COLOR CORRECTION OF UNDERWATER IMAGES BASED ON MULTI-ILLUMINANT ESTIMATION WITH EXPOSURE BRACKETING IMAGING

Kohei Nomura, Daisuke Sugimura and Takayuki Hamamoto

Graduate School of Engineering, Tokyo University of Science,
Katsushika-Ku, Tokyo, 125-8585, Japan

ABSTRACT

We propose a method for color correction of underwater images based on multi-illuminant estimation. We regard the color distortion of underwater images as the color cast that is illuminated by multiple light sources. In order to effectively remove the color distortions from the underwater image, we capture underwater scenes by exposure bracketing imaging. Using multiple images taken with different exposure times, we fuse an image where the attenuation differences in the spectra information of the incoming light are mitigated. We apply a multi-illuminant estimation to the fused image to reconstruct the underwater images so as to be those in a canonical (white) illumination environment. Our experiments demonstrate the effectiveness of our method.

***Index Terms*—** Underwater image, Color correction, Illuminant estimation, Exposure bracketing imaging

1. INTRODUCTION

The development of underwater imaging techniques have attracted considerable attentions in recent years. In underwater imaging, however, absorption and scattering of light travelling in a underwater scene cause heavy color distortions. Once underwater images can be corrected so as to be those in a canonical (white) illumination environment, they could contribute to the progress in marine biology. Thus, the aim of this study is set to correcting color distortions of underwater images.

The color distortions of underwater images are caused by the following facts. Because of the absorption and scattering of light travelling in underwater scenes, the spectrum components that correspond to wavelength range of 620 - 750nm (i.e., red light) particularly attenuate compared to those of the other wavelength ranges. Further, the amount of color distortions of underwater images increases as the travelling distance of light incoming to the camera gets to be larger. In particular, the amount of color distortions are characterized by how much vertical depth of the target scene is.

Many researchers have attempted restoring underwater images based on optical (physical) imaging models [1]. They extended formation models of hazy images for underwater images by considering the attenuation discrepancy of light traveling in underwater scenes [2, 3, 4, 5, 6, 7, 8]. Based on the underwater optical imaging models, methods for restoring underwater images have been proposed such as: dark channel prior (DCP) [1], underwater dark channel prior (UDCP) [5], depth from disparity [6], depth from blurriness [7], minimum information loss principle [8], and etc. In fact, however, methods based on the optical imaging models require estimating the background light accurately. Thus, these methods are hard to apply to underwater images where no background lights are observed.

On the other hand, statistical-based approaches have been proposed such as: grey-world hypothesis-based color correction [9], von kries hypothesis-based histogram equalization [10], histogram equalization using the mean value and the mean square error [11], contrast limited adaptive histogram equalization (CLAHE) [12] and etc. However, their statistical-based methods would cause over-emphasis or under-emphasis in correcting underwater images where the small amount of red spectrum components can only be captured.

In this study, we propose a method for color correction of underwater images based on multiple illuminant estimation, which is a technique to remove the color cast triggered by light sources in a scene. We regard the color distortion of underwater images as the color cast that is illuminated by multiple light sources with different colors. Unlike the previous methods that used underwater optical imaging models [2, 3, 4, 5, 6, 7, 8], techniques of multi-illuminant estimation can be applied to scenes where no background lights are observed.

Many methods for illuminant estimation have exploited achromatic information of a scene (e.g., grey world [13], grey edge hypothesis [14] and grey pixels [15]). In underwater images, however, it is difficult to extract reliable achromatic information accurately. This is due to the fact that achromatic pixels in underwater images are likely to have quite low intensity values because of salient attenuations in the red color channel.

