Underwater Image Enhancement using Bayesian Retinex

Name - Rahim Khan
Roll No.- 222123040

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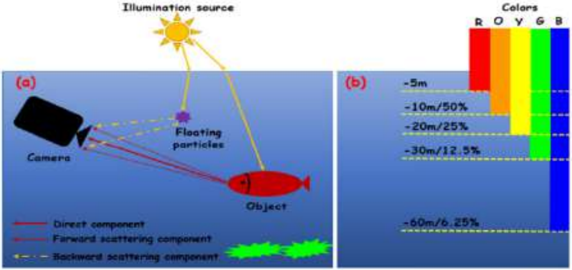
Introduction

Underwater imaging is a crucial research field, given the abundant resources present in oceans, rivers, and lakes. However, underwater image processing poses unique challenges due to the complex physical properties of the underwater environment. Factors such as color distortion and contrast degradation arise from light absorption and scattering in water. The underwater optical imaging model is explained, illustrating that captured light consists of three main components: direct, forward scattering, and backward scattering. The forward scattering component causes blurred structures in underwater images, while the backward scattering component obscures image edges and details. Additionally, color distortion results from the varying absorption rates of different wavelengths of light in water.

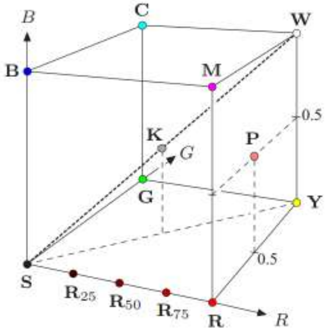
Introduction

To address this problem the given research paper proposes a retinex-based algorithm using bayes theorem and l_1 prior to Reflectance and l_2 prior to illumination. This algorithm enhances a single underwater image by correction of color distortion and contrast degradation, ultimately striving to produce high-quality underwater images for further processing.



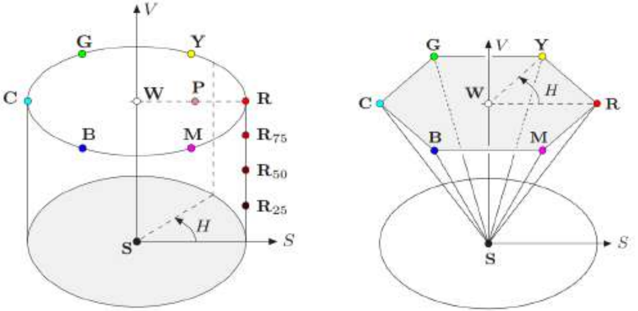
RGB Color Space

Every color image has 3 channels consisting of 3 prinmary color values for *Red*, *Green*, *and* *Blue*. Every color value is in the range 0 to 255. It can be visualized as a cube.



HSV Color Space

HSV color space can be visualized as the six-sided inverted pyramid. where the top point is the point that represents the black color. White color is the center point of base. Three primary colors and their pairwise combination makes the base of pyramid. It can also be visualized as a cylinder. Brightness is the verticle axis. Saturation S is the distance from the center and H is the angle from red color line in the anticlockwise direction.



Underwater Image Colourfulness Measure(UICM)

Underwater images frequently encounter color-casting problems caused by light absorption in water, resulting in color distortion. As water depth increases, colors diminish in a predictable manner, starting with red due to its shorter wavelength, often giving underwater images a bluish or greenish appearance. Moreover, inadequate lighting conditions can worsen color desaturation. Effective enhancement algorithms for underwater images should prioritize accurate color representation. Studies suggest that natural scene colorfulness can be accurately captured using statistical image values.
To calculate this measure we use the following formulae:-

$$RG = R - G$$
$$YB = \frac{R + G}{2} - B$$

[default]

Underwater Image Colourfulness Measure(UICM)

Let K=$M \times N$ and $T_{\alpha_L} = \lceil \alpha_L K \rceil$,$T_{\alpha_R} = \lfloor \alpha_R K \rfloor$

$$\mu_{\alpha,RG} = \frac{1}{K - T_{\alpha_L} - T_{\alpha_R}} \sum_{i=T_{\alpha_L}+1}^{K-T_{\alpha_R}} Intensity_{RG,i}$$

$$\sigma^2_{\alpha,RG} = \frac{1}{N} \sum_{p=1}^{N} (Intensity_{RG,p} - \mu_{\alpha,RG})^2$$

$$UICM = -0.0268\sqrt{\mu^2_{\alpha,RG} + \mu^2_{\alpha,YB}} + 0.1586\sqrt{\sigma^2_{\alpha,RG} + \sigma^2_{\alpha,YB}}$$

