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Accurate Corrosion Detection and Segmentation on Ship Hull with Pixel Property Method

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ABSTRACT

The ship's hull is primarily exposed to salt-laden sea spray and high moisture, making it susceptible to corrosion. This has become a major issue in the shipping industry, as corrosion weakens the ship's structural integrity, necessitating expensive maintenance and posing safety concerns. Despite the latest advancements in corrosion maintenance technology, it is essential to detect corrosion as early as possible using computer vision or image processing techniques. However, both approaches have limitations when it comes to detecting weak corrosion boundary and blurry prominent corrosion features. Therefore, the primary objective of this research is to accurately detect corrosion boundaries on the ship's hull using pixel property method. Firstly, data acquisition is performed to identify suspected corrosion regions on the ship's hull. Next, a threshold is calculated by averaging 100 corrosion images of the ship's hull. Afterward, each pixel in the image is analysed to determine the connected components of the corrosion areas. The pixel list and area coordinates are collected after analysing all connected components. Large connected components are merged into a single larger region using morphological closing and flood-fill operations. Finally, the pixel property method is applied using the pixel list and area coordinates to accurately detect corrosion boundaries on the ship's hull. According to the results, the proposed method successfully detected corrosion regions on the ship's hull with a high level of accuracy. Furthermore, the robustness of this method was demonstrated by its ability to segment the weak corrosion boundary and blurry prominent corrosion features on the ship's hull. These findings indicate that the proposed method is highly accurate for detecting corrosion on ship hulls.

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1. Introduction

Corrosion is a natural process that involves the gradual deterioration or destruction of materials, typically metals, due to chemical reactions with their surroundings [1]. This phenomenon is often linked to the interaction between metal surfaces and substances such as oxygen, water, acids or salts. Corrosion can result in the weakening, rusting or disintegration of metal objects or structures over time [2]. It poses a significant concern across various industries and can be expensive to mitigate or prevent, as it has the potential to inflict damage on infrastructure and equipment [3]. Corrosion presents a series of substantial challenges and risks to marine structures, infrastructure and transportation, including ships, vessels and boats, which are continually exposed to the corrosive marine environment. The ship's hull, in particular, is constantly exposed to salt-laden sea spray and high moisture levels, making it susceptible to corrosion [4]. Its repercussions encompass diminished structural integrity, heightened maintenance expenses, reduced lifespan, safety hazards, environmental impacts, disruptions in navigation and economic costs.

In recent years, there has been extensive research into new methods of corrosion detection, particularly in the realms of computer vision and image processing [5]. Computer vision and image processing techniques have emerged as comprehensive and valuable approaches for assessing, monitoring and managing the impact of corrosion on a ship's hull and metallic components. This approach involves various steps, including the acquisition of digital images, pre-processing to enhance image quality, segmentation to isolate areas of interest, feature extraction to characterize corrosion patterns, corrosion detection and quantification and the visualization and reporting of results. This technology not only aids in identifying and evaluating corrosion but also supports proactive maintenance and decision-making, contributing to the safety, reliability and longevity of maritime vessels in the challenging marine environment [6]. Furthermore, the primary features of computer vision and image processing for corrosion detection are based on the colour and texture of surfaces [7].

In the literature, a wide range of computer vision and image processing techniques have been employed for detecting cracks and corrosion on ships and vessels. Several computer vision methods [8-10] have been tailored for crack detection on concrete surfaces with elongated and narrow shapes, while image processing techniques have been applied to detect corrosion on metallic surfaces, such as ship hulls and decks. Previously, the image processing method known as the saliency mechanism was introduced by Bonnin-Pascual *et al.,* [11] and it has been demonstrated to provide superior precision in corrosion detection compared to other conventional approaches based on texture and colour. This method utilizes symmetry and contrast as features to filter out non-defective areas in vessel structures. A Bayesian framework and probability density function were employed to combine both top-down and bottom-up saliency for the detection of corrosion and coating breakdowns. Comprehensive reviews of the saliency mechanism for corrosion detection can be found in papers by various authors [12,13]. Meanwhile, Jamaludin *et al.,* [14] utilized an active contour method to accurately segment the corrosion boundaries in noisy and blurry images of ship corrosion. Both pre-processing and segmentation methods were employed, specifically the Wiener filter to eliminate Gaussian noise and blurry elements in the image. Subsequently, active contour techniques were applied to refine the remaining boundaries for detecting defective areas. The results indicated that the performance of the proposed method improved when the corrosion boundaries were clear and prominent. Detailed reviews of the active contour segmentation can be found in research papers [15-17].

Nevertheless, both methods are contrast dependent. Generally, corrosion images are captured in non-cooperative and uncontrolled environments due to factors such as sunlight, illumination and wave conditions. The camera's position, lighting conditions and distance all play a significant role in creating ideal datasets. These conditions can affect the image quality by introducing non-uniform contrast, potentially reducing the effectiveness of both methods. Consequently, both techniques have limitations when it comes to detecting weak corrosion boundaries and blurry prominent corrosion features. Moreover, the RGB (red, green and blue) and HSV (Hue, Saturation, Value) colour spaces require conversion for corrosion detection, which can increase computational complexity and, in turn, affect execution time. In addition, both methods employ two approaches; texture and colour features for corrosion detection in corrosion images. This necessitates more execution time to identify the defective and non-defective areas due to the additional processes and complex algorithms required for corrosion identification. Therefore, this research makes significant contributions in terms of segmenting weak corrosion boundaries and blurry prominent corrosion features in ship hull corrosion images while maintaining a fast-processing time. As a result, the research's objective is to accurately detect corrosion boundaries on ship hulls with minimal processing time using the pixel property method.

