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Modification of Canny Edge Detection for Coral Reef Components Estimation Distribution From Underwater Video Transect

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Abstract—In recent years, monitoring of coral reef status and health are done with the assist from image processing technique. Since underwater images are always suffer from major drawbacks, research in this area is still active. In this paper, we propose to use edge based segmentation where we modify the original canny edge detector and then use the blob processing technique to extract dominant features from the images. We conduct the experiments using images that are extracted from video transect and the results are promising for estimating coral reefs distribution.

I. INTRODUCTION

Coral reefs exist with different natural characteristics such as varying colors, shapes, sizes and textures. Colors may vary significantly due to light attenuation and light scattering phenomena. Besides that they are visibly pale (bleach) when affected by phenomena of the global climate change. In the case of shapes and textures of coral reefs, their varieties largely rely on the type of corals such as hard and pointed-shaped coral as well as soft and rounded shaped corals. In spite of that, the location of the coral contributes to the different shapes of coral reefs where coral with robust mounds or flattened shapes grow in the strong waves while branching patterns grow in more sheltered areas. The structure of the same type of corals may also vary as algae and plankton lives on them. For the purpose of automatic estimation of distribution and classification of coral reefs images, these problems must be coped beforehand. One solution to the aforementioned issue is to do preprocessing step based on image segmentation before proceed with further processes. However, to the best of our knowledge, there is no segmentation technique that is best suited for all types of images. Therefore, many segmentation techniques have been proposed to perform in different fields of applications such as color image segmentation [1], texture segmentation [2], threshold-based segmentation [3], edge detection segmentation [4], etc. In this paper, edge-based segmentation is used to perform the pre-processing part. It is done by modifying the Canny edge detection proposed by [5] which incorporates Canny with anisotropic diffusion [6] for better noise suppression and at the same time preserve the significant edges simultaneously. Once the objects edges information have been extracted, the blob processing techniques is used to estimate some important features such as area of the objects, number of objects, size of the objects, boundary of the objects, etc. which then used for estimating the percentage cover of coral reef components in the image. The remainder of this paper organized as follows. Section II describes several related works on image segmentation. Section III discusses the background concepts and theories of modified Canny edge detection with anisotropic diffusion technique and blob processing techniques. Section IV presents the experimental results of the study using several coral reef images datasets. Section V discusses the experimental results of the paper. Finally, section IV concludes this paper.

II. RELATED WORKS

Technological advances in underwater digital devices such as the use of underwater camera over the past decade have been widely used for classifying coral reef benthic components using image processing techniques. [6] proposed a texture-based algorithm using image processing technique for classifying coral reef species namely the *Montastrea annularis* that commonly growth more than 10 meter depth with less light source. However, algorithm proposed by [6] was able to classify only for one species of coral reefs. In addition, the thresholds proposed in their study are sensitive to intensity change and color variations throughout the dataset. Moreover, the use of 20 samples dataset in their study were too small to evaluate the algorithm performance and scalability. [8] proposed the use of color and texture features for classifying six type classes of coral reef benthic components, i.e. live corals, dead corals, algae on dead corals, soft coral, abiotic and other organisms. However, the limitation due to many classes involved shows a low accuracy of classification rate where only 48 percent was achieved. This happens because of too many input of classes and the numbers of sample images were not properly separated among different classes.

To cope with the problem, edge detection technique is used to avoid from too many elimination of coral components within the images. Edge detection technique is commonly performed based on a multistage process to determine the edges of the objects in the image [10]. The edge detection technique has been used in many applications such as image segmentation [11] and [12], image enhancement [13], image compression [14], etc. Besides that, edge detection techniques are used to indicate overlapping objects, calculate the basic properties of the object like area and shape [14] and classification [16]. [17] proposed combination of Canny edge detection and anisotropic diffusion by replacing the Gaussian filter on the original Canny edge detection to detect edges in ultrasound images. [18] used edge detection techniques with combination features of energy and skewness to determine the fat region in marbled meat. [19] used partial differential equation (PDE) denoising based on Perona-Malik nonlinear diffusion model to propose a novel diffusivity function. The proposed method provides promising for noise removal and edge enhancement. [20] used anisotropic diffusion based on Perona-Malik model to smooth the image by reducing the noise and preserving retina vessels boundaries.

