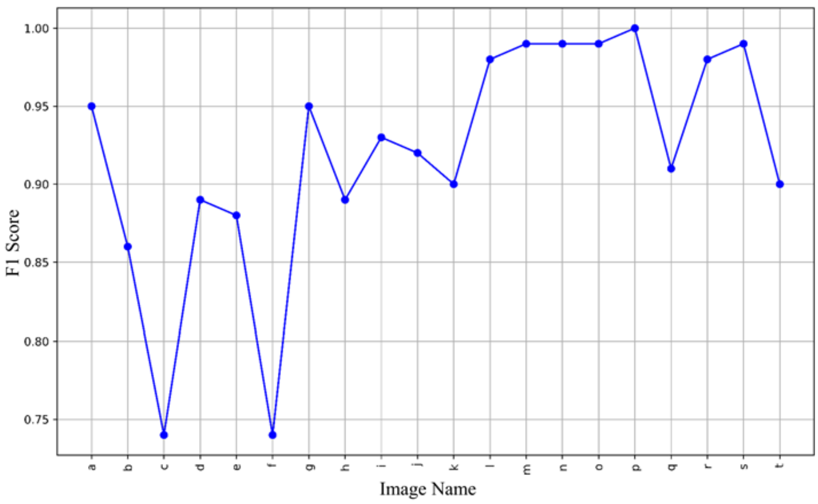

Figure 10 F1 Score Comparison Between Hough-Detected Edges and Ground Truth – The F1 scores, ranging from 0.75 to 1.0, represent the accuracy of Hough-detected edges compared to ground truth edge pixels across 20 selected images (a–s), showing variations in detection performance across different sections of the SCR.

1.7. Simulation Result

The results of the simulated experiment are presented in Figure 11 and Figure 12. Figure 11 illustrates the top view (X, Y plane) of the steel catenary riser, showing its oscillations and how the AUV tracked these oscillations. For better clarity, this view is divided into nine segments, covering the riser from its starting point to its endpoint. Figure 12 presents the side view (X, Z plane), showing how the AUV accurately followed the true curve of the riser. As shown, the AUV successfully tracked the riser's path, accurately following its curve in both the side view (X, Z plane) and the top view (X, Y plane).

The AUV maintained its position directly above the steel catenary riser while adjusting its lateral motion and consistently keeping a stable distance from the riser. This was observed across all sections, including the catenary, buried, and surface zones. The AUV managed to stay above the riser by processing data from the camera sensor and adjusting its position based on hydrodynamic forces and water currents. The motion adjustments were non-linear and designed to respond proportionally to the variation between the AUV and the center of the riser, ensuring precise and stable tracking throughout the experiment.

