Computers and Electrical Engineering 70 (2018) 904–913

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

An imaging-inspired no-reference underwater color image quality assessment metric[☆]

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ARTICLE INFO

Article history:
Received 10 August 2017
Revised 23 November 2017
Accepted 2 December 2017
Available online 15 December 2017

Keywords:
No-reference image quality assessment
Underwater imaging
Underwater image
Underwater color image quality

ABSTRACT

Underwater color image quality assessment (IQA) plays an important role in analysis and applications of underwater imaging as well as image processing algorithms. This paper presents a new metric inspired by the imaging analysis on underwater absorption and scattering characteristics, dubbed the CCF. This metric is feature-weighted with a combination of colorfulness index, contrast index and fog density index, which can quantify the color loss caused by absorption, the blurring caused by forward scattering and the foggy caused by backward scattering, respectively. Then multiple linear regression is used to calculate three weighted coefficients. A new underwater image database is built to illustrate the performance of the proposed metric. Experimental results show a strong correlation between the proposed metric and mean opinion score (MOS). The proposed CCF metric outperforms many of the leading atmospheric IQA metrics, and it can effectively assess the performance of underwater image enhancement and image restoration methods.

1. Introduction

Currently, the most widely used method for assessing color image quality is the subjective mean opinion score (MOS). However, subjective assessments are usually restricted by time and many other resources. Therefore, objective image quality assessments attract more attention from researchers. With the consideration of whether there is a reference image, the objective image quality assessment (IQA) methods can be classified into three categories: full-reference (FR) metrics, reduced-reference (RR) metrics and no-reference (NR) metrics. Because of the fact that most of the images taken from underwater environment do not have their reference images, hence, no-reference (NR) metrics would be the best choice for assessing the quality of underwater color images.

In underwater environment, various kinds of distortions on the image can be caused due to the absorption, scattering and other underwater imaging characteristics. Color loss is a notable characteristic of underwater images because the absorption coefficients of light waves in the water are different from each other. Besides, forward scattering can cause point spread phenomenon, which affects the details of the image and blurs the edges information of the image, and finally leads to underwater image blurring. Moreover, backward scattering makes the gray range of underwater image smaller, and the contrast between pixels reduces, resulting in a special fog superimposed on the image, thus seems like a foggy.

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Associate Editor Dr. Huimin Lu.

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https://doi.org/10.1016/j.compeleceng.2017.12.006

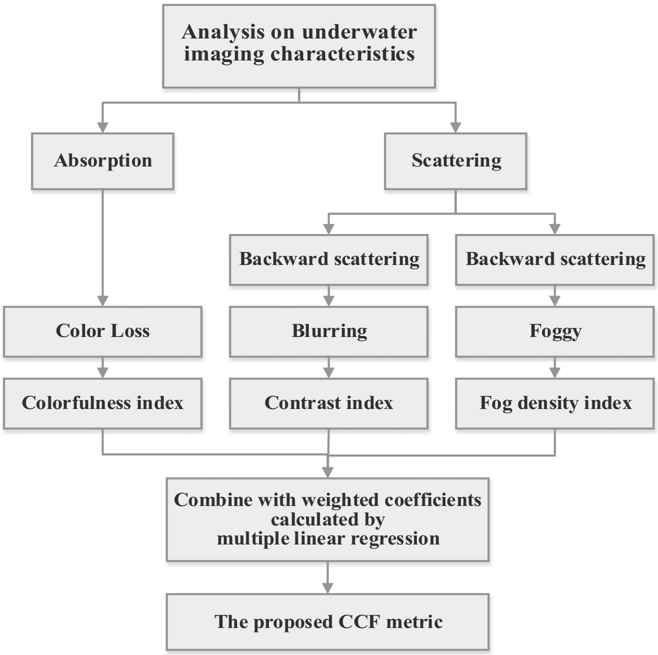


Fig. 1. The flow chart of the proposed CCF metric.

Therefore, it is hard to use atmospheric IQA metrics to effectively assess underwater image quality as a result of different imaging principles. Meanwhile, as Lu et al. listed in [1], there are only a few metrics proposed for underwater image quality assessment.

