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Underwater Image Enhancement Through Smooth Gridded Adaptive Color Compensation with Green-Tint Removal and Integrated CLAHE

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ABSTRACT

Underwater images frequently have low contrast, color distortion, and a greenish hue, due to wavelength-dependent light absorption and scattering. These issues limit the efficacy of underwater imaging applications and negatively impact visual perception. This paper presents a unique enhancement framework called Smooth Gridded Adaptive Color Compensation (SGACC) with Green Tint Removal (GTR) and adaptive Contrast Limited Adaptive Histogram Equalization (CLAHE) to address these issues. While GTR adjusts for red-channel attenuation to lessen green dominance, the SGACC module uses Gaussian-blended grids for smooth and targeted color correction. By adapting to changes in brightness while maintaining image features, adaptive CLAHE significantly improves local contrast. The proposed method consistently outperforms state-of-the-art techniques, according to experimental assessments on Large-Scale Underwater Image (LSUI) and Underwater Image Enhancement Benchmark (UIEB) datasets. It offers significant Underwater Image Quality Measure (UIQM) / Underwater Color Image Quality Evaluation (UCIQE) improvements, 2.0% Structural Similarity Index (SSIM) gain, and up to 3.6 dB better Peak Signal-to-Noise Ratio (PSNR) on LSUI. It achieves 21.11 dB PSNR and 0.9631 SSIM on UIEB, indicating exceptional perceptual quality. The proposed technique, SGACC-GTR, with adaptive CLAHE architecture, successfully restores natural color balance and enhances underwater image quality.

1. INTRODUCTION

Natural resources, many of which are running low on land, are in higher demand because of the rapid growth of human civilization. With its abundance of essential resources like oil, gas, minerals, and marine food, as well as renewable energy sources like tidal and wave power. Sustainable development depends on accurate monitoring and exploration of these underwater resources. However, the underwater environment is hostile and hard to access, so manual observation is not practical. As a result, underwater imaging is essential for collecting visual data for underwater robotics, marine biology, archaeology, and oceanographic study.

Applications in marine biology, archeological documentation, underwater robotics, and environmental monitoring all depend on underwater imaging. However, light absorption and scattering in water often cause images taken in aquatic environments to deteriorate significantly. Severe color distortions and reduced vision occur due to the rapid loss of red wavelengths and the dominance of green and blue channels. Suspended particles create haze and backscatter, which also lowers visual clarity and contrast even more.

To address these issues, a number of conventional and learning-based strategies have been put forth. Although the Dark Channel Prior (DCP) [1, 2] has been widely employed to remove haze, its effectiveness is largely dependent on atmospheric assumptions that are not always true in underwater settings, which frequently leads to color bias and halo distortions. Although it issues with uneven lighting and over-compensation of colors, the Underwater Dark Channel Prior (UDCP) [3] makes an effort to handle channel-specific attenuation. Brightness and color constancy are improved by enhancement-based techniques such as the Unsupervised Color Correction Method (UCM) [4] and Extended Multi-Scale Retinex (EMSR) [5], but they may result in overly saturated or artificial appearances.

Hybrid methods, such as Gray World with Enhanced DCP [6] or CLAHE with percentile-based contrast adjustment [7], offer limited flexibility and often do not perform well in various underwater situations. Moreover, while deep learning-based methods show potential, they depend heavily on large annotated datasets and may not adapt well to different types of water, lighting, and camera settings. When used in different lighting and water conditions, many approaches often lead to over-enhancement and color distortion. This creates artificial visual effects. Additionally, most methods have difficulty handling various underwater conditions, where light scattering and absorption change across regions. This is due to their low ability to manage uneven degradation.

Conventional image improvement methods, like histogram equalization and white balance correction, often fall short. They struggle to adjust to the uneven quality across a picture. Removing green dominance and compensating for missing red tones are also important steps in restoring natural colors in underwater images.

