An approach for underwater image enhancement based on color correction and dehazing

Yue Zhang¹, Fuchun Yang¹,² and Weikai He³

Abstract
Due to the absorption and scattering effect on light when traveling in water, underwater images exhibit serious weakening such as color deviation, low contrast, and blurry details. Traditional algorithms have certain limitations in the case of these images with varying degrees of fuzziness and color deviation. To address these problems, a new approach for single underwater image enhancement based on fusion technology was proposed in this article. First, the original image is preprocessed by the white balance algorithm and dark channel prior dehazing technologies, respectively; then two input images were obtained by color correction and contrast enhancement; and finally, the enhanced image was obtained by utilizing the multiscale fusion strategy which is based on the weighted maps constructed by combining the features of global contrast, local contrast, saliency, and exposedness. Qualitative results revealed that the proposed approach significantly removed haze, corrected color deviation, and preserved image naturalness. For quantitative results, the test with 400 underwater images showed that the proposed approach produced a lower average value of mean square error and a higher average value of peak signal-to-noise ratio than the compared method. Moreover, the enhanced results obtain the highest average value in terms of underwater image quality measures among the comparable methods, illustrating that our approach achieves superior performance on different levels of distorted and hazy images.

Keywords
Underwater image, multiscale fusion, dark channel prior, color correction, dehazing

Introduction
In recent years, underwater images have been widely used in marine energy exploration, marine environment protection, marine military, and other fields.¹ However, when light propagates in water, the water medium and water particles will absorb and scatter light, respectively, as shown in Figure 1. The absorption effect causes the color distortion of underwater images; the scattering effect causes the low contrast and blur of underwater images.² Therefore, underwater images present defects such as color deviation, low contrast, and blurry details. Such degraded

¹ Key Laboratory of High Efficiency and Clean Mechanical Manufacture of MOE, School of Mechanical Engineering, Shandong University, Jinan, China
² National Demonstration Center for Experimental Mechanical Engineering Education, Shandong University, Jinan, China
³ School of Aeronautics, Shandong Jiaotong University, Jinan, China

Corresponding author:
Fuchun Yang, School of Mechanical Engineering, Shandong University, 17923 Jingshi Road, 517 Building 8, Jinan 250061, China.
Email: yfc26@163.com or fuchunyang@sdu.edu.cn
images have a huge impact on subsequent feature extraction and object recognition. As a result, the clarity of underwater images has gradually become a research hotspot. The existing methods to improve the visibility of underwater images can be divided into image restoration methods (IRMs) and image enhancement methods (IEMs).3

The IRM is based on the underwater image degradation model, and the image is restored by inversely solving the underwater imaging model. A multitude of methods has been emerged for underwater image restoration based on dark channel prior (DCP) which was proposed initially by He4 for image dehazing. However, directly applying the DCP algorithm to underwater images does not provide a good enhancement effect. Since the dark channel value obtained based on the minimization, operation is likely to be the red channel component in the dark channel calculation process, which leads to a dark image after restoration. Recently, some improved algorithms have been proposed, such as Chiang and Chen5 combined the wavelength compensation method with the DCP algorithm to enhance the underwater image; Han and Chen6 adopted the combination of the DCP algorithm and color correction. Besides, Nascimento et al.7 proposed the underwater dark channel prior algorithm, an improved version of the DCP algorithm, which can accurately calculate the transmission map. Galdran et al.8 proposed a DCP algorithm based on the red channel (R-DCP), which is considered to be an improvement of the DCP method. In his research, colors associated with short wavelengths were restored, which help restore the lost contrast.

The abovementioned IRMs improve the quality of underwater images to a certain extent. However, the disadvantages of these physics-based methods are that they require high computing resources and consume a long execution time. Moreover, these approaches are usually only suitable for image processing in specific scenes. Thus, the scope of their practical applications is limited.

