Image Contrast Enhancement for Deep-sea Observation Systems

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Abstract

This paper describes a novel method for enhancing ocean optical images. While light traveling through the water, light rays are distorted depending on the wavelength. That is, absorption, scattering and color distortion are three major distortion issues for underwater optical imaging. In this paper, our key contributions are proposed include a novel deep-sea imaging model to compensate for the attenuation discrepancy along the propagation path and an effective underwater scene enhancement scheme. The recovered images are characterized by a reduced noised level, better exposure of the dark regions, and improved global contrast where the finest details and edges are enhanced significantly. The experiments show that the average value of PSNR and SSIM is improved than the state-of-the-art-methods.

Keywords: deep-sea imaging, inherent optical properties, image reconstruction.

1. Introduction

With the development of exploring the deep-sea by autonomous underwater vehicles (AUVs) and unmanned underwater vehicles (UUVs), the resolution of underwater images remains as a major issue. That is, how to acquire a clear underwater image is a question. From the 1960s, sonar has been widely used for detection and recognition of objects in oceans. Because of acoustic imaging principle, the sonar imaged images have many shortcomings, such as the low signal to ratio, low resolution et al. Consequently, optical vision sensors must then be used instead for short-range identification because of the low quality of images restored by sonar imaging [1].

In contrast to normal images, underwater images suffer from poor visibility owing to the medium. The light is absorbed when sunlight is reflected by a water surface. Furthermore, light is also deflected and scattered by many

particles in water. In addition, absorption substantially reduces the atmospheric light energy. The random attenuation of light primarily causes a hazy appearance, while the fraction of light scattered back from the water along the line of sight considerably degrades the scene contrast. In particular, objects at a distance of more than 10 meters are almost indistinguishable, because the colors are faded owing to the characteristic wavelengths that are filtered according to the water depth [2]. Furthermore, a distinctive footprint of the light beam is typically left on the seafloor when an artificial light source is employed.

In the last decade, there are some researchers focused on underwater image quality improvement. Y.Y. Schechner et al. exploited a polarization imaging method to compensate for visibility degradation [3], while Ancuti et al. used an image fusion method in a turbid medium to reconstruct a clear image [4]. Hou et al. combined a point spread function and modulation transfer function to reduce the effects of blurring [5]. Ouyang et al. proposed bilateral filtering based on an image deconvolution method [6]. Although the aforementioned approaches can enhance the image contrast, these methods have demonstrated several drawbacks that reduce their practical applicability. First, the equipment for imaging is difficult to use in practice (e.g., a range-gated laser imaging system, which is hardly applied in practice). Second, multiple input images are required [7]. Third, they cannot alleviate color distortion very well.

Instead of multiple input images, underwater scene reconstruction methods using a single image have been proposed. The ICA based dehazing method was first proposed by Fattal [8]. He estimated the scene radiance and derived the transmission image by a single image. However, this method cannot sufficiently process images with heavy haze. Then, He et al. [9] proposed a scene depth information-based dark channel prior dehazing algorithm using a matting Laplacian. However, this algorithm requires significant computation time. To overcome this disadvantage, they also proposed a new guided image filter [10] with the foggy image used as a reference image. However, this method leads to incomplete haze removal.

Hence, in this paper, we introduce a novel approach that is able to enhance underwater images based on a single image to overcome the drawbacks of the conventional methods mentioned above. The organization of this paper is as follows. Section 2 explains the ocean imaging model. Section 3 describes the model for underwater image enhancement and proposes our guided trigonometric bilateral filter. Section 4 applies our proposed method to underwater optical images. Finally, Section 5 concludes this paper.

