

# Computer Vision Final Report

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## Topic: RGHS: Shallow-Water Image Enhancement Using Relative Global Histogram Stretching Based on Adaptive Parameter Acquisition (2018)

### Introduction

Underwater image often shows low contrast, fuzzy, and color cast. The reason is because water turbidity scatters light and affect light absorption for the image. Besides, deep sea image appears the bluish tone since different wave length of the colour attenuates differently through the water. Green and blue lights attenuate extraordinarily lower than the red counterpart because of their shorter wavelength and high frequency. Lastly, under different illuminants, because of the difference of the spectrum distribution, the colour performance for the same object will not be the same. In this report, we are trying to improve the traditional method in addressing underwater image. The proposed method uses adaptive parameters of each channel and adjust the image dynamically. And it also uses different colour space to modify and make it more vivid.

### Underwater Model

A well-known haze image function model is often used to approximate the propagation equation of underwater scattering in the background light. It is shown from the following equation that different wave length has different residual energy reaching the camera. Hence, the quality of the underwater image is affected.

$$I_{\lambda}(x) = J_{\lambda}(x)t_{\lambda}(x) + (1 - t_{\lambda}(x))B_{\lambda}$$

$$t_{\lambda}(x) = Nrer(\lambda)^{d(x)}$$

$$Nrer(\lambda) = \begin{cases} 0.8 \sim 0.85 & \text{if } \lambda = 650 \sim 750 \mu\text{m (red)} \\ 0.93 \sim 0.97 & \text{if } \lambda = 490 \sim 550 \mu\text{m (green)} \\ 0.95 \sim 0.99 & \text{if } \lambda = 400 \sim 490 \mu\text{m (blue)} \end{cases}$$

light wavelength  $\lambda$ :  $\in\{\text{red,green,blue}\}$

underwater image :  $I_{\lambda}(x)$

X: pixel point

$J_{\lambda}(x)$ : scene radiance at point x

$t_{\lambda}(x)$ : the residual energy ratio of after reflecting from point x in the underwater scene and reaching the camera (a function of both  $\lambda$  and the scene-camera distance  $d(x)$ )

$B_{\lambda}$ : the uniform background light

## Related work

Traditional methods often used the histogram stretching in RGB color model and then saturation-intensity stretching in HSI color model to enhance the contrast of the images and correct color cast. Yet, the output results of these methods do not have significant difference and still exist blue-green illumination, and may bring serious noise to the enhanced image. The reasons will further be discussed later on.

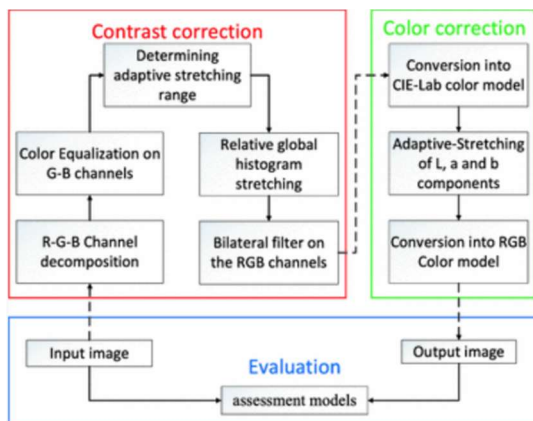
The following methods are the related work in handling under water image.

RayleighDistribution: Underwater image quality enhancement through composition of dual-intensity images and Rayleigh-stretching (2014)

integrated color model (ICM)

unsupervised color correction method (UCM)

## Presented method



In our proposed method, there are four steps. The first step is colour equalization. Second step is relative global histogram stretching. Third step is Bilateral filtering. And the last step is colour correction using  $L^*a^*b^*$  colour space.

### Step1-Colour equalization

#### Traditional method:

Based on the UCM model, once the average of one channel is extraordinary low, the channel must multiply with a bigger multiplier. The logic behind is that, when you have a lower intensity average in that colour channel, which means it is originally dark and should multiply some coefficient to make it brighter. Yet, the result shows that it will cause the wrong pretreatment of image color. The equations of the traditional method are listed below. As you can see, it uses the average of every channel intensity average as the

numerator of the multiplier. Hence, it is possible that the adjustment of each colour channel may be affected by the distribution of other colour channels.