The IEM can directly improve the visibility of underwater images without knowing the underwater optical model and any physical characteristics. IEM mainly includes9: underwater image enhancement algorithm based on the histogram, underwater image enhancement algorithm based on Retinex, and underwater image enhancement algorithm based on fusion technology. Among the image enhancement algorithms based on histograms, the best algorithm is the contrast limited adaptive histogram equalization (CLAHE) method proposed by Zuiderveld,10 which has been validated to be effective for enhancing the contrast of underwater images. Besides among the underwater image enhancement algorithms based on Retinex, the best processing effect of the algorithm is the multiscale Retinex with color restoration (MSRCR) proposed by Jobson et al.,11,12 which has been verified to effectively correct the color cast of color-distorted images.

However, the main deficiency of the CLAHE and MSRCR methods is that they cannot achieve both color cast correction and contrast enhancement. To further improve the image quality, some multistep methods that fuse different algorithms are beginning to attract attention. These multistep methods based on fusion technology can achieve better results than single measure in solving main problems of underwater images such as color deviation, low contrast, nonuniform illumination, noise, and blurry details. Li et al.2 proposed a multistep fusion method based on the principles of minimum information loss and the histogram distribution prior to remove the blur of underwater images. Ancuti et al.13 proposed a fusion-based approach (FB) to enhance the visibility of underwater images and videos without concentration on specific conditions. This method obtains two input images by utilizing white balance (WB) and bilateral filtering to original image. And then Gaussian pyramid and Laplace pyramid are used to fuse different weights from the two input images. However, there is a partial reddish effect in the enhanced image processed by the FB method. Moreover, the limitation of the FB method is that it does not consider the underwater image degradation process, and it cannot achieve uniform enhancement.

Therefore, an improved approach for eliminating the local reddish effect and achieving uniform enhancement for underwater images is proposed in this article. In our fusion framework, the first input is the same as the FB method. But the second input is computed from the color-corrected version of the original image and then this input is obtained by utilizing the DCP algorithm. This input is designed to reduce degradation due to particle scattering. Then the multiple features of the two input images are extracted as the weight map of fusion. Ultimately, a high-quality image with vivid color and fine details can be acquired by fusing the two input images based on a multiscale fusion strategy. The advantage of the proposed approach is that by changing the CLAHE algorithm used in the second input of the FB method to the DCP algorithm, which takes into account the underwater image degradation
process, it can effectively eliminate the partial reddish effect introduced by the FB algorithm and has a wide range of applications.

The remainder of this article is arranged as follows. In the second section, the proposed approach is introduced in detail. In the third section, results and discussion are illustrated to demonstrate the superior performance of the proposed approach. In the fourth section, the conclusions are presented.

The proposed approach

The flow chart of the proposed approach implementation is shown in Figure 2. The proposed approach is composed of three parts, that is, design input images, calculate the weight of input images, and multiscale fusion.

First, the first input image (input 1) is obtained by utilizing the WB algorithm to correct color from the original image and the second input image (input 2) is obtained by applying the DCP algorithm to input 1 to reduce the degradation due to particle scattering. Then calculate the global contrast weight, local contrast weight, saliency weight, and exposure weight of input 1 and input 2, respectively, and normalize the four weights of the two images to obtain the normalized weights $W_1$ and $W_2$. Finally, input 1 and input 2 are fused according to normalized weights $W_1$ and $W_2$. To avoid undesirable halos in the output image caused by edge mutation, a multiscale fusion strategy is adopted.

Processing algorithm for input images

In our fusion strategy, a well-designed input image is the key to obtaining a high-quality output image. As shown in Figure 2, the first derived input image (input 1) processed by the WB algorithm is obtained to correct the color deviation of the original image, while the second (input 2) processed by the DCP dehazing algorithm is computed to enhance contrast and sharpness of input 1.

