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Underwater image de-scattering and classification by deep neural network

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ABSTRACT

Vision-based underwater navigation and object detection requires robust computer vision algorithms to operate in turbid water. Many conventional methods aimed at improving visibility in low turbid water. High turbid underwater image enhancement is still an opening issue. Meanwhile, we find that the de-scattering and color correction of underwater images affect classification results. In this paper, we correspondingly propose a novel joint guidance image de-scattering and physical spectral characteristics-based color correction method to enhance high turbidity underwater images. The proposed enhancement method removes the scatter and preserves colors. In addition, as a rule to compare the performance of different image enhancement algorithms, a more comprehensive image quality assessment index Q_u is proposed. The index combines the benefits of SSIM index and color distance index. We also use different machine learning methods for classification, such as support vector machine, convolutional neural network. Experimental results show that the proposed approach statistically outperforms state-of-the-art general purpose underwater image contrast enhancement algorithms. The experiment also demonstrated that the proposed method performs well for image classification.

1. Introduction

Sonar has been utilized to detect and recognize objects in oceans. However, it has short comings for short-range identification. Sonar yields low-resolution images due to the limitation of the low quality acoustic aperture. Consequently, vision sensors are typically used for detection and classification [1].

In recent years, researchers have developed several methods to improve underwater optical images [2]. Lu et al. reviewed most of the recent underwater optical image enhancement methods [3]. There are many different techniques to improve the contrast of the image. These techniques can be classified in to two approaches: hardware based methods and non-hardware base approach.

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1.1. Hardware based approach

Hardware based approach requires special equipment. There are two common examples includes polarization and range-gated imaging approaches.

1.1.1. Polarization

Light has three properties, that is, intensity, wavelength, and polarization. The human and some animals can detect polarization and use it in many different ways for enhancing visibility. Natural light is initially unpolarized. However, light reaching to a camera often has biased polarization due to scattering and refection. Light polarization coveys different information of the scene. Inspired by animal polarization vision, a polarization imaging technique has been developed. To collect light polarization data, polarization sensitive imaging and sensing systems are required. Schechner et al. designed a polarization filter, which is attached in the front of normal camera, to compensate for visibility degradation in water [4]. However, it has the issues for capturing the floating or moving objects. Because capturing the same scene of polarized images at the same time is difficult.

1.1.2. Range-gated imaging

Range-gated (RG) or time-gated imaging is a kind of the hardware methods to improve the image quality and visibility in turbid conditions [5]. In RG underwater imaging system, the camera is adjacent to the light source, as well as the targets are behind the scattering water [6]. The operation of range-gated system is to select the reflected light from the object that arrives at the camera and to block the optical back-scatter light [7]. However, the captured images by lasers lead to less color information.

1.2. Software based approach

1.2.1. Image enhancement

Image enhancement is usually used for underwater image quality improvement. Bazeille et al. proposed an image filtering method to improve the image's quality [8]. Fattal analyzed the hazed images, and found that the color lines can be used to estimate the turbidity of haze. Finally he used a Markov Random Fields model to remove the smokes [9]. He et al. firstly proposed the dark channel prior to estimating the depth map [10]. Nicholas et al. used graph-cut method to refine the depth map of dark channel prior model for obtaining the clear image [11]. Martin et al. used a stereo matching and light attenuation model to recover visibility under water [12]. Lee et al. proposed a stereo image defogging method by using an estimation of scattering parameters through a stereo image pair [13]. Tarel et al. firstly proposed the median dark channel prior method to recover a foggy image [14].

1.1.2. Image restoration

On the other hand, the physical based image restoration methods are also studied. Lu et al. proposed the physical based model to restore the underwater images, such as physical wavelength [11–13], spectral characteristics [14,15].

All of the above mentioned approaches can enhance the image contrast, but they do not perform well for high turbidity underwater images. In high turbidity water, it is difficult to obtain the ambient light and fine depth map using the conventional methods. In this paper, we propose a contrast enhancement based on a joint normalized image and color correction. Furthermore, we explore a new index to measure the enhanced images.

This paper is organized as the following. In Section 2, we present the details of the proposed contrast enhancement method. In Section 3, we introduce well-known image quality indexes, and propose Q_u for image indexing. Experimental de-scattering and classification results are given in Section 4. In Section 5, we conclude this paper.

