CORAL REEF TEXTURE CLASSIFICATION
USING SUPPORT VECTOR MACHINES

Anand Mehta[a], Eraldo Ribeiro[a], Jessica Gilner[b] and Robert van Woesik[b]

[a]*Department of Computer Sciences*
[b]*Department of Biological Sciences*
Florida Institute of Technology
Melbourne, FL 32901

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Abstract: The development of tools to examine the ecological parameters of coral reefs is seriously lagging behind available computer-based technology. Until recently the use of images in environmental and ecological data gathering has been limited to terrestrial analysis because of difficulties in underwater image capture and data analysis. In this paper, we propose the application of computer vision to address the problem of monitoring and classifying coral reef colonies. More specifically, we present a method to classify coral reef images based on their textural appearance using support vector machines (SVM). Our algorithm uses raw pixel color values directly as sample vectors. We show promising results on region classification of three coral types for low quality underwater images. This will allow for more timely analysis of coral reef images and broaden the capabilities of underwater data interpretation.

1 INTRODUCTION

The analysis of underwater images is a challenging computer vision problem with several important applications in the fields of archeology, military, navigation and biology. In recent years, stimulated by the current availability of digital optics technology, the demand for solutions for underwater image analysis has increased significantly. In this paper, we describe a supervised texture classification method for automatic classification of coral reef images. The work reported here is part of a ongoing research effort aiming to develop an image-analysis system to monitor temporal changes of coral colonies on coral reefs. Our classification method uses a support vector machine(SVM) classifier (Vapnik, 1995). Depending on the application, support vector machines have several advantages when compared to classical supervised classification methods such as maximum likelihood. In the particular case of texture classification, support vector machines allow for very good class separation even when the size of the feature vectors is large and the number of training samples is limited. Another advantage is that it allows for the use of raw image data as feature vectors which is specially interesting for natural random textures where geometrical

features and descriptors are difficult to obtain (Kim et al., 2002; Li et al., 2003). This is particularly relevant to the classification of coral reef images which present rich patterns of colors, shapes and textures.

Coral reefs are among the most complex natural systems on earth, both structurally and biologically. Indeed, high structural topographic complexity allows coral reefs to support more species than any other marine system. Coral reefs have recently risen to global prominence in terms of their capacity to act as early warning indicators of global climate change. They are accurate proxies of thermal stress events, where corals visibly pale (bleach), which often leads to mortality and relative shifts in species composition (Hoegh-Guldberg, 1999). Yet, quantifying diversity and relative abundance of species on coral reefs is time consuming. Most serious are the delays in data compiling and synthesis, where twelve months is not uncommon.

In this paper, we apply computer vision to the problem of monitoring and classifying coral reef colonies. Our texture classification approach does not require any explicit feature extraction. The feature extraction is implicitly performed by the support vector classifier. As a result, no pre-processing is required, and the pixel raw data is directly used for both training

and classification. This is possible since support vector machines implicitly perform feature extraction by means of a kernel which is defined by a dot product of two non-linear mapped patterns. Support vector machines are binary classifiers in essence but multiclass separation can be achieved by means of the one-against-all decomposition procedure. This is equivalent to decomposing the multiclass problem into multiple independent binary classification tasks. Alternatively, better results can be obtained when multiclass predictors are trained directly as described in (Crammer and Singer, 2001). The classification presented in this paper is a binary one.

2 RELATED WORK

The first method used to quantify benthic coral reef organisms was borrowed from plant ecologists. It involved the use of line intercept transect method (Loya, 1972), where fiberglass lines are laid over a given reef and meticulous measurements are made, to the nearest centimeter, of each benthic (bottom dwelling) coral reef organism while the researcher is underwater. Only small spatial tracks of reefs can be examined using this technique. Other methods involve similar small scale data gathering exercises, involving quadrats and belt transects. Capturing subsections of reef on still and video digital images has increased the area of observation, but there are still delays in data gathering and compilation due to manual processing.

