Classification of Coral Reef Components Using Color and Texture Features

Ezmahamrul Afreen Awalludin[1], Muhammad Suzuri Hitam[2], Wan Nural Jawahir Hj Wan Yussof[2] and Zainudin Bachok[3]

[1] *School of Fisheries and Aquaculture Sciences,*
[2]*School of Informatics and Applied Mathematics,*
[3]*Institute of Oceanography and Environmental,*
Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia.
e.afreen@umt.edu.my

***Abstract*—This paper presents classification of coral reef benthic components that composed of live corals, dead corals, rubbles and sands. Since coral reef exist with different of shapes, colours and textures, the use of image processing technique provides advantages to estimate percentage cover of coral reef benthic components. Color and texture are used to extract features of coral reef benthic components. Hue Saturation Value (HSV) color model is utilized by calculating its color histogram to obtain color features. Meanwhile, the Local Binary Pattern (LBP) descriptor is used to extract texture features. The color and texture features are combined as the input into the Multi-layer Perceptron Neural Network (MLPNN) classifier. The performances of the coral reef classification are evaluated based on color feature, texture feature or combination of both color and texture features. It is found out that the joining feature set of color and texture features provide the highest classification accuracy, i.e. 92.60% accuracy rate as compared to the use of individual feature such as color and texture features alone that achieved only 81.30% and 88.10% accuracy classification rate, respectively.**

***Index Terms*—Coral Reef Classification; Hue Saturation Value Color; Local Binary Pattern; Multi-layer Perceptron Neural Network.**

I. Introduction

Coral reef is a unique marine ecosystem with rich of biodiversity productivity and provides huge natural resources. It often exposes to danger such as strong waves, erosion, floods and others natural impact. In addition, an unplanned development, overfishing, pollution and others increasing threaten to coral reefs population for every year. Therefore, the conservation program and monitoring surveys are necessary to ensure coral reef areas save from any destruction. These programs become a fundamental work to estimate the population of coral reef components such as live corals, dead corals, algae and others [5].

Marine scientists around the world have started several program conservations in term of monitoring health and status of coral reef components. For example, the use of remote sensing technology [3], hydro-acoustic sensing techniques [1], manual diving techniques [2] and video transect monitoring techniques [6]. In conventional approach, coral reef components are captured using underwater video transects and analysis of each coral reef components are commonly analyzed in the laboratory by marine scientists using Coral Point Count with Excel extensions (CPCe) proposed by [4]. However, this method is time consuming and laborious during the counting of coral reef components in the laboratory. The benthic distribution is estimated by calculating random points on the monitor screen and labeled the objects which requiring a skilled eye and a substantial processing. In contrast, image processing techniques based on color and texture features are used to classify six coral reef components such as live corals, dead corals, dead corals with algae, abiotics, soft coral and other fauna [7]. However, a lower of 48.0% accuracy classification rate was achieved due to many classes involved and the image samples were not equally distributed among the different classes. Therefore, in this study, only three coral reef benthic components are used to reduce misclassification rate such as live corals, dead corals and sand or rubble.

In the study, HSV color model and the LBP descriptor are used to extract features of color and texture. The extracted features are then used as input to a MLPNN classifier. Performances of color and texture features are measured based on accuracy classification rate.

This paper is organized as follows. Section II describes the background concepts and theories of color and texture technique for feature extraction and MLPNN model for classifying the benthic components. Section III presents the experimental results of color, texture and joining both color and texture feature vectors using the MLPNN. Finally, section IV concludes this paper.

II. Methodology

A. HSV Color Features

Different objects in the image with different colour properties are difficult to measure by human visual because of the different electromagnetic spectrum from 300 nm to 830 nm [9]. Therefore, combination of various spectrums into colour properties provides benefits to human visual for interpreting the colour of an object. For that reason, nowadays the segmentation process tends to use the Hue Saturation Value (HSV) colour space to decompose the images into meaningful information. In this study, we use the HSV color histogram to separate coral reef image intensity from colour information. These color features are easy to compute by separating different color of coral reef benthic components. Healthy live corals are commonly colorful and mixed with different types of color such as red, green, blue, yellow, brown. Dead corals or bleached coral usually represent with white color. Rubbles have grayish color and sometimes greenish due to algae growth. Sand provides light grayish and sometimes dark grayish because of brightness change. HSV color model can be calculated using equation as follow:

$$H = cos^{-1}\left\{\frac{\frac{1}{2}[\,(R-G)+(R\,-B)]}{\sqrt{(R-G)^2\;+(R-B)(G-B)}}\right\} \tag{1}$$

$$S = 1\;-\frac{3}{R+G+B}[min(R,G,B)] \tag{2}$$

$$V = \frac{1}{3}(R+G+B) \tag{3}$$

where, *H*, *S* and *V* describe the components of Hue, Saturation and Value, respectively. The *R*, *G* and *B* component correspond to the channels of Red, Green and Blue. Figure 1 shows the process of HSV color processing.

