An Underwater Color Image Quality Evaluation Metric

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***Abstract*— Quality evaluation of underwater images is a key goal of underwater video image retrieval and intelligent processing. To date, no metric has been proposed for underwater color image quality evaluation (UCIQE). The special absorption and scattering characteristics of the water medium do not allow direct application of natural color image quality metrics especially to different underwater environments. In this paper, subjective testing for underwater image quality has been organized. The statistical distribution of the underwater image pixels in the CIELab color space related to subjective evaluation indicates the sharpness and colorful factors correlate well with subjective image quality perception. Based on these, a new UCIQE metric, which is a linear combination of chroma, saturation, and contrast, is proposed to quantify the non-uniform color cast, blurring, and low-contrast that characterize underwater engineering and monitoring images. Experiments are conducted to illustrate the performance of the proposed UCIQE metric and its capability to measure the underwater image enhancement results. They show that the proposed metric has comparable performance to the leading natural color image quality metrics and the underwater grayscale image quality metrics available in the literature, and can predict with higher accuracy the relative amount of degradation with similar image content in underwater environments. Importantly, UCIQE is a simple and fast solution for real-time underwater video processing. The effectiveness of the presented measure is also demonstrated by subjective evaluation. The results show better correlation between the UCIQE and the subjective mean opinion score.**

***Index Terms*— Colour image, CIELab, no reference (NR) image quality evaluation, underwater image.**

I. Introduction

Establishing an effective and objective quality evaluation metric for images taken in underwater environments is a critical component in underwater image processing, classification and analysis [1]–[4], especially in underwater engineering and monitoring tasks. Subjective quality metrics are considered to give the most reliable results, but are expensive, time-consuming and impractical for real-time implementation and system integration. Objective Image Quality Evaluation (IQE) methods can be classified by whether a reference image, representing the original signal, exists. When such a reference is accessible, the evaluation is known as full-reference (FR) image quality assessment. Another IQE approach is the reduced-reference (RR) quality assessment, which assumes that partial information about the reference signal is available and used for quality evaluation. For underwater images where a reference image cannot be obtained, a no-reference, or blind, objective image quality metric is needed to measure the perceptual image quality. Such a measure should be capable of identifying the differences in distortied images; correlate with human perception; reliably benchmark image processing algorithms and assist in selecting the optimal operating parameters; have low computational complexity, and be implementable in real time.

Many studies have been made in the area of underwater colour image processing in recent years [1], [5], [6]. However most of the restoration and enhancement methods are for underwater photography. Also, there is no colour image quality metric that can be applied to judge and optimize these algorithms. While quality metrics for atmospheric colour images are available [7]–[18], they are not applicable to underwater images. Due to poor lighting conditions and the effect of serious absorption and scattering in turbid water, underwater monitoring and survey images suffer from the problems of limited visibility, low contrast, non-uniform illumination, blurring, non-uniform colour cast and complex noise. The extent of these degradations depends on the inside and outside optical properties of the water body, imaging system, artificial lighting, turbulence and other complex factors. The distinction between varying degrees of underwater image colour enhancements and restorations is often ambiguous. Besides, different underwater tasks target different image features. Existing natural colour image quality metrics cannot be applied to the underwater images effectively.

This work is aimed at a simple objective metric for measuring image quality of real-time underwater monitoring and survey colour images. An underwater colour image quality evaluation (UICQE) metric based on CIELab chroma, contrast and saturation measure is introduced. To get a best fit combination, a psychophysical test was set up, where observers were asked to rate the colour image quality by choosing between 5 levels. The performance of the proposed metric was

Manuscript received August 17, 2014; revised February 10, 2015 and July 20, 2015; accepted October 5, 2015. Date of publication October 19, 2015; date of current version November 12, 2015. This work was supported in part by the Priority Academic Program Development of Jiangsu Higher Education Institutions, in part by the Natural Science Foundation of the Jiangsu Higher Education Institutions of China under Grant 12KJB170001, and in part by the Natural Science Fund through the Foundation Research Project of Jiangsu Province under Grant BK20140445. The associate editor coordinating the review of this manuscript and approving it for publication was Dr. Ivana Tosic.

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Digital Object Identifier 10.1109/TIP.2015.2491020

gauged by tank testing and on real underwater images, and its correlation with human subjective judgements of quality. It is demonstrated that the proposed method performs better than three other commonly used natural colour image metrics when applied to underwater environments. The contributions of the paper are summarized as follows:

(i) it organizes the subjective test for underwater image and introduces the first underwater colour image quality evaluation metric

(ii) with the three quality measures namely chroma, contrast and saturation, it can measure more accurately the relative amount of degradation with similar content in underwater environment than other natural colour image metrics

(iii) it obtains a higher correlation between the metric predictions and observer ratings

(iv) it is an effective real-time algorithm, and is capable of being applied to underwater video.

This paper is organized as follows. An overview of existing atmospheric colour image and underwater image quality metrics is presented in Section II. Relevant analysis of underwater image degradation is provided in Section III. The proposed new underwater colour image quality evaluation method is presented in Section IV. Experimental results are reported in Section V. A conclusion is given in Section VI.

