Turbidity Underwater Image Restoration Using Spectral Properties and Light Compensation

Huimin LU†††, Yujie LI††, Shota NAKASHIMA††, Nonmembers, and Seiichi SERIKAWA††, Member

SUMMARY Absorption, scattering, and color distortion are three major issues in underwater optical imaging. Light rays traveling through water are scattered and absorbed according to their wavelength. Scattering is caused by large suspended particles that degrade underwater optical images. Color distortion occurs because different wavelengths are attenuated to different degrees in water; consequently, images of ambient underwater environments are dominated by a bluish tone. In the present paper, we propose a novel underwater imaging model that compensates for the attenuation discrepancy along the propagation path. In addition, we develop a fast weighted guided normalized convolution domain filtering algorithm for enhancing underwater optical images. The enhanced images are characterized by a reduced noise level, better exposure in dark regions, and improved global contrast, by which the finest details and edges are enhanced significantly.

key words: underwater image enhancement, wavelength compensation, guided filter

1. Introduction

Following the recent development of deep-sea observations, the application of autonomous underwater vehicles (AUVs) or remotely operated vehicles (ROVs) has been limited by the need to recognize underwater objects. In the last two decades, sonars have been widely used for detecting and recognizing objects in underwater environments. However, for short-range identification, vision sensors must be used instead of sonars because sonars yield low-quality images

In contrast to common photographs, underwater optical images suffer from poor visibility owing to the medium, which causes scattering, color distortion, and absorption. Large suspended particles cause scattering similar to the scattering of light in fog or turbid water that contain many suspended particles. Color distortion occurs because different wavelengths are attenuated to different degrees in water; consequently, images of ambient underwater environments are dominated by a bluish tone, because higher wavelengths are attenuated more quickly. Absorption of light in water substantially reduces its intensity. The random attenuation of light causes a hazy appearance as the light backscattered by water along the line of sight considerably degrades image contrast. In particular, objects at a distance of more than 10 m from the observation point are almost indistinguishable because colors are faded as characteristic wavelengths are filtered according to the distance traveled by light in water.

Many researchers have developed techniques to restore and enhance underwater images. Schechner et al. exploited a polarization filter to compensate for visibility degradation [3], while Bazeille et al. proposed an image pre-processing pipeline for enhancing images in turbid water [4]. Fattal designed a graphic-theory-based independent-component analysis model to estimate the synthetic transmission and shading for recovering clean images [5]. He et al. estimated the dark channel prior from over 5000 nature images, then used soft matting to refine the depth map, and finally obtained clear images [6]. Nicholas et al. improved the dark channel prior and used the graph-cut method instead of soft matting to refine the depth map [7]. Hou et al. combined a point spread function and modulation transfer function to reduce the effects of blurring [8]. Ouyang et al. proposed bilateral filtering based on an image deconvolution method [9]. Ancuti et al. used an exposed fusion method in a turbid medium to reconstruct a clear image [10]. Chiang et al. considered the effects of variations in wavelength on underwater imaging and obtained the reconstructed image by using the dark channel prior model [11]. Although the aforementioned approaches can enhance the image contrast, they have several drawbacks that reduce their practical applicability. First, the imaging equipment is difficult to use in practice (e.g., a range-gated laser imaging system, which is rarely applied in practice [8], [9]). Second, multiple input images are required [3] (e.g., different polarization images or different exposed images) for fusing a high-quality image. Third, the image processing approaches are not suitable for underwater images [4], [6], [7] as they ignore the imaging environment, in addition to being time consuming. Fourth, manual operation is needed in processing, which may be difficult to set the parameters correctly [5].

Instead of multiple input images, we focus on enhancement methods that use a single optical image. Fattal [5] estimated the scene radiance and derived the transmission image using a single image. However, this method cannot be used to sufficiently process images with heavy haze. It also needs manual operation, which limits the application scope. He et al. [6] analyzed abundant natural sky im-
ages, found that it contains a dark channel in most color images, and proposed a scene-depth-information-based dark channel prior dehazing algorithm. However, this algorithm requires significant computation time with a complexity of O(N^2), and the processed images may have artificial halos in some cases. To overcome this disadvantage, He et al. also proposed a guided image filter [12], which used the foggy image as a reference image. However, this method leads to incomplete haze removal and does not meet the requirements for real-time processing.

