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Advanced Techniques in Ship Corrosion Analysis: Integrating Active Contour Algorithms for Image Segmentation

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ABSTRACT

Corrosion represents a critical structural challenge for marine vessels, necessitating meticulous inspection and maintenance procedures. Current automated visual corrosion inspection methods suffer from complexities, impracticality and limitations in distinguishing heavily corroded from non-heavily corroded areas, primarily due to the vagueness of corrosion boundaries on ship surfaces. Active contour algorithms, renowned for their precision in image processing, offer a promising solution. However, the accuracy of contour initialization, a pivotal aspect of active contour techniques, remains underexplored due to inherent challenges. Detecting weak and ill-defined corrosion boundaries in low to medium-quality images is further complicated by noise, reflections, motion blur and off-angle factors. Moreover, the convergence speed of active contour algorithms remains a concern, especially when dealing with precise boundaries. This research endeavours to investigate the robustness of contour initialization and active contour algorithms for ship corrosion detection. The proposed methodology commences with enhancing the texture quality of a comprehensive dataset comprising over 3700 ship corrosion images obtained from diverse Malaysian shipyards, achieved through a modified Wiener filter. For contour initialization, a pixel property method is integrated with an active contour algorithm bolstered by a curve restrained and stopping function. The normalization and feature extraction phases leverage a modified rubber sheet model, 1D-log Gabor filter and Hamming distance. The results demonstrate a remarkable segmentation accuracy of 94.45% and an efficient execution time of 0.91s. These findings present an exciting avenue for comprehending the mechanisms behind accurate contour initialization and developing robust corrosion detection algorithms. The potential integration of this cutting-edge technology into innovative ship maintenance systems holds significant promise for asset health monitoring and predictive maintenance, thus advancing the sustainability of the marine industry. This research is poised to revolutionize ship maintenance practices, fostering efficiency and environmental responsibility in alignment with the overarching goals of the marine industry towards sustainable future.

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1. Introduction

In the maritime industry, safeguarding vessel structures stands as a fundamental imperative, pivotal not only for ensuring the safety of maritime operations but also for sustaining the economic vitality of the shipping sector [1-3]. A significant problem within this realm revolves around identifying and evaluating corrosion on ship bodies, a menace that can precipitate structural decay, imperil maritime endeavours and incur formidable repair expenses [4]. In response to this compelling predicament, technology has advanced considerably, introducing automated visual inspection techniques for corrosion detection [5]. Nevertheless, this promising avenue toward efficient and precise corrosion assessment traverses a labyrinth of intricacies and limitations. Despite the strides made, ascertaining corrosion on ship structures with the requisite precision for sound decision-making remains a formidable challenge [6,7]. Figure 1 shows some ship structures affected by corrosion.

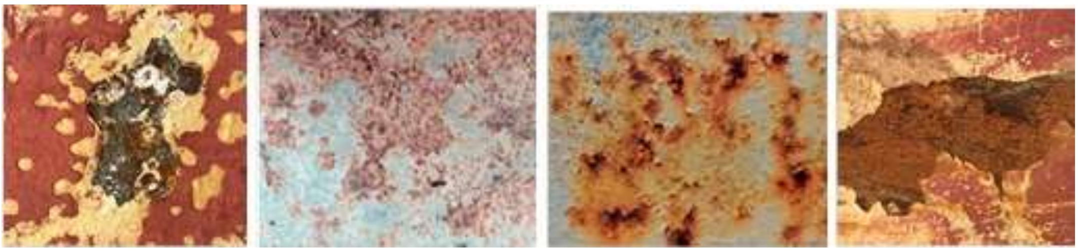


Fig. 1. Ship structure affected by corrosion

The current landscape of automated visual corrosion inspections, typified by methodologies such as Faster R-CNN and HRTC R-CNN, certainly exhibits potential. However, their tethering to sensitive parameter configurations renders them susceptible to false positives, imposing substantial barriers to real-time deployment [8]. Moreover, the existing automated visual corrosion inspections are encumbered by impracticality, complexity and time-consuming processes. Discerning between heavily and non-heavily corroded areas is particularly arduous due to the indistinct and ill-defined corrosion boundaries adorning the ship's surface. The differentiation of corrosion areas poses a substantial challenge, predominantly stemming from the incapacity to identify feeble corrosion textures [7,9,10]. On the contrary, due to its precision, the active contour technique emerges as a promising image processing method. Yet, the infrequent reporting on the accuracy of contour initialization underscores the challenges associated with this approach. The initialization of the initial contour presents formidable difficulties, as the efficacy of the active contour method hinges heavily upon this crucial step [11,12].

Furthermore, detecting faint and weak corrosion boundaries in low and medium-quality corrosion images remains elusive, beset by the omnipresent spectres of noise, reflections, motion blur and off-angle distortions [13]. Compounding these issues, the convergence speed of the active contour technique remains an unresolved concern, especially as it navigates the intricate boundaries through a high number of iterations. Hence, the need arises to develop a robust algorithm tailored explicitly for corrosion detection on ship structures [14,15]. As such, the focal objective of this study is to embark on a comprehensive investigation and evaluation of contour initialization techniques and active contour algorithms in the context of corrosion detection. Additionally, this research endeavours to rigorously scrutinize the reliability and efficacy of these methods, with a particular emphasis on their aptitude for surmounting the multifaceted challenges posed by corrosion detection on the intricate and diverse structures of marine vessels.

2. Literature Review

Corrosion detection is a comprehensive process involving several distinct steps. It begins with acquiring images depicting the surface or object under examination. These images must be of high quality to ensure accurate corrosion assessment. Subsequently, the acquired images undergo pre-processing, encompassing tasks like noise reduction, contrast enhancement and colour correction, to optimize their suitability for analysis. Image segmentation follows, where the image is partitioned into regions of interest, often employing threshold-based segmentation, edge detection, region-based segmentation, clustering or pattern matching to isolate corrosion areas from the background. After segmentation, relevant features are extracted from the identified regions, including texture, colour, shape and statistical properties. These features are crucial for subsequent image classification, where machine learning or deep learning techniques are employed to categorize the segmented regions as either corrosion or non-corrosion. Figure 2 illustrates the corrosion detection process and associated algorithms.

Image segmentation involves partitioning images into significant segments representing surfaces or objects. This task is a crucial challenge in computer vision, as it underpins tasks like recognition and reconstruction. Addressing this challenge, numerous researchers have dedicated significant efforts, resulting in a diverse array of methods for effective image segmentation. Kass *et al.,* [16] proposed the active contour model (ACM), which stands out as one of the most effective models for image segmentation. ACM operates on the fundamental concept of evolving a curve to extract the desired object using an energy-minimizing approach. ACM's strength in image segmentation lies in its ability to divide an image into sub-regions characterized by closed and smooth boundaries.