II. Image Quality Metrics: An Overview

A. No-Reference Colour Image Quality Metrics

Most existing no-reference image quality metrics were developed for measuring the grayscale image quality of JPEG-2000 coded images, where the pre-dominant distortions are due to blurring and ringing. The widely used quality metrics for grayscale images are contrast [19]–[21] or edge sharpness [22]–[24]. Measuring the perceived quality of a colour image is extremely difficult because human vision is highly nonlinear for different colours. Most proposed colour image quality metrics for atmospheric images are based on modifications of grayscale image quality measures. Some methods apply grayscale measures on colour images by converting the colour image into a grayscale image [7] or by measuring the quality in each colour component individually and then combining the measure values with different weights [8]. However, the colour-to-grayscale conversion is a lossy procedure. Other existing colour image quality metrics for atmospheric images focus on only one aspect of colour image quality such as entropy [9], [10], brightness [11]–[13], sharpness [14], [15], contrast [14] or colourfulness [16]. Hasler and Suesstrunk [16] try to quantify the colourfulness in natural images to perceptually qualify the effect that processing or coding has on colour. They set up opponent red-green and yellow-blue colour spaces, and obtain a colourfulness metric based on their mean values and standard deviations. Fu [17] also used this opponent spaces to propose a generic Colour Image Quality Index (CIQI), which is formulated as a linear combination of colourfulness, sharpness and contrast metrics. But the metric value does not linearly correspond to human perceptions [18]. Panetta *et al.* [18] propose another similar colour image quality measure, Colour Quality Enhancement (CQE), with different colourfulness, sharpness and contrast metrics. They also explored the 3D contrast measure relationships of RGB colour channels and propose a Colour Root Mean Enhancement (CRME) to measure the relative difference of the colour cube centre and all the neighbours in the current colour cube [18].

All of the aforementioned metrics were developed for atmospheric colour images and are complex. The main degradation in underwater images is not only due to blurring and low contrast caused by absorption and scattering, but also the non-uniform colour cast depending on the absorption of different wavelength spectra and the distribution of the lighting spectrum.

B. Underwater Image Quality Metrics

Several quantitative metrics were used to evaluate enhancement algorithm performance and restore underwater grayscale images. Schechner and Karpel [25] applied global contrast as a measure of underwater image quality. Hou *et al.* [26] measured restored images by a quality metric based on the weighted gray scale angle (WGSA) for scattering blurred underwater images. Arnold-Bos *et al.* [27] proposed a simple criterion based on a general result by Pratt [28]. For most well-contrasted and noise-free images, the distribution of the gradient magnitude histogram is close to exponential, except for a small peak at low gradients corresponding to homogeneous zones. Arnold-Bos *et al.* defined a robustness index between 0 and 1 that measures the closeness of the histogram to an exponential distribution. Arredondo and Lebart [29] proposed a methodology to quantitatively assess the robustness of algorithms to underwater noise. The true motion of the sequence for underwater video is known and the angular deviation between the estimated velocity and the correct one was measured. In our previous work [30], a synthetic metric was proposed for predicting the objective quality of underwater grayscale images. While measurement of the colour image enhancement or restoration results for different underwater assignments is difficult, it is important for automatic and real-time underwater processing. Therefore, an effective and simple underwater colour image quality metric is still a major goal of the underwater research community.

For underwater colour image processing, many of the authors use subjective quality measurements to evaluate the performance of their methods [3]. Chiang and Chen [31] applied SNR and MSE to measure the performance of their methods. Pramunendar *et al.* [5] described the performance of their method by the increased number of SIFT image matching points. As far as can be ascertained, there is currently no colour underwater image quality metric that can be applied to real-time monitoring. This work is aimed at a simple measurement of underwater colour image quality.

III. The Evaluation of Underwater Colour Image

A. Underwater Image Degradation

The absorption and scattering of light in water influence the overall performance of underwater imaging systems, including absorption and scattering by phytoplankton, absorption by coloured dissolved organic matter (cDOM) and finally, light scattering by total suspended matter (TSM) [32]. Forward scattering (randomly deviated light on its way from an object to the camera) generally leads to blurring of the image features. On the other hand, backward scattering (the fraction of the light reflected by the water towards the camera before it actually reaches the objects in the scene) generally limits the image contrast, generating a characteristic veil that superimposes itself on the image and hides the scene. Floating particles (marine snow) increase the absorption and scattering effects. As a result of different absorption spectra, the reflection of colours will vary between different water types depending on the contribution from the different Inside Optical Parameters (IOP). The concentration of IOP and the distance to the object of interest are therefore important factors when evaluating image quality [33]. The visibility range can be increased with artificial lighting but these sources not only suffer from some scattering and absorption, but in addition tend to illuminate the scene in a non-uniform fashion, producing bright spots in the image and poorly illuminated areas surrounding the spots. As depth increases, colours drop off one by one depending on their wavelengths. First, red colour disappears at a depth of 3m approximately. At 5m, orange colour is lost. Most of the yellow goes off at 10m and finally the green and purple disappear at further depth. Blue colour travels the longest in water due to its shorter wavelength. Underwater images are therefore dominated by blue-green colour. Also the light source variations will affect colour perception. As a consequence, a strong and non-uniform colour cast characterizes the typical colour distortion of underwater images [4]. Finally, the underwater engineering and monitoring colour images are chroma decreased and hue shifted towards blueness, non-uniform cast, blurring and noise. A group of typical underwater monitoring and survey images and their polar hue histograms are shown in Fig.1. It can be seen that the distributions of hues are non-uniform and prominently blue-green or yellow.

B. Colour Image Quality Metrics for Atmospheric Images

Hasler and Suesstrunk [16] show that colourfulness can be represented effectively with a combination of image statistics. This feature is incorporated to our new metric. Fu [17] and Panetta *et al.* [18] define colourfulness in the opponent colour space with red-green channel and yellow-blue channel. For an RGB image I, let α denote the rg channel, and β denote the yb channel.

$$a = R - G \tag{1}$$
$$\beta = 0.5 \times (R + G) - B \tag{2}$$

Based on the opponent colour space, Fu [17] combined chrominance information with sharpness and contrast and proposed the CIQI metric defined by:

$$CIQI = c_1 \times CIQI\_colorfulness + c_2 \times CIQI\_sharpness + c_3 \times CIQI\_contrast \tag{3}$$

