Underwater Image Enhancement via Higher-Order Moment CLAHE Model and V Channel Substitute

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***Abstract*—Images captured underwater often exhibit low contrast and color distortion attributed to special properties of light in water. Underwater image enhancement methods have become an effective solution to address these issues due to its simplicity and effectiveness. However, underwater image enhancement methods (such as CLAHE) face challenge of increasing image contrast, improve generalization of method. Here, underwater image enhancement via higher-order moment CLAHE model and V channel substitute is proposed to enhance contrast and correct color distortion. Firstly, analyze statistical features of image histograms, use higher-order moments to quantify features in a targeted manner, add them to CLAHE, so that improved CLAHE can accurately enhance contrast of underwater image according to dynamic features of image blocks, avoiding over- or under-enhancement of image. Then, for problem of color distortion, this paper novelty uses gray data to substitutes V channel in HSV color space, compensated for lost information, so as to achieve purpose of color correction in terms of visual perception. Finally, color correction of image through gray world method, which effectively improve color distortion problem. Our method is qualitatively and quantitatively compared with multiple state-of-the-art methods in public dataset, demonstrating that this method better solved low contrast and color distortion, in addition, details were more realistic, and evaluation indexes of underwater image quality were better.**

***Keywords*—Underwater images; contrast enhancement; adaptive CLAHE; high-order moments; dynamic features**

I. Introduction

As a huge part of the Earth, the ocean still has many unknown and unexplored fields for humanity. Driven by curiosity and longing for rich resources, it becomes an important way to know more about underwater world through imaging systems [1], technologies linked to underwater exploration and resource development have consistently commanded substantial attention [2] [3]. Throughout the ages, within exploration in this field, images have consistently been one of essential instruments of cognition. Unfortunately, due to strong absorption and scattering of underwater light, underwater imaging usually faces degradation problems that seriously affect detection of underwater environment [4], resulting in the destruction of the structural and dynamic properties of different areas of the image, leading to problems such as low contrast, color distortion [5]. The degraded underwater image severely limits performance of various computer vision algorithms. In Fig. 1, examples of real-world underwater images, which have obvious different features of underwater image quality degradation, e.g., low contrast and color casts. In order to promote further research and application, it is necessary to improve underwater image. The variation of light with different wavelengths traveling underwater leads to uneven pixel distribution in underwater optical images and further results in low contrast and color distortion in images. However, using a single contrast enhancement method ignores extraction of texture features of images and results in localized contrast over or under enhancement and color distortion. Similarly, a single-color correction method cannot improve contrast and detail of images. To address these problems simultaneously, a variety of approaches have been presented in the last decade [6]-[11],[13]-[17],[20]-[23], which can be broadly categorized into three types: image enhancement methods, image restoration methods, and deep learning methods.

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A. Image Enhancement Methods

Image enhancement is based on the direct modification of image pixel values to adjust one or more image attributes to improve the overall visual quality of underwater images [19]. Zhang et al. [9] used an extended multiscale retinex-based method (Lab-MSR) to process underwater images in the CIELab color model. Zhang et al. [10] presented a new color correction and dual-interval contrast enhancement method supported by multiscale fusion, using a simple linear fusion method to fuse the processed high and low frequency components. Wang et al. [11] proposed an intelligent protocol called meta-underwater camera that uses reinforcement learning to intelligently configure seven underwater image enhancement techniques, including fading channel compensation, white balance, tone mapping, saturation adjustment based on the hue-saturation-luminance (HSL) model, contrast stretching, gamma correction, and high-pass fusion. This protocol works while the underwater camera is capturing the underwater image and optimizes the original, poorly visible underwater image into a highly visible image. With these methods, the structural and dynamic properties of the underwater image are hardly taken into account. Image enhancement methods aim to change the pixel values of the image to improve the visual quality and have the advantage of improving the contrast of distorted underwater images with relatively little computational effort. However, the same processing technique is used for all scene images, which means that the texture details of underwater images are not fully utilized, resulting in over- or underestimation [12].

