# Low-Level Color and Texture Feature Extraction of Coral Reef Components

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## ABSTRACT

The purpose of this study is to develop a computer-based classifier that automates coral reef assessment from digitized underwater video. We extract low-level color and texture features from coral images to serve as input to a high-level classifier. Low-level features for color were labeled blue, green, yellow/brown/orange, and gray/white, which are described by the normalized chromaticity histograms of these major colors. The color matching capability of these features was determined through a technique called "Histogram Backprojection". The low-level texture feature marks a region as coarse or fine depending on the gray-level variance of the region.

## INTRODUCTION

Coral reefs are considered as one of the richest ecosystems on earth and an essential source of livelihood for many people. Marine scientists assess the condition of coral reefs from population estimates of biotics and abiotics in the reef area (Alcala & Gomez, 1982). In coral reef assessment, marine scientists classify videos or images of transects of corals into six main categories or "benthos": (1) abiotic (rock, rubble, sand); (2) live coral; (3) dead coral (and dead coral with algae); (4) algae; (5) soft coral; and (6) other fauna.

Some popular methods used for reef assessment are Line Intercept Transect (LITR) and In-Situ Mapping (ISMP). Both methods employ a diver to assess or film, in-situ, the coral reef, which is lined with transects, a kind of tape measure utilized by marine scientists to record the length or area of the reef. Although filming the benthic organisms in a reef area reduces diving time, video analysis still requires identification of items in each frame by expert individuals (Uychiaoco et al., 1992; Carleton & Done, 1995). A software known as PointCount'99 (http://www.cofc.edu/~coral/pc99/Pcppintro.htm) has been developed to aid in the assessment, but user-intervention is still required. Most of these techniques are often labor-intensive, requiring experience and a trained eye. There are works on remote sensing or spectral imaging of seafloors using airborne multispectral cameras (Bierwirth et al., 1993; Carper et al., 1990), but close-up inspection of the coral reefs are still needed to correlate spectral signatures with actual reef conditions. Hence, the purpose of this study is to computer-automate the coral reef assessment from digitized underwater video, thus making the analysis less tedious. It is also worth noting that this is, to the best of our knowledge, the first attempt to automate coral reef assessment through a computer.

In computer vision, "color" is a point property 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

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regions in the image which defines the texture. Incidentally, color and texture are some indicators used by marine scientists to identify components in a reef. Hence, this study aims to show the feasibility of using color and texture as features for classifying coral reef components.

One approach in pattern recognition is classification by minimum distance between model and test image features, such as color, texture, and color-texture (Huang et al., 1997; Kondepudy & Healey, 1994; Ojala & Pietikainen, 1999). In Marcos et al. (2001), we attempted to classify coral reef components directly from color and texture feature vectors. Recognition rates were low, which could mean that such a direct approach to classification is not suitable for corals.

We attempt another approach to image classification based on the presence or absence of features. For example, abiotics such as rocks would normally be gray and craggy. Dead corals are bright white, while live corals are mostly colorful and regularly textured. Note that a combination of features such as "irregular+gray" would most likely point to the existence of rocks, while a region which is "regular+colorful" would most likely mean the region has a living coral. If we have a binary-valued feature such as "regularity", which has a value of 1 when the region is regularly textured, and 0 otherwise; and if we have another feature such as "colorfulness", which is 0 when the region is gray or white, and 1 if otherwise, then we can preclassify an image region with binary numbers. For example, rock will be 00 (regularity-colorfulness) and coral will be 11. If we have *f* binary-valued features, then the total number of combinations is $2^f$. In this paper, we test two features, color and coarseness-fineness, in preclassifying image regions in a video frame of a coral reef.

# METHODOLOGY

## Image data

Fifty frames from a digitized video of Australia's Great Barrier Reef (© Australian Institute of Marine Science) were used for testing. The video (frame rate = 25 frames/second) was taken from a shallow depth, with sunlight as the illumination source. Distance between camera and corals were kept to 30 cm. Still frames were digitized to an image size of 640 x 480 pixels.

