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Area-Calibrated Automation of Coral Classification for Near And Subsurface Reef Videos

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Abstract. Groundwork for an area-calibrated computer-automated system for benthic classification through underwater video is presented. Data acquisition through an underwater video camera is fast, less expensive and processing can be done in one day. Two video acquisition schemes were considered: (1) near-reef videos, where height of 30 cm from the reef surface is maintained, and (2) subsurface video of a reef where the camera is fixed 0.2-0.5m below the surface. Rapid classification is implemented via downsampling a reef image into blocks. Benthic components are classified into living and nonliving categories. For near-reef videos, an overall success rate of 79% is achieved even for corals occurring in various morphologies. Color and texture features derived from video stills were used as inputs to the classifier system. For subsurface reef video, an overall recognition rate of 60 – 70% was achieved. A more accurate percent cover is obtained via an area calibration model developed. This model is based on camera optics and removes the need for an underwater reference object for area correction. The development of an automated rapid reef classification system is most promising for reef studies that need fast and frequent data acquisition of percent cover of living and nonliving components.

Key words: coral classification, reef monitoring, automation, computer vision, pattern recognition

Introduction

The general approach to coral reef monitoring is determining population of benthic organisms or components in a reef such as living coral, dead coral, algae and sand, rock or rubble (Kenchington and Hudson 1984). Data on percent cover of different benthic components in a reef also helps in assessing damages or degradation on the reef incurred by trawling, storm or anthropogenic factors. A framework for an automated coral reef classification system from underwater video captured from near-reef and subsurface locations is presented. The goal is to automatically identify benthic components and to output an accurate percent cover with appropriate area calibration. An automated classification system is applicable for fast and frequent monitoring of reef organisms for temporal observations which can be correlated at once with specific occurrences, e.g. storm, dynamite fishing, etc. Investigation towards reef community studies can also be done using the system.

The science of determining benthic population data depends on the scale needed for assessment. For reef areas needing a resolution of at least 25 m^2, the commonly-used methods for monitoring are multi-spectral satellite imagery and aerial remote sensing (Mumby et al. 2004). Results from this method however need on-site validation. A limitation as well is the monetary cost of one remotely-sensed image. The method introduced in this study is a rapid, low-cost technique for on-site benthic cover estimation.

To estimate benthos distribution on site, several protocols have been put in practice such as manta tow, and Line-Intercept Transect (LIT) (Kenchington and Hudson 1984) which is an application of SCUBA. Recent monitoring methods such as Video Point Sampling (Uychiaco et al. 1992; Carleton and Done 1995) employ image and video capture in LIT to reduce diving time by allowing the counting to be done in the lab through playback. At playback, random points are generated on the screen and distribution is estimated by identifying and counting the objects directly underneath the points. Software such as *Coral Point Count with Excel* (Kohler and Gill 2006) has been developed for determining coral and substrate coverage using advanced methods in image processing. However, the method uses random point count sampling, which still requires user intervention and expertise in identifying the benthic components underneath overlaid points on the video frames. The aforementioned methods are quite taxing and take weeks to complete data collection for a reef span of only a kilometer. The tediousness of analysis and the long duration of time for acquisition and processing are not practical for marine management studies that require rapid observation of the effect of ecological disturbances on a reef that can occur in a matter of days.

The first published research on benthic component classification using computer vision techniques were applied to conventional LIT video and subsurface video (Marcos et al. 2005; Marcos et al. 2007). These papers introduced good classification for near-reef and subsurface video. In this study, area calibration is applied to benthic classification for underwater video using simple mathematical derivations from camera optics. This provides a more accurate benthic percent cover that accounts for changing camera-reef distances especially for subsurface videos. Area calibration removes the need for submerged reference objects for area estimation. The applicability of the automated system on new reef areas with a comparison on the results from a five-point sampling method is also presented in this paper.

Color and texture are utilized as cues to assign unique numerical identifiers for benthic categories. Color features are reliable indicators because it has minimum if not negligible variability across image scales and illumination. Also, there is good separability in color feature space for living and dead corals which are predominantly chromatic and achromatic, respectively. Texture features are utilized to distinguish living benthos, often occurring in regular and smooth textures, from sand and rubble substrates that generally have irregular textures. The combination of color and texture features can distinguish dead corals and dead coral with algae categories.