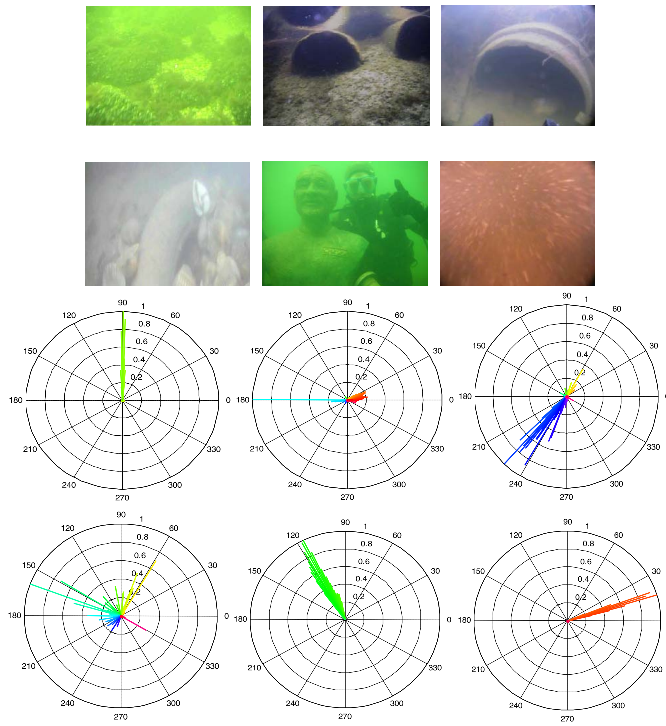

Fig. 1. Underwater colour images, and their hue histograms in polar coordinates.

where

$$CIQI\_colorfulness = (\sqrt{\sigma_\alpha^2 + \sigma_\beta^2} + 0.3\sqrt{\mu_\alpha^2 + \mu_\beta^2})/85.59 \tag{4}$$

$$CIQI\_sharpness = 1 - (1 - (tep_{estimated} - tep_{sobel})/tep_{sobel})^{0.2} \tag{5}$$

$$CIQI\_contrast = \max\ (\text{local\_contrast} = \sum_{i=9}^{15} Bond_i / \sum_{i=1}^{8} Bond_i) \tag{6}$$

and σ_α^2, σ_β^2, μ_α, μ_β represent the variance and mean values along the two opponent colour axes defined in (1) and (2). $tep_{estimated}$ denotes number of edge pixels estimated; tep_{sobel} denotes number of edge pixels counted using Sobel operator; $Bond_i$ is the ith coefficient of the total 15 bands of 8×8 blocks of DCT coefficients. c_1, c_2, c_3 are weighted coefficients.

CQE metric [18] is similar to the CIQI measure but differs in the colourfulness, sharpness and contrast definitions.

$$CQE = c_1 \times CQE\_colorfulness + c_2 \times CQE\_sharpness + c_3 \times CQE\_contrast \tag{7}$$

where

$$CQE\_colorfulness = 0.02 \times \log\left(\frac{\sigma_\alpha^2}{|\mu_\alpha|^{0.2}}\right) \times \log\left(\frac{\sigma_\beta^2}{|\mu_\beta|^{0.2}}\right) \tag{8}$$

$$CQE\_sharpness = \sum_{c=1}^{3} \lambda_c EME_{sharpness}(grayedge_c) \tag{9}$$

TABLE I
PERFORMANCE OF EXISTING COLOUR IMAGE QUALITY METRICS

Index / Metrics	1	2	3	4	5	6
μ_α	-0.2853	-0.0044	-0.0072	-0.0159	-0.4213	0.2311
μ_β	0.4409	0.0162	-0.0767	0.0015	0.2418	0.2139
σ_α	0.0015	0.0336	0.00031	0.0003	0.0046	0.0007
σ_β	0.0039	0.0154	0.0060	0.0006	0.0033	0.0011
CQE	0.0829	0.1104	0.0271	0.0053	0.0300	0.0607
CRME	5.0426	9.6428	8.7627	6.3213	3.1555	9.2603
CIQI	0.0672	0.2037	0.0693	0.0119	0.0877	0.0388

$$EME_{sharpness} = \frac{2}{k_1 k_2}\sum_{l=1}^{k_1}\sum_{k=1}^{k_2}\log(\frac{I_{\max,k,l}}{I_{\min,k,l}}) \tag{10}$$

$$CQE\_contrast = AME_{contrast}(Intensity) \tag{11}$$

$$AME\_contrast = \frac{1}{k_1 k_2}\sum_{l=1}^{k_1}\sum_{k=1}^{k_2}(\log(\frac{I_{\max,k,l}+I_{\min,k,l}}{I_{\max,k,l}-I_{\min,k,l}}))^{-0.5} \tag{12}$$

$k_1 \times k_2$ is the size of the image block, and $I_{k,l}$ is the pixel intensity in the image block. λ_c represents the weight for different colour components. Panetta *et al.* [18] also expand the grayscale contrast measures to the multidimensional colour image contrast and propose the CRME to measure the relative difference of the colour cube centre and all the neighbours in the current colour cube. The CRME metric is

$$CRME = \frac{1000}{k_1 k_2}\sqrt{\sum_{i=1}^{k_1}\sum_{j=1}^{k_2}\left|\frac{\log\left|I_{i,j} - \sum_{c=1}^{3}\lambda_c \frac{I_{c1}+I_{c2}+\cdots+I_{cn}}{n}\right|}{\log\left|I_{i,j} + \sum_{c=1}^{3}\lambda_c \frac{I_{c1}+I_{c2}+\cdots+I_{cn}}{n}\right|}\right|}. \tag{13}$$

where, $I_{i,j}$ is the centre pixel intensity in the block and n is the total number of pixels within each block.

In marine habitats, the rough absorption of the colours toward the red end of the spectrum lowers the value of the red component in RGB space as the depth increases. For all these three colour image metrics, as the red component decreases in underwater images, the value of α panel will be negative and the absolute value will increase. Marine snow with artificial lighting will cause increased local contrast and a wrongly high quality value. The statistical values of α, β and performance results of CQE, CRME and CIQI metrics for the images shown in Fig.1 are in Table I. The data reveals that these natural colour image quality metrics fail to predict the degradation of the underwater images. For example, all of these three metrics give a higher score to the 6th image, while only snowing noise can be seen in it.