**WB algorithm of input 1.** In our experiments, input 1 was first obtained by applying a simple and efficient WB operation to an original image. The simple WB algorithm based on the shades of grey$^{14}$ with gain factor is more computationally effective. The parameter settings are the same as in reference.$^{13}$

In this algorithm, the first input image $I_{out}$ processed by color correction is estimated by original image $I$ and the value $\mu$

$$
\begin{align*}
\begin{cases}
I_{out} = \frac{I}{\mu} \\
\mu = \lambda_1 \frac{I_{ref}}{\mu_{ref}} + \lambda_2
\end{cases}
\end{align*}
$$

(1)

where $\mu = (\mu_R, \mu_G, \mu_B)$ denotes the sum of red, green, and blue (RGB) channels of the underwater image according to shades of grey. $\mu_{ref}$ is the average of the scene obtained by Minkowski norm when $p = 1$. The RGB gain factor.
\( \lambda_1 = (\lambda_R, \lambda_G, \lambda_B) \) is calculated by the maximum value of RGB channels of the underwater image. The value range of \( \lambda_2 \) is \([0, 0.5]\), and the default value of 0.2 can help to obtain more pleasing image processing results. The color-corrected image will be brighter when \( \lambda_2 \) comes closer to 0. Namely, the brightness of the color-corrected image is inversely proportional to the value of \( \lambda_2 \).

This WB method derives the first input of the fusion process from the original underwater image efficiently. However, the WB method is insufficient for the amelioration of visibility. To obtain a better-enhanced image, the second input of the fusion process is defined to enhance the contrast of the underwater image.

**DCP dehazing algorithm of input 2.** DCP algorithm is another major processing step that aims to enhance the contrast of the color-corrected image by dehazing due to volume scattering. To achieve an optimal contrast level of the image, the color-corrected image by dehazing due to volume scattering major processing step that aims to enhance the contrast of the underwater image.

**Weight calculation of input images**

To further improve the quality of underwater image restoration, this article extracts the feature information of the two input images, thereby defining the fusion weight map, that is, the global contrast weight map \( (W_G)_k \), local contrast weight map \( (W_L)_k \), saliency weight map \( (W_S)_k \), and the exposedness weight map \( (W_E)_k \). The calculation results of these weight maps are shown in Figure 2.

**Multiscale fusion technology**

To generate consistent results, their four weight maps based on the input images \( I_1 \) and \( I_2 \) are extracted, respectively. Firstly, sum the four weight maps of the input image \( I_1 \) to obtain the weight map \( \hat{W}_1 \) of \( I_1 \). Similarly, the weight map \( \hat{W}_2 \) of the input image \( I_2 \) can be obtained; then, normalize the \( \hat{W}_1 \) and \( \hat{W}_2 \) to obtain the corresponding standardized weights figure \( \bar{W}_k \), namely

\[
W_k = \frac{W_k}{\sum_{k=1}^{2} W_k}
\]

where \( k \) is the serial number of the input images, \( W_G^k \) is the global contrast weight map of the input image \( k \), \( W_L^k \) is the local contrast weight map of the input image \( k \), \( W_S^k \) is the saliency weight map of the input image \( k \), \( W_E^k \) is the exposedness weight map of the input image \( k \), and \( \hat{W}_k \) is the normalized weight map of the input image \( k \).

The enhanced image version \( J(x, y) \) is obtained by fusing the defined inputs with the weight measures at every pixel location \((x, y)\)

\[
J(x, y) = \sum_{k=1}^{K} \hat{W}_k(x, y)I_k(x, y)
\]

where \( \hat{I}_k \) symbolizes the input that is weighted by the normalized weight maps \( \hat{W}_k \). \( K \) is the index of the inputs and \( K \) is 2 in our case.

To avoid undesirable halos in the output image during single-scale fusion, this article uses multiscale fusion technology. The basis is the Laplacian pyramid originally proposed by Burt and Adelson, which has now become a mature
image fusion technology. The specific methods are shown in reference.\textsuperscript{13} Multiscale fusion calculation is as follows

\begin{equation}
J_l(x, y) = \sum_{k=1}^{K} G_l \{ \hat{W}_k(x, y) \} L_l \{ I_k(x, y) \}
\end{equation}

where $l$ denotes the number of the pyramid levels ($l = 5$), $L_l \{ I \}$ represents the Laplacian version of the input $I$, and $G_l \{ \hat{W} \}$ denotes the Gaussian version of the normalized weight map $\hat{W}$. The recovered output is obtained by adding the fusion contributions of all inputs.