Ancuti et al. [10] compared Laplacian contrast, contrast, saliency, and exposedness features between a white-balanced image and color-corrected image. Then, they utilized the exposure fusion algorithm to obtain the final result. However, this method has two main disadvantages: images are obtained with dark corners and processing parameters are difficult to set, which is problematic because the exposure blending algorithm used is sensitive to the parameters set. In our previous work [13], we proposed a guided trigonometric filter to refine the depth map. However, this method does not take the wavelength into account.

In an underwater environment, the captured images are significantly influenced by inherent optical properties (e.g., wavelength, scatter, and absorption). Inspired by Chiang’s work [11], in the present paper, we propose a novel underwater optical imaging model and a corresponding enhancement algorithm. We first estimate the depth map through dark channels. Second, considering the positions of the lighting lamp, camera, and imaging plane, we develop a rational imaging model. The effects of scattering are removed by using a weighted guided normalized convolution (WGNC) domain filter. Finally, color correction is performed by spectral properties. The performance of the proposed method is evaluated both analytically and experimentally.

2. Underwater Imaging Model

Artificial light and atmospheric light traveling through water are sources of illumination in an underwater environment. Let suppose that the intensity of light $W(x)$ after wavelength attenuation can be formulated by the energy attenuation model as follows:

$$E_\lambda^W(x) = E_\lambda^A(x) \cdot \text{Nrer}(\lambda)^D(x) + E_\lambda^F(x) \cdot \text{Nrer}(\lambda)^L(x),$$

where $E_\lambda^W(x)$ is the amount of illumination at the scene point, $E_\lambda^A(x)$ is the amount of illumination of atmospheric light, $E_\lambda^F(x)$ is the illumination of artificial light, and Nrer is the normalized residual energy ratio [14]. In Ocean Type I, Nrer has the following values:

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

The artificial light is reflected at a distance $L(x)$ to the camera, forming an energy $E_\lambda^I(x)$, $\lambda \in \{r, g, b\}$. $D(x)$ is the underwater scene depth. Color distortion (absorption) and scattering occurs in this process. Supposing that the absorption and scattering rate is $\rho_\lambda(x)$, the illumination of ambient light $E_\lambda^A(x)$ is

$$E_\lambda^A(x) = (E_\lambda^A(x) \cdot \text{Nrer}(\lambda)^D(x) + E_\lambda^I(x) \cdot \text{Nrer}(\lambda)^L(x)) \cdot \rho_\lambda(x), \lambda \in \{r, g, b\}$$

As per the modified dehazing model [11], the scene image $I_\lambda(x)$ formed at the camera can be formulated as follows:

$$I_\lambda(x) = [(E_\lambda^A(x) \cdot \text{Nrer}(\lambda)^D(x) + E_\lambda^I(x) \cdot \text{Nrer}(\lambda)^L(x)) \cdot \rho_\lambda(x)] \cdot t_\lambda(x) + (1 - t_\lambda(x)) \cdot B_\lambda, \lambda \in \{r, g, b\},$$

where the homogenous background $B_\lambda$ represents the part of the light reflected by the object, and $E_\lambda^X$ represents the ambient light scattered toward the camera by particles in water. The residual energy ratio $t_\lambda(x)$ can be represented in terms of the energy of a light beam of wavelength $\lambda$ before and after it propagates through a distance $d(x)$ within the water, represented by $E_\lambda^{\text{residual}}(x)$ and $E_\lambda^{\text{initial}}(x)$, respectively, as follows:

$$t_\lambda(x) = \frac{E_\lambda^{\text{residual}}(x)}{E_\lambda^{\text{initial}}(x)} = 10^{-\beta(\lambda)d(x)} = \text{Nrer}(\lambda)^D(x),$$

where the normalized residual energy ratio Nrer(\lambda) corresponds to the ratio of residual energy to initial energy for every unit of distance propagated, and $\beta(\lambda)$ is the extinction coefficient of the medium.

