Weighted Generalization of Dark Channel Prior with Adaptive Color Correction for Defogging

Yosuke Ueki, Masaaki Ikehara
EEE Dept., Keio Univ., Yokohama, Kanagawa 223-8522, Japan
Email: {ueki,ikehara}@tkhm.elec.keio.ac.jp

***Abstract*—Images and video captured in water or fog suffer from low contrast and color distortion due to light scattering and absorption. An image formation model for hazy images is commonly used to restore both underwater images and hazy images because of the similarity between the two types of images. However, red light is attenuated faster than blue and green light in underwater, and underwater images are distorted by changes of color tone. Therefore, most current methods are specialized for either hazy images or underwater images. In this paper, we propose a novel defogging method which is efficient for both hazy images and underwater images. Our method is composed of adaptive color correction and weighted generalization of dark channel prior (WGDCP). Experimental results show that our algorithm can recover both underwater images and hazy images.**

***Index Terms*—Image processing, image enhancement, image restoration, underwater image, dehazing, defogging**

I. Introduction

Capturing high quality digital images by a basic or small camera is quite important for society and the demands are high. However, digital images are not always taken under good conditions but sometimes taken under bad conditions. We can use special cameras or devices to take images or videos in such condition, but these devices are usually expensive and often large and heavy. Therefore, enhancing the quality of the image which are taken under bad conditions by software have been tried. There are various types of images to enhance or recover the quality and image defogging is one of them. In hazy images, the contrast and visibility of images are often degraded due to turbid media such as haze or water. In addtion, underwater images and hazy images on land have something in common and similar methods are presently used to recover or enhance the images.

Image formation models have been used to recover or enhance the quality of hazy images. Many researches have tried assmuptions to solve the image formation model for hazy images. He et al. [1] proposed the dark channel prior model (DCP) which is effective for the reconstruction of hazy images taken outdoors . DCP introduced the special assumption for haze images on the analysis of the haze images and outdoor haze-free images. They found that the lowest intensity among RGB channels in local region (dark channel) of haze-free image are often very low except the sky region and the intensity of dark channel in the haze image is not low due to the haze. Many other approaches such as . [2] have been proposed based on DCP because of its prominence. DCP has also been applied to underwater image restoration due to the similarity between underwater images and hazy images. However, the intensity of red channel in underwater images is often much lower than other color channels because red light attenuates much faster than green and blue light. Therefore, DCP are changed to specialize for underwater image, so red channel prior [3] by Galdran et al. and UDCP [4] by S.Yang et al. have been proposed. These methods utilize only red and blue channel to calculate dark channel.

(a) Underwater Image (b) Haze Image

Fig. 1. Examples of images for defogging

There are also image formation model methods which are not based on DCP. One example, IBLA [5], achieved remarkable results for underwater image enhancement. There are also methods which are not based on image formation model. Ancuti et al. proposed an image fusion method for dehazing on land [6] and underwater image enhancement [7]. These methods involve fusing color corrected images and white balanced images by multi-scale fusion.

However, it is difficult to recover both underwater images and hazy images by a single method because the attenuation of light underwater is not the same for the different wavelengths. Red light, which has longer wavelengths, is attenuated faster than blue and green light, which have shorter wavelengths. As such, underwater image enhancement or restoration present more complex and difficult problems than the dehazing of images taken on land.

Y.Peng et al. focuses on expanding DCP to other types of hazy images by introducing new ambient light estimation and transmission estimation in GDCP [8]. However, the quality of images which are recovered by GDCP are not high compared to the other specialized state-of-art methods.