III. METHODOLOGY

A. Modified Canny Edge Detection Using Anisotropic Diffusion Technique

Canny edge detection algorithm involves with a series of steps process such as Gaussian filtering, non-maxima suppression and hysteresis process. However, the use of Gaussian filter in an original Canny is not appropriate for detection of coral reef edges since the images suffer with attenuation problems. The popular Canny edge detector is implemented using Gaussian filter in the first step to minimize disorder noise through detecting edges [10]. However, the use of Gaussian filtering tends to loss the significant edges of the object in the image. The Gaussian function used in Canny edge technique is given as follows:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/(2\sigma^2)} \qquad (1)$$

To overcome this problem, we adapt the anisotropic diffusion technique proposed in [7] by replacing it with the Eq. 1 in Canny edge detector. The anisotropic diffusion approach is basically a modification of the linear diffusion (or heat equation), and the continuous anisotropic diffusion which is given by

$$\frac{\partial I_t(x,y)}{\partial t} = div(c_t(x,y,t)\nabla I_t(x,y)) \qquad (2)$$

where I_t (x, y) denotes the image at time t, div is the divergence operator, ∇I_t (x, y) corresponds to the gradient image and c_t (x, y, t) represents the diffusion coefficient. Diffusion coefficient is used to control the diffusion rate of image gradient. Diffusion coefficient reduces the noise in the image by smoothing process while edges of objects are preserved. Diffusion coefficient is commonly performed with non-negative function of gradient magnitude to smooth the small variations in intensity for example noise and the edges that have large intensity are preserved in the image. The diffusion coefficient is calculated based on an exponential function or an inverse quadratic function. Both an exponential function and an inverse quadratic function are defined as follows:

$$c\ (|\nabla I|) = e^{-(\nabla/K)^2} \qquad (3)$$

and

$$c(|\nabla I|) = \frac{1}{\left(\frac{\nabla I}{K}\right)^2} \quad (4)$$

Parameter K is the constant value in the diffusion coefficient function c and normally adjusted for a particular application. If the K value is too large, the diffusion process will over smooth and result in a blurred image. In contrast, if the K value is too small, the diffusion process will stop smoothing in early iterations and yield a restored image similar to the original one. The partial differential equation with discrete computation is used based on eight nearest neighbors of the Laplacian operator and can be estimated as follows:

$$I_{t+1}(x,y) = It(x,y) + \frac{1}{8}\sum_{i-1}^{8}\left(c_t^i(x,y).\nabla I_t^i(x,y)\right) \quad (5)$$

Where $I\frac{i}{t}(x,y)$, i = 1, 2, 3, ..., and 8 denote the gradient value with eight neighbors that related to directions of north, south, east, west, northeast, northwest, southeast and southwest, respectively. Meanwhile, $c\frac{i}{t}(x,y)$ represents the diffusion coefficient that associates with gradient $I\frac{i}{t}(x,y)$ and are considered as a gradient function. The eight nearest neighbor's directions differences are estimated using the following equations:

$$\begin{aligned}
\nabla I_t^1\,(x,y) &= It(x-1,y) - It(x,y)\\
\nabla I_t^2\,(x,y) &= It(x,y+1) - It(x,y)\\
\nabla I_t^3\,(x,y) &= It(x+1,y) - It(x,y)\\
\nabla I_t^4\,(x,y) &= It(x,y-1) - It(x,y)\\
\nabla I_t^5\,(x,y) &= It(x-1,y-1) - It(x,y)\\
\nabla I_t^6\,(x,y) &= It(x-1,y+1) - It(x,y)\\
\nabla I_t^7\,(x,y) &= It(x+1,y-1) - It(x,y)\\
\nabla I_t^8\,(x,y) &= It(x+1,y+1) - It(x,y) \quad (6)
\end{aligned}$$

The algorithm of the modified Canny edge detection based on anisotropic diffusion techniques is shown below. It is a multi-stage process that involves noise removal, gradient magnitude computation, non-maximum suppression and hysteresis process.

Algorithm 1: Modified Canny Edge Detection

Data: Input image
Result: Edge Image
Total iterations=K;
k = 0;
while $k < K$ **do**
    smooth image using anisotropic diffusion;
end
find gradient magnitude;
perform non-maximum suppression;
perform hysteresis process;

B. Estimating Distribution of Coral Reefs Components

The output of the process described in the previous subsection is edges of coral reef which then is used as inputs for blob processing. The blob processing is used to calculate the centroid, area and boundary of coral reef regions within the frames. All these three features provide very meaningful information of the coral reef objects in the image. The centroid feature of the blob processing represents the number of the objects in the image. Meanwhile, the area feature is used to measure number and size of the objects in the image. The area property is a vector that represents the number of pixels in areas that are labeled on the objects in the picture. The size of the object in the picture whether small or large can be measured by calculating the number of pixels in the area of the object. Finally, the boundary features is used to separate the objects boundary of different components in the image.