2. Contrast enhancement

Underwater dark channel prior-based image enhancement methods use a depth map to remove scatter. However, if the input images are highly distorted, the real depth maps cannot be calculated correctly using most recent methods. To solve this problem, we propose a guidance image filtering method to refine the depth map. Next, we take the physical spectral characteristics-based color correction.

2.1. Underwater imaging model

The traditional underwater imaging model [12–16] is usually adopted, which simply assumes the imaging model similar to that in atmospheric. In the proposed model, we assumed the ambient light is only contributed by artificial light. Therefore, a modified underwater imaging model is employed for underwater lighting conditions.

The modified underwater imaging model can be written as follows:

$$I^c(x) = J^c(x)e^{-\eta d(x)} + \rho(x) \cdot J^c(x)(1 - e^{-\eta d(x)}), c \in \{r, g, b\} \tag{1}$$

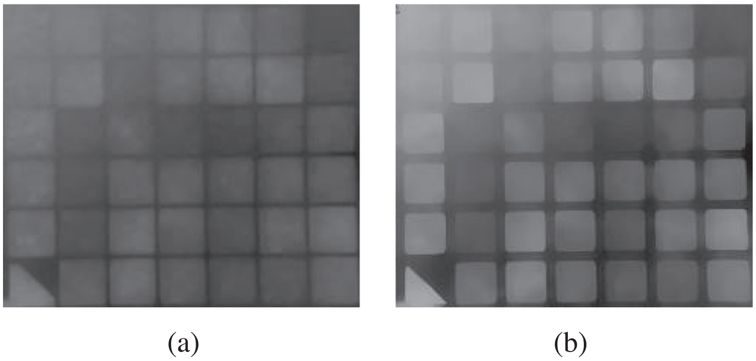

Fig. 1. Depth map refinement. (a) Coarse depth map by UDCP. (b) Refined depth map by our method.

where $J^c(x)$ is the real scene at depth D, $\rho(x)$ is the normalized radiance of a scene point, $d(x)$ is the distance from the scene point to the camera, and η is the total nonlinear beam attenuation coefficient.

The proposed method is based on [13–17]. The minimum operation is suitable for reducing the halo effect when estimating the coarse transmission. Thus, the underwater dark channel priors (UDCP) can be defined as:

$$\tilde{d}(x) = \min_{\Re(m,n)} \left(\min_{c\in\{r,b\}} \frac{I^c(x)}{\rho(x)\cdot J^c(x)} \right), c \in \{r, b\} \tag{2}$$

where $\Re$ is a square patch of size 5×5. For each pixel located at position (m, n) in the patch $\Re$, the pixel values from the red color channel and blue color channel are compared, and the lower value is selected. Then, the depth map is calculated by:

$$d(x) = 1 - \omega\tilde{d}(x), \tag{3}$$

where ω is chosen as 0.8 in most cases.

2.2. Depth map refinement by guidance image

In Section 2.1, we discussed the rough estimation of the depth map. However, its depth map contains ring artifacts and yields less accurate de-scattering results. Therefore, we have developed a joint guidance image filter to reduce such artifacts. The normalized image is obtained as follows:

$$I_f^c(x) = \begin{cases} \frac{I^c(x) - I^c_{\min}(x)}{I^c_{\max}(x) - I^c_{\min}(x)}, & if\ 0 < I^c(x) < 1 \\ 0, & if\ 0 > I^c(x) \\ 1, & if\ 1 < I^c(x) \end{cases}, c \in \{r, g, b\} \tag{4}$$

The refinement of the joint filtered is first performed under the guidance image $I_f^c(x)$. Here, let $d_p(x)$, $d_q(x)$, $I^c_{f,p}(x)$ and $I^c_{f,q}(x)$ be the intensity value at the pixel p, q of the depth map and the guidance image, respectively, while w_k is the kernel window centered at pixel k. The refined depth map is then formulated as:

$$R(x) = \frac{1}{\sum_{q\in w_k} W_{pq}(I_f^c(x))} \sum_{q\in w_k} W_{pq}(I_f^c(x)) d_q(x) \tag{5}$$

where the kernel weight function $W_{G_{pq}}(I_f^c(x))$ is expressed as:

$$W_{pq}(I_f^c(x)) = \frac{1}{|w|^2} \sum_{k:(p,q)\in w_k} \left(1 + \frac{(I^c_{f,p}(x) - \mu_k)(I^c_{f,q}(x) - \mu_k)}{\sigma_k^2 + \varepsilon} \right) \tag{6}$$

where μ_k and σ_k^2 are the mean and variance of the guidance image in the local window w_k, and |w| is the number of pixels in this window. After the refined depth map is obtained, we can recover the real scene using the underwater dark channel prior de-scattering model. Fig. 1 shows the result of refined depth map.