## Low-level color feature extraction

Humans perceive color in an object through the nature of light reflected by that object. The characteristics generally used to distinguish one color from another are brightness, hue, and saturation (Gonzales & Woods, 1992). In computer vision, color represents a property of a point picture element or a "pixel" in a digitized image. For a given colored pixel, hue and saturation represent the chromaticity, while brightness, the intensity of the pixel.

The purpose of color spaces or color models is to represent how color is to be perceived according to some standard. Some color spaces are modeled on how the human eye perceives color. Other color spaces are used as hardware-oriented models, such as the RGB (red, green, blue) for color monitors. In this study, we transformed image RGB into the normalized chromaticity coordinates (NCC) or normalized *rg* (Gonzales & Woods, 1992). The normalized *rg* coordinates are computed from RGB space by the following expressions:

$$I = R + G + B; \qquad r = R/I; \qquad g = G/I \tag{1}$$

where $I$ is the brightness value and $r$ and $g$ are the chromaticity values. Note that $b$ is no longer unique because of the relationship $r + g + b = 1$. This color space has three advantages: (1) it is easy to compute; (2) it separates brightness and chromaticity information (intrinsic color); and (3) the colors created in combining two colors in different brightness proportion appear in the line joining the two chromaticities of the two colors in *rg*-space. The *rg* chromaticity histogram of an image will then be a 3D plot where the $x$- and $y$-coordinates are the chromaticity values ($r$ and $g$) while the $z$-coordinate is the frequency of occurrence in the image.

Most live corals in the video are either blue, yellowish, brown, or green, while dead corals have a bleached or white color. Rocks, on the other hand, have grayish color, or sometimes greenish due to algae growth.

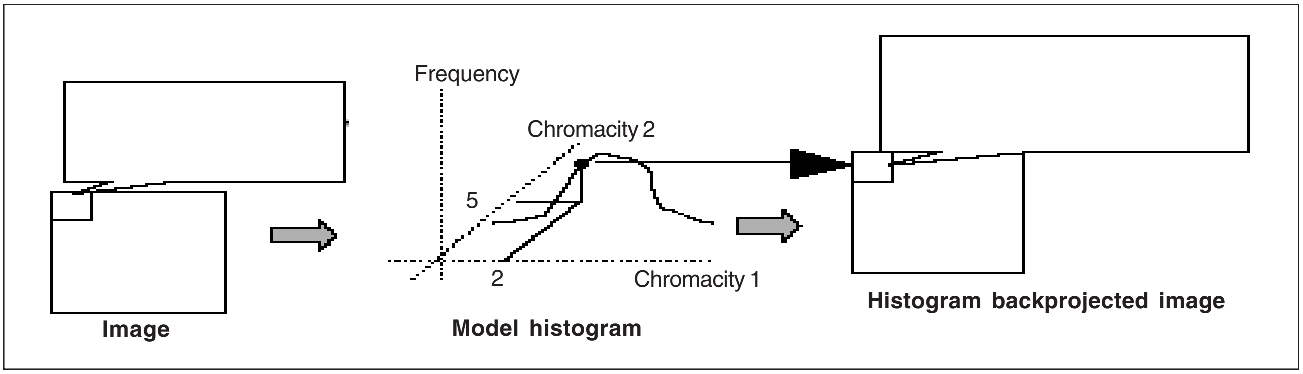


Fig. 1. Illustration of the Histogram Backprojection technique. The chromaticity values of a pixel are traced into the color histogram of a query image and its frequency value is assigned to that pixel.

Heuristically, it was determined that four groups of colors, namely blue, green, yellow/orange/brown, and gray/white, are dominant in the coral reef images. Since gray is merely an incidence of white, gray and white are grouped into one major color. For each major color, an average *rg* chromaticity histogram was obtained from manually cropped image patches which visually possess the major color. These major colors are the low-level color features utilized in this study.

