Automatic Segmentation of Coral Reefs Implementing Textures Analysis and Color Features with Gaussian Mixtures Models

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Abstract

The applications of digital image processing techniques over coral reefs are emerging research field due to coral reefs importance in marine ecosystems. One important step to make a correct analysis of these reefs is segmentation stage. Few automatic segmentation techniques in corals have been used to solve this problem, which is why in this paper we propose a texture segmentation algorithm with applications to coral reefs segmentation. Our goal is reached using a combination of texture analysis, color features and Gaussian Mixture Model, varying the parameters for each one. The results show that automatic segmentation of corals using texture and color is a good approach, in most cases the corals are correctly segmented, even in a real environment the images are successfully segmented.

1. Introduction

Coral reefs are some of the most rich and diverse ecosystems on earth. These fill less than 0.1% of the ocean surface but they are the habitat for at least 25% of all marine species [1]. For its strategic location between coast and open sea, reefs serve as a barrier that protects mangroves and seagrass against onslaught of the waves. Mangroves and prairie grasses, in turn, protect the reefs against sedimentation and serve as spawning and nursery grounds for many species that are part of the reef ecosystem [2]. This ecosystem is home to a large variety of animals and provides ecosystem goods and services to tourism, fisheries and coastal protection.

Due to the importance of coral reefs in the ecosystem of the earth is necessary to stop its deterioration. Control and diagnostic of reefs state are the first step to interrupt this deterioration. For this task, various techniques of digital image processing are used to make an automatic diagnostic. Since coral reefs are three dimensional structures only certain parts are focus and occlusion between different organisms is common. Identification process must face changing nature of the corals and algae over time in addition to the random variation of the appearance on the subjects of the same species [3]. Finally the ecosystem adds some complications like water turbidity that can significantly decrease visibility and other animal occlusion. Analysis of coral with computer vision also needs to deal with data acquisition task which have been tackled through different approaches [4].

Color and pattern details of each species are an important part of the coral reefs study based on computer vision, due to these characteristics it is possible to identify and recognize visually coral species, as a result of that various techniques apply an analysis using the texture to represent these patterns [5]. These techniques apply the Maximum Response (MR) filter bank and filters over the L*a*b* color space in order to highlight the patterns that differentiate corals. Other texture descriptors such as the local binary patterns (LBP) have been applied due to LBP is robust to brightness change and Gaussian blurring and was shown to be better in recognizing tilted 3D textures than other texture paradigms [6].

Segmentation process before data is acquired, could be performed using different strategies, manual annotation is slow and requires knowledge of an expert, but the time of this person is limited [5]. Due to manual segmentation is time consuming, different efforts have been used in order to automatize the process. In [7] Neural networks are used to classify among live coral, dead coral and sand making changes to HSV color space, extracting local binary patterns to describe the spatial relationship between pixels having accuracy rates up to 86%. In the work of Mehta et. Al. [8] three types of corals Acropora species are classified using raw pixels of image as input of a support vector machine with 95% accuracy classifying images of this species on their database. In [9] is implemented a method that use the discrete cosine transform to extract a features vector and a k-nearest neighbor classifier to do classification, but this strategy was tested with just 16 images. In recent years it highlights the work of Beijbom et. Al. [5] where a k-means clustering is done per channel color space L*a*b* with 15 centers to generate dictionaries and train a support vector machine, first separating coral from the rest of the image with a percentage of accuracy of 89% and then try to classify among Crustose Coralline Algae, Turf algae, Macroalgae, sand, Acropora, Pavona, Montipora, Pocillopora, Porites and the percentages of success in the classification are 89%, 46%, 19%, 83 %, 62%, 60%, 42%, 76% and 60% respectively.

In the presented work an automatic segmentation method on corals using image processing is proposed. The method exposed does not require human interaction or previous training, unlike other similar methods that require a large database to obtain results. Our technique implements analysis of the textures on the coral reef using Gabor and color features and a Gaussian mixture model to join the textures.