2.3. Color correction

After de-scattering, the colors are seriously distorted. We use the physical spectral characteristics based color correction method to address this distortion. Different from Lu et al.'s method [1], we consider the effect of artificial lights. We take the chromatic transfer function (CTF) τ to weight the atmospheric light from the water surface to a given water depth of objects as follows:

$$\tau_\lambda = \frac{E_\lambda^{surface}}{E_\lambda^{object}} \tag{7}$$

where CTF τ at wavelength λ is derived from the irradiance of the water surface $E_\lambda^{surface}$ by the irradiance of the object E_λ^{object}. Next, we convert τ in different wavelength to the RGB domain as follows:

$$\tau_{RGB} = \int_{400nm}^{725nm} \tau_\lambda \cdot C_c(\lambda) d\lambda, c \in \{r, g, b\} \tag{8}$$

where the weighted RGB transfer function is τ_{RGB}, and $C_c(\lambda)$ is the underwater spectral characteristic function of the color band c, $c \in \{r,g,b\}$. Considering the spectral power distribution transfer function, the finally corrected image is gathered as follows:

$$J_\lambda^c(x) = \nu_{RGB} \cdot \hat{J}_\lambda^c(x) \cdot \tau_{RGB} \tag{9}$$

where $J_\lambda^c(x)$ is the color corrected image and $\hat{J}_\lambda^c(x)$ is uncorrected images. ν_{RGB} is the spectral power distribution transfer function. It can be measured by spectrometer.

3. Quality assessment rule

There are many methods for underwater image enhancement; however, there are few image quality assessment rules for underwater images. We typically conducted quantitative analysis for underwater image quality assessment. This analysis includes contrast to noise ratio (CNR) [18], structural similarity (SSIM) [19], and color distance [20]. Here, we introduce a new quality assessment rule for underwater images.

The metric ΔE represents the Euclidean distance between two colors in the *Lab* color space. It is calculated from their *L*, *a*, and *b* values as follows:

$$\Delta E(A, B) = \sqrt{(L_A - L_B)^2 + (a_A - a_B)^2 + (b_A - b_B)^2} \tag{10}$$

where smaller of ΔE values indicate greater similarity between images *A* and *B*. The inverse normalized color distance is defined as:

$$\overline{\Delta E(A, B)} = 1 - \frac{\Delta E(A, B)}{E_{\max}} \tag{11}$$

where $E_{\max}$ is the maximum color distance value. The values of $\overline{\Delta E}$ are between 0 (worst) to 1 (best).

Although SSIM performs well for measuring the structural similarity of images, there is no color information for comparison. Thus, we propose a comprehensive image quality index Q_u, which is defined as follows:

$$Q_u = \alpha SSIM(A, B) + \beta \overline{\Delta E(A, B)} \tag{12}$$

where α, β are the parameters. Here, we set $\alpha = \beta = 0.5$. The proposed index combines the merits of SSIM and Euclidean distance. The proposed Q_u can evaluate the similarity of both the structures and colors of images.

4. Experiments and discussions

The performance of the proposed method was compared objectively and subjectively by using ground-truths. Both of them demonstrate the superior de-scattering and color restoration capabilities of the proposed method over the other methods. In the first experiment, we compared the proposed method to recent state-of-the-art methods. Here, we selected the best parameters for each method. The computer used was equipped with Windows 8.1 and four Intel Core i7 (2.0 GHz) CPUs with 8 GB RAM.

In the first experiment, we first captured the image of a color chart in clean water. We then added deep-sea soil to the water (from 100 mg/L to 500 mg/L). Fig. 2 shows the simulation results obtained using the different methods in the water tank with a turbidity of 200 mg/L.

