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Analysis of Coral Reefs Distribution using Edge Detection and Blob Processing Techniques

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Abstract— The paper presents an approach for estimating the distribution coral reefs from still images based on commonly used edge detection and blob processing techniques. Five popular edge dtection techniques namely Roberts, Prewitt, Sobel, LoG and Canny edges detectors have been evaluated to detect edges of coral reefs under natural scene and noisy environment. In this paper, three groups of coral reefs have been investigated, i.e. Acropora branching (ACB), Acropora submassive (ACS) and Coral foliose (CF) . The experimental findings show that Canny edge detector is the best in detecting edges of coral reefs and produces minimum noise as compared to the other four edge detectors. In the later part of this paper, a blob processing technique has been used to automate the analysis of coral reefs distribution. In conclusion, this paper has contributed in enhancing the current traditional manual distribution estimation method of coral reefs from still images into a fast automatic method by using computer vision techniques. This appoach helps marine scientists to monitor coral reef in more efficient manner.

Index Terms— Edge detection, Blob processing, Recognition, Coral reef.

1 INTRODUCTION

CORAL reefs provide humans with various living resources, serve as shorelines buffer and vital to fisheries and tourism industry. Thus, there are numerous researches and scientific programs have been conducted to monitor coral reef around the world. There are many coral reefs monitoring methods exist. Among them are by using remote sensing [1], hydro-acoustic sensing [2], manual diving [3] and perhaps the most accurate method is by using video transect monitoring technique [4]. In the video transect monitoring technique, coral reef images were manually analysed to estimate the distribution of some predetermined coral reef types. This process is highly labour intensive and time consuming. In this paper, an alternative solution to the manual analysis of coral reefs from still images is proposed where image analysis method is employed to automatically analyse the distribution of coral reefs. Specifically, various edges detection methods have been used to automatically segment coral reefs and coral reef recognition is estimated using blob processing technique.

Since coral reefs exist in various shapes, colours and textures, the process to recognize its types is a very challenging task. In addition, coral reefs monitoring survey is carried out in natural underwater seafloor environment which involves varying depth and different water turbidity which leads to illumination changes that will affect the quality of image captured. To avoid mis-classification of coral reef types, manual observation analysis of coral reefs is carried out on a clear still image of the video transect. Thus, in this paper, some samples of three group of coral reefs extracted from video transect were used namely Acropora branching (ACB), Acropora submassive (ACS) and Coral foliose (CF).

Various types of established edge detection techniques have been applied to extract edge information of these image samples. Based on coral edges information, the properties of detected coral reefs were later been computed using blob processing technique. In this way, various coral reef features could be computed such as area, perimeter, aspect ratio, solidity, compactness, roundness and others.

This next section of this paper describes the concepts and theoretical background of various edge detection techniques. Section 3 presents the datasets that we have collected, and provide results for our experimental investigations on this data. The paper is concludes with a discussion of future work and outstanding problems.

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2 METHODS

In this paper, the process of coral reef recognition is shown in Fig. 1. Three groups of coral reef images were used as input image i.e., Acropora branching (ACB), Acropora submassive (ACS) and Coral foliose (CF). All input images are converted from colour image to grayscale images before edge detection technique is applied. Based on the results obtained from edge detection, coral reefs feature values are computed using Blob processing technique.

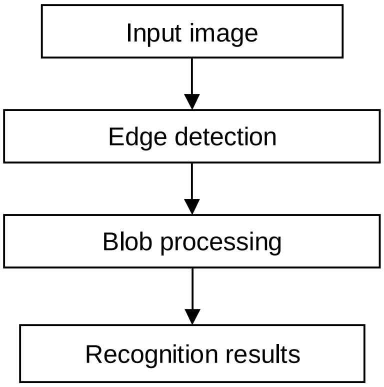


Fig. 1. The general coral reef recognition process.