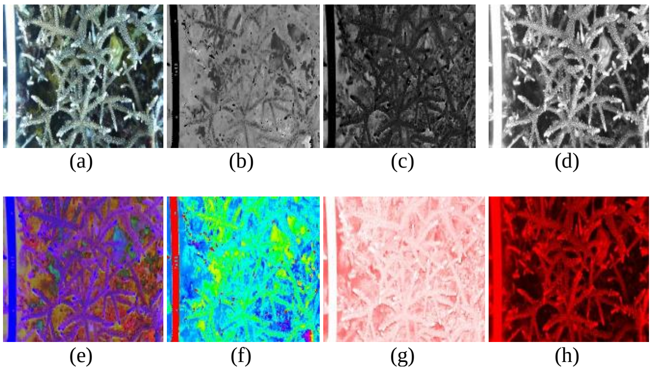

Figure 1: (a) Original Image. (b) – (d) The channels of H, S, and V on gray images. (e) Image conversion from RGB space to the HSV colour space. (f) – (h) The channels of H, S, and V on color images.

Coral reef components are extracted using color histogram which widely used as global color descriptors [10]. It is used to solve translation and rotation invariant problems. Color Histogram (CH) composed of each color occurrences by counting all image pixels having that color. Each pixel is associated to a specific histogram bin only according to its own color and can be estimated using (4).

$$H = \{H_0, H_1, H_2 \ldots H_c \ldots H_N\} \tag{4}$$

where H_c denotes the number of pixels color in the image and H_n represents the bin number of the color histogram. The color histogram is performed by calculating each of pixels in the image and assigned it to a bin histogram. Thus, each input image with different size of color histograms can be normalized as follow:

$$H' = \{H'_0, H'_1, H'_2 \ldots H'_c \ldots H'_N\} \tag{5}$$

$$H'_c = H'_c / Max\,(H'_N) \tag{6}$$

where H' represents the color histogram normalization.

The HSV color histogram features are derived by calculating the number of pixels in each channel of *H*, *S* and *V*. Each channel is assigned with bin of 8 x 2 x 2 to construct 32 bins histogram. Each bin composed a range of color characteristics of the image. Thus, the HSV color histogram is constructed between the pixels intensities within bin.

B. LBP Texture Features

The LBP is an operator that was first introduced by [8] and has been shown to be an effective descriptor in texture classification. To create an LBP representation an input texture image must first be converted to grayscale before this operator is applied to each individual pixel within the image. A feature vector describing the textural properties of the image is then obtained from a histogram of the LBP values of the image. The image pixels can be computed using LBP by comparing its neighbor as follow:

$$LBP_{P,R} = \sum_{p=0}^{P-1} t(g_p - g_c)2^p \tag{7}$$

$$t(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{8}$$

where, g_c denotes the gray value of the central pixel and g_p correspond to the value of its neighbor. The term of *P* and *R* represent the total number of neighbors and the radius of the neighborhood, respectively. Meanwhile, *t* represents a threshold function of LBP. If the coordinates g_c is (0, 0), then the coordinates of g_p can be estimated as in (9).

$$\left(Rcos\left(\frac{2\pi p}{P}\right), Psin\left(\frac{2\pi P}{P}\right)\right) \tag{9}$$

The gray values of neighbors that are not included in the image grids can be estimated using interpolation. Suppose the image of size *I*J* after the LBP pattern of each pixel is identified. Then a histogram is constructed to represent the texture image based on (10) and (11).

$$H(k) = \sum_{i=1}^{I}\sum_{J=1}^{j} f\big(LBP_{P,R}(i,j),k\big), k\; \in\; [0,k] \tag{10}$$

$$f(x,y) = \begin{cases} 1, x = y \\ 0, otherwise \end{cases} \tag{11}$$

where *k* denotes the maximal LBP pattern value. The uniform LBP pattern with rotation invariance can be measured as follow:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{P=0}^{P-1} t\big(g_p\;-g_c\big), if\;U\;\big(LBP_{P,R}\big) \leq 2 \\ P+1\,, otherwise \end{cases} \tag{12}$$

where, *U* represents the spatial transitions number which can be defined as follow:

$$(LBP_{P,R}) = \left|t\big(g_{p-1}\;-g_c\big) - t(g_0 - g_c)\right| + \sum_{p=1}^{P-1}\left|t\big(g_p\;-g_c\big) - t\big(g_{p-1} - g_c\big)\right| \tag{13}$$

The gray values of the 8 pixels in the 3 x 3 neighborhood can be illustrated in Figure 2.

