Single Image Enhancement for Underwater Imaging

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Abstract

Underwater images captured with minimum processing are subject to poor image quality due to light scattering and absorption. As a medium, the optical properties of water are unique because color attenuation is dependent on the wavelength, unlike terrestrial images, where the attenuation is assumed to be uniform across the visible spectrum. In this report, we leverage an existing single image processing pipeline and replace the attenuation coefficient with properties generated by the HydroLight radiative transfer model to calculate the ratio. HydroLight is a commercially available software product that is designed to compute the radiance distribution for natural water bodies. We estimate the transmission and restore the image for a variety of water types and select the best result based on global color distribution. The transmission map is generated from a single image and does not require additional hardware or prior knowledge of the scene. The result is evaluated quantitatively by calculating the Pearson correlation coefficient between the estimated transmission map and the 3D stereo depth map. Color charts in the post-processed images can be compared to the reference qualitative evaluation of the restored color accuracy.

1. Introduction

In outdoor images, the light reflected from the subject and ambient light in the medium, known as veiling light [1], is absorbed and scattered by particles in the medium before it reaches the camera. In underwater photography, this phenomenon is referred to as backscatter and its impact is amplified in turbid waters, where the medium contains large, suspended debris. As a result, underwater images captured with minimum processing are often hazy and suffer from color distortion.

Oceanic water as an optical medium, has the unique property such that the light attenuation observed varies by wavelength. Color loss begins from the longest wavelength to the shortest, beginning from red. As depth increases, we start to observe color loss in the shorter wavelengths, such as the green channel and eventually even the blue channels. Coastal waters containing elevated levels of debris contributes to light scattering and as a result, water will appear brown or gray. [2] Jerlov developed a classification scheme for different natural water bodies based on water clarity. Through his expeditions, he categorized the world's oceans in types I, IA, IB, II and III for open ocean water types, and 1C, 3C, 5C, 7C and 9C for coastal water types[3].

Light propagation from an object to the camera is attenuated by water along the line of sight. This effect is distance-dependent, as it contributes to haze and reduced contrast in a scene. This suggests that improving underwater image quality is closely related to single image dehazing for terrestrial scenes, however the spectral properties of water need to be considered in order to produce good results. In particular, since the attenuation underwater varies by wavelength, we introduce attenuation coefficient ratios to represent the disparity between blue-green and blue-red color channels. The attenuation coefficients used to calculate the ratio were obtained from HydroLight, a widely used radiative transfer model [4].

The dataset used in this report is leveraged from Berman [5], which includes the RAW image files captured from a Left and a Right camera. The dataset includes the stereo calibration parameters to reconstruct the 3D structure and compare the result with the estimated transmission map. The dataset also includes color charts which serve as a ground truth for color correction.

The motivation for this project comes from my interest in scuba diving and underwater photography. There is potential to leverage this post processing method for scientific datasets, such as visual surveys. Advanced computer vision and machine learning algorithms can be applied on accurate and consistent underwater images to open new doors for marine conservation/exploration.

2. Related Work

After taking a brief survey of related works in the field, it became clear that the common image formation model to

address light absorption and scattering by particles in a medium contains two main components, the direct transmission of light from the object, and the scattering of the ambient light in the medium, also known as *veiling light*:

$$I(\boldsymbol{x}) = t(\boldsymbol{x})J(\boldsymbol{x}) + \big(1 - t(\boldsymbol{x})\big)A \tag{1}$$

This equation is defined for each color channel (RGB). The variable I is the perceived image, the t represents the transmission which captures the depth of the scene. The variable J is the surface radiance of the scene, and A is the veiling light. The $\boldsymbol{x}$ = (x, y) refers to a pixel in the image. This model is widely accepted in the field of computer vision to describe the formation of a haze image, including both terrestrial and underwater examples.