The proposed technique, SGACC, uses the mean channel to conduct color balancing per block after dividing the image into overlapping grid blocks. By avoiding block artifacts, Gaussian blending guarantees seamless transitions between neighbouring blocks. In order to combat wavelength-dependent attenuation, the GTR module adaptively decreases excessive green dominance while enhancing the red channel. When the dynamic range of the image is inadequate, contrast is selectively improved using an adaptive CLAHE step that is based on luminance variation. This prevents over-enhancement in areas that are already well-enhanced.

2. RELATED WORK

The exploration of underwater resources began during the 1970s. The earlier techniques focused on basic image processing to address the issues related to light scattering and absorption in underwater environment. Many techniques that are used for underwater image enhancement and restoration do not overcome all the challenges, issues and limited for real world applicability [8]. This is a perception-aware decomposition and fusion framework that simultaneously takes structural and perceptual priors into account in order to improve the underwater photos.

Constructed wetland systems can successfully support more comprehensive water-reuse strategies in areas experiencing water shortages. The study evaluated the reuse potential of the treated wastewater and found it suitable for various non-potable applications [9]. An EMSR technique designed for underwater enhancement was presented in this paper. This technique successfully enhances visibility and dynamic range in deteriorated photos. However, it frequently creates artificial color tones and generates halo aberrations, especially in scenes with significant illumination change.

Zhang et al. [10] proposed a method that greatly increases image contrast and restores visual clarity by combining color correction and bi-interval contrast enhancement. The technique, however, suffers in badly deteriorated underwater images where color casts and haze are still noticeable. Zhu [11] proposed an improved DCP that enhances contrast and reduces haze in underwater images. However, the method's robustness is limited because it frequently results in over-saturated colors and obvious artifacts in bright or uniform regions. Table 1 shows the methods of various techniques and their advantages and limitations.

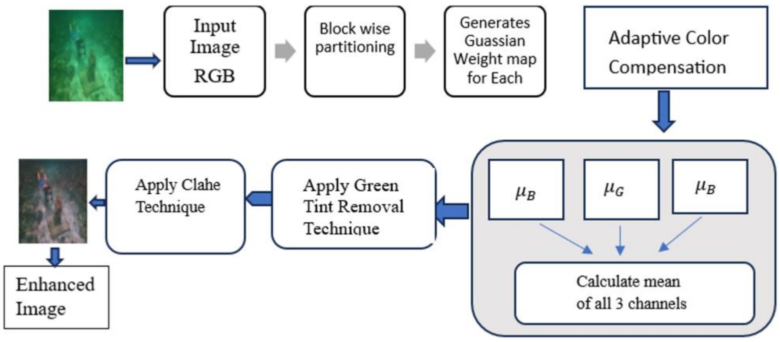


Figure 1. Underwater image enhancement process diagram

Table 1. Comparative summary of underwater image enhancement methods

Ref.	Method	Strengths	Limitations
[12]	Attenuated color channel correction + detail-preserved contrast enhancement	Enhances natural color tones.	Intensify noise overenhancement edges.
[13]	Color balance and fusion framework	Uses multi-image fusion to restore natural color.	Heavily reliant on input weight and result in an imbalance of colors.
[14]	Auto color correction using depth information	Successfully restore accurate color tones.	Sensitive to inaccurate depth estimation; fails in murky water.
[15]	Dual color space and contrast learning	Improves enhancement quality by combining RGB and perceptual domain learning.	Requires a lot of training data and has little ability to generalize to new situations.
[16]	Piecewise color correction + dual prior optimized contrast enhancement	Effectively increases contrast and maintains color balance.	Computationally demanding and inappropriate for use in real time.
[17]	Preprocessing-based contrast and color correction	Easy to use and efficient for improving basic visibility.	Incapable of adapting to a variety of underwater circumstances.
[18]	Wavelength compensation method	Compensates for spectral attenuation to restore color fidelity.	Not adaptable to dynamic underwater conditions.
[19]	Gradient and CLAHE-based smoothing	Enhances LAB* color space's local contrast and clarity.	May result in color imbalance and over-enhancement in bright areas.
[20]	Polarization-based multi-image enhancement	Uses several polarization states to effectively decrease haze and scattering.	Not appropriate for real-time use of a single image.
[21]	Wavelet-based variational enhancement	Enhances contrast while preserving multi-scale detail.	Fails significant wavelength attenuation.
[22]	Fuine-gan (fast underwater image enhancement gan)	Deep learning-based algorithm effectively enhances visibility, color, and contrast.	Struggles to capture underwater images in poor light or with significant degradation.

