Paper

A Comparative Study of Various Edge Detection Techniques for Underwater Images

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Abstract—Nowadays, underwater image identification is a challenging task for many researchers focusing on various applications, such as tracking fish species, monitoring coral reef species, and counting marine species. Because underwater images frequently suffer from distortion and light attenuation, pre-processing steps are required in order to enhance their quality. In this paper, we used multiple edge detection techniques to determine the edges of the underwater images. The pictures were pre-processed with the use of specific techniques, such as enhancement processing, Wiener filtering, median filtering and thresholding. Coral reef pictures were used as a dataset of underwater images to test the efficiency of each edge detection method used in the experiment. All coral reef image datasets were captured using an underwater GoPro camera. The performance of each edge detection technique was evaluated using mean square error (MSE) and peak signal to noise ratio (PSNR). The lowest MSE value and the highest PSNR value represent the best quality of underwater images. The results of the experiment showed that the Canny edge detection technique outperformed other approaches used in the course of the project.

Keywords—edge detection, mean square error, median filtering, peak signal to noise, wiener filtering.

1. Introduction

Exploration of the underwater environment with the use of video and images is a challenging and fascinating procedure due to several problems, including noise, limited visibility, light scattering, attenuation concerns, non-uniform lighting, and other factors affecting the seawater environment [1], [2]. Artificial light sources also cause image blur, haziness, and are a source of a bluish or greenish hue in underwater images, leading to high absorption, scattering, color distortion, and noise [3]. As a result of this scenario, researchers will find it difficult to perform more extensive research harnessing computer technology, particularly while classifying, recognizing and segmenting coral reef components and numerous fish species. It is vital to understand the underwater ecology to manage and monitor marine resources effectively. Therefore, image analysis techniques based on computer vision and image processing technologies have been established to monitor marine resources properly. However, no quantitative or qualitative assessment of all underwater marine resources has been conducted, according to [4].

With these constraints in mind, the edge detection process is used as the first computation approach aiming to reduce noise in underwater images, while preserving the important edges. It is commonly used in low-level image processing to retain the best possible edges for higher-level processing [5], [6]. On the other hand, noise content and the density of edges in the image all influence how well edge detection works. Apart from image enhancement, edge detection is extensively applied in pattern recognition and classification techniques [8], [9]. Advanced research concerned with underwater image analysis also used edge detection techniques, for instance in recognizing underwater sonar images [10]. Edge detection techniques also have also been used in conjunction with autonomous underwater vehicles (AUVs) [11] and acoustic devices [12].

The remainder of this paper is organized in the following manner. Several related works on underwater image and edge detection techniques are discussed in Section 2. The technique's principles and hypotheses related to multiple edge detection algorithms, data acquisition, experimental design, and image quality measurement based on mean square error (MSE) and peak signal noise ratio (PSNR) are discussed in Section 3. The analysis of the experimental results using coral reef image datasets are presented in Section 4. Section 5 concludes the discussion.

2. Related Works

Most underwater images are texture images that contain both living and non-living objects. For segmenting and detecting objects in underwater images, many researchers have carried out several different studies. We review some of the studies that are similar to the proposed work.

Acoustic underwater images are challenging to edge-identify. Article [12] improved underwater acoustic images by applying edge detecting algorithms. The authors employed Wiener filtering to reduce speckle noise while maintaining high-frequency components. Meanwhile, the median filter was used to remove small objects from the image. Overall performance was assessed by obtaining a local minimum and maximum from morphological operations. The resulting edge maps tracing objects in underwater acoustic images were compared with Canny and Sobel edge detection algorithms. The results outperformed conventional methods but were still contaminated by noise.

Paper [13] suggested an edge identification method based on fractional order differentiation for underwater images. A texture improvement filter based on the Grünwald Letnikov (G-L) fractional differential operator was devised and explored. Diverse underwater images were selected to analyze both conventional and fractional differential operators, respectively. The findings were also compared with the Riemann-Liouville fractional differential operator technique (R-L). The recommended strategy outperformed both traditional and R-L-based methods in recognizing the edges of low-contrast underwater images, offering a high level of accuracy, excellent brightness and more information.

Almost all segmentation approaches aim to classify images. However, images can be misclassified into various clusters, leading to overlapping pixels being identified over the actual edges. Article [15] used Canny edge detection for segmentation to manage challenging underwater images and to expose essential information without distortion. The paper showed that Canny improves the signal-to-noise ratio, reduces analytical error rate, and ensures high efficiency, good localization, and precise response while dealing with underwater images.

Paper [11] used edge detection methods and the Lab color model to improve underwater image quality. The authors performed edge detection after color correction and contrast enhancement. Due to light illumination, water velocity, and suspended particles, they preferred to use color detection due to the poor results obtained from direct edge recognition performed on underwater images. Although their approach was efficient at detecting the shapes of objects, some noise remained. They hoped to improve current edge detection results by applying deep networks for automated operations.

According to [16], underwater environmental research still has a great deal of unrealized potential. They discussed numerous alternative image quality enhancement techniques in their review paper, including a deep learning approach, color restoration, color evaluation metrics, and image processing approaches. Meanwhile, article [17] suggested segmenting selected underwater objects in the images using Canny edge detection and the active contour model. Furthermore, [4] used contrast limited adaptive histogram equalization (CLAHE) in conjunction with an adaptive histogram and a Haar wavelet to reduce noise in underwater images while maintaining their edges. PSNR, contrast to noise ratio (CNR), image enhancement metric (IEM), and absolute mean brightness error (AMBE) are all used to quantify edge detection efficiency.