Recently, there have been several methods proposed in the scientific community for single image dehazing. They typically follow the image formation model previously stated (1), and try to recover the haze free image by making a prior assumption. The Dark Channel Prior (DCP) is one example and it is based on the key observation that in local patches in the original image, there are always some pixels that are low intensity in at least one color channel. Based on this observation, one can assume that dark pixel intensities are mainly contributed by the veiling light and therefore can be used to reconstruct the depth of the scene. This prior is used in several single image dehazing techniques including some in the underwater scenario [6], [7], [8]. Other priors that have been exploited in this area include a color-lines prior which assumes pixels of small image patches exhibit a one-dimensional distribution in RGB color space [9], and a haze lines prior [10] which is used in Berman's pipeline leveraged in this project.

Furthermore, there is another approach that has been effective in recovering color loss from underwater scenes. *Sea-thru* is a method that revises the image formation model from the atmospheric to address the optical properties of water where attenuation is not uniform across the scene [11]. This method combines the DCP with known range information to estimate the veiling light.

3. Technical Approach

The technical approach I took to improve underwater image quality leverages the method described in the paper "Underwater Single Image Color Restoration Using Haze-Lines and a New Quantitative Dataset" [5]. The method aims to solve the common image formation model presented in the previous section for the object radiance J by estimating the veiling light A and transmission t. Instead of using the original Jerlov attenuation coefficients, I investigated more recent optical models to explore if this created improvements to the results. The major blocks of the pipeline are shown in Fig. 1 below.

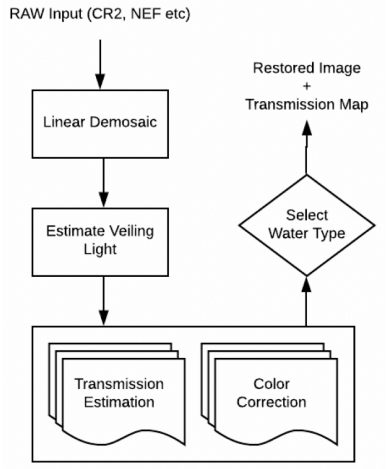


Fig. 1. Flowchart of the Method

3.1. Input Image

The underwater imaging dataset I used can be found on http://csms.haifa.ac.il/profiles/tTreibitz/datasets/ambient_forwardlooking/index.html. The contents of this dataset include RAW images, camera calibration files and distance maps. If using RAW images, the MATLAB code requires the input image to be converted to a de-mosaiced format, which can be done using the algorithms we implemented in EE367 or using Adobe DNG converter. I selected 5 images from the various scene locations listed on the website in order to gather images that resolve to different Jerlov water types.

3.2. Estimate Veiling Light

The veiling light or backscatter, is the ambient light scattered in the line of sight. We assume such an area in the image that is purely impacted by the scattering of ambient light should not have textures and appear fairly uniform. In order to estimate the veiling light, the first step is to apply a contrast stretch on the scene to compensate for the haze in the image. Then, the method uses the Structured Edge Detection Toolbox to create an edge map, and use thresholding to locate the largest smooth patch in the image. The intensity of the pixels belonging to the largest smooth patch are averaged to obtain the value A.

3.3. Transmission Estimation and Color Restoration

Light attenuation underwater varies by wavelength, as previously mentioned. This inherent optical property is unique to water and can be represented by the attenuation

coefficient β. The transmission depends on both the object distance and β.

$$t(\boldsymbol{x}) = \exp\left(-\beta z(\boldsymbol{x})\right) \tag{2}$$

After rearranging the image formation model and substituting the peak attenuation ratios for each color channel, $\beta_{BR} = \beta_B/\beta_R$ and $\beta_{BG} = \beta_B/\beta_G$, the resulting formula is with one unknown transmission per pixel across all color channels.

$$\begin{bmatrix} (I_R(\boldsymbol{x}) - A_R)^{\beta_{BR}} \\ (I_G(\boldsymbol{x}) - A_G)^{\beta_{BG}} \\ (I_B(\boldsymbol{x}) - A_B) \end{bmatrix} = t_B(\boldsymbol{x}) \begin{bmatrix} (J_R(\boldsymbol{x}) - A_R)^{\beta_{BR}} \\ (J_G(\boldsymbol{x}) - A_G)^{\beta_{BG}} \\ (J_B(\boldsymbol{x}) - A_B) \end{bmatrix} \tag{3}$$

As a study for this project, I chose to compare the diffuse attenuation coefficients found in Solonenko's [12] paper where he compares the reference spectra of the more recent HydroLight model to the calculated β_{BR} and β_{BG} ratios for each Jerlov water type in Table 1.