## Histogram Backprojection

The dominance of each group of color at each region of an image was tested using Histogram Backprojection (Swain & Ballard, 1991) (Fig. 1). The chromaticity histogram of a target image is first obtained before the test image is transformed into chromaticity space. The chromaticity values of each pixel in the test image are traced onto the target chromaticity histogram, and the corresponding frequency value is assigned to the same pixel in the test image (backprojection). This process produces a bright region in the backprojected image where the image matches the colors in the histogram with high frequencies. In this paper, we aim to match regions in the coral images exhibiting the four major colors (blue, green, yellow/brown/orange, and gray/white).

Dead corals and sand have the same chromaticity and differ only in brightness. To distinguish between the two, intensity information was included in the color matching. Thus, whenever a region is labeled as gray, we test further if its intensity is beyond a certain threshold.

## Low-level texture feature extraction

In computer vision, “texture” is the spatial or black and white or tonal property of an image (Haralick, 1979). An image is composed of texture primitives, which is a region in an image with little variation in tone. Texture is exhibited by an image when there is a large variation in the texture primitives. Fine textures have higher spatial frequencies and its texture primitives are small, while coarse textures have larger primitives and lower spatial frequencies.

Most texture paradigms utilize methods that extract the spatial frequency information of an image, for example, Fourier Transform. Some analyze the spatial distribution of the gray level of each region in an image and derive statistical information from the distribution. In this study, gray-level variance was utilized to characterize the texture of coral reef components. A gray-level image of the frame to be analyzed is obtained using $I$ in Eq. (1). The gray-level values may be scaled from 0 to 1 or 0 to 255. A region of the image has fine texture if the gray-level variance relative to the average gray value of that region is small, and has coarse texture if the variance is large.

Rocks, live corals, algae, and dead corals usually have coarse texture, while sand and certain live corals perceptually have fine textures. These characteristics of texture, or low-level features, aid marine scientists in the classification of corals. Thus, coarse and fine will be the low-level texture features to be used in this study.

## RESULTS AND DISCUSSION

### Color matching results

Although colors are illumination dependent, the light source for the video used in this study is constant all throughout the film (sunlight). Therefore, no color shifting due to light source change is observed in the images. The average major color histograms were used as model histograms. On the upper left side of Fig. 2a is a massive blue-colored coral; on the upper right, a dead coral. Histogram backprojection was applied to Fig. 2a using the average blue histogram, resulting in Fig. 2b; in Fig. 2c, the gray/white histogram was used. The results for both show that the blue and white parts registered as bright areas. For effectively matching bleached or pale white regions in the image, we incorporated the intensity information into the histogram backprojection of the test image. We emphasize that from this technique alone, the dead coral population of a reef can be determined.