The rest of this paper is organized as follows. First the methods implemented in the system are explained in Section 2. In Section 3 are described the experiments used to test the system and the results are showed. In Section 4 the discussion of the results and conclusions are presented.

2. Methodology

The method presented in this work is based on the analysis of textures on corals, for this task two steps are defined. First, a characterization step is applied to image, where Gabor and color features are extracted to each pixel. After that, a clustering step is applied, where to each pixel a type of texture is assigned and is grouped with other pixel of the same type.

2.1.Characterization:

Corals are compact colonies of identical individual animals (polyps) [3], this feature makes entire colonies looks like textured object. Polyps are of different colors and arrange in several ways giving to each species a characteristic appearance. In practice, biologists use this issue to recognize coral species as main strategy and reserve laboratory methods to less characteristic organism like algae [5].

Coral reefs are not composed just of corals but also algae, sponges, sand and rocks are also present in these landscapes. Algae coexist in a symbiotic relation with corals, its natural appearance does not give significant information between species and laboratory identification is common approximation, sand and rocks have a repetitive appearance thought images of the same coral reef. Although many algae does not let identify species by visual inspection it can be included in a general “algae” class as sand and rock.

If a polyp is assumed as an elementary pattern, an ideal coral model can be described as an arrangement of these patterns with a placement rule and can be viewed as a regular texture [10], an example of this behavior is shown in figure 1. However three dimensional characteristic of corals structure as body, shape and size arises common problems in natural textures like non-uniform illumination, lose, absence or non-clear elementary pattern and stochastic nature. The random pattern present in sand, rock, algae and non-ideal corals can be modeled with texture framework since there is a local variation of a pattern but with unknown parameters.

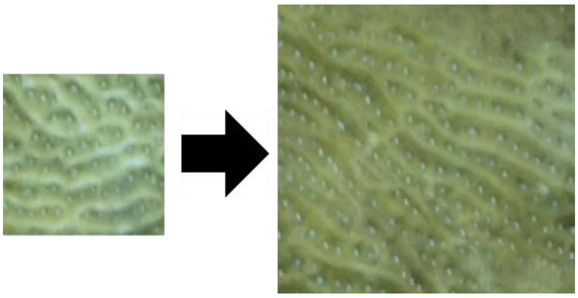

Figure (1). Elementary pattern and formed texture of corals.

2.1.1 Color Features:

Corals present local variation in texture, but color and shape are also important differentiating factors in visual identification between species [11]. From a computer vision perspective, colors are sensible to illumination changes and using color features without preprocessing could lead to noisy source. Due to standardize input images to uniform illumination RGB color space must be converted to a representation where color information is independent of brightness like L*a*b* color space [12]. Also is necessary to improve the contrast, so a Contrast Limited Adaptive Histogram Equalization (CLAHE) [13]. This method consists in transforming each pixel with a transformation function derived from a neighbourhood region.

Classic image quantization algorithms cluster pixel intensities without using spatial information but human vision perception is more sensitive to changes in smooth regions than in detailed regions, this fact is exploited by peer group filtering (PGF) quantization algorithm [14]. First a peer group filtering is used for smooth image and remove noise, this process set a pixel vector $x(n)$ in a window W based on similarity with center pixel, then pixel center intensity is replaced with the mean of pixels at distance d or less in the window, d is calculated using 1D Fisher discriminant estimation.

After PGF each pixel has the maximum distant peer group $T(n)$ that indicates the smoothness of the region, the weight of each pixel is calculated in Equation (1):

$$v(n) = exp(-T(n)) \quad (1)$$

T_{AVG} is the average of $T(n)$ and indicates the smoothness of the entire image, initial number of clusters N for quantization is calculated as follows in Equation (2):

$$N = \beta * T_{AVG} \quad (2)$$

The generalized Lloyd algorithm (GLA) is used for clustering, modifying update rule to incorporate pixels weights, each color cluster (C_i) centroid c_i is calculated by Equation (3):

$$c_i = \frac{\sum_{n=1}^{p} v(n)x(n)}{\sum_{n=1}^{p} v(n)}, \; x(n) \in C_i \quad (3)$$

Initial number of clusters is determined using splitting initialization algorithm, in the final step cluster centroids are calculated without pixel weights and an agglomerative clustering algorithm is performed to merge close cluster canters, at the end each pixel assigned with its closest cluster centroid.

