Color-Texture Image Analysis of Coral Reefs

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EXTENDED ABSTRACT

Marine scientists assess the condition of coral reefs from estimates of the population of living corals, dead corals, algae, rocks, and other animals coexisting in the reefs. Some popular methods used for assessment are Line Intercept Transect (LITR) and In-Situ Mapping (ISMP) where both methods employ a diver that notes the population of benthic organisms in an area of a reef of interest though of different techniques of sampling. A rapid and consistent method employed since 1992 to estimate percentage cover of sessile reef organisms is the Video Recording (VIDR) (Uychiaoco et al., 1992). The area of interest is filmed and then processed by a method called Video Point Sampling (VIDS) (Carleton & Done, 1995). Expert individuals estimate the percent cover through random or fixed points placed on the monitor screen while the film is paused at random or even intervals and identifying the items underlying the sampling points on the appropriate benthos category (e.g. alive coral, dead coral, rock). A software called *PointCount'99* (http://www.cofc.edu/~coral/pc99/Pcppintro.htm) also operates as that of the VIDS, using the random point count method and still requiring user-intervention to classify items at specified points. Assessment in the said methods is visual, requiring a trained eye and experience. By automating the assessment with a computer, the analysis is more precise, less subjective and less tedious.

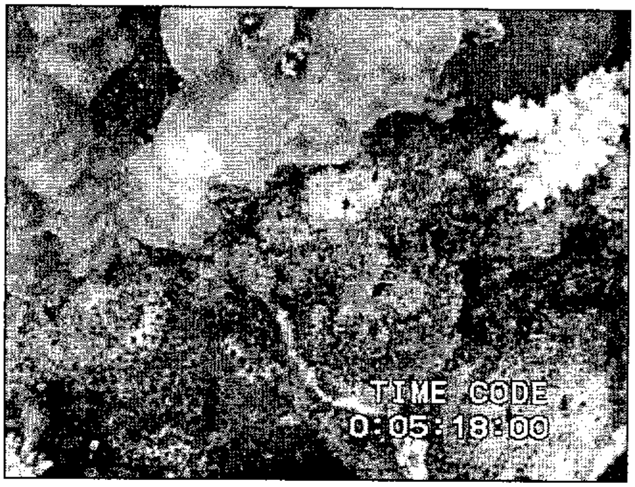

Fig. 1. An image of a coral reef area (image courtesy of the Australian Institute of Marine Science)

In computer vision, several techniques for image classification using color and texture have been developed. *Color* is a property of one point in the digitized image. Pattern recognition techniques using color often operate on the color distribution alone, ignoring the spatial, black and white (tonal) property of regions in the image which can be provided by the *texture*. Recently, these two features have been combined as one feature called *color-texture*, or the spatial distribution of colors in a region. Coral reefs have various color and texture and regular 3D structures that are cues used by scientists for

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classification. The objective now is to investigate existing color-texture paradigms and 3D texture classification techniques to classify images of coral reefs.

There are two kinds of color-texture paradigms that were considered recently. The first kind is when color and texture are considered as separate features, such as the paradigm used by M. Pietikainen et al., (1996), wherein the color and texture features are concatenated to form the color-texture feature vector. The second kind of color-texture paradigm is to consider color and texture as only one feature. Such are the approaches done by J. Huang et al., (1997), where the correlation statistics (correlogram) of each pixel in an indexed image will serve as the color-texture feature. The same kind of approach was done by R. Kondepudy et al., (1994), where the correlation of a pixel in an image (of RGB bands) with the pixels inside and outside a band would serve as the color-texture feature. In this study, the first color-texture paradigm mentioned was implemented.

A digitized video of regions of corals from Australia's Great Barrier Reef was used for testing. Six classes were used: (1) abiotic (rock, rubble, sand); (2) live coral; (3) dead coral (with or without algae); (4) algae; (5) soft coral; and (6) other fauna (organisms other than corals), and these classes were manually classified by a marine scientist and will be used as *ground truth*. Using *Matlab* (a powerful matrix calculation software), items of each class were cut from the images that were frame-grabbed at equal intervals. The average histogram of each class was computed in color spaces such as *HSV (hue-saturation-value)*, *normalized rg*, and *NTSC standard*. It was determined that *HSV* gives better separation than the other color spaces mentioned.