In a general context, most of the ACMs studied within the level set framework can be classified into two main categories: edge-based [17,18] and region-based [19,20] models. Edge-based models rely on the image gradient to generate forces guiding contours toward the desired object boundaries. These models exhibit high sensitivity to noise and struggle to detect faint boundaries. Additionally, the outcome of segmentation is heavily reliant on the initial placement of the contour. On the other hand, region-based models make use of statistical information from the image to establish constraints, offering several advantages over edge-based approaches. Firstly, they are not reliant on the image gradient, enabling them to segment objects with weak boundaries effectively. Secondly, by leveraging global region information, they generally exhibit robustness to noise. The Mumford–Shah model, initially proposed by Mumford *et al.,* [21] as a general image segmentation model, involves decomposing the image into distinct regions, approximating each region by a smooth function. The optimal image partition is determined by minimizing the Mumford–Shah functional. However, the generality of this function leads to non-convexity, making it challenging to minimize.

One widely accepted region-based model is the Chan–Vese (CV) model [22], which simplifies the Mumford–Shah functional for segmentation. The CV model has successfully segmented images with two regions characterized by distinct mean pixel intensities. Nevertheless, the CV model assumes statistical homogeneity of image intensities within each region, which is not always the case in more general images, limiting its applicability. To address the limitations of the CV model, Vese *et al.,* [23] and Tsai *et al.,* [24] introduced two similar region-based active contour models that minimize the Mumford *et al.,* [21] functional. These models, commonly called piecewise smooth (PS) models, are based on a piecewise smooth representation of images. While PS models demonstrate some ability to handle intensity variations, their computational cost is relatively high due to the intricate procedures involved.

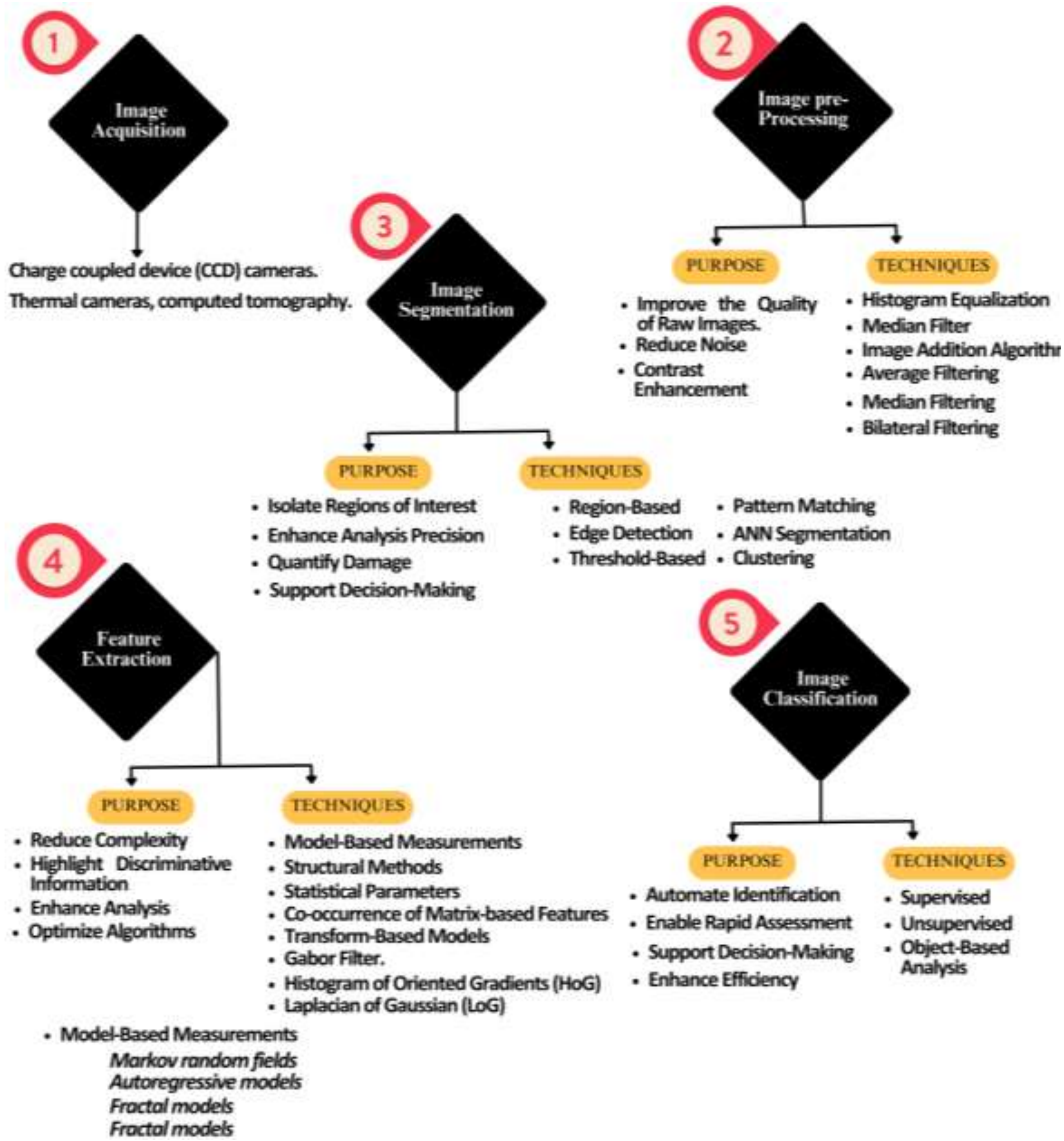


Fig. 2. Corrosion detection process and related algorithms

In marine corrosion detection, diverse methodologies have been explored, each contributing uniquely but revealing certain limitations. Bahrami *et al.,* [25] utilized Faster R-CNN for ship container corrosion detection. While they improved accuracy and recall with anchor box optimization, their model had limitations, including sensitivity to anchor box settings and potential false positives. HRTC R-CNN [26] employed temporal context and high resolution for corrosion detection but faced computational intensity issues, making it less efficient for real-time applications. Xu *et al.,* [27] encountered difficulties forecasting the proportion of corrosion area with their Faster R-CNN and suggested additional categorization methods. Their model was sensitive to variations in corrosion types and severities. Andersen *et al.,* [28] used Faster-RCNN and YOLO for marine vessel corrosion detection but struggled with dataset specificity, potentially leading to false positives and overestimated the extent of corroded regions due to limitations in the model's architecture and training data. Aijazi *et al.,* [29] focused on 3D point clouds and HSV conversion, which might not effectively capture the nuanced details of corrosion. Ortiz et *al.,* [30] utilized deep learning and neural networks, respectively, but these methods struggle with weak and edge boundary detections, a critical area where the Chan-Vese model excels. Similarly, Igoe *et al.,* [31] used smartphone sensors for corrosion detection, which lack the comprehensive analysis capabilities of more advanced image processing techniques.