2.1.2 Gabor:

Coral reef images include multiple species of corals, algae, rocks and sand. To characterize individual regions they must be localized but their position is unknown, this issue is named uncertainty principle in signal processing. The uncertainty principle tells that we cannot simultaneously know what happens and where happens, formally this is expressed as shown in Equation (4):

$$(\Delta t)^2(\Delta \omega)^2 \geq \frac{1}{4} \quad (4)$$

Where Δt is the duration of the signal and $\Delta \omega$ is the bandwidth of the signal. For image processing (two-dimensional signal) the joint uncertainty principle is shown in Equation (5) [10]:

$$(\Delta x)^2(\Delta \omega_x)^2(\Delta y)^2(\Delta \omega_y)^2 \geq \frac{1}{16} \quad (5)$$

Gabor is the most general function that obtains the minimum in the uncertainty principle for signal processing [10], this leads to obtain texture information of entire image assuming each pixel contains information about the texture region it belongs.

One-dimensional Gabor function is defined as shown in Equation (6), in this equation σ is the standard deviation of the Gaussian and $\omega_o$is the radian frequency.

$$g(t) = exp(-\frac{(t-t_o)^2}{2\sigma^2} + j\omega_o t) \quad (6)$$

Two-dimensional Gabor function as one-dimensional are a modulation of a complex exponential carrier wrapped by a Gaussian function. 2-D Gabor function does not have a standard expression yet [14], but we can express the main idea as shown in Equation (7):

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp(\frac{-x^2}{2{\sigma_x}^2} + \frac{-y^2}{2{\sigma_y}^2}) exp[j\omega(xcos\theta + ysin\theta)] \quad (7)$$

Where σ_x y σ_y represent the standard deviation of the Gaussian envelope in the *x* and *y* direction, ω is the radial center radian frequency and θ is the rotation angle.

To analyses an image into Gabor function, we take the discrete Fourier transform (DFT) of the image, multiply the image with an appropriate Gaussian window, and take the inverse Fourier transform of the result, we use a bank of filters to make sure we consider all possible frequencies that might be present in the image.

2.2. Clustering:

After characteristics are extracted is necessary to make analysis on these data to determine the different region with similar texture. For this task is require to explore the relations that exist between pixels with similar characteristics, expressed with the Gabor and color features. At this point the features samples do not have an associated class label, so it is necessary to apply an unsupervised learning or cluster analysis method. Cluster analysis consist on divide data into clusters that have common characteristics, assuming that these characteristic are close in feature space. Clusters should comprise objects that are similar to each other and different from those in other clusters [16].

For clustering phase a Gaussian Mixture Model (GMM) is used to determine if a sample belongs to a cluster or another. This distribution is used assuming that the Gabor and colors features of each texture have a normal behavior and are close to a mean. For a D-dimensional vector x the multivariate Gaussian distribution takes the form of Equation (8):

$$N(x|\mu,\Sigma) = \frac{1}{(2\pi)^{D/2}}\frac{1}{|\Sigma|^{1/2}} exp\left\{-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right\} \quad (8)$$