Consequently, substituting (5) in (4), we obtain:

$$I_\lambda(x) = [(E_\lambda^A(x) \cdot \text{Nrer}(\lambda)^D(x) + E_\lambda^I(x) \cdot \text{Nrer}(\lambda)^L(x)) \cdot \rho_\lambda(x)] \cdot \text{Nrer}(\lambda)^D(x) + (1 - \text{Nrer}(\lambda)^D(x)) \cdot B_\lambda, \lambda \in \{r, g, b\}.$$

The above equation incorporates the light scattered during the course of propagation from the object to the camera through a distance $d(x)$ and the wavelength attenuation along the object–light path $L(x)$, scene depth $D(x)$,
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and camera–object path \( d(x) \). Once the object–light distance \( L(x) \), scene depth \( D(x) \), and camera–object distance \( d(x) \) are known, a clean image can be recovered. Figure 1 shows a schematic of the proposed model. For improving image quality, we consider the processing flowchart shown in Fig. 2.

3. De-Scattering and Color Correction

3.1 Camera-Object Distance \( d(x) \) Estimation

The authors of [11] found that the red color channel is the dark channel of underwater images. During our experiments, we found that the lowest pixel value of the RGB channels in turbid water is not always the red color channel; the blue color channel is sometimes the lowest channel. This is usually caused by artificial light in imaging. Although light of red wavelength is easily absorbed when it propagates in water, the distance between the camera and object is not sufficient for light of red wavelength to be significantly absorbed (See Fig. 3). The blue channel is absorbed the least. Consequently, in this paper, we take the dual-channel (red and blue) value as a rough depth map or transmission map.

As indicated in (6), we suppose \( J_d(x) \) as:

\[
J_d(x) = \left( E^A_d(x) \cdot Nrer(\lambda)^{D(x)} + E^B_d(x) \cdot Nrer(\lambda)^{L(x)} \right) \rho_d(x), \quad \lambda \in \{r, g, b\}.
\]

We define the minimum dual channel \( J_{dark}(x) \) for the underwater image \( J_d(x) \) as

\[
J_{dark}(x) = \min \min_{\lambda} J_d(y), \quad \lambda \in \{r, b\}.
\]

If \( x \) is a part of the foreground object, the value of the minimum dual channel is very small. Applying the min operation to a local patch \( \Omega(x) \) on the hazy image \( I_h(x) \) in (6), we have

\[
\min_{y \in \Omega(x)} \left( I_h(y) \right) = \min_{y \in \Omega(x)} \left( J_d(y) \cdot Nrer(\lambda)^{d(y)} \right).
\]

\[
+ \left( 1 - Nrer(\lambda)^{d(y)} \right) B_\lambda,
\]

\[
\lambda \in \{r, b\}.
\]

Because \( B_\lambda \) is the homogeneous background light and the residual energy ratio \( Nrer(\lambda)^{d(x)} \) on the small local patch \( \Omega(x) \) surrounding pixel \( x \) is essentially a constant \( Nrer(\lambda)^{d(x)} \)), the min operation on the second term on the right-hand side of (9) can be removed to obtain

\[
\min_{y \in \Omega(x)} (I_h(y)) = \min_{y \in \Omega(x)} J_d(y) \cdot Nrer(\lambda)^{d(x)} + \left( 1 - Nrer(\lambda)^{d(x)} \right) B_\lambda,
\]

\[
\lambda \in \{r, b\}.
\]

We rearrange the above equation and perform on more minimum operation among two channels as follows:

\[
\min_{\lambda} \left( \min_{y \in \Omega(x)} \frac{J_d(y)}{B_\lambda} \right) = \min_{\lambda} \left( \min_{y \in \Omega(x)} \frac{J_d(y)}{B_\lambda} \cdot Nrer(\lambda)^{d(x)} \right) + \min_{\lambda} \left( 1 - Nrer(\lambda)^{d(x)} \right), \quad \lambda \in \{r, b\}.
\]

\[
\lambda \in \{r, b\}.
\]