In order to accurately perform color correction by multi-illuminant estimation even in underwater images, we capture underwater scenes based on exposure bracketing, which is a

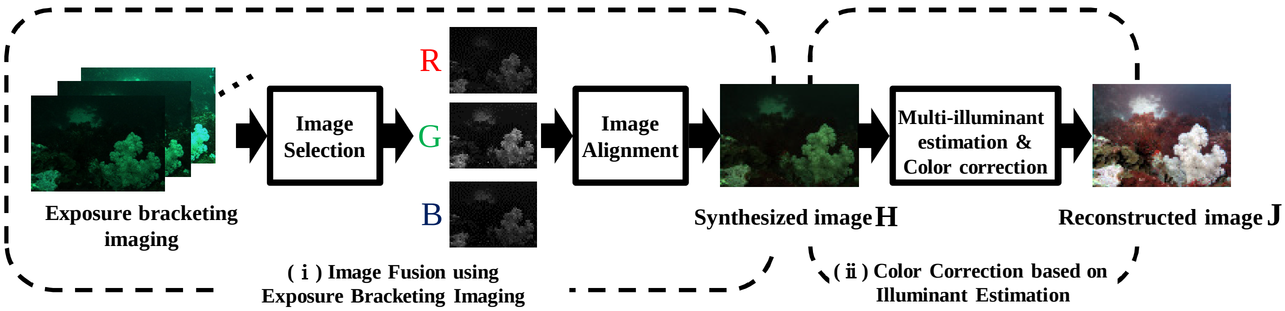


Fig. 1. Overview of the proposed method: (i) Image fusion using exposure bracketing imaging; (ii) Color correction based on multi-illuminant estimation.

technique used to acquire multiple images with different exposure times. The long-exposure image is useful for sufficiently acquiring red spectrum information that are particularly attenuated in underwater scenes. In contrast, pixel values in the green and blue channels in the long-exposure image will saturate because the green and blue components are unlikely to attenuate compared to the red one. To avoid this, we take the green and blue pixel values from the short-exposure image. In this way, we fuse an image that contains adequate spectral information of underwater scenes. It thus allows our multi-illuminant estimation to accurately detect pixels having achromatic information even in underwater images. Consequently, our method enables to perform color correction of underwater images.

The contributions of this study are summarized as follows. (1) We propose a novel approach based on multi-illuminant estimation to color correction of underwater images. To the best of our knowledge, this work is the first to exploit multi-illuminant estimation techniques for underwater image correction. (2) The use of multiple images obtained with exposure bracketing imaging enables us to perform accurate multi-illuminant estimation even in underwater images.

2. IMAGE FUSION USING EXPOSURE BRACKETING IMAGING

Figure 1 illustrates an overview of the proposed method. We first synthesize an image including sufficient spectral information of a scene by using multiple exposure images taken with exposure bracketing imaging. We perform a color correction of this synthesized underwater image based on multi-illuminant estimation. In this section, we describe the details of our image fusion with the help of exposure bracketing imaging.

2.1. Image Selection based on Over/Under-exposed Pixel Detection

Let $\mathbf{I} = \{\mathbf{I}_1, \mathbf{I}_2, ..., \mathbf{I}_M\}$ be a set of RGB images taken with exposure bracketing imaging. They are taken with M different exposure times. Using $\mathbf{I}$, we synthesize an image $\mathbf{H}$ that contains sufficient spectral information of underwater scenes. In practice, it is difficult to obtain red spectral information from the short-exposure image because of the salient attenuations of red components. In contrast, the green and blue components are likely to saturate in the long-exposure image. Thus we select images that have less over- and under-exposed pixels in each color channel.

We first separate $\mathbf{I}$ into each color channel as $\mathbf{I} = (\mathbf{I}^{\mathrm{R}}, \mathbf{I}^{\mathrm{G}}, \mathbf{I}^{\mathrm{B}})$ where they are defined as $\mathbf{I}^{\mathrm{R}} = \{\mathbf{I}_1^{\mathrm{R}}, ..., \mathbf{I}_M^{\mathrm{R}}\}$, $\mathbf{I}^{\mathrm{G}} = \{\mathbf{I}_1^{\mathrm{G}}, ..., \mathbf{I}_M^{\mathrm{G}}\}$ and $\mathbf{I}^{\mathrm{B}} = \{\mathbf{I}_1^{\mathrm{B}}, ..., \mathbf{I}_M^{\mathrm{B}}\}$, respectively. For each image $\mathbf{I}_m^l$, we count over- and under-exposed pixels as

$$C(\mathbf{I}_m^l) = \sum_{j=1}^{N} \mathrm{Bin}(\mathbf{I}_m^l(j); \sigma) \ , \tag{1}$$

