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LACC-RCE: A Local Adaptive Color Correction and Rayleigh-Based Contrast Enhancement Method for Underwater Image Enhancement

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Abstract: Underwater images are inherently degraded by color distortion, contrast reduction, and uneven brightness, primarily due to light absorption and scattering in water. To mitigate these challenges, a novel enhancement approach is proposed, integrating Local Adaptive Color Correction (LACC) with contrast enhancement based on adaptive Rayleigh distribution stretching and CLAHE (LACC-RCE). Conventional color correction methods predominantly employ global adjustment strategies, which are often inadequate for handling spatially varying color distortions. In contrast, the proposed LACC method incorporates local color analysis, tone-weighted control, and spatially adaptive adjustments, allowing for region-specific color correction. This approach effectively enhances color fidelity and perceptual naturalness, addressing the limitations of global correction techniques. For contrast enhancement, the proposed method leverages the global mapping characteristics of the Rayleigh distribution to improve overall contrast, while CLAHE is employed to adaptively enhance local regions. A weighted fusion strategy is then applied to synthesize high-quality underwater images. Experimental results indicate that LACC-RCE surpasses conventional methods in color restoration, contrast optimization, and detail preservation, thereby enhancing the visual quality of underwater images. This improvement facilitates more reliable inputs for underwater object detection and recognition tasks.

Keywords: Underwater; Image enhancement; Local adaptive color correction; Rayleigh distribution stretching; Contrast enhancement

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1. Introduction

Underwater imaging is frequently degraded by blurring, color distortion, and reduced contrast, primarily due to the distinct optical properties of the underwater environment. The selective absorption of light in water leads to severe attenuation of red wavelengths, whereas blue and green wavelengths penetrate more effectively, resulting in a characteristic bluish-green appearance in underwater images. Furthermore, suspended particles and water molecules contribute to multiple scattering of light, which significantly diminishes image contrast. Additionally, underwater currents and environmental disturbances often induce camera instability, further degrading image quality and leading to blurring of object edges and contours. These degradation effects severely compromise feature representation in underwater images, creating significant challenges for downstream computer vision tasks, such as object detection, image segmentation, and recognition. Consequently, underwater image restoration and enhancement remains a topic of substantial practical significance. Existing approaches in this field can be generally categorized into three main types: non-physical model-based enhancement methods, physical imaging model-based restoration methods, and deep learning-based enhancement techniques.

Physical model-based underwater image restoration methods reconstruct degraded images by formulating underwater optical imaging models and estimating key parameters based on predefined priors. The restoration process is then conducted through inverse computation techniques. These methods primarily follow two technical pathways: one approach exploits the statistical characteristics of the darkest pixels to estimate and invert the dark channel, thereby facilitating image restoration. Notable algorithms include the Dark Channel Prior (DCP) [1] and its enhanced variant, the Underwater Dark Channel Prior (UDCP) [2]. Another approach to underwater image restoration relies on parameter estimation within underwater optical imaging models. Yu *et al.* [3] proposed a dehazing algorithm incorporating dual transmission maps, designed to adapt to varying underwater environments. Liu and Liang [4] employed grayscale morphological closing operations to estimate background light, effectively mitigating interference from white objects. Furthermore, they introduced a new underwater light attenuation prior (NULAP) and an adjusted reverse saturation map (ARSM) to enhance the accuracy and refinement of transmission map (TM) estimations. While these methods have demonstrated effectiveness in recovering color fidelity and fine details, their stability and consistency across diverse underwater conditions require further refinement.

Non-physical model-based underwater image enhancement methods focus on direct pixel-level enhancement without relying on physical imaging models. For instance, Song and Wang [5] employed white balance-based color correction to compensate for color distortions induced by medium attenuation. Additionally, they incorporated contrast and spatial cues through a saliency-weighted coefficient update strategy, aiming to achieve high-quality image fusion and enhancement. Zhang *et al.* [6] proposed an approach that enhances both global and local contrast using a dual-histogram-based iterative thresholding method and a limited histogram approach. To further refine the enhanced images, they employed a multi-scale fusion (MSF) strategy and a multi-scale unsharp masking (MSUM) technique. However, these methods may exhibit limited adaptability to diverse and complex underwater environments, often resulting in over-enhancement artifacts.

In recent years, deep learning-based image enhancement approaches have proliferated. For instance, Yan *et al.* [7] introduced a model-driven CycleGAN that integrates a physical model, enhancing both the effectiveness and generalization capability of traditional GAN-based methods in complex real-world underwater environments. Additionally, Wang *et al.* [8] developed UPGformer, a physics-guided transformer architecture designed to improve depth estimation accuracy. Ren *et al.* [9] introduced an enhanced Swin-Convs Transformer Block (RSCTB) designed to reinforce local attention mechanisms across both channel and spatial domains. This approach enhances the model's ability to perceive and restore images degraded by non-uniform medium distributions. However, deep learning-based methods demand extensive training data and impose high computational costs, while acquiring high-quality underwater datasets remains a critical challenge.