There has been a considerable increase in the effort to provide remote sensing solutions to the problem of coral reef monitoring for both aerial and underwater imagery. A review of the application of both acoustic and optical imaging devices in analyzing the physiology, behaviour, and interactions between benthic species can be found in (Solan et al., 2003). While progress has been made in the use of remote sensors, namely airborne scanners and satellites (Mumby et al., 2004), ground truth comparisons have revealed high error estimates rarely surpassing 60% accuracy (Hedley et al., 2004).

Solutions based on satellite imagery have limited resolution and are not suitable for monitoring small variations in both shape and color of coral colonies. Imaging coral colonies directly using underwater video and high-resolution images represent a contemporary consideration of coral reef assessment. Our analysis is focused on underwater imagery. Our classification method does not require the estimation of any intermediary feature vector or histogram. The general visual appearance of the corals is implicitly extracted in the support vector machine classification

process. Our work follows the line of texture classification as described by (Kim et al., 2002) and (Li et al., 2003). Li et al (Li et al., 2003) use translation-invariant features generated from the discrete wavelet frame transform together with a fusion scheme based on multiple support vector classifiers, each with a different setting of the kernel parameter. Kim et al (Kim et al., 2002) use raw pixel data as input for the support vector classifier of textures. Their results are demonstrated for sets and mosaics of Brodatz textures.

3 SUPPORT VECTOR MACHINES

Support vector machines (SVM) are binary classifiers that estimate the optimum separating hyperplane that maximizes the margin between two classes. The margin can be defined as the distance of the closest point, in each class, to the separating hyperplane. In statistical learning theory, this is equivalent to performing structural risk minimization on a nested set structure of separating hyperplanes (Vapnik, 1995; Burges, 1998).

Given a set of training examples $(\mathbf{x}_i, y_i) \in \mathbf{R}^N \times \{\pm 1\}, i = 1, \ldots, l$, the objective is to determine the function $f : \mathbf{R}^N \rightarrow \{\pm 1\}$, from a class of functions, such that f will correctly classify new examples $(\mathbf{x}, y)$, i.e., $f(\mathbf{x}) = y$, which were generated under the same underlying probability distribution $p(\mathbf{x}, y)$ as the training data. Support vector machines use hyperplanes for class separation:

$$(\mathbf{w} \cdot \mathbf{x}) + b = 0 \quad \mathbf{w} \in \mathbf{R}^N, b \in \mathbf{R}, \quad (1)$$

and the corresponding decision function is given by:

$$f(\mathbf{x}) = \text{sign}[(\mathbf{w} \cdot \mathbf{x}) + b] \quad (2)$$

Solving for the optimal separating hyperplane $\mathbf{w}$ consists of finding the solution of a constrained optimization problem using quadratic programming, where the optimization criterion is the width of the margin between the classes (Vapnik, 1995; Burges, 1998). The optimal separating hyperplane can be represented as a linear combination $\mathbf{w} = \sum_i v_i \mathbf{x}_i$ of a subset of the training examples that lie on the margin. These training examples or patterns carry all relevant information about the classification problem and they are called *support vectors*. Once the support vectors $\mathbf{x}_i$ are estimated, classifying a new test pattern $\mathbf{x}$ is done using the following expression:

$$f(\mathbf{x}) = \text{sign}[\sum_i v_i (\mathbf{x} \cdot \mathbf{x}_i) + b] \quad (3)$$

where the sign of $f(\mathbf{x})$ determines the class membership of $\mathbf{x}$.