[23]	Deep learning survey on UIE metrics and methods	Provides detailed analysis of new datasets, loss functions, and metrics.	A new enhancement algorithm is not suggested.

3. PROPOSED METHODOLOGY

This section outlines the proposed underwater image enhancement pipeline. It uses flexible methods to restore color balance and contrast. Underwater images often have color distortion and low visibility because of light scattering and absorption. The method, shown in Figure 1, combines Smooth Gridded Adaptive Color Compensation with Green Tint Removal (SGACC-GTR) and adaptive CLAHE to improve image quality. The technique is tested on two datasets: Underwater Image Enhancement Benchmark (UIEB), which includes 950 real underwater images and is commonly used for performance comparison, and Large-Scale Underwater Image (LSUI), a large dataset with over 4,000 paired underwater and reference images that allows for a solid evaluation of enhancement methods.

3.1 Smooth gridded adaptive color correction

The process starts by reading the input image and finding its dimensions (h, w). Using a set grid size and overlap ratio, the image is split into overlapping blocks. This helps reduce local color bias and lighting changes. Two arrays, weight_map (for collecting blending weights) and corrected_img (to hold the improved output), are set up. To ensure smooth transitions between blocks, the matching picture region and its precomputed Gaussian blending weights are pulled for each block location (y start, x start). A Gaussian blending mask is precomputed and applied to each block to provide smooth transitions between nearby areas.

$$B_h = \frac{H}{R}, B_w = \frac{W}{C} \tag{1}$$

The above equation defines the block dimensions, where B_h is the height of each block and B_w is the width of each block.

$$S_h = B_h.(1 - overlap), S_w = B_w.(1 - overlap) \tag{2}$$

S_h and S_w are the step sizes in vertical and horizontal directions. This equation controls the overlap between neighbouring blocks and ensures smooth, enhanced natural images.

The mean intensity values of the blue, green, and red channels (mean b, mean g, and mean r) are computed for each block. After that, the gray mean value of the block is calculated, which is used as a guide for intensity balance.

In order to properly correct for color imbalances and improve visual uniformity throughout the image, each channel is then normalized proportionately to this gray mean.

$$\mu_{gray} = \frac{\mu_B + \mu_G + \mu_R}{3} \tag{3}$$

Through the above equation, each block is processed individually to maintain color balance and equalize illumination across all the channels.

3.2 Green Tint Removal

The GTR stage identifies excessive green by calculating the ratio of the green channel mean to the average of the red and blue channel means. If this ratio goes above a certain threshold (Tg), a suppression factor is applied to the green channel. Additionally, a red boost factor is introduced to restore warmer tones. This adjustment improves color intensity and results in a more natural look. The corrected blocks are then combined into corrected_img using Gaussian weighting. Finally, the image is normalized by dividing by weight_map, and pixel values are clipped to the valid intensity range of [0, 255].

$$\gamma_G = \frac{\mu_G}{\frac{\mu_R + \mu_B}{2} + \epsilon} \tag{4}$$

The above equation calculates the green dominance ratio is estimated and suppression factor and red boost factor are applied to reduce excessive green dominance and restore natural green color in the image.