In this paper, we propose a novel image enhancement method for both dehazing images taken on land and underwater image enhancement. Our method is motivated by GDCP [8] and WDCP [9]. WDCP solves the problems of local constant

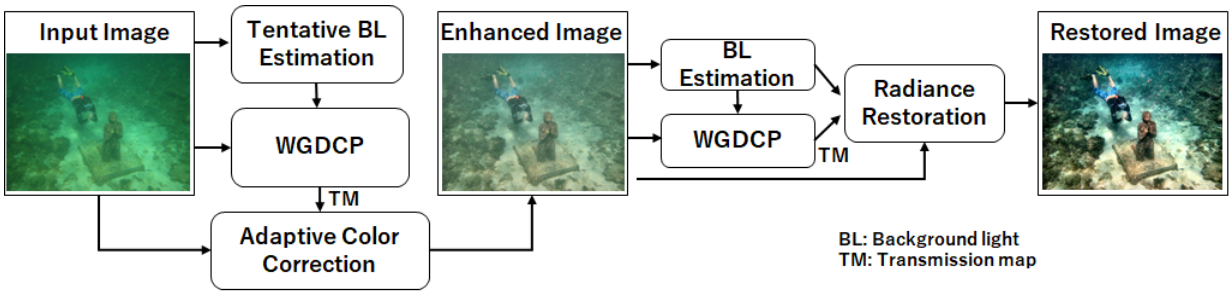


Fig. 2. Weighted Generalization of Dark Channel Prior

assumption which DCP use by splitting the concept of dark channel into dark pixels and local constant assumption. In addition, adaptive color correction is introduced to deal with the underwater images which have strong color casts. The rest of paper is as follows: In section 2, background of image formation model. In section 3, we introduce our method in detail. In section 4, we show some experimental results to demonstrate the improvement. And in section 5, we conclude the paper.

II. Background

An image formation model is commonly used to describe a hazy image

$$I_c = t_c \cdot J_c(x) + (1 - t_c(x)) \cdot B_c, c \in \{r, g, b\} \tag{1}$$

where, I_c represents the intensity of the captured hazy image,J_c is scene radiance, B_c is the background light in the image, x represents the location of a pixel and $t_c(x)$ is the transmission rate in a pixel, where c is one of the RGB channels. For this model, background light is firstly estimated in order to estimate the transmission rate. Researchers have developed various methods to solve this model especially for the transmission rate. DCP [1] ,which is wildly used to recover hazy images defines dark channel as

$$\min_c(\min_{y\in\Omega}(J_c)), c \in \{r, g, b\} \tag{2}$$

However, DCP often ends up selecting only the red channel for underwater image because red light attenuates faster than blue and green light. Therefore, GDCP [8] defines different assumption to generalize DCP for other types of hazy images such as underwater images. In GDCP, (1) can be changed to

$$|I_c - A_c| = t_c(x)|J_c(x) - A_c| \tag{3}$$

Dividing both sides by $\hat{A}_c = max\{A_c, 1 - A_c\}$,

$$\max_{c,y\in\Omega}(|I_c(y) - A_c|/\hat{A}_c) = \max_{c,y\in\Omega}(t(y)|J_c(y) - A_c|/\hat{A}_c) \tag{4}$$

where, Ω denotes a small local patch in the image. GDCP defines

$$I_A(x) = \max_{c,y\in\Omega}(|I_c(y) - A_c|/\hat{A}_c),$$
$$J_A(x) = \max_{c,y\in\Omega}(|J_c(y) - A_c|/\hat{A}_c) \tag{5}$$

Substituting (5) for (4), (1) can be transformed into $I_A(x) = t(x)J_A(x)$. where the size of local patch Ω is 15×15. Y.Peng et al. found that $J_A(x) > 0.88$ for more than 75% of pixels in 60 degradation-free images with a wide variety of natural content. Therefore, $J_A(x)$ can be approximated to 1 and the transmission rate is roughly $I_A(x)$

$$\hat{t}(x) \approx I_A(x) = \max_{c,y\in\Omega}(|I_c(y) - A_c|/\hat{A}_c) \tag{6}$$

However, the transmission map t which are calculated from (6) is not accurate in detail, especially for edges. Therefore, GDCP applies Guided Filtering [10] to the transmission map for refinement. Finally, scene radiance $J_c(x)$ can be calculated from

$$J_c(x) = \frac{(I_c(x) - A_c)}{\max(\hat{t}(x), 0.1)} + A_c \tag{7}$$

III. Proposed Algorithm

Our method is motivated by GDCP and WDC, and is based on the image formation model. We introduced WGDCP based on these methods. In addition, we added adaptive color correction to deal with color distorted images such as underwater images. Fig.2 shows the flow chart of our algorithm. Firstly, tentative background light is estimated and a tentative transmission map is calculated by WGDC and the tentative back ground light. Applying adaptive color correction into the input image, an enhanced image is gained. Finally, a recovered image is obtained from an enhanced image by WGDCP. Adaptive color correction helps WGDCP to recover the underwater images which have strong color casts. WGDCP uses 7 as radiance restoration.