2. Methodology

2.1 Image Acquisition

Firstly, digital images of ship hull corrosion will be captured using a camera. Several ships and boats will be selected for collecting these corrosion images, with the assistance of a corrosion inspector. These images will be organized into a dataset in both jpeg and tiff formats, with a resolution of 640 x 480 pixels. Ideally, the captured images should be free from any noise or interference [18]. However, in a real-world environment, noise and interference are common in images due to factors such as illumination, sensor size and target distance. Typical types of noise in digital images include Gaussian, impulse, Poisson, speckle, salt-and-pepper, shot, quantization, film grain, anisotropic and periodic noise [19-23]. Since this research aims to investigate the robustness of the proposed algorithm in non-cooperative and uncontrolled environments, these types of noise will be prevalent in the collected dataset. The selected corrosion images are illustrated in Figure 1.

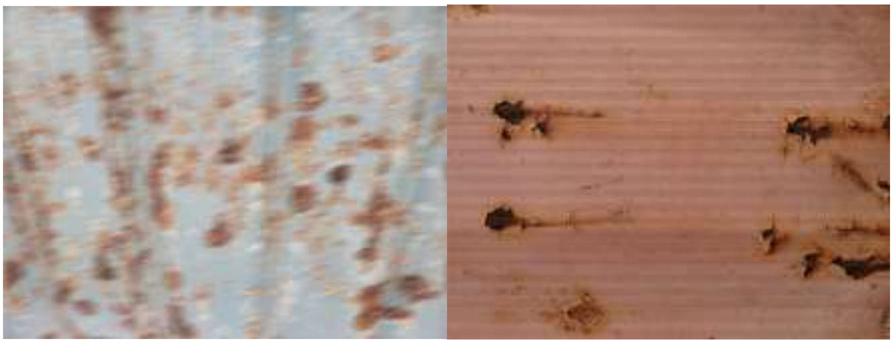


Fig. 1. Noisy corrosion images in the collected dataset

2.2 Pre-Processing with Wiener Filter

Pre-processing involves a set of techniques and operations applied to an input image before the actual analysis or manipulation of the image's content [24]. The primary objective of pre-processing is to enhance the image's quality, make it more suitable for a specific task or eliminate unwanted artifacts or noise. Pre-processing plays a pivotal role in object detection, including corrosion detection [25]. Therefore, pre-processing is essential for improving the quality of corrosion images in the collected dataset.

In this research, the Wiener filter will be employed to deblur noisy corrosion images. The Wiener filter is a deconvolution technique that can reduce image blurriness by estimating and reversing the effects of blur in the frequency domain [26]. This method is effective when a good estimate of the point spread function (PSF) and noise characteristics are available. However, it may have limitations in real-world scenarios where blur and noise patterns are complex or unknown. Consequently, this research will modify the existing algorithm to determine suitable parameters for unknown blur, estimated PSF and noise patterns. Striking the right balance between reducing blur and avoiding noise amplification in the process is crucial. Figure 2 illustrates an example of a pre-processed image using the Wiener filter for a corrosion image on a ship hull.

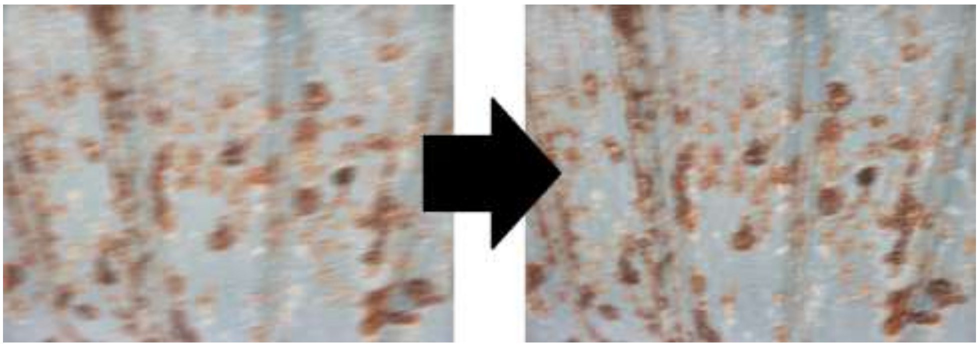


Fig. 2. Pre-processing corrosion image from left to right

2.2.1 Blur element identification

Firstly, the blur element is identified from defocus and motion blur elements. Since the images are captured using a digital camera while ships and vessels are docked and moored, they are often affected by motion blur. Therefore, motion blur is more commonly associated with the images in the dataset. Following this, the PSF is determined by estimating how a point source of light is spread in the image. The estimated PSF will be used for comparison with the noisy corrosion image.

2.2.2 Frequency domain conversion

Next, the Fast Fourier Transform (FFT) is applied to convert both the estimated PSF and the noisy corrosion image from the time domain to the frequency domain. FFT is chosen for its higher efficiency compared to the more commonly used Fourier Transform (FT).

2.2.3 Noise power spectrum (NPS) estimation

Following that, the power spectral density (PSD) is computed based on the distribution of noise power across multiple frequencies. The characteristics of the noise are estimated using statistical distribution and additive noise. Additive noise is a basic noise model that simulates noises occurring in nature.

2.2.4 Filter calculation

Then, the Wiener filter [27] is used to attenuate the low frequency components and amplify the high frequency components of the noisy corrosion image. The formula for the Wiener filter, denoted as *H (w)* is defined in Eq. (1):

$$H(w) = \frac{G(w)}{G(w)+N(w)} \quad (1)$$

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

2.2.5 Filter employment

For filter employment, the point-wise (element-wise) multiplication is used where the Wiener filter is multiplied with the Fourier transform of the noisy corrosion image. Both elements must be in the frequency domain.

2.2.6 Inverse Fourier transform

Finally, the inverse Fourier Transform is applied to the product of the filter employment in the spatial domain. This process enhances the quality of the noisy corrosion image in the dataset, reducing the blur effect to reveal the prominent corrosion features in the image.

2.3 Corrosion Segmentation with Pixel Property

The pixel property method is a computational technique used to determine pixel values in digital images [28]. This method is employed for image segmentation because it can precisely identify the location of each individual pixel in an image. Its algorithm calculates the boundary, centroid and area of all connected components in both contiguous and non-contiguous regions of an image. Additionally, it can measure circularity, convex area, convex hull, eccentricity, Euler number, extrema points, ferret properties orientation, perimeter, pixel list and solidity in an image.