Fig. 1 illustrates the flow process of coral reef distribution estimation. First of all, the original coral reef as in Fig. 1(a) is transformed from RGB color space to Hue Saturation Value (HSV) space (see Fig. 1(b)). The use of the HSV color space is to separate image intensity components from color information. Using HSV color space, we are able to separate color of four types of coral reef components i.e. live coral, dead coral, rubble and sand. This can be achieved by adjusting each of the H, S and V channel. After separating the components based on color information, a modified Canny edge detection with anisotropic is used with aim to suppressed noise and preserving the significant edges in the images (see Fig. 1(c-f)). The edges obtained from modified Canny edge detection are further processed using the blob processing technique to obtain the areas and the centroids as shown in Fig. 1(g-j) and Fig. 1(k-n), respectively. From the areas, automatically the size of the each coral components distribution can be calculated. Then, to estimate the percentage cover of each components, the following formula is applied.

$$\%Ci = \frac{areas\ of\ Ci}{areas\ of\ (C1 + C2 + C3 + C4)} \quad (7)$$

where i = 1, 2, 3, 4 and $C1$, $C2$, $C3$ and $C4$ corresponds
to live coral, dead coral, rubble and sand, respectively. The extracted components are shown in Fig. 1(o-r).

IV. EXPERIMENTAL SETUP

Three different datasets of coral reef images that composed of *acropora branching*, *acropora submassive* and *coral foliose* are used in the study. The experiments are conducted based on small, medium and large sample dataset with dimension sizes 300 x 300 pixels, 750 x 1020 pixels and 1920 x 1080 pixels, respectively. The coral reefs distribution for each component is estimated based on the percentage cover of the particular component area. Results and discussions are presented in the following section.

V. RESULTS AND DISCUSSION

A. Comparison of Coral Reefs Components distribution

Table I shows the estimation of the first experiment on small size of coral reefs image. Based on the observation, a live coral class covers the largest area by 60.99% of the total area and labeled with eight data points. Sand or shadow class covers the second largest area with 33.28% of the total area where 16 data points are automatically generated on the objects. Rubble class covers only 3.80% of total area with 11 data points plotted to the objects. Finally a dead coral class has only 1.94% of total area and considered as the lowest area within the image. Only eight data points are labeled to the objects.

TABLE I. DISTRIBUTION OF CORAL REEFS USING SMALL S IZE IMAGE

Components	Total Area (Pixel)	Percent Cover (%)	Data Points
Live coral	55558	60.99	8
Dead coral	1763	1.94	8
Sand/Shadow	30316	33.28	16
Rubble	3460	3.80	11

Table II presents the estimation of coral reefs distribution using medium size image. From the experiment, a live coral class covers the largest area with percentage cover of 40.71% and total numbers of 47 data points are automatically generated. The second largest area is covered by a dead coral class with 33.09% of the total area. A total number of 44 data points were labelled to the objects. Sand or shadow class represents 15.13% of the total areas and provides 36 data points in the image. A rubble class is the smallest area with percentage cover is 11.07% with total number of 60 data points is generated.

TABLE II. ESTIMATION DISTRIBUTION OF CORAL REEFS USING MEDIUM SIZE IMAGE

Components	Total Area (Pixel)	Percent Cover (%)	Data Points
Live coral	33201	40.71	47
Dead coral	26983	33.09	44
Sand/Shadow	12338	15.13	36
Rubble	9029	11.07	60

For the third experiment, the results of Table III shows that a live coral class covers the largest area of 71.34% with only five data points are generated. A rubble class covers only 12.03% of the total areas, which is the second largest area behind a live coral and generates 43 data points. Sand or shadows class has 9.41% of the total areas and provides a total number of 26 data points. Finally, dead coral class has the smallest area covers only 7.22% but produces a total number of 21 data points. The live coral class is presented as dominant class for coral reef estimation distribution.