A. Background light estimation

1) Tentative Background Light Estimation: There are various ways to estimate background light, but basically most of them try to extract the sky or water region in the image and define the average intensity of the pixels in the region as background light. DCP defines the intensity of the brightest pixels in dark channel (top 0.1%) as background light. GDCP defines the average intensity of the top 0.1% farthest pixels in the images as background light by estimating a rough depth map. To deal with various hazy images, we divided the images into two types for background light estimation.

$$\begin{cases} \min_c(mean(I_c))/max_c(mean(I_c)) < t & BL1 \\ otherwise & BL2 \end{cases} \tag{8}$$

where, c $\in \{r, g, b\}$. BL1 is that the average intensity of the top 0.1% brightest pixels in a light channel, and we define light channel as

$$\max_{c}(\max_{y\in\Omega}(I_c)), c \in \{r, g, b\} \tag{9}$$

We use the background light esimation which is defined in [11] as BL2.

$$B^r = \frac{140}{1 + 14.4 \times (-0.034 \times Med_r)} \tag{10}$$

$$B^c = 1.13 \times Avg^c + 1.11 \times std^c - 25.6, c \in \{g, b\} \tag{11}$$

Where, B^r is the background light for the red channel, B^c is the background light for the green and blue channel,Med_r is the median value of the red channel, Avg^c is the average value of the color channel and std^c is the standard deviation of the color channel. The middle 80% values of the entire channel intensity is used to calculate Med, Avg, std in order to avoid the effects of noise and extreme values of pixels. This BL estimation is based on Statistical analysis for the database of MABLs(manually annotated background lights). The dataset is composed of 500 underwater images whose background light is manually annotated. We combined these two methods because BL1 is efficient for the images which do not have strong color casts and BL2 is strong for the images which have strong color casts, especially for underwater images. This model is effective for both underwater images and hazy images on land.

2) Background Light Estimation: Background light is estimated after color correction. We also divide the images into two types by (8). In enhanced images, red components are compensated by Adaptive color correction. Therefore, we use the top 0.1% brightest pixels in dark channel which is defined in DCP [1] as BL1. We define BL2 as

$$B^c = 1.13 \times Avg^c + 1.11 \times std^c - 25.6, c \in \{r, g, b\} \tag{12}$$

B. Weighted Generalization of Dark Channel Prior

DCP introduced dark channel to estimate the transmission map in haze images. DCP is quite effective for hazy images on land, but DCP lacks the information of local structure because dark channel is calculated based on the patch. Therefore, DCP and other DCP-based methods utilize soft matting [12] or guided filtering [10] to refine transmission maps and adjust them to the local structures. However, this lowers the accuracy of the transmission map. M.Zhu et al. proposed WDC [9] to avoid this defect. WDC calculates a transmission map pixel by pixel and introduces a weight map to refine the transmission map by WLS Filter by Farbman [13]. The weight map is based on the assumption of the transmission rate in dark pixels which means $J^c(z) = 0$ is reliable. Where z means one of pixels in images. We confirmed that this solves the problems related to DCP and enhances the quality of hazy images. In addition, we found that this assumption can also be applied to GDCP [8] and named the GDCP with the weighted map as "Weighted Generalization of Dark Channel Prior(WGDCP)". In WGDCP, transmission map is locally calculated from (4) as

$$\hat{t}(x) = \frac{\max_c(|I_c(x) - A_c|/\hat{A}_c)}{\max_c(|J_c(x) - A_c|/\hat{A}_c)} \tag{13}$$