Idris *et al.,* [32] enhancing edge detection algorithms focused on pipeline inspection. These methods, while effective for inspections, reducing false positives and improving edge intensity, are not as suitable for the complex surfaces of ships, where the Chan-Vese model can be more advantageous. Alkanhal [33] used wavelet packet transforms for pitting corrosion analysis, a technique that might not effectively capture broader corrosion patterns. Idris *et al.*, [34], with their multiple image filters, such as Homomorphic, Bayer, Wavelet Denoising, Gaussian, Linear and Anisotropic Diffusion, in conjunction with neural networks to optimize results and Bonnín-Pascual *et al.,* [35], using a Bayesian framework, introduced sophisticated approaches. Yet, they struggle with the real-time processing demands of ship corrosion detection.

Motamedi *et al.,* [36] proposed using CCTV and laser methods for corrosion detection, a less precise process for detailed corrosion analysis. Ji *et al.,* [37] and Ghanta *et al.,* [38] employed watershed transform and wavelet transformation, respectively. While innovative, these techniques do not effectively capture the subtle nuances of corrosion patterns. Mohsin *et al.,* [39], Medeiros *et al.,* [40] and Xie [41] explored texture and colour-based analysis. Still, these methods do not offer the same level of accuracy in boundary detection and overall corrosion assessment as provided by our approach.

Furthermore, Yao *et al.,* [42] achieved successful detection of various superficial structural damages in hull plates but faced challenges in generalization due to a limited dataset and suboptimal performance in specific environmental conditions. Soares *et al.,* [43] achieved a high precision level (92%) in corrosion detection in marine vessel structures, primarily using synthetic underwater photos. However, concerns have been raised about the practicality of their approach because of its heavy reliance on synthetic images, which may not fully represent real-world conditions. Ranjan *et al.,* [44] and Acosta *et al.,* [45] focused on essential edge detection and texture-based classifiers. While these methods are helpful, they lack comprehensive and nuanced corrosion analysis, especially in complex maritime settings. Fernández-Isla *et al.,* [46] and Jahanshahi *et al.,* [47] employed wavelet-based techniques for image reconstruction and corrosion detection, but not directly applicable to the maritime context, where the specific challenges of sea-going vessels could necessitate a more tailored approach.

Daira *et al.,* [48] combined electrochemical and optical methods, which are impractical for large-scale ship inspections. Shen *et al.,* [49] explored GLCM and colour-texture segmentation approaches, but these approaches lack the robust adaptability needed for diverse maritime environments. Chen *et al.,* [50] used Fourier transform and thermal imaging, respectively, techniques potentially limited by environmental factors. Medeiros *et al.,* [40] explored the classification of corroded and non-corroded surfaces using texture descriptors from GLCM and colour descriptors based on statistical moments in the HSI colour space. However, limitations in their approach include potential challenges in accurately distinguishing between subtle corrosion variations and the sensitivity of the method to lighting conditions and image quality, which could affect classification accuracy in real-world scenarios.

From the above literature discussion, a significant research gap has emerged due to the limitations of existing methods. Various techniques, such as Faster R-CNN, HRTC R-CNN, neural network, BPNN, SVM, active contour models and vision-based corrosion detection, while effective to some extent, suffer from sensitivity to parameter settings, computational intensity and difficulties in accurately classifying corrosion areas. These complexities hinder their practicality for real-time ship corrosion inspection. Additionally, edge detection and texture-based analysis often fall short of capturing the subtle nuances of corrosion patterns, particularly the weak and edgeless boundaries typical in ship corrosion. Moreover, specific research approaches that rely heavily on synthetic images may not fully represent the real-world conditions encountered in maritime environments. Given these challenges, a tailored and versatile approach is essential to comprehensively address ship corrosion detection's complexity. Our study leverages the Chan-Vese active contour method with other hybrid approaches to bridge this research gap. This approach is well-suited for precisely delineating weak and edgeless corrosion boundaries, making it promising for addressing the subtle corrosion patterns found on ship structures.

3. Materials and Method

3.1 Datasets

The primary research materials utilized in this study consist of ship corrosion images sourced from various locations. These images were acquired from the shipyard in Port Klang, Selangor, Malaysia, as well as from fishing vessels and boats in Kuala Nerus and Kuala Terengganu, Malaysia. The corrosion observed on the ship's body, encompassing areas such as the ship hull, deck, bow and superstructures, was meticulously documented in images ranging from 480p to 1080p. Each sample was meticulously captured at least ten times, varying the angle and offset for a comprehensive analysis.

3.2 Chan Vase Active Contour

The Chan-Vese (CV) active contour model approximates the segmentation method presented by Mumford *et al.,* [21], utilizing the level set method. The goal is to minimize the energy function F (c_1, c_2, C) to segment an image into background and foreground components. Subsequently, the contour evolves to align with the desired boundary. Eq. (1) depicts the energy function as initially proposed by Mumford *et al.,* [21]:

$$
\begin{aligned}
F(c_1, c_2, C) = {} & \mu . Length(C) + v . Area(C)) \\
& + \lambda_1 \int |\mu_0(x, y) - c_2|^2 \, dxdy \\
& + \lambda_2 \int |\mu_0(x, y) - c_2|^2 \, dxdy
\end{aligned}
\tag{1}
$$

The equation presented encapsulates the core components of the Chan-Vese (CV) active contour model used for image segmentation. Within this equation, we encounter several vital variables and constants. Notably, c_1 and c_2 represent constants that signify the average values μ_0 inside and outside the curve C, respectively. The parameter μ serves as a length-scaling factor, while μ_0 represents the image. Additionally, the equation incorporates constants λ_1, λ*2* and υ. Each term in the formula serves a distinct purpose: the first term governs the regularity of curve C, the second term controls the area enclosed by this curve and the third and fourth terms collectively capture the discrepancy between c_1 and c_2. In practice, the Chan-Vese active contour model leverages this energy function to optimize curve C, ultimately achieving image segmentation by distinguishing foreground and background regions.

3.3 Image Pre-Processing

Pre-processing involves employing techniques and operations on an input image before initiating the actual analysis or manipulation of its content [51,52]. The principal objective of pre-processing is to improve the image's quality, making it more apt for a particular task or removing undesirable artifacts or noise, thereby playing a pivotal role in object classification. Consequently, the significance of pre-processing lies in its ability to enhance the quality of corrosion images within the gathered dataset.