Table 1. Peak diffuse attenuation coefficients from the HydroLight Model and calculated β_{BR} and β_{BG}

Type	K_d^H(475nm)	K_d^H(525nm)	K_d^H(600nm)	β_{BR}	β_{BG}
I	0.023	0.051	0.242	0.095	0.451
IA	0.026	0.052	0.242	0.107	0.5
IB	0.03	0.056	0.248	0.120	0.536
II	0.044	0.07	0.261	0.169	0.629
III	0.101	0.118	0.328	0.308	0.856
1C	0.123	0.105	0.288	0.427	1.171
3C	0.225	0.172	0.358	0.628	1.308
5C	0.382	0.26	0.388	0.984	1.469
7C	0.614	0.399	0.481	1.277	1.539
9C	1.192	0.792	0.691	1.725	1.505

HydroLight was developed to solve a wide range of problems from optical oceanography to ocean color remote sensing. [4] The inputs to this model include the scattering and absorption properties of a particular water type, wind blowing at the sea surface, and the sun and sky radiance incident on the sea surface. Additional factors HydroLight considers is the chlorophyll fluorescence and can even simulate layers of bioluminescent microorganisms. The output of this model includes the full radiance distribution and the diffuse attenuation coefficients that are useful to solve this image enhancement problem.

3.4. Selecting the Water Type

While working on this project, it became clear that the color accuracy heavily depends on the attenuation coefficient ratios used as the input to the transmission estimation and color restoration. Since it is hard to predict which pair of attenuation coefficient ratios will produce the best result, this method brute forces all the options from I, IA, IB, II and III for open ocean water types, and 1C, 3C, 5C, 7C and 9C for coastal water types. From there, we apply the Gray-World Assumption [13], a color balancing technique which assumes that the average reflectance of surfaces is achromatic or gray. Since the veiling light region of the image should only be the medium (water) itself, we mask this area out when we apply the assumption. Therefore, out of all the different water types we tested, we choose the image with the smallest difference between the average values of the red, green and blue channels.

4. Results

The five images from the underwater dataset were processed through this image enhancement pipeline. I compared the results with the original approach in Berman's paper qualitatively using a ground truth color chart. In addition, I evaluated the correlation of the transmission output compared to the 3D structure obtained from stereo images.

4.1. Qualitative Analysis

In general, the output images from this algorithm improved in both haziness and color accuracy on underwater images. The color distortion on the input image due to the wavelength dependent attenuation appears blue green. After processing, the algorithm seems to compensate for the imbalance in color channels by increasing the red in the image. This is very noticeable at the horizon of the image (between the water and the sea floor).

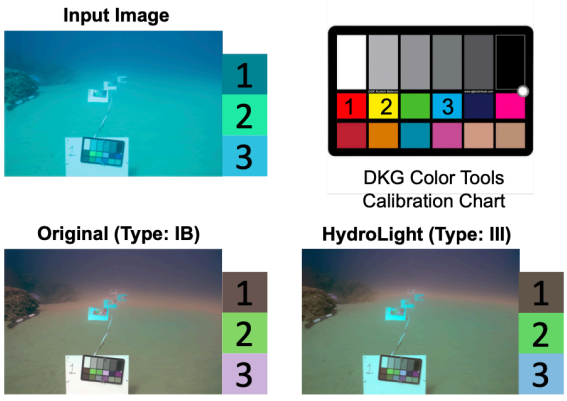


Fig. 2. Color chart image comparison using RGT_5444 input image

I compared the HydroLight attenuation coefficients with the Jerlov reference spectra as seen in Figure 2. In this case, the attenuation coefficients from HydroLight restored the blue (3) color closer to the ground truth DKG Color Tools Calibration Chart. The output image from the original

reference spectra had higher intensity in the red channel for the blue color patch, which deviates from the ground truth expectation.