[default]

Underwater Image Sharpness Measure(UISM)

In underwater photography, achieving sharpness is particularly difficult because of considerable blurring caused by forward scattering. This blurring impairs the retention of fine details and edges in underwater images. To evaluate sharpness, the Sobel edge detector is applied to each RGB color component, producing an edge map. This map is then combined with the original image to generate a grayscale edge map, highlighting only the pixels associated with edges. The Enhancement Measure Estimation (EME). This is defined as follows

$$EME = \frac{2}{k_1 k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} log \left(\frac{I_{max,k,l}}{I_{min,k,l}} \right)$$

$$UISM = \sum_{c=1}^{3} \lambda_c EME(grayscale\ edge_c)$$

where $\lambda_R = 0.299, \lambda_G = 0.587, \lambda_B = 0.114$

[default]

Underwater Image Contrast Measure(UIConM)

Contrast has been identified as a key factor affecting underwater visual performance, such as stereoscopic acuity. In underwater imagery, contrast degradation often results from backward scattering. This paper proposes measuring contrast using the logAMEE (logarithmic Angular Measure of Edge Enhancement) applied to the intensity image. The logAMEE is defined as:

$$\text{logAMEE} = \frac{1}{k_1 k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} \frac{I_{\max,k,l} - I_{\min,k,l}}{I_{\max,k,l} + I_{\min,k,l}} \times \log\left(\frac{I_{\max,k,l} - I_{\min,k,l}}{I_{\max,k,l} + I_{\min,k,l}}\right)$$

where the image is partitioned into blocks of size $k_1 \times k_2$ and above formula is applied on each block.

[default]

Underwater Image Quality Measure(UIQM)

Underwater Image Quality Measure is linear combination of UICM, UISM and UIConM.

$$UIQM = 0.0282 \times UICM + 0.2953 \times UISM + 3.5753 \times UIConM$$

Underwater Color Image Quality Evaluation Metric(UCIQE)

To calculate UCIQE we first convert the image in CIElab color space, we calculate the following :-

$$chroma_{ij} = \sqrt{a_{ij}^2 + b_{ij}^2}$$

$$\mu_c = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} chroma_{ij}$$

$$\sigma_c = \sqrt{\frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left(chroma_{ij}^2 - \mu_c^2 \right)}$$

$$saturation_{ij} = \frac{chroma_{ij}}{l_{ij}}$$

[default]

Underwater Color Image Quality Evaluation Metric(UCIQE)

$$\mu_s = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} saturation_{ij}$$

$$con_l = max(l) - min(l)$$

$$UCIQE = c_1 \times \sigma_c + c_2 \times con_l + c_3 \times \mu_s$$

here I have used c_1=0.4680, c_2=0.2745 ans c_3=0.2576 as used in official implementation.

[default]

Step 1 : Color Correction :-
for each channel in RGB image do the color correction according to the given formula:-

$$U^c = \frac{255}{2}\left(1 + \frac{S^c - M^c}{\mu V^c}\right)$$

where S^c = Color channel having values in [0,1].
M^c = Mean of the channel .
V^c = Variance of the channel.

Step 2 : Color Conversion :-
In HSV color space H is the angle from Red color point in anticlockwise direction, S is the distance of the point from the central axis and V is the distance of the point from the bottom. The conversion process is defined as follows:-

for any given color pixel having RGB values P(R,G,B)

$C_{high} = max(R, G, B)$, $C_{low} = min(R, G, B)$ and $C_{rng} = C_{high} - C_{low}$

$$S_{HSV} = \begin{cases} \frac{C_{rng}}{C_{high}}, & for \ C_{high} > 0 \\ 0, & otherwise \end{cases}$$

$$V_{HSV} = \frac{C_{high}}{C_{max}}$$

$$R' = \frac{C_{high} - R}{C_{rng}}, B' = \frac{C_{high} - B}{C_{rng}}, G' = \frac{C_{high} - G}{C_{rng}}$$