3.3.1 Deblurring

The Wiener filter is applied to enhance the quality of corrosion images, specifically focusing on deblurring. Operating as a deconvolution technique, the Wiener filter mitigates image blurriness by estimating and counteracting the effects of blur in the frequency domain [37,38]. While its efficacy is apparent when a reliable estimate of the point spread function (PSF) and noise characteristics are available, challenges arise in real-world scenarios characterized by intricate or unknown blur and noise patterns. Consequently, the existing algorithm is adapted to determine suitable parameters for unknown blur, estimated PSF and noise patterns, emphasizing the delicate balance between reducing blur and preventing noise amplification. Figure 3 shows the methodology flowchart used for deblurring.

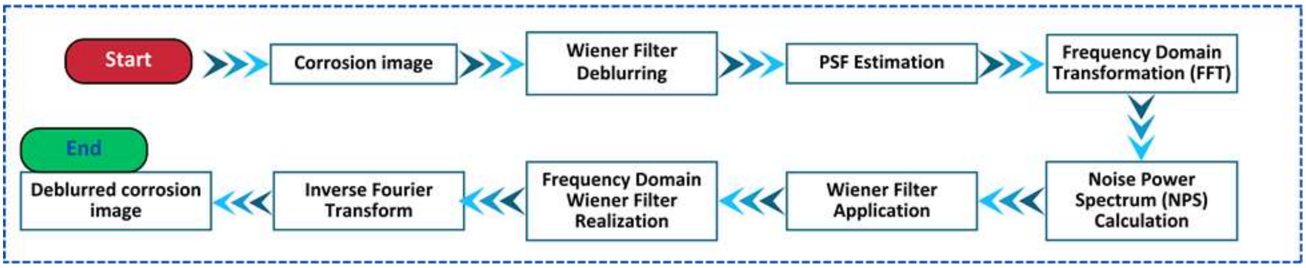


Fig. 3. Methodology flow for deblurring

The methodology initiates by estimating how light from a point source spreads across the corrosion image to derive the Point Spread Function (PSF). A comparative analysis between the noisy corrosion image and the predicted PSF facilitates this process. The estimated PSF and the noisy image transform the time domain to the frequency domain using the Fast Fourier Transform (FFT). Measurement of noise power across various frequencies enables the calculation of the Power Spectral Density (PSD). Estimations are then made regarding the noise's characteristics, including its statistical distribution and additive nature. The winner filer formula is shown in Eq. (2).

$$W(f_1, f_2) = \frac{H*(f_1,f_2)S_{xx}(f_1,f_2)}{|H(f_1,f_2)|^2\, S_{xx}(f_1,f_2) + S_{nn}(f_1,f_2)} \tag{2}$$

Where, S_{xx} (f_1, f_2) is the original corrosion image power spectra, S_{nn} (f_1, f_2) is the noise power spectra and H (f_1, f_2) is the blurring filter.

The blurry corrosion image's deblurring is accomplished by applying the well-regarded Wiener filter. This filter reduces the volume of low-frequency signals while amplifying high-frequency signals. In the frequency domain, the Wiener filter is implemented through point-wise multiplication and its formula, denoted as H(w), is defined in Eq. (3). Subsequently, the inverse Fourier Transform is applied to the product of the filter in the spatial domain. This comprehensive methodology significantly elevates the quality of the blurry corrosion images in the dataset, effectively minimizing the blur effect and highlighting distinct features within the images. Moreover, the adaptability of the approach to real-world scenarios with complex or unknown blur and noise patterns enhances its practical utility.

$$H(w) = \frac{G(w)}{G(w) + H(w)} \tag{3}$$

Where, G(w) is the FT of the corrosion image and N(w) is the calculated NPS.

3.3.2 Reflection removal

The methodology for reflection removal from corrosion images involves a systematic series of steps to enhance the images' clarity and accuracy for subsequent analysis. The process begins with acquiring a raw corrosion image, serving as the foundational input for the entire procedure. Figure 4 shows the methodology flowchart used for reflection removal.

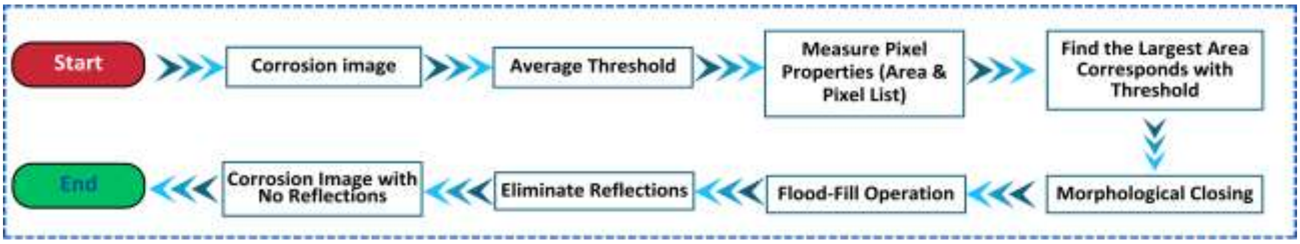


Fig. 4. Methodology flow for reflection removal

In the initial step, an average threshold (Eq. (4)) is determined to segment the corrosion image, facilitating the differentiation of distinct regions. This thresholding operation lays the groundwork for subsequent pixel property measurements, where characteristics such as area and pixel lists are meticulously quantified. Following the measurement of pixel properties, the algorithm identifies the region with the most significant area corresponding to the determined threshold. This strategic selection focuses on isolating the most significant portion of the corrosion image for further refinement. Morphological closing operations are then applied to this chosen region, utilizing mathematical morphology techniques to smooth and close gaps, thereby enhancing its structural integrity.

$$Threshold = \frac{1}{n}\sum_{i=1}^{n} A_i \tag{4}$$

Where, n is the number of ship structure corrosion images and A_i is the contrast threshold of the corrosion image.

A subsequent flood-fill closing operation fills any remaining gaps and ensures continuous, seamless integration within the processed region. The goal of these closing operations is to create a more coherent representation of the selected area, addressing potential discontinuities and irregularities. The critical stage of reflection elimination follows, where targeted measures are implemented to remove or mitigate undesired reflections within the processed region strategically. The culmination of these steps yields the final output – a refined corrosion image devoid of reflections. This improved image retains the essential corrosion features, providing a more precise and more accurate representation for in-depth analysis. By systematically implementing this methodology, the process ensures the effective removal of reflections from corrosion images, contributing to an enhancement in image quality and precision in subsequent analytical endeavours.

3.4 Corrosion Image Segmentation using Chan-Vase Active Contour

In tackling the intricate task of corrosion image segmentation, this methodology adopts the robust Chan-Vese Active Contour approach to refine the precision and effectiveness of contour initialization. Figure 5 shows the methodology flowchart used for the image segmentation process.