Material and Methods

Near-reef videos are acquired through LIT method via video capture done at approximately 30 cm from the reef surface. Underwater videos of coral reef transects from Talibon, Bohol (FISH Project, Marine Science Institute, UP Diliman) are utilized. Classification categories are living (live coral and algae) and nonliving components (dead coral, sand and rubble). 625 sub-images are employed for the training and the test set (living: 240; nonliving: 385). Selection of these sets is based on clarity and vividness of contrast and color. Alive corals are generally colorful and regularly textured while nonliving components are achromatic. Ground truth is provided by the Marine Science Institute of UP Diliman.

The subsurface reef videos are acquired in Ngedarrak reef, Republic of Palau. A Sony Model 2020IR bullet-type underwater submersible camera and an echo sounder are lowered on a motor-powered boat about 0.2-0.5 m from the water level. Boat speed is maintained at around 2 knots. The echo sounder was attached beside the video camera to simultaneously estimate the depth. Video acquisition was done on April 14, 2006.

Raw image sizes of 480×720 pixels were reduced to half (240×360 pixels) for fast computation. Percent cover from reef video is obtained by "downsampling" (Marcos et al. 2007) the video frame into small blocks (30×30 pixels), and each block is classified whether it is living or nonliving. Doing this for all blocks in a video of a reef area vis a vis per pixel classification provides a fast measure of living and nonliving benthos distribution. Prior analysis of the effect of varying block sizes and video frame interval sampling have found that recognition rates do not differ by more than ± 5-6%.

Fig. 1 illustrates video acquisition of the camera throughout the reef topology. Because the reef has variable height, the field of view varies with changing camera-reef distances (e.g. regions 1 and 2 in the figure). When counting the distribution of a benthos type, it will have more block counts for the shallower depth (region 1) than in greater depths (region 2) for a fixed actual benthos size/area. It is then more appropriate to estimate physical area distribution rather than using point-intercept method in reporting benthic distribution especially for subsurface video. For the system to obtain accurate and reliable percent count of any benthos, area calibration is needed.

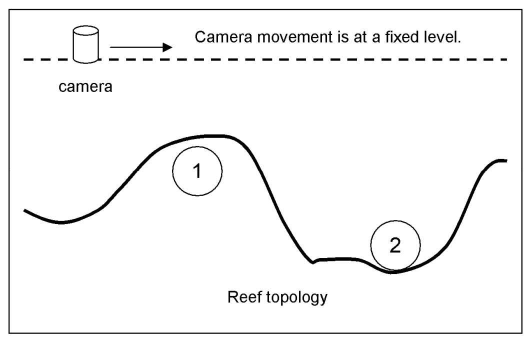


Figure 1: Illustration of video acquisition at different heights of the reef topology. Percent cover counting should be corrected for varying field of view due to changing distance between camera and reef.

For pinhole imaging as shown in Fig. 2, the field of view angle of an imaging system varies with object distance by the following equation:

$$\alpha = 2\tan^{-1}\left(\frac{I_V}{2x_I}\right) \quad (1)$$

where x_I is the lens to imager distance and I_V is the vertical measurement of the camera's imager. From the camera optics of Figure 2.6 combined with the thin lens equation: $1/x_O + 1/x_I = 1/f$, where x_O is the lens to object distance and f is the focal length, the actual vertical and horizontal field of view equation for a CCTV camera is derived as:

$$H = I_H\left(\frac{x_O}{f}\right); \quad V = I_V\left(\frac{x_O}{f}\right) \quad (2)$$

where I_H and I_V are the horizontal and vertical sizes of the CCD imager of the camera, respectively. For underwater video capture, imaging variation due to the index of refraction of sea water is accounted through Snell's law where seawater decreases the field of view by 33%. Hence by multiplying I_H, I_V, $1/f^2$ and 0.33 a calibration factor C can be obtained for any submersible CCTV camera:

$$FOV_{horiz} \times FOV_{vert} = 0.33 \frac{I_H I_v}{f^2} x_0^{\ 2} = C x_0^{\ 2} \tag{3}$$

A calibration factor of C = 0.44 was found for the camera setup used in this study. This means that area calibration can be done when there is numerical data on camera specifications and camera-reef distance (obtained through echo sounder). Thus a submerged reference object is no longer required.