where $\mathbf{I}_m^l(j)$ is the j-th pixel value in the l-th color channel in the m-th image $\mathbf{I}_m^l$, and N is the number of pixels. In Eq.(1), $\mathrm{Bin}(\cdot;\cdot)$ is a binary classification operator that is defined as

$$\mathrm{Bin}(\mathbf{I}_m^l(j); \sigma) = \begin{cases} 1 & \text{if } (\mathbf{I}_m^l(j) < \sigma) \text{ or } (\mathbf{I}_m^l(j) > U - \sigma) \\ 0 & \text{otherwise} \end{cases} , \tag{2}$$

where U is the maximum pixel value that can be represented in an image (e.g., if the bit depth of the image is 8, U becomes 255). In addition, σ is a truncation parameter. Using the number of over- and under-exposed pixels $\{C(\mathbf{I}_m^l)\}_{l \in \{\mathrm{R,G,B}\}, 1 \leq m \leq M}$, the number for the image that has the least over- and under-exposed pixels can be obtained as

$$m^{l*} = \arg\min_m C(\mathbf{I}_m^l) \ . \tag{3}$$

2.2. Image Fusion

Exposure bracketing imaging records multiple images with different timings; thus spatial misalignment between the captured images are observed. In order to compensate such misalignment, we apply a SIFT flow [16], which is a method to estimate the visual correspondences between two images, to $\mathbf{I}^{\mathrm{R}}_{m^{\mathrm{R}*}}$, $\mathbf{I}^{\mathrm{G}}_{m^{\mathrm{G}*}}$ and $\mathbf{I}^{\mathrm{B}}_{m^{\mathrm{B}*}}$. Using the image correspondences estimated by SIFT flow, we perform an image alignment of $\mathbf{I}^{\mathrm{R}}_{m^{\mathrm{R}*}}$ and $\mathbf{I}^{\mathrm{B}}_{m^{\mathrm{B}*}}$ so as to correspond to $\mathbf{I}^{\mathrm{G}}_{m^{\mathrm{G}*}}$. The resulting aligned images are denoted as $\hat{\mathbf{I}}^{\mathrm{R}}_{m^{\mathrm{R}*}}$ and $\hat{\mathbf{I}}^{\mathrm{B}}_{m^{\mathrm{B}*}}$, respectively.

Finally, we fuse an image $\mathbf{H}$ as

$$\mathbf{H} = (\mathbf{H}^{\mathrm{R}}, \mathbf{H}^{\mathrm{G}}, \mathbf{H}^{\mathrm{B}}) = (\hat{\mathbf{I}}^{\mathrm{R}}_{\mathbf{m}^{\mathrm{R}*}}, \mathbf{I}^{\mathrm{G}}_{\mathbf{m}^{\mathrm{G}*}}, \hat{\mathbf{I}}^{\mathrm{B}}_{\mathbf{m}^{\mathrm{B}*}}) \; . \tag{4}$$

3. COLOR CORRECTION USING MULTI-ILLUMINANT ESTIMATION

The fused image $\mathbf{H}$ mitigates the salient attenuation of red components of light travelling in underwater scenes. However, the color distortions of underwater images in $\mathbf{H}$ still remain. In order to remove the remaining color distortions, we apply a multi-illuminant estimation [15] to the synthesized image $\mathbf{H}$. The multi-illuminant estimation allows us to have an illuminant map that represents a pixel-wise distribution of multiple light source colors (i.e., color distortions of $\mathbf{H}$). We denote this as $\mathbf{E} = (\mathbf{E}^{\mathrm{R}}, \mathbf{E}^{\mathrm{G}}, \mathbf{E}^{\mathrm{B}})$.