In this research, the pixel property method is employed to accurately segment corrosion regions in ship hull images. Pixel property is a valuable technique for assessing corrosion pixels in images. However, non-uniform and mixed contrast can lead to incorrect identification of corrosion and non-corrosion pixels. As a result, this research will enhance the existing algorithm to effectively differentiate between corrosion and non-corrosion pixels in images. The steps involved in the pixel property method are explained in the following subsections.

2.3.1 Assign threshold

Firstly, a set of 100 ship hull corrosion images from the dataset is used for training to obtain a specific threshold. Assigning a threshold is necessary because the non-uniform and mixed contrast present in each corrosion image can compromise the accuracy of corrosion region segmentation. Contrast normalization based on the assigned threshold helps reduce segmentation errors in images with non-uniform and mixed contrast. Subsequently, all values from the training are averaged to calculate and establish the threshold. The formula for the assigned threshold, denoted as *T* is defined in Eq. (2):

$$T = \frac{1}{n}\sum_{i=1}^{n} a_i \quad (2)$$

Where, a_i is the contrast threshold of corrosion image, *i* and *n* is the number of ship hull corrosion images.

2.3.2 Pixel list

Subsequently, pixel properties of image regions are measured based on the assigned threshold. This method supports pixel properties for both contiguous and discontinuous regions. It measures only connected components, blobs and objects while ignoring others. All connected components, blobs and objects are also defined as a set of foreground pixels in a binary image. Following that, pixel neighbourhood connectivity is determined using the assigned threshold. Pixel neighbourhood connectivity specifies which other pixels each pixel is connected to. In this research, 8-connected neighbourhoods are used for pixel neighbourhood connectivity to accurately measure unique objects in 2-D corrosion images. This is particularly suitable for 2-D images where pixels are considered connected if their edges or corners touch. Two adjacent pixels are considered part of the same object if they are both on and connected along the horizontal, vertical or diagonal directions [29]. On the other hand, 4-connected neighbourhoods are less effective in this research because pixels are connected only if their edges touch. Two adjacent pixels are part of the same object if they are both on and connected along the horizontal or vertical direction [30]. The choice of pixel neighbourhood connectivity is crucial as it can influence the boundaries and the number of connected components in an image. Therefore, post-processing in the pixel property method may vary depending on the selected pixel neighbourhood connectivity.

2.3.3 Corrosion seed

From the obtained pixel list, only the properties of centroid, area and pixel coordinate are selected to determine the corrosion seed in the ship hull corrosion images. These properties are measured for each connected component, object and labelled region of both binary and grayscale images. The objects in the binary image are sorted from left to right based on the top-left extremum of each component. In cases where multiple objects share the same horizontal position, the function then sorts those objects from top to bottom and again along any higher dimensions [31]. The centroid, area and pixel coordinates of all connected components, blobs and objects in the image are analysed to determine the largest corrosion region in the image. Finally, the identified largest corrosion region in the image is designated as the corrosion seed. The corrosion seed, C_S is defined in Eq. (3):

$$C_S = \sum_{i=1}^{n} C_i \qquad (3)$$

Where, C_i is the corrosion region in the corrosion image, *i* and *n* is the total number of detected corrosions in the corrosion image, *i*.

2.3.4 Post-processing

After the corrosion seed and all corrosion regions are detected, post-processing steps involving morphological closing and flood-fill are applied to enclose and delineate the boundaries of each corrosion region in the image. Firstly, the corrosion image is complemented and expanded to connect all bright regions within the detected connected components, blobs and objects using morphological closing. Subsequently, flood-fill is employed to fill all dark regions with the nearest neighbour pixel. Both methods utilize 4-connected neighbourhoods for pixel neighbourhood connectivity. The morphological closing is the closing of an image, *A* by a structuring element, *B* as defined in Eq. (4):

$$A \bullet B = \left(A \oplus B\right) \Theta B \tag{4}$$

Where, $\oplus$ is the dilation and $\ominus$ is the erosion.

2.3.5 Develop skeleton and curvature data

Finally, the accurate corrosion regions are obtained by developing boundaries from the skeleton and curvature data. These boundaries are generated during the post-processing stage for both the corrosion seed and the corrosion regions within the image. The skeleton and curvature data of the corrosion regions are then derived from these created boundaries, allowing for the distinction between the corrosion and non-corrosion regions in the ship hull corrosion image. This approach enables a more in-depth exploration of the prominent corrosion features, facilitating the extraction of additional corrosion characteristics from the images.

2.4 Experimental Configuration

The configuration of the experimental setup, including the workstation, software and hardware, is detailed in Table 1. An experiment was conducted using a dataset consisting of 500 ship hull corrosion images. Within this dataset, 50 corrosion subjects were selected, with each subject featuring 10 different positions showcasing similar corrosion features. The selected dataset exhibits variations in orientation, off-angle views, reflections, motion blur and non-uniform contrast, making it inherently noisy and challenging to segment.

Table 1
Experimental setup

Environment	Configuration
Operating system	Windows 8.1, 64-bit
Processor	Intel Core i5-4690K
Graphic unit	GTX 960, 4 GB DDR5
Memory	16 GB DDR3, 1600 MHz
Software	Matlab 2023b

2.5 Performance Evaluation

The performance of the proposed method is assessed through both qualitative and quantitative evaluations. In the qualitative evaluation, precise corrosion boundaries are visually presented for the ship hull corrosion images. All corrosion regions are displayed using the *vis boundaries* function, while the non-corrosion regions are excluded. Meanwhile, for quantitative evaluation, the segmentation accuracy and execution time are calculated based on the images. The formula for segmentation accuracy, S_i is defined in Eq. (5):

$$S_i = \frac{1}{r \times c} \sum_{x=1}^{r} \sum_{y=1}^{c} \left(I(x,y) \otimes G(x,y)\right) \tag{5}$$

Where, *I(x,y)* is the segmented ship hull corrosion image, *G(x,y)* is the ground-truth image, *r x c* is the image resolution in pixels, *r* is the row of the image and *c* is the column of the image [32]. The ground-truth image comprises manually created corrosion boundaries using a human interface. Both *I(x,y)* and *G(x,y)* are Boolean XORed to determine the segmentation accuracy of the proposed algorithm.