3.3 Adaptive CLAHE

Finally, the corrected image is converted into the LAB color space for adaptive CLAHE enhancement. The luminance standard deviation (σ_L) of the L-channel is measured to assess contrast variation. If σ_L falls below a defined threshold (T_σ), the CLAHE clip limit is dynamically increased using a scaling factor to enhance low-contrast regions without over-amplifying bright areas. The adjusted L-channel is then recombined with the original A and B channels, and the image is converted back to BGR space to produce the final enhanced output.

If $\sigma_L < T_\sigma$, the clip limit is increased dynamically.

$$C_{limit} = 1.5 + s(C_{max} - 1.5) \tag{5}$$

The above equation controls and enhances the contrast in low contrast regions and also prevents over-enhancement in bright areas.

Algorithm 1. SGACC–GTR Balanced with Adaptive CLAHE

Input: BGR underwater image $I_{(x,y)} \in R^{h \times w \times 3}$

Output: Enhanced Image I_{enh}

Step 1. Block partitioning

Divide *I* into overlapping blocks of sizes.

$$B_h = \frac{H}{R}, B_w = \frac{W}{C}$$

The above formula defines the block dimensions.

$$\Delta_h = B_h(1 - \alpha), \Delta_w = B_w(1 - \alpha) \tag{6}$$

The Eq. (6) controls the overlap between neighbouring blocks.

Step 2. For each block, generate Gaussian blending mask

$$W_G(u, v) = e^{-4(\mu^2 + v^2)}, u, v \in [-1,1]$$

Step 3. For each block b, compute channel means

$$\mu_B = \overline{b}_B, \mu_G = \overline{b}_G, \mu_R = \overline{b}_R$$

$$\mu_{gray} = \frac{\mu_B + \mu_G + \mu_R}{3} \tag{7}$$

The Eq. (7) balances the color in each block.
Compensate channels: $b_k^i = b_k \cdot \frac{\mu_{gray}}{\mu_k + \epsilon}, k\epsilon\{B, G, R\}$.

Step 4. Green tint detection and removal
Green ratio: $\gamma_G = \frac{\mu_G}{\frac{\mu_R+\mu_B}{2}+\epsilon}$.

$$If\ \gamma_G > T_g : \begin{cases} E_g = min\left(\frac{\gamma_G - T_g}{0.5}, 1\right) \\ S_f = (1 - (1 - S_{\max})E_g \\ R_b = (1 - (R_{\max} - 1)E_g \end{cases} \tag{8}$$

Apply correction: $b_G' = b_G' \cdot S_f, b_R' = b_R' \cdot R_b$.

Step 5. Apply weighted block fusion

$$I_{corr}(x, y) = b'(x, y) \cdot W_G(x, y) \tag{9}$$

$$M_w(x, y) += W_G(x, y)$$

$$\text{Normalize} = I_{corr} = \frac{I_{corr}(x, y)}{M_w(x, y)}$$

Step 6. Apply adaptive CLAHE

Convert to LAB: $I_{corr} = (L, A, B)$.
Luminance std. dev: $\sigma_L = std\left(\frac{L}{255}\right)$.
If $\sigma_L < T_\sigma$: s=$\frac{T_\sigma - \sigma_L}{T_\sigma}$.

$$C_{limit} = 1.5 + s(C_{max} - 1.5) \tag{10}$$

Step 7. Output enhanced image I_{enh}

4. EXPERIMENTAL RESULTS

4.1 Dataset

Experiments were conducted using two datasets, the LSUI dataset and UIEB (950 real-world underwater photos from various aquatic environments; Li et al., IEEE TIP 2019), to evaluate the strength of the proposed method. Some of the raw images and their histograms are shown in Figures 2 and 3, respectively. The UIEB is a well-known dataset for testing underwater image enhancement techniques. It includes 950 real-world underwater photos taken in different environments. This dataset is suitable for a thorough evaluation of enhancement methods because it covers a variety of underwater conditions, including different lighting levels, depths, water types, and color distortions. UIEB has become a standard for testing image quality improvement in terms of both how images are perceived visually and using metrics like Underwater Image Quality Measure (UIQM) and Underwater Color Image Quality Evaluation (UCIQE). The LSUI dataset includes over 4,000 high-quality underwater photos and matching reference photos.