The lower bound satisfying $\max_c(|J_c(x) - A_c|/\hat{A}_c) = 1$ for pixel z (light pixel) as

$$b(z) = |I_c(z) - A_c|/\hat{A}_c \tag{14}$$

Transmission rates in light pixels are equal to their lower bounds. Transmission map in GDCP is used as an initial transmission map in WGDCP. Therefore, the initial transmission map is defined as

$$t_0(x) = \max_{c,y\in\Omega}(|I_c(y) - A_c|/\hat{A}_c) \tag{15}$$

where the size of a local patch Ω is 25×25 for the maximun width and height of the input image are 640. Based on the assumption that transmission rates in dark pixel are reliable, the weight map is defined as

$$W(x) = \frac{1}{\max((b(x) - t_0(x))^2, 0.001)/1000} \tag{16}$$

The initial transmission map t_0 is refined by WLS Filter [13] using W and the transmission map t is estimated.

C. Adaptive Color Correction

One of the color channels is often too dark in underwater images (especially red) and researchers made efforts to try and solve this problem. Methods that includes color correction, such as [7], are effective for these images, and white balance and gamma correction are widely used for color correction. However, color correction methods are designed for the images whose colors are equally distorted. In underwater images, the color casts are caused by the difference of the attenuation rate in different light Therefore, the color casts are not uniform in such images. If the objects are located farther away in the image, the color casts become stronger. Adaptive color correction is based on gray world assumption and considers the transmission map. Adaptive color correction is defined as

$$\hat{I}_c = \frac{I_c}{\min\{(u_c/u_{ref}) + dif * a * \hat{t}, \max(u_c)/u_{ref}\}} \tag{17}$$

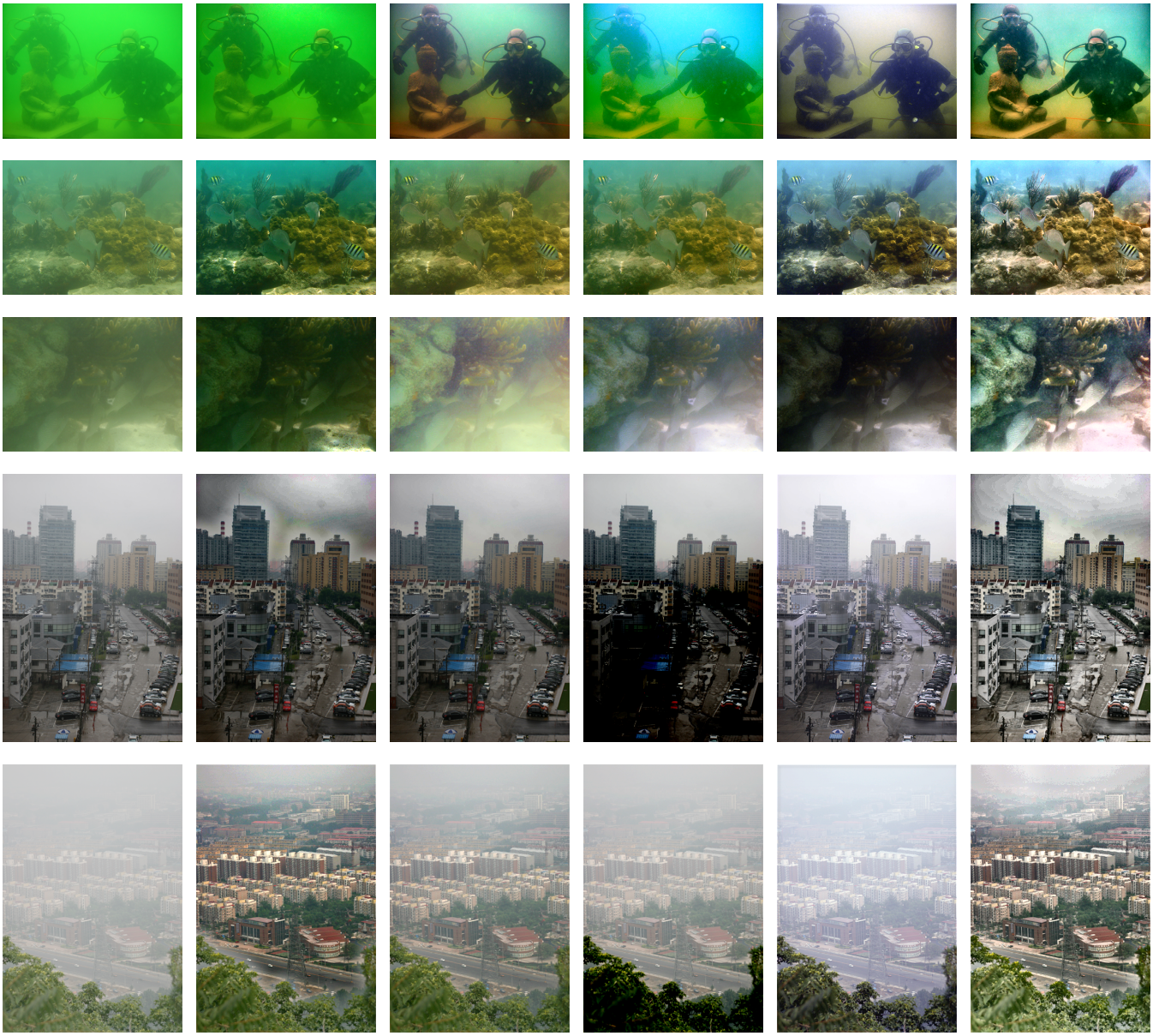
where u_c means the average intensity of the image for each color channel, u_{ref} means the average intensity of the image, $dif = u_{ref} - \min_c(u_c)$ and $a = 3$. $\hat{t}$ is introduced to adjust transmission map t and defined as