In this paper, a new imaging-inspired underwater color image quality assessment metric CCF is proposed, which combines colorfulness index, contrast index and fog density index to predict the color loss caused by absorption, the blurring caused by forward scattering and the foggy caused by backward scattering, respectively. Finally, we perform these three indices with multiple linear regression on an underwater image database of our lab to calculate weighted coefficients.

In order to verify the performance of the proposed CCF metric, a new underwater image database is built. Meanwhile, we use another group of underwater images to validate whether the proposed metric can accurately measure the performance of underwater image enhancement methods as well as underwater image restoration methods.

Finally, based on the comprehensive analysis of all the experimental results, the contributions of the proposed CCF metric are summarized as follows:

a. It is an imaging-inspired NR-IQA with the full consideration of underwater imaging characteristics.
b. With colorfulness, contrast and fog density, it can evaluate the quality of underwater color images which suffer from different degrees of distortion and different levels of underwater visibility.
c. It outperforms many of the leading atmospheric IQA metrics and it can effectively assess the performance of image restoration methods and image enhancement methods.

This paper is organized as follows. The proposed new underwater color image quality assessment metric is presented in Section 2. Experiments are reported in Section 3. A conclusion is given in Section 4.

2. Underwater color image quality assessment metric

In this paper, the proposed underwater image quality assessment metric is based on a polling method which is to combine colorfulness feature with contrast feature and fog density feature.

The flow chart of the proposed CCF metric is shown in Fig. 1. This metric comprises five steps: (a) Calculate the colorfulness index. (b) Calculate the contrast index. (c) Calculate the fog density index. (d) Calculate the weighted coefficients of three indices. (f) Obtain the overall underwater color image quality assessment metric CCF.

2.1. Colorfulness index

Underwater images suffer from serious color distortion because light attenuates a lot through water. Fu [2] and Panetta et al. [3] demonstrate that we can use a combination of image statistics to represent colorfulness. During the process of

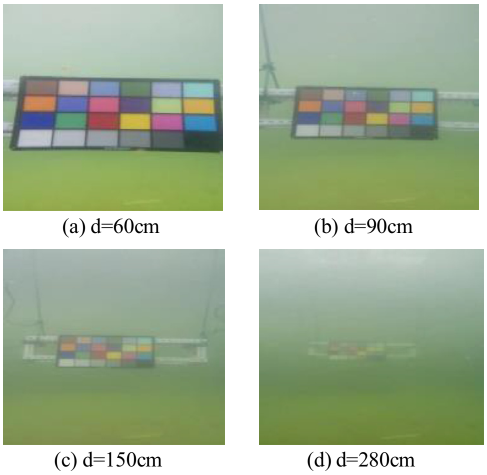


Fig. 2. Underwater images of colorchecker.

Table 1
Colorfulness index values of colorchecker images in Fig. 2 on different color models.

	a	b	c	d
Lab	0.7369	0.6548	0.5719	0.5866
YIQ	0.5290	0.5280	0.5310	0.5345
HSI	0.4119	0.4273	0.4530	0.4460
l$\alpha\beta$	**0.8937**	**0.7231**	**0.4336**	**0.2525**

calculating colorfulness index, as mentioned in [4], three channels R(i, j), G(i, j), and B(i, j) of a RGB underwater image are converted into logarithmic signals based on logarithmic-scale space. The conversion formulas are shown as follows,

$$\mathrm{R}(\mathrm{i},\mathrm{j}) = \log\mathrm{R}(\mathrm{i},\mathrm{j}) - \mu_{\mathrm{R}} \tag{1}$$

$$\mathrm{G}(\mathrm{i},\mathrm{j}) = \log\mathrm{G}(\mathrm{i},\mathrm{j}) - \mu_{\mathrm{G}} \tag{2}$$

$$\mathrm{B}(\mathrm{i},\mathrm{j}) = \log\mathrm{B}(\mathrm{i},\mathrm{j}) - \mu_{\mathrm{B}} \tag{3}$$

where μ_{R}, μ_{G}, μ_{B} are the mean values of logR(i, j), logG(i, j), and logB(i, j), respectively.