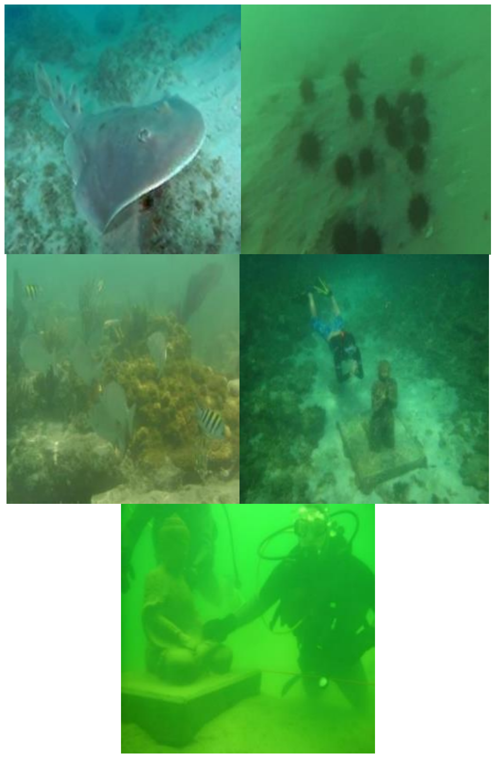
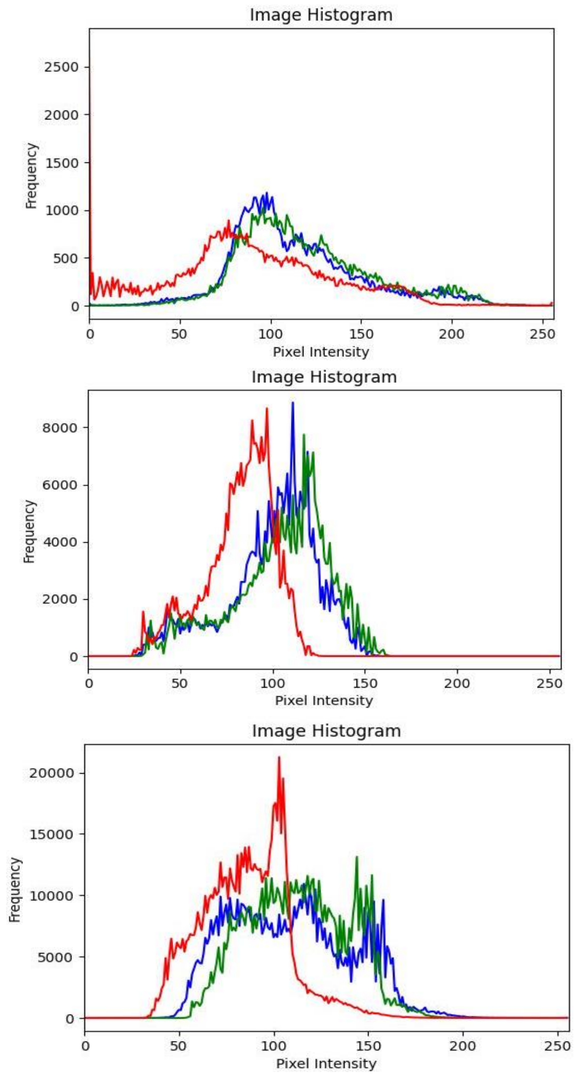