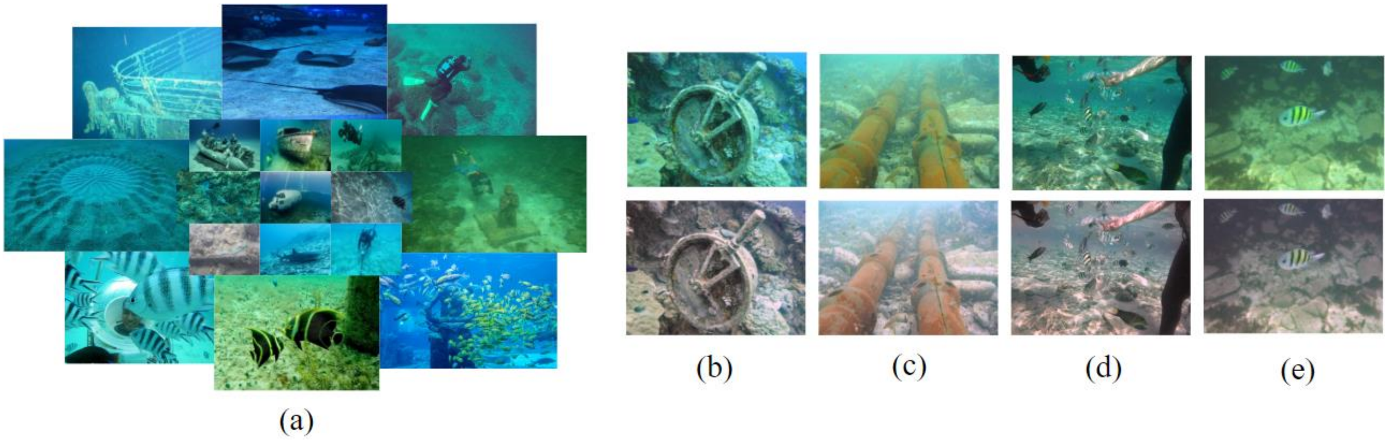

Fig. 1. (a) Real-world underwater images. (b) - (e) our method enhanced results (bottom) for several raw images with degraded quality (top).

B. Image Restoration Methods

Image restoration methods solve the parameters of the image model using priors to restore well-visible images [13]-[17]. A representative method is the dark channel prior (DCP) theory proposed by He et al. [15] which was originally used for haze removal but has been adapted by many researchers for underwater image processing. In fact, the estimated transmittance is too large [15], which makes final enhanced image dark. Peng et al. [16] proposed a depth estimation method to accurately estimate depth of underwater scene. Zhu et al. [17] proposed an underwater image enhancement with dark channel prior, which improves contrast and color by advanced light estimation, retinex, and channel-specific coefficients. These methods achieve clear images by solving an inverse problem for the parameters of the image model. Although certain effects are achieved, spatial and textural a priori of the image are not adequately accounted for, resulting in insufficient detail in the restored image [18]. More importantly, these methods usually require a complicated mathematical optimization process, which is very computationally intensive [19].

C. Deep Learning Methods

Deep learning has made remarkable advances in computer vision and has driven the development of techniques to enhance underwater images. The successful application of these methods is due to the extensive training data [18]. Han et al. [20] introduced a novel spiral generative adversarial network (GAN) to enhance image details and remove noise caused by scattering and attenuation. Fu et al. [21] designed SCNet for capturing desensitized underwater representations that can be adapted to different waters, but enhanced images have blurred detailed textures. Meanwhile, Cycle Generative Adversarial Network [22] and Twin Adversarial Contrastive Learning [23] have also been used to enhance underwater images. Although deep learning techniques have many advantages, the parameters in the networks remain unchanged after training is completed, which limits the adaptability of deep learning methods [19]. Most importantly, deep learning methods rely on an extensive dataset containing both distorted and clear underwater images. Many of these images are synthetically created and do not accurately represent the features of real underwater images [24]. Furthermore, deep learning methods require more time to train networks than traditional methods [4] , but they still have higher requirements for hardware equipment and training datasets. Different from deep learning methods, image enhancement and image restoration methods emphasize the specific performance of degraded underwater images. Image restoration methods utilize different prior assumptions to invert to a clear image before degradation [25]. However, the accuracy and universality of complex scenarios need to be improved because of the limitations of prior knowledge [16]. Image enhancement methods utilize processing technology to enhance contrast, i.e., CLAHE [26] and retinex-based [27] methods.

Compared with general natural images, underwater images have some unique structural features. The acquisition of underwater visual images is affected by light attenuation, absorption, and scattering, resulting in the destruction of the structural and dynamic properties of different areas of the image. As a result, underwater images often suffer from color distortion, low contrast, and blurred details. Traditional image enhancement methods fail to effectively personalize and improve these features. We thus propose underwater image enhancement via a higher-order moment CLAHE model and a V-channel substitute. More precisely, our main contributions can be summarized as follows:

1) *CLAHE* is widely used in underwater images; however, it lacks an accurate and comprehensive description of dynamic features. We propose to utilize higher-order moments to quantitatively portray statistical features of image histograms. These quantitative data are incorporated into the clipping model to improve the description of statistical features of the histogram in CLAHE. The improved algorithm has stronger generalization ability and a wider application range and effectively solves the problem that underwater images are prone to over- or under-enhancement.

2) *In* view of the fact that light is absorbed in water, which leads to the destruction of the structural and dynamic properties of the regions in the underwater image, triggering the color distortion of the underwater image, To address this challenge, this paper proposes a color compensation strategy

with V-channel substitution. By compensating the color-damaged channels with the histogram distribution characteristics of underwater images, color correction in visual perception is achieved.

3) We use contrast enhancement and color correction to enhance underwater images. Compared with existing similar methods, our proposed method has achieved better results on PSNR, AMBE, UCIQE, and UIQM.

The rest of this paper is organized as follows: Section II delves into related work, proposed method is given in Section III, and an experimental comparison is given in Section IV. Finally, Section V concludes the paper.