Then we use l$\alpha\beta$ color model proposed by Ruderman et al. [5] to evaluate the color loss of an underwater color image. The l$\alpha\beta$ color model is based on human vision system, and it will not be affected by environment or device. The α and β are achieved as follows,

$$\alpha = \mathrm{R} - \mathrm{G} \tag{4}$$

$$\beta = 0.5 \times (\mathrm{R} + \mathrm{G}) - \mathrm{B} \tag{5}$$

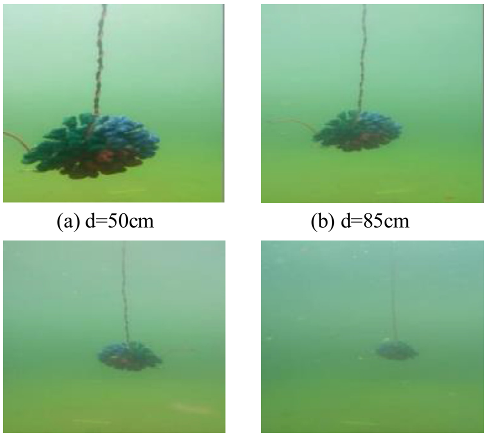
Therefore, the colorfulness index of an underwater color image is calculated as followed,

$$\mathrm{Colorfulness} = \frac{\sqrt{\sigma_\alpha^2 + \sigma_\beta^2} + 0.3\sqrt{\mu_\alpha^2 + \mu_\beta^2}}{85.59} \tag{6}$$

where σ_α^2, σ_β^2, μ_α^2, μ_β^2 represent the variance and mean value of the two color axes, and the value 85.59 is referred from Ref. [2].

An experiment is implemented to prove that, the proposed colorfulness index using l$\alpha\beta$ color model achieves better results to evaluate the quality of underwater images than the Lab color model, YIQ color model and HSI color model. Figs. 2 and 3 show some underwater images of colorchecker and colorful coral. The capture distances are shown below each of the image. Tables 1 and 2 give the two groups of colorfulness index values based on different color models, respectively.

From Tables 1 and 2, it can be seen that as the distance increases, the underwater image quality degrades, so the value of colorfulness index should decrease. Therefore, compared with three other color models, the proposed colorfulness index can effectively measure the color loss of underwater color images by using l$\alpha\beta$ color model.



(a) d=50cm (b) d=85cm (c) d=120cm (d) d=175cm

Fig. 3. Underwater images of colorful coral.

Table 2
Colorfulness index values of underwater colorful coral images in Fig. 3 on different color models.

	a	b	c	d
Lab	0.6245	0.5922	0.5832	0.4215
YIQ	0.7141	0.7101	0.7090	0.7086
HSI	0.5632	0.5751	0.4602	0.4566
l$\alpha\beta$	**0.6812**	**0.5682**	**0.4041**	**0.3161**

2.2. Contrast index

Underwater color images are seriously degraded from blurring because of the scattering effect of water medium, especially forward scattering. Therefore, the blurring assessment is also an essential part of underwater color image quality assessment. In this paper, we use the sum of contrast index values from edge image blocks to represent the blurring of an underwater color image.

First of all, as suggested in Ref. [6], the underwater color image is divided into 64 * 64 blocks. Next, we use the Sobel operator edge detection to judge if the block is an edge block or a flat block. It is worth noticing that the method we use to find out edge blocks is to judge whether the number of edge pixels is larger than 0.2% of the total pixels in one block. Then, the blurring index of an underwater color image is the sum of RMS contrast values of all the edge blocks, and the formula for calculating RMS contrast index is shown as follows,

$$\mathrm{Contrast} = \sum_{i=1}^{T} \sqrt{\frac{1}{MN}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(I_{ij}-\bar{I})^2} \tag{7}$$

where intensity I_{ij} is the i, j-th element of the two-dimensional image with size M by N, T indicates the number of edge blocks, and $\bar{I}$ is the average intensity of all pixel values in the image.