2.1 Input Images

In this paper, three categories of coral reef images were used as input images i.e., ACB, ACS and CF. All the images are captured by using 30 frames per second with video resolution 640x480. In this a typical coral reef monitoring method using line intercept transect, a 100 meter video recording of coral reefs is recorded at a predetemined survey area. This video ransect were later divided into 4 segments and each segment produce 20 image frames. From each image frames, 100 hundred of coral reef still images were cropped to form image database for this study. It should be noted that all of video transects were obtained from Marine Portal Database Laboratory at Institute Oceanography and Environment (INOS), Universiti Malaysia Terengganu (UMT).

2.2 Theoretical Edge Detection Techniques

Edge detection is one of the most important technique in preprocessing step of image processing to find the significant edges in the image while minimizing noise. Typically, the edge detection technique is performed in image segmentation based on Gradient and Laplacian method. In gradient method, first order derivative is applied to find the maximum and the minimum intensity pixel values over input image [5]. Among the edge detections that are operated in first order derivative i.e, Sobel [6], Prewitt [7], and Roberts [8]. In the Laplacian method [9], second order derivative is used by determining the zero crossing points that exactly matched on edges. The Laplacian of Gaussian (LoG) is one of the edge detection techniques that operated in the second order derivative. The LoG edge detection used Gaussian filter to minimize noise in the image. Then the Laplacian operator is combined Gaussian filter to preserve the selected edges.

Generally, edge detection method used a convolution mask or sometimes been referred to as filter, windows or kernel. The convolution mask is convolved with input image to produce a new gradient image. Let $x_1 \ldots . x_9$ be the number of neighboring pixels and $f(x, y)$ denotes the location of neighboring pixel values. Table I shows a 3x3 convolution mask with its neighboring pixels.

TABLE 1. A 3X3 CONVOLUTION MASK

$X_1\,(f(x-1, y-1))$	$X_2\,(f(x-1, y))$	$X_3\,(f(x-1, y+1))$
$X_4\,(f(x, y-1))$	$X_5\,(f(x, y))$	$X_6\,(f(x, y+1))$
$X_7\,(f(x+1, y-1))$	$X_8\,(f(x+1, y))$	$X_9\,(f(x+1, y+1))$

2.3 First Order Derivative for Edge Detection

The gradient method is commonly used to detect edges in first order derivative by determining the maximum and the minimum intensity pixel values. Among that edge detection techniques that used in the gradient based are Sobel [5] Prewitt [6] and Roberts [7].

Sobel edge detection [5] is one of the earliest establish edge detector which used a 3x3 convolution mask to produce a new gradient image. Sobel operator computed the image values in horizontal and vertical direction. Both directions also can be used together to estimate edges over the image. Table II shows a 3x3 convolution mask on horizontal and vertical direction that is applied by Sobel edge detection. Let $f(i, j)$ be the input image and $Gx(x, y)$ and $Gy(x, y)$ are convolution mask of horizontal and vertical direction, respectively. The computation of gradient value in the horizontal direction, Gx, the computation of gradient values in the vertical direction, Gy, is shown in (1) and (2), respectively. These masks are design to respond maximally to edges running horizontally and vertically relative to pixel grid; one mask for each of the two perpendicular orientations. These masks can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation of Gx and Gy.

TABLE 2. THE SOBEL EDGE DETECTOR CONVOLUTION MASK FOR HORIZONTAL AND VERTICAL DIRECTION.

Edge Detector	Convolution Mask, Gx	Convolution Mask, Gy
Sobel	$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$	$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$

$$Gx(x,y) = f(i,j) * ((X_7 + 2X_8 + X_9) - (X_1 + 2X_2 + X_3)) \quad (1)$$

$$Gy(x,y) = f(i,j) * ((X_3 + 2X_6 + X_9) - (X_1 + 2X_4 + X_7)) \quad (2)$$

Based on these gradient values, the absolute magnitude of the gradient at each point and the orientation of the gradient can be computed. The gradient magnitude, $\nabla G(x,y)$ at each point in the image can be calculated by using (3) as follows:

$$\nabla G(x,y) = \sqrt{G_x^2 + G_y^2} \quad (3)$$

The angle of orientation of the edge that is relative to pixel grid, $\theta(x,y)$ can be computed as follows:

$$\theta(x,y) = arctan(Gy/Gx) \quad (4)$$

Similar to Sobel convolution mask, Prewitt edge detection [7] used a 3x3 convolution mask but with slightly different coefficient values. Table III shows the Prewitt convolution mask for both horizontal and vertical directions. Prewitt edge detection performed in both directions by using (5) and (6) to produce the gradient values.