$$\begin{cases} R_{avg} = \frac{1}{M \times N} \sum_{x=1}^M \sum_{y=1}^N I_r(x, y) \\ G_{avg} = \frac{1}{M \times N} \sum_{x=1}^M \sum_{y=1}^N I_g(x, y) \\ B_{avg} = \frac{1}{M \times N} \sum_{x=1}^M \sum_{y=1}^N I_b(x, y) \end{cases}$$

$$\begin{cases} I_r'(x, y) = I_r(x, y) \times A_{avg}/R_{avg} \\ I_g'(x, y) = I_g(x, y) \times A_{avg}/G_{avg} \\ I_b'(x, y) = I_b(x, y) \times A_{avg}/B_{avg} \end{cases}$$

$$A_{avg} = (R_{avg} + G_{avg} + B_{avg})/3$$

*Our method:*

In our method, the whole structure is basically the same, but we make a slight adjustment of the parameters. This approach is inspired by the gray world assumption. We set the numerator of the multiplier as 0.5 of the possible intensity. That is,  $256 \times 0.5$ . Besides, we only correct the G and B channels, and R channel is not considered because the red light in the water is hard to compensate by simple color equalization, which may bring about red over-saturation.

$$\begin{aligned} G_{avg} &= \frac{1}{255 * MN} \sum_{i=1}^M \sum_{j=1}^N I_g(i, j), \theta_g = \frac{0.5}{G_{avg}} \\ B_{avg} &= \frac{1}{255 * MN} \sum_{i=1}^M \sum_{j=1}^N I_b(i, j), \theta_b = \frac{0.5}{B_{avg}} \end{aligned}$$

Here, we did a small experiment using three method. The first one is the traditional approach. The second one uses our approach but we still consider the adjustment of the red channel. The Third one uses our approach and it ignores the adjustment of red channel. As you can see from the image below, the first image is still green and blue. The second image is red oversaturated, and the third image shows perfect adjustment of the colour.

*Original colour equalization*



*Set Aavg as 128(with correction of Red channel)*



*Set Aavg as 128(without correction of Red channel)*



### *Step2- relative global histogram stretching*

Due to the relative-concentrated distribution and quite low histogram range, underwater images often have low contrast and visibility. So we use histogram stretching to make better pixel distribution of the image channels. Traditionally, histogram stretching uses the same parameters (e.g., 0, 255) for all R-G-B channels of the images, ignoring the histogram distribution characteristics of different channels and in different images. The problem is that it may over-stretch or under-stretch certain color channel and damage the details of the original image. For example, for underwater image, the intensity distribution of the red channel often ranges between 50 and 150, while that for green and blue channel range between 70 and 210. Since it is colour channel sensitive, we need to propose a dynamic approach for our stretching model. The structure of the equation below is the same as histogram stretching. The difference is that we need to find the adaptive parameters  $I_{max}$ ,  $I_{min}$ ,  $O_{max}$ ,  $O_{min}$ .  $I_{max}$ ,  $I_{min}$  are the upper bound and lower bound for the stretching range.  $O_{max}$ ,  $O_{min}$  are the upper bound and the lower bound of the desired range.

$$p_{out} = (p_{in} - I_{min}) \left( \frac{O_{max} - O_{min}}{I_{max} - I_{min}} \right) + O_{min}$$

### *I<sub>max</sub>, I<sub>min</sub>*

From the histogram distribution of various shallow-water images, we can observe that the histogram distribution of R-G-B channel are similar to the variation of Rayleigh distribution. The function is listed below.

$$RD = \frac{x}{a^2} e^{-x^2/2a^2}, \quad x \geq 0, \quad a > 0$$

Here, 'a' is the mode of each colour channel, which represents the peak of R-G-B channel histograms. We will take it as a dividing line to separately decide the minimum (left) and maximum (right) intensity level values of the input image in the histogram stretching.

From the peak division line, we separate the pixels which values are in the smallest 0.1% of the total number on the left side and the biggest 0.1% of the total number on the right side from the histogram distribution. This is to reduce the impact of extreme values. We use mode value as our dividing line because if the histogram is not normally distributed, traditional method that removes an equal number of pixels from two tails of the histogram may not be reasonable. In our approach, I<sub>min</sub> and I<sub>max</sub> are both image and channel-sensitive. Equations listed below are the pseudo code for this algorithm.

$$I_{min} = S.sort[S.sort.index(a) * 0.1\%]$$
$$I_{max} = S.sort[-(S.length - S.sort.index(a)) * 0.1\%]$$

S :set of image pixel values for each R-G-B channel

S.sort: ascending order

S.sort.index(a): the index number of the mode in the histogram distribution

### *O<sub>min</sub>*

Based on the observation that underwater image is of Rayleigh distribution. We can derive That O<sub>min</sub> is equal to (1-0.655)\*mode of the colour channel intensity.