3. Methodology

Detecting edges is a crucial task in digital image processing and is required to increase confidence levels related to image segmentation, pattern recognition and detection of objects. This study uses various edge detection techniques, such as Sobel, Prewitt, Roberts, LoG and Canny. Figure 1 presents a flowchart of the comparative study of various edge detections techniques for underwater images. First, we intentionally corrupted such images with Gaussian noise, as well as salt and pepper noise (SPN). In the next

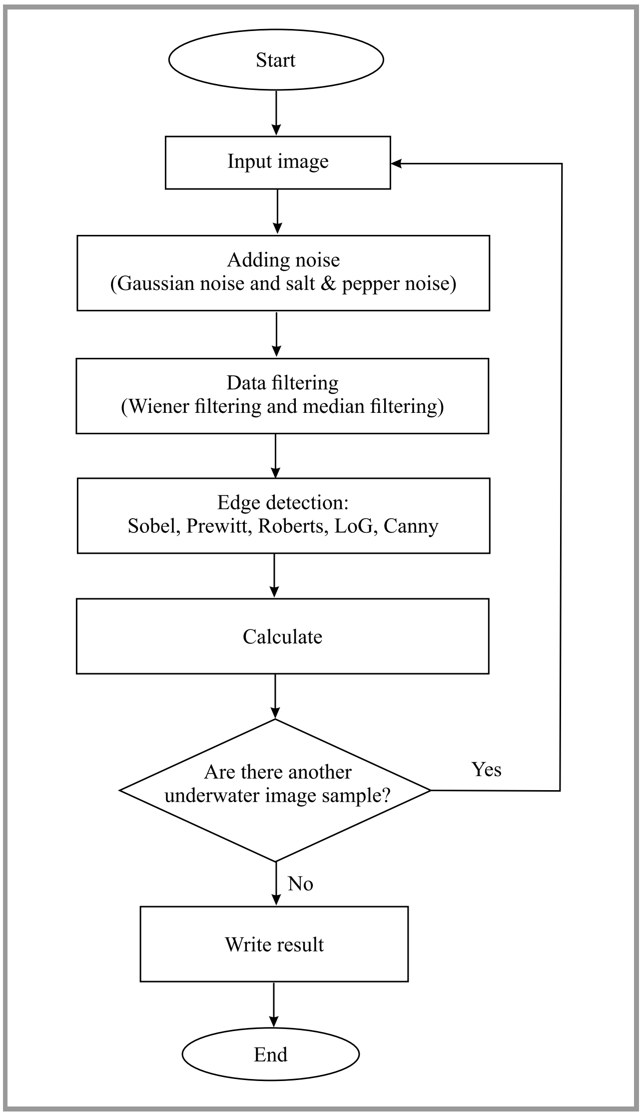

Fig. 1. Flowchart presenting a comparative study of edge detection techniques for underwater images.

step, Wiener filtering and median filtering were applied to effectively remove noise disorder from images. Then, all edge detection techniques mentioned above are used as a pre-processing stage in the study. The best edge detection result is determined based on successfully preserving true edges and minimizing noise from the image. We use MSE and PSNR to evaluate edge detection algorithms for quantitative measurement.

3.1. Data Acquisition

The study used Acropora branching images that served as an underwater image sample dataset. The data was collected from three different sample sites in the Redang islands, such as Pulau Lima, Pulau Kerengga and Pasir Panjang. Our group worked with the Institute of Oceanography and Environment (INOS) at Universiti Malaysia Terengganu to collect the data. Line intercept transect (LIT) video images were obtained with the use of a high-quality underwater video camera. 100 m transect lines were built at each dive site using measuring tape positioned at the depth of 3 m and 10 m. A diver towed the transect line to record videos and images of the coral reef. The Acropora branching images were set to measure 300×300 pixels, as shown in Fig. 2b.

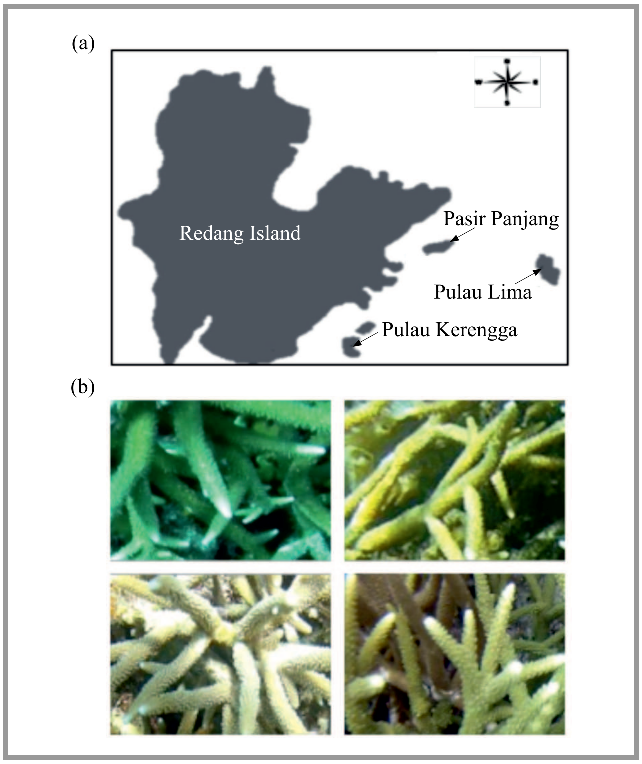

Fig. 2. (a) Data collection at Redang islands, (b) Acropora branching images.