Usually, general pattern classification problems cannot be solved using a linear classifier such as a separating hyperplane, and the classification procedure should allow for non-linear separating surfaces. A crucial property of the SVM is that both the quadratic programming problem and the final decision function depend only on dot products between the patterns. This property allows the classification procedure to be generalized to cases when the patterns are not linearly separable. In this case, the decision function is a non-linear function of the data. The method consists of mapping the data into a higher dimensional dot product space where they are considered linearly separable. Once the mapping is performed, SVM can be applied to the new space to calculate the decision boundary. This linear boundary leads to a non-linear separation surface in the original space. The mapping procedure is based on the Cover's theorem (Cover, 1965) that shows that a multidimensional space consisting of nonlinearly separable patterns can be transformed into a new feature space where the patterns are linearly separable with a high probability. The theorem is valid under the conditions that the transformation is nonlinear and the dimension of the feature space is high. The kernel function $k(\mathbf{x}, \mathbf{y}) = \Phi(\mathbf{x}) \cdot \Phi(\mathbf{y})$ is introduced and does not require explicit knowledge of $\Phi(.)$ The solution has the form:

$$f(\mathbf{x}) = \mathrm{sgn}[\sum_{i=1} v_i k(\mathbf{x}, \mathbf{x}_i) + b]$$
$$= \mathrm{sgn}[\sum_{i=1} v_i (\Phi(\mathbf{x}) \cdot \Phi(\mathbf{x}_i)) + b]. \quad (4)$$

Table 1 lists the three most commonly used kernel functions in SVM classification.

Table 1: Kernel functions used for SVM classification.

kernel name	function
Polynomial	$k(\mathbf{x_i}, \mathbf{x_j}) = (\mathbf{x_i} \cdot \mathbf{x_j})^p$
Radial basis function	$k(\mathbf{x_i}, \mathbf{x_j}) = e^{\left(-\frac{1}{2\sigma^2}\|\mathbf{x_i}-\mathbf{x_j}\|\right)}$
Sigmoid kernel	$k(\mathbf{x_i}, \mathbf{x_j}) = \tanh(\mathbf{x_i} \cdot \mathbf{x_j}) - \Theta)$

4 CORAL REEF CLASSIFICATION

In this section, we describe the details of our classification algorithm. The algorithm consists of a direct application of the support vector machine classifier using raw pixel data as sample vectors. We chose the radial basis function kernel to perform the experiments where σ is manually selected and kept fixed for all experiments. In our trials, the radial basis function kernel performed better than the polynomial (Table 1). We plan to investigate approaches for the selection of σ as suggested by (Muller et al., 1997).

We commenced by extracting a number of $N \times N$ subregions of previously labeled coral images. Since our current classification approach is a supervised one, we selected the images to match a particular class of coral reef that we wanted to classify. The pixel values inside these regions became the sample vectors to be fed into the classifier for the training stage. During the training phase, the support vectors were identified. Once the support vectors were at hand, we classified each pixel in an image according to the class predicted by the support vector machine classifier. This is a simple algorithm that allows for very good texture classification results of coral reef images.

5 EXPERIMENTS

In this section, we present results for classification of coral reef images. We applied the support vector machine method for the classification of three types of coral: corymbose *Acropora*, branching *Acropora*, and tabulate *Acropora*. The classifier was trained for about 100 subregions of each coral type. Each subregion had a size of 25×25 square pixels. The classification results were obtained for two classes only, but multiclass classification can be obtained using a one-against-all approach, as mentioned earlier. We make use of the support vector machine implementation provided by the libsvm library by Chang and Lin (Chang and Lin, 2001). Figures 1, 2, and 3 show both the original test images(a) and the results of the texture classification(b). Our algorithm achieved a 95% correct classification for all classified images. However, several small regions were still misclassified. The main reason seems to be the lack of a proper model for the underwater illumination. We plan to approach this problem in future implementations. The
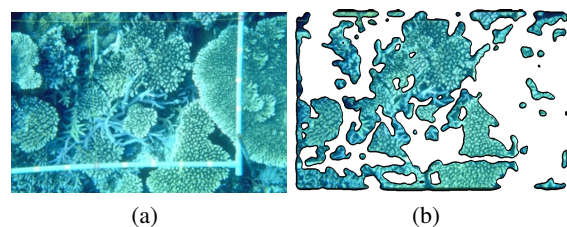

Figure 1: Coral classification results. (a) corymbose *Acropora*, and (b) resulting labeled regions.