As seen in Fig. 2, Chiang's [15], and Fattal's [9] methods cause color distortion. Some scatter remained in the resulting images of Nicholas's [11] and Trael's [14] methods. He's [10], and Lee's [13] methods cause inhomogeneous scatter (right-upper corner of the resulting images are too dark). While the result of Gibson's [21] method yields additional noise. Lu's method also cannot solve highly turbidity images as well. As shown in Fig. 2(k), the proposed method removes scatter and recovers colors effectively.

We also conducted quantitative analysis of the images in Fig. 2 (see Table 1). This analysis includes CNR, SSIM, inverse color distance $\overline{\Delta E}$, and Q_u. Table 1 shows the numerical results of CNR, SSIM, Color Distance and Q_u on several images. The results indicate that the proposed approach works well for scatter removal.

Fig. 2. Simulation results of different methods in a water tank. (a) Clean water image; (b) Captured image in turbidity water; (c) He's method; (d) Nicholas's method; (e) Chiang's method; (f) Fattal's method; (g) Trael's method; (h) Gibson's method; (i) Lee's method; (j) Lu's method; (k) Proposed method.

Table 1
Comparative analysis of different enhancement methods (Fig. 2).

Methods	CNR	SSIM	$\overline{\Delta E}$	Q_u
He et al. (2011) [10]	75.6850	0.5121	0.8621	0.6871
Nicholas et al. (2010) [11]	63.2756	0.5918	0.9571	0.7745
Chiang et al. (2012) [15]	56.0769	0.6014	0.9865	0.7940
Fattal et al. (2014) [9]	66.1249	0.5373	0.9727	0.7550
Trael et al. (2012) [14]	85.8001	0.6488	0.9555	0.8022
Gibson et al. (2012) [21]	45.8750	0.7077	0.9756	0.8417
Lee et al. (2014) [13]	90.1283	0.6535	0.9810	0.8173
Lu et al. (2015) [1]	85.8830	0.6982	0.8888	0.7935
Proposed	**98.0757**	**0.7110**	**0.9883**	**0.8497**

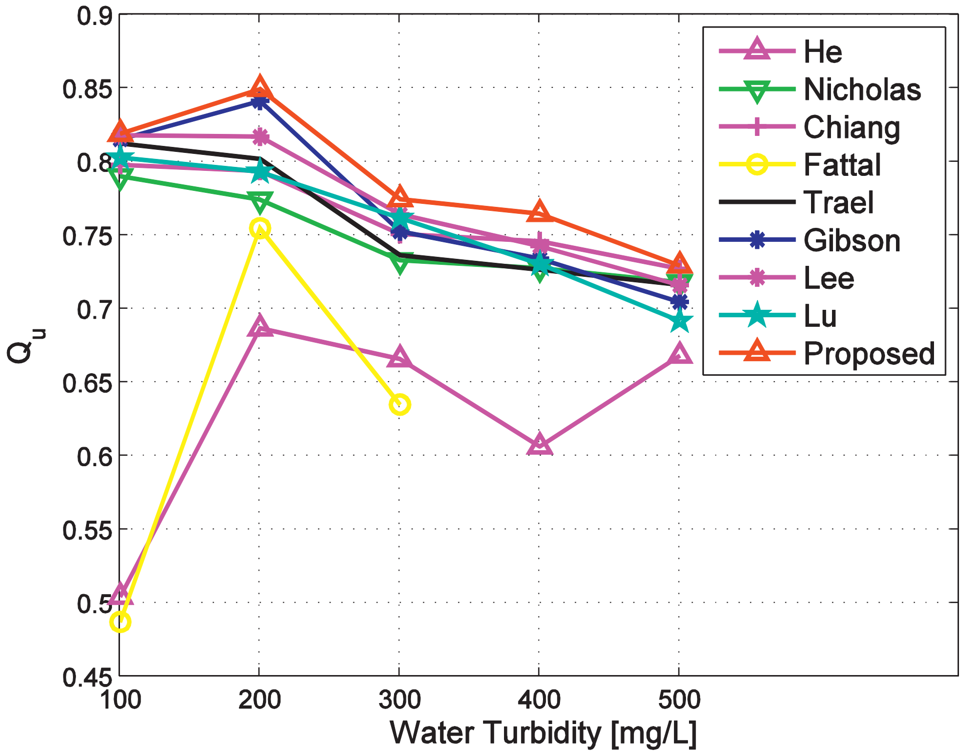

Fig. 3. Comparison results of underwater enhancement methods in different water turbidity.