2.3. Fog density index

Lark Kwon Choi proposed a model [7] to predict the degree of a foggy scene from a natural image. This model calculates the deviations from statistical regularities obtained in fog-free images and foggy images. Finally, twelve features, which are extracted from nature scene statistical (NSS) model, such as offset brightness and entropy loss, are used to predict the fog density of an image.

The mean vector ν and covariance matrix Σ are obtained by fitting all the statistical features extracted from the test image into multivariate Gaussian (MVG) model, which is calculated as follows,

$$\mathrm{MVG}(f) = \frac{1}{(2\pi)^{\frac{d}{2}}|\Sigma|^{\frac{1}{2}}}\exp\left[-\frac{1}{2}(f-v)^t\Sigma^{-1}(f-v)\right] \tag{8}$$

where f is a d-dimensional feature vector representing statistical features and t indicates transposition.

Then the foggy level D_f can be calculated by measuring the Mahalanobis distance between the MVG model of the test image and the MVG model of 500 natural fog-free images. Similarly, the fog-free level D_{ff} can be calculated by measuring

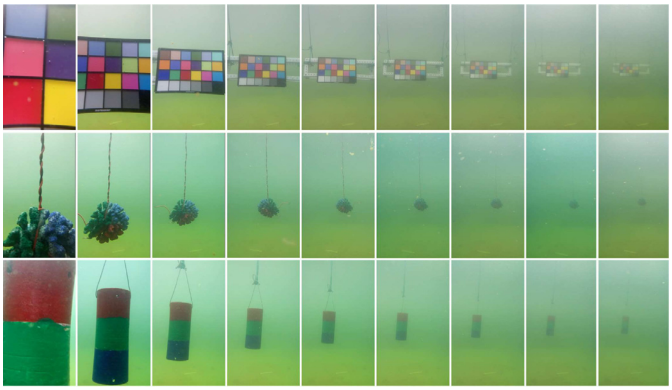


Fig. 4. Some images from our underwater image database to calculate the weighted coefficients.

the Mahalanobis distance between the MVG model of the test image and the MVG model of 500 foggy images. For example, the D_f can be calculated as follows,

$$D_f(v_1, v_2, \Sigma_1, \Sigma_2) = \sqrt{(v_1 - v_2)^t \left(\frac{\Sigma_1 + \Sigma_2}{2} \right)^{-1} (v_1 - v_2)} \tag{9}$$

where v_1, v_2 and Σ_1, Σ_2 represent the mean vectors and covariance matrices of the two MVG models, respectively.

Finally, the fog density index of an image can be calculated as follows,

$$D = \frac{D_r}{D_{ff} + 1} \tag{10}$$

2.4. Weighted coefficients calculation

In this part, as mentioned in Refs. [8–10], we need to set the value of the three weighted coefficients. We can transform this problem into a multivariable linear regression (MLR) model. The quality of each underwater image can be assumed as one dependent variable Y, while the value of three indices can be assumed as three independent variables X_1, X_2 and X_3 because they are mutually independent. The formula is shown as follows,

$$Y_i = \omega_1 X_{1_i} + \omega_2 X_{2_i} + \omega_3 X_{3_i} \ (i = 1, 2, \ldots, n) \tag{11}$$

where ω_1, ω_2 and ω_3 are three regression coefficients, i indicates the label of underwater image and n is the number of underwater images.

Meanwhile, in the existing underwater image database which is built by our laboratory, the subjective MOS Y of each underwater image has been set, while the value of color index X_1, contrast index X_2 and fog density index X_3 can be calculated respectively, which implies that the dependent variable and three independent variables are known. Then we can use MLR to obtain the three regression coefficients, which are exactly the three weighted coefficients of colorfulness index, contrast index and fog density index, respectively.

Fig. 4 shows some images from this underwater image database.