After that, the average segmentation accuracy, S is computed by averaging S_i over N. The formula for this calculation is defined in Eq. (6),

$$S = \frac{1}{N}\sum_{i=1}^{n} S_i \tag{6}$$

Where, N is the total number of ship hull corrosion images. In this study, 500 images were used in the experiment, so N = 500. However, the number of images can be increased based on the preliminary segmentation accuracy results.

The stopwatch timer function in Matlab is used to measure the time performance of the proposed algorithm. It records the current time and then utilizes the recorded value to calculate the elapsed time. This function is called multiple times to calculate the median of the measured time. It also computes the individual CPU time for each thread and sums across all threads. In order to improve the time measurement efficiency, the developed algorithm is put into a function instead of measuring it in a script or command line of Matlab.

3. Results

3.1 Corrosion Segmentation

The results of corrosion segmentation on selected ship hull images are illustrated in Figure 3.

(a)

(b)

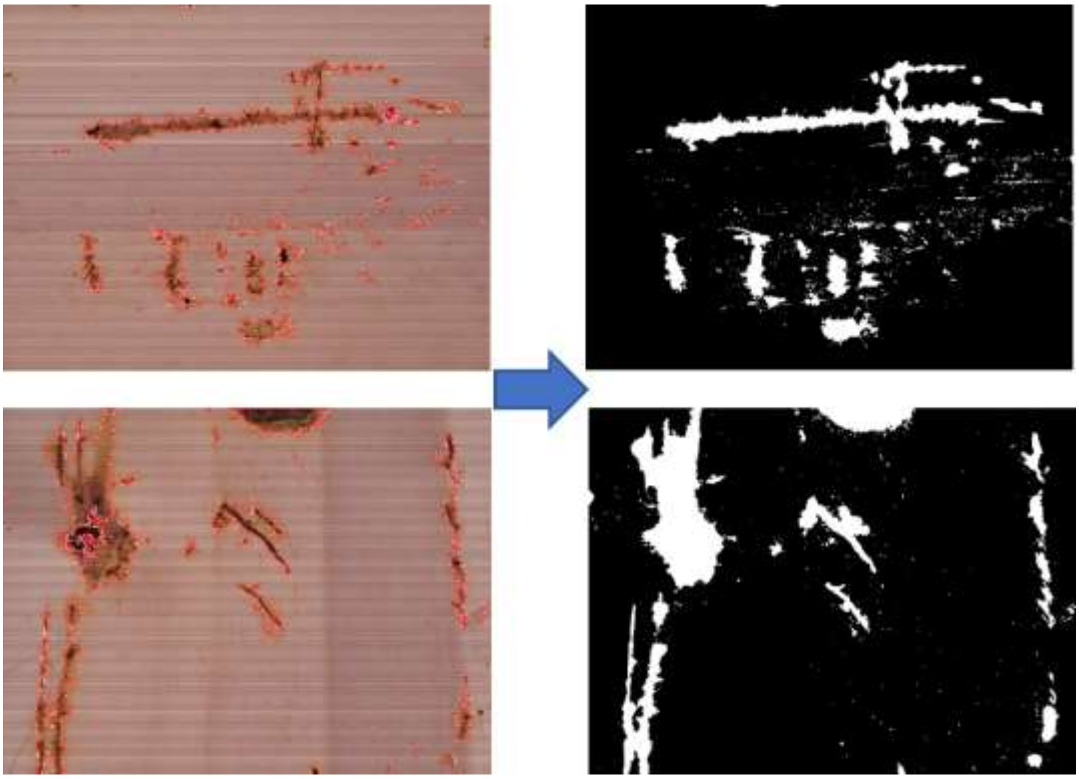
(c)

Fig. 3. Corrosion segmentation results (a) before segmentation (b) after segmentation (c) corrosion levels

According to Figure 3(b), the proposed method successfully segmented accurate corrosion boundaries in the ship hull corrosion images. The algorithm effectively detected the prominent corrosion boundaries of small, medium and large corrosion regions in the images. Surprisingly, it also identified weak (green), moderate (orange), high (yellow) and severe (red) levels of corrosion regions while excluding low-level corrosion regions from its detection as shown in Figure 3(c). Furthermore, the proposed method not only recognized clear boundaries and distinctive shapes of corrosion regions but also detected weaker boundaries and complex shapes in the images. It could localize multiple corrosion regions that intersected with each other and differentiate non-corrosion elements such as stamping marks, scratches and rough surfaces, leaving them out from the detection. On the other hand, the algorithm effectively excluded the effects of coating and paint bubbling, blistering, chipping and peeling from automatic detection. It also remained efficient regardless of different colour schemes on the ship hull surfaces, not detecting darker colour schemes as corrosion regions in the images. Consequently, shadow and non-uniform contrast in the images were also excluded from the detection. The presence of periodic noise in the images did not trigger false detections as corrosion boundaries. Even though periodic noise contained numerous prominent horizontal boundaries, the algorithm managed to discriminate against them. Moreover, the algorithm successfully characterized blurry prominent corrosion features. The motion blur in the images was reduced using the Wiener filter, allowing the algorithm to detect the blurry corrosion boundaries. It's worth noting that the developed algorithm was only implemented on corrosion images in RGB format. This streamlined the complexity of the algorithm by avoiding the need for multi-conversion into various colour spaces such as binary, grayscale, XYZ (X, Y and Z axis), HSL (hue, saturation and lightness), HSV (hue, saturation and value), YUV (Y component luma and two chroma components U and V), YCbCr (luma component, blue-difference and red-difference chroma) and CMYK (cyan, magenta, yellow and key) for each image in the dataset.