The texture operator known as *Local Binary Patterns (LBP)* (Ojala & Pietikainen, 1999) were employed as texture descriptor. The code was also implemented in *Matlab*. *LBP* is very robust to rotations, brightness change and Gaussian blurring (Soriano et al., 2000) and is capable of recognizing 3D textures better than any other texture paradigm. Fig. 3 illustrates the LBP_8 ("8" is for 8 pixels) technique. The gray-level values of each pixel in a 3x3 neighborhood containing 8 pixels is thresholded to the gray value of the center pixel (Fig. 3a). If the value of the pixel is greater than the gray value of the center pixel, a value of 1 is assigned to it, and if lesser, a value of 0. This "binarizes" the whole image (Fig. 3b). Weights (Fig. 3c) are then multiplied to the binary image to obtain the LBP image (Fig. 3d). Invariance to grayscale transformation was achieved by computing the joint distribution of gray values of a 3x3 circularly symmetric neighbor set of

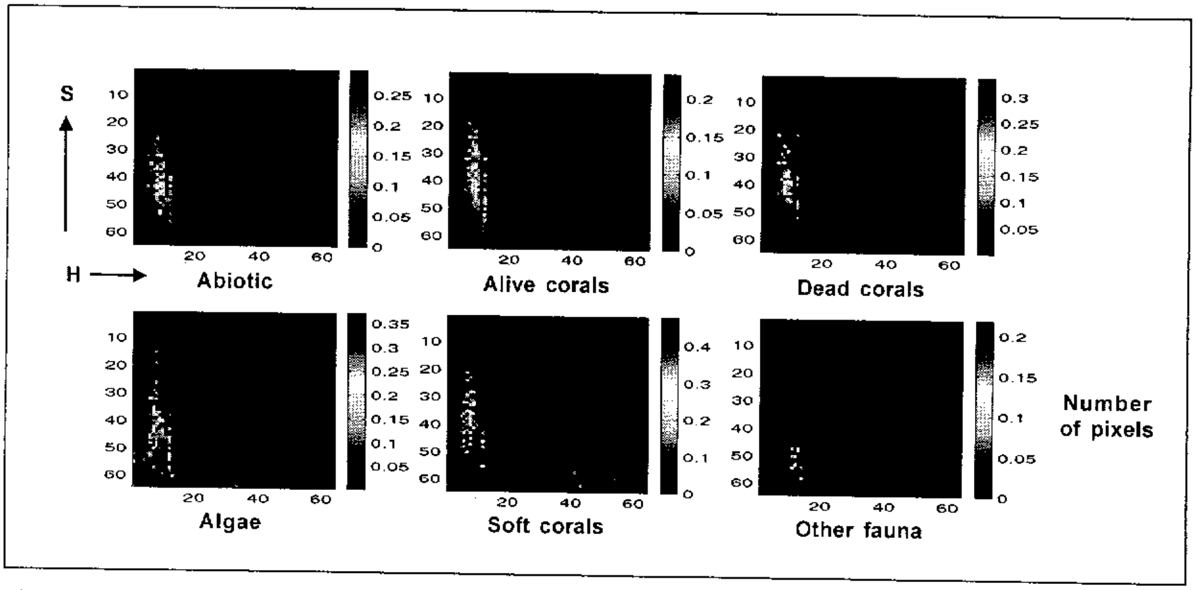

Fig. 2. Hue-Saturation histograms for the 6 classes for an image size of 160x120 pixels