2. Underwater Imaging Model

Artificial light and atmospheric light traveling through the water is the source of illumination in an ocean environment. Let suppose the amount of radiation light $W(x)$ formed after wavelength attenuation can be formulated according to the energy attenuation model as follows:

$$E_{\lambda}^W(x) = E_{\lambda}^A(x) \cdot Nrer(\lambda)^{D(x)} + E_{\lambda}^I(x) \cdot Nrer(\lambda)^{L(x)}, \quad (1)$$

$$\lambda \in \{r, g, b\}$$

where $E_{\lambda}^W(x)$ is the amount of illumination at point x , $E_{\lambda}^A(x)$ is the amount of illumination of atmospheric light at point x , $E_{\lambda}^I(x)$ is the illumination of artificial light, and $Nrer$ is the normalized residual energy ratio. At the scene point x , artificial light reflected again travels distance $L(x)$ to the camera forming pixel $I_{\lambda}(x)$, $\lambda \in \{r, g, b\}$. $D(x)$ is the scene depth underwater. We suppose the absorption and scattering rate is $\rho(x)$, artificial light $J_{\lambda}(x)$ emanated from point x is equal to the amount of illuminating ambient light $E_{\lambda}^W(x)$ reflected,

$$E_{\lambda}^W(x) = (E_{\lambda}^A(x) \cdot Nrer(\lambda)^{D(x)} + E_{\lambda}^I(x) \cdot Nrer(\lambda)^{L(x)}) \cdot \rho(x), \quad (2)$$

$$\lambda \in \{r, g, b\}$$

By following the improved Nayar-Narasimhan hazing model [13], the image $I_{\lambda}(x)$ formed at the camera plane can be formulated as,

$$I_{\lambda}(x) = (E_{\lambda}^A(x) \cdot Nrer(\lambda)^{D(x)} + E_{\lambda}^I(x) \cdot Nrer(\lambda)^{L(x)}) \cdot t_{\lambda}(x) + (1 - t_{\lambda}(x)) \cdot B_{\lambda}, \quad \lambda \in \{r, g, b\} \quad (3)$$

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

$$t_{\lambda}(x) = \frac{E_{\lambda}^{residual}(x)}{E_{\lambda}^{initial}(x)} = 10^{-\beta(\lambda)d(x)} = Nrer(\lambda)^{d(x)} \quad (4)$$

where $Nrer$ is the normalized residual energy ratio [14], in the Ocean Type I, it follows:

$$Nrer(\lambda) = \begin{cases} 0.8 \sim 0.85 & \text{if } \lambda = 650 \sim 750 \mu m(\text{red}) \\ 0.93 \sim 0.97 & \text{if } \lambda = 490 \sim 550 \mu m(\text{green}) \\ 0.95 \sim 0.99 & \text{if } \lambda = 400 \sim 490 \mu m(\text{blue}) \end{cases} \quad (5)$$

Consequently, subscribing the Eq. (3) and Eq. (4), we can obtain:

$$I_{\lambda}(x) = [(E_{\lambda}^A(x) \cdot Nrer(\lambda)^{D(x)} + E_{\lambda}^I(x) \cdot Nrer(\lambda)^{L(x)}) \cdot \rho_{\lambda}(x)] \cdot Nrer(\lambda)^{d(x)} + (1 - Nrer(\lambda)^{d(x)}) \cdot B_{\lambda}, \quad \lambda \in \{r, g, b\} \quad (6)$$

The above equation incorporates the light scattering during the course of propagation from object to the camera $d(x)$, and the wavelength attenuation along both the light-object path $L(x)$, scene depth $D(x)$ and object-camera path $d(x)$. Once the light-object distance $L(x)$, scene depth $D(x)$ and object-camera distance $d(x)$ is known, the final clean image will be recovered.

Figure 1. Diagram of Shallow Ocean Optical Imaging Model.

Figure 2. Pipeline of video frame improvement method.

Figure 1 shows the diagrammatic sketch of the proposed model. For improving the image quality, we take the processing flowchart as Figure 2.

3. Underwater Image Improvement Methods

3.1 Artificial Light Adjustment

In the deep sea, we must use artificial light for imaging. However, it will cause the vignetting effect. In ref. [28], K. Sooknanan et al. proposed a multi-frame vignetting correction model for removing the vignetting phenomenon which involves estimating the light source footprint on the seafloor. This artificial light correction can well done, however, it cost large time for computing. So, in this paper, we intend to introduce a signal frame-based vignette removal method [29].