The first term on the right-hand side of (11) is dark channels equal to 0. Consequently, the estimated depth map is

\[
\max_{\lambda} (Nrer(\lambda)^{d(x)}) = 1 - \min_{\lambda} \left( \frac{\min_{y \in \Omega(x)} I_h(y)}{B_\lambda} \right), \quad \lambda \in \{r, b\}.
\]

3.2 Depth Map Refinement

In the Sect. 3.1, we roughly estimated the camera-object distance \( d(x) \). This distance depth contains mosaic effects and produces less accurately. Consequently, we need to use the proposed weighted guided normalized convolution domain filter to reduce the mosaicking. In this section, we introduce our constant time algorithm for weighted guided normalized convolution domain filter.

The traditional median filter has been considered successfully.
as an effective way of removing “outliers”. The traditional median filter usually leads to morphological artifacts like rounding sharp corners. To address this problem, the weighted median filter [15] has been proposed. The weighted median filter is defined as

\[ h(x, i) = \sum_{y \in N(x)} W(x, y) \delta(V(y) - i) \]  

(13)

where \( W(x, y) \) corresponds to the weight assigned to pixel \( y \) inside a local region \( N(x) \) centered at the corresponding pixel \( x \), the weight \( W(x, y) \) depends on the input image, which can be different from the pixel value \( V \). \( i \) is the discrete bin index (usually \( i = 16 \)), and \( \delta \) is the Kronecker delta function, \( \delta = 1 \) when the argument is 0, and is 0 otherwise.

Then the compute the refined depth map by weighted median filter with 2D normalized convolution domain transform filtering in the spatial domain as:

\[ h(x, i) = \sum_{y \in N(x)} NC(x, y) \delta(V(y) - i) \]  

(14)

where \( NC(x, y) \) is the 1D normalized convolution domain filter [16], which is defined as:

\[ NC(x, y) = (1/K_x) \sum_{y \in D_2(1)} I_{NC}(y) H(t(x), t(y)) \]  

(15)

where \( K_x = \sum_{y \in D_2(1)} H(t(x), t(y)) \) is a normalization factor for \( x \), and \( t(x) = t(x, c(t(x))) \). Taking the efficient moving-average approach to perform NC with a box filter, the box kernel is

\[ H(t(x), t(y)) = \delta_B[|t(x) - t(y)| \leq r] \]  

(16)

where \( r = \sigma_H \sqrt{3} \) is the filter radius, and \( \delta_B \) is a Boolean function that return 1 when its argument is true, and otherwise 0. \( \sigma_H \) is the standard deviation. The final refined depth map is produced by (see Fig. 4):

\[ h(d(x), i) = \sum_{y \in N(x)} NC(d(x), I_1(x)) \delta(V(I_1(x)) - i) \]  

(17)

Figure 4 shows the pipeline of weighted normalized convolution domain filter. This filters images, preserving edges and filters noise based on a dimensionality reduction strategy, having high quality results, while achieving significant speedups over existing techniques, such as bilateral filter [17], guided filter [18], trilateral filter [19] and weighted bilateral median filter [20]. The refined depth image is shown in Fig. 5.

3.3 De-Scattering

From above subsection, we obtained the refined depth map \( d(x) \). In order to remove the scatter, we also need to solve the reflectivity \( \rho_\lambda(x) \). We take the least squares solution for achieving this by

\[ \rho_\lambda(x) = \left( J_\lambda(x)^T \cdot J_\lambda(x) \right)^{-1} \cdot J_\lambda(x)^T \cdot \left( E_\lambda^R(x) \cdot N_{rer}(\lambda)^{D(x)} + E_\lambda^R(x) \cdot N_{rer}(\lambda)^{J(x)} \right), \]  

(18)

\[ \lambda \in \{r, g, b\} \]