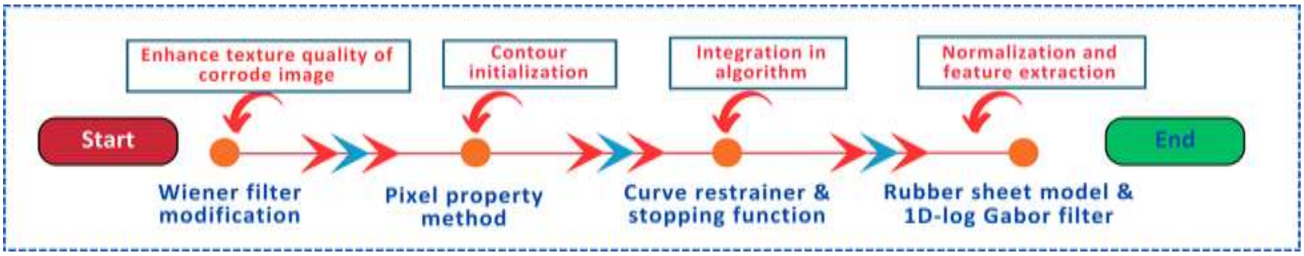


Fig. 5. Image segmentation flowchart

3.4.1 Contour mechanisms

Building upon the pixel property analysis, the methodology delves into the intricate process of contour initialization. Leveraging information obtained regarding the centroid and radius, a contour initialization is meticulously crafted for the ship corrosion image. The introduction of the function ϕ(x) assesses factors such as size and position, ensuring accurate contour initialization. This method is applied to weak and edgeless corrosion boundaries.

3.4.2 Curve restrainer and stopping function

The investigation of curve restraint and stopping functions assumes prominence in the subsequent phase of the methodology. A novel curve restrainer, δ, is introduced, formulated from rich edges and high energy levels in the ship corrosion image. This δ restrains the length of the evolution curve, contributing to more nuanced and precise contour initialization. Simultaneously, the stopping function undergoes modification to control and halt curve convergence, especially as it approaches weak and edgeless corrosion boundaries. Adjustments ensure the convergence threshold surpasses the length of the active contour. The initial active contour for this study is shown in Eq. (5),

$$AIC = \varepsilon r_p \sqrt{(x - x_P)^2 + (y - Y_P + k)^2} \tag{5}$$

3.4.3 Modification of rubber sheet model

Normalization of processed ship corrosion images is addressed through the modification of the rubber sheet model, compensating for changing angles. This model undergoes optimization by reducing the number of points for normalization.

3.4.4 1D-log Gabor filter and matching process

The subsequent application of the 1D-log Gabor filter extracts corrosion features encoded into a binary code representing pixel values in the corrosion region. The Hamming distance is then employed for the matching process.

3.4.5 Segmentation accuracy

The overall segmentation accuracy method is employed to assess the accuracy of the proposed curve restrainer and stopping function for detecting weak and edgeless corrosion boundaries. This method evaluates the similarity between images generated from the contour initialization and manually crafted ground truth images.

3.5 Evaluation Matrix

In order to evaluate the performance of the proposed method, evaluation metrics such as MAE, PSNR, MSE, MSSIM and SSIM are denoted in Eqs. (6) to (10).

$$MAE = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} |I\ (x, y) - Z(x, y)| \tag{6}$$

$$PSNR = 10. log_{10} \left(\frac{MAX^2}{MSE}\right) \tag{7}$$

Where, *M & N* = Image dimension, *I (x, y)* = pixel value of the original image, *Z (x, y)* = pixel value of the de-noised image.

$$MSE = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} [I\ (x, y) - Z(x, y)]^2 \tag{8}$$

$$MSSIM = \frac{1}{N} \sum_{i=1}^{N} \text{SSIM}\ (x_{i,}y_i\ ) \tag{9}$$

$$SSIM(x_{i,}y_i\ ) = \frac{(2\mu_x\mu_y + c_1\ )\ (2\sigma_{xy} + c_2\ )}{(\mu_x^2 + \mu_y^2 + c_1\ )(\sigma_x^2 + \sigma_y^2 + c_2\ )} \tag{10}$$

Where, μ_x & μ_y are local mean values of the pixel intensities within the image, σ_x & σ_y are local standard deviations, σ_{xy} = local cross-covariance between pixel intensities, c_1 & c_2 are constant for numerical stability.

The accuracy of segmenting each image (E_i) is displayed in Eq. (11). In this equation, m represents the image's height, n represents its width, S(x, y) denotes the segmented region and G(x, y) represents the ground-truth region. To calculate the overall segmentation accuracy (E), we average E_i across all tested images (N), as demonstrated in Eq. (12). The highest percentage of the overall segmentation accuracy signifies the most precise segmentation algorithm.

$$E_i = \frac{1}{m \times n} \sum_{x=1}^{m} \sum_{y=1}^{n} \big(S(x, y) \otimes G(x, y)\big) \tag{11}$$

$$E = \frac{1}{N}\sum_{i=1}^{N} E_i \quad (12)$$

3.6 Experimental Configuration

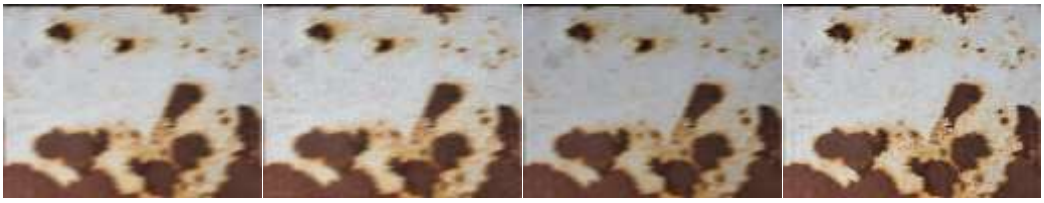
The experiment was carried out using a dataset comprising 700 ship structure corrosion images, including ship hull, deck, bow and superstructures. From this extensive dataset, 100 corrosion subjects were deliberately chosen. Each selected subject was characterized by 10 distinct positions, each highlighting similar corrosion features. This deliberate selection aimed to ensure a diverse representation of corrosion scenarios within the dataset. Notably, the chosen dataset intentionally incorporates variations in orientation, off-angle views, reflections, motion blur and non-uniform contrast, rendering it inherently noisy and posing a significant challenge for segmentation. Table 1 shows the configuration of the device utilized for this study.