With the estimated illuminant map $\mathbf{E}$, we perform color correction of $\mathbf{H}$ so as to be that in a canonical (white) illumination environment. The color-corrected image $\mathbf{J}$ is represented as

$$\mathbf{J}^l = \mathbf{T}^l \circ \mathbf{H}^l \; , \tag{5}$$

where $\circ$ denotes an operator that computes a Hadamard product. In Eq. (5), $\mathbf{T}^l = \{\mathbf{T}^l(j)\}_{1 \leq j \leq N}$ is an operator for correcting the color distortions of $\mathbf{H}^l$. Specifically, $\mathbf{T}^l(j)$ is represented using the value of illuminant map $\mathbf{E}^l$ at the j-th pixel as

$$\mathbf{T}^l(j) = \mathbf{W}^l(j) / \mathbf{E}^l(j) \; , \tag{6}$$

where $\mathbf{W}^l(j)$ represents the j-th pixel value of the l-th color channel of a white illuminant map $\mathbf{W}$, i.e., $\mathbf{W}^{\mathrm{R}}(j) = \mathbf{W}^{\mathrm{G}}(j) = \mathbf{W}^{\mathrm{B}}(j) = U$ (the maximum pixel value that can be represented in an image).

In this way, our method performs color corrections of underwater images.

4. EXPERIMENTAL RESULTS

We tested the proposed method using 4 underwater scenes we recorded. We named them as "Scene1", "Scene2", "Scene3" and "Scene4", respectively. These images were captured by using the Canon Powershot G7X camera with AutoExposure-Bracketing mode. The number of images taken with this exposure bracketing imaging was set to 3 (i.e., $M = 3$). The truncation parameter for image selection σ was set to 15. We used the same parameters for all the experiments.

4.1. Comparisons with State-of-the-art Methods

We compared the proposed method with two state-of-the-art methods that performed color correction of underwater images: Iqbal *et al.*'s method [10] and Fu *et al.*'s method [11]. We used the image taken with the shortest-exposure time as the input for the comparison methods.

To quantitatively compare the performance in color correction of underwater images, we placed two color checker boards in "Scene1" and "Scene2". In these scenes, the one checker board was located near to the camera while the other one was positioned far from the camera. We denote them "Near" and "Far", respectively. In this quantitative evaluation, we adopted CIEDE 2000 [17], which is a metric that measures color differences between two images.

Table 1 shows the quantitative comparison results in color correction. As shown in Table 1, we observed that our method outperformed the other comparison methods.

Figure 2 shows qualitative comparisons in the reconstructed underwater images for all the scenes we used. We observed that our method enabled to have better reconstruction results than those obtained using the comparison methods.