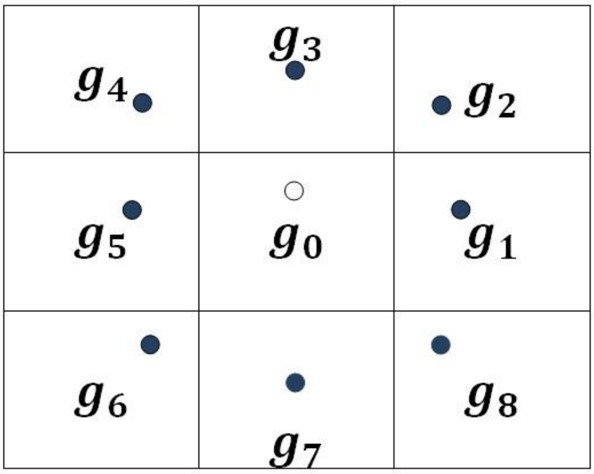

Figure 2: The circularly symmetric neighbor set in of 8 pixels in a 3 x 3 neighborhood.

An LBP histogram is computed independently for each region. Then, all the resulting histograms are concatenated together into a single vector. This method tends to produce fairly high dimensional vectors. In the paper, $LBP_{8,1}^{riu}$ is used to provide 36 different values of the unique rotation invariant local binary pattern. The $LBP_{8,1}^{riu}$ represent the occurrence statistics of the patterns and corresponds to certain features in the image. Thus, the binary patterns of 36 unique rotation invariant can be considered as feature of texture LBP.

C. The Multi-Layer Perceptron Neural Network Model

The Multi-Layer Perceptron Neural Network (MLPNN) model is used for training in classification task as shows in Figure 3. The MLPNN is developed with three layers that composed of the input layer, the hidden layer and the output layer. The number of neurons is varied from layer to another except the output layer consist of 4 neurons since we need to classify 4 coral reef components that consists of live corals, dead corals, rubbles and sands. The performance of MLPNN classifier is measured using precision, recall and accuracy which can be measured using (14) to (16). A high precision shows that features are extracted more relevant results than irrelevant. Meanwhile, recall returned most of relevant features. Accuracy classification rate is measured of average precision and recall.

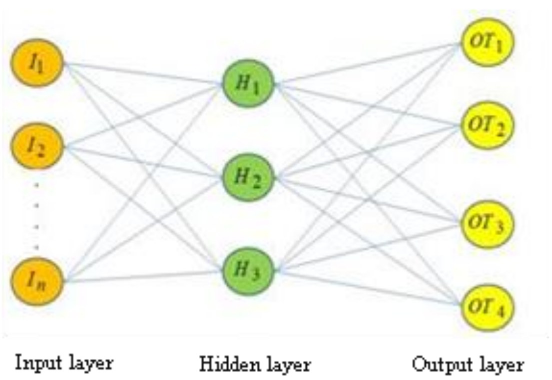

Figure 3: The MLPNN model.

$$Precision = \frac{\sum TP}{\sum TP + \sum FP} \tag{14}$$

$$Recall = \frac{\sum TP}{\sum TP + \sum FN} \tag{15}$$

$$Accuracy = \frac{\sum TP + \sum TN}{\sum (TP + TN + FP + FN)} \tag{16}$$

where, *TP* and *TN* represent the true positive rate and true negative rate, respectively. Meanwhile, *FP* and *FN* correspond to false positive rate and false negative rate.

Multi-Layer Perceptron Neural network (MLPNN) are evaluated by comparing them using 800 sample datasets. All sample datasets are divided within portion of 70% (560 samples) for training and 30% (240 samples) for testing. The result of the best classifier is considered when the highest accuracy rate achieved in the experiment.