We compared the Q_u of different methods in different scattered turbidity water. From Fig. 3, the average value of Q_u of the proposed method improved approximately 0.01 over the value of the best of traditional methods. Note that Fattal's method cannot remove the heavy scattered image, because the ambient light cannot be calculated by color lines.

In the second experiment, we tested different methods by real world objects. Fig. 4 shows the experimental results of the methods. Table 2 shows the numerical results of CNR, SSIM, Color Distance and Q_u on the results. The results indicate that the proposed approach works well for scatter removal. Notice that, in Table 2, because Gibson's method highly improved the contrast of the image, the CNR value of Gibson's method is better than the proposed method. However, the Gibson's result is over-enhancement, both color and structures of the result is seriously distorted ($\overline{\Delta E}$ and SSIM are lower than the proposed method).

In the third experiment, in order to certify the utility of the proposed method, we compared the classification accuracy of recently most used classification methods [22,23]. The result is shown in Fig. 4. In this experiment, we used 7330 images from the database of JAMSTEC [24]. Images are manually classified into four classes (squid, crab, shark and minerals). We chose 5330 images for training and 2000 images for classification. Our underwater image database is fine-tuned by ImageNet, which is the largest image database in the world and contains over 14 million images. From Fig. 5 we can find that the proposed method can improve all of the popular classification algorithms. The average accuracy rate is improved about 1.5%. We also can conclude that the proposed method can be well applied in convolutional neural network-based classification applications.