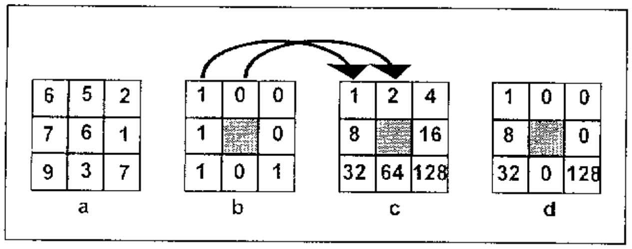

Fig. 3. LBP_8 method (image: Ojala & Pietikainen, 1999); 3a. 3x3 circularly symmetric neighbor set of 8 pixels; 3b. 9 "uniform" patterns considered, black=0; white=1

eight pixels (computed through bilinear interpolation of the gray values of the diagonal pixels) and thresholding the local neighborhood at the gray value of the center pixel into a binary pattern (Fig. 4a). The *LBP* histograms for each class were computed but a suboptimal result was obtained because of the same points of occurrences of the peaks at certain bins. It was resolved that these points were simply rotations of neighbor sets having two spatial transitions (bitwise 0/1 changes). Thus, a rotation invariant texture descriptor called LBP_8^{riu2} (Ojala et al., 2000) was investigated to compute for the histograms of the 6 classes. In this technique, only 9 LBP values are considered that exhibit the 9 "uniform" patterns given in Fig. 4b. Each of these values has a corresponding bin and the other rotation patterns are compressed into the 10^{th} bin.

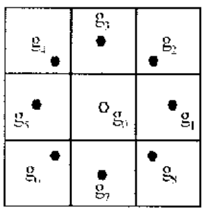

Fig. 4a. 3x3 circularly symmetric neighbor set of 8 pixels

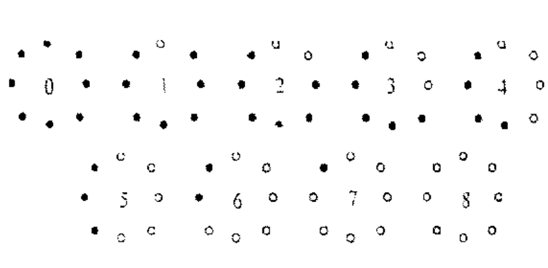

Fig. 4b. 9 "uniform" patterns considered, black = 0; white = 1

Fig. 4. LBP_8^{riu2} method (image: Ojala et al., 2000)

Both color and texture histograms were again computed for reduced image sizes, and it was found that distinct features for color and texture are obtained at an image size of 160x120 pixels. Fig. 5 shows the LBP_8^{riu2} histograms for the 6 classes at a size of 160x120. The bin size was cut down from 255 (*LBP*) to 10 (LBP_8^{riu2}) bins. We note that each class has a unique histogram, although class (2), alive corals, and class (3), dead corals, have almost the same shape of histogram but different in peak values. This is expected since there is no alteration in texture and structure when corals die, only they become bleached (pale white) or covered with algae.

Classification was achieved through two techniques. The first technique is the log-likelihood ratio statistics called the G-statistics. A test sample of histogram S_b is classified to a model M_b with the smallest value for G where

$$G = 2\sum_{b=1}^{B} S_b \log \frac{S_b}{M_b}$$

S_b = sample histogram
M_b = model histogram
B = number of bins

The other technique for classification is through Neural Network.

The HS histograms were parameterized through PCA (Principal Components Analysis) resulting to 21 coefficients (Fig. 6). This was done to reduce the 2-D histogram into a 1-D feature in application for G-statistics. For the Neural Network, the training set of sparser classes were shown to the network more often, i.e. the training set was evened out through repetition. The color-texture feature was obtained through concatenating the HS histograms (HS-coefficients for the G-statistics) which is the color feature, with the LBP_8^{riu2} histograms which is the texture feature. Classification is then implemented using color alone, texture alone, and finally color and texture combined.

Table 1 shows the results after classification. There were consistent high recognition rate values for alive corals in color and color-texture for both classification techniques. Using texture only in the classification, recognition was obtained for more than 2 classes. Also, algae, soft coral and other fauna were classified poorly and inconsistently using Neural Network.