The three weighted coefficients are calculated by MLR as follows,

$$\omega_1 = 0.17593 \quad \omega_2 = 0.61759 \quad \omega_3 = 0.33988 \tag{12}$$

2.5. CCF metric

Finally, we combine colorfulness index, contrast index and fog density index with three weighted coefficients. Then, the proposed CCF metric is calculated as follows,

$$\mathrm{CCF} = \omega_1 \times \ \mathrm{Colorfulness} + \omega_2 \times \ \mathrm{Contrast} + \omega_3 \times \ \mathrm{Fogdensity} \tag{13}$$

3. Experiments

3.1. Underwater image database

In this section, we built a new underwater image database, which includes 87 underwater images taken in a water tank (length: 4.40 m, width: 2.36 m, depth: 1.95 m) by using a colorchecker (length: 38 cm, width: 26 cm) to be the observing target. The water tank and the colorchecker are shown in Fig. 5. Ten groups of underwater images were collected with

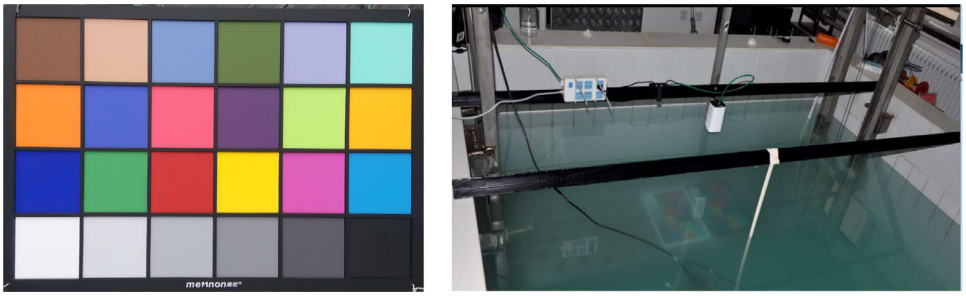


Fig. 5. (a) The colorchecker (left). (b) The water tank (right).

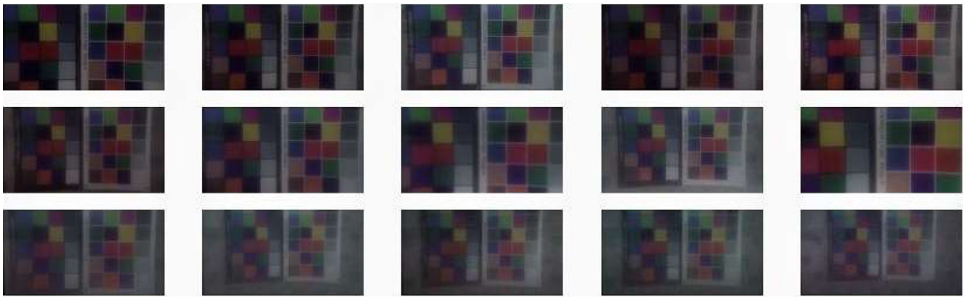


Fig. 6. Some images of colorchecker from our underwater image database.

Table 3
Performance evaluation with different IQA metrics on our underwater image database.

	PLCC	SROCC	RMSE	MAE
CBPD [11]	0.6103	0.7719	25.1131	21.7471
SSEQ [12]	0.7615	0.6654	16.2766	12.4783
BRISQUE [13]	0.3076	0.3371	23.9073	20.9107
NIQE [14]	0.3809	0.3046	26.2199	19.8259
ILNIQE [4]	0.7033	0.6507	17.8524	13.9872
CCF	**0.9053**	**0.8469**	**11.0135**	**9.2869**

increasing capture distance by moving the target away from the camera, and with increasing turbidity by adding aluminium hydroxide to water every 30 min.

After acquiring all the underwater images, 20 graduate students were invited to assess the perceptual quality for each underwater image by giving them a score from 1 to 5, which mean “Bad”, “Poor”, “Fair”, “Good” and “Excellent” of the image quality, respectively. Then the MOS of an underwater image is obtained by calculating the mean value of all the scores. This database can help to validate the performance of IQA metrics. Fig. 6 shows some images from this new underwater image database.