Several factors may contribute to the obtained results. Firstly, the proposed method managed to segment the accurate corrosion boundaries with multiple interference and noise in the images because of the effectiveness of pixel property method in predicting and then calculating corrosion seed. The obtained corrosion seed determined the most corroded region in the image. Then, the remaining corroded regions in the image were detected from the corrosion seed. The origin of corrosion searching direction also started from the corrosion seed. The accurate corrosion segmentation also contributed from the contrast normalization from the assigned threshold. The proposed contrast normalization helped the algorithm to deal with the non-uniform and mixed contrast in the images. It normalized the surface contrast and managed to improve the quality of corrosion surface. Consequently, even weak corrosion boundaries in the images could be detected as reported in Jamaludin *et al.,* [33]. It's worth noting that this method shares similarities with machine learning and deep learning techniques that employ training samples to train algorithms and gain knowledge. However, our training approach was more precise, as it combined computer processing with a knowledge-based model of corrosion experts, rather than relying solely on computer calculations and processing. Furthermore, the proposed algorithm benefited from efficient pre-processing to mitigate the effects of motion blur on the images. This significantly improved the algorithm's ability to detect blurry prominent corrosion features in the images. Post-processing also played a vital role in closing and delineating the boundaries of each corrosion region within the images, enhancing the detection quality of the pixel property method, particularly for discriminating moderate, high and severe levels of corrosion features. This finding aligns with the work reported in Jamaludin *et al.,* [33], which emphasizes that post-processing can enhance detection quality. However, it's important to note that the detection of corrosion rate levels was not addressed in their study. Therefore, in this research, the proposed method has made a significant contribution to improved detection quality by effectively distinguishing moderate, high and severe levels of corrosion features, while excluding low-level corrosion regions from its detection mechanism.

Meanwhile, Figure 4 illustrates the process of detecting corrosion boundaries in the ship hull corrosion images. In Figure 4(a), the detected corrosion regions are displayed, with red markers representing boundaries derived from the skeleton and curvature data. The skeleton and curvature data of the corrosion regions played a critical role in distinguishing between corrosion and non-corrosion regions in the images, revealing the prominent corrosion features. Meanwhile, Figure 4(b) shows the skeleton and curvature data from the pixel property method. The origin or starting point of the algorithm to search the moderate, high and severe levels of corrosion regions initiated from the corrosion seed. Then, the algorithm grew outward or expanded from the corrosion seed until it reached the maximum limit of image boundaries. During this process, it calculated and analysed every pixel within the search region to locate every corrosion region accurately. For that reason, the algorithm successfully detected the remaining corrosion regions in the images.



(a) (b)

Fig. 4. Corrosion segmentation result (a) Created boundaries (b) Corrosion regions with pixel property

In summary, the proposed method successfully detected weak corrosion boundaries and blurry prominent corrosion features in the ship hull corrosion images using the pixel property method. This achievement can be attributed to the accuracy of the proposed method in determining the corrosion seed, which serves as the foundation for locating other corrosion regions within the images. This underscores the precision and robustness of the proposed algorithm in detecting moderate, high and severe levels of corrosion regions even in cases with weak boundaries and blurry images. Next, the quantitative evaluation of the proposed method will be presented and discussed.

3.2 Quantitative Evaluation

The results of segmentation accuracy and execution time of the proposed method are provided in Table 2. The other methods in the literature are also compared in order to gain a better understanding of the performance and processes of each investigated method. The proposed method is validated with Bonnin-Pascual *et al.,* [11] of saliency mechanism and Jamaludin *et al.,* [14] of active contour.

Table 2
Comparison of segmentation accuracy and execution time

Method	Accuracy, %	Time, s
Bonnin-Pascual *et al.,* [11]	83.78	1.43
Jamaludin *et al.,* [14]	88.71	1.33
Proposed method	93.83	0.91

According to Table 2, the proposed method achieved the highest segmentation accuracy than the other investigated methods. The proposed method recorded 93.83% segmentation accuracy. The closest one was Jamaludin *et al.,* [14] with 88.71% accuracy. Meanwhile, the method of Bonnin-Pascual *et al.,* [11] only recorded 83.78% accuracy. A higher value of segmentation accuracy percentage indicates a better segmentation process between the ground-truth image and input image. Other than that, it also indicates a better corrosion detection and segmentation ratio on the corrosion images. Any method with segmentation accuracy value above 90% is considered the most accurate segmentation method or algorithm. The proposed method recorded the highest accuracy because of the highest conflicting pixels calculated from the ground-truth and input images. The other factors contributed to the higher segmentation accuracy of the proposed method have been discussed earlier in subsection 3.1.

As regards to execution time, the proposed method also exhibited the fastest processing time compared to the other methods. Specifically, the proposed method achieved an execution time of 0.91 seconds. The closest competitor was Jamaludin *et al.,* [14], with a processing time of 1.33 seconds. Meanwhile, the method proposed by Bonnin-Pascual *et al.,* [11] recorded an execution time of 1.43 seconds. A lower value of execution time indicates a more efficient and faster implementation of the investigated algorithm for accurately segmenting corrosion regions in ship hull corrosion images. Conversely, a higher value suggests a slower process and greater computational complexity of the detection algorithm. This evaluation is crucial for assessing the scalability and efficiency of the algorithms, enabling researchers to optimize performance and identify potential bottlenecks.