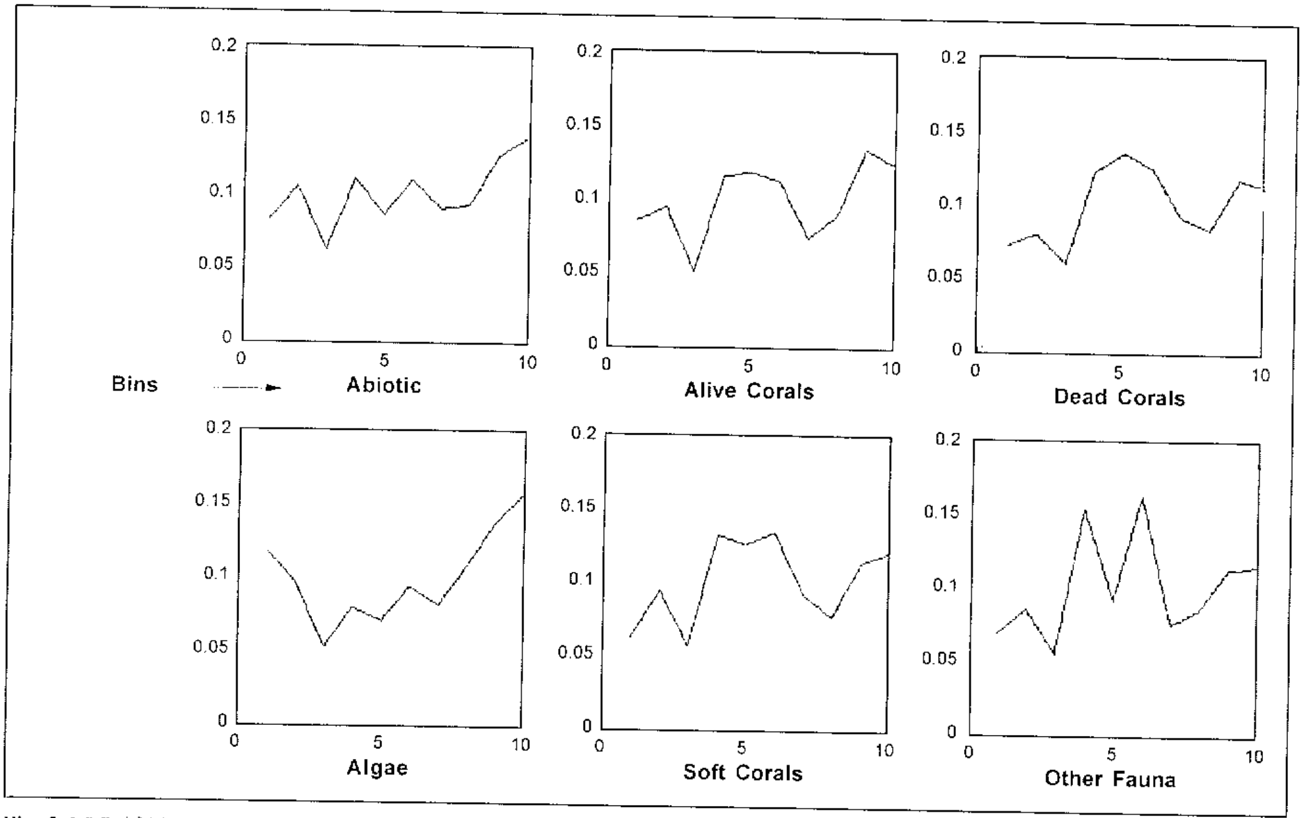

Fig. 5. LBP$_8^{riu2}$ histograms for 6 classes in an image size of 160x120 pixels