$$\hat{t} = \frac{[tt - \min(tt)](\max(tt) - l_b)}{\max(tt) - \min(tt)} + l_b \tag{18}$$

where, l_b=0.6 and $tt = t/\max(t)$. (17) makes the images too dark because of the transmission term ($dif*a*hatt$). Therefore, gamma correction and adaptive histogram equalizationis are finally applied to $\hat{t}$.

IV. Experiment Results

In this section, we compared our proposed algorithm with other methods. Ideally, comparison methods should be designed to be able to deal with both images underwater and haze images on land, but should include a specialized method for either underwater image enhancement or dehazing on land because most methods are specialized for one of them. We compared our method with DCP [1], GDCP [8], IBLA [5] and MIF [7] through subjective and objective comparison.



(a) original image (b) DCP (c) GDCP (d) IBLA (e) MIF (f) Ours

Fig. 3. Comparison Results

Fig. 4. Dataset for Objective Comparison

TABLE I
OBJECTIVE COMPARISON

	Methods				
	DCP	GDCP	IBLA	MIF	Ours
UIQM	1.84	2.22	1.80	3.24	3.35
BRISQUE	27.6	26.6	27.0	27.0	24.4
Entropy	7.17	7.31	7.23	7.46	7.74

A. *Subjective Comparison*

Fig.3 shows subjective comparison. In this comparison, we used both underwater images and hazey images on land. Firstly, we can compare our method with GDCP, which also focuses on defogging both underwater images and haze images on land. On the whole, proposed method recovers them efficiently in both types of images. Secondly, we can compare our method with other specialized methods, and needless to say, specialized methods only recover either underwater images or haze images on land well. In addition, our proposed method can match either specialized method in terms of image recovery.

B. Object Comparison

For objective comparison, we decided to compare our methods with other methods by using underwater images since the differences in enhanced underwater images is clearer than haze images on land. We adopted three non-reference image quality metrics in order to evaluate the performance of algorithms for underwater images. UIQM [14] is an image quality measure for underwater images, the Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) [15] quantifies possible losses of ‘naturalness’ in an image due to the presence of distortions, and Entropy measures the abundance of information. Table I shows the results of objective comparison. We compared our algorithm with other 4 methods by 14 underwater images shown in Fig.4. Overall, our algorithm outperforms other methods in this comparison.