II. RELATED WORK

CLAHE pipeline consists of 4 main steps. First, input image is divided into non-overlapping blocks of equally sized, each block contains M pixels, and histogram adjustment is performed in each block. Secondly, histogram adjustment includes histogram creation, clipping histogram, and redistributing pixels according to a clipping point. The higher clipping point is, more contrast is enhanced, clipping limit value N_{cl} is calculated as follows:

$$N_{cl} = N_{Aver} + [\beta \times (\mu_x \times \mu_y - N_{Aver})] \tag{1}$$

where, N_{Aver} is average number of block pixels, β is clipping factor, μ_x is number of pixels in horizontal direction of block image; μ_y represents number of pixels in vertical direction, and calculation formula of N_{Aver} is

$$N_{Aver} = \frac{U_x \times U_y}{L_{gray}} \tag{2}$$

where, L_{gray} is number of gray levels in block. The number of pixels exceeding N_{cl} in histogram of each block are cut out and reassigned. Then, mapping function is obtained by cumulative distribution function (CDF) of clipped histogram.

$$N_{Clip} = \sum_i \{\max[H(i) - N_{cl}, 0]\} \tag{3}$$

$$N_{Acp} = \frac{N_{Clip}}{L_{gray}} \tag{4}$$

where, $H(i)$ is gray histogram of block; N_{Clip} is total number of cut pixels; N_{Acp} is number of pixels assigned to each gray level; after cutting, it becomes a piecewise function.

$$N_{Clip} = \begin{cases} N_{Clip}, H(i) > N_{cl} \\ N_{Clip} - (N_{cl} - H(i)), H(i) + N_{Acp} \geq N_{cl} \\ N_{Clip} - N_{Acp}, else \end{cases} \tag{5}$$

Finally, bilinear interpolation is performed to remove artifacts that exist between blocks [28]. CLAHE not only expands the contrast range but also optimizes the entropy of the image, so it is widely used in underwater image processing [29]. CLAHE is different from conventional HE in that contrast is limited by a clipping point, which changes the kurtosis of each block histogram. To keep the total count of the histogram the same, clipped pixels are required to be evenly redistributed to each gray level. If there are pixels that have not been allocated, cyclic allocation is required. During allocation, the remaining pixels will be evenly allocated to gray levels less than the clipping point until the remaining pixels are fully allocated [30]. To eliminate artificially induced boundaries, each pixel value is obtained by linearly interpolating the pixel values of surrounding blocks [31]. In CLAHE, bilinear interpolation is used; that is, interpolation is performed in two directions. This allows CLAHE to achieve contrast enhancement, eliminate block artifacts, and improve image quality at a lower computational complexity [32]. Therefore, CLAHE is widely used in underwater images to improve contrast and to use a uniform clipping point for different image block histograms.

Algorithm1：CLAHE

Input*：*image-input
Parameter：block size (eg：8×8), clipping limit (threshold value in [0, 1], eg：0.1), nbins (eg：256)
Output*：*image-output

1：Divide image-input into non-overlapping blocks (nbins) of equal size
2：Calculate block histogram
3：Calculate clipping point
4：Pixel point reassignment. For each block, use extra pixels from step 3 to reassign.
5：Histogram equalization
6：Bilinear interpolation reconstructs gray values
7：Show result image

This does not fully and accurately characterize the dynamics of the histogram, which causes the processed image to be prone to over-enhancement or under-enhancement. To address this problem, researchers have proposed some improvement methods. For example, Chang et al. [33] and Kan et al. [28] pointed out that for uniform regions in an image, lower shear values are needed to avoid over-enhancement, while for textured regions (non-uniform regions), higher clipping values are needed to emphasize texture details and contrast. For uniform regions, a lower clipping value is used to maintain the natural color tone and brightness of the image; while for textured regions, a higher clipping value is used to highlight texture details and contrast. Such processing can more accurately capture the localized features of the underwater image and avoid over-enhancement or under-enhancement. Chang et al. give Eq. (6) and Khan et al. give Eq. (7).

$$N_{cl} = N_{Aver} + N_{Aver} \times (p\frac{l_{max}}{R} + \frac{\lambda}{100}(\frac{\sigma}{N_{Aver} + c})) \tag{6}$$

where, p and λ are the parameters that control the dynamic range of the histogram and the relative magnitude of data change respectively, l_{max} is the maximum value in the sub-block, R indicates the dynamic range of the histogram of the whole sub-block, and is generally taken as 255, σ is the standard deviation of the sub-block, and c is a very small value that prevents it from being divisible by zero. Chang et al. use the sub-block mean as the main part, the sub-block maximum value, and the standard deviation as the quantitative index of the dynamic features, and the standard deviation is called the second-order central moment in statistics, and the order moment (moment) is a statistic that describes the distribution of the data, which measures the expected value of the values in the data set to the power of a particular value.

$$N_{cl} = N_{Aver} \times \mu(\frac{LcGc}{\eta} - E) \tag{7}$$

$$LcGc = \text{Local complexity+Global complexity} \tag{8}$$

where, μ and $LcGc$ are both control parameters, is the complexity of the local and global information of the image, obtained using Laplace operator filtering, and E is the sub-block information entropy. Khan et al. use the sub-block mean value as the main part and use the local information, global information, and information entropy as the dynamic feature expression. This formula undoubtedly aggravates the computational efficiency of the program and prevents the algorithm from being widely used.

Based on the three formulas introduced previously, this paper is inspired to find a more accurate quantitative way to feature the dynamics of histograms and hopefully to ensure the efficiency of the algorithm.