3.2. Theoretical Edge Detection Techniques

Edge detection is an excellent way to discover crucial edges in an image while reducing noise. Edge detection using first and second-order derivatives has been widely used for image enhancement [18], [19]. First-order derivative operators are more prone to noise and spurious edges. First-order derivative operators include Sobel, Prewitt, Roberts, and Canny. Second-order derivative operators are more efficient but still sensitive to noise [20], [21]. Two examples of second-order derivative edge detection techniques the include difference of Gaussian (DoG) and the Laplacian of Gaussian (LoG) (e.g. the Marr-Hildreth meth).

Table 1
Kernel mask of each edge detection techniques

Technique	Kernel mask G_x	Kernel mask G_y
Sobel	$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}$	$G_y = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}$
Prewitt	$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix}$	$G_y = \begin{bmatrix} -1 & -1 & +1 \\ 0 & 0 & 0 \\ +1 & +1 & +1 \end{bmatrix}$
Roberts	$G_x = \begin{bmatrix} +1 & 0 \\ 0 & -1 \end{bmatrix}$	$G_y = \begin{bmatrix} 0 & +1 \\ -1 & 0 \end{bmatrix}$
LoG	$G_x = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	$G_y = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$
Canny	$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}$	$G_y = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}$

Table 2
Formula for gradient magnitude and orientation angle

Gradient magnitude $\|G\|$	Orientation angle θ
$\|G\| = \sqrt{Gx^2 + Gy^2}$	$\theta = \arctan \frac{Gy}{Gx}$

As shown in Table 1, different kernel masks are used in different edge detection techniques. The aspects of the input image that affect the kernel mask operator include brightness and lighting [22], [23]. Typically, two mask kernels respond to vertical and horizontal edges. These were created by mixing two convolution mask kernels. Edge orientation was computed using magnitude gradient data. Table 2 shows the gradient's magnitude and angle direction. These methods work best when edges are well retained. Image localization is sound and minimal noise disturbance is experienced.

The x- and y-gradients are generated using a set of 3×3 kernel masks based on each edge detection, as shown in Table 1. The gradient magnitude is computed by adding Gx and Gy. Table 2 explains how to use the Pythagoras' law to calculate gradient magnitude. We can also determine the orientation angle of the edge location (x,y) with the gradient magnitude.

The Canny operator is a well-known technique for recognizing edges since it removes image noise. It uses a multi-stage method to find absolute edge boundaries affected by noise and position selection, and it only responds to single edges. The Gaussian kernel is used to smooth out image noise and can be described as:

$$G_\sigma = \frac{1}{\sqrt{2\sigma^2}} \mathrm{e}^{\frac{x^2+y^2}{2\sigma^2}}\,, \tag{1}$$

where standard deviation is used to calculate the distance between Gaussian distributions. The gradient magnitude and orientation are computed using the equations from Table 2. Non-maximum suppression is also used to thin out the edges while eliminating pixels that are not part of the edge. Meanwhile, non-maximum suppression pixels can be measured using:

$$g_T(x,y) = \begin{cases} g(x,y), & \text{if } g(x,y) \geq T \\ 0, & \text{otherwise} \end{cases}. \tag{2}$$

Non-maxima pixels are suppressed by comparing them with two neighbors in the gradient's direction. If nothing changes, set the number to 1. When the density gradient value approaches a higher threshold, double thresholding considers the pixels as edges. Pixels are eliminated as edges if the gradient strength is less than a threshold. A pixel is only taken into account if it is adjacent to another pixel above the upper threshold.

The Laplacian operator is a second-order derivative edge detector commonly used in signal processing. A second-order derivative edge detection approach produces a lot of noise in the output image, necessitating a smoothing procedure. A Gaussian filter is applied to the image before applying the LoG operator. The Gaussian filter formula is:

$$G_\sigma = \frac{1}{\sqrt{2\pi\sigma^2}} \mathrm{e}^{\frac{x^2+y^2}{2\sigma^2}}\,, \tag{3}$$

and the Laplacian operator is computed as:

$$\nabla^2 g = \frac{(\partial^2 f)}{(\partial^2 x)} + \frac{(\partial^2 f)}{(\partial^2 y)}\,, \tag{4}$$

$$\nabla^2 g(x,y) = \frac{1}{\sigma^2}\left[\frac{x^2+y^2}{\sigma^2} - 2\right] \mathrm{e}^{\frac{-(x^2+y^2)}{2\sigma^2}}\,. \tag{5}$$

The image gradient output is marked by the symbol $\nabla^2 g$, and the Laplacian edge operator is denoted by the sign $g(x,y)$. It is responsible for determining the location of the pixel intensity in the image. The LoG is a convolution mask that may be calculated using the Eqs. (4) and (5). In this case, the gradient output value of LoG is $g(x,y)$. Meanwhile, the x and y axes reflect the horizontal and vertical direction values of the input image, respectively. The sign σ denotes the standard deviation value that is utilized in the Gaussian distribution.

3.3. Wiener and Median Filtering

The median filter is a simple and effective non-linear filter. It is used to reduce the difference in intensity between two pixels. The median is calculated by ascending all pixel values and then replacing the calculated pixel with the middle pixel value. The median filter can be calculated as:

$$I'(u,v) \leftarrow \text{median}\,\{I(u+i, v+j) \mid (i,j)\varepsilon w\}\,. \tag{6}$$

The w sign signifies a user-defined neighborhood inside the image centered on (u,v). Meanwhile, i and j represent the coordinates of the image's pixel values.

On the other hand, the Wiener filter reduces the amount of noise that has distorted a signal. The goal of the Wiener filter is to minimize the mean square error as much as possible. It is a useful technique for reducing image noise and blurring. As part of image processing, it considers both the degradation mechanism and noise. The formula given below can be used to calculate the Wiener filter:

$$\nabla^2 g(x,y) = \frac{H*(u,v)}{|H(u,v)|^2 Ps(u,v) + Pn(u,v)}\,. \tag{7}$$

$H(u,v)$ shows the degradation conjugate complex form. $P_s(u,v)$ represents the signal power spectrum density, which is the most crucial thing when it comes to noise. Meanwhile, $P_n(u,v)$ indicates the power spectral distribution density of the original image. Finally, $H(u,v)$ denotes the degradation function.