Several factors may contribute to the obtained results. Firstly, the proposed method featured a less complex algorithm with fewer operations executed for detecting corrosion boundaries in the images. The proposed method used the pixel property method and employed less complex pre-processing and post-processing techniques for corrosion detection. Additionally, the proposed method required a simple conversion between RGB and binary colour space for skeleton and curvature data, thereby reducing execution time. Other than that, the searching region for corrosion detection was minimized with corrosion seed. The searching region was determined, controlled and selected by the obtained corrosion seed. Because of that, the algorithm was not implemented to the entire image, thus reduced its computation. Contrast normalization also played an important role to reduce the complexity of the proposed algorithm. Less computation and processes were used as the contrast normalization allowed the algorithm to easily segment the foreground and background images with a minimum contrast difference. This finding aligns with the work reported in Hasan *et al.,* [34], which highlights that detection algorithms with fewer operations and lower computational complexity tend to have shorter running times. However, it's important to note that the impact of detecting moderate, high and severe corrosion levels on the algorithm's complexity was not previously addressed. Therefore, this study contributes to the understanding that corrosion level detection does not affect the computational complexity of the detection algorithm, a point that has not been mentioned before. Additionally, the size of the input images in the dataset (640 x 480 pixels) also played a role in reducing the computation time of the proposed algorithm. The size of an input image in proportion to the number of operations of an algorithm also affects the algorithm's computation time, as demonstrated in a study reported in Jamaludin *et al.,* [35]. However, it's worth noting that the impact of the corrosion seed on corrosion search time with different image sizes had not been previously addressed [36-38]. Therefore, this study contributes to the understanding that an accurate corrosion seed can effectively reduce corrosion search times, even with varying image sizes.

On the other hand, Bonnin-Pascual *et al.,* [11] and Jamaludin *et al.,* [14] achieved lower segmentation accuracy and longer execution times than the proposed method. This can be attributed to the techniques employed by Bonnin-Pascual *et al.,* [11], who used a saliency mechanism for corrosion detection. This segmentation method combined both symmetry and contrast information for corrosion detection. However, some corrosion regions may presence in the low contrast regions in the images and these regions cannot be excluded from the corrosion detection. Because of that, this algorithm obtained a lower segmentation accuracy in the dataset. In terms of execution time, this method recorded a lower execution time than the proposed method because of the Bayesian framework and probability density function. Both techniques performed training on contrast and symmetry information, which required more processes than the training in the proposed method. Moreover, both top-down and bottom-up saliency were utilized for image reconstruction. In contrast, the proposed method selected only a few image regions from the corrosion seed, resulting in a faster processing time. Because of these factors, the saliency mechanism method was slower than the proposed method. Meanwhile, Jamaludin *et al.,* [14] used active contour to segment corrosion boundaries on the ship hull images. This segmentation method required a number of iterations or loops to accurately segment corrosion regions. The high number of iterations increased the algorithm's execution time, which also increased its computational complexity. Additionally, this method involved more operations to implement the active contour algorithm, further extending its execution time. In terms of segmentation accuracy, this method achieved respectable results. However, it was highly dependent on the initial contour and an inaccurate positioning of the initial contour could lead to reduced segmentation accuracy. Hence, active contour was found to be very sensitive to contour initialization.

Overall, the proposed method achieved the highest segmentation accuracy and the fastest execution time for corrosion detection on ship hull corrosion images using the pixel property method. This occurred because of the effectiveness in detecting corrosion regions even in low contrast areas of the images. Additionally, the proposed method featured fewer operations and a less complex algorithm compared to other methods. These findings highlight the accuracy of the pixel property method in accurately segmenting corrosion boundaries in ship hull corrosion images while maintaining a speedy execution.

4. Conclusions

Corrosion has become a major issue in the shipping industry as corrosion weaken the strength of the ship's construction. Despite the emerging of image processing, there are many limitations for corrosion detection in terms of segmentation accuracy and quality. Therefore, this paper proposes the use of the pixel property method for detecting corrosion, particularly focusing on weak corrosion boundaries and blurry prominent corrosion features in ship hull images. Firstly, several ships and boats are chosen for the collection of corrosion images. After that, pre-processing, pixel property method and post-processing are employed to the images. Other than pixel property method, it also consists of Wiener filter, morphological closing and flood-fill techniques. Finally, the proposed method is evaluated in terms of segmentation accuracy and execution time. The experimental data of pixel property segmentation for ship hull corrosion images have been presented here. The presented results show that the proposed method achieved the highest segmentation accuracy (93.83 %) and the fastest execution time (0.91 s) than the other investigated methods. The proposed algorithm detected the weak corrosion boundaries in the images with different shadow and ununiform contrast. Moreover, the motion blur effect was reduced in order to detect the blurry prominent corrosion features in the images. Furthermore, the searching region for corrosion detection was minimized with corrosion seed, thus reduced the algorithm's execution time. The proposed method also featured fewer operations and a less complex algorithm compared to other methods. These findings underscore the proposed method's contribution to a robust, efficient and rapid corrosion detection algorithm for ship hull corrosion. Future research should focus on conducting additional experiments to assess the algorithm's performance in the presence of rust.

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References
[1] Foorginezhad, Sahar, Masoud Mohseni-Dargah, Khadijeh Firoozirad, Vahid Aryai, Amir Razmjou, Rouzbeh Abbassi, Vikram Garaniya, Amin Beheshti and Mohsen Asadnia. "Recent advances in sensing and assessment of corrosion in sewage pipelines." *Process Safety and Environmental Protection* 147 (2021): 192-213. https://doi.org/10.1016/j.psep.2020.09.009

[2] Liu, Pan, Qinhao Zhang, Xinran Li, Jiming Hu and Fahe Cao. "Insight into the triggering effect of (Al, Mg, Ca, Mn)-oxy-sulfide inclusions on localized corrosion of weathering steel." *Journal of Materials Science & Technology* 64 (2021): 99-113. https://doi.org/10.1016/j.jmst.2020.06.031

[3] Ayob, Ahmad Faisal Mohamad, N. I. Jalal, M. H. Hassri, S. A. Rahman and S. Jamaludin. "Neuroevolutionary autonomous surface vehicle simulation in restricted waters." *TransNav, International Journal on Marine Navigation and Safety od Sea Transportation* 14, no. 4 (2020): 865-873. https://doi.org/10.12716/1001.14.04.11

[4] Chavez Morales, R. and V. Eliasson. "The effect of moisture intake on the mode-ii dynamic fracture behavior of carbon fiber/epoxy composites." *Journal of Dynamic Behavior of Materials* 7 (2021): 21-33. https://doi.org/10.1007/s40870-020-00260-w

[5] Imran, M. M. H., A. F. Ayob and S. Jamaludin. "Applications of artificial intelligence in ship berthing: A review." (2021).