III. Proposed Method

In this work, the paper aims to improve the visual quality of underwater images based on dynamic features of image histograms. While CLAHE excels in local detail handling, it suffers from over-enhancement and halo artifacts, when processing darker images. CLAHE restricts enlargement by pruning the histogram at a user-defined value called clipping value. However, clipping level determines how much noise information in the histogram should be smoothed out and therefore how much contrast should be increased [34]. That is why, the global clipping point is not suitable for the enhancement of dark regions, and adaptively setting the clipping point is of importance in image enhancement. Eustice et al. [35] experimented with different ideal gray distributions and proposed that the Rayleigh distribution is most appropriate for underwater images. Fig. 2 shows the overview of the proposed method.

In this work, we integrate histogram dynamic features into the clipping model to adaptively set clipping points based on image textures for enhancing contrast. By applying this approach to the CIELab color space, we improve the contrast of underwater images by enhancing the L channel. Histogram equalization applied to sub-channels ensures a more uniform color distribution across the entire image [36]. Next, we utilize the Gradient Correlation Similarity (Gcs) method to merge information from the R, G, and B channels and substitute the V channel in the HSV color space, achieving color correction for human visual perception. This compensates for the absence of R channel information in underwater images. The replaced image undergoes color correction using the gray world method, effectively avoiding red shading in the enhanced image. Subsequent sections will delve into the details of these sub-modules.

A. High-Order Moment-based Clipping Point Acquisition

To improve texture and image details more effectively by CLAHE, this paper uses mean gray value and standard deviation represent texture of block, skewness represents symmetry of histogram distribution, skewness is close to 0, and histogram distribution is close to symmetry. The kurtosis indicates peak height of histogram distribution, and high kurtosis indicates that there are more extreme values in histogram, and variance increases. Their combination makes clipping value smaller in homogeneous regions and larger in texture regions, which more accurately describes dynamic features of different blocks. Thus, we adaptively set clipping points as follows:

$$N_{cl} = N_{Aver} + \sigma + \alpha(S + K) \tag{9}$$

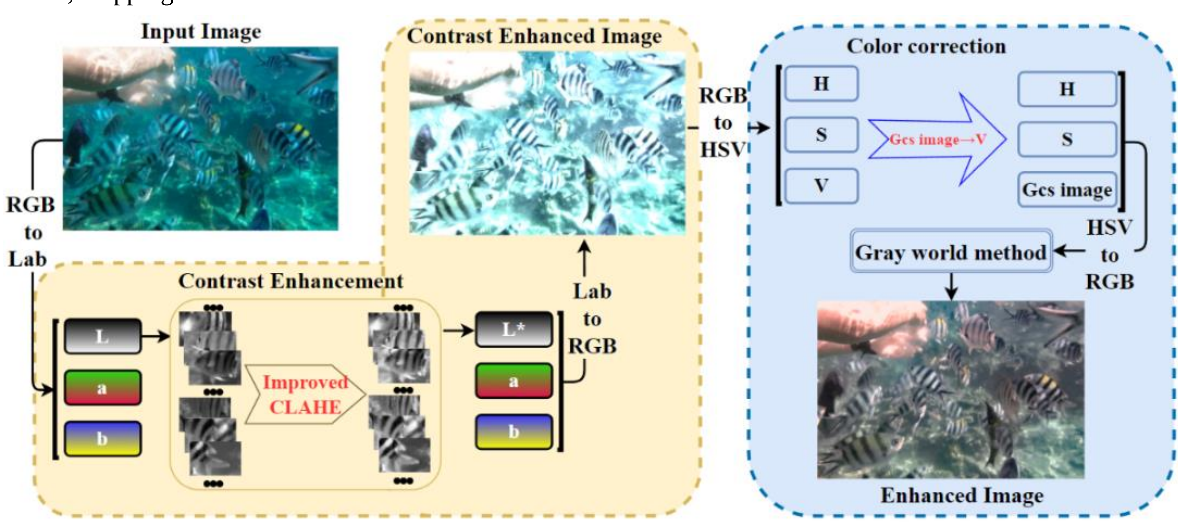

Fig. 2. Overview of the proposed method.

where, α is a parameter that controls weights of dynamic range. The S and K represent skewness and kurtosis of block histograms, respectively. Different actual scenes can use different α, S and K to make the method describe dynamic feature of block more accurately, which enables the method to obtain better contrast enhancement effects in different underwater scenes as shown in Fig. 3.

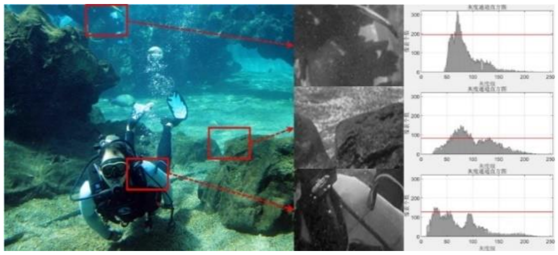

Fig. 3. Clipping point with different block image.

To validate the validity and reliability of the proposed formulas, we employed various combinations of clipping models for comparison with the original model. The dataset utilized in this experiment is the SUID dataset [37], as depicted in Table I. From the results, it is evident that although our method does not perform satisfactorily in no-reference evaluation metrics (PSNR, SSIM), it exhibits a clear advantage in underwater image evaluation metrics (UIQM, UCIQE). It is important to note that higher values of PSNR, SSIM, UIQM, and UCIQE indicate better performance.