TABLE 3. THE PREWITT EDGE DETECTOR CONVOLUTION MASK OF HORIZONTAL AND VERTICAL DIRECTION.

Edge Detector	Convolution Mask Gx	Convolution Mask Gy
Prewitt	$\begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$	$\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$

$$Gx(x,y) = f(i,j) * ((X_7 + X_8 + X_9) - (X_1 + X_2 + X_3)) \quad (5)$$

$$Gy(x,y) = f(i,j) * ((X_3 + X_6 + X_9) - (X_1 + X_4 + X_7)) \quad (6)$$

The gradient magnitude and the angle of orientation of the edges are estimated using (3) and (4).

Meanwhile, the Robert's operator [8] uses 2x2 convolution mask which is the smallest mask among other edge detection masks. Table 4 shows the convolution mask for both horizontal and vertical directions. Since the Roberts edge detection computed in simple and quick computation, a lot of noise introduced in the image that becomes a difficult problem to be solved. The convolution process with input image is computed using (7) and (8).

$$Gx(x,y) = f(i,j) * ((X_9) - (X_5)) \quad (7)$$

$$Gy(x,y) = f(i,j) * ((X_8) - (X_6)) \quad (8)$$

TABLE 4. THE ROBERTS EDGE DETECTOR CONVOLUTION MASK OF HORIZONTAL AND VERTICAL DIRECTION.

Edge Detector	Convolution Mask, Gx	Convolution Mask, Gy
Roberts	$\begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$

2.4 Second Order Derivative for Edge Detection

The Laplacian operator [9] is a second order derivative edge detector that is commonly used to find edges. Since it is based on second order derivative, it produces a lot of noise in the output image and thus smoothing technique is required. The Laplacian of Guassian (LoG) edge detection used Gaussian filter to reduce some amount of noise in the image before Laplacian operator is applied. The formula for Gaussian filter is expressed in (9) and Laplacian operator is computed using (10).

$$g(x,y;\sigma) = \frac{1}{2\pi\sigma^2} \, . exp^{-\frac{x^2+y^2}{2\sigma^2}} \quad (9)$$

where σ is the standard deviation value that is used to control the width of Gaussian distribution, x is the distance values of horizontal direction, y is the distance values in the vertical direction and $g(x,y)$ denotes the new output value for Gaussian filter.

$$\boldsymbol{\nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2}} \quad \textbf{(10)}$$

In Equation (10), the $\boldsymbol{\nabla^2 f(x,y)}$ denotes the output value of the Laplacian edge operator $f(x,y)$ is defined as location of pixel intensity values of the image. The Laplacian of Gaussian (LoG) used convolution mask in as defined in Table V. The LoG edge detector is applied by using (11) with combination of the Gaussian filtering and the Laplacian operator.

$$LoG\ (x,y) = -\frac{1}{\pi\sigma^4}\left[1 - \frac{x^2 + y^2}{2\sigma^2}\right] e^{\frac{x^2+y^2}{2\sigma^2}} \quad (11)$$

where $LoG(x,y)$ is the gradient output value of LoG. σ is is defined as the standard deviation value that used in the Gaussian distribution, x and y are the horizontal and vertical direction values over the input image, respectively.

TABLE 5. THE LOG EDGE DETECTOR CONVOLUTION MASK OF HORIZONTAL AND VERTICAL DIRECTION.