IV. UNDERWATER COLOUR IMAGE QUALITY EVALUATION METRIC

One would like to use a measure in the underwater monitoring and survey colour image analysis that: (a) is correlated with human perception; (b) is suitable for classical types of distortion of images taken in turbid water; (c) is reliable for underwater image enhancement processing; (d) can measure the different distortion levels for similar image content; (e) has low computational complexity and can be implemented in real time.

A. The Colour Statistics Metrics

CIELab space is a uniform colour space and device independent. Hasler and Suesstrunk [16] studied twelve metrics of image pixels in the CIELab colour space, including the standard deviation along the a axis, b axis, chroma and saturation, the mean of chroma and saturation and so on. Since they assume that image colourfulness can be represented by a linear combination of a subset of these metrics, to find the best correlated metric for degradations in underwater monitoring and survey colour images, a set of subjective tests were conducted as follows.

44 underwater images were shown to human observers. These images were obtained from different underwater environments including pipeline detection in muddy water, and shallow sea survey. The concentration of micro particles is usually high. The lighting conditions include natural day lighting, lighting with green laser and LED white-light sources. The contents are varied. The distortions include blurring, low contrast, low saturation, colour cast, marine snow and motion muddy caused by underwater creatures. Some of these images are shown in Fig.1.

The images were randomly displayed; for each displayed image, the subject was asked to rate the image quality using a scale from 1 to 5 corresponding to "Very annoying," "Annoying," "Slightly annoying," "Perceptible but not annoying," and "Imperceptible", respectively. In order to reduce the effect of outliers, each image was presented 4 times. A subject could not proceed to the next image until the current image was scored. 12 subjects took the test and the Mean Opinion Score (MOS) was computed.

For each subjective level, 9 CIELab space statistics were computed including average of chroma μ_c, variance of chroma σ_c, average of saturation μ_s, variance of saturation σ_s, a pseudo-area in ab space, the standard deviation along the a and b axis, the Root Mean Enhancement (RME) contrast [18] of a and b, and the contrast of l channel, as shown in Fig.2. The histograms of these metrics larger than the average are shown in Fig.2 (a). It can be seen that, for the underwater monitoring and survey images, the MOS are generally low. For images with higher MOS, the σ_c, contrast of l, σ_s and μ_s are all higher than the averages, and they change linearly with decreasing MOS. In Fig.2 (b), the mean values of these 9 metrics with different MOS levels are shown. Clearly, that the mean values of σ_c, the contrast of l, σ_s and μ_s increase linearly with the MOS. That is to say, for underwater monitoring and survey colour images, the deviation of hue, the contrast of brightness and saturation correlate well with the observers' perceptions. In addition, the statistics that correlate with MOS will change with different environments and degradation features. For example, colourful seafloor photography images (not included in the 44 images) have generally higher MOS than others, as variance of saturation σ_s, sharpness of luminance and a, b channel, mainly determine the extent of observers visual perception.

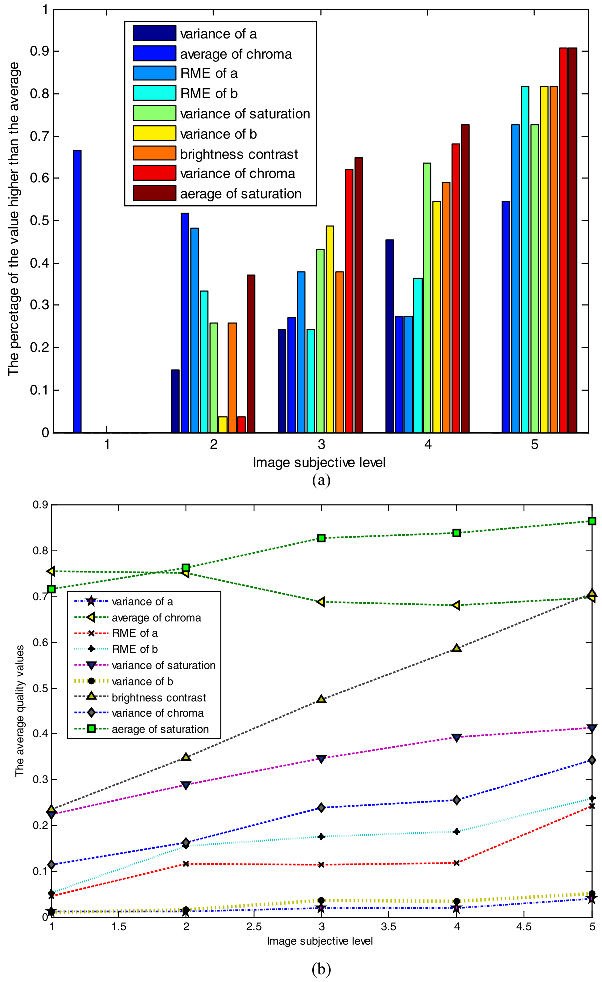

Fig. 2. The distribution of CIELab space statistics against the MOS, (a) histograms of nine metrics higher than the average values of different MOS level groups; (b) average values of nine metrics for different MOS level groups.

B. Proposed Underwater Colour Image Quality Evaluation Metric

In this work, the underwater colour images of concern are the raw images taken in underwater pipeline monitoring or engineering survey. Most of these underwater images are blurred, have low contrast and severe colour cast. To select the best metric, several aspects must be considered: the most obvious is the correlation to the subjective test data, the second is the computational cost, and the last is related to the limitation of the experiment due to the initial choice in the selection of the 44 scenes. As the CIELab space is designed to be a uniform colour space, it does not seem reasonable to emphasize the blue-yellow axis, as described by Hasler and Suesstrunk [16].