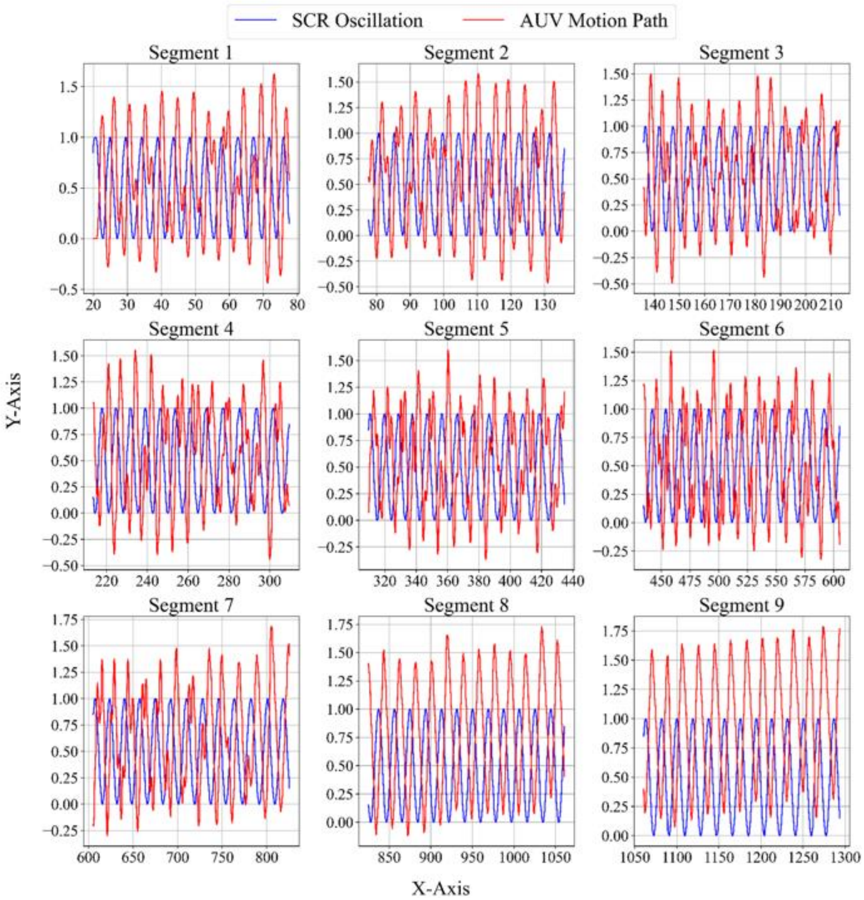

Figure 11 AUV's Path and SCR Oscillation in the (X, Y) Plane – The AUV's actual path (red) compared to the SCR position (blue) across divided length segments for clearer analysis. All dimensions are in meters.

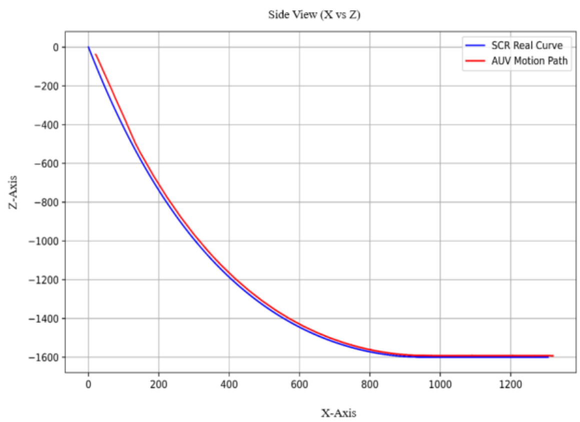

Figure 12 AUV Path and SCR Profile in the (X, Z) Plane – The AUV's actual path (red) compared to the SCR's real curve (blue) in the side view. All dimensions are in meters.

5. CONCLUSION

This research has demonstrated the feasibility of using a torpedo-shaped Autonomous Underwater Vehicle (AUV) equipped with multi-sensor fusion techniques to autonomously track Steel Catenary Risers (SCRs) in a 3D underwater environment. The proposed system integrates a stereo camera for lateral tracking and a multibeam echosounder for depth estimation, enabling the AUV to dynamically adjust its position in response to real-time environmental variations. By leveraging image processing techniques such as bilateral filtering, Canny edge detection, Hough Transform, and K-means clustering, the system effectively enhances riser feature extraction while mitigating the impact of underwater noise and visibility limitations.

The UUV Sim simulation results validate the accuracy and robustness of this tracking approach. The optimized Hough Transform parameters significantly improved edge detection precision, achieving F1 scores between 0.75 and 1.0 across different riser sections. The AUV's motion control strategy, based on Fossen's equations of motion, enabled stable 3D path-following along the SCR, with real-time pitch, yaw, and thrust adjustments. Comparative analysis between Hough-detected edges and ground truth data confirms the system's reliability in detecting riser structures despite varying seabed textures and background complexity.

This research addresses a critical gap in subsea infrastructure tracking, as no prior studies have demonstrated fully autonomous tracking of Steel Catenary Risers (SCRs) in 3D space. Accurate and reliable tracking is a key prerequisite for any autonomous subsea monitoring system. By addressing this foundational challenge, the proposed approach enables real-time riser following through multi-sensor fusion, combining stereo vision and echosounder data. The developed SCR tracking solution allows an AUV to autonomously navigate along the riser down to the touchdown zone, capturing the detailed geometry of the seabed trench and riser profile. This spatial data can be fed into numerical simulations to improve fatigue and integrity assessments by incorporating the dynamic effects of riser–seabed interaction. The proposed method offers a non-invasive, cost-effective, and scalable solution, laying the groundwork for future extensions such as anomaly detection or structural health monitoring.

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