Edge Detector	Convolution Mask, Gx	Convolution Mask, Gy
Laplacian of Gaussian (LoG)	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$

2.5 Canny Edge Detection

The Canny operator [10] is a well-known method for detecting edges with minimum noise in the image. It is operated in multi-stage algorithm to find absolute edges boundaries which depend on three criteria such as noise effect, location selection and only respond to single edges [11]. In Canny edge detection algorithm, noise effect in an image is removed by using Gaussian filter which is defined in (12).

$$g(x, y; \sigma) = \frac{1}{2\pi\sigma^2} \cdot exp^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (12)$$

where $g(x, y)$ denotes the output value of the noise, σ is the standard deviation value that used to estimate the width of Gaussian distribution, while x and y are the values of the horizontal and vertical direction, respectively.

In canny edge detection, a 3x3 convolution mask is used to convolve with input image using (1) and (2). The gradient magnitude is then measured using (3) while the angle of orientation is computed using (4). In the preceeding stage, the pixel value that are not at maximum are suppressed by using non-maximum suppression technique. Finally to preserve selected edges, the hysteresis technique is employed by using low and high threshold values.

3 EXPERIMENTAL RESULTS

In this paper, we used three groups of coral reef images i.e., Acropora branching (ACB), Acropora submassive (ACS) and Coral foliose (CF). In Case Study 1, we evaluate the effect of the before mentioned edge detection techniques on the collected coral reef images. In Case Study 2, we further evaluate the effect of previously mentioned edge detection methods for coral reef images that have been corrupted by Gaussian noise with its mean and variance values of 0.1 and 0.01, respectively. In the case of LoG and Canny edge detector, the standard deviation value is set to 2.0. In general, the standard deviation value is used to estimate the width of a Gaussian filter to reduce amount of noise in coral image. The threshold values are determined during experiment and were chosen merely based on trial and error basis which produced best edges by observation. From the experimental runs, it is fund out that an appropriate threshold value is in the range between 0.05 to 0.2. It should be noted that if a threshold value below than 0.05 is used, a lot of noises were produced and many spurious edges were generated in the output image. On the other hand, if threshold value of more than 0.2 is used, some significant edges will be lost and less edges information is obtained.

3.1 The effect of Different Edge Detector Techniques on Original Coral Reef Images

In the first case study, five types of edge detectors were used to extract the important edges namely Sobel, Prewitt, Roberts, LoG and Canny edge detectors. Fig. 2 to Fig. 4 shows the results of applying these edge detectors to the three groups of coral reefs. It can be clearly observed that the Canny edge detector produced the best edges as compared to other edge detectors. It produces less noise as compared with other edge detectors and at the same time could detect almost all significant edges present in the image. The other edge detectors produces either produces a lot of noise or the edges could not be detected fully. This experimental findings imply that Canny edge detector will be used in the subsequent coral reef analysis and recognition in the later stage.

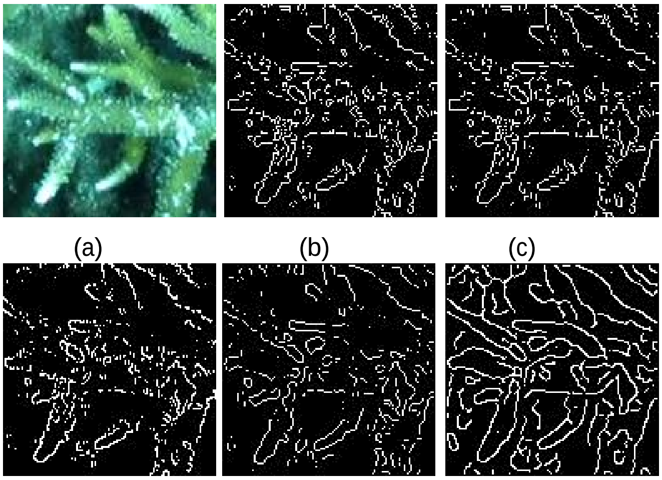
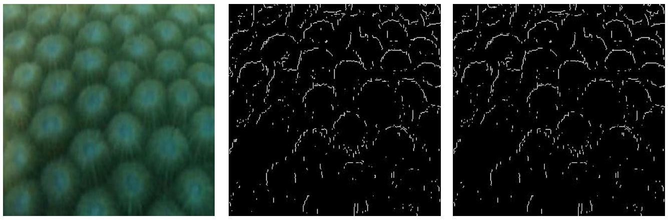
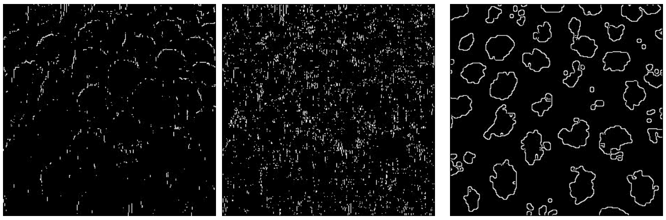