3.4. Quantitative Measurement

MSE and PSNR are numerical measures used to evaluate edge detection efficiency. An underwater image of the best quality has the lowest mean square error and the highest peak signal to noise ratio. We measured the parameters below to compare the original and filtered images. The MSE computes the change in square error between the encoded and original images. It is the most crucial factor to consider when evaluating a predictor or estimator. Instead of an absolute difference, the loss between two separate edge detectors is calculated using a squared difference in a random variable. MSE is expressed as follows:

$$MSE = \frac{1}{mn}\sum_m \sum_n (x_{mn} - y_{mn})^2\,, \tag{8}$$

where: m – number of rows in cover image, n – number of columns in cover image, x_{mn} – pixel value from original image, y_{mn} – pixel value from filtered image.

The x symbol represents the original image, whereas the y symbol represents the filtered version of the same image. The images have a resolution of $m \times n$ pixels in resolution, representing the number of rows and columns, respectively. PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise [14]. It determines how well an image is reconstructed. PSNR can be calculated as:

$$PSNR(x,y) = \frac{10\log_{10}[\max\left(\max(x),\max(y)\right)]^2}{|x-y|^2}. \quad (9)$$

3.5. Sensitivity Measurement

In this section, sensitivity estimation distribution is used to evaluate the performance of each edge detection algorithm. The fraction of edges that are correctly categorized as edges is addressed in the study as sensitivity. The sensitivity curve has the form of a series of distinct threshold values ranging from 0 to 0.5. The formula for calculating the quantitative value of sensitivity is:

$$Sensitivity = \frac{TP}{TP+FN}. \quad (10)$$

Table 3

Sensitivity variable definition

	Edges present	Edges absent
Edges detected	True positive (TP)	False positive (FP)
Edges not detected	False negative (FN)	True negative (TN)

4. Experimental Results

The experiments were all conducted using Matlab. All edge detection techniques were evaluated using Wiener and median filters. The effects of both filters were compared using Gaussian and SPN. The best edge detection algorithms have the lowest MSE and the highest PSNR values.

4.1. Experiment 1

The effects of processing Acropora branching images by applying the Wiener filter with additional Gaussian noise are shown in Fig. 3. The effects of processing Acropora branching images by applying the Wiener filter with additional Gaussian noise are shown in Fig. 3, these edge detection techniques generally suffer from information loss due to Gaussian noise sensitivity. While the LoG algorithm is able to categorize edges, it fails to obtain ideal edges and struggles to reduce Gaussian noise in the image. The Canny edge detection technique surpasses all other edge detection algorithms because it incorporates Gaussian filtering. The

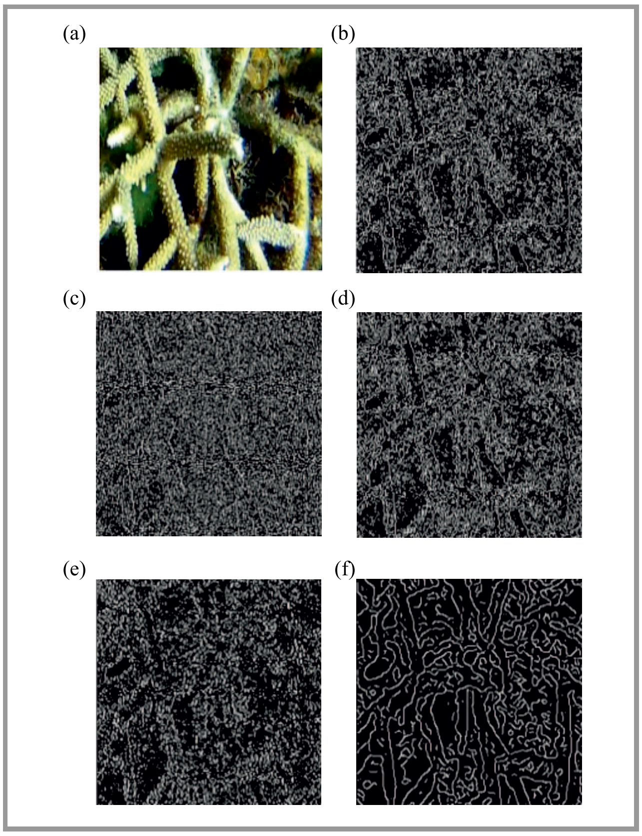

Fig. 3. (a) original image, (b) Prewitt, (c) Roberts, (d) Sobel, (e) LoG, and (f) Canny edge detectors.