After removing the artificial light, the Eq. (6) can be written as

\[ I_\lambda(x) = E_\lambda^A(x) \cdot N_{rer}(\lambda)^{D(x)} \cdot \rho_\lambda(x) \cdot N_{rer}(\lambda)^{d(x)} \]  

\[ + \left( 1 - N_{rer}(\lambda)^{d(x)} \right) \cdot B_\lambda, \quad \lambda \in \{r, g, b\} \]  

(19)

According to Nayar-Narasimhan hazing model, we can obtain the descattered image by

\[ J_\lambda(x) = \frac{I_\lambda(x) - \left( 1 - N_{rer}(\lambda)^{d(x)} \right) \cdot B_\lambda}{N_{rer}(\lambda)^{d(x)}} \]  

\[ = E_\lambda^A(x) \cdot N_{rer}(\lambda)^{D(x)} \cdot \rho_\lambda(x) \cdot N_{rer}(\lambda)^{d(x)}, \]  

(20)

\[ \lambda \in \{r, g, b\} \]

After descattering, due to the lack of natural global lighting, and to the necessary use of artificial light sources with limited power, the lighting inhomogeneity problem is caused. We need to inhomogeneity correction, and then estimate the background \( B_\lambda \) correctly. Considering the illumination-reflectance model [21], we assume that an image is a function of the product of the illumination and the reflectance as:

\[ J_\lambda(x) = F_\lambda(x) \cdot R_\lambda(x) \]  

(21)

where \( J_\lambda \) is the image sensed by the camera, \( F_\lambda \) the illumination multiplicative factor, and \( R_\lambda \) is the reflectance function. By taking the logarithm and transfer in Fourier domain, the (22) can be written as:

\[ \tilde{J}_\lambda(x) = \tilde{F}_\lambda(x) + \tilde{R}_\lambda(x) \]  

(22)

Taking the Homomorphic filter \( H \) to remove the vignetting-like artifacts [22].
3.4 Color Correction

In Ref. [11], the author simply corrected the scene color by the attenuation of water depth. However, in practice, the spectral response function [23] of a camera maps the relative sensitivity of the camera imaging system as a function of the wavelength of the light. We take the chromatic transfer function $\tau$ for weighting the light from the surface to a given depth of objects as

$$\tau_\lambda = \frac{E_{\lambda}^{\text{surface}}}{E_{\lambda}^{\text{object}}}$$  \hspace{1cm} (23)

where the transfer function $\tau$ at wavelength $\lambda$ is derived from the irradiance of surface $E_{\lambda}^{\text{surface}}$ by the irradiance of the object $E_{\lambda}^{\text{object}}$. We convert the transfer function to RGB domain:

$$\tau_{\text{RGB}} = \sum_k \tau_\lambda \cdot C_\lambda(\lambda)$$  \hspace{1cm} (24)

where the weighted RGB transfer function is $\tau_{\text{RGB}}$, $C_\lambda(\lambda)$ is the underwater spectral characteristic function for color band $\lambda$, $\lambda \in \{r, g, b\}$, $k$ is the number of discrete bands of the camera spectral characteristic function.

Finally, the corrected image as gathered from the weighted RGB transfer function by

$$J_\lambda(x) = \hat{J}_\lambda(x) \cdot \tau_{\text{RGB}}$$  \hspace{1cm} (25)

where $J_\lambda(x)$ and $\hat{J}_\lambda(x)$ are the color corrected and uncorrected images respectively.

4. Experiments

The performance of the proposed algorithm is evaluated both objectively and subjectively, utilizing ground-truth color patches. We also compare the proposed method with the state-of-the-art methods. Both results demonstrate superior haze removal and color balancing capabilities of the proposed method over the others.

In the first experiment, we compare our method with the state-of-the-art methods with the underwater images offered by Dr. Y.Y. Schechner. The computer used is equipped with Windows XP and an Intel Core 2 (2.0 GHz) with 2 GB RAM. The size of the images is 345 $\times$ 292 pixels.