III. EXPERIMENTAL RESULTS

In the experiment, four coral reef components were used namely live corals, dead corals, rubbles and sands as shows in Figure 4. Total of 800 samples of each coral reef components are used as input images for features extraction with dimension size of 300 x 300. The first experiment describes about feature extraction of color technique using HSV color model. Second experiment discusses the used of the LBP texture descriptor for extracting texture features. Finally, collection features of color, texture and joining color-texture are evaluated using the MLPNN classifier. The best classification results are assigned when the higher accuracy classification rate is achieved.

A. The Coral Reef Components Dataset

In this experiment, total of 800 dataset of coral reefs components were used and obtained from the Ekor Tebu Island located at the Redang Island in Malaysia. The dataset composed of live corals (200 images), dead corals (200 images), rubble (200 images) and sand (200 images). Datasets of coral reef components are recorded using the Underwater Video GoPro HERO HD Camera at different water level depths of 3m and 10m. The original image sizes are captured of both water level depths at dimension of 1920 x 1080 pixels. In the experiment, the raw image size is reduced to dimension size of 300 x 300 pixels due to time computation constrain [7]. Reducing the large size of the images provide fast process in classifying or identifying each coral reef components. Figure 4 shows some sample datasets of coral reefs components that used in the experiment.

B. The Multi-Layer Perceptron Neural Network Classifier

Although the MLPNN normally requires a long training time to learn a specific task, however it can make a complicated decision compared to linear pattern classifier. Since coral reef componnets exists with complexity of color and texture, the use of the neural network classifier can help to classify each coral reef componnets. The neural network based on MLPNN were used to evaluate performance of color, texture and combination of color and texture. In the MLPNN classifier, the weight updates are achieved by gradient descent with a momentum term and an adaptive learning rate. The first two layers use the tangent and logarithmic sigmoid is assigned as activation functions, respectively. The NN is trained using the mean square error of 0.01 as the learning convergence criterion. Total of ten hidden units were utilized to improve neural network perfomance. In the experiment, the HSV Color features, LBP texture features and combination of both color and texture are used as input to the network.

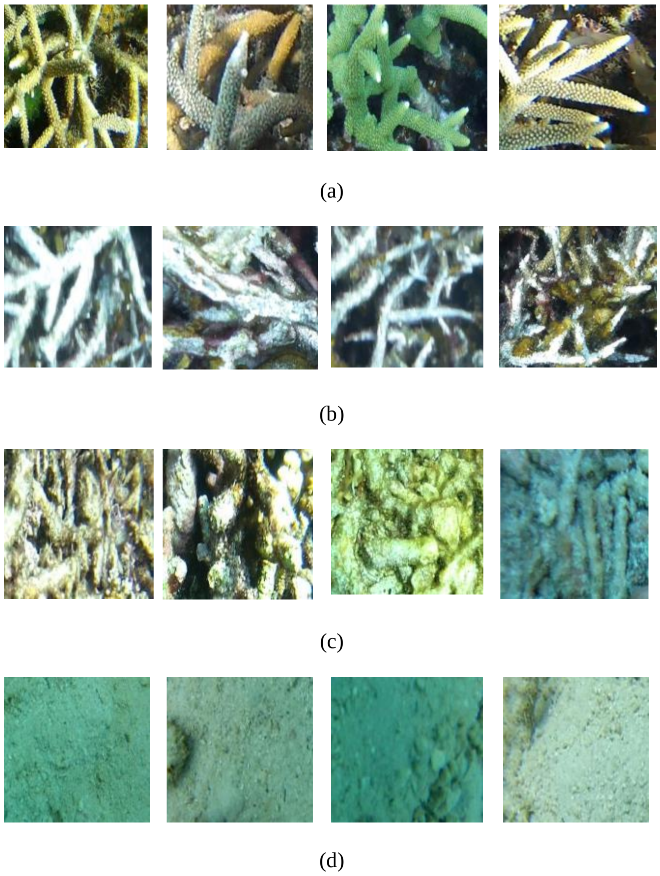

Figure 4: (a) Live corals dataset. (b) Dead corals dataset. (c) Rubbles dataset. (d) Sands dataset.

1) Experiment on HSV Color Classification

For HSV color features, the MLPNN performance achieved of 81.30% accuracy classification rate and miscalssification rate is 18.70% of the accuracy classification. The accuracy classification is calculated based on summation of true positive and true negative which is then divided to samples of data as shown in Table 2. Thus, the precision is calculated by summation the true positive and divided with summation of test outcome positive. The recall value is estimated using summation of true positive and divided by summation of condition positive. The precision and recall value of each coral reef components is illustrated in Table 1. Table 2 shows the confusion matrix table for HSV color histogram features.