Figure 2. Images before enhancement



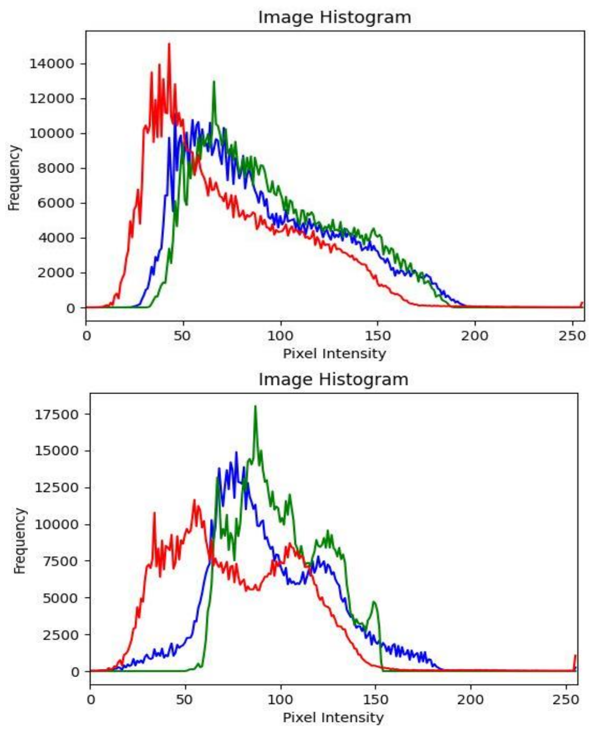


Figure 3. Histogram of the raw images

Deep learning improvement models can be trained and assessed in many underwater environments. LSUI includes various visibility conditions, light levels, and water quality. Due to its size and paired structure, LSUI is helpful for data-driven methods that require substantial training data. It can also be used to fairly compare learning-based and traditional augmentation techniques. Both full-reference (Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM)) and no-reference (UIQM, UCIQE) measures are commonly employed in UIEB testing, which captures typical underwater issues such as color distortion, poor visibility, and uneven lighting. Some of the raw images and their histogram are shown in Figures 2 and 3.

4.2 Comparative results

The suggested SGACC–GTR Balanced framework was quantitatively evaluated utilizing PSNR, SSIM, UIQM, and UCIQE measures to evaluate the enhanced underwater images' structural fidelity and perceptual quality. In comparison to current enhancement algorithms, the suggested method successfully preserves small features, as seen by a higher PSNR value that represents decreased noise and distortion.

$$\mathrm{PSNR} = 10.\log_{10}\left(\frac{MAX^2}{MSE}\right) \tag{11}$$

In a similar vein, the improvement in SSIM shows improved structural similarity and contrast preservation, indicating that edges and spatial information are preserved following augmentation. The efficacy of color and contrast restoration is further confirmed by the perceptual quality measures UIQM and UCIQE. In particular, better sharpness, colorfulness, and contrast are shown by higher UIQM values, whilst balanced chromatic and brightness enhancement throughout underwater scenes is highlighted by higher UCIQE scores.

$$SSIM(x,y) = \frac{(2u_x\mu_y + C_1) + (2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{12}$$

$$UCIQE = c_1 \times Chroma + c_2 \times Saturation + c_3 \times Contrast \tag{13}$$

$$UIQM = c_1 \times UICM + c_2 \times UIConM + c_3 \times UISM \tag{14}$$

4.2.1 Qualitative results

Qualitatively, the improved images showed a noticeable decrease in the usual green-blue tinge and haze that occurs underwater. With reds fully returned and green's dominance diminished, color tones seemed more realistic and more in line with reality. Block-wise contrast stretching and LAB color correction improved the image's illumination balance and brought out features in previously washed-out or dark areas. The feeling of depth in the image and underwater items was enhanced by the sharpening and definition of edges and textures. The subfigures (a)-(f) illustrated in Figure 4 show the visual quality of the underwater images with the proposed technique and other techniques. Each row highlights how different algorithms affect visibility, color balance, and contrast restoration under diverse underwater conditions.