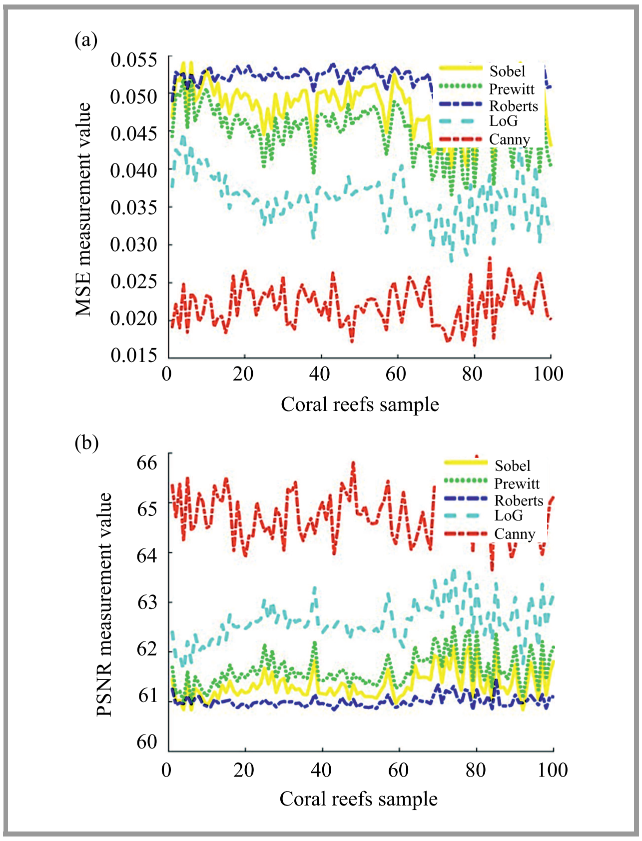

Fig. 4. (a) MSE and (b) PSNR analysis of various edge detection algorithms with Wiener filtering by adding Gaussian noise.

technique is capable of reducing the Gaussian noise while maintaining good edge orientation.
In terms of quantitative measurements, the Canny algorithm outperforms Sobel, Prewitt, Roberts, and LoG algorithms when using 100 sample images. The Canny algorithm achieves the lowest MSE values and the highest PSNR values, ensuring good quality while minimizing noise. This shows that the Canny algorithm could eliminate Gaussian noise. The results are presented in Fig. 4. Meanwhile, Table 4 shows the average MSE and PSNR values measured.

Table 4
Average MSE and PSNR values for experiment 1

	Sobel	Prewitt	Roberts	LoG	Canny
MSE	0.051	0.048	0.058	0.081	0.022
PSNR	61.144	61.386	60.527	59.092	64.768

4.2. Experiment 2

Figure 5 shows the results achieved with the use of all edge detection techniques by deploying Wiener filtering and adding SPN to the image. From the experimental results, one can observe that Prewitt, Sobel, Roberts and LoG algorithms cannot preserve Acropora coral reef branching edges and are not capable of suppressing unwanted noise

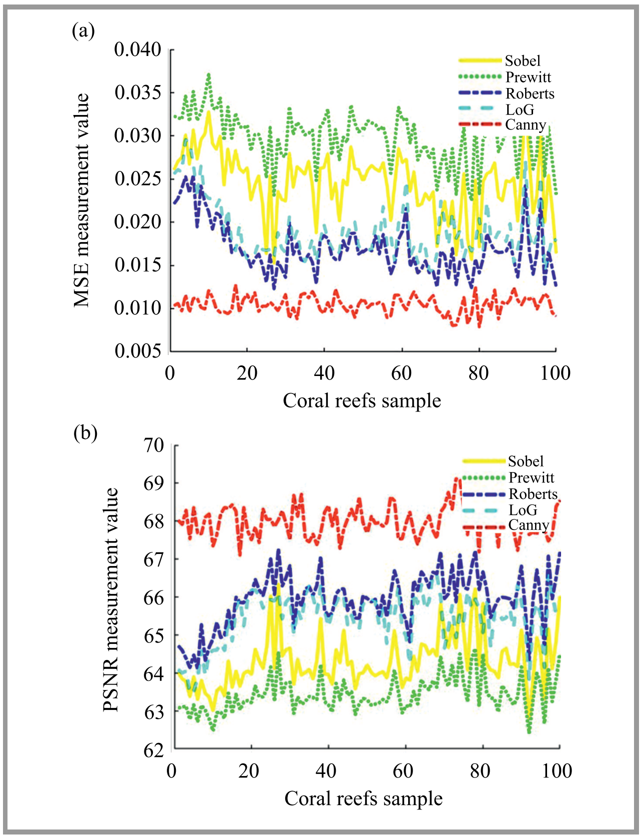

Fig. 6. (a) MSE and (b) PSNR analysis of various edge detection algorithms with Wiener filtering by adding SPN.

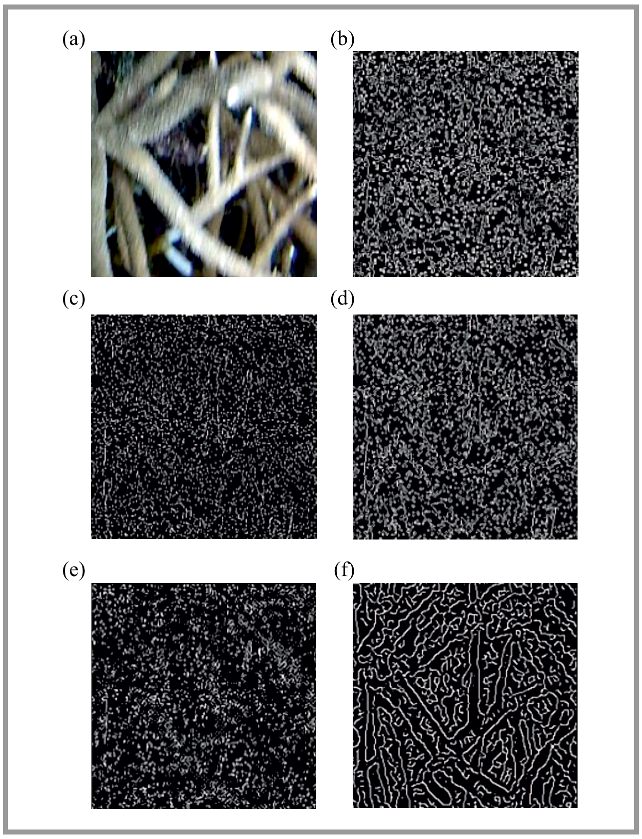

Fig. 5. (a) original image, (b) Prewitt, (c) Roberts, (d) Sobel, (e) LoG, and (f) Canny edge detectors.

properly. In addition, high MSE and low PSNR values produced by these techniques are significant as well – see Fig. 4. Meanwhile, the Canny algorithm outperforms all other edge detection techniques in this scenario, with the lowest MSE and the highest PSNR. However, some edges are not sufficiently simplified by Canny edge detection techniques. This problem occurs when the two filters interact. The first of them was the Wiener filter used to reduce the noise from underwater images. The other was the Gaussian filter to affect the pixel edges by removing noise with information. Table 5 shows the average MSE and PSNR values for 100 Acropora branching images.