TABLE I. ABLATION EXPERIMENT OF CLIPPING MODE

Clipping Model	Quality Evaluation				
	PSNR	*SSIM*	*UIQM*	*UCIQE*	*Run Time/s*
Original	19.83	0.79	2.88	0.49	**0.0394**
$N_{cl} = N_{Aver} + \sigma$	**20.43**	0.77	3.07	0.48	0.0843
$N_{cl} = N_{Aver} + \sigma + K$	18.62	0.76	3.20	0.49	0.0763
$N_{cl} = N_{Aver} + \sigma + S$	19.83	0.79	3.10	0.48	0.0737
This study	19.37	**0.80**	**3.21**	**0.51**	0.0814
Ref. [28]	14.08	0.61	3.10	0.55	0.1441
Ref. [33]	14.39	0.62	1.06	0.46	0.0475

TABLE II. ABLATION EXPERIMENT OF CLIPPING LIMIT

Clipping limit	Quality Evaluation				
	PSNR	*SSIM*	*UIQM*	*UCIQE*	*Run Time/s*
0.1	15.18	0.34	**4.53**	0.34	0.0783
0.2	14.17	0.61	3.21	0.51	0.0786
0.3	20.23	0.66	4.24	0.40	0.0773
0.4	**21.36**	**0.81**	3.75	0.49	**0.0771**
0.5	19.51	0.80	3.22	0.49	0.0781
0.6	17.28	0.74	2.77	0.50	0.0775
0.7	15.91	0.69	2.43	0.51	0.0785
0.8	15.08	0.65	2.20	0.51	0.0776
0.9	14.54	0.63	2.10	0.51	0.0780
1.0	19.90	0.80	1.85	**0.52**	0.0776

To determine optimum clipping limit, we increased it from 0.1 to 1, each time by 0.1, to test performance of different clipping limit on image enhancement. Table II shows the ablation experiment of clipping limit.

B. Color Correction Based on Fusion Channel Substitution

The Gray World method, commonly used for color distortion correction in engineering applications [38], often leads to red shading in underwater images when directly applied. This is because the method assumes equal average gray values for the R, G, and B channels. Additionally, the R channel frequently lacks sufficient information due to underwater imaging conditions, resulting in an overall greenish or bluish appearance in the original image [39]. Directly applying the Gray World method to correct the color of original underwater images can thus lead to overcompensation issues.

$$\overline{Gray} = \frac{\overline{R}+\overline{G}+\overline{B}}{3} \tag{10}$$

$$k_r = \frac{\overline{Gray}}{R}, k_g = \frac{\overline{Gray}}{G}, k_b = \frac{\overline{Gray}}{B} \tag{11}$$

$\overline{Gray}$ represents average gray value of RGB; $\overline{R}$, $\overline{G}$, $\overline{B}$ is average value of R, G, B channels, respectively; k_r, k_g, k_b means gain coefficients. Based on VonKries diagonal model, each pixel C in underwater optical image is adjusted for its R, G, B channels.

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \begin{bmatrix} k_r & 0 & 0 \\ 0 & k_g & 0 \\ 0 & 0 & k_b \end{bmatrix} \times \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{12}$$

In this paper, we present a processing compound based on HSV color space to improve overall correction algorithm and further refine solution to underwater color distortion problem [40].

Color-distorted images can lead to unnatural or poor visual perception. The HSV color space was designed with psychological and visual considerations in mind [41]. It uses three channels to describe image to better match visual perception of the human eye. From Eq. (15), it appears that for underwater images, V channel more often takes pixel values from G channel (greenish images) or B channel (bluish images) and very rarely from R channel. To support this idea, we counted proportion of V-channel pixels from R, G, and B channels in 890 underwater images in the UIEB dataset. The results show that average gray value of pixels from R channel is 4.82, which is about five times lower than that of G channel and six times lower than that of B channel. The average percentage of pixels from R channel is about 9.67%, while G channel is about 41.52% and B channel is 48.81%. Based on this, we propose a color compensation algorithm with fusion channel replacement, which replaces V channel with gray image obtained by fusion of R, G, and B channels to compensate for problem of insufficient information in R channel of underwater images, together with gray world method, to visually better improve color distortion of underwater images.

$$H = \begin{cases} 0, if \max = \min \\ 60 \times \dfrac{G-B}{\max - \min} + 0, if \max = R \text{ and } G \geq B \\ 60 \times \dfrac{G-B}{\max - \min} + 360, if \max = R \text{ and } G < B \\ 60 \times \dfrac{B-R}{\max - \min} + 120, if \max = G \\ 60 \times \dfrac{R-G}{\max - \min} + 240, if \max = B \end{cases} \quad (13)$$

$$S = \begin{cases} 0, if \max = 0 \\ \dfrac{\max - \min}{\max} = 1 - \dfrac{\min}{\max}, other \end{cases} \quad (14)$$

$$V = \max\{R, \mathrm{G}, \mathrm{B}\} \quad (15)$$

where, max means largest of R, G, and B, and min stands by smallest.