[6] Jalal, Nur Izzati Mohd, Ahmad Faisal Mohamad Ayob, Shahrizan Jamaludin and Nur Afande Ali. "Evaluation of neuroevolutionary approach to navigate autonomous surface vehicles in restricted waters." *Defence S&T Tech. Bull.* 16, no. 1 (2023): 24-36.

[7] Crognale, Marianna, Melissa De Iuliis, Cecilia Rinaldi and Vincenzo Gattulli. "Damage detection with image processing: a comparative study." *Earthquake Engineering and Engineering Vibration* 22, no. 2 (2023): 333-345. https://doi.org/10.1007/s11803-023-2172-1

[8] Imran, Mahadi Hasan, Mohammad Ilyas Khan, Shahrizan Jamaludin, Ibnul Hasan, Mohammad Fadhli Bin Ahmad, Ahmad Faisal Mohamad Ayob, Wan Mohd Norsani bin Wan Nik *et al.*, "A critical analysis of machine learning in ship, offshore and oil & gas corrosion research, part I: Corrosion detection and classification." *Ocean Engineering* 313 (2024): 119600. https://doi.org/10.1016/j.oceaneng.2024.119600

[9] Ali, Ahmad Ali Imran Mohd, Md Mahadi Hasan Imran, Shahrizan Jamaludin, Ahmad Faisal Mohamad Ayob, Mohammed Ismail Russtam, Syamimi Mohd Norzeli Suhrab, Saiful Bahri Hasan Basri and Saiful Bahri Mohamed. "A review of predictive maintenance approaches for corrosion detection and maintenance of marine structures." *Journal of Sustainability Science and Management* 19, no. 4 (2024): 182-202. https://doi.org/10.46754/jssm.2024.04.014

[10] Ahn, Eunjong, Hyunjun Kim, Seongwoo Gwon, Sung-Rok Oh, Cheol-Gyu Kim, Sung-Han Sim and Myoungsu Shin. "Monitoring of self-healing in concrete with micro-capsules using a combination of air-coupled surface wave and computer-vision techniques." *Structural Health Monitoring* 21, no. 4 (2022): 1661-1677. https://doi.org/10.1177/14759217211041002

[11] Bonnin-Pascual, Francisco, Alberto Ortiz, Emilio Garcia-Fidalgo and Joan P. Company-Corcoles. "A reconfigurable framework to turn a MAV into an effective tool for vessel inspection." *Robotics and Computer-Integrated Manufacturing* 56 (2019): 191-211. https://doi.org/10.1016/j.rcim.2018.09.009

[12] Bonnin-Pascual, Francisco and Alberto Ortiz. "A novel approach for defect detection on vessel structures using saliency-related features." *Ocean Engineering* 149 (2018): 397-408. https://doi.org/10.1016/j.oceaneng.2017.08.024

[13] Yao, Kai, Alberto Ortiz and Francisco Bonnin-Pascual. "A DCNN-based arbitrarily-oriented object detector with application to quality control and inspection." *Computers in Industry* 142 (2022): 103737. https://doi.org/10.1016/j.compind.2022.103737

[14] Jamaludin, Shahrizan and Imran, Md Mahadi Hasan. "Artificial intelligence for corrosion detection on marine structures." *Journal of Ocean Technology 19*, no. 2 (2024): 19-24.