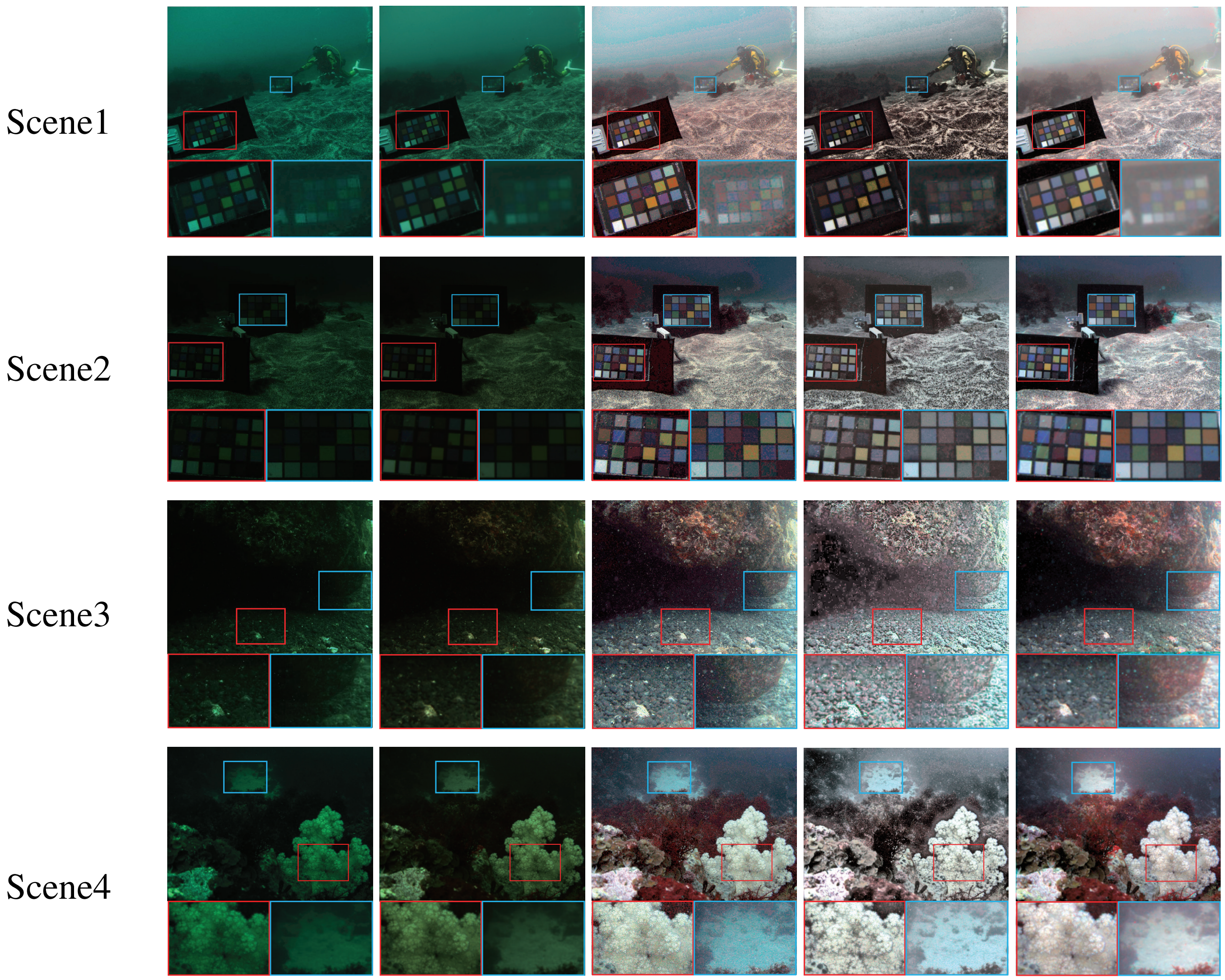
4.2. Effects of Exposure Bracketing Imaging

In order to see the effectiveness of our use of exposure bracketing imaging, we tested the proposed method using the shortest- and the longest-exposure images as input for the multi-illuminant estimation (i.e., our image selection and image fusion (Sect. 2) were not performed).

Figure 3 shows the reconstruction results using the different input images for "Scene1". We can see that the use of $\mathbf{H}$ was more effective than the others.

5. CONCLUSION

We proposed a method for color correction of underwater images based on multi-illuminant estimation. In order to effectively remove the color distortions from underwater images, we used an exposure bracketing imaging. Using multiple images taken with different exposure times, we fused an image where the attenuation difference in the spectral information of the incoming light are mitigated. We finally applied a multi-illuminant estimation to the fused image to remove the color cast from the underwater image. Experimental results showed the superiority of our method over the comparison methods.

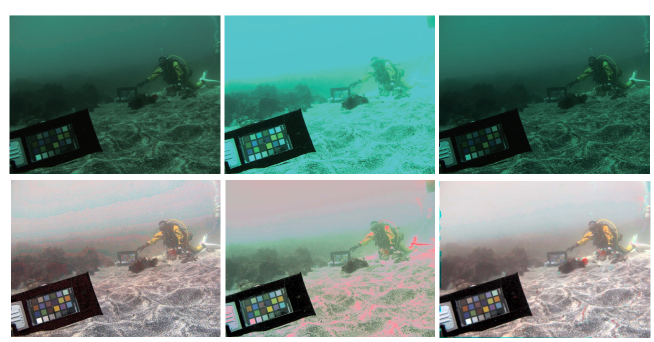


(a) Short-exp. img. (b) Fused img. **H** (b) Iqbal *et al.* [10] (d) Fu *et al.* [11] (e) Ours

Fig. 2. Visual comparisons in color correction of underwater images. (a) Shortest-exposure image (input image for the comparison methods); (b) Fused image **H** (input image for our method); (c) Results using Iqbal *et al.*'s method [10]; (d) Results using Fu *et al.*'s method [11]; (e) Our results.

Table 1. Comparisons in CIEDE2000 values. Note that these values were measured using the pixel values of regions of the color checker boards. Best scores are represented in **bold**.