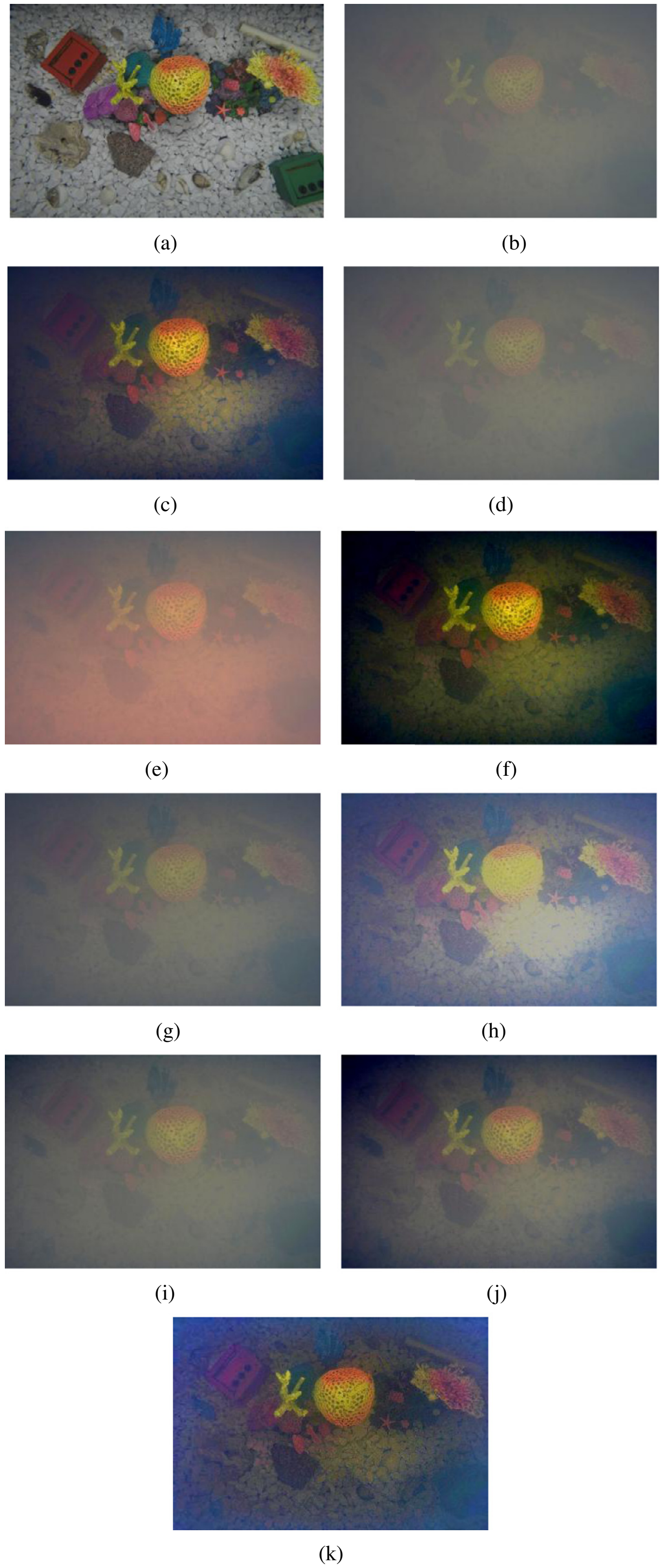

Fig. 4. Simulation results of different methods in real world. (a) Clean water image; (b) Captured image in turbidity water; (c) He's method; (d) Nicholas's method; (e) Chiang's method; (f) Fattal's method; (g) Trael's method; (h) Gibson's method; (i) Lee's method; (j) Lu's method; (k) Proposed method.

Table 2
Comparative analysis of different enhancement methods (Fig. 4).

Methods	CNR	SSIM	$\overline{\Delta E}$	Q_u
He et al. (2011) [10]	43.1713	0.5161	0.8673	0.6917
Nicholas et al. (2010) [11]	46.5932	0.4111	0.9523	0.6817
Chiang et al. (2012) [15]	50.9659	0.4266	0.9829	0.7048
Fattal et al. (2014) [9]	45.1160	0.4046	0.8200	0.6123
Trael et al. (2012) [14]	49.7132	0.4388	0.9400	0.6894
Gibson et al. (2012) [21]	**58.3641**	0.5758	0.9467	0.7613
Lee et al. (2014) [13]	51.2332	0.4399	0.9432	0.6916
Lu et al. (2015) [1]	46.9668	0.4701	0.9045	0.6873
Proposed	52.2897	**0.6027**	**0.9830**	**0.7929**

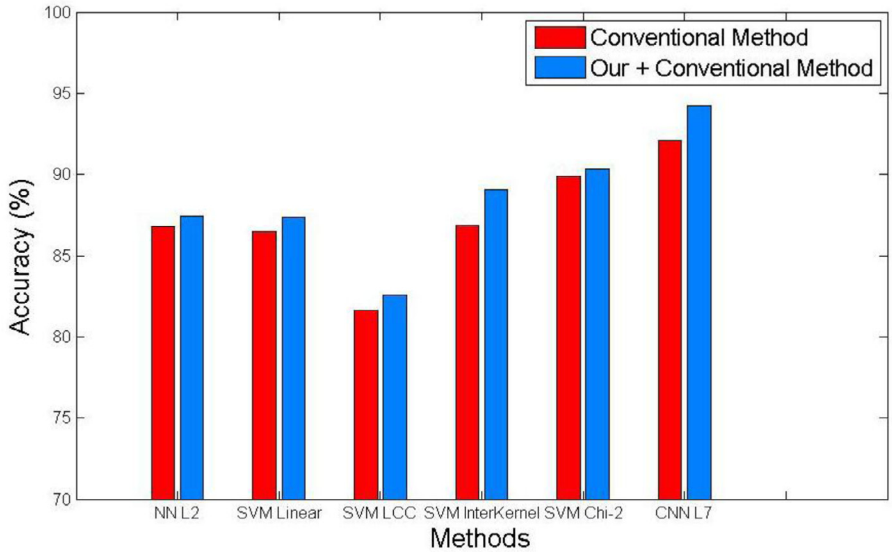

Fig. 5. Comparison results of effectiveness of the proposed method in conventional classification methods.

5. Conclusion

In this paper, we have explored and successfully implemented contrast enhancement techniques and the quality assessment method for images in high turbid water. We have proposed a joint guidance image filter to refine the coarse depth map that outperforms conventional methods. Moreover, the proposed color correction method restores the scene color correctly, because it fully considers illumination lighting and camera spectral characteristics. Furthermore, we have tested that the proposed method can be applied for preprocessing of deep learning-based classification and recognition architecture. In the future, we plan to design new deep learning-based algorithms for inhomogeneous scatter removal.