TABLE III. ESTIMATION DISTRIBUTION OF CORAL REEFS USING LARGE SIZE IMAGE

Components	Total Area (Pixel)	Percent Cover (%)	Data Points
Live coral	59833	71.34	5
Dead coral	6056	7.22	21
Sand/Shadow	7893	9.41	26
Rubble	10084	12.03	43

Fig. 1 presents the process of coral reefs estimation distribution for analysis. Fig. 2 shows all the labeling results from the above experiments. The boundary for each component are separated by applying different colors such as green, red, yellow and blue for live coral, dead coral, rubble and sand, respectively.

B. Comparison of Coral Reefs edges detection

For the edge detection process, the threshold value is set at 0.1 and the sigma value in range 1.0 The output results of different edge detection techniques using the underwater coral reef images are shown in the Fig. 3 to Fig. 4. Based on these results, it can be observed that the proposed method provides the best method in preserving the significant edges with minimum noise under all conditions of the coral reef images.

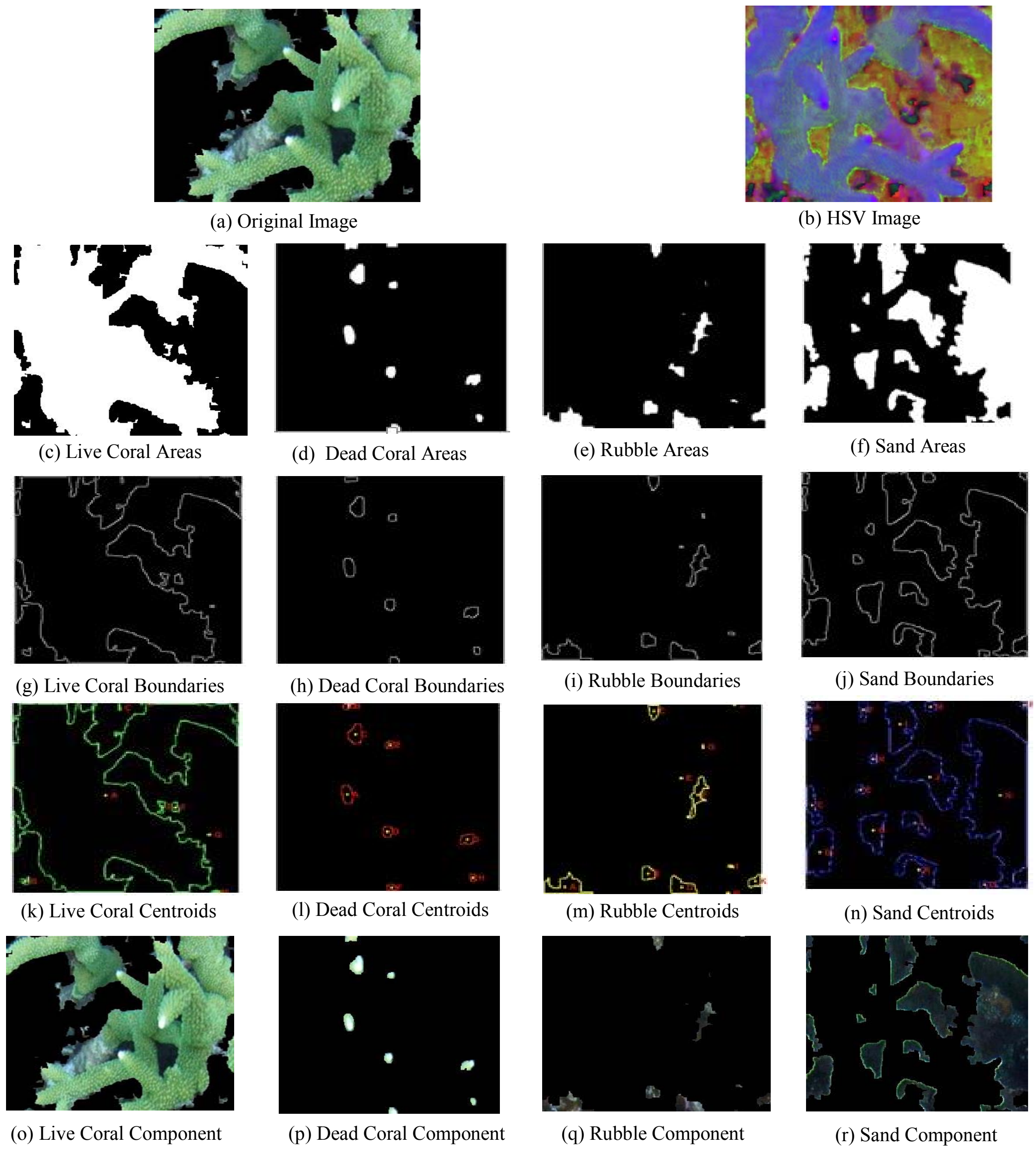

Fig. 1. The Flow Process of Coral Reefs Distribution Estimation

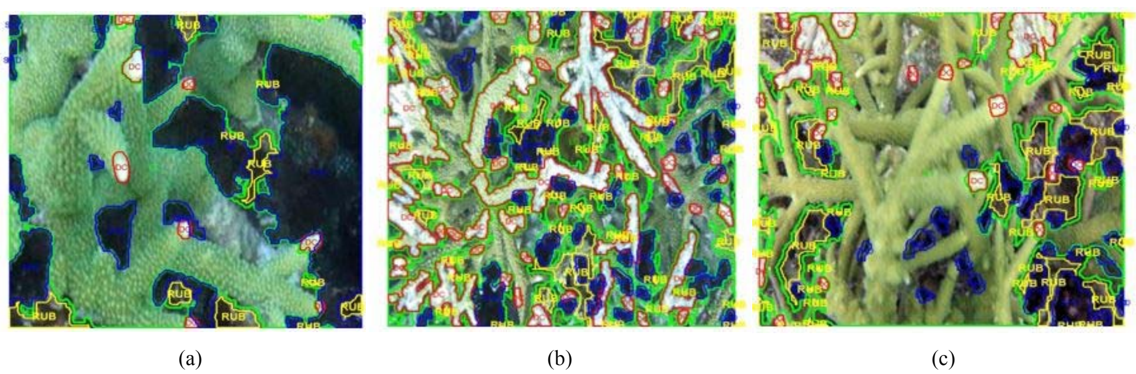