Figure 3. Simulation result of artificial light correction. (a) Input image; (b) Artificial light adjusted image.

3.2 Absorption and Scattering Removal

In Ref. [19], the author found the red color channel is the dark channel of underwater images. During our experiments, we found that the lowest channel of RGB channels in turbidly water is not always the red color channel; the blue color channel is very significant [25, 27]. The reason is that we usually take artificial light in imaging. Although the red wavelength absorbed easily through traveling in water, the distance between the camera and object is not enough to absorb the red wavelength significantly. The blue channel may be the lowest. Consequently, in this paper, we take the minimum pixel value as the rough depth disparity.

We propose a guided trigonometric bilateral filter (GTBF) to overcome the occurrence of gradient reversal artifacts. The filtering process of the GTBF is first performed under the guidance of image G that can be another image or the input image I itself. Let I_p and G_p be the intensity value at the pixel p of the minimum channel image and the guided image, respectively, and w_k be the kernel window centered at pixel k , consistent with the bilateral filter. GTBF is then formulated by,

$$GTBF(I)_p = \frac{1}{\sum_{q \in w_k} W_{GTBF_{pq}}(G)} \sum_{q \in w_k} W_{GTBF_{pq}}(G) I_q, \quad (7)$$

where the kernel weight function $W(G)$ can be written by

$$W_{GTBF_{pq}}(G) = \frac{1}{|w|^2} \sum_{k \in \{p, q\} \in w_k} \left(1 + \frac{(G_p - \mu_k)(G_q - \mu_k)}{\sigma_k^2 + \varepsilon} \right), \quad (8)$$

where μ_k and σ_k^2 are the mean and variance of the guided image G in the local window w_k , and $|w|$ is the number of pixels in this window. When both G_p and G_q are concurrently on the same side of an edge, the weight

assigned to pixel q is large. When G_p and G_q are on different sides, a small weight will be assigned to pixel q .

As we obtained the refined depth disparity $d(x)$, 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 [19] as,

$$\rho_\lambda(x) = \left(J_\lambda(x)^T \cdot J_\lambda(x) \right)^{-1} \cdot J_\lambda(x)^T \cdot \left(E_\lambda^A(x) \cdot Nrer(\lambda)^{D(x)} + E_\lambda^I(x) \cdot Nrer(\lambda)^{L(x)} \right), \quad (9)$$

$$\lambda \in \{r, g, b\}$$

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

$$I_\lambda(x) = E_\lambda^A(x) \cdot Nrer(\lambda)^{D(x)} \cdot \rho_\lambda(x) \cdot Nrer(\lambda)^{d(x)} + (1 - Nrer(\lambda)^{d(x)}) \cdot B_\lambda, \quad \lambda \in \{r, g, b\} \quad (10)$$

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

$$\tilde{J}_\lambda(x) = \frac{I_\lambda(x) - (1 - Nrer(\lambda)^{d(x)}) \cdot B_\lambda}{Nrer(\lambda)^{d(x)}} = E_\lambda^A(x) \cdot Nrer(\lambda)^{D(x)} \cdot \rho_\lambda(x) \cdot Nrer(\lambda)^{d(x)}, \quad (11)$$

$$\lambda \in \{r, g, b\}$$

Figure 4. Simulation result of absorption and scattering removal. (a) Artificial light adjusted image; (b) Absorption corrected result; (c) De-scattered result.

3.3 Color Correction

In Ref. [19], the author simply corrected the scene color by the attenuation of water depth. However, in practice, the spectral response function [30] 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 τ for weighting the light from the surface to a given depth of objects as

$$\tau_\lambda = \frac{E_\lambda^{surface}}{E_\lambda^{object}} \quad (12)$$

where the transfer function τ at wavelength λ is derived from the irradiance of the surface $E_\lambda^{surface}$ by the irradiance

of the object E_{λ}^{object} . Based on the spectral response of RGB camera, we convert the transfer function to RGB domain:

$$\tau_{RGB} = \int_{\lambda=400}^{\lambda=725} \tau_{\lambda} \cdot C_b(\lambda) d\lambda \quad (13)$$

where the weighted RGB transfer function is τ_{RGB} , $C_b(\lambda)$ is the underwater spectral characteristic function of color band b , $b \in \{r, g, b\}$.