Where μ is a D-dimensional mean vector, Σ is a D×D covariance matrix, and $|\Sigma|$denotes the determinant of Σ [17]. A Gaussian Mixture Model is defined like the sum of K Normal distributions shown in Equation (9):

$$p(x|\theta) = \sum_{k=1}^{K} w_k N(x|\mu_k,\Sigma_k) \quad (9)$$

Where each Gaussian density $N(x|\mu_k,\Sigma_k)$ is called a *component of the mixture* and has its own μ and Σ. The parameters w_k in (9) are called *mixing coefficients* and each one must satisfied retractions of Equation (10) and Equation (11):

$$\sum_{k=1}^{K} w_k = 1 \quad (10)$$

$$0 \leq w_k \leq 1 \quad (11)$$

Therefore the *mixing coefficients* must comply with the restrictions of a probability function. In the clustering context, each of the Gaussian mixtures in the GMM is a cluster, so the objective is to associate a sample x to a Gaussian. When a sample x is evaluated in the model, the probability of belonging to each mixture is obtained, and the cluster with the highest probability is the class of x. In the present work the features of each pixel are evaluated in the GMM and each pixel is associated to a cluster, where each group is a type of texture. Each texture is represented with a different color in a final image.

3. Experiments and Results

3.1. Database description:

The database was taken by Ecoral Company in Barú in the National Natural Park Rosario´s Reef (PNNCR) in Colombian Caribbean. The images were taken along transects on three points in Barú called La Montañita, Octubre Rojo and Trompada to 30, 40, 50, 60 and 70 meters under the sea using the method proposed by the “Sistema Nacional de Monitoreo de arrecifes coralinos en Colombia” (SIMAC) [18].

The SIMAC method consist on take a quadrant of 1 meter by 1 meter and sub-divide this in 16 sub quadrants of 25 centimeters by 25 centimeters, thus the quadrant is put over coral reef and captures the image, the quadrant is a reference for hold a scale and size of the coral reef. This process is repeated along the selected transect. The images were saved with a resolution higher than 1500x1500 pixels with an uncompressed Tagged Image File Format (TIFF).

3.2. Experimental Setup:

The method proposed in this work was tested using eight artificial images. In order to build these images, various types of coral textures were extracted manually from the database. The textures selected are zones with a high percent of this coral type in the images and with distinguishable colors and patterns. Each image used for test has five different types of textures.

In the characterization step two, color spaces were evaluated RGB and L*a*b*, additionally the CLAHE method was applied to each color space. In quantization method, the level parameter was changed from 10 to 20. Gabor features were extracted varying the scale (from 1 to 8) and the orientation (from 2 to 12). In this step the features vector was built join each one of the type of characteristics generating a vector of 11 features for each pixel in the image.

In clustering step the number of Gaussians was varied using 5, 7 and 10 mixtures, these numbers were changed to evaluate if certain types of textures need more of one mixture to be defined.

3.3. Experimental results:

The images presented are result of our method with the best parameter combination. Parameter combination with best results is get using L*a*b* color space, 12 level in quantization, scale value 1 and orientation value 7 in Gabor features and 7 mixtures in GMM. Each color in the result image is a different texture. Additionally our method is compare with JSEG method [19], which is standard method in segmentation of natural scene images. JSEG method segments the zones enclosing each area by a white line. The results of apply this method are presented in figure 2, on the left column are original images, on the center column are the results of the proposed method, and on the right column are the results of JSEG method.

The results show that our method has problems to uniform areas, e.g. image 2b where the region are not uniform and each one had noise, but the method has the capacity to differentiate similar regions like in image 5a, which JSEG method confused the right and up areas as one. Additionally our method is not as susceptible to small changes in color, like in image 3a and 4a, where JSEG method split each texture in various zones.

Finally to validate our method behavior in a real environment, various images of real coral reefs in the database were tested. In these images best parameter combination is used, only the Gaussian mixtures number is changed, because the number of different textures in a real environment varies a lot and can change between images. The results of these images are shown in figure 3, left column is the original image and left column is the result of our approach. In these images the biggest coral species and with most representative characteristics are correctly segmented, but the method present problems in little corals where the method classify these corals in the same texture as the biggest textures, also present problems in irregular textures, like in image 4b, where the textures are clear but are very variable, the method represent each little change like a different texture. The same problem presented with the artificial images is shown in image 6b y 7b, where the method do not unifies the area making the big coral look like various small corals.