Fig. 2. Coral Reefs Components Labeling for (a) small, (b) medium and (c) large sample sizes images

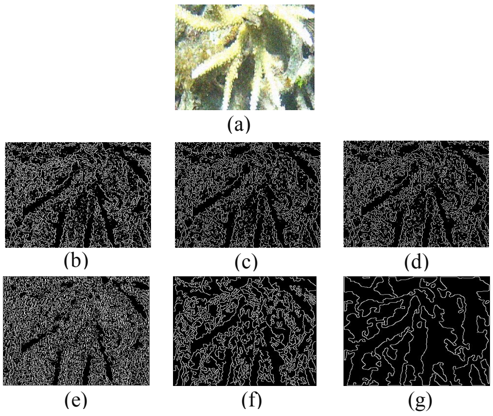

Fig.3. The comparison of edge detection technique on Acropora branching (ACB): (a) Original image with Gaussian noise (b) Sobel operator (c) Prewitt operator (d) Robert's operator (e) LoG operator (f) Canny operator (g) Proposed method.

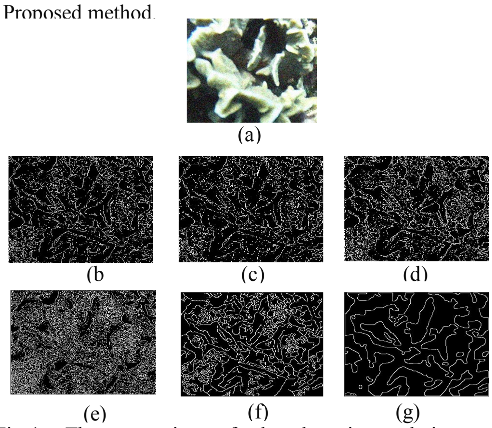

Fig.4. The comparison of edge detection technique on Coral foliose (CF): (a) Original image with Gaussian noise (b) Sobel operator (c) Prewitt operator (d) Robert's operator (e) LoG operator (f) Canny operator (g) Proposed method.

VI. CONCLUSION

In this paper, we have presented a new method for estimating coral reefs distribution. We modified Canny edge detection to detect edges of the coral reefs components. Subsequently, blob processing technique is used to estimate the percentage cover of the components that consists of live coral, dead coral, rubble and sands. This simple idea worked well for all sizes of images used in this study. For future work, we will extend our work for automatically classify coral reefs components.

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