**Results and discussion**

In this section, experimental results are exhibited to assess the performance of the proposed approach. Qualitative results, quantitative results, and applications are implemented, respectively. Four existing excellent underwater images processing methods are utilized to compare with the proposed approach, that is, CLAHE,\textsuperscript{10} DCP,\textsuperscript{4} MSRCR,\textsuperscript{12} and FB.\textsuperscript{13} Most of the images used for the experiments come from FB data set,\textsuperscript{13} U45 data set,\textsuperscript{19} and real-world underwater image enhancement (RUIE) data set.\textsuperscript{20} All experiments in this article were implemented in Matlab R2018b with the same CPU (Intel i7-7700 3.60 GHz), and share the same parameter settings that have been specified in corresponding equations.

**Qualitative results**

In qualitative assessment, eight original underwater images are displayed and corresponding results processed by different methods are compared with the proposed approach. The images for qualitative evaluation tests come from reference.\textsuperscript{13} The eight original images were divided into two groups. The first group has different degrees of color distortions, as shown in Figure 3 (image 1–image 4); and the second group of original images has different degrees of blur, as shown in Figure 4 (image 5–image 8).

Figure 3(a) to (f) shows the comparison of different underwater image processing methods for color distortion image. Figure 3(b) shows the results of CLAHE. Although the CLAHE algorithm can enhance the contrast of the image, the color cast of the processed image still exists. As shown in Figure 3(c), due to the lack of color compensation in DCP, there is still a color cast phenomenon in the processed image, which causes the overall color of the image to be bluish and invalid for images with various color distortions. There are many artificial adjustment parameters for MSRCR in Figure 3(d). The same set of parameters can restore color-distorted images, but when processing other color-distorted images, due to improper color compensation and gain, the image appears grayish-white and there are a lot of halos at the edges of the image. In Figure 3(e), the FB method performs well in hazy images. However, this method can introduce a local reddish effect in processed images. It can be found that underwater images enhanced by the proposed approach show neither under enhancement nor over enhancement as shown in Figure 3(f). The results of the proposed approach show a natural color in comparison with the results of the above-mentioned methods.
Figure 4(a) to (f) shows the comparison of different underwater image processing methods for a hazy image. Figure 4(b) presents the processed results of the CLAHE algorithms for different images. The contrast was improved and the images were clear for slight hazy images. However, for severe hazy images, some local areas of the images were overbright or overlark. As shown in Figure 4(c), after the DCP method processed the second group of underwater images, the image contrast was improved, but as the backscattering intensified, the algorithm gradually failed. Figure 4(d) shows the processed results of the MSRCR algorithm. The results show that the MSRCR enhancement algorithm can improve contrast and restore color. However, the MSRCR algorithms suffer from noise amplification in relatively local regions, which may lead to serious color mottles. As shown in Figure 4(e), the FB algorithm has an excellent performance in processing serious hazy images, but for slight hazy images, it may lead to the excessive enhancement and the image is overbright. In Figure 4(f), the proposed approach exhibits superior performance whether it is for images with slight backscatter or severe backscatter. For example, the backscattering of the eighth group of images (image 8) is the most serious. After processing with the proposed approach, the cylindrical outline behind the diver is visible, and the blue–green occlusion is better removed.

Quantitative results

In quantitative evaluation, the performance of the proposed approach is evaluated and corresponding results processed by different approaches are compared by performing a small sample test of 30 images from U45 data set\(^{19}\) (Figure 1A(a) in Appendix 1) and a large sample test of 400 images from RUIE data set\(^{20}\) and the Internet. The 400 images are regularly divided into four groups, that is, G1: blueish image, G2: greenish image, G3: blue-and-greenish image, and G4: random image. A nonreference underwater image quality measure (UIQM)\(^{21}\) is employed to quantify the results of the five mentioned methods in consideration of the high-quality images share universal features: genuine colors, high contrast, and fine sharpness. The default settings for UIQM are implemented in this study. A higher UIQM value indicates that the image has better performance in terms of color, contrast, and sharpness.