Underwater images frequently suffer from color distortion, contrast degradation, and uneven brightness distribution due to the selective absorption and scattering of light in water. To address these challenges, this study introduces a novel Local Adaptive Color Correction (LACC) method, integrated with a contrast enhancement framework leveraging adaptive Rayleigh distribution stretching and Contrast Limited Adaptive Histogram Equalization (CLAHE). This approach establishes a comprehensive underwater image enhancement pipeline. Unlike traditional global color correction techniques, which often fail to effectively adapt to spatially varying color distortions, the proposed method provides localized corrections, mitigating issues of under-correction or over-correction. Experimental results indicate that the proposed approach surpasses conventional methods in color fidelity and detail preservation.

2. Methods

Underwater images are inherently degraded by color distortion, contrast attenuation, and uneven brightness distribution, primarily caused by light absorption and scattering in water. To mitigate these effects, this study introduces a LACC method, integrated with a contrast enhancement technique that leverages adaptive Rayleigh distribution stretching and CLAHE.

Traditional color correction techniques primarily rely on global adjustments, which are often insufficient for addressing spatially varying color distortions. This limitation may result in some regions retaining noticeable color shifts while others experience excessive correction. The proposed LACC method incorporates local color analysis, tone-weighted control, and spatially adaptive adjustments, enabling region-specific correction and producing more perceptually natural and realistic color restoration. For contrast enhancement, the proposed method integrates adaptive Rayleigh distribution stretching and CLAHE. Initially, the global mapping properties of the Rayleigh distribution are leveraged to enhance overall contrast, followed by an adaptive truncation strategy to regulate the pixel stretching range. Subsequently, CLAHE is applied to refine local contrast adaptively, and a weighted fusion strategy is employed to synthesize the final enhanced image. The methodological flowchart is illustrated in **Figure 1**.

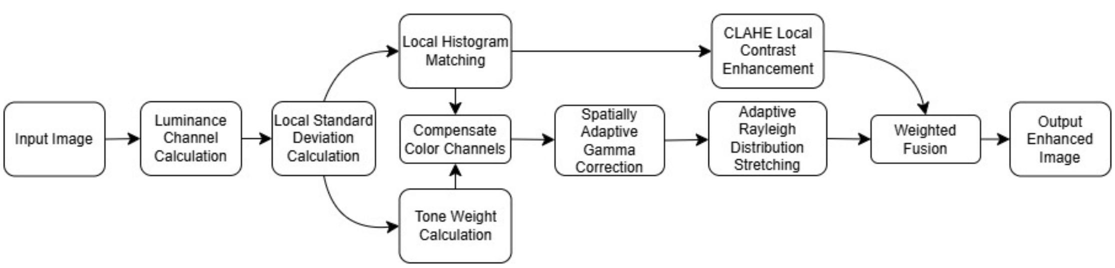

Figure 1. Methodological flowchart

2.1. Local Adaptive Color Correction (LACC) method

To enhance the accuracy of color distortion correction, this study employs a local standard deviation ratio approach to compensate for attenuation across color channels. The entire image is segmented into multiple small regions, where local statistical characteristics of both the luminance and color channels are computed independently. The luminance channel is defined as follows:

$$I_l(i,j) = max\{I_r(i,j), I_g(i,j), I_b(i,j)\} \tag{1}$$

where I_r, I_g, and I_b, correspond to the pixel values of the red, green, and blue channels, respectively, while

$I_l(i,j)$ represents the luminance of the given pixel.

Subsequently, the standard deviation of each color channel within the local window is calculated as follows:

$$\sigma_c^{local} = \sqrt{\frac{1}{K}\sum(I_c - \bar{I}_c)^2} \tag{2}$$

where K is the total number of pixels within the window, and $\bar{I}_c$ represents the mean intensity of the corresponding color channel.

Using the standard deviation ratio, the color channel values are modified to align more closely with the luminance channel:

$$I_c^{new} = I_c + (I_l - I_c) \times \frac{\sigma_c^{local}}{\sigma_l^{local}} \tag{3}$$

A smaller standard deviation in a color channel indicates lower variation, allowing for stronger alignment with the luminance channel. Conversely, a larger standard deviation suggests greater variability, warranting less adjustment to maintain the channel's original characteristics.

Despite compensating for color channel attenuation, regional variations in color distribution may still persist. To mitigate this issue, this study adopts a Local Histogram Matching (LHM) approach to ensure a more uniform color distribution across different regions of the image.