$$RD = \frac{x}{a^2} e^{-x^2/2a^2}, \quad x \geq 0, \quad a > 0$$

$$\sigma_\lambda = \sqrt{\frac{4-\pi}{2}} a_\lambda = 0.655 a_\lambda, \quad \lambda \in \{R, G, B\}$$

$$O_{\lambda min} = a_\lambda - \beta_\lambda * \sigma_\lambda, \quad 0 \leq O_{\lambda min} \leq I_{\lambda min}$$

$$\beta_\lambda = \frac{a_\lambda - O_{\lambda min}}{\sigma_\lambda}, \quad \frac{a_\lambda - I_{min}}{\sigma_\lambda} \leq \beta_\lambda \leq \frac{a_\lambda}{\sigma_\lambda}$$

$$O_{\lambda min} = a_\lambda - \sigma_\lambda$$

a :mode in a channel.

$\beta\lambda \leq 1.526$ .  $\beta\lambda \in \mathbb{Z}$ :  $\beta\lambda = 1$

*O<sub>max</sub>*

Because of different degrees of attenuation of the different light bands in the water, we must take separate analysis of RGB channels to calculate. The first equation listed below is the underwater model. The goal to find O<sub>max</sub> is equivalent to maximizing  $I_\lambda(x)$ , which is the scene radiance at point x. The derivation of the result is listed below. There are some assumptions where  $\kappa=1.1$  and  $\kappa=0.9$  are an experiential value for red channel and green-blue channel respectively. And we set  $t_\lambda(x)$  as 0.83, 0.95, 0.97 for R, G, B channels respectively. Here, when  $u_\lambda$  has no integer solution, we set  $O_{\lambda max}$  to 255.

$$I_\lambda(x) = J_\lambda(x)t_\lambda(x) + (1 - t_\lambda(x))B_\lambda$$

$$J_\lambda(x) = \frac{I_\lambda(x) - (1 - t_\lambda(x))B_\lambda}{\kappa t_\lambda(x)}$$

$$Max((J_\lambda(x))) = Max\left(\frac{I_\lambda(x) - (1 - t_\lambda(x))B_\lambda}{\kappa t_\lambda(x)}\right)$$

$$O_{\lambda max} = \frac{I_\lambda}{\kappa t_\lambda} = \frac{a_\lambda + \mu_\lambda * \sigma_\lambda}{\kappa * t_\lambda}, \quad I_{\lambda max} \leq O_{\lambda max} \leq 255$$

$$t_\lambda(x) = Nrer(\lambda)^{d(x)}$$

$$\mu_\lambda = \frac{\kappa * t_\lambda * O_{\lambda max} - a_\lambda}{\sigma_\lambda}$$

$$\frac{\kappa * t_\lambda * I_\lambda}{\sigma_\lambda} \leq \mu_\lambda + 1.526 \leq \frac{\kappa * t_\lambda * 255}{\sigma_\lambda}$$

*Step3-Bilateral filtering*

The bilateral filter is a simple, non-iterative scheme for edge-preserving smoothing to be used to effectively capture the fine details after the image is stretched in RGB color model.

*Step4-CIELAB color space stretching*

CIELAB was designed so that the same amount of numerical change in these values corresponds to roughly the same amount of visually perceived change.

The adaptive-stretching of 'L', 'a' and 'b' will improve the saturation and brightness of the image to obtain more vivid color. The range of each L, a, b channel is listed below.

L\* :lightness 0(black)~100(white)

a\* :from green (-) to red (+), -128 to +127

b\* from blue (-) to yellow (+), -128 to +127

*'L' component: linear slide stretching*

For the value that ranges between 0.1% and 99.9% of all L value, it is stretched to range 0~100. The 0.1% of the lower and upper values are set to 0 and 100 respectively.

*'a' and 'b' : apply S-model curve*

The adjustment of the a\* and b\* channel is based on the S model proposed below. When the value is closer to 0, by definition of L\*a\*b\* colour model, it is more gray, so we want to multiply a larger adaptive parameter for the value to make it much more vivid.

$$p_{\chi} = I_{\chi} * \left( \varphi^{1 - \left| \frac{I_{\chi}}{128} \right|} \right), \quad \chi \in \{a, b\}$$

$\phi$  :optimally-experimental value, set to 1.3 in the method

$I_{\chi}$  : input pixels, the closer the values to 0 (gray), the further they will be stretched.