3.2. Experimental results and discussions

The experiment is divided into two parts. The first part is designed to obtain the accuracy of the proposed CCF metric on the new underwater image database mentioned above. The second part is designed to verify whether the proposed CCF metric could effectively evaluate the performance of underwater image restoration methods and enhancement methods.

In the first part of experiment, as shown in Table 3, five existing natural NR-IQA metrics are selected as a comparison. The performances of these metrics are described by four indicators, which are Pearson linear correlation coefficient (PLCC), Spearman rank-order correlation coefficient (SROCC), root mean squared error (RMSE) and mean absolute error (MAE). The upper bound for PLCC and SROCC is 1, and the higher the PLCC and SROCC are, the better the metrics are. While for the RMSE and MAE, the lower the indicators are, the better the metrics are.

From Table 3, it can be seen that, the PLCC value and SROCC value of the proposed CCF metric are larger than the other five methods. Meanwhile, the RMSE value and MAE value of the proposed CCF metric are smaller than the other five methods. Therefore, these results could illustrate the superior performance of the proposed CCF metric, and it performs better than many other existing atmospheric IQA metrics.

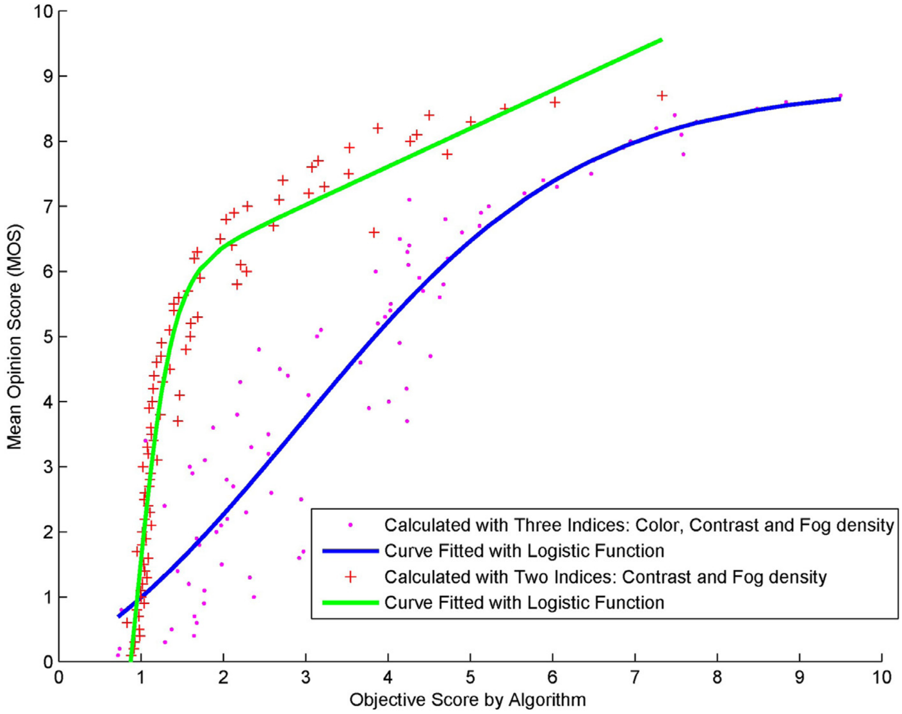


Fig. 7. The distribution of scatter plots and their fitting curves for metrics with three indices and two indices.

Table 4
Performance evaluation with different combinations of indices on our underwater image database.

	PLCC	SROCC	RMSE	MAE
Colorfulness & Contrast	0.8412	0.8204	13.9475	13.1020
Colorfulness & Fogdensity	0.7909	0.8133	15.2305	14.3218
Contrast & Fogdensity	0.8560	0.8220	13.3543	11.8301
CCF	**0.9053**	**0.8469**	**11.0135**	**9.2869**

A supplementary experiment is implemented in order to illustrate that the proposed CCF metric has better performance when all of the three indices are combined together to assess image quality rather than only considering two of them randomly, for example, contrast index and fog density index. Firstly, the weighted coefficients of contrast index and fog density index are calculated by MLR. Then the underwater image quality can be calculated by two indices as follows,

$$\text{Quality Score} = \omega_4 \times \text{Contrast} + \omega_5 \times \text{Fogdensity} \tag{14}$$

where $\omega_4 = 0.44807$, $\omega_5 = 0.36083$.