Substituting V channel with a Gcs image based on criteria of minimal loss of structural parameters and gradient information, effectively compensating for R channel information while preserving color image structure and detail. Combining this with the gray world method enhances compensation for V channel information in the HSV color space, facilitating color correction for visual perception. Additionally, substituting V channel with a grayscale image derived from merging R, G, and B channels mitigates distortion in blue or green-biased underwater images. This method, coupled with the gray world technique, achieves color correction. Experimental results demonstrate that the grayscale image optimally utilizes intensity and detail information in the RGB color space. For RGB format source images, intensity can be computed by linearly summing R, G, and B channels with fixed weights, exemplified by the traditional gradient error (GE) method.

$$GE = 0.299 \times R + 0.587 \times G + 0.114 \times B \quad (16)$$

However, in some color images, such as color images with equal luminance regions, the use of luminance channel images alone does not truly reflect structure and contrast of image, Liu et al. [42] proposed a decolorization model based on Gcs measure to well solve above problem, proposed method can better reflect degree of feature distinguishability and color ordering preservation in color-grayscale conversion, using Gcs image can effectively compensate for loss of R channel information, and improve intensity values and details of underwater color image (see Fig. 4). The core model is

$$\min_{w_c} - \sum_{(x,y) \in P} \sum_{c=\{r,g,b\}} \frac{2\left|I_{c,x} - I_{c,y}\right|\left|\nabla g_{x,y}\right|}{\left|I_{c,x} - I_{c,y}\right|^2 + \left|\nabla g_{x,y}\right|^2}$$
$$s.t. \quad g = \sum_{c=\{r,g,b\}} w_c I_c ; \sum_{c=\{r,g,b\}} w_c = 1 \quad (17)$$

where, w_c is a unique weight that determines mapping function; p is all pixel pairs; $I_{c,x}$ is pixel value in horizontal direction on color map image; $I_{c,y}$ is pixel value in vertical direction; weighting coefficients are $\{w_c | c = r, g, b\}$.

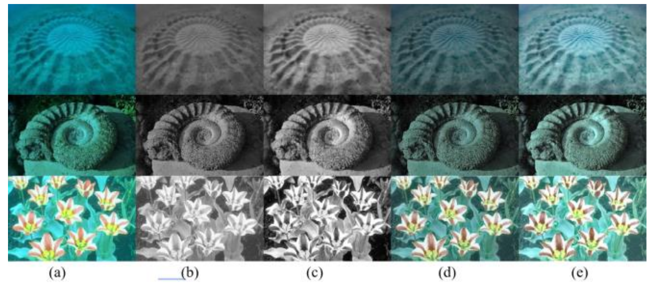

Fig. 4. (a) Original image; (b) GE image; (c) Gcs image; (d) GE image substitution V channel; (e) Gcs image substitution V channel.

The proposed method possesses fast and robust performance and runs very fast and can be used in engineering practice. It can also be used directly in RGB color space for color correction without conversion to other color spaces [43].

IV. Experimental Results

To verify effectiveness of the method, six representative underwater images were selected from public underwater images UIEB [44] datasets. We have chosen four conventional methods for comparison, they are HE [45]; CLAHE proposed by Zuiderveld et al. in 1994 [46]; contrast enhancement of low-contrast medical images using modified contrast limited adaptive histogram equalization is an improved CLAHE method proposed by Khan et al. [28]; automatic contrast-limited adaptive histogram equalization with dual gamma correction is an improved CLAHE method proposed by Chang et al. [33], but this experiment did not reproduce double gamma correction, only modification of CLAHE was compared. The contrast-enhanced image is then color corrected using gray world method. This chapter evaluates the method from both subjective vision and objective image quality indicators. The platform is Matlab 2018a, computer processor is AMD Ryzen 5 5600H with Radeon Graphics, and CPU is 3.30 GHz. In this experiment, α is 0.4; distribution is rayleigh distribution.

A. Qualitative Evaluation

The L channel of the CIELab color space underwent processing using the corresponding method, as shown in Fig. 5, to enhance contrast. Subsequently, color correction was applied using the gray world method. Comparative analysis revealed that the proposed method consistently outperformed other methods in terms of visual effects, resulting in visually pleasing underwater images. Histogram Equalization (HE) tended to excessively enhance contrast, resulting in an overall darker appearance in processed images. Specifically, Img1, Img2, Img5, Img7, and Img8 exhibited a reddish overall tint, along with some loss of detail. CLAHE effectively mitigated contrast over-enhancement caused by HE. Notably, (c) demonstrates the excellent contrast enhancement capabilities of CLAHE, but the processed image appears overexposed, with an overall tendency to be white, worsening overall visual perception. Processing images using the method referenced in Ref. [28] resulted in significant red shadows and blurred details, leading to an overall poor visual impression. The method in Ref. [33] made the image darker overall, with lower contrast and fuzzy details. Red shading was prevalent in Img5, Img6, Img7, and Img8. Fig. 6 shows underwater color image enhancement results. This study resulted in images leaning towards a gray color tone while significantly enhancing contrast and improving portrayal of details compared to other methods. Importantly, it effectively mitigated the occurrence of red shadows caused by the gray world method and alleviated the common issue of underwater images appearing bluish or greenish. To objectively analyze experimental results, this paper selects underwater image quality measures such as UIQM [47], UCIQE [48], PSNR [49], and AMBE [50].