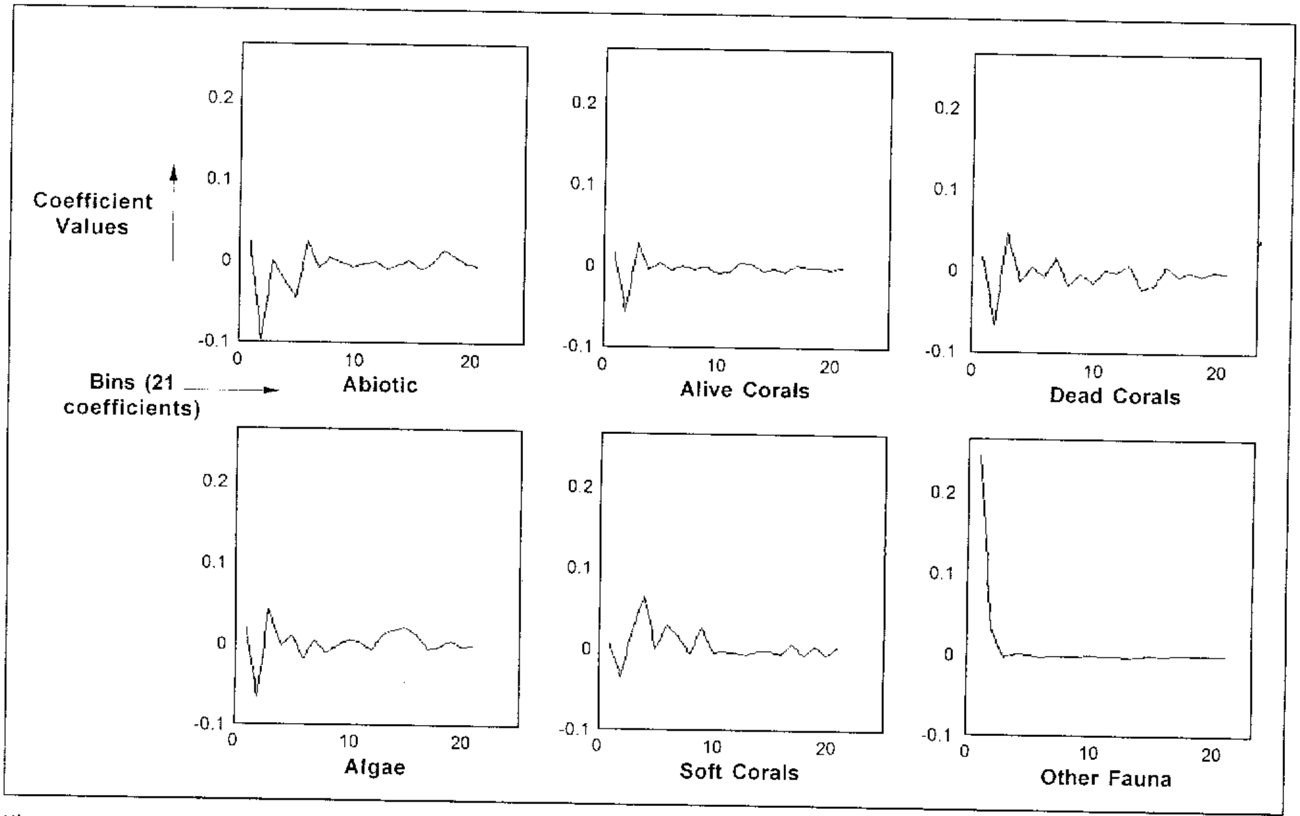

Fig. 6. Plot of the Hue-Saturation coefficients for 6 classes through PCA

Table 1. % Recognition rates for G-statistics and Neural Network (NN)

Class	G-statistics			NN (uneven samples)			NN (even samples)		
	Color	Texture	Color-Texture	Color	Texture	Color-Texture	Color	Texture	Color-Texture
(1) Abiotic	0	57.9	10.5	0	9.5	0	5.3	89.5	0
(2) Alive Coral	86.6	7.5	58.2	97	62.6	100	85.1	16.4	94
(3) Dead Coral	4.8	14.3	4.8	4.8	0	4.8	4.8	4.8	0
(4) Algae	0	100	66.7	0	0	0	0	100	0
(5) Soft Coral	0	100	50	0	50	0	0	0	0
(6) Other fauna	0	0	0	0	0	0	0	0	0

Alive corals are the most successfully recognized class in both G-statistics and the Neural Network. As a feature for classification, texture is more discriminating than color. The poor results do not mean that combining color and texture as one feature does not improve the recognition rates. It only means that the paradigm used is not sufficient to classify coral images. Also, poor classification may be due to uneven number of samples and less samples for some classes. Therefore, it is recommended that the number of samples per class for training be increased. Reduction of the number of classes (e.g. dead and alive corals only) can also be implemented. If better classification is still not achieved, then other texture paradigms for feature extraction should be investigated (e.g., Gabor wavelets, Gaussian Markov Random Fields, etc.).

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