[default]

RGB to HSV Conversion

$$H' = \begin{cases} B' - G', & if \;\; R = C_{high} \\ R' - B', & if \;\; G = C_{high} \\ G' - R', & if \;\; B = C_{high} \end{cases}$$

$$H_{HSV} = 60^\circ \times \begin{cases} H' + 6, & if \;\; H' < 0 \\ H', & otherwise \end{cases}$$

[default]

Step 3 : Model Description :-

Now select the V channel and let L=V , $L = L \times 255$. By Retinex theory, $L = I \circ R$ where R is Reflectance and I is Illumination. $\circ$ is the element wise multiplication.

$$I_{ij} \in [0, 255]$$
$$R_{ij} \in [0, 1]$$

Now consider L,I,R as Random Variables then :-

$$p(I, R|L) \propto p(L|R, I)p(I)p(R)$$

where $p(L|R, I)$ is the likelihood of L given R and I, $p(I)$ is the prior of I and $p(R)$ is the prior of R.

Underwater Image Enhancement using Bayesian Retinex

Now consider that $p(L|R, I)$ follows the standard multivariate Normal distritribution for given errors are zero. Priors for R and I are considered as product of two priors. Prior1 of R follows the laplacian distribution of first order gradient of R and Prior 2 follows the 2nd order gradient of the R. Similarly we assume that the Prior of I is the product of two Priors which are prior1 of first order gradient of I which follows standard multivariate Normal distritribution and prior2 of the 2nd order gradient of I which follows standard multivariate Normal distritribution :-

$$e = L - I \circ R$$

$$p(L|I, R) \sim \mathcal{N}(e|0, \sigma^2 I)$$

$$p_1(R) \sim \mathcal{L}(\nabla R|0, s_1 I)$$

$$p_2(R) \sim \mathcal{L}(\triangle R|0, s_2 I)$$

$$p(R) = p_1(R)p_2(R)$$

[default]

Underwater Image Enhancement using Bayesian Retinex

$$p_3(I) \sim \mathcal{N}(\nabla I | 0, \sigma_1^2 I)$$
$$p_4(I) \sim \mathcal{N}(\triangle I | 0, \sigma_2^2 I)$$
$$p(I) = p_3(I) p_4(I)$$

where $\mathcal{N}$ is the Gaussian distribution and $\mathcal{L}$ is the Laplacian distribution.

$$\nabla_h = [-1, 1], \nabla_v = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$
$$\triangle = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

[default]

Underwater Image Enhancement using Bayesian Retinex

$$\mathcal{L}(x|\mu, b) = \frac{1}{2b} exp\left(-\frac{|x-\mu|}{b}\right)$$

$$\mathcal{N}(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

[default]

Step 4 : Objective Function :-

Since we want to maximize the probability of $p(I, R|L)$ so we will minimize the negative log likelihood of $p(I, R|L)$.

$$\mathcal{E}(L, I, R) = -\log p(I, R|L)$$
$$\mathcal{E}(I, R) = \|I \circ R - L\|_2^2 + \nu_1 \|\nabla I\|_2^2 + \nu_2 \|\triangle I\|_2^2 + \nu_3 \|\nabla R\|_1 + \nu_4 \|\triangle R\|_1$$

where $\nu_1 = \frac{\sigma^2}{2\sigma^2}$, $\nu_2 = \frac{\sigma^2}{2\sigma_1^2}$, $\nu_3 = \frac{\sigma^2}{s_1}$, $\nu_4 = \frac{\sigma^2}{s_2}$ are constants.

[default]

Step 5 : Numerical Optimization :- To optimize the objective function. We have to convert l_1 norm to l_2 norm. We introduce two auxiliary variables d, h and two error terms m, n.

$$\mathcal{E}(I,R) = \|I \circ R - L\|_2^2 + \nu_3\|\nabla I\|_2^2 + \nu_4\|\triangle I\|_2^2 + \nu_1\|\nabla R\|_1 + \nu_2\|\triangle R\|_1$$

$$\mathcal{E}(I,R) = \|I \circ R - L\|_2^2 + \nu_3\|\nabla I\|_2^2 + \nu_4\|\triangle I\|_2^2 + \nu_1\left(\|d\|_1 + \lambda_1\|\nabla R - d + m\|_2^2\right) + \nu_2\left(\|h\|_1 + \lambda_2\|\triangle R - h + n\|_2^2\right)$$