Table 1
Precison and Recall for HSV color features.

Componnets	Precison	Recall
Live corals	80.80%	94.50%
Dead corals	86.50%	96.00%
Rubbles	87.10%	37.00%
Sands	75.30%	97.50%

Table 2
The confusion matrix of classification performance for the MLPNN based on HSV color features.

	800 Samples				
	Actual Class				
Live coral	189 23.60%	2 0.30%	41 5.10%	2 0.30%	80.80% 19.20%
Dead Coral	3 0.40%	192 24.00%	25 3.10%	2 0.30%	86.50% 20.30%
Rubble	7 0.90%	3 0.40%	74 9.30%	1 0.10%	87.10% 12.90%
Sand	1 0.10%	3 0.40%	60 7.50%	195 24.40%	75.30% 24.70%
	94.50% 5.50%	96.00% 4.00%	37.00% 63.00%	97.50% 2.50%	81.30% 18.70%
	Live coral	Dead coral	Rubble	Sand	

Table 2 presents coral reefs classification using a single HSV color histogram. In the first test of using 800 samples, the live coral, dead coral and sand class achieve more than 90.00% of recall value except rubble class obtain below than 40.00%. Meanwhile, the precision of live coral, dead coral and rubble obtain more than 80.00% but sand class achieves only 75.30%. Since the sand class has many samples classified but the precision rate is much lower as compared to the other classes with 75.30% of precision. Overall classification obtained for 800 samples is 81.30% and misclassification is 18.70%.

2) Experiment on LBP Texture Classification

The LBP texture features obtained 88.10% accuracy classification rate and misclassification achieved 11.90% of accuracy classification rate which shown in Table IV. The precision and recall of each coral reef componnets using LBP texture histogram are estimated in Table 3.

Table 3
Precison and Recall for LBP texture features.

Componnets	Precison	Recall
Live corals	87.00%	94.00%
Dead corals	87.00%	97.00%
Rubbles	86.20%	97.00%
Sands	94.90%	64.50%

Table 4
The confusion matrix of classification performance of the NN based using LBP Texture features.

	800 Samples				
	Actual Class				
Live coral	188 23.50%	3 0.40%	0 0.00%	25 3.10%	87.00% 13.00%
Dead Coral	1 0.10%	194 24.30%	4 0.50%	24 3.00%	87.00% 13.30%
Rubble	6 0.80%	3 0.40%	194 24.30%	22 2.80%	86.20% 13.80%
Sand	5 0.60%	0 0.00%	2 0.30%	129 16.10%	94.90% 5.10%
	94.00% 6.00%	97.00% 3.00%	97.00% 3.00%	64.50% 35.50%	88.10% 11.90%
	Live coral	Dead coral	Rubble	Sand	

Table 4 shows the confusion matrix for coral reefs classification using a single LBP texture features. For 800 samples, both of dead coral and rubble classes have the same number of correctly classified components with 194 samples correctly classified and both classes has 97% recall. However, the precision of dead coral is higher than rubble because more samples are wrongly classified in rubble class as compared to samples that are wrongly classified as dead coral. Even though the number of samples that is correctly classified in dead coral is higher than in live coral, they share the same accuracy rate with 87.00%. This is due the lesser samples from other classes that are misclassified as live coral as compared to dead coral. The recall rate of live coral is however 3.00% lower than dead coral. The lowest recall rate goes to sand class with 64.50% but its precision is the highest among all classes with 94.90%. Overall classification for 800 samples is 88.10% and misclassification is 11.90%.

3) Experiment on Joining HSV Color and LBP Texture Clasisifcation

Using a single color and texture features of MLPNN provide a lower accuracy classification rate as shown in Table 2 and Table 4 of the confusion matrices. To improve the performance of MLPNN classification, color and texture features are combined together. The classification using joined features of color and texture derived a higher classification rate as shown in Table 5. Based on the experiment, the joint features of color and texture achieved of 95.0% accuracy classification rate and misclassification present only of 5.0% accuracy classification rate. The precision and recall value of joining color and texture features are illustrated in Table 6.

Table 5
Precison and Recall for both HSV features and LBP texture features.