Figure 6 shows the results using different de-scattering methods. Schechner’s work produces blurring effects in the processed image. While Bazeille’s pre-processing is serious distortion. The drawback of Fattal’s method is that it needs to manually determine the background and foreground in the image. It is hard to use in practical application. Nicholas’s Graph-cut based method cost a lot of processing time, while the processed image is also blurred. In comparison with He’s method, our approach performs better, and as visible mosaic artifacts are observed in He’s approach owing to the use of soft matting. Some of the regions are too dark (e.g. the right corner of the coral reefs), and scatter is not removed elsewhere (e.g. the center of the image). In addition, there are also some unresolved scatters around the coral reefs in Ancuti’s method. How to select the parameters for fusion is a hard work. Moreover, Chiang’s work is distorted in colors. Our previous work (Serikawa’s) is performs well in descat-tering, however it cost a lot of time. Meanwhile, the selection of parameters is also di ffi cult. In the proposed model, we just need 2 parameters (turbidity rate $w$ and regularization parameter $\varepsilon$) to de-scattering. Its CPU processing is less than 1 second.

In addition to the visual analysis mentioned above,
Table 1 Comparative analysis of different de-scattering methods (Fig. 6).

| Methods       | PSNR  | Q-MOS  | SSIM  |
|---------------|-------|--------|-------|
| Scheckner '05 | 15.7184 | 40.8985 | 0.3362 |
| Bazeille '06  | 18.4609 | 49.8972 | 0.6157 |
| Fattal '08    | 28.1155 | 91.9044 | 0.8328 |
| Nicholas '10  | 24.8454 | 78.0455 | 0.6184 |
| He '11        | 21.4759 | 92.5893 | 0.8191 |
| Ancuti '12    | 21.7877 | 82.1602 | 0.7937 |
| Chiang '12    | 25.3353 | 90.3737 | 0.8258 |
| Serikawa '14  | 26.2918 | 92.3127 | 0.8293 |
| The proposed  | 28.4134 | 93.2458 | 0.8378 |

we conducted quantitative analysis, mainly from the perspective of mathematical statistics and the statistical parameters for the images (see Table 1). This analysis includes High-Dynamic Range Visual Difference Predictor2 (HDR-VDP2) [24] PSNR, and SSIM [25]. In HDR-VDP2, “Ampl.” means the amplification of the image (values are between 0 (worst) to 100 (best)), and “Loss” means the loss of visible contrast (values are between 0 (best) to 100 (worst)). Similarly, the Q-MOS value [24] is between 0 (best) to 100 (worst). Table 1 displays the values of PSNR, Q-MOS, and SSIM of the processed images. The reference image for calculating PSNR and SSIM produced by Gibson et al. [26]. The results indicate that our approach not only works well for scatters removal, but also results in lower computation time.

In the second experiment, we simulate to recover the underwater objects in water tank. We utilize OLYMPUS uTough 8000 underwater camera, INON LE700-W/S underwater light, and SLIK SBH-320 DS panheads for imaging. The equipment is set as Fig. 8. The spectral response of OLYMPUS uTough 8000 is shown in Fig. 8.

In this experiment, in order to simulate the single light source, overcome the atmospheric radiation and the reflection of tank glass, we covered black cloth around in the tank. We added abundant sediment when capturing the image, the experimental results are shown in Fig. 9.

In this simulation, we took Sedlazeck et al.’s method [27] to simulate the deep sea imaging environment. Then, we used the different de-scattering methods to process the simulated images. The processed results in Fig. 9 (c)–Fig. 9 (e), Fig. 9 (g) and Fig. 9 (h) remain some haze or...
scatters. Most of the results also cause the color shifts. While Fig. 9 (f) and Fig. 9 (i) can remove the scatter, the recovered image has color distortion. Notice that there are some halos or ring artifacts around the object cup in Fig. 9 (i). Compare with the other methods, the proposed method not only completely removes the scatter, but preserves the color well. Table 2 reports the quantitative analysis results. It also demonstrates that the proposed method outperforms the other methods.