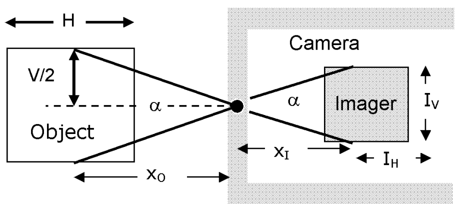


Figure 2: Basic optics of a CCTV camera

Color and Texture Features

The color features in (Marcos et al. 2005), the normalized *r-g* color space, are used which was found to be the best color feature among several color spaces tested for benthic classification. The color feature is computed from the RGB pixel values of the raw image frames from video.

A texture feature is a numerical description of intensity patterns (or patterns of pixels or group of pixels) in an image area. The rotation-invariant Local Binary Pattern histogram (Ojala et al. 2002) is utilized because it was proven to perform well on rotated, tilted and illumination-varied three-dimensional textures (Maenpaa et al. 2004). It was also shown to be a suitable texture descriptor for benthic components (Marcos, et al., 2005).

Classifier

Linear Discriminant Analysis (LDA) which is based on Bayesian theory is used as classifier. LDA is simple to calculate from data and is reasonably robust, i.e. the results are good even when the classes do not have normal distributions (Kuncheva 2004). Using the classification criterion to minimize total error of classification (TEC), the classifier will attempt to make the proportion of object that it misclassifies as small as possible. LDA employs Bayes Rule to assign an object to the group with highest conditional probability. All probabilities are assumed to have a multivariate normal distribution and all groups have the same covariance matrix C. An x_k is assigned to group i with the maximum value of

$$f_i = \mu_i C^{-1} x_k^T - \tfrac{1}{2} \mu_i C^{-1} \mu_i^T + \ln(p_i) \tag{5}$$

where μ_i is the mean of group i and p_i is equal to total sample of each group divided by the total samples.

Ground Truth

Expert-analyzed ground truth data was used to verify the output benthic cover of the system. To facilitate a fast point-by-point analysis (Fig. 3) a Matlab-based Graphical User Interface coral reef ground truth system (GUI-Coral Truth) was developed. The GUI-Coral Truth allows all sections of an image to be classified into five categories: coral, dead coral, dead coral with algae, sand and rubble for depths of 1 to 8 meters. Due to poor visibility at depths of more than 6 meters, ground truth error from visual inspection of the videos is expected to be large.

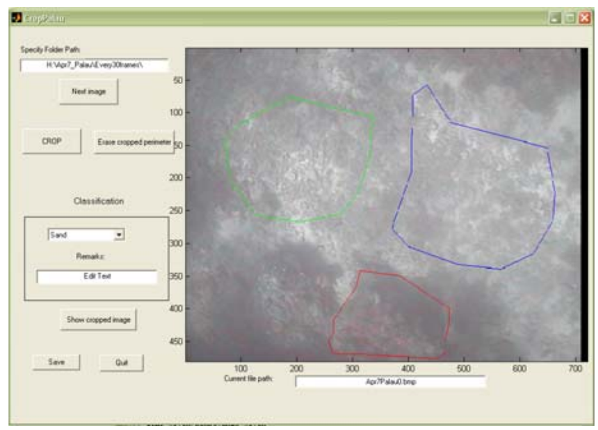


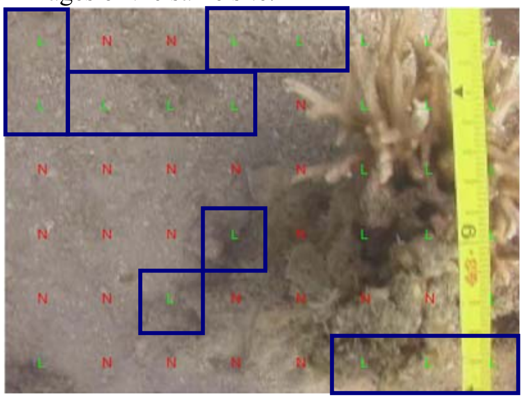
Figure 3: Graphical User Interface (GUI) developed for ground truth establishment