Componnets	Precison	Recall
Live corals	91.50%	96.50%
Dead corals	94.70%	97.50%
Rubbles	92.50%	80.00%
Sands	91.90%	96.50%

Table 6
The confusion matrix of classification performance for the NN using both HSV color and LBP texture features.

	800 Samples				
	Actual Class				
Live coral	193 24.10%	3 0.40%	14 1.80%	1 0.10%	91.50% 8.50%
Dead Coral	0 0.00%	195 24.40%	10 1.30%	1 0.10%	94.70% 5.30%
Rubble	6 0.80%	2 0.30%	160 20.00%	5 0.60%	92.50% 7.50%
Sand	 0.10%	0 0.00%	16 2.00%	193 24.10%	91.90% 8.10%
	96.50% 3.50%	97.50% 2.50%	80.00% 20.00%	96.50% 3.50%	92.60% 7.40%
	Live coral	Dead coral	Rubble	Sand	

For joining color and texture features, the precision of 800 samples shows that all classes achieved over 90.00%. Meanwhile, the recall value achieve more than 95.00% value for classes of live coral, dead coral and sand except the rubble. The rubble class is most overlapping class with 80.00% of recall value but achieve higher precision value with 92.50%. Overall classification for joining color and texture features of 800 samples is much higher than using single features as shown in previous experiment with 92.60% accuracy rate and 7.40% misclassification rate.

IV. CONCLUSION

In this study, an approach of coral reef components classification was introduced using low level features of HSV color histogram and LBP texture features. The experiments were conducted to classify four components of coral reefs including live corals, dead corals, rubbles and sand. The results have shown that by combining both color and texture features; the accuracy was 95% which is consider good as compared to using single features alone which gave 82.5% and 75.8% for color features and texture features, respectively. As a conclusion, combination of features provides several advantages for marine scientists to estimate more benthic groups which are important in marine conservation efforts.

ACKNOWLEDGEMENT

The authors are greatly pleased and indebted to Institute of Oceanography and Environment (INOS), Universiti Malaysia Terengganu (UMT), which sponsored different types of coral reef dataset for this study and grant permission to conduct this research with excellent lab facilities that make this work possible.

REFERENCES

[1] A. L. Abdullah, J. Mohamed, and Z. Yasin. “Incorporating Hydroacoustic signal classification technique for effective application to limits of acceptable change framework for natural heritage conservation at Pulau Payar marine park,” *Malaysian Journal of Environment Management*, vol. 12, no. 1, pp. 23-37, 2011.

[2] D. K.. Bass. and I. R. Miller, “Crown-of-thorns starfish and coral surveys using the manta tow and scuba search techniques, long term monitoring of the great barrier reef,” Standard Operational Procedure Number 1. Australian Institute of Marine Science, Townsville, Australia, 1996.

[3] H. Holden, E. L. Drew, C. Derksen. and M. A Wulder, “Coral reef ecosystem change detection based on spatial autocorrelation of multispectral satellite data,” in *Proc. of the Second International Asia Pacific Symposium on Remote Sensing of the Atmosphere*, Environment, and Space, 2000, 9-12.

[4] K. E. Kohler, and S.M. Gill, “Coral Point Count with Excel extensions (CPCe): A Visual Basic program for the determination of coral and substrate coverage using random point count methodology,” *Computers and Geosciences*, vol. 32, no. 9, pp. 1259–1269, 2006.

[5] R. Kenchington and B. Hudson, *Coral Reef Management Handbook.* UNESCO, 1984.

[6] K. Lam, P.K.S. Shin, R. Bradbeer, D. Randall, K. K. K. Ku. P. Hodgson and S. G. Cheung, “A comparison of video and point intercept transects methods for monitoring subtropical coral communities,” *Journal of Experiment Marine Biology and Ecology*, vol. 333, no. 1, pp. 115-128, 2006.

[7] M. S. A. C. Marcos, L. T .David, M. N. Soriano, “Area-calibrated automation of coral classification for near and subsurface reef videos,” in *Proc. of the 11th International Coral Reef Symposium*, 2008, pp. 507-511.

[8] T. Ojala, M. Pietikäinen, and T. Mäenpää, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971-987, 2002.

[9] K. N. Plataniotis and A. N. Venetsanopoulos, *Color Image Processing and Applications*. Springer-Verlag, 18 February 2000.

[10] M. Swain and D. Ballard, “Color indexing,” *International Journal of Computer Vision*, vol. 7, no. 1, pp.11-32, 1991.