Table 1 exhibits UIQM values on 30 images from U45 data set.\(^{19}\) Due to limitation of pages, the processed results of the 30 images are shown in Figure 1A(b) to (f) from Appendix 1. The maximum values have been marked in bold for each row in the tables, which represents the best result among compared methods. Note that since the poor qualitative results (Figure 1A(c) in Appendix 1) after processing by the DCP method are different from the better quantitative results, it is not compared with other methods here. Table 1 reveals that 12 of the 30 tested images show the highest UIQM value by the proposed approach. Although the proposed approach does not perform best for every image among compared methods, the results of the proposed approach show the highest average UIQM value, which demonstrates that the proposed approach exceeds the compared methods in terms of the UIQM values and achieve a better performance in high contrast and fine sharpness of the processed images.
Table 1. Qualitative results in terms of UIQM.

| Method  | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 | 11 | 12 | 13 | 14 | 15 | Avg. |
|---------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|------|
| CLAHE   | 2.73 | 3.92 | 1.66 | 1.72 | 3.98 | 3.57 | 4.11 | 2.17 | 3.46 | 4.55 | 1.95 | **2.88** | 4.28 | 3.01 | **4.32** | 2.66 |
| DCP     | 1.58 | 1.02 | **3.69** | 1.34 | 2.27 | **3.32** | 0.64 | 1.93 | 2.23 | 1.76 | 0.39 | **2.26** | **4.51** | 1.73 | 2.96 |     |
| MSRCR   | 7.22 | 4.67 | 3.40 | 4.96 | 5.86 | 5.08 | 4.52 | 3.44 | 4.74 | 4.78 | 4.62 | 4.62 | 4.76 | 4.02 | 4.97 | 4.42 |
| FB      | 3.64 | 3.35 | 4.64 | 4.25 | 4.14 | 4.29 | 3.06 | 3.97 | 4.21 | 3.87 | 3.13 | 4.18 | 4.83 | 5.09 | 4.22 |     |
| Proposed approach | 3.73 | 4.24 | 0.84 | 3.12 | 3.27 | 2.24 | 3.15 | 3.16 | 4.24 | 3.07 | **5.12** | 0.55 | 4.51 | 2.31 | 2.65 | 2.11 |
| G1      | 0.04 | 0.45 | 2.16 | 2.31 | 0.84 | 0.52 | 0.50 | 1.60 | 1.46 | 0.64 | 0.42 | 0.56 | 0.39 | 1.47 | 0.81 |     |
| G2      | 3.64 | 4.49 | **2.97** | 4.49 | 3.90 | 3.46 | 3.56 | 3.58 | 4.17 | 4.01 | 3.97 | 1.96 | 4.20 | **3.21** | 3.48 | 3.23 |
| G3      | 2.41 | 1.13 | 3.06 | 2.47 | 2.18 | 2.37 | 1.85 | **3.57** | 5.38 | **2.64** | **2.92** | 1.59 | 4.43 | 2.67 | **3.07** |     |
| G4      | **3.85** | **4.62** | 2.81 | **4.69** | **4.05** | **3.64** | 3.49 | **3.84** | **4.29** | 4.06 | 4.31 | 2.10 | 3.91 | 2.99 | 3.39 | **3.32** |
| Avg.    | 2.22 | 0.99 | 3.06 | **2.49** | **2.48** | 2.17 | **2.98** | **3.12** | **5.96** | 1.93 | 1.40 | 1.78 | 4.18 | **5.91** | 2.99 |     |

Bold font represents the maximum value of underwater image quality measure (UIQM) among the four processing methods (CLAHE, MSRCR, FB, Proposed approach).