Table 1
Device configurations

Title	Description
Edition	Windows 10 Pro
Processor	Intel(R) Core (TM) i7-4770 CPU @ 3.40GHz 3.40 GHz
Installed RAM	16.0 GB
System type	64-bit operating system, x64-based processor
Software	Matlab 2023b

4. Results and Discussion
4.1 Results for Image Pre-Processing
4.1.1 Deblurring

From Figure 6 (a), it can be observed that the captured ship corrosion images were affected by noise, distortion and interference during image acquisition. The ship corrosion images became blurry, reducing the visibility of corrosion boundaries. On the other hand, the corrosion features in these images have been reduced, which can decrease the number of prominent boundaries for ship corrosion segmentation.



(a) (b) (c) (d)

Fig. 6. (a) Original blurry image (b) Deblurring using [53] (c) Deblurring using [52] (d) Deblurring using the proposed method

Meanwhile, Figure 6 (b) shows the results of corrosion image deblurring [53]. That method was based on the Wiener filter and spectral extrapolation. The signal time resolution and signal-to-noise ratio (SNR) were used to improve the performance of the Wiener filter. Then, spectral extrapolation was used to detect the accurate neighbourhood of the Wiener filter. According to the results, this method managed to improve the corrosion features and boundaries of the blurry ship corrosion images, as shown in Figure 6 (b). The sharpness and visibility of the blurry images had been increased a little bit to unveil the prominent features and boundaries. This happened because the PSF was obtained from the width of blurry pixels with spectral extrapolation. The obtained PSF constraint from spectral extrapolation was more accurate than the customarily used Gaussian low-pass filter. Despite that, the changes were minimal and insufficient to be used in segmentation. Because of that, this method is not optimal for use for corrosion image deblurring. Table 2 shows the different deblurring methods' results in terms of MAE, PSNR and MSSIM.

Table 2
Comparison of deblurring methods

Methods	MAE	PSNR	MSSIM
[52]	3.84	26.98	0.88
[53]	8.93	27.92	0.91
Proposed method	1.30	37.83	0.94

Next, Figure 6 (c) shows the results of the method [52] for corrosion image deblurring. It had been developed from the combination of the Wiener filter and the median filter. In this method, the colour images were converted into grey-scale images. After that, the piecewise linear transformation and Sobel edge detector were used to improve the prominent contrast for the Wiener filter. According to the results, this method increased the sharpness and visibility of the prominent corrosion features and boundaries, as shown in Figure 6 (c). The quality of the blurry images was improved to a certain extent to unveil the prominent boundaries for segmentation. This happened because of the use of piecewise linear transformation to calculate blurry pixel width. The obtained PSF constraint was also better than the Gaussian low-pass filter. However, similar to the method [53], this method also obtained minimal changes in the quality of blurry corrosion images. Furthermore, the blurry corrosion images became darker because of colour conversion and median filter. Thus, this method is also not optimal for corrosion image deblurring.

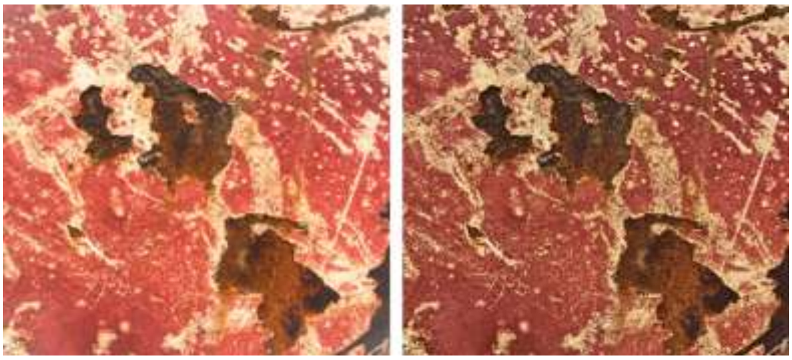
On the other hand, Figure 6 (d) shows the results of the proposed method on the blurry ship corrosion images. According to the results, the proposed method reduced the blurry effect and significantly increased the sharpness and visibility of the corrosion features and boundaries in those images. The proposed method also unveiled the prominent corrosion features and boundaries, better than the Jamaludin *et al.,* [53] and Hasan *et al.,* [52] methods. This happened because the PSF was obtained from the width of blurry pixels by specifying a certain degree of blurry pixels across the linear motion. Each blurry pixel's standard deviation and mean are estimated from the specified local neighbourhood size. Moreover, the estimated noise was calculated from the blurry pixels in order to create an accurate PSF constraint.

Other than that, the proposed method self-tuned itself by adapting to the image's local variance. This improved Wiener filter performed more smoothing when the local variance was slight. Otherwise, it performed little smoothing when the local variance was significant. This shows that the proposed method can adapt its mechanism in order to produce better corrosion features and boundaries specified by the PSF constraint. The proposed method was more selective than Jamaludin *et al.,* [53] and Hasan *et al.,* [52] methods; thus, the high-frequency parts, edges and essential characteristics from corrosion features can be restored and preserved. Thus, the improved pixel-wise adaptive Wiener filter contributed to a better technique for corrosion image deblurring.

4.1.2 Reflection removal

The experiment focused on reflection removal from ship structures' corrosion images demonstrated significant success, showcasing the effectiveness of the proposed methodology. The multi-step process involving average thresholding, measurement of pixel properties (area and pixel list), identification of the most significant area corresponding to the threshold, morphological closing and flood fill closing effectively eliminated unwanted reflections, resulting in corrosion images with improved clarity and reduced interference from reflective elements.

The initial step of inputting the corrosion images was followed by average thresholding, a critical stage in differentiating between reflection and corrosion features. The subsequent measurement of pixel properties, such as area and pixel list, facilitated the identification of the most significant area corresponding to the established threshold. This strategic approach ensured that the most significant and relevant features were retained while unwanted reflections were systematically eliminated. Figure 7 displays the outcomes of the reflection removal process.



(a) (b)

Fig. 7. (a) Original image (b) After removing the addition reflection

The application of morphological closing further enhanced the removal of detected reflections. Complementing the corrosion image, where dark regions represented reflections, facilitated identifying and enlarging bright regions. The connected morphological closing effectively filled pixels into the dark regions, eliminating reflections and enhancing the overall quality of the corrosion images. The flood fill closing step further refined the removal of reflections, contributing to a more comprehensive elimination of unwanted elements. This iterative process, tailored to the characteristics of ship corrosion images, successfully minimized the impact of reflections, resulting in corrosion images devoid of disruptive reflective interference.