One other qualitative observation I made was the last step of the pipeline where the final image is selected using Gray World Assumption, will not always produce the best result qualitatively. A visual example is the output image of RGT_4336 in Figure 3, which appears very green and dark, with the top edge of the image blown out. Other water types tested had more realistic color restoration results for this particular image.

4.2. Quantitative Analysis

It is difficult to obtain the ground truth image of an underwater scene because water cannot be removed from the line of sight. However, one alternative approach is the evaluate the accuracy of the transmission estimation *t*, by

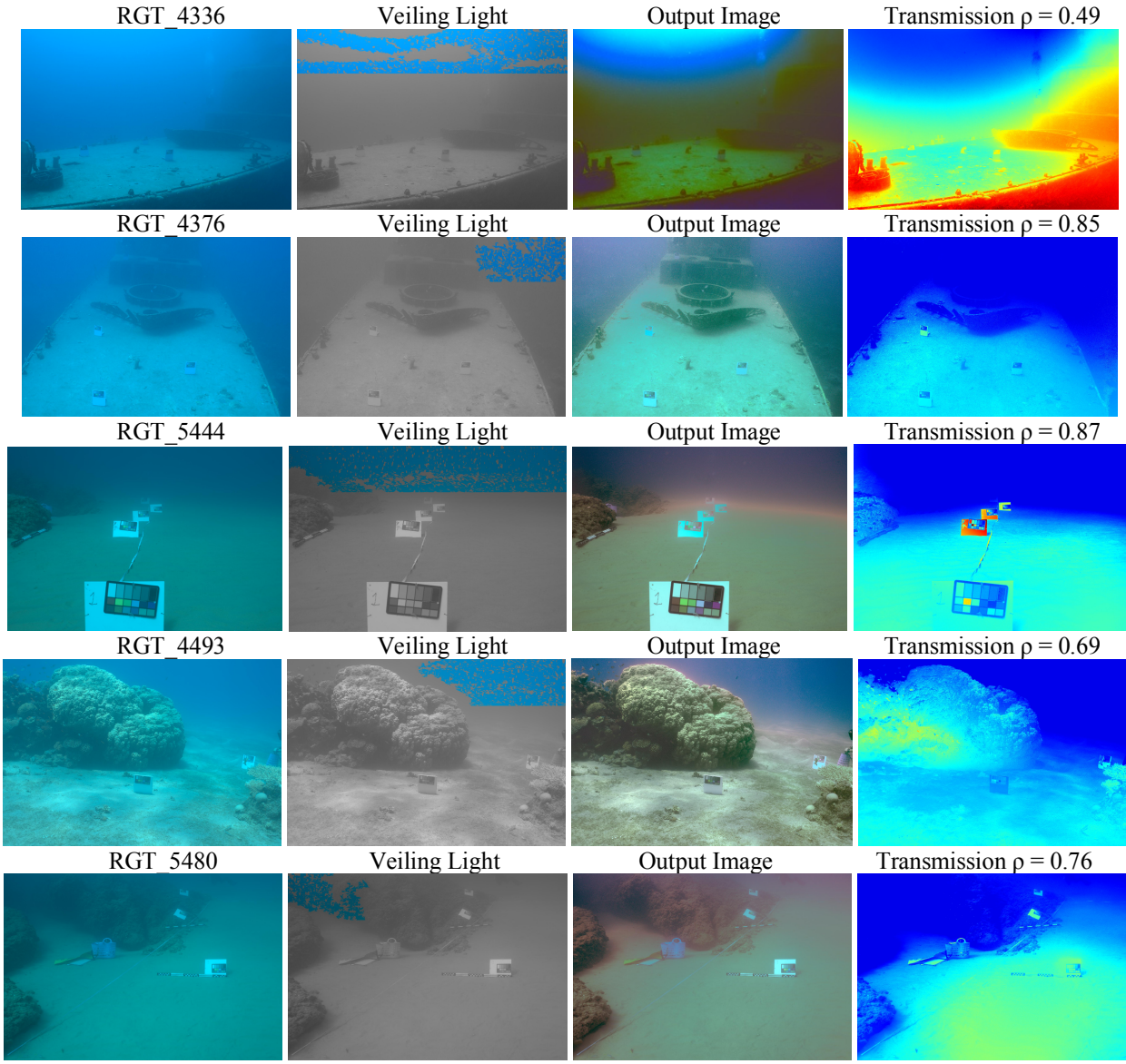


Fig. 3. The results of this project. The leftmost image is the input image converted from RAW. The second image shows the blue area where the veiling light region is located. The third image is the final output image from the pipeline, after selecting the best result based on Gray World Assumption. The final image is the transmission map generated from the process, and the Pearson correlation coefficient ρ is a calculated as a comparison metric to the ground truth 3D structure.

calculating the Pearson Correlation Coefficient ρ between the negative logarithm of the estimated transmission and the true distance z_{GT}, obtained through stereo imaging:

$$\rho = \frac{cov(z_{GT} - \log(t))}{\sigma_{z_{GT}} \sigma_{\log(t)}} \tag{4}$$

The Pearson Correlation Coefficient will resolve to a value between -1 to +1. An ideal correlation is +1, and lower positive values mean weaker correlation. Negative values could be due to using a prior not valid for the scene. Comparing my results to the results in Berman's paper, as seen in Table 2, RGT_5444 showed improved results for transmission estimation accuracy, however the rest of the images produced similar ρ values.

Table 2. Comparison between the HydroLight model and the original reference spectra in Berman's paper. The resulting Jerlov water type and its associated Pearson Correlation Coefficient is provided here.

	HydroLight		**Original**	