$P_{\chi}$ : output pixels

## Experimental results

From the below images, we can observe that the image that is processed by our method has been well contrasted and it is not red oversaturated.

(1)

*Original image*





RGHS(our model)



(2)

Original image



RGHS(our model)



*Comparison of the 2014 model and our model:*

We can see from the images below that our proposed model is better than the 2014 model. Our colour is much more vivid and natural while the image processed by the 2014 model is red



oversaturated and has noises at the corner. From mean squared error of the image processed by our method, we can see that it is much larger than the older model.

(1)



composition of dual-intensity images and Rayleigh-stretching (2014)

Mean squared error:331.5131238301595



RGHS(2018)

Mean squared error:5470.202645068516

(2)



composition of dual-intensity images and Rayleigh-stretching (2014)

Mean squared error:302.31619413326456



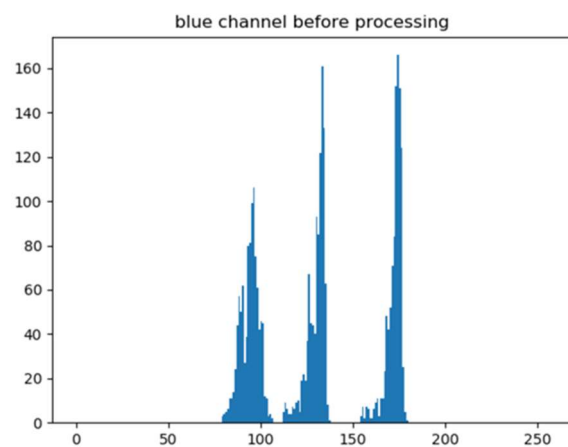
RGHS(2018)

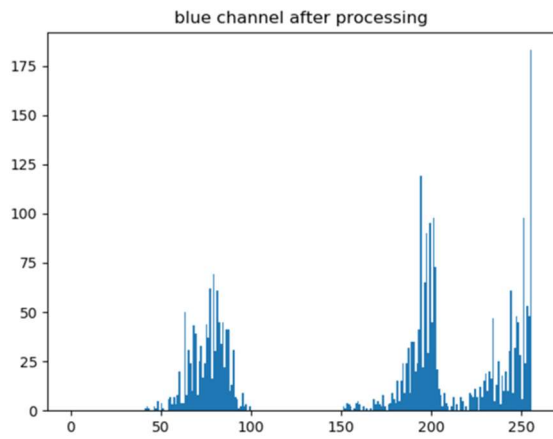
Mean squared error:6907.911796477734

*Comparison(histogram before and after processing)-our model*

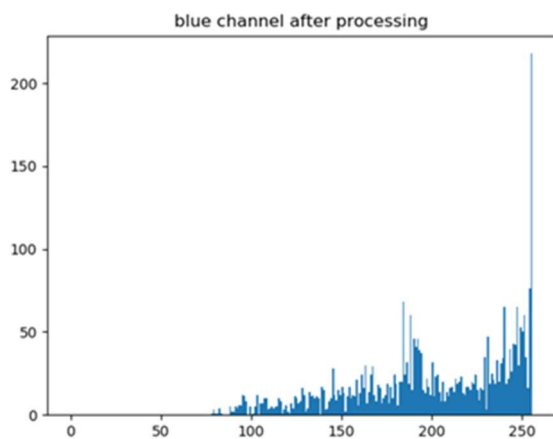
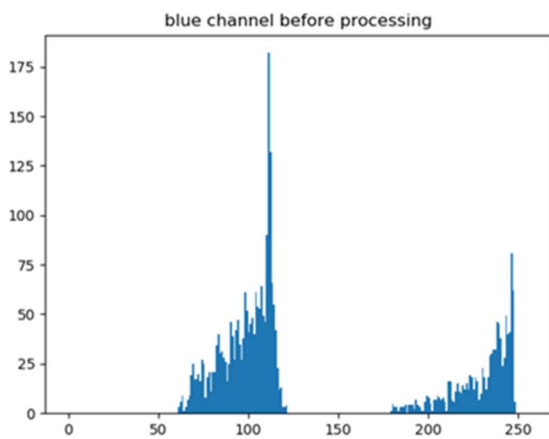
The below images shows the histogram distribution of the blue colour channel. We can see that the range is wider than the original one, which represent improvement of contrast enhancement of the image.