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References

[1] Lu H, Li Y, Zhang L, Serikawa S. Contrast enhancement for images in turbid water. J Opt Soc Am A 2015;32(5):886–93.
[2] Serikawa S, Lu H. Underwater image dehazing using joint trilateral filter. Comput Electric Eng 2014;40(1):41–50.
[3] Lu H, Li Y, Serikawa S. Single underwater image descattering and color correction. In: Proc. of IEEE international conference on acoustics speech and signal processing; 2015. p. 1–5.
[4] Schechner YY, Karpel N. Recovery of underwater visibility and structure by polarization analysis. IEEE J Ocean Eng 2005;30(3):570–87.
[5] Tan CS, Sluzek AL, Jiang TY. Range gated imaging system for underwater robotic vehicle. In: Proceedings of IEEE international symposium on the applications of ferroelectrics; 2007. p. 1–6.

[6] Tan C, Sluzek G, He DM. A novel application of range-gated underwater laser imaging system (ulis) in near target turbid medium. Opt Laser Eng 2005;43:995–1009.
[7] Li H, Wang X, Bai T, Jin W, Huang Y, Ding K. Speckle noise suppression of range gated underwater imaging system. Appl Opt 2009;38(18):3937–44.
[8] Bazeille S, Quidu I, Jaulin L, Malkasse JP. Automatic underwater image pre-processing. In: Proceedings of Caracterisation Du Milieu Marin (CMM '06); 2006. p. 1–8.
[9] Fattal R. Dehazing using color-lines. ACM Trans Graph 2014;34(1):1–10.
[10] He K, Sun J, Tang X. Single image haze removal using dark channel prior. IEEE Trans Pattern Anal Mach Intell 2011;33(12):2341–53.
[11] Nicholas C-B, Anush M, Eustice RM. Initial results in underwater single image dehazing. In: Proceedings of IEEE OCEANS; 2010. p. 1–8.
[12] Roser M, Dunbabin M, Geiger A. Simultaneous underwater visibility assessment, enhancement and improved stereo. In: Proceedings of IEEE ICRA; 2014. p. 3840–7.
[13] Lee Y, Gibson K, Lee Z, Nguyen T. Stereo image defogging. In: Proceedings of IEEE ICIP; 2014. p. 5427–31.
[14] Tarel J-P, Hautiere N, Caraffa L, Cord A, Halmaoui H, Gruyer D. Vision enhancement in homogeneous and heterogeneous fog. IEEE Intell Transp Syst Mag 2012;4(2):6–20.
[15] Chiang JY, Chen YC. Underwater image enhancement by wavelength compensation and dehazing. IEEE Trans Image Process 2012;21(4):1756–69.
[16] Koschmieder H. Theorie der horizontalen sichtweite. Beitrage zur Physik der freien Atmosphare; 1924.
[17] Lu H, Li Y, Serikawa S. Underwater image enhancement using guided trigonometric bilateral filter and fast automatic color correction. In: Proceedings of ICIP; 2013. p. 3412–16.
[18] Chambah M, Semani D, Renouf A, Courtellemont P, Rizzi A. Underwater color constancy: enhancement of automatic live fish recognition. In: Proceedings of SPIE, vol. 5293; 2004. p. 157–68.
[19] Wang Z, Bovik AC, Sheikh HR, Simoncelli EP. Image quality assessment: From error visibility to structural similarity. IEEE Trans Image Process 2004;13(4):600–12.
[20] Bertalmio M, Caselles V, Provenzi E, Rizzi A. Perceptual color correction through vibrational techniques. IEEE Trans Image Process 2007;16(4):1058–72.
[21] Gibson KB, Vo DT, Nguyen TQ. An investigation of dehazing effects on image and video coding. IEEE Trans Image Process 2012;21(2):662–73.
[22] Vision Lab Features Library, http://www.vlfeat.org/.
[23] Krizhevsky A, Sutskever I, Hinton G. ImageNet classification with deep convolutional neural networks. In: Proceedings of NIPS; 2012. p. 1–9.
[24] Japan Agency for Marine-Earth Science and Technology, http://www.jamstec.go.jp/.

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