	Type	ρ	Type	ρ
RGT_5444	III	0.87	IB	0.73
RGT_4493	III	0.69	II	0.71
RGT_4468	5C	0.61	5C	0.6
RGT_4376	III	0.85	II	0.84
RGT_4336	C9	0.49	C7	0.49
RGT_5480	III	0.76	II	0.76

5. Conclusions

In conclusion, underwater image restoration remains a challenge because many variables impact how light travels through water. The output images from this algorithm compared to the input images were less hazy, and the red color channel was amplified to compensate for the wavelength-dependent attenuation property of open oceanic waters. In some cases, the HydroLight attenuation coefficient ratios produced better results than the original spectra used in Berman's, however in most cases, the results between them were very similar.

The quantitative comparison between the transmission estimation and the ground truth 3D stereo-obtained depth images was completed by calculating the Pearson Correlation Coefficient. The value of ρ I obtained using the HydroLight correlation coefficient ratios fall between 0.49 to 0.87 as seen in the last column of Figure 3. This indicates that the correlation between the transmission map and the true distance has reasonable correlation.

6. Future Work

Since this project needed to be completed within a certain time frame, I did not get the chance to test further methods of post processing to improve image quality. The output image of this pipeline removes much of the haze and restores color, however the noise in the image is amplified as seen in the image in Figure 4. The next step could be to add a de-noising section to the end of the pipeline to improve the overall result.

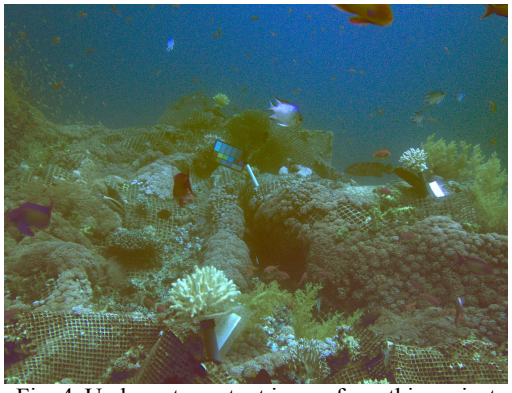


Fig. 4. Underwater output image from this project

The other possibility of future work is to go out and collect my own underwater imaging dataset during a scuba diving trip. In my experience taking photos underwater, I have encountered the same issues being addressed in the project. It would be interesting to try this algorithm on my own underwater image dataset and see if I get similar results to the reference dataset.

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