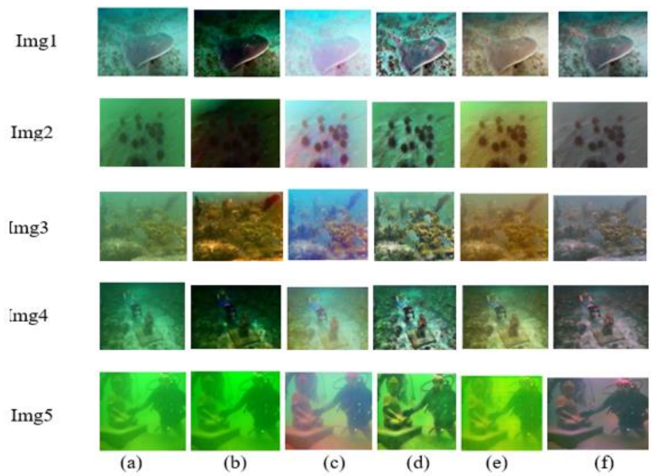


Figure 4. Original images processed by various techniques: (a) Original image, (b) UDCP, (c) EMSR, (d) CLAHE & percentile, (e) FUNIE-GAN, (f) proposed

4.2.2 Quantitative results

Using both quantitative measurements and qualitative visual evaluation, the effectiveness of the suggested Smooth GACC-based underwater image enhancing technique was assessed. The improved image quantitatively demonstrated a significant improvement in objective image quality. In comparison to the original image, the PSNR rose, suggesting less distortion and better pixel accuracy [24]. The visual quality of the images with various techniques can be viewed in Figure 4. In a similar vein, a higher score on the SSIM indicated better structural detail preservation. The UCIQE and UIQM scores also showed a considerable improvement in terms of perceptual no-reference metrics, as shown in Tables 2 and 3.

From Tables 2 and 3, it is evident that the proposed method consistently achieves higher PSNR, SSIM, UIQM, and UCIQE values compared to other techniques, indicating superior visual quality and color fidelity. The bar chart in Figures 5 and 6 further confirms this trend, where the proposed method outperforms existing approaches across all metrics. Overall, the results clearly demonstrate that the proposed approach provides more effective underwater image enhancement. Because the Gaussian-weighted gamma correction adjusts for uneven loss across RGB channels, the green-tint suppression in the suggested method works well. The method improves visual realism and restores spectral balance by reducing the excessive green intensity caused by the shallow penetration of red wavelengths.

However, the adaptive CLAHE module may over-amplify noise and edges in some situations with very low illumination or high particle density, particularly in dark areas. This occurs because when input histograms are sparse, CLAHE's local contrast enhancement may amplify intensity changes. Although the framework uses smooth block transition averaging and a clip limit tuning factor to lessen this, moderate over-enhancement may still happen in severe circumstances. However, by combining both global tone correction and localized adaptive contrast adjustment, reducing halo artifacts, and maintaining color naturalness, the suggested SGACC–GTR method delivers a more balanced enhancement than conventional CLAHE or Retinex-based procedures.

Table 2. Comparison of different methods on LSUI dataset in terms of PSNR, SSIM, UIQM and UCIQE

Dataset	Images	Metrics	[3]	[5]	[6]	[22]	Proposed
LSUI	Img1	PSNR	22.098	14.7899	23.247	22.799	23.321
		SSIM	0.9589	0.8531	0.8975	0.9621	0.9753
		UIQM	3.3052	1.8070	3.9995	4.6562	4.7326
		UCIQE	0.5578	0.4038	0.5514	0.4943	0.6503
	Img2	PSNR	16.544	10.7342	13.7073	13.517	19.141
		SSIM	0.9223	0.8566	0.8566	0.9371	0.9649
		UIQM	4.8280	3.4790	4.3381	5.1494	5.0848
		UCIQE	0.5656	0.5241	0.5435	0.4799	0.5889