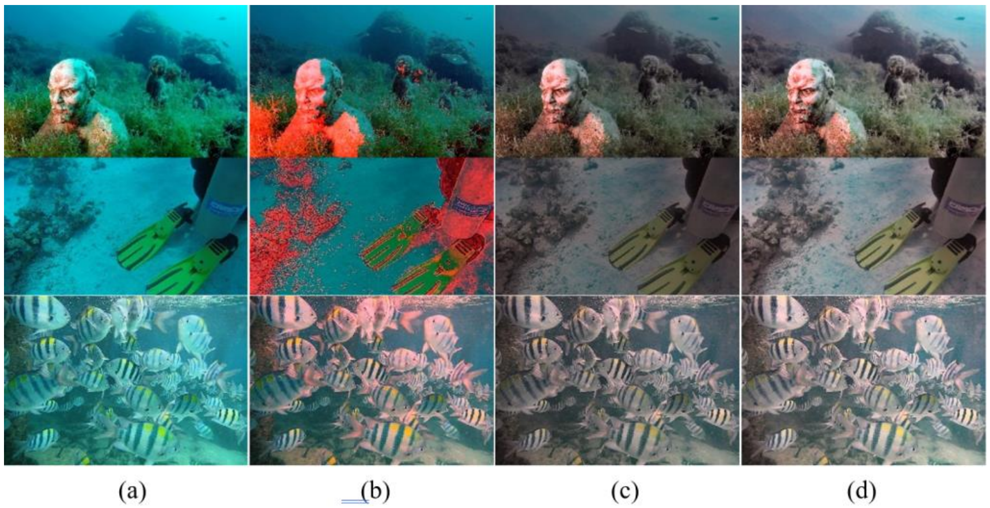

Fig. 5. (a) Original image; (b) Gray world method; (c) GE + gray world method; (d) Gcs + gray world method.

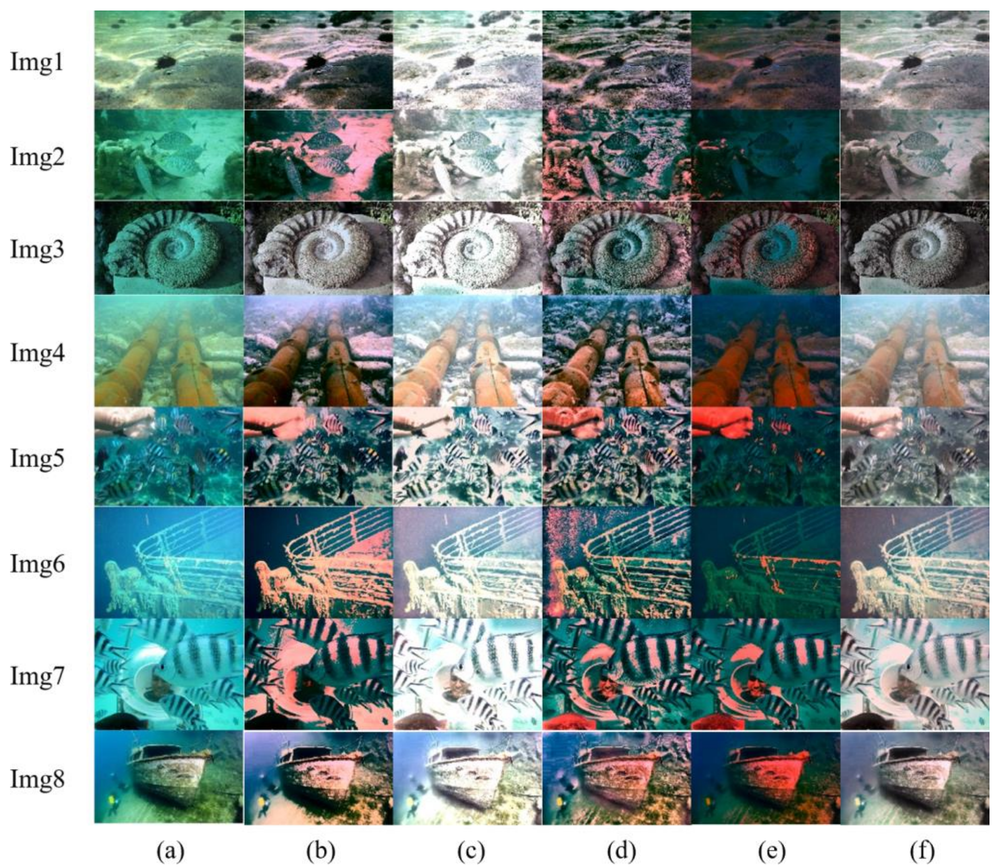

Fig. 6. Underwater color image enhancement results based on different method. (a) Original image; (b) HE; (c) CLAHE; (d) Ref. [28]; (e) Ref. [33]; (f) Proposed method.

1) Underwater Image Quality measure (UIQM): UIQM is based on a model of human visual system and works without reference images. UIQM includes three main measurements, UICM underwater image color measurement, UISM underwater image sharpness measurement, and UIConM underwater image contrast measurement [51]. Higher values of UIQM indicate superior cumulative enhancement effects achieved by the algorithm. The results are outlined in the table below, with the most optimal outcome prominently highlighted in bold for easy reference.