Table 5
Average MSE and PSNR values for experiment 2

	Sobel	Prewitt	Roberts	LoG	Canny
MSE	0.025	0.03	0.017	0.019	0.010
PSNR	64.312	63.428	65.925	65.446	67.999

4.3. Experiment 3

Figure 7 shows the effects of using median filtering and Gaussian noise. Similar results are obtained as in the previous experiment, with LoG, Roberts, Sobel, and Prewitt techniques failing to decrease Gaussian noise consider-

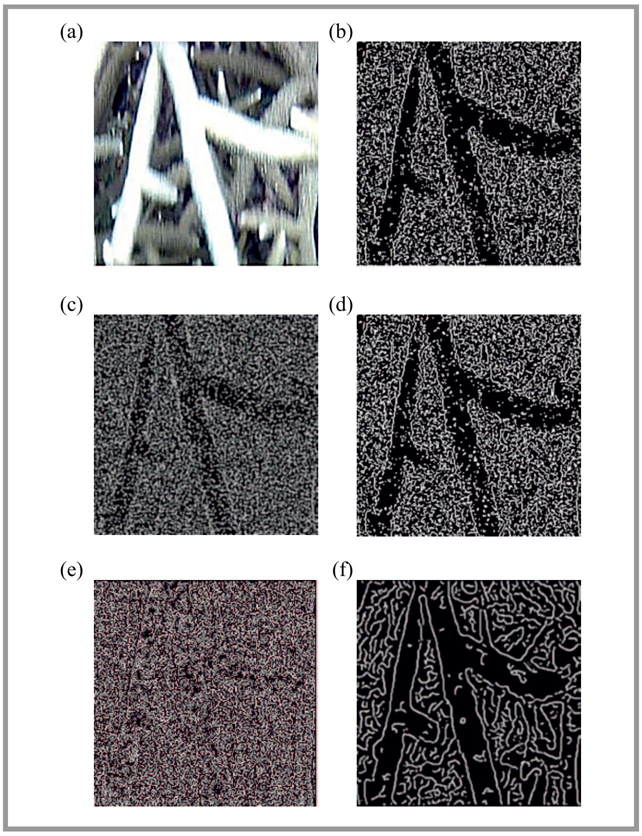

Fig. 7. (a) original image, (b) Prewitt, (c) Roberts, (d) Sobel, (e) LoG, and (f) Canny edge detectors.

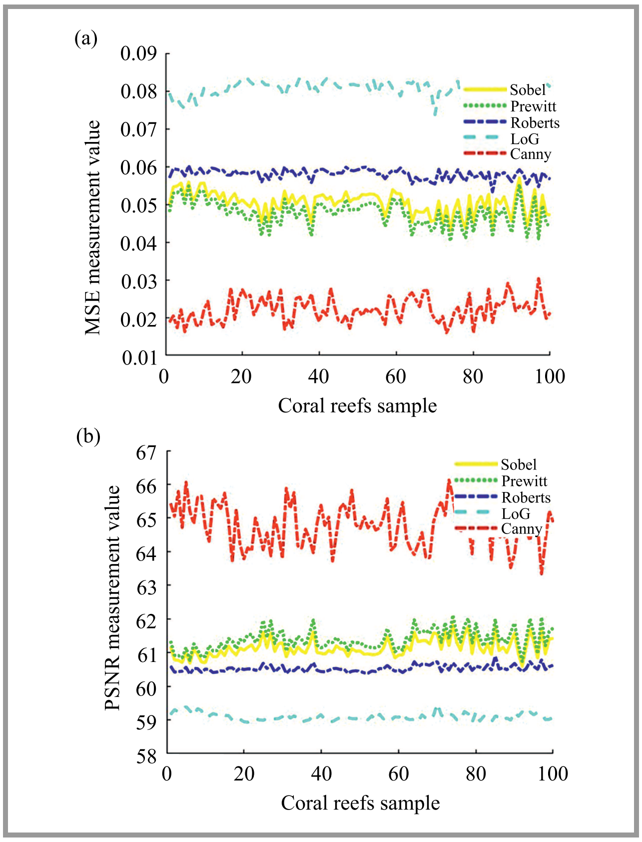

Fig. 8. (a) MSE and (b) PSNR analysis of various edge detection algorithms with median filtering by adding Gaussian noise.

ably. When applied to Gaussian noise images, these techniques tend to distort edges and cannot remove Gaussian noise. When applied to Gaussian noise images, these techniques tend to distort edges and cannot remove Gaussian noise. The Canny algorithm offered better image quality than the LoG, Roberts, Sobel, and Prewitt techniques during the experiment. However, some edges are missing when using the Canny approach.

The LoG, Roberts, Sobel, and Prewitt algorithms produce the worst image quality, as illustrated in Fig. 8. Again, the Canny edge detection algorithm produces the best edge detection result for the second part of the experiment, with the lowest MSE and the highest PSNR. Table 6 below shows the average MSE and PSNR values for 100 coral reef Acropora branching images.