It is also reasonable to avoid using deviation of saturation σ_s, since it over-emphasizes dark areas, which are precisely the areas that some underwater images contain because of limited lighting. Let I_p be the pixel values of an image in CIELab space, $p = 1 \ldots N$. The image has N pixels. I_p=[l_p, a_p, b_p]. C_I is the chroma [16]. The underwater colour image quality evaluation metric UCIQE for image I in CIELab space is defined as:

$$UCIQE = c_1 \times \sigma_c + c_2 \times con_l + c_3 \times \mu_s. \qquad (14)$$

where, σ_c is the standard deviation of chroma, con_l is the contrast of luminance and μ_s is the average of saturation, and c_1, c_2, c_3 are weighted coefficients. As described above, the variance of chroma has good correlation with human perception for underwater colour images of interest. There are also other reasons for adopting the variance of chroma to describe the colour cast. One reason is that for colour images taken in muddy water with artificial lighting, marine snow is notably a major source of image degradation as the scattering creates white bright spots that may strongly impact the performance of image processing methods. The common metrics based on contrast and gradient will give higher scores. However, the hue distribution will not be influenced by marine snow. Tank images taken in 680cm transparencies of water with increasing camera distances are shown in Fig. 3 (a). The corresponding hue channels are shown in Fig.3 (b) and the histograms of hue can be seen in Fig.3(c). The data shown in Fig. 3(c) show that with increased camera distances, the variance of hue decreases, although there are more spots in the image with increased camera distance.

Contrast is used to measure the local contrast of a single target seen against a uniform background. It is one of the most perceived factors when the water environment is muddy and particle rich. Here, con_l was computed by the difference between the bottom 1% and the top 1% of all pixel values in luminance channel. The value returned can represent the global gray distribution of an image.

After the standard deviation of chroma, contrast and average of saturation are obtained, for the 44 test image data set, 4-fold cross-validation was performed, three folds were used for training and a multiple linear regression (MLR) on training images from subjective data was applied to obtain the three coefficients (14). The last fold was used for evaluation. This process was repeated 4 times, leaving a different fold for evaluation each time and the median of the values across iterations is reported. It is observed that the contrast, chroma and saturation are calculated independently so they can be processed in parallel to accelerate computation speed. For underwater monitoring and survey colour images with blurring, colour cast and marine snow distortions, the obtained coefficients are c_1=0.4680, c_2=0.2745, c_3=0.2576. For other underwater colour images with a specific type of distortion, the UCIQE with different metrics combination achieves better performance if the training set has the same distortion.

To obtain the performance of the major natural colour image quality metrics on underwater images, MLR was also applied on the 44 testing underwater images to get the optimized coefficients in (3) and (7). For CIQI metric, c_1=0, c_2=0.5141, c_3=0.4859. For CQE metric, c_1=0, c_2=0.2351, c_3=0.7649. The optimization results also indicate that for images taken in turbid water with high concentration suspended matter, sharpness and contrast are more important than the colorfulness for perceptual image quality in CIQI and CQE metrics. The experimental results of CIQI and CQE listed in the next section are computed with the optimized coefficients.

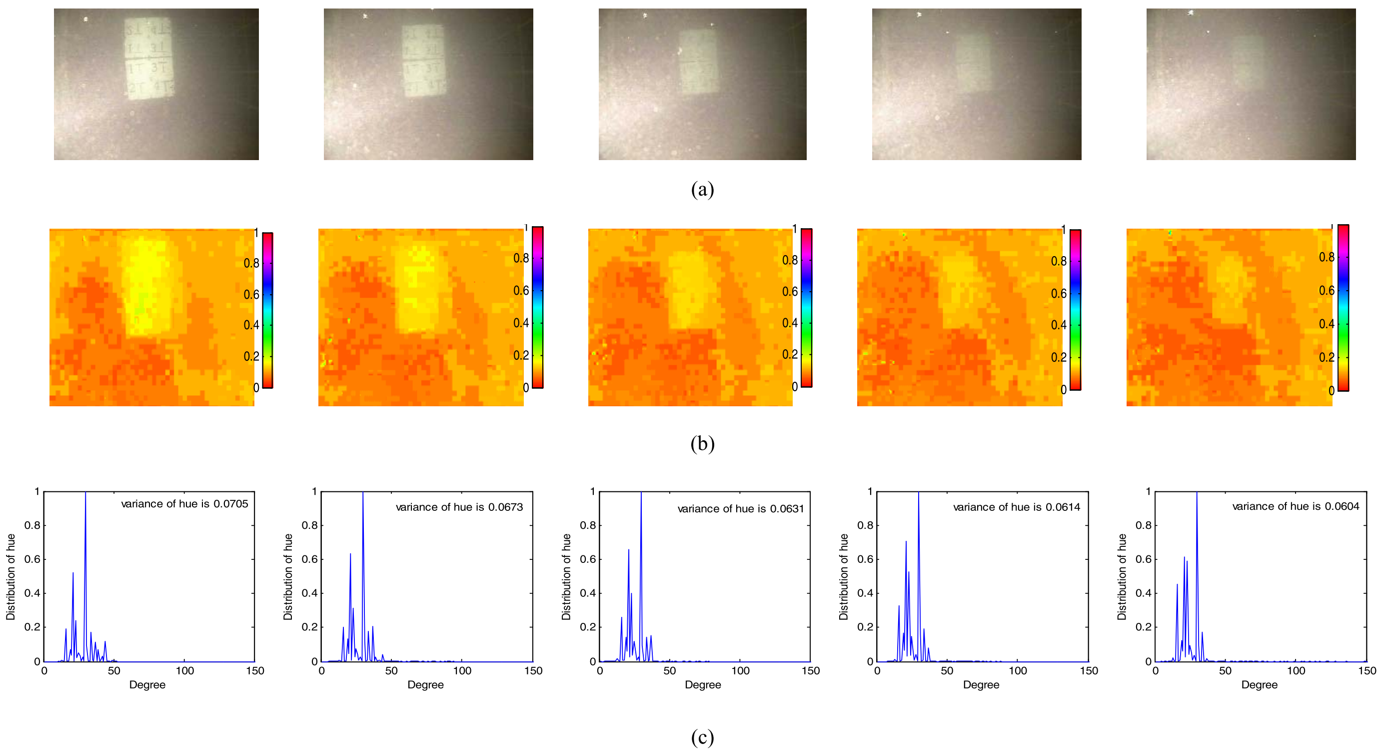

Fig. 3. Tank board images taken in 680cm transparency with artificial lighting and the hue distributions. (a) Tank board images with 240cm, 270cm, 300cm, 330cm and 360cm far from camera, respectively. (b) The corresponding hue channels. (c) The histograms of hue.