2) Underwater Color Image Quality Evaluation (UCIQE): UCIQE is a perceptual image quality assessment metric used to quantitatively assess color deviation, blurriness and low contrast in underwater images. It is a linear combination of color intensity, saturation and contrast. A higher value indicates better color intensity, saturation and contrast of the underwater image.

3) Peak Signal-to-Noise Ratio (PSNR): PSNR measures quality of enhanced image from a statistical point of view by calculating difference between corresponding pixel gray values of image to be evaluated and reference image and is a measure of peak error. The higher PSNR value, less distortion between reference image and enhanced image, and the better image quality.

4) Absolute Mean Brightness Error (AMBE): AMBE helps to compute brightness content that is preserved after process of image enhancement. Median values of AMBE metric indicate good preservation of brightness. The results are shown in the table below. The smaller the value, the better the image quality.

The comparison indicates that the proposed objective metrics have yielded favorable results. As shown in Table III, images processed using the algorithms presented in this paper exhibit good performance across the comprehensive evaluation criteria of color, clarity, and contrast. In Table IV, except for Img5 and Img7, the images processed by the algorithm proposed in this paper outperform other algorithms in terms of overall visual effect, effectively mitigating biased color phenomena in underwater images. Table V demonstrates that the proposed algorithm performs well in terms of image distortion, with the enhanced images displaying improved texture features. Additionally, as shown in Table VI, the paper demonstrates good performance in contrast enhancement, effectively highlighting the fine details of underwater images.

TABLE III. EVALUATION RESULTS OF UIQM

Images	Original	HE	CLAHE	Ref. [28]	Ref. [33]	Proposed
Img1	5.46	6.63	7.41	6.01	7.67	**7.73**
Img2	1.85	6.62	5.64	6.71	3.38	**7.00**
Img3	3.07	6.64	5.08	6.55	5.59	**6.79**
Img4	1.40	5.30	5.57	**6.38**	4.17	4.46
Img5	0.50	6.66	5.83	6.68	4.18	**6.81**
Img6	-0.83	4.79	**10.39**	6.85	1.24	5.92
Img7	-3.12	1.20	2.25	2.57	0.58	**4.10**
Img8	2.25	5.81	6.16	5.93	5.45	**7.16**

TABLE IV. EVALUATION RESULTS OF UCIQE

Images	Original	HE	CLAHE	Ref. [28]	Ref. [33]	Proposed
Img1	0.50	0.57	0.48	0.56	0.49	**0.67**
Img2	0.48	0.63	0.52	0.63	0.52	**0.70**
Img3	0.56	0.54	0.54	0.59	0.57	**0.72**
Img4	0.51	0.62	0.55	0.63	0.56	**0.72**
Img5	0.58	0.63	0.57	**0.64**	0.61	0.55
Img6	0.47	0.67	0.56	0.67	0.50	**0.75**
Img7	0.57	0.65	0.57	**0.67**	0.64	0.56
Img8	0.63	0.66	0.60	0.65	0.64	**0.82**

TABLE V. EVALUATION RESULTS OF PSNR

Images	HE	CLAHE	Ref. [28]	Ref. [33]	Proposed
Img1	13.54	11.16	12.29	9.48	**19.37**
Img2	12.23	9.68	10.47	9.41	**14.17**
Img3	15.64	7.56	12.11	15.38	**18.61**
Img4	12.69	12.70	11.82	8.84	**16.39**
Img5	13.68	7.98	11.93	11.90	**13.90**
Img6	9.60	11.36	8.90	7.69	**11.95**
Img7	9.77	8.55	9.06	9.04	**10.87**
Img8	**15.00**	8.69	13.83	12.10	14.85

TABLE VI. EVALUATION RESULTS OF AMBE

Images	**HE**	**CLAHE**	**Ref. [28]**	**Ref. [33]**	**Proposed**
Img1	51.92	48.10	48.34	88.48	**11.37**
Img2	35.06	51.91	27.74	83.85	**13.97**
Img3	24.38	86.98	26.62	20.57	**4.92**
Img4	51.67	33.32	47.59	95.74	**19.48**
Img5	**0.38**	78.16	5.65	49.39	25.29
Img6	46.34	25.94	39.89	91.32	**10.58**
Img7	55.55	63.59	49.86	65.02	**33.03**

Hence, it can be concluded that the proposed method exhibits significant improvements in contrast, chromaticity, and brightness based on objective evaluation metrics.

V. CONCLUSION

We propose a method for underwater images through the higher-order moments CLAHE model and V-channel substitution. Specifically, in the contrast enhancement stage, higher-order moments describe the dynamic features of image sub-blocks, improving CLAHE's fuzzy and incomplete description of histogram statistical features and achieving more accurate contrast enhancement. In the color correction stage, we utilize gray data instead of the V-channel to compensate for information loss in the color channel, effectively achieving color correction aligned with human visual perception. Extensive experiments on real underwater images across various challenging scenarios demonstrate the robustness and effectiveness of the proposed method in contrast enhancement and color correction. Both qualitative and quantitative experimental results further validate the method's superiority over other state-of-the-art methods.

In summary, our proposed method effectively addresses color distortion, low contrast, and blurred details in underwater images, offering valuable insights into the marine world. Future research may consider introducing higher-dimensional histogram dynamic features or unique scene-specific features to further enhance the effect and quality of image enhancement.

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