Table 6

Average MSE and PSNR values for experiment 3

	Sobel	Prewitt	Roberts	LoG	Canny
MSE	0.050	0.048	0.017	0.058	0.022
PSNR	61.144	61.386	60.526	59.092	64.767

4.4. Experiment 4

The Acropora branching image effects are shown in Fig. 9 using median filtering with SPN. As a result, the Canny

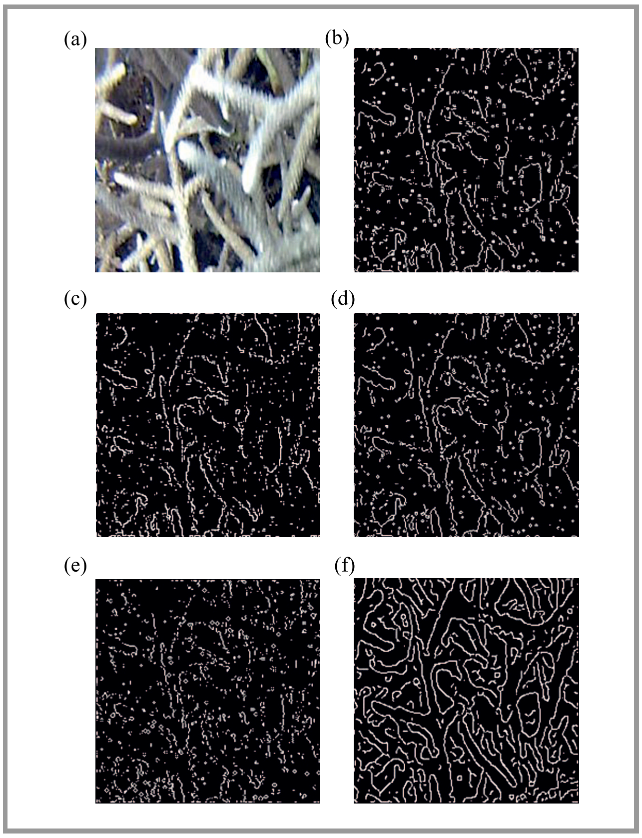

Fig. 9. (a) original image, (b) Prewitt, (c) Roberts, (d) Sobel, (e) LoG, and (f) Canny edge detectors.

approach outperforms conventional edge detection techniques when it comes to maintaining critical edges while decreasing noise. Quantitative measurements reveal that the LoG, Prewitt, Sobel and Roberts algorithms provided the lowest image quality due to the highest MSE and lowest PSNR values, respectively. However, the Canny approach offers better results based on the quantitative measurement analysis, which achieving the lowest MSE (Fig. 10a) and the highest PSNR (Fig. 10b) values (Table 7).

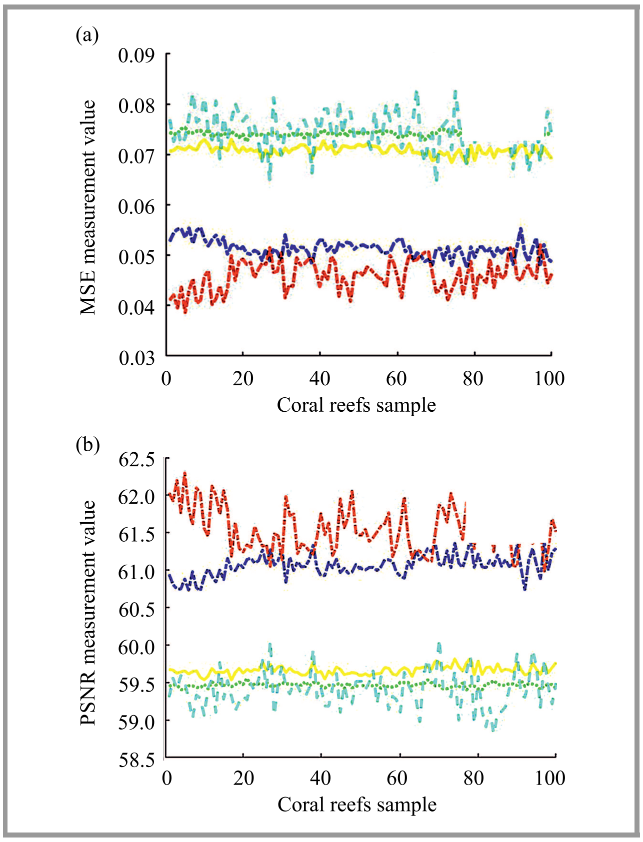

Fig. 10. (a) MSE and (b) PSNR analysis of various edge detection algorithms with median filtering by adding salt and pepper noise.

Table 7

Average MSE and PSNR value for experiment 4

	Sobel	Prewitt	Roberts	LoG	Canny
MSE	0.071	0.074	0.051	0.075	0.046
PSNR	59.664	59.464	61.065	59.493	61.551

4.5. Sensitivity Results

Sensitivity is increased by varying the threshold value, as illustrated in Fig. 12. Table 8 summarizes the results of all detectors with various threshold values. Meanwhile, Fig. 11 presents the graph of the sensitivity of different edge detectors. As a consequence of the average, it was determined that the Canny operator was the most susceptible to all other operators. Sensitivity of the Canny edge detection approach offers the average success rate of approximately 85%.