(1)





(2)

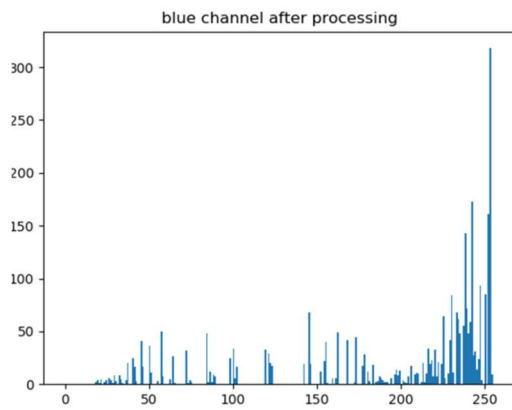
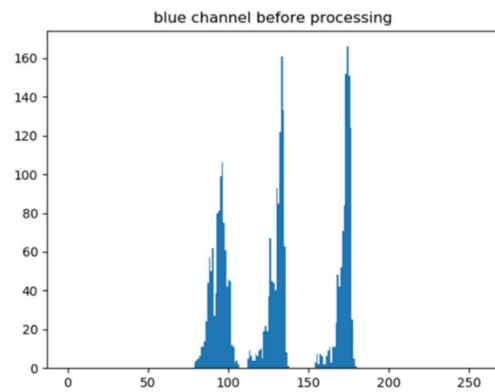


### *Comparison(histogram before and after processing)-2014 model*

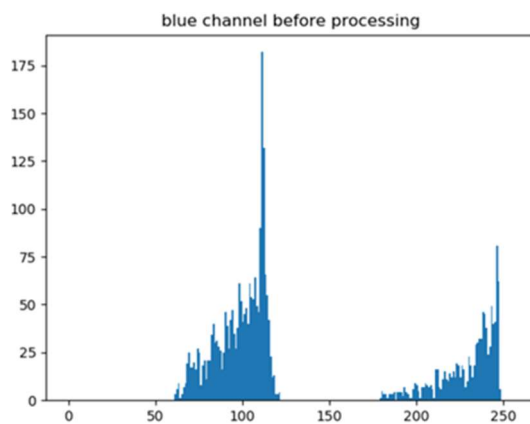
The below images show the histogram distribution of the 2014 model before and after processing. Even though the distribution is much more equalized than our model, the performance of the image is not better. Obviously, we need more evaluation method for

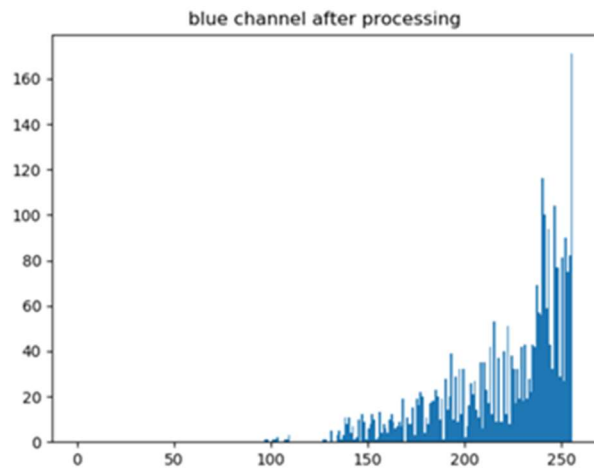
addressing underwater image because deciding whether the image has been adjusted well not only depends on the degree of the histogram equalization but also other features, such as colour saturation, perception of different colours by human eyes, and etc.

(1)



(2)





## Conclusion

In our approach, adaptive parameters have considered both the light transmission and the original image histogram distribution, preserving from overstretching or under-stretching. Yet, there are still some problems in our method. For example, in the colour equalization process, we ignore the adjustment of the red channel to avoid red oversaturation. It may have problems when the object has most of the intensity distribution in red channel. In this situation, ignoring red channel and only consider the other 2 channel may not make a big improvement of the image.

## Reference

<https://xueyangfu.github.io/projects/icip2014.html>

[https://link.springer.com/chapter/10.1007/978-3-319-73603-7\\_37#:~:text=Because%20the%20underwater%20images%20are,and%2099.9%25%20of%20the%20histogram.](https://link.springer.com/chapter/10.1007/978-3-319-73603-7_37#:~:text=Because%20the%20underwater%20images%20are,and%2099.9%25%20of%20the%20histogram.)

[https://link.springer.com/content/pdf/10.1007%2F978-3-319-73603-7\\_37.pdf](https://link.springer.com/content/pdf/10.1007%2F978-3-319-73603-7_37.pdf)

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<https://github.com/wangyanckxx/Single-Underwater-Image-Enhancement-and-Color-Restoration>