Simulation of Underwater Imaging Systems

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The worldwide decline of coral reefs is attributed to the increase in atmospheric CO_2 and water temperature. We use simulations to show that it is possible to classify coral reef pigments from underwater images captured by consumer RGB cameras. These simulations will help us design experiments in a controlled laboratory environment and to quantify the effect that water temperature has on the spectral signature of coral reef pigments. .

1. Introduction

Scientists estimate that the Earth has lost 40% of the coral reefs in the last 50 years [1]. They attribute this loss to rising water temperatures and the increase in atmospheric CO_2 that is absorbed in the water [2–4]. This worldwide decline in coral reefs is monitored at the macroscopic scale using remote sensing devices such as hyperspectral cameras and at the microscopic scale using in situ imaging sensors such as fluorometers. These devices measure the spectral signatures of organisms that live in the coral reefs. Changes in these spectral signatures are correlated with coral reef mortality [5].

In vivo measurements of fluorescence and reflectance require expensive spectrophotometers or multispectral imaging systems that have been adapted for aquatic use. For example, Zawada and Mazel [6] reported that they could classify coral species based on analysis of fluorescence emission spectra measured using a customized multispectral imaging system. A recent paper by Trebitz, Neal et al [7] suggests that is possible to estimate reef fluorescence with pairs of underwater camera images captured with and without flashes from high power strobe lighting. These results are very promising, although the method requires removing the NIR filter from the consumer digital camera and do not produce quantitative results.

We extend this prior work by modeling an inexpensive and unmodified consumer digital camera with attached lighting to simultaneously estimate reflectance and fluorescence emissions from coral reefs. We use computer simulations to model and quantify the effects of 1) spectral illumination, 2) light absorption by water at different depths, 3) spectral sensitivities of camera sensors, including the presence or absence of an NIR filter, 4) sources of sensor noise, 5) exposure duration, and 6) the amount and type of organic pigments in coral reefs. Finally, we use modern state-of-the-art machine learning methods for classifying RGB pixels into coral types in order to quantify the health of the coral reef.

2. Simulation environment

We simulated image acquisition in Matlab using the Image Systems Engineering Toolbox (ISET) [8, 9]. This section describes how we modeled the excitation and absorbance of light by coral reef pigments. The following section describes how we model the spectral properties of light propagation and absorption in water, spectral sensitivities of the imaging sensors, and temporal integration in order to predict the camera RGB values for different coral reef pigments.

The spectral radiance of different coral reef pigments were represented in a test target with 10 x 10 different samples. Each sample in the target was generated by synthesizing its reflectance and fluorescence emission spectra. The reflectance spectrum for each test chart was either the *blue* or *brown* coral type reflectance functions reported by Hochberg et.al. [10]. The mean reflectance varied across the 10x10 samples in each test chart. The fluorescence spectrum for each sample in the test chart was simulated using the method presented in Zawada and Mazel [6]. In brief, we used seven fluorescence spectra end members to create different coral species. A species was defined by the particular choice of end members while a particular instance was generated by varying the proportions with which the selected spectra were mixed. In our simulations, we modeled both the depth at which the targets were placed and the distance between the camera and the target.

2.1. Image formation model

We assume that the light propagating through a water column of thickness D is attenuated due to absorption and scattering according to the Beer-Lambert's law

$$I(\lambda) = I_0(\lambda)e^{-DK_d(\lambda)}, \tag{1}$$

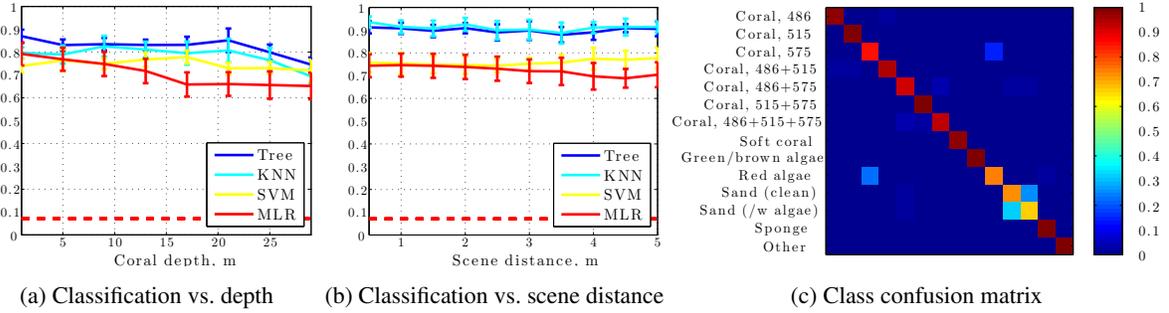(a) Classification vs. depth   (b) Classification vs. scene distance   (c) Class confusion matrix

Fig. 1: Coral classification accuracy using RGB data from a simulated consumer camera (NikonD1).