According to Table 3, the reflection removal experiment demonstrated the proposed methodology's effectiveness compared to two alternative methods, labelled as Aydi *et al.,* [54] and Ali *et al.,* [55]. The key performance metrics, including average execution time, segmentation accuracy and Structural Similarity Index (SSIM), were used for a comprehensive evaluation. The proposed method exhibited a noteworthy improvement in average execution time, achieving an impressive 0.11 seconds and outperforming both Aydi *et al.,* [54] and Ali *et al.,* [55], which recorded times of 0.13 seconds and 0.14 seconds, respectively. This reduction in execution time highlights the efficiency of the approach in swiftly and effectively removing reflections from ship hull corrosion images. In terms of segmentation accuracy, the proposed method achieved an impressive accuracy rate of 97.5%, surpassing the performance of Aydi *et al.,* [54] (95%) and Ali *et al.,* [55] (94%). This enhancement underscores the efficacy of the methodology in accurately distinguishing between corrosion features and unwanted reflections, resulting in a more precise segmentation process.

Table 3
Comparison of different reflection removal methods

Methods	Average execution time (S)	Segmentation accuracy (%)	MSSIM
[54]	0.13	95	0.9868
[55]	0.14	94	0.9891
Proposed method	0.11	97.5	0.9953

Furthermore, when evaluating the SSIM, the proposed method demonstrated superior performance with a score of 0.9953, surpassing the SSIM scores of Aydi *et al.,* [54] (0.9868) and Ali *et al.,* [55] (0.9891). This signifies that the methodology not only improves accuracy but also enhances the structural similarity between the processed and ground truth images, resulting in more transparent and more visually faithful corrosion images.

4.2 Corrosion Segmentation

The application of Chan-Vase Active Contour for initial contouring in ship corrosion images exhibited notable efficacy. Figure 8 showcases the initial contouring process, where contours are overlaid onto the ship corrosion images. In Figure 8, the initial contours are visualized in red, providing a clear representation of the starting points for the subsequent segmentation process. The Chan-Vase Active Contour method successfully initialized contours around the corrosion regions, effectively capturing the intricate details of the corrosion boundaries.

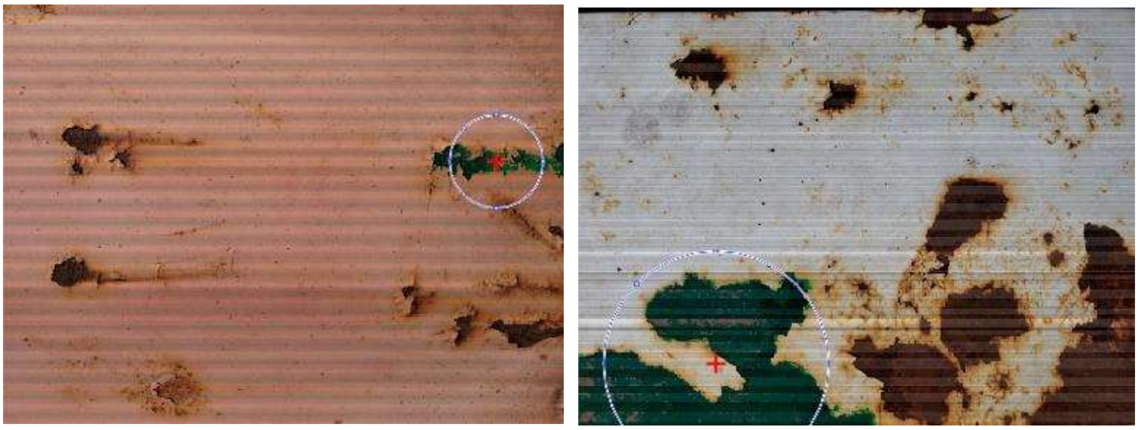


Fig. 8. Initial contour visualization

The initial contours, generated by the Chan-Vase Active Contour, strategically adapt to the underlying features of the corrosion regions. This adaptability is crucial for initiating the segmentation process accurately, as the contours align with the nuanced shapes and boundaries of the corrosion areas. Moving beyond the initial contouring, the Chan-Vase Active Contour method demonstrated robust performance in segmenting ship corrosion images. Figure 9 presents the segmentation results, illustrating the contours delineating the corrosion boundaries effectively.

Fig. 9. Corrosion image segmentation results

As depicted in Figure 9, the segmentation results reveal the contours (depicted in red) accurately encapsulating the corrosion regions. The Chan-Vase Active Contour method adeptly distinguishes between corrosion and non-corrosion elements, showcasing its capability to identify the extent of corrosion in ship hull images precisely. Additionally, Figure 9 provides a closer look at the detailed segmentation output, emphasizing the method's proficiency in capturing intricate corrosion boundaries. The segmentation results emphasize the Chan-Vase Active Contour's effectiveness in accurately delineating corrosion boundaries in ship structure images. The contours adapt dynamically to corrosion regions' varying shapes and sizes, showcasing the method's adaptability and precision.

Furthermore, in evaluating the performance of the proposed method, we utilized a confusion matrix to quantify the model's classification accuracy across multiple corrosion datasets. In Figure 10, the diagonal elements of the matrix revealed high true positive rates, demonstrating the model's strength in correctly identifying distinct corrosion states. Notably, dataset 7 was most frequently observed with 356 correct predictions, indicating a high presence and accurate detection of this particular corrosion state within the dataset. The precision and recall rates were calculated for each condition, denoting the algorithm's capability to precisely predict a condition (precision) and its effectiveness in capturing all actual instances of a condition (recall). For instance, the model achieved 94.5% recall for condition 0, reflecting its high sensitivity in detecting this specific corrosion state. Precision ranged from 79.2% for dataset 15 to 96.2% for dataset 7, suggesting that the model is generally reliable in its predictions but can benefit from further refinement for certain datasets.