4. Conclusions

The results presented in figure 2 showed that a good election of parameters allow to make a correct segmentation of the corals and separating the coral reef textures. One of the parameters that enhance the performance of the method is the color space, where the L*a*b* space let to discriminate in a better way the regions. Use of L*a*b* space makes the method less susceptible to little color changes, which highlights the textures of each coral, additionally applying CLAHE as preprocessing method benefit this step.

Other important point is the number of mixture Gaussians. When the number of mixtures is low the textures are not represented in a good way and images tends to under segmentation, but when this number is too high the system is overfit and even the littlest areas are identified and do not contribute with the segmentation of the biggest textures causing over segmentation.

In images of real environment the method presents satisfactory results in the segmentation of the biggest areas, additionally can group on a cluster, textures that are not close to each other, making our approach a good start to powerful methods that requires seeds to begin.

Future work will look for a way to determine the number of Gaussians automatically, because in a coral reef the number of corals types is aleatory and depends of the location and depth. Also is necessary to find a way to eliminate the anomalies inside coral textures to uniformed segmentation, finally is required to provide a way to make segmentation of the textures with a little area avoiding over segmentation.

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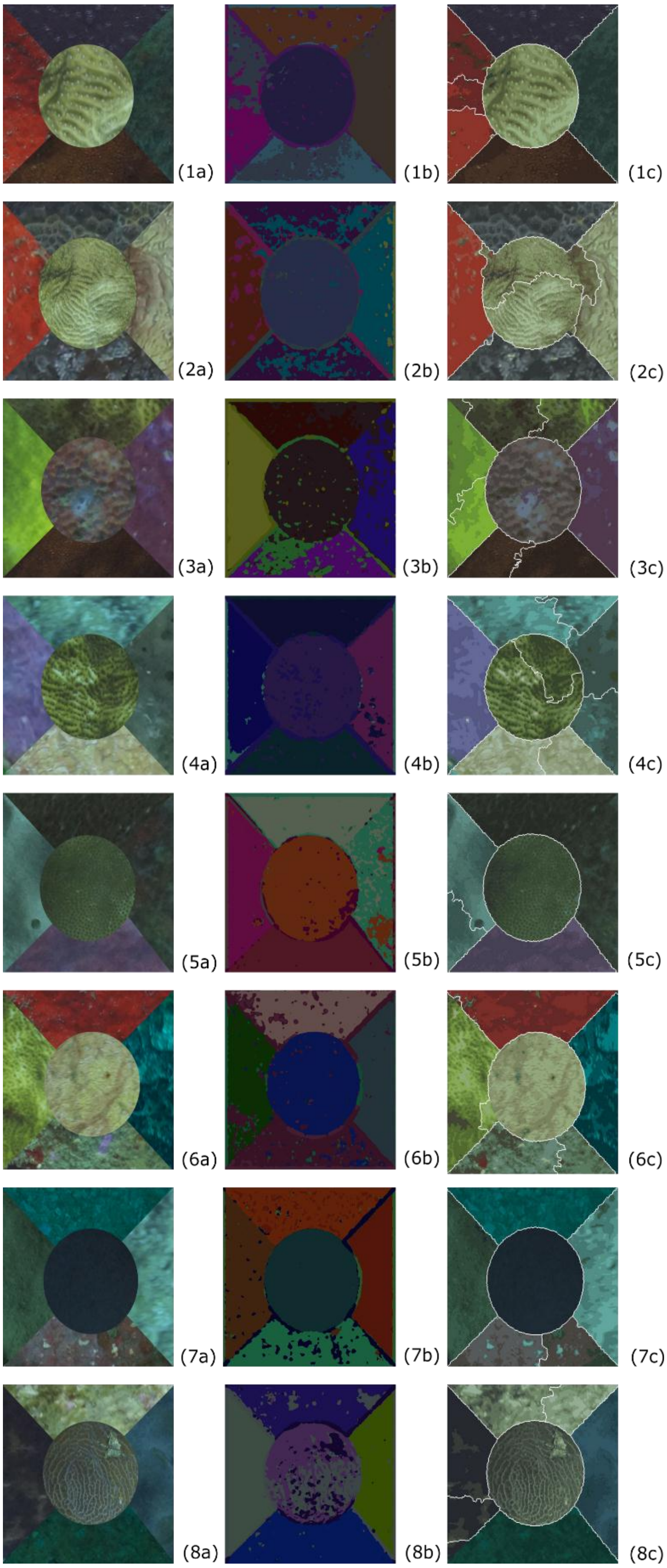

Figure (2). Results of apply the proposed method and JSEG method.