Now we split this into three parts and optimize it using ADMM algorithm

P-1

$$d^k = \arg\min_d \left(\|d\|_1 + \lambda_1\|\nabla R^{k-1} - d + m^{k-1}\|_2^2\right)$$

$$h^k = \arg\min_h \left(\|h\|_1 + \lambda_2\|\triangle R^{k-1} - h + n^{k-1}\|_2^2\right)$$

[default]

Underwater Image Enhancement using Bayesian Retinex

P-2

$$
\begin{aligned}
R^k &= \arg\min_R \Bigg(\| R - \frac{L}{I^{k-1}} \|_2^2 + \nu_1 \lambda_1 \| \nabla R - d^k + m^{k-1} \|_2^2 \\
&\quad + \nu_2 \lambda_2 \| \triangle R - h^k + n^{k-1} \|_2^2 \\
m^k &= m^{k-1} + \nabla R^k - d^k \\
n^k &= n^{k-1} + \triangle R^k - h^k
\end{aligned}
$$

P-3

$$
I^k = \arg\min_I \Bigg(\| I - \frac{L}{R^k} \|_2^2 + \nu_3 \| \nabla I \|_2^2 + \nu_4 \| \triangle I \|_2^2 \Bigg)
$$

[default]

Algorithm :-

Input : $-$input value channel L, weighting parameters $\nu_{\mathbf{1}}, \nu_{\mathbf{2}}, \nu_{\mathbf{3}}, \nu_{\mathbf{4}}$ and λ_1, λ_2 and the number of iterations T

Initialization : $-$ initialize $\mathbf{I^0} =$ Gausian filter of L $\mathbf{R^0} = \mathbf{0}$ and $d_h^0 = d_v^0 = h_h^0 = h_v^0 = m_h^0 = m_v^0 = n_h^0 = n_v^0 = 0$ and k=1

Iteration on k : $-$ repeat until k=T :

update $d_h^k, d_v^k, h_h^k, h_v^k$ using update for P-1;

update R^k using update for P-2

update m_h^k, m_v^k, n^k using update for P-2;

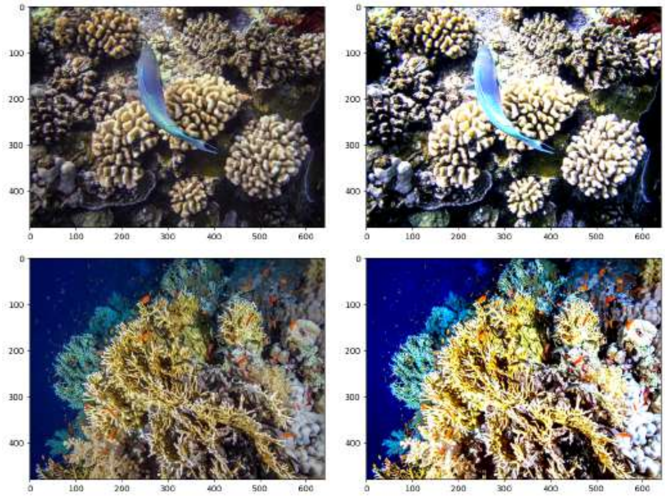
update I^k using update for P-3

Stopping Criteria : $-$ terminate iteration

if k=T otherwise continue iteration k=k+1;

Output : $-$ output the reflectance R and illumination I

Results



Underwater Image Enhancement using Bayesian Retinex

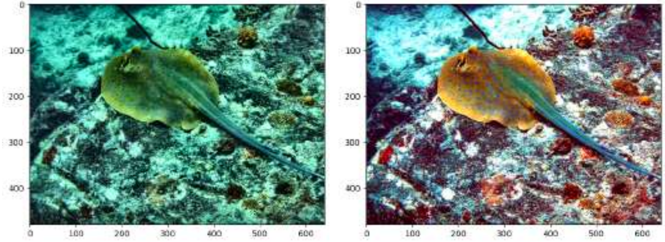
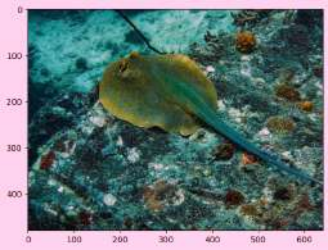


