Computer Vision Applications for Assessing Coral Reef Health

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Introduction

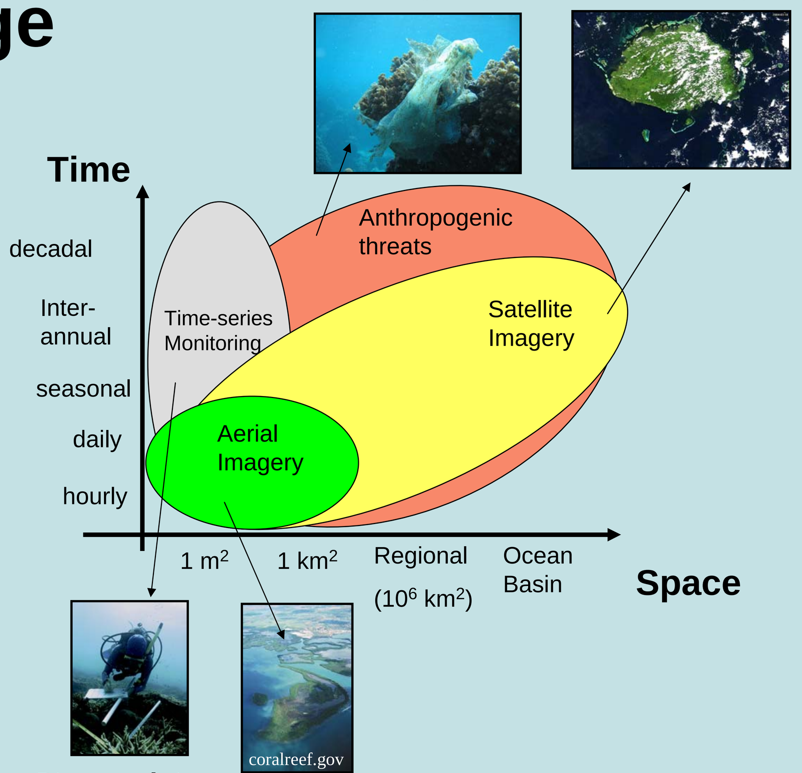
Coral reefs have experienced serious declines in recent decades due to commercial and subsistence harvesting, environmental degradation related to burgeoning human communities, and rising ocean temperatures[5,6,9]. An important part of understanding these events is obtained though observation and collection of data. New technologies are needed to improve the efficiency of monitoring and assessing the health of global coral reef communities. A convergence of several rapidly advancing technologies, including digital imaging, computational mass storage and processing speed, integrated with computer vision image analysis now makes it feasible to acquire, archive, and digitally classify aspects of coral reef community structure. Simple initial goals include distinguishing hard corals from their background and detecting evidence of bleaching or disease on hard corals.

Main Challenge

Threats to coral reefs and their associated biodiversity happen on a variety of time and space scales. Local sampling is limited by man-power and the time it takes to analyze photos and videos is often the limiting step. We explore computer vision techniques in an effort to evaluate their potential.

Plastic bag smothering a coral

Satellite image, Vanua Levu, Fiji



Diver completing reef transect

Aerial photo

Background

Methods addressing this problem demonstrate the feasibility of classifying coral reef ecology using computer-vision based techniques with proper image training sets:

•Clement *et al.* (2004) use texture-based classification to identify the destructive Crown of Thorn starfish on coral reefs[2].

Computer detected COT (Clement *et al.* 2004)

•Using images classified by marine scientists, Marcos *et al.* (2005) applied neural networks to classify images as live coral, dead coral or sand/rubble, resulting in a recognition rate of 86.5%[7].

Left: L = live coral, D = dead coral, and S= sand/rock. Right: Examples of reef images with different textures (Marcos *et al.* 2005)

Study Sites

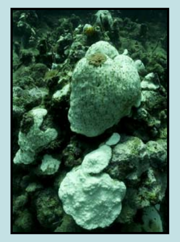
Namena Marine Reserve, Fiji Islands

Bocas del Toro, Panama

"Healthy" Namea Reef

Bleached coral, Fiji

"Healthy" Reef, Panama



Massive bleaching, Panama

Image Segmentation and Classification: Graph Cuts

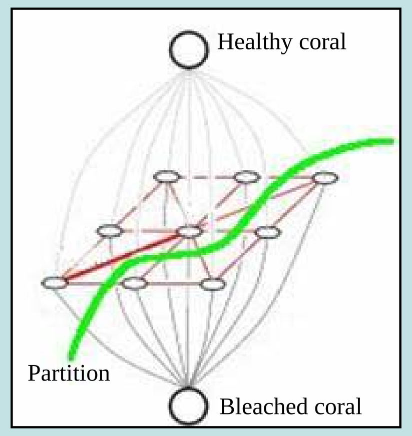
At this stage, the computer vision goal has been to classify each pixel in the image as being either healthy coral, bleached coral or the background. Our approach uses a recently developed algorithm based on *graph cuts*[1] that segments (partitions) the image into regions that have similar image characteristics within a region (and look like one of the three classes) and differing characteristics across the regions. For each pixel *i* in the image, a set of local image descriptors is computed using an image neighborhood around pixel *i*. Texture is characterized by filtering the image with a bank of 60 Gabor filters. A 2-D Gabor filter is the product of an oriented sinusoid and a circularly symmetric Gaussian function. The three (R,G,B) color components at pixel *i* are appended to the filter outputs to create a 63 dimensional real valued vector ***wi.***