Table 3. Comparison of different methods on UIEB dataset in terms of PSNR, SSIM, UIQM and UCIQE

Dataset	Images	Metrics	[3]	[5]	[6]	[22]	Proposed
UIEB	Img3	PSNR	16.5440	10.7342	13.7073	13.5175	20.2312
		SSIM	0.9223	0.8566	0.8566	0.9371	0.9622
		UIQM	4.8280	3.4790	4.3381	5.1494	5.2596
		UCIQE	0.5656	0.5241	0.5435	0.4799	0.5862
	Img4	PSNR	19.3282	4.3373	12.3490	17.5074	21.1114
		SSIM	0.9182	0.9594	0.8972	0.9783	0.9789
		UIQM	2.9824	2.5684	3.6874	4.2443	3.9503
		UCIQE	0.5219	0.5370	0.5370	0.5079	0.6023
	Img5	PSNR	14.1854	4.9634	22.7752	16.8332	14.5671
		SSIM	0.8873	0.8613	0.8184	0.9248	0.9380
		UIQM	-0.6203	3.6282	2.5716	1.8615	3.8183
		UCIQE	0.4189	0.5255	0.5035	0.4018	0.5683

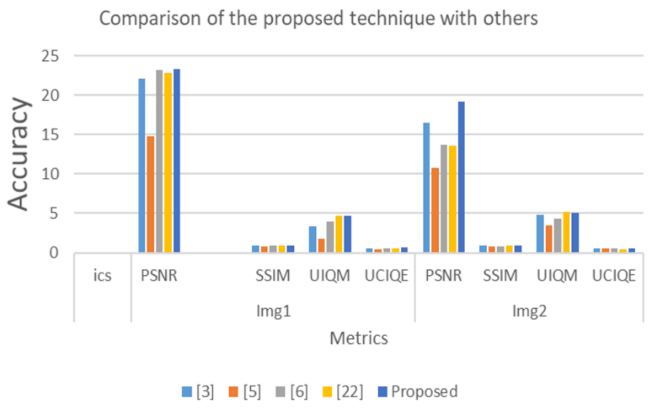


Figure 5. Chart of the various techniques metric results on LSUI dataset

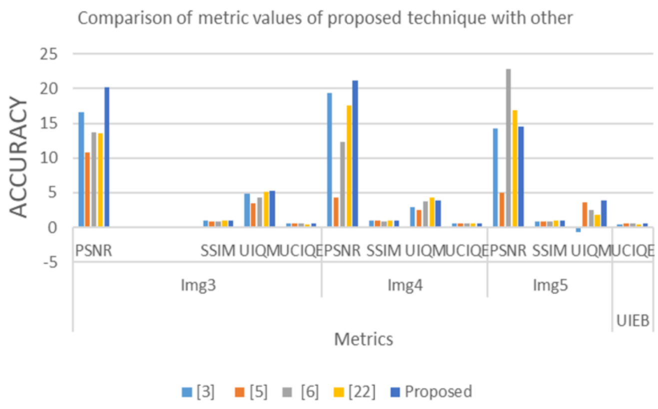


Figure 6. Chart of the various techniques metric results on UIEB dataset

5. CONCLUSION

The proposed SGACC–GTR Balanced framework integrated with adaptive CLAHE effectively enhances underwater images by correcting color distortion, reducing green dominance, and improving contrast while maintaining natural visual balance. Quantitative evaluations using PSNR, SSIM, UIQM, and UCIQE show consistent improvements in perception and structure compared to existing methods. These results highlight strong potential for practical use in underwater robotics, marine exploration, and environmental monitoring. Clear, color-accurate images are essential for reliable perception and analysis in these fields. However, performance drops in highly turbid or low-light conditions, and the complexity of the computations limits real-time use. Future research will concentrate on tuning parameters, optimizing for depth, and developing lighter implementation strategies to improve robustness, efficiency, and scalability in various underwater environments.

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