Table 2. Average values of UIQM for 400 underwater images.

| Group | CLAHE | DCP | MSRCR | FB | Proposed approach |
|-------|-------|-----|-------|----|--------------------|
| G1    | 3.54  | 4.28 | 1.50  | 2.83 | 2.97               |
| G2    | 2.10  | 4.96 | 2.51  | 3.49 | 3.60               |
| G3    | 2.28  | 4.67 | 2.01  | 2.97 | 3.08               |
| G4    | 2.93  | 4.60 | 2.11  | 3.01 | 3.29               |
| Avg.  | 2.71  | 4.63 | 2.04  | 3.08 | 3.23               |

CLAHE: contrast limited adaptive histogram equalization; DCP: dark channel prior; MSRCR: multiscale Retinex with color restoration; FB: fusion-based approach; UIQM: underwater image quality measure.

Table 3. MSE, PSNR, and processing time values of 400 underwater images.

| Method | MSE   | PSNR  | Processing time (s) |
|--------|-------|-------|--------------------|
| FB     | 2558.52 | 15.34 | 0.20 0.67 2.57  |
| Proposed approach | 2147.03 | 15.86 | 0.19 0.70 2.62 |

MSE: mean square error; FB: fusion-based approach; PSNR: peak signal-to-noise ratio

Applications

The goal of image enhancement is to provide high-quality images for further applications, such as feature matching.
edge detection, and target recognition. Aiming to verify the utility of the proposed approach, an application test is carried out. The original implementation of speeded-up robust features (SURF) is applied exactly in the same way in six cases, namely the original image, CLAHE, DCP, MSRCR, FB, and the proposed approach.

Figure 5 presents the number of correct SURF feature points matching. The amounts of the feature point matching are 2 for original images, 15 for images processed by CLAHE, 9 for images processed by DCP, 5 for images processed by MSRCR, 1 for images processed by FB, and 21 for images processed by the proposed approach, respectively. The results demonstrate that the proposed approach significantly increases the number of matched pairs of keypoints by enhancing the global contrast and the local sharpness in underwater images.

To further verify the utility of the proposed method, the comparative experiments before and after image processing were performed. We employed the SURF operator to calculate feature points for processed image and corresponding affine transformation and matched the feature points for the pair of images. Table 4 exhibits the number of correct SURF feature points matching on 30 images from U45 data set. The average amounts of correct SURF feature points matching on images processed by our methods are far larger than that of the original images. The high scores presented by the proposed approach can be attributed to well-pleasing color and clear visibility of enhanced images. Therefore, the application tests further illustrate the effectiveness and practicality of our proposed approach in feature extraction.

### Conclusion

In this article, an improved approach for eliminating the local reddish effect and reducing image noise is proposed. The approach first applies the WB and DCP dehazing technologies to the original image, respectively; then two input images were obtained by color correction and contrast enhancement; finally, the restored image was obtained by...
utilizing the multiscale fusion strategy which is based on the weighted maps constructed by combining the features of global contrast, local contrast, saliency, and exposedness.

The results show that the proposed approach has the characteristics of vivid color, improved contrast, and natural appearance. The qualitative results show that the proposed approach has achieved the goal of correcting color cast and removing haze of the underwater image. The quantitative results demonstrate that the proposed approach also maintains an excellent performance on different levels of distorted and hazy images by achieving the highest average UIQM value compared with that of the four advanced methods. Moreover, the lower average MSE values and higher average PSNR values indicate that the proposed approach introduces less noise and retains more valuable image information in comparison to that of the FB method. Consequently, experimental results prove the effectiveness of the proposed approach in underwater image enhancement.

Declaration of conflicting interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding
The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study was supported by the Scientific and Technological Development Project of Shandong Province (2019GGX104013 and No. 2019GGX101063) and a Project of Shandong Province Higher Educational Youth Innovation Science and Technology Program (2020KJN002).