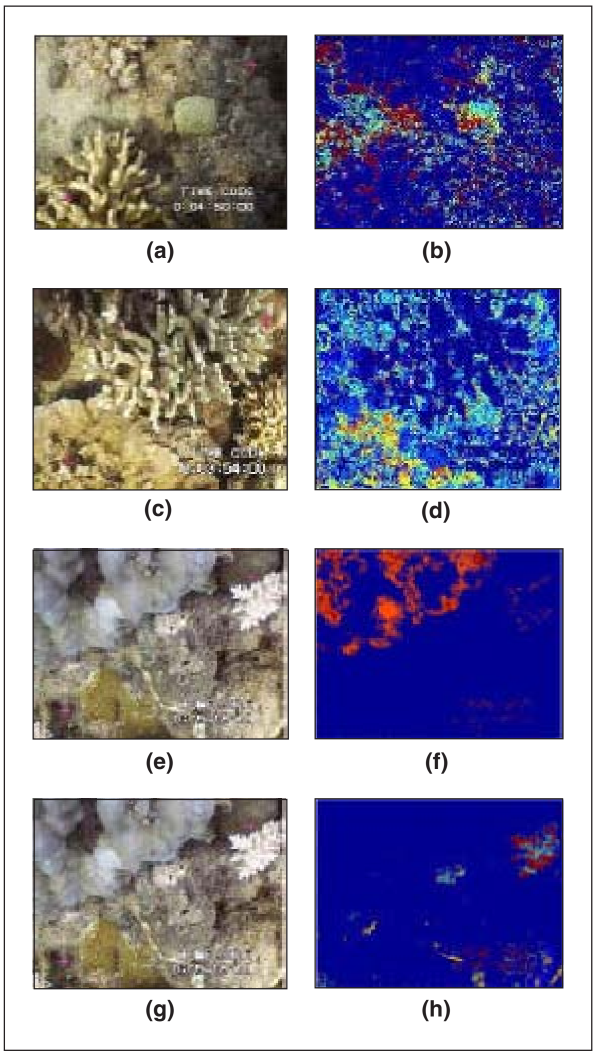


Fig. 2. Test images (a, c, e, and g) and their corresponding histogram backprojected images (b, d, f, and h) using the four image chromaticity histograms: averaged green *rg* histogram (a & b); averaged yellow/brown/orange *rg* histogram (c & d); averaged blue *rg* histogram (e & f); and averaged gray/white histogram (g & h).

We have implemented histogram backprojection in video. An example showing the labeling of blue corals and dead corals may be downloaded from http://www.nip.upd.edu.ph/ipl/members/jing/corals.

### Texture labeling

The mean of the gray-level variances of each low-level texture was computed using 10 cut-out image samples per low-level class (i.e., images exhibiting coarse and fine textures). It was found that the mean of the variances for coarse texture regions fall in the range of 0.01 to 0.1, while that for fine texture regions have an order of magnitude of 0.001. The results imply that these low-level texture features are dissimilar or non-overlapping.

We further tested the low-level feature by getting the variance of each N x N block in an image. If the variance of the image is within the range of 0 to 0.01, this area is classified as “of fine texture”, and the center of this block is marked by a green letter “F”. If the variance of the N x N block is within 0.01 to 1, this area is “of coarse texture”, and we mark a red letter “C” on the center of the block. This approach was tested for different window sizes and it was found that effective texture characterization is achieved using window sizes in the range of 40 x 40 to 70 x 70 pixels. Fig. 3 shows the result of the block processing using a 60 x 60 block size. Perceptually, we can see that fine and coarse textures in the image are effectively recognized by merely using the gray-level variance of the image.

Coarseness or fineness of an image region can depend on illumination direction. In our case, the videos are illuminated by diffused sunlight (corals were shallow); thus, image coarseness does not change.

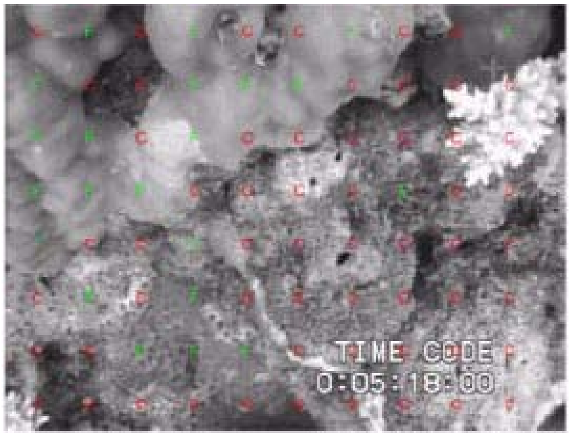


Fig. 3. A frame classified into coarse (C) and fine (F) blocks. Each block is 60 x 60 pixels. The whole image is 640 x 480 pixels.

## CONCLUSION

In this work, we introduced an approach to coral reef image labeling utilizing low-level features for both color and texture. The low-level color features using four major colors (blue, green, yellow/brown/orange, gray/white) can effectively label colored reef images with histogram backprojection. The low-level texture features (coarse and fine texture as described by gray-level variances) can effectively label perceptually coarse and fine texture regions in the images. Having obtained the low-level features, the next step would be a higher-level of classification.

## RECOMMENDATIONS

These low-level features can serve as weights, or "on-off" inputs to the classifier, such that certain combinations of these low-level features can describe a certain benthic category. If color and texture are not enough as low-level inputs, then a third feature, shape, may be included. If there are $f$ features, each having only two states, then the number of possible combination of feature states is $2^f$. For example, three binary features ($f = 3$) would be able to label up to eight classes. In our case, we have six benthic categories; therefore, we only need three dual-state features for combinatorial classification.

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