	Iqbal *et al.* [10]	Fu *et al.* [11]	Ours
Scene 1(Near)	**23.93**	40.16	25.14
Scene 1(Far)	36.50	46.81	**36.31**
Scene 2(Near)	35.16	32.61	**28.46**
Scene 2(Far)	43.22	34.18	**33.57**



(a) (b) (c)

Fig. 3. Effects of image fusion. Top row: input images. From left to right, they represent the shortest-exposure image, the longest-exposure image, and the fused image **H**, respectively. Second row: Reconstructed images.

6. REFERENCES

[1] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," in *IEEE CVPR*, 2009, pp. 1956 – 1963.

[2] N.C. Bianco, A. Mohan, M.R. Eustice, and A. Arbor, "Initial results in underwater single image dehazing," in *IEEE OCEANS*, 2010, pp. 1–8.

[3] H.Y. Yang, P.Y. Chen, C.C. Huang, Y.Z. Zhuang, and Y.H. Shiau, "Low complexity underwater image enhancement based on dark channel prior," in *IEEE IBICA*, 2011, pp. 17–20.

[4] C.Y. Li, J.C. Guo, R.M. Cong, Y.W. Pang, and B. Wang, "Underwater image enhancement by wavelength compensation and dehazing," *IEEE TIP*, vol. 21, no. 4, pp. 1756 – 1769, 2012.

[5] H. Wen, Y. Tian, T. Huang, and W. Gao, "Single underwater image enhancement with a new optical model," in *IEEE ISCAS*, 2013, pp. 753–756.

[6] S. Zhang, J. Zhang, S. Fang, and Y. Cao, "Underwater stereo image enhancement using a new physical model," in *IEEE ICIP*, 2014, pp. 5422–5426.

[7] Y.T. Peng, X. Zhao, and P.C. Cosman, "Single underwater image enhancement using depth estimation based on blurriness," in *IEEE ICIP*, 2015, pp. 4952–4956.

[8] C.Y. Li, J.C. Guo, R.M. Cong, Y.W. Pang, and B. Wang, "Underwater image enhancement by dehazing with minimum information loss and histogram distribution prior," *IEEE TIP*, vol. 25, no. 12, pp. 5664–5677, 2016.

[9] C. Ancuti, C.O. Ancuti, T. Haber, and P. Bekaert, "Enhancing underwater images and videos by fusion," in *IEEE CVPR*, 2012, pp. 81–88.

[10] K. Iqbal, M. James, R.A. Salam, and A.Z.H. Talib, "Enhancing the low quality images using unsupervised colour correction method," in *IEEE SMC*, 2010, pp. 1703–1709.

[11] X. Fu, P. Zhuang, Y. Huang, Y. Liao, and X.P. Zhang, "A retinex-based enhancing approach for single underwater image," in *IEEE ICIP*, 2014, pp. 4572–4576.

[12] M.S. Hitam, W.N. Jawahir, H.W. Yuss, E.A. Awalludin, and Z. Bachok, "Mixture contrast limited adaptive histogram equalization for underwater image enhancement," in *IEEE ICCAT*, 2013, pp. 1–5.

[13] G.D. Finlayson and E. Trezzi, "Shades of gray and colour constancy," *IS&T CIC*, vol. 2004, no. 1, pp. 37–41, 2004.

[14] J.V.D. Weijer and T. Gevers, "Color constancy based on the grey-edge hypothesis," in *IEEE ICIP*, 2005, pp. II–722.

[15] K.F. Yang, S.B. Gao, and Y.J. Li, "Efficient illuminant estimation for color constancy using gray pixels," in *IEEE CVPR*, 2015, pp. 2254–2263.

[16] C. Liu, Y. Jenny, and T. Antonio, "Sift flow: Dense correspondence across scenes and its applications," *IEEE TPAMI*, vol. 33, no. 5, pp. 978–994, 2011.

[17] M.R. Luo, G. Cui, and B. Rigg, "The development of the cie 2000 colour-difference formula: Ciede2000," *WILEY CRA*, vol. 26, no. 5, pp. 340–350, 2001.