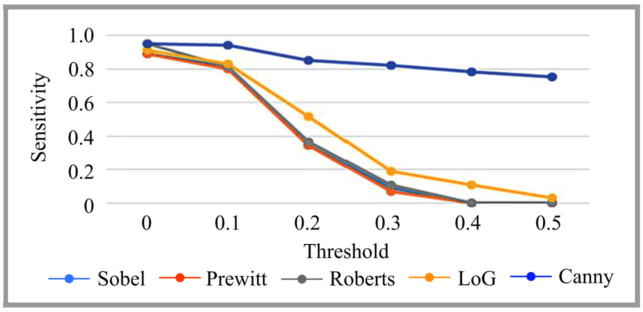

Fig. 11. Sensitivity of different edge detectors.

Table 8

Results concerning sensitivity of specific edge detectors

Threshold	Sobel	Prewitt	Roberts	LoG	Canny
0.00	0.891	0.891	0.950	0.911	0.950
0.10	0.812	0.802	0.812	0.832	0.941
0.20	0.347	0.347	0.366	0.515	0.852
0.30	0.089	0.069	0.109	0.188	0.822
0.40	0.000	0.000	0.000	0.109	0.782
0.50	0.000	0.000	0.000	0.030	0.752
Average	0.356	0.351	0.373	0.431	0.850

5. Conclusion

Prewitt, Sobel, Roberts, and LoG techniques suffer from some difficulties when extracting noise from underwater images compared with the well-known Canny edge detection algorithm. While the latter is better at eliminating most noise, it is not capable of easily distinguishing certain important edges. The effectiveness of each edge detection method was compared using Wiener and median filtering. Wiener filtering did not improve the images significantly. The Wiener filter is suitable just when it comes to removing noise, but not when it comes to maintaining edges in underwater images. Meanwhile, by incorporating median filtering into the edge detection algorithms, Gaussian as well as salt and pepper noise can be removed with the edges still being effectively preserved in the images.

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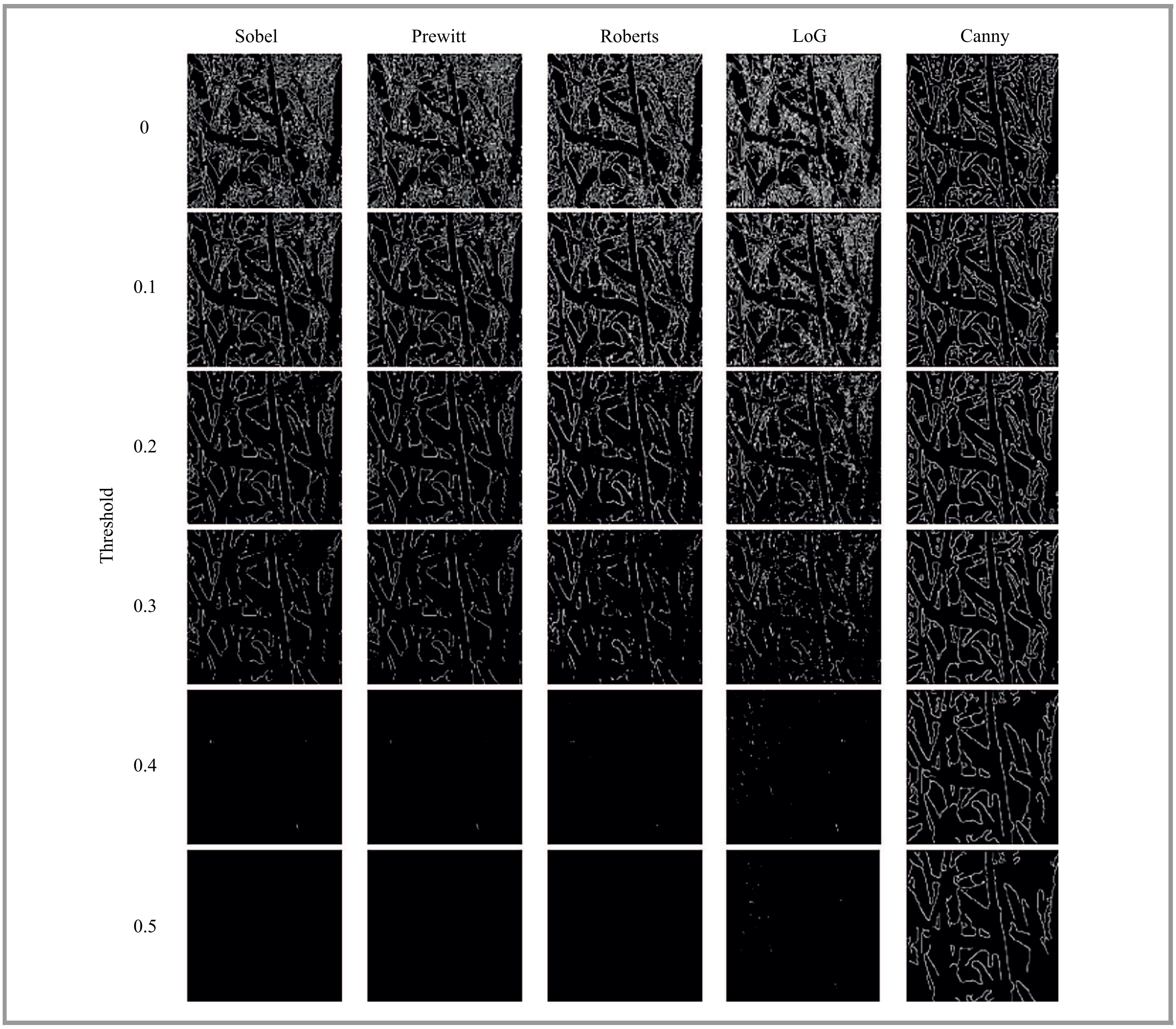

Fig. 12. The sensitivity results of images are affected by different threshold values.

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