Figure: CLAHE

Underwater Image Enhancement using Bayesian Retinex



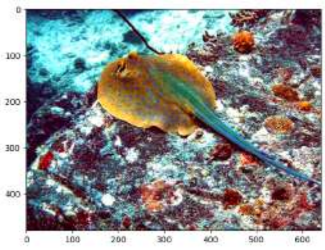


Figure: Grey World

Underwater Image Enhancement using Bayesian Retinex

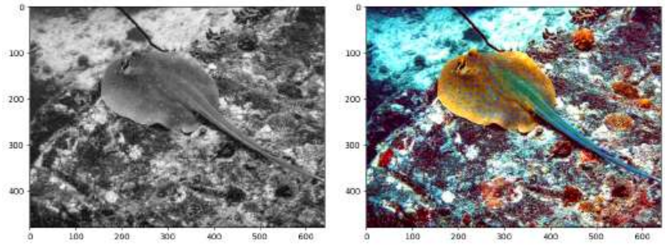


Figure: Max RGB

[default]

Underwater Image Enhancement using Bayesian Retinex

Table: Comparison of Image Processing Methods

Method	UCIQE	UIQM	UIConM	UISM	UICM	Entropy	CCF
Raw	34.5435	0.9638	-0.1489	4.0165	10.9910	6.4360	6.1078
Processed	36.1423	1.3170	-0.1368	4.8742	13.0017	6.7837	12.9806
Clahe	34.2644	1.2024	-0.1560	4.9006	11.1018	6.7788	11.365
Grey World	30.8121	0.9518	-0.1493	3.9647	11.1663	6.4246	6.5771
Max RGB	27.3190	0.9303	-0.1473	4.3682	5.9217	6.5853	2.852
MSR	34.5479	1.3611	-0.1393	5.1399	12.1020	7.7569	17.6559
MSRCP	38.2102	1.0643	-0.1327	4.4564	7.8934	7.0115	5.1098
MSRCR	15.0838	0.7142	-0.1198	3.8844	-0.1653	6.0080	2.3201
SSR	36.0846	1.2733	-0.1338	4.8325	11.5080	7.0979	19.3236
WCID	32.6000	0.7255	-0.0979	2.5337	11.6125	4.3645	12.4484
White Balance	34.9375	0.8975	-0.1495	3.8324	10.6460	6.3755	7.1807

[default]

Underwater Image Enhancement using Bayesian Retinex

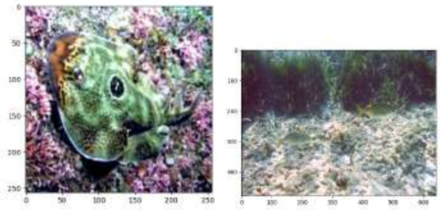


Fig. 5.8: (A) & (B)

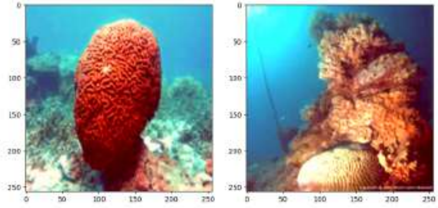


Fig. 5.9: (C) & (D)

[default]

Table: Recovered Edges by different algorithms

	Image A	Image B	Image C	Image D
Clahe	38020	51369	18999	17576
Grey World	19387	36991	10709	8438
Max RGB	21602	38101	10566	8929
MSR	36897	55918	22716	18669
MSRCP	13458	41676	10444	6818
MSRCR	5300	4512	4402	4159
Processed	38291	43419	17687	15331
Raw	21127	37759	9440	8196
SSR	37285	48639	16494	14904
WCID	10238	23330	7293	5832
White Balance	20123	37840	11066	9094

[default]

Refences

- Peixian Zhuang; Chongyi Li ; Jiamin Wu. Bayesian retinex underwater image enhancement. Engineering Applications of Artificial Intelligence, Jan 2021.
- Xueyang Fu; Peixian Zhuang; Yue Huang; Yinghao Liao; Xiao-Ping Zhang; Xinghao Ding. A retinex-based enhancing approach for single underwater image. IEEE International Conference on Image Processing (ICIP), oct 2014.

Thank You....