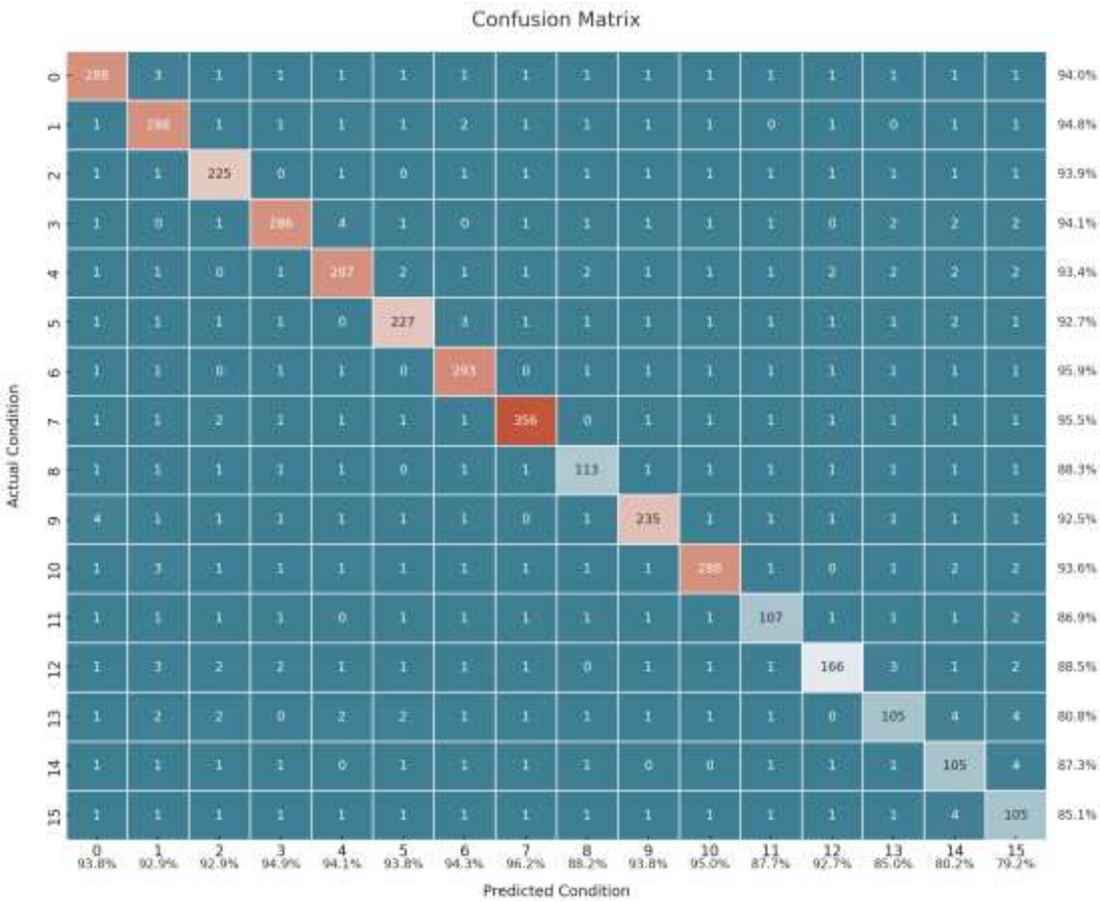


Fig. 10. Confusion matrix

As illustrated in Table 4, the proposed Chan-Vase Active Contour method demonstrates superiority in both segmentation accuracy and execution time when compared to Chang *et al.,* [56] and Jalal *et al.,* [57]. The proposed method achieved an outstanding segmentation accuracy of 94.45%, outperforming Chang *et al.,* [56] (85.98%) and Jalal *et al.,* [57] (89.32%). This substantial improvement underscores the efficacy of the Chan-Vase Active Contour in accurately delineating corrosion boundaries within ship structure images. Additionally, the proposed method exhibited notable efficiency in execution time, recording a time of 0.91 seconds. In comparison, Chang *et al.,* [56] and Jalal *et al.,* [57] registered longer execution times of 1.23 seconds and 1.49 seconds, respectively. The reduced execution time of the proposed method reflects its computational efficiency in processing corrosion images and achieving accurate segmentation.

Table 4
Segmentation results using different methods

Method	Accuracy, %	Time, s
[56]	85.98	1.23
[57]	89.32	1.49
Proposed method	94.45	0.91

5. Discussion

The investigation into the utilisation of active contour algorithms for ship corrosion detection has produced encouraging outcomes, showcasing a notable level of accuracy and effectiveness in identifying areas of corrosion on marine vessels. The effective utilisation of the Chan-Vese Active

Contour model, along with strong image pre-processing techniques, represents significant improvement in the automated visual examination of ship corrosion.

The proposed method achieved segmentation accuracy of 94.45% indicates a significant enhancement compared to existing methodologies [56-59]. The improvement in accuracy of corrosion detection can be credited to the careful pre-processing of images, which successfully addressed problems such blurring and reflections that have traditionally impeded accurate detection of corrosion. The utilisation of the Chan-Vese Active Contour model for contour initialization and segmentation highlights the capability of active contour algorithms in addressing the difficulties posed by ambiguous and weak corrosion boundaries. Furthermore, the proposed method demonstrates high efficiency, both in terms of accuracy and execution time (0.91 seconds), indicating the capabilities of utilizing huge datasets in short time.

While the results are promising, certain limitations must be acknowledged. The study's scope was primarily focused on image-based detection, which may not fully encapsulate the complexity of corrosion as it occurs in varying environmental conditions and on different ship materials. Additionally, the performance of the proposed method in scenarios of extreme corrosion or minimal visible corrosion has not been extensively tested, indicating a need for further validation across a broader spectrum of corrosion stages.

6. Conclusion

In conclusion, this research has made significant strides in addressing the critical issue of ship corrosion detection. Corrosion remains a persistent challenge for the structural integrity of marine vessels, demanding advanced inspection and maintenance methodologies. Existing automated visual inspection techniques often struggle to accurately identify corrosion boundaries, particularly under challenging image conditions. Our investigation into contour initialization's robustness and active contour algorithms' application has yielded promising outcomes. The proposed methodology, which incorporates texture enhancement, innovative contour initialization techniques and feature extraction, has demonstrated an impressive segmentation accuracy of 94.45%.

In the pursuit of advancing ship corrosion analysis and detection, several avenues of future research merit exploration. First and foremost, there is a need for continued refinement and innovation in contour initialization techniques. Investigating the application of advanced machine learning and artificial intelligence methods, such as deep learning, for automated contour initialization can enhance precision and reduce the reliance on manual intervention. Additionally, exploring the potential benefits of multi-sensor fusion, including visual and non-visual sensors like ultrasonic and thermal imaging, holds promise for improving corrosion detection accuracy and reliability in diverse maritime environments.

Furthermore, future research should prioritize comprehensive real-world testing and validation of the proposed methodology across various ship types, underwater structures, offshore oil and gas structures. This rigorous assessment is essential to confirm the robustness and generalizability of the corrosion detection system. To facilitate practical adoption, developing user-friendly interfaces and software tools tailored to ship maintenance personnel is advisable, ensuring accessibility for routine inspections.

Future studies should conduct thorough cost-benefit analyses to establish the economic and environmental advantages of implementing advanced corrosion detection systems. Such analyses should consider factors such as reduced maintenance costs, extended vessel lifespan and minimized environmental impact, providing stakeholders with a clear understanding of the technology's long-term benefits. Exploring cross-industry applications for the developed techniques in other sectors grappling with corrosion-related challenges, such as offshore structures, pipelines and infrastructure, can broaden the impact of this research. Lastly, integrating machine learning algorithms for automatic corrosion severity assessment and prediction should be investigated to enable more proactive and data-driven maintenance strategies. In summary, future research endeavours should focus on these recommendations to further enhance the capabilities of ship corrosion detection technologies, contributing to safer, more sustainable and cost-effective practices in the maritime industry and beyond.

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