As shown in Fig. 7, the scatter plots of all the underwater images in our database are mapped by the objective and subjective scores fitting with a logistic function. It is clear that the blue curve which is connected with three indices appears to be closer to the straight line Y = X than the green curve, which indicates that there is a stronger correlation between the proposed CCF metric and the MOS. Meanwhile, the performance of three different combinations of two indices can also be evaluated by four indicators mentioned above. As shown in Table 4, all of the results demonstrate the necessity of three indices proposed in this paper.

In the second part of experiment, some underwater image enhancement results are shown in Fig. 8, (a) shows some original underwater images, (b) shows the images enhanced by UCM [15] method, and (c) shows the images enhanced by CLAHE [16] method. The experimental results of them are shown in Table 5. It can be seen that all of the CCF metrics calculated on original images become larger after image enhancement, which indicates that the proposed CCF metric could effectively judge the performance of image enhancement methods. Similarly, the proposed CCF metric can also be used to evaluate the performance of underwater image restoration methods.

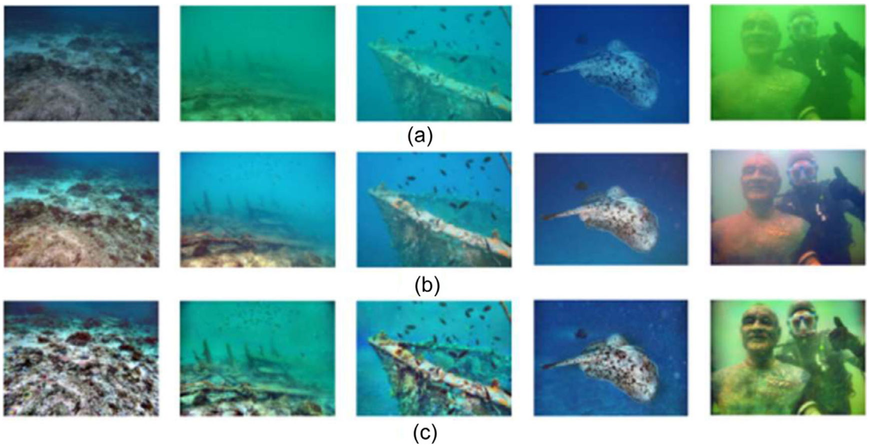


Fig. 8. Underwater image enhancement results.

Table 5
Performance evaluation by proposed CCF metric about image enhancement methods.

	Image 1	Image 2	Image 3	Image 4	Image 5
Original Image	4.3725	5.0884	5.3016	3.9135	1.9651
UCM	5.4575	6.6324	6.3177	4.5541	4.5816
CLAHE	6.7205	7.9690	6.9701	4.3264	4.4785

4. Conclusion

In this paper, a new imaging-inspired no-reference IQA metric was proposed to measure underwater color image quality, dubbed the CCF. This metric is a feature-weighted combination of colorfulness index, contrast index and fog density index, which are used to predict the color loss caused by absorption, the blurring caused by forward scattering and the foggy caused by backward scattering. Two parts of experiments was carried out in this work. Experimental results show that the proposed metric CCF is able to predict the quality of underwater color images which were taken from different scenes and suffered from different degrees of distortion. The new metric performs better than many other existing atmospheric IQA metrics. Moreover, the proposed CCF metric can effectively evaluate the performance of image restoration methods and image enhancement methods.

Funding

This work was supported by the National Natural Science Foundation of China [grant numbers 41776113, 61771440]; the Qingdao Municipal Science and Technology Program [grant number 17-1-1-5-jch]; and the International S&T Cooperation Program of China [grant number 2012DFG22080].

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