where I and I_0 are the attenuated and initial light intensities respectively, and $K_D(\lambda)$ is the diffuse attenuation coefficient. When the incident illumination, attenuated by the water column, reaches the surface it is reflected towards the camera and it also causes the excitation of fluorescence in the substrate [11]. The total radiance e_t emitted towards the camera is therefore given by

$$e_t(\lambda) = I(\lambda)r(\lambda) + \Phi f_e(\lambda) \int I(\lambda')f_a(\lambda')d\lambda', \tag{2}$$

where r is the surface reflectance, I is the incident illuminant energy and f_a and f_e describe the normalized fluorescence absorption and emission spectra respectively. The scalar Φ denotes the *practical fluorescence efficiency* [12]. Before the reflected radiance e_t reaches the sensor it travels some distance d in water that separates the camera from the scene. Finally, we model the captured pixel values m_s using linear image formation [13]

$$m_s = g \int e_i(\lambda)c_s(\lambda)d\lambda, \tag{3}$$

where c_s is the sth pixel responsivity function and the scalar g represents the global effect of the aperture setting, integration time and analog amplifier gains.

3. Results

Using simulations, we first confirmed that we could reproduce results reported by Zawada and Mazel [6] and then showed that we could obtain comparable results with a consumer RGB camera. Zawada and Mazel [6] applied simple classification algorithms to multispectral data to differentiate between different coral types. Our simulations of their multispectral imaging system and fluorescent pigments produced similar results. We also simulated a popular consumer digital camera, including the effects of reflectance, as well as fluorescence, and used modern machine learning algorithms to show that it is still possible to reliably discriminate between coral types (Fig 1). While our performance is a little lower than the one reported in [6], this is to be expected since we are analyzing an off-the-shelf camera rather than custom designed system.

We modeled and analyzed the FluorIS system developed by Treibitz, Neal et al. [7]. This system included a Canon DSLR without the NIR filter, a short wavelength excitation light, and a longpass filter. The authors used a flash/no-flash method to estimate fluorescence emissions from coral reef pigments: They captured two images of a coral reef during the day, with (I_{ds}) and without (I_d) a strobe light. Then they captured an image of the same coral reef at night using the strobe only. The authors reported that the camera pixel values captured at night with the strobe (capturing only the fluorescence emissions) were highly correlated with the difference in camera pixel values captured during the day, $I_{ds} - I_d$. We replicated their findings using simulations (Fig 2a). We also analyzed the capacity of our simulated system to resolve weak fluorescence signals. Figure 2b plots the average ratio between pixel contributions due to fluorescence and daylight as a function of the daylight intensity, for three camera ISO settings. For higher ISO values, images are more noisy and therefore the detection threshold is increased. This type of analysis allows us to determine how well a system can detect fluorescent signals given the amount of fluorescent pigment, the spectral power in the illumination, the quantum efficiency of the digital camera and the noise characteristics for a particular choice of settings.

(a) Pure fluorescence estimation
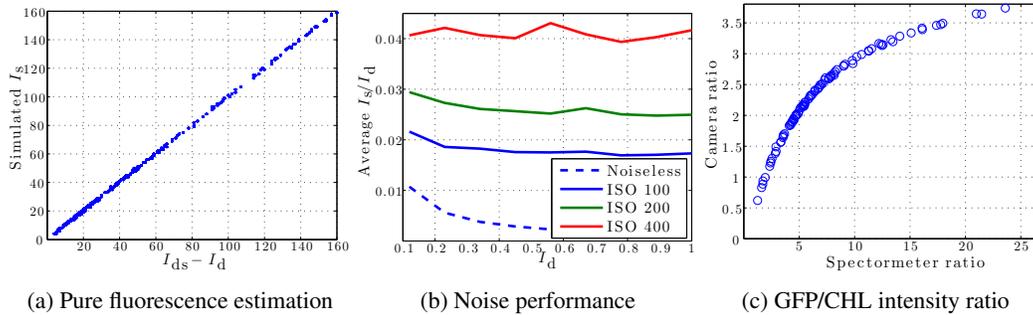
(b) Noise performance

(c) GFP/CHL intensity ratio

Fig. 2: Simulation based FluorIS system characterization [7].

Our simulations reproduced other results reported by Treibitz, Neal et al. [7] as well. For example, the authors reported that there is a high correlation between the ratio of the intensities of chlorophyll-a and the green fluorescent protein GFP fluorescence and the ratio of red and green camera pixels values. When we varied the ratios of different amounts of chlorophyll-a and the green fluorescent protein GFP fluorescence, we obtained a similar correlation (Fig 2c). Interestingly, our analysis reveals that when these ratios are less than two, this relationship is linear as reported by Treibitz, Neal et al. [7], but for larger ratios, the relationship is approximately logarithmic.

In summary, our simulations demonstrate that it is possible to classify coral reef pigments by analyzing images captured with an unmodified consumer RGB camera. It is also possible to estimate the reflectance and fluorescence components of coral reef pigments by analysis of camera images captured with and without strobe illumination. These results will guide future experiments in which we will capture images of real coral reefs in a controlled laboratory environment while increasing water temperature. We will then be able to quantify the effect that water temperature has on the spectral signature of coral reef pigments (i.e. coral mortality) and how we can detect these effects using relatively inexpensive consumer digital cameras.

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