ORCID iD
Yue Zhang https://orcid.org/0000-0003-2418-2147

Reference
1. Lu H, Li Y, Zhang Y, et al. Underwater optical image processing: a comprehensive review. Mobile Net Appl 2017; 22: 1204–1211.
2. Li C, Member S, Guo J, et al. Underwater image enhancement by dehazing with minimum information loss and histogram distribution prior. IEEE Transact Image Process 2016; 25(12): 5664–5677.
3. Schettini R and Corchs S. Underwater image processing: state of the art of restoration and image enhancement methods. EURASIP J Adv Sign Process 2010; 2010: 746052.
4. He K. Single image haze removal using dark channel prior. IEEE Trans Pattern Anal Mach Intell 2009; 33: 1956–1963.
5. Chiang JY and Chen YC. Underwater image enhancement by wavelength compensation and dehazing. IEEE Transact Image Process 2012; 21(4): 1756–1769.
6. Han M and Chen C. Enhancing underwater image by dark channel prior and color correction. In: 6th international conference on information science and technology. Piscataway, USA, 2016, pp. 505–510.
7. Nascimento E, Moraes F, Botelho S, et al. Transmission estimation in underwater single images. IEEE International Conference on Computer Vision Workshops 2013; 2(1): 825–830.
8. Galdran A, Pardo D, Picón A, et al. Automatic red-channel underwater image restoration. J Vision Commun Image Represent Elsevier Inc 2015; 26: 132–145.
9. Dai C, Lin M, Wu X, et al. Single underwater image restoration by decomposing curves of attenuating color. Opt Laser Technol 2020; 123: 105947.
10. Zuiderveld K. Contrast limited adaptive histogram equalization [Internet]. Graphics gems IV. Cambridge, MA: Academic Press Inc., 1994, pp. 474–485.
11. Jobson DJ, Rahman Z, and Woodell GA. Properties and performance of a center/surround retinex. IEEE Transact Image Process 1997; 6(3): 451–462.
12. Jobson DJ, Rahman Z, and Woodell GA. A multiscale retinex for bridging the gap between color images and the human observation of scenes. IEEE Transact Image Process 1997; 6(7): 965–976.
13. Ancuti C, Ancuti CO, Haber T, et al. Enhancing underwater images and videos by fusion. In: 2012 IEEE conference on computer vision and pattern recognition, Providence, RI, USA, 16–21 June 2012, 2012, pp. 81–88. IEEE.
14. Finlayson GD and Trezzi E. Shades of gray and color constancy. In: Color and imaging conference, Scottsdale, Arizona, USA, 2004; 2004(1): 37–41.
15. Dubok P, Hyungjo P, David KH, et al. Single image dehazing with image entropy and information fidelity. In: ICIP, Paris, France, 27–30 October 2014, pp. 4037–4041. IEEE.
16. Mertens T, Kautz J, and Reeth FV. Exposure fusion: A simple and practical alternative to high dynamic range photography. Comp Graph Forum 2009; 28(1): 161–171.
17. Achanta R, Hemami S, Estrada F, et al. Frequency-tuned salient region detection. In: 2009 IEEE conference on computer vision and pattern recognition, Miami, FL, USA, 20–25 June 2009, pp. 1597–1604. IEEE.
18. Burt PJ and Adelson EH. The Laplacian pyramid as a compact image code. IEEE Transact Comm Citation 1983; 31: 532–540.
19. Li H, Li J, and Wang W. A fusion adversarial underwater image enhancement network with a public test dataset. 2019, pp. 1–8.
20. Liu R, Fan X, Member S, et al. Real-world underwater enhancement: challenges, benchmarks, and solutions. 2019, pp. 1–14.
21. Panetta K, Gao C, and Agaian S. Human-visual-system-inspired underwater image quality measures. IEEE J Ocean Eng 2016; 41: 541–551.
22. Bay H, Tuytelaars T, and Gool L.V. SURF: speeded up robust features. In: Leonardis A, Bischof H, and Pinz A (eds) Computer vision—ECCV 2006. ECCV 2006. Lecture notes in computer science. vol. 3951. Berlin, Heidelberg: Springer, 2006, pp. 404–417.
Appendix 1

Figure 1A. Comparison of the results of 30 images processed by different methods. The number of each image is “image 1”–“image 30”, respectively: (a) original images, (b) CLAHE, (c) DCP, (d) MSRCR, (e) FB, and (f) the proposed approach. CLAHE: contrast limited adaptive histogram equalization; DCP: dark channel prior; MSRCR: multiscale Retinex with color restoration; FB: fusion-based approach.