A reference set of high-quality underwater images is selected, from which the Cumulative Distribution Function (CDF) is computed as a standard. The histogram of each local window in the target image is then calculated and adjusted through CDF-based matching:

$$I_c^{match} = H_{ref}^{-1}\left(H_{input}(I_c)\right) \tag{4}$$

where H_{input} denotes the histogram of the input image, and H_{ref}^{-1} represents the inverse cumulative mapping of the reference image histogram.

During color correction, some regions may undergo overcompensation, resulting in color distortion. For example, blue tones may become overly dominant in certain areas, while red tones may be excessively enhanced. To mitigate this effect, this study introduces a Tone Weighting mechanism, ensuring that the correction magnitude is proportional to the deviation of the original tone. The tone weighting is formulated as follows:

$$W_c(i,j) = 1 - \left|\frac{I_c(i,j) - \bar{I}_c^{local}}{\bar{I}_c^{global}}\right| \tag{5}$$

where $\bar{I}_c^{local}$ denotes the mean intensity of the local window, represents the mean intensity of the entire image, and $W_c(i,j)$ regulates the extent of color compensation.

The final color adjustment is expressed as:

$$I_c^{final} = W_c \cdot I_c^{match} + (1 - W_c) \cdot I_c \tag{6}$$

In areas with significant color distortion, a lower W_c value leads to stronger color adjustments. Due to the uneven illumination in underwater environments, this study applies Spatially Adaptive Gamma Correction (SAGC) to enhance darker regions while mitigating overexposure in brighter areas.

2.2. Underwater image contrast enhancement based on adaptive Rayleigh distribution stretching and CLAHE

This study proposes a contrast enhancement approach that integrates adaptive Rayleigh distribution stretching with CLAHE. The method first leverages the global mapping properties of the Rayleigh distribution to improve overall contrast, while an adaptive truncation strategy is employed to constrain the pixel stretching range. Subsequently, CLAHE is applied for localized contrast enhancement, and a weighted fusion strategy is utilized to synthesize the final enhanced image.

To improve global contrast and ensure a more uniform brightness distribution, the Rayleigh distribution is employed for pixel value stretching. The probability density function (PDF) of the Rayleigh distribution is given by:

$$PDF(I) = \frac{I}{\sigma^2}\exp\left(-\frac{I^2}{2\sigma^2}\right) \tag{7}$$

where I denotes the pixel value of the input image, and σ serves as the distribution control parameter.

To accommodate diverse underwater lighting conditions, an adaptive computation method is utilized for determining σ:

$$\sigma = k \times \frac{I_{max} - I_{min}}{I_{avg}} \tag{8}$$

Where I_{max}, I_{min} denote the maximum and minimum pixel values of the image, respectively, I_{avg} represents the average pixel value, and k serves as the adjustment factor.

The Rayleigh distribution mapping function is formulated as follows:

$$I_{SR} = (I_{max} - I_{min}) \times \left(\frac{I - I_{min}}{I_{max} - I_{min}}\right)^{\sigma} + I_{min} \tag{9}$$

This transformation adjusts the pixel values to follow the Rayleigh distribution after enhancement, effectively enhancing overall contrast.

In the pixel stretching process, direct mapping may cause excessive enhancement of certain pixel values, leading to brightness distortion or loss of details. To address this, the Otsu thresholding method is utilized to determine the optimal pixel adjustment range, ensuring that the enhanced image preserves a well-balanced brightness distribution. The adjustment range is formulated as follows:

$$I_{out,min} = \max\left(I_{c,min}, T_{low}\right) \tag{10}$$

$$I_{out,max} = \min\left(I_{c,max}, T_{high}\right) \tag{11}$$

where $I_{c,min}$ and $I_{c,max}$ denote the minimum and maximum pixel values following the Rayleigh distribution transformation. T_{low} and T_{high} are derived from the Otsu thresholding method, representing the adaptive brightness range tailored to the current image.

This strategy effectively mitigates local overexposure and detail loss that may arise from global stretching, thereby improving the overall visual quality of the image.

Given that global contrast enhancement focuses on adjusting the overall brightness distribution, certain localized details may remain under-enhanced. To compensate for this limitation, CLAHE is incorporated to enhance local contrast adaptively.

$$I_{CLAHE} = \mathrm{CLAHE}(I_{SR}) \tag{12}$$

where I_{CLAHE} denotes the CLAHE-enhanced image, and CLAHE(I_{SR}) represents the CLAHE transformation applied to the input image.

CLAHE improves local contrast by applying independent histogram equalization within small regions while restricting pixel values to mitigate over-enhancement artifacts, which are often observed in traditional histogram equalization. Given the complementary strengths and limitations of global and local contrast enhancement, a weighted fusion strategy is implemented to synthesize the final enhanced image:

$$I_{final} = \alpha \cdot I_{SR} + (1 - \alpha) \cdot I_{CLAHE} \tag{13}$$