Results and Discussion

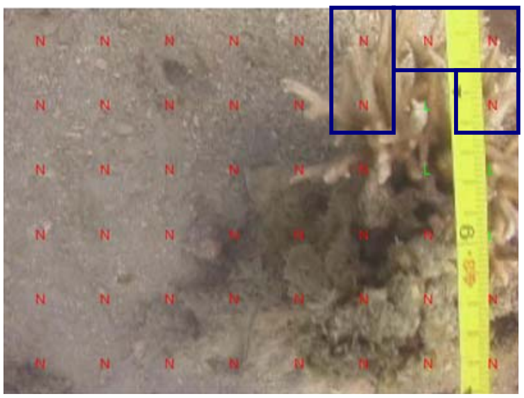
Near-reef Video

Table 1 shows the result of classification for the Bohol reef images where 79% recognition rate is obtained. This result verifies the potential of the classification system for identifying coral reef components from video of different reef areas.

Benthic cover result from a training set obtained from the same test site (Bohol reef) is compared with the result from a training set of a foreign/different site (Table 1). A non-zero trace with zero off-diagonal elements indicates a perfect (100%) recognition rate in a confusion matrix. The difference in percent cover count for foreign vs. same site training set reveals site-specificity in choosing the training set for classification. This is expected mainly because of different water quality conditions for both sites, which affects the signal-to-noise ratio of images acquired. Fig. 4 show visual comparison of this result Most regions in the image are misclassified when a foreign training set is used. It is recommended then that training images for a specific reef area be taken from reef images of the same site.



(a)



(b)

Figure 4: Labeled Bohol reef images from percent cover count obtained through our classification system. Bold perimeter boxes designate regions of misclassification. (a) Result from using AIMS training set; (b) Result from using training set from the site itself.

Table 1: Confusion matrix for classifying Bohol reef images using combined color and texture. Classifier used is LDA.

Category	Living	Nonliving	Recognition Rate
Living	175	68	72%
Nonliving	65	317	83%
Overall Recognition Rate			79%

Subsurface Video

The subsurface benthic classifier achieved a high success rate in identifying living components especially at shallower depths, reaching a high 85% recognition rate at 3-meter depths. 75% recognition rate was obtained for nonliving components. Incorrect classification is attributed to occurrences of non-achromatic rubble images due to shadows cast by their structures and/or algae growing on them. A decline in success rate was observed with increasing camera-reef distances, as expected with the decrease in visibility . The automation was accomplished in approximately two hours using Matlab software and a computer with a Pentium 4 processor (1.5 GHz) and 1 GB memory.

Percent Cover with Area Calibration

To validate the area calibration in eq. 3, real-world area of field of view obtained from image measurements was plotted against various camera-object (resolution target) distances as shown in Figure 5. A quadratic fit of $y = 0.442x_O^2 + 0.512x_O$ was computed, where y is the area of field of view and x_O is the object distance from the camera. This is in good agreement with the derived calibration factor (Eq. 3) of $0.44x_O^2$. The second term in the quadratic fit is attributed to nonlinear factors inherent to the camera optics and the water column (refractive index of sea water may not be constant or equal to 1.33). It is also ascribed to skewing of the camera during video capture.

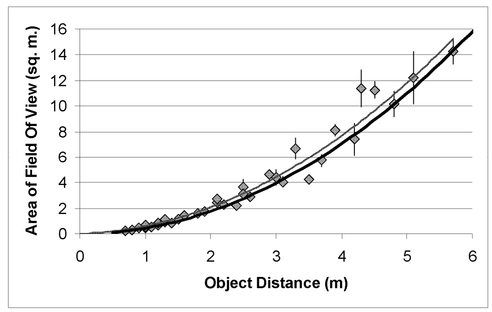


Figure 5: Validation of the area calibration factor. Data points represent actual field of view area measured directly from the images and processed via equation 12. The light trend line denotes a quadratic fit of $y = 0.442x_O^2 + 0.512x_O$ ($R^2 = 0.96$), where y is the area of field of view and x_O is the object distance from the camera. The field of view calibration factor we derived in equation 3 ($y = 0.44x_O^2$) is represented by the bold line.