Figure 10 illustrates the water tank experiment results obtained using the different methods. In this experiment, we added the deep-sea soil into the clean water at the turbidity of 200 mg/L. Some scatter remains in the resulting images using the methods proposed by Nicholas et al. (Fig. 10(e)), Ancuti et al. (Fig. 10(g)), and Serikawa et al. (Fig. 10(i)). While those using the method proposed by Fattal et al. (Fig. 10(d)) and Chiang et al. (Fig. 10(h)) show color distortion. The result of Bazeille’s method (Fig. 10(c)) is seriously distorted. The result of He’s method (Fig. 10(f)) performs better than the previous mentioned other methods. However, parts of color are distorted in the recovered image. It cannot remove the heavy scatters. In contrast, our proposed method can remove the scatter as well as preserve the color information.

In the experiment, we made a linear scale of five turbidity steps ranging from 100mg/L to 500mg/L by adding deep-sea soil to the water. We use The Contrast-to-Noise ratio (CNR) to measure the quality of the results. CNR is similar to the signal-to-noise ratio and robust in measuring scatter images. The higher value of CNR, the better visually appearance is. From Fig. 11, the CNR values demonstrate that our method performs better than other methods.

We also apply the proposed method to deep-sea image restoration. For deep-sea imaging, although there is no atmospheric light, the usually used multiple lighting can assume as the shallow ocean environment. We captured deep-sea images using ROV for surveying Muroto at Nankai Trough, Japan, which was provided by Japan Agency for Marine-Earth Science and Technology (JAMSTEC) in August 11, 1997. This image was captured at latitude 32.3515°N and longitude 134.5368°E. The water depth is 3627 m.

From Fig. 12, we can find that both Bazeille’s (Fig. 12(b)) and Fattal’s (Fig. 12(c)) results are significantly distorted. Retinex (Fig. 12(d)) [25], Serikawa’s (Fig. 12(h)), and Ancuti’s (Fig. 12(f)) results contain some turbidity sediments. The color is distorted in Chiang’s result (Fig. 12(g)). Although He’s method (Fig. 12(e)) perform much better than the above mentioned methods, it is time consuming and takes about 30 s to process the input.

### Table 2

| Methods        | PSNR  | Q-MOS  | SSIM   |
|----------------|-------|--------|--------|
| Bazeille ’06   | 9.5787| 33.0082| 0.4330 |
| Fattal ’08     | 13.9595| 35.5432| 0.6338 |
| Nicholas ’10   | 12.4260| 42.2650| 0.5859 |
| He ’11         | 21.4046| 40.6062| 0.8534 |
| Ancuti ’12     | 10.7715| 30.8455| 0.5530 |
| Chiang ’12     | 11.7472| 45.7409| 0.5198 |
| Serikawa ’14   | 26.2365| 63.7723| 0.9204 |
| The proposed   | 27.0520| 71.1706| 0.9266 |

![Fig. 10](image)  
Figure 10 Water tank experiment. (a) Captured image in clean water. (b) Captured image in turbid water. (c) Bazeille’s method. (d) Fattal’s method. (e) Nicholas’s method. (f) He’s method. (g) Ancuti’s method. (h) Chiang’s method. (i) Serikawa’s method. (j) Our method.
pared with the other methods, our proposed method performs well. The contrast of the result is sufficiently high.

5. Conclusions

In this study, we have explored and successfully implemented novel image enhancement techniques for underwater optical image processing. We have proposed a simple prior based on the difference in attenuation among the different color channels, which inspired us to estimate the depth map. Another contribution compensated the depth map by weighted guided normalized convolution domain filtering, which has the benefits of edge-preserving, noise removing, and a reduction in the computation time. Moreover, the proposed underwater image colorization method successfully created colorful underwater distorted images that are better than the state-of-the-art methods. Furthermore, our proposed method solved the limitations due to the influence of possible artificial light sources. Our experiments showed that the proposed methods are suitable for underwater imaging and solved the major problem of underwater optical imaging. In the future, we will consider developing a new underwater imaging model to eliminate the scatter problem.

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