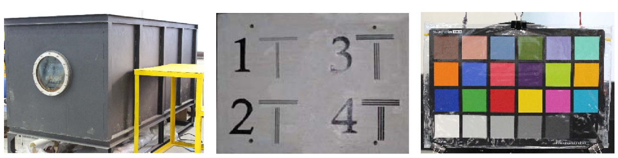

Fig. 4. Tank and targets.

V. Results and Discussion

The experiments were divided into three parts. The first series of experiments were conducted to confirm the accuracy of the proposed metric for predicting different degradations with increased camera distances. The second part is subjective experiments, to compare the perceptual relevance of the metric. The third part is to evaluate the suitability of the proposed metric for underwater image enhancement algorithms.

A. Tank Tests

The tank is 2.53m long, 1.02m wide, 1.03m high, with two observation windows measuring 33cm diameter on both sides of the tank. The images were taken with OTI-UWC-325/P/E colour camera, and the artificial lighting source is a 500w halogen lamp. Several sequences of images (960×576) were taken under different conditions, including 680cm, 190cm and 94.5cm transparencies of water [34], in natural and artificial lighting with board and ColorChecker 24 X-Rite Chart (21.59×27.94cm) targets, as shown in Fig.4.

An attempt was made to compare the proposed metric UCIQE to other state-of-art colour image quality metrics including CIQI, CQE and CRME. The proposed UCIQE is also compared with WGSA [26] and gradient magnitude histogram metric (R) [27], although they were designed for grayscale underwater image restoration. Part of the testing board and colour chart images taken in clear and medium muddy water with increased camera distances are shown in Figs. 5 and 7. Corresponding values of image quality with increased camera distances for the two sequences are plotted in Figs. 6 and 8. With the increased camera distances, the attenuations are more serious, and the added artificial lighting aggravated the back scattering and noise degradation, as shown in Figs. 5 and 7. While the natural colour image quality metrics mentioned in this paper failed to predict the degradation tendency as shown in Figs 6 and 8. For example, non-uniform light spot and the strong backscattering of suspended matter as shown in Fig. 5 (c) increases the contrast value in CIQI measure and result in a deviating point as pointed in Fig 6. (c). The curves plotted in Figs. 6 (f) and 8 (f) illustrate that the proposed metric UCIQE indicates the linear change more accurately than the three leading colour and the two grayscale underwater image quality metrics. Whereas, note that WGSA and R were applied to test images after transforming colour images to grayscale images first.

B. Subjective Experiments

To get meaningful results, it is important not to use the same data in computing the correlation and in optimizing the parameter set. As mentioned above, when applying 4-fold cross-validation, one of the four folds is used to compute the

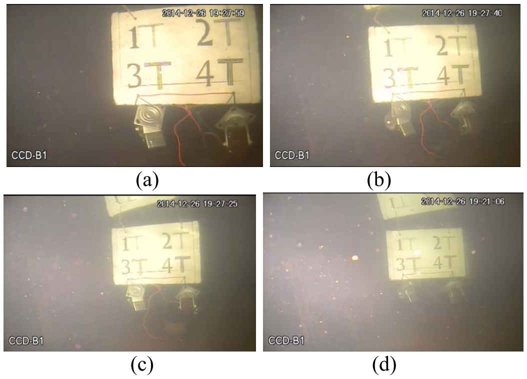

Fig. 5. Samples of board image sequence taken in 680cm transparency of water with led lighting. (a) 90cm (b) 120cm. (c) 150cm (d) 180cm.

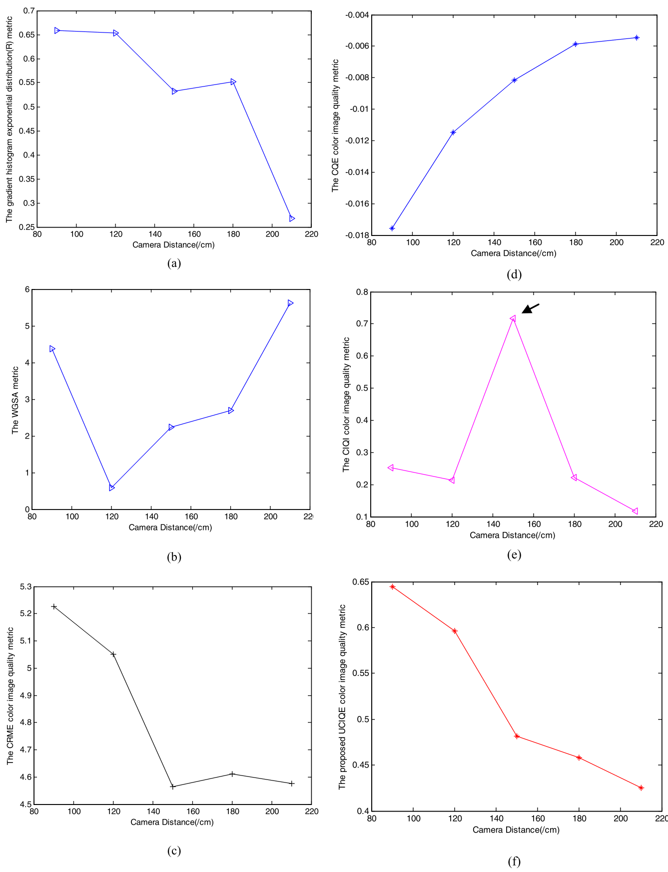

Fig. 6. Quality values of board images (Fig.5). (a) R. (b) WGSA. (c) CRME. (d) CQE. (e) CIQI. (f) UCIQE.