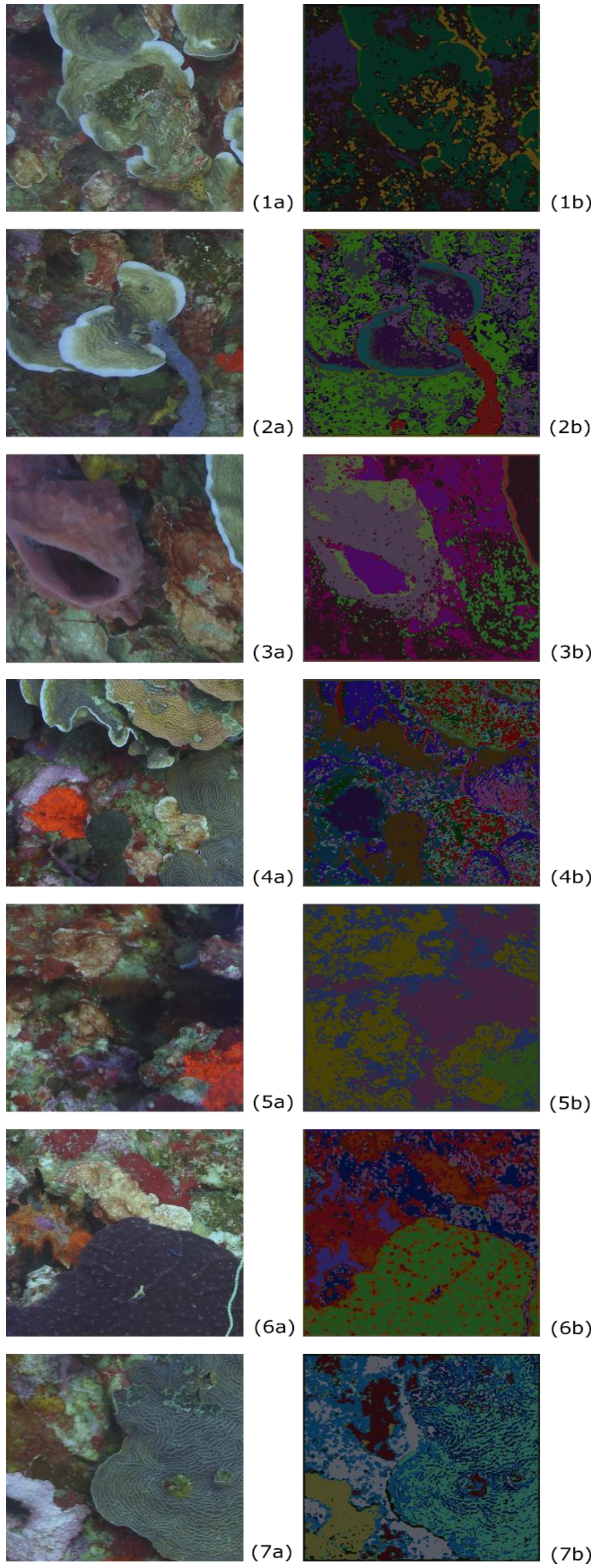

Figure (3). Results of the method proposed in real environment of coral reefs. In each image the best parameter combination found was used. The results images have different Gaussians mixtures, 1b has 6, 2b has 7, 3b has 6, 4b has 12, 5b has 4, 6b has 9 and 7b has 6.

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