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

$$J_{\lambda}(x) = \hat{J}_{\lambda}(x) \cdot \tau_{RGB} \quad (14)$$

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

Figure 5. Simulation result of absorption and scattering removal. (a) De-scattered image; (b) Color corrected result.

4. Experiments and Discussions

The performance of the proposed algorithm is evaluated both objectively and subjectively by utilizing ground-truth color patches. Both results demonstrate superior haze removal and color balancing capabilities of the proposed method over the others. In the experiment, we compare our method with Schechner's model, Bazeille's model, Fattal's model, Nicholas's model; He's model, Xiao's model, Ancuti's model, and Chiang's model. Here, we select the best parameters for each model. The computer used is equipped with Windows XP and an Intel Core 2 (2.0 GHz) with 1 GB RAM.

Figure 6 shows the results using different reconstruction methods. The size of the images is 600×424 pixels. The processed image of Bazeille's pre-processing method is seriously distorted. The drawback of Fattal's method is obviously, which is because it needs to manually determine the background and foreground in the image. It is hard to use in practical application. While Nicholas's Graph-cut based method cost a lot of processing time, while the processed image is also blurred. The right corner of the processed image is seriously distorted. 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), and haze is not removed elsewhere (e.g. the center of the image). The contrast of Xiao's model is not strong. In addition, there are

also some unresolved scatters or haze-like objects around the coral reefs in Ancuti's model. How to select the parameters for fusion is a hard work. Moreover, Chiang's work is distorted in colors. Our proposed method takes the guided trigonometric bilateral filter and spectral properties based color correction method to recover the distorted underwater images, which are shown superior to the state-of-the-art methods both on computation complex and visual effects. Consequently, compare with the above methods, our proposed method is the best.

Figure 6. Different models for underwater coral image reconstruction: (a) Input image; (b) Bazeille's model; (c) Fattal's model; (d) Nicholas's model; (e) He's model; (f) Xiao's model; (g) Ancuti's model; (h) Chiang's model; and (i) our proposed model.

In addition to the visual analysis mentioned above, we conducted quantitative analysis, mainly from the perspective of mathematical statistics and the statistical parameters for the images (see Table 1). This analysis includes Peak Signal to Noise Ratio (PSNR) [22], Quality mean-opinion-score (Q-MOS) [18], and Structural SIMilarity (SSIM) [23]. Table 1 displays the numerical results of Q-MOS, PSNR and SSIM measured on several images. The results indicate that our approach works well for haze removal.

Table 1. Comparative Analysis of Different De-scattering Methods

<i>Methods</i>	<i>PSNR</i>	<i>Q-MOS</i>	<i>SSIM</i>
Bazeille	13.0844	19.8556	0.2061
Fattal	11.7316	19.2204	0.4581
Nicholas	18.9630	43.0762	0.7763
He	23.2120	77.8366	0.9642
Xiao	24.5089	66.0857	0.9493
Ancuti	27.0414	39.8664	0.9074
Chiang	27.3216	71.7899	0.9597
Our	27.7829	77.6780	0.9698

5. Conclusions

In this paper, we have explored and implemented novel image enhancement techniques for shallow water optical image reconstruction. We have proposed a simple prior based on the difference in attenuation among the different color channels, which inspired us to estimate the transmission depth map. Another contribution compensated the transmission by weighted guided trigonometric bilateral filter, which has the benefits of edge-preserving, noise removing, and a reduction in the computation time. Moreover, the proposed spectral-based underwater image colorization method successfully created colorful underwater distorted images that are better than the state-of-the-art methods.

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