V. Conclusion

In this paper, we proposed a novel defogging method which is composed of weighted generalization of dark channel prior and adaptive color correction. Clearly, our WGDCP solves the defect issues of DCP and GDCP, which can ignore local structure in detail. Adaptive color correction reduces color casts, which negatively affect image formation models for haze images.

Combining these two methods enables our methods to enhance the quality of both underwater images and haze images on land. Moreover, our experimental results show the effects of our algorithm through both subjective comparison and objective comparison.

However, some underwater images cannot be enhanced well because defogging methods based on image formation models are strongly affected by the quality of background light estimation and defining the background light is difficult in some types of underwater images. Therefore, enhancing the quality of background light further can be better in our method.

References

[1] K. He, J. Sun, and X. Tang, “Single image haze removal using dark channel prior,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 12, pp. 2341–2353, Dec 2011.

[2] Z. Tufail, K. Khurshid, A. Salman, I. Fareed Nizami, K. Khurshid, and B. Jeon, “Improved dark channel prior for image defogging using rgb and ycbcr color space,” *IEEE Access*, vol. 6, pp. 32 576–32 587, 2018.

[3] A. Galdran, D. Pardo, A. Picón, and A. Alvarez-Gila, “Automatic red-channel underwater image restoration,” *Journal of Visual Communication and Image Representation*, vol. 26, pp. 132 – 145, 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1047320314001874

[4] S. Yang, Z. Chen, Z. Feng, and X. Ma, “Underwater image enhancement using scene depth-based adaptive background light estimation and dark channel prior algorithms,” *IEEE Access*, vol. 7, pp. 165 318–165 327, 2019.

[5] Y. Peng and P. C. Cosman, “Underwater image restoration based on image blurriness and light absorption,” *IEEE Transactions on Image Processing*, vol. 26, no. 4, pp. 1579–1594, April 2017.

[6] C. O. Ancuti and C. Ancuti, “Single image dehazing by multi-scale fusion,” *IEEE Transactions on Image Processing*, vol. 22, no. 8, pp. 3271–3282, Aug 2013.

[7] C. O. Ancuti, C. Ancuti, C. D. Vleeschouwer, and P. Bekaert, “Color balance and fusion for underwater image enhancement,” *IEEE Transactions on Image Processing*, vol. 27, no. 1, pp. 379–393, Jan 2018.

[8] Y. Peng, K. Cao, and P. C. Cosman, “Generalization of the dark channel prior for single image restoration,” *IEEE Transactions on Image Processing*, vol. 27, no. 6, pp. 2856–2868, June 2018.

[9] Z. Mingzhu, H. Bingwei, J. Liu, and Y. Junzhi, “Boosting dark channel dehazing via weighted local constant assumption,” *Signal Processing*, vol. 171, p. 107453, 06 2020.

[10] K. He, J. Sun, and X. Tang, “Guided image filtering,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 6, pp. 1397–1409, June 2013.

[11] D. H. A. L. C. P. Wei Song, Yan Wang, “Enhancement of underwater images with statistical model of background light and optimization of transmission map,” *IEEE Transactions on Broadcasting*, 2019.

[12] A. Levin, D. Lischinski, and Y. Weiss, “A closed-form solution to natural image matting,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 2, pp. 228–242, Feb 2008.

[13] Z. Farbman, R. Fattal, D. Lischinski, and R. Szeliski, “Edge-preserving decompositions for multi-scale tone and detail manipulation,” in *ACM SIGGRAPH 2008 Papers*, ser. SIGGRAPH ’ 08. New York, NY, USA: Association for Computing Machinery, 2008. [Online]. Available: https://doi.org/10.1145/1399504.1360666

[14] K. Panetta, C. Gao, and S. Agaian, “Human-visual-system-inspired underwater image quality measures,” *IEEE Journal of Oceanic Engineering*, vol. 41, no. 3, pp. 541–551, July 2016.

[15] A. Mittal, A. K. Moorthy, and A. C. Bovik, “No-reference image quality assessment in the spatial domain,” *IEEE Transactions on Image Processing*, vol. 21, no. 12, pp. 4695–4708, Dec 2012.