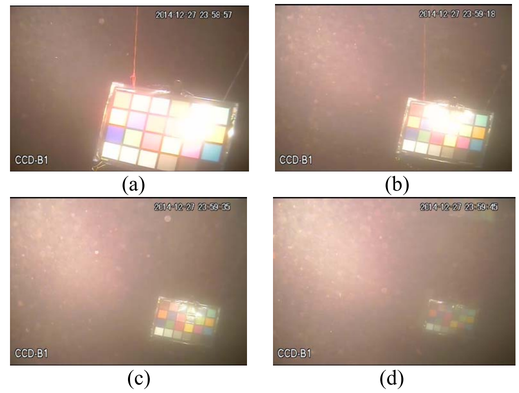

Fig. 7. ColorChecker chart images taken in 190cm transparency of water with led lighting. (a) 90cm. (b) 120cm. (c) 150cm. (d) 180cm.

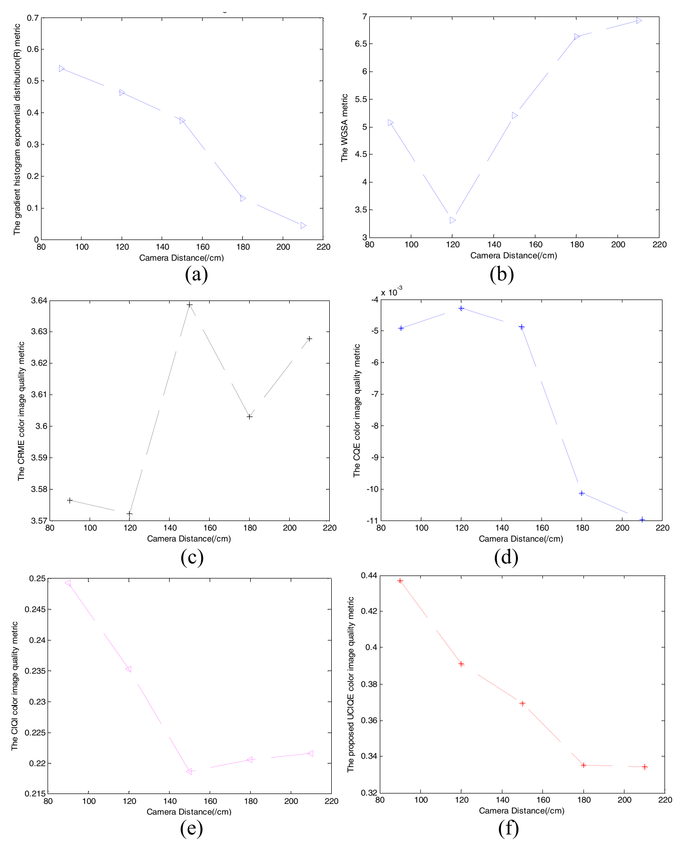

Fig. 8. Quality values of ColorChecker chart images (Fig.7). (a) R. (b) WGSA. (c) CRME. (d) CQE. (e) CIQI. (f) UCIQE.

correlation of the metrics with the experiment data. The objective quality predictions do not map directly to the subjective mean opinion scores (MOS) and there is a non-linear mapping function between subjective and objective predictions. A cubic polynomial with four parameters is fitted to account for this mapping. Common correlation coefficients are used to analyse the statistical relationship between two sets of images. Pearson's product moment correlation (PRCC) measures how far each measure value deviates from the MOS. Spearman's rank order correlation (SRCC) compares the rank of image qualities and the root mean square error (RMSE) measures the accuracy of the image qualities [35]. The results are summarized in Table II in terms of PRCC, RMSE and SRCC. The results show the superiority of the proposed UCIQE metric in terms of accuracy, monotonicity and consistency, as compared to the existing metrics for underwater pipeline monitoring and survey colour images. The proposed metric has good correlation with MOS on the order of 0.76 and performance range from 20, 9 and 25 percent better than CQE, CRME and CIQI.