[15] Ge, Pengqiang, Yiyang Chen, Guina Wang and Guirong Weng. "A hybrid active contour model based on pre-fitting energy and adaptive functions for fast image segmentation." *Pattern Recognition Letters* 158 (2022): 71-79. https://doi.org/10.1016/j.patrec.2022.04.025
[16] Fang, Jiangxiong, Huaxiang Liu, Jun Liu, Haiying Zhou, Liting Zhang and Hesheng Liu. "Fuzzy region-based active contour driven by global and local fitting energy for image segmentation." *Applied Soft Computing* 100 (2021): 106982. https://doi.org/10.1016/j.asoc.2020.106982
[17] Ge, Pengqiang, Yiyang Chen, Guina Wang and Guirong Weng. "An active contour model driven by adaptive local pre-fitting energy function based on Jeffreys divergence for image segmentation." *Expert Systems with Applications* 210 (2022): 118493. https://doi.org/10.1016/j.eswa.2022.118493
[18] Tang, Gang, Yichao Zhuge, Christophe Claramunt and Shaoyang Men. "N-YOLO: A SAR ship detection using noise-classifying and complete-target extraction." *Remote Sensing* 13, no. 5 (2021): 871. https://doi.org/10.3390/rs13050871
[19] Khmag, Asem. "Additive Gaussian noise removal based on generative adversarial network model and semi-soft thresholding approach." *Multimedia Tools and Applications* 82, no. 5 (2023): 7757-7777. https://doi.org/10.1007/s11042-022-13569-6
[20] Syed, Mohammad Haider, Kamal Upreti, Mohammad Shahnawaz Nasir, Mohammad Shabbir Alam and Arvind Kumar Sharma. "Addressing image and Poisson noise deconvolution problem using deep learning approaches." *Computational Intelligence* 39, no. 4 (2023): 577-591. https://doi.org/10.1111/coin.12510
[21] Kumar, Virendra, Atul Kumar Dubey, Mayank Gupta, Veena Singh, Ankit Butola and Dalip Singh Mehta. "Speckle noise reduction strategies in laser-based projection imaging, fluorescence microscopy and digital holography with uniform illumination, improved image sharpness and resolution." *Optics & laser technology* 141 (2021): 107079. https://doi.org/10.1016/j.optlastec.2021.107079
[22] Alibabaie, Najmeh and AliMohammad Latif. "Adaptive periodic noise reduction in digital images using fuzzy transform." *Journal of Mathematical Imaging and Vision* 63, no. 4 (2021): 503-527. https://doi.org/10.1007/s10851-020-01004-0
[23] Suradi, Saifullah Harith, Kamarul Amin Abdullah and Nor Ashidi Mat Isa. "Improvement of image enhancement for mammogram images using fuzzy anisotropic diffusion histogram equalisation contrast adaptive limited (fadhecal)." *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization* 10, no. 1 (2022): 67-75. https://doi.org/10.1080/21681163.2021.1972344
[24] McCombe, Kris D., Stephanie G. Craig, Amélie Viratham Pulsawatdi, Javier I. Quezada-Marín, Matthew Hagan, Simon Rajendran, Matthew P. Humphries *et al.,* "HistoClean: Open-source software for histological image pre-processing and augmentation to improve development of robust convolutional neural networks." *Computational and Structural Biotechnology Journal* 19 (2021): 4840-4853. https://doi.org/10.1016/j.csbj.2021.08.033
[25] Balamurugan, D., Seshadri S. Aravinth, P. Chandra Shaker Reddy, Ajay Rupani and A. Manikandan. "Multiview objects recognition using deep learning-based wrap-CNN with voting scheme." *Neural Processing Letters* 54, no. 3 (2022): 1495-1521. https://doi.org/10.1007/s11063-021-10679-4
[26] Zhu, Wenhao, Haoting Wu, Weixuan Chen, Meiting Zhou, Guolu Yin, Nan Guo and Tao Zhu. "Submetric spatial resolution ROTDR temperature sensor assisted by wiener deconvolution." *Sensors* 22, no. 24 (2022): 9942. https://doi.org/10.3390/s22249942
[27] Dong, Jiangxin, Stefan Roth and Bernt Schiele. "DWDN: deep wiener deconvolution network for non-blind image deblurring." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 44, no. 12 (2021): 9960-9976. https://doi.org/10.1109/TPAMI.2021.3138787
[28] Lai, Qiang, Genwen Hu, Uğur Erkan and Abdurrahim Toktas. "A novel pixel-split image encryption scheme based on 2D Salomon map." *Expert Systems with Applications* 213 (2023): 118845. https://doi.org/10.1016/j.eswa.2022.118845
[29] Xiong, Jinbo, Renwan Bi, Youliang Tian, Ximeng Liu and Dapeng Wu. "Toward lightweight, privacy-preserving cooperative object classification for connected autonomous vehicles." *IEEE Internet of Things Journal* 9, no. 4 (2021): 2787-2801. https://doi.org/10.1109/JIOT.2021.3093573
[30] Yang, Ziyun, Somayyeh Soltanian-Zadeh and Sina Farsiu. "BiconNet: An edge-preserved connectivity-based approach for salient object detection." *Pattern recognition* 121 (2022): 108231. https://doi.org/10.1016/j.patcog.2021.108231
[31] Zeng andy, Shuran Song, Kuan-Ting Yu, Elliott Donlon, Francois R. Hogan, Maria Bauza, Daolin Ma *et al.,* "Robotic pick-and-place of novel objects in clutter with multi-affordance grasping and cross-domain image matching." *The International Journal of Robotics Research* 41, no. 7 (2022): 690-705. https://doi.org/10.1177/0278364919868017
[32] Filali, Idir, Malika Belkadi, Rachida Aoudjit and Mustapha Lalam. "Graph weighting scheme for skin lesion segmentation in macroscopic images." *Biomedical Signal Processing and Control* 68 (2021): 102710. https://doi.org/10.1016/j.bspc.2021.102710

[33] Jamaludin, Shahrizan, Nasharuddin Zainal and W. Mimi Diyana W. Zaki. "A fast specular reflection removal based on pixels properties method." *Bulletin of Electrical Engineering and Informatics* 9, no. 6 (2020): 2358-2363. https://doi.org/10.11591/eei.v9i6.2524
[34] Hasan, Tawheed, Shahrizan Jamaludin and WB Wan Nik. "Analysis of intelligent solar ICU water ambulance to optimize energy." *Annals of Medicine and Surgery* 80 (2022): 104141. https://doi.org/10.1016/j.amsu.2022.104141
[35] Jamaludin, Shahrizan, Ahmad Faisal Mohamad Ayob, Syamimi Mohd Norzeli and Saiful Bahri Mohamed. "Adaptive initial contour and partly-normalization algorithm for iris segmentation of blurry iris images." *Journal of Information and Communication Technology* 21, no. 3 (2022): 411-435. https://doi.org/10.32890/jict2022.21.3.5
[36] Ali, Ahmad Ali Imran Mohd, Shahrizan Jamaludin, Md Mahadi Hasan Imran, Ahmad Faisal Mohamad Ayob, Sayyid Zainal Abidin Syed Ahmad, Mohd Faizal Ali Akhbar, Mohammed Ismail Russtam Suhrab and Mohamad Riduan Ramli. "Computer vision and image processing approaches for corrosion detection." *Journal of Marine Science and Engineering* 11, no. 10 (2023): 1954. https://doi.org/10.3390/jmse11101954
[37] Tat, Toh Wei, Norzelawati Asmuin, Ishrizat Taib and Riyadhthusollehan Khairulfuaad. "Acoustic pressure simulation for fluid piping leakages." *CFD Letters 14*, no. 7 (2022): 77-86. https://doi.org/10.37934/cfdl.14.7.7786
[38] Triwibowo, Bayu, Widayanti, Heni Wahyu and Rukmanasari, Miftakhul Indra. "Prediction of erotion rate in two elbows for coal-air flow based on computational fluid dynamics simulation." *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences 97*, no. 2 (2022): 115-125. https://doi.org/10.37934/arfmts.97.2.115125