Fig. 2. The comparison of edge detection techniques results on Acropora branching (ACB) image: (a) Original image (b) Sobel operator (c) Prewitt operator (d) Robert's operator (e) LoG operator (f) Canny operator.

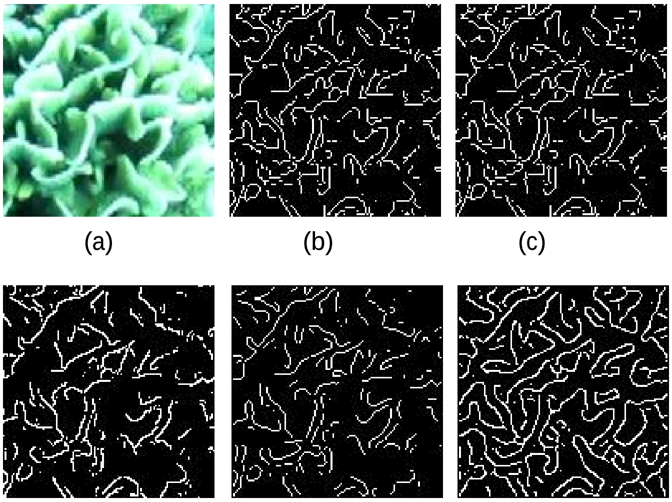


(a) (b) (c)



(d) (e) (f)

Fig. 3. The comparison of edge detection results on Acropora submassive (ACS) image: (a) Original image (b) Sobel operator (c) Prewitt operator (d) Robert's operator (e) LoG operator (f) Canny operator.



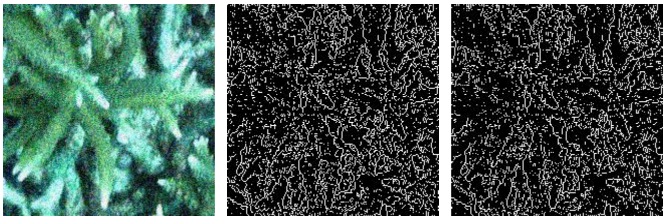
(a) (b) (c)

(d) (e) (f)

Fig. 4. The comparison of edge detection results on Coral foliose (CF) image: (a) Original image (b) Sobel operator (c) Prewitt operator (d) Robert's operator (e) LoG operator (f) Canny operator.

3.2 Comparison of Different Edge Detection Techniques on Noisy Coral Reef Images

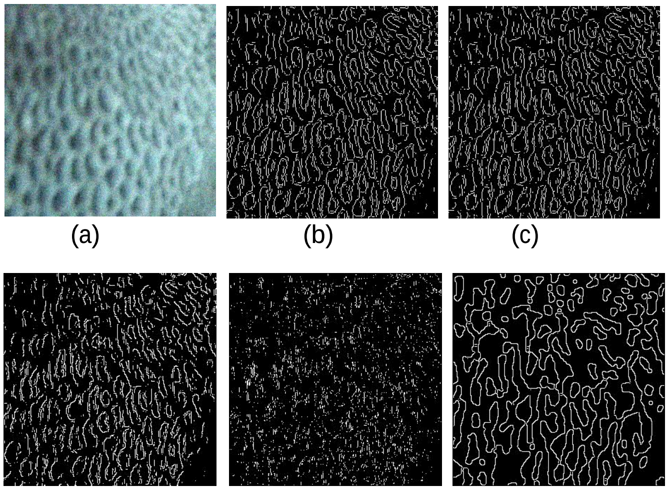
Fig. 5 to Fig. 7 show the results of applying Gaussian noise to the original image in Case Study 1. Again, it can be clearly seen that Canny edge detector produces the best edge detection results as compared to other methods. The amount of noise produces is very small and almost all the significant edges could be fully detected under Canny detector. However, most of other edge detectors failed in this case study.