For class *j={Healthy, Bleached, Background}*, we learn a probability distribution of the appearances of each class using a set of training images that have been hand-segmented by a coral expert. In this work, we model the probability of feature vector ***wi*** given that pixel i is from class *j* as a mixture of Gaussian

$$p(\mathbf{w}\mid i\in j)=\sum_{i=1}^{N}\alpha_{ij}\frac{1}{2\pi\sqrt{\left|\Sigma_{ij}\right|}}e^{-\frac{(w-\mu_{ij})^{T}\Sigma_{ij}^{-1}(w-\mu_{ij})}{2}}$$

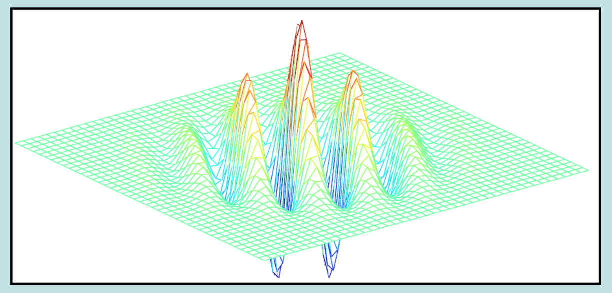
functions and the mean and covariance matrices are estimated from hand-labeled training data using the EM algorithm.

To segment an input image using graph cuts, a weighted undirected graph is formed whose nodes are the pixels in the image and whose arcs connect all pairs of pixels within a fixed image distance of each other. The weights between nodes are a measure of similarity (affinity) computed from the texture/color feature vector. Two nodes *S* and *T*, representing two of the classes {*Healthy, Bleached, Background*}, are added to the graph; arcs connect S, T to all other nodes, and the weight connecting *S* (respectively *T*) to node *i* is related to *P(wi | i ∈ S)*. Once the graph is constructed, it is partitioned into two disjoint subgraphs using the min cut/max flow algorithm; this divides the pixels in the image into two set corresponding to the two classes. This basic 2-class algorithm is augmented to work for multiple classes.



Adapted from Boykov *et al.* 1999

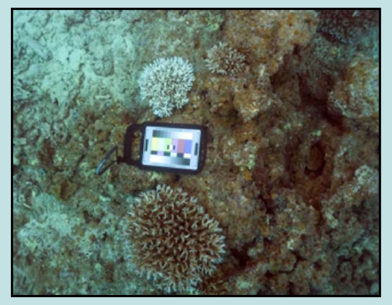
Graph representing a 3-by-3 neighborhood of an image. Red line indicates arcs (edges) connecting neighboring pairs of nodes (pixels) with weight (affinity). The special nodes (top and bottom) indicate two material classes for which labeled examples are available from an expert. The partition is specified by a *cut*, shown in green, that assigns pixels to one of the two classes.



Gabor Filter Kernel. This convolution kernel is applied at several orientations and scales to compute local texture features that, together with local color features, characterize small neighborhoods of the image.

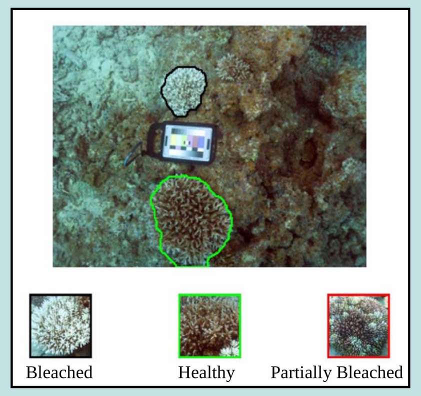
Preliminary Results

Input Image



Application of the graph cuts method to an input image displaying both live and bleached coral and the resulting partitioned image. Chart shown at lower left is used for calibrating the color response of the camera. This allows for consistency in color measurements

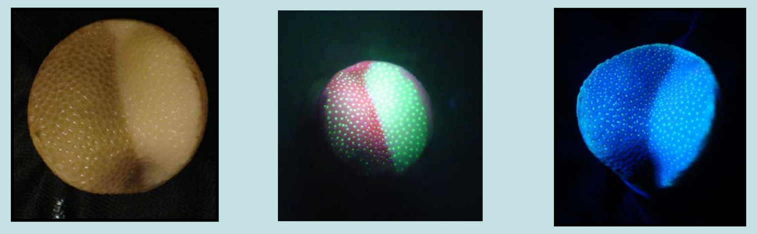
Segmented/labeled Image



Technology Development

We envision adding the following classification dimensions:
•Fluorescence to assess bleaching and physiological health[8]
•Spectral reflectance to provide ground truth for remote sensing
•Burst imagery or video to determine mobility of targets
•Stereo photography to obtain 3-D information
•Laser ranging system to get distance to target
•Turbidity correction
•Additional classes of reef objects (e.g. soft corals, invertebrates)
•Greater accuracy is expected using algorithms which include richer descriptions of features of each class provided by ecology experts.

Fluorescent image of coral, Sarawak



Natural light

Fluorescent Filter #1

Fluorescent Filter #2

Coral core with White Plague disease on the right side. As photographed under natural light (left) and using various fluorescence filters. Photos by Alistair Grinham, University of Queensland, 2006.

Fluorescence can distinguish healthy vs. bleached coral tissue

Importance

Developing rapid, objective and quantitative classification is essential for time-series monitoring, evaluation of the effectiveness of marine reserves, and to improve global assessments of coral community biodiversity and health.

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