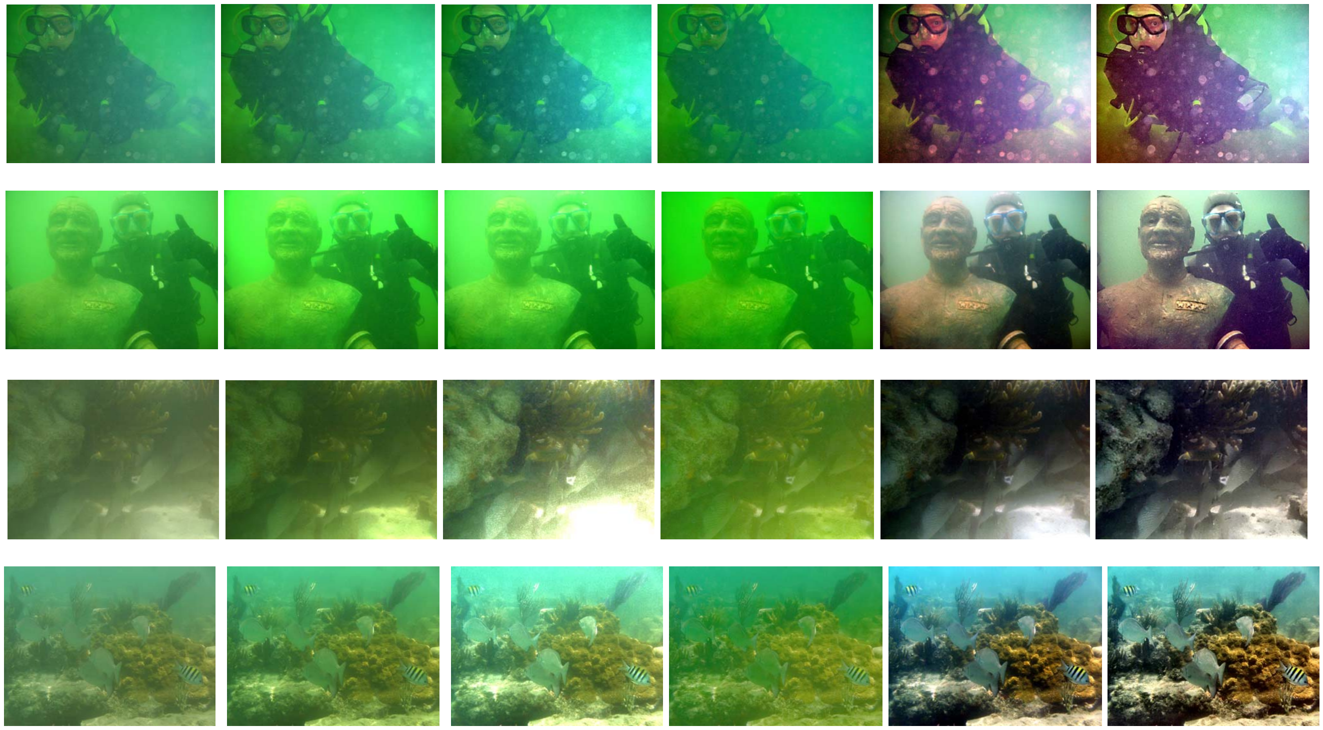

Fig. 9. Real underwater monitoring images enhancement test. (a) Raw images (b) He *et al.* (c) Fattal *et al.* (d) Tarel *et al.* (e) Iqbal *et al.* (f) Ancuti *et al.*

TABLE II
PERFORMANCE COMPARISON OF PROPOSED METRIC WITH STATE-OF-ART COLOUR METRICS

	PRCC	RMSE	SRCC
UCIQE	0.7549	0.0837	0.7543
CQE	0.5573	0.1027	0.5331
CRME	0.6945	0.0917	0.5823
CIQI	0.5626	0.1187	0.2832

C. Image Enhancement Results Evaluation

There have been lots of attempts to enhance the visibility of single degraded underwater colour images, such as defogging based algorithms [36], [37], contrast stretching methods [38], [39] and the newest image fusion enhancement [6]. The capability of the proposed UCIQE as an effective metric to measure the image enhancement results was tested. Five underwater image enhancement algorithms were presented including: scene depth information-based dark channel prior dehazing method proposed by He *et al.* [36], single image dehazing algorithm proposed by Fattal [37], fast visibility restoration method proposed by Tarel and Hautiere [38] and underwater colour image enhancement method based on integrated model proposed by Iqbal *et al.* [39] and the fusion based method [6]. A group of underwater degraded images and corresponding enhancement processing results are shown in Fig.9. Among those enhancements methods compared, the images enhanced by image fusion method [6] obtain comparably better results. Comparisons of different colour image quality evaluation approaches with UCIQE are list in Table III. The data verifies the better coherence of UCIQE with the subjective perspective than the others.

TABLE III
COMPARISON OF ENHANCEMENT METHODS EVALUATION ON REAL UNDERWATER IMAGES

Target	Metric	Image 1	Image 2	Image3	Image4
Degraded image	CIQI	0.3048	0.3064	0.0677	0.1293
	CRME	2.9922	3.1555	3.0253	3.0457
	CQE	-0.0465	-0.0285	-0.0427	-0.0377
	UCIQE	0.5400	0.4775	0.3930	0.5009
He [36]	CIQI	0.3060	0.3078	0.0935	0.1544
	CRME	3.0217	3.1855	3.1244	3.1131
	CQE	-0.0421	-0.0248	-0.0390	-0.0346
	UCIQE	0.5874	0.5228	0.4818	0.5631
Fattal [37]	CIQI	0.3106	0.3139	0.1055	0.2031
	CRME	2.9527	3.1783	2.8858	3.0473
	CQE	-0.0418	-0.0220	-0.0274	-0.0211
	UCIQE	0.6448	0.5439	0.6158	0.6503
Tarel [38]	CIQI	0.3087	0.3090	0.0838	0.1288
	CRME	3.0489	3.2361	3.1884	3.1535
	CQE	-0.0690	-0.0422	-0.0538	-0.0438
	UCIQE	0.5821	0.5046	0.5308	0.5828
Iqbal [39]	CIQI	0.5177	0.4532	0.5035	0.4674
	CRME	2.8687	2.7290	2.6302	2.7417
	CQE	-0.0403	-0.0287	-0.0734	-0.0405
	UCIQE	0.7684	0.6797	0.5919	0.7507
Ancuti [6]	CIQI	0.4061	0.3755	0.4888	0.6216
	CRME	2.8670	2.8390	2.6644	2.7973
	CQE	-0.0280	-0.0272	-0.0345	-0.0465
	UCIQE	0.8937	0.8551	0.7441	0.8814

In Table IV, the average execution time for 60 underwater colour test images is shown. The size of the test images is $960 \times 576 \times 3$, tests are on 2.8 GHz frequency Intel i7

TABLE IV
AVERAGE EXECUTION TIME FOR THE UCIQE, CQE, CRME AND CIQI

	UCIQE	CQE	CRME	CIQI
Average execution (s)	0.20	7.09	8.65	0.83

double-core CPU and 4GB of RAM using Matlab 2012b. The simulation results show that UCIQE has the fastest execution speed. The CIQI measure requires 4 times running time than the UCIQE metric although they all combine colourfulness and contrast metrics. This is useful for real-time underwater applications.

VI. CONCLUSION

A first-of-kind underwater colour image quality evaluation metric is proposed. The approach extracts the most relevant CIELab space statistical features that are representative for underwater image degradations such as colour cast, blurring and noise caused by attenuation, floating particles and lighting. The results indicate that the proposed metric has fast processing time, which makes it applicable for real-time image processing. It is able to successfully predict the relative distortion with similar scenes and the difference between enhancement results. It also shows better correlation with subjective evaluation. The proposed approach is promising in terms of both computational efficiency and practical reliability for real-time applications and most importantly it is a meaningful structural model to realize effective underwater colour image quality evaluation for different applications.

ACKNOWLEDGMENT

The authors would like to thank Z. Wei and B. Zheng of Department of Information, Ocean University of China, Qingdao, Shandong, China, for providing the tank images.

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