The actual spatial area cover of living and nonliving components of subsurface reef video captured from the Ngedarrak Reef, Palau was computed after area calibration. Depths greater than 6 meters produce video frames that lack visual clarity and thus were excluded because of a large uncertainty in ground truth establishment through video inspection. Cumulative area cover of living and nonliving components was computed at increments of 1 meter camera-reef distance (Table 2). This will determine the maximum depth to acquire subsurface video where accuracy of percent area cover may fall below acceptable values. It is emphasized though that acceptability of any experimental result is dependent on the end user. From Table 2, it can be surmised that for a user requiring a spatial cover accuracy of more than 70%, the classification system can be applied to videos acquired up to depths of 2 meters. It is emphasized that identification of coral reefs only at depths of 2 meters is already immensely useful for marine scientists especially when analyzing results of environmental catastrophes such as typhoons which affects shallow reefs in general.

Table 2: Comparison of cumulative derived area of living and nonliving components from classification system and from ground truth. The success rate based from ground truth area are indicated.

Camera -reef distance	Area derived from classification (m2)		Area derived from ground truth (m2)		% Success Rate
	Living	Nonliving	Living	Nonliving	
1 to 2 m	0.73	0.38	0.93	0.18	75.70
1 to 3 m	6.65	3.35	6.54	3.46	56.20
1 to 4 m	14.52	7.83	12.60	9.75	46.90
1 to 5 m	22.18	15.13	19.17	18.15	46.10
1 to 6 m	26.19	17.30	24.65	18.85	48.00

Comparison of Method with Video Point Sampling

The system developed in this study for subsurface video analysis of reef video is compared with video point sampling using five points as markers. The point sampling classification was done by Mr. Victor Ticzon of the Marine Science Institute, UP Diliman. Subsurface video was sampled from 9 stations along the Lingayen gulf, Pangasinan.

Comparison of computed hard coral cover from both methods are illustrated in Fig. 6. For the automated classification, training images were obtained from the site itself. Nine of 11 stations analyzed by both methods have less than 10% difference in percent cover estimates of live coral cover. Small difference in these results reveals that both methods can gain similar or comparable results. It is emphasized though that frames that lack visual clarity are removed from the analysis in both methods. Although fixed point sampling is the standard method used by most marine scientists in determining percent cover, the classification system introduced in this paper exploits all information from the image, i.e. every region in the image is considered.

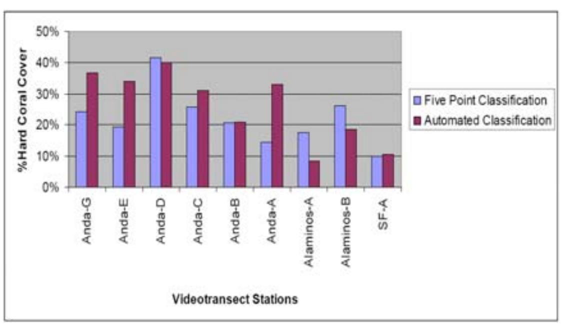


Figure 6: Bar graph of the percent cover of hard corals in 9 stations of the Lingayen gulf as assessed by five point classification and the automated classification developed.

This study on classification for near and subsurface reef videos provides groundwork for developing rapid automated systems for benthic classification and mapping using a simple reef transect video. Area calibration is introduced since point-intercept method is inadequate in reporting percent cover due to variability in camera-reef distances. This calibration model also eliminates the need for submerged reference objects. Although this study, which is the first to explore automation of subsurface benthic images, have obtained a fair accuracy rate in classifying living benthos, it is highly likely that improved image quality from better camera optics and electronics can yield higher recognition rates even at greater depths.

The applicability of the system's current performance would depend on the field study objectives and the needed accuracy. If rapid assessment of coral cover is desired especially in reef areas affected by typhoon and oil spill, then the system would suffice as long as video is taken at 2 meter depths. Although video point sampling protocol is the current standard in determining benthic cover because of its high recognition accuracy, this process is quite tedious and needs expert manning. Nonetheless, our system can be used to supplement results from multi-spectral imagery, and even video point sampling.

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