(a) (b) (c)

(d) (e) (f)

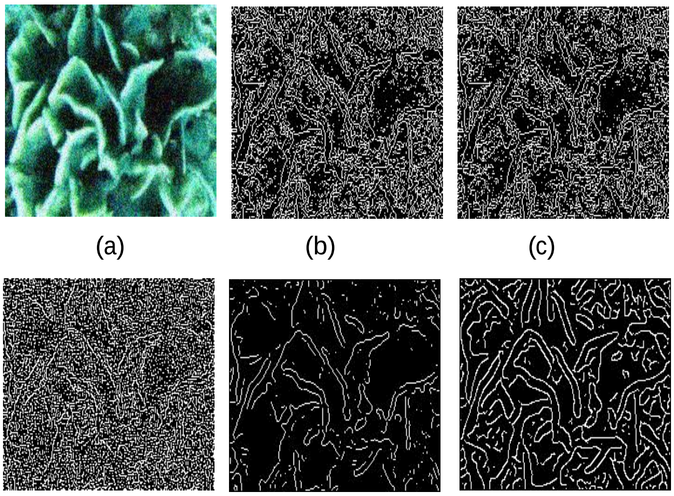
Fig. 5. The comparison of edge detection results via noise image of Acropora branching (ACS): (a) Original image (b) Sobel operator (c) Prewitt operator (d) Robert's operator (e) LoG operator (f) Canny operator.



(a) (b) (c)

(d) (e) (f)

Fig. 6. The comparison of edge detection results through noise image of Acropora submassive (ACS) image: (a) Original image (b) Sobel operator (c) Prewitt operator (d) Robert's operator (e) LoG operator (f) Canny operator.



(a) (b) (c)

(d) (e) (f)

Fig. 7. The comparison of edge detection results using noise image of Acropora foliose (ACF) image: (a) Original image (b) Sobel operator (c) Prewitt operator (d) Robert's operator (e) Laplacian of Gaussian operator (f) Canny operator.

3.3 Feature Extraction of Coral Reef Images.

In the third case study, we used blob processing technique to compute each of the coral reef properties. Among the extraxted properties are perimeter, aspect ratio, compactness, roundness and solidity. From this information, marine scientists could use this information for detail analysis of coral reef groups. A sample of graphical user interface output for such analysis is illustrated in Fig. 8.

	ACB Features Values	ACS Features Values	CF Features Values
Total Area	36.00	39.00	15.00
Maximum Area	2173.00	533.00	15592.00
Solidity > 0.90	21.00	29.00	7.00
Solidity < 0.89	15.00	9.00	8.00
Total Solidity	36.00	38.00	15.00
Aspect Ratio	2.97	1.46	1.09
Compactness	0.33	0.69	0.64
Roundness	0.14494	0.40546	0.02214

Fig. 8. The properties of each type of coral reef measured by blob processing technique.

4 CONCLUSION

In this paper, the performances of 5 types of edge detector method namely Robert operator, Prewitt operator, Sobel operator, LoG operator and Canny operator, have been used to detect coral reef edges in natural environment scene as well as under noise disturbances. The experimental findings show that Canny edge detector is the best method to extract edges in both cases as compared to the other four methods. In the later part of this paper, blob processing has been used to analyse the properties of each type of coral reefs. The output of blob processing technique has resulted in avaluable information for marine scientists for coral reefs distribution estimation analysis which is very time consuming if conducted manually. In the future, it is proposed to embed the blob processing anaysis for coral reef video transect analysis so that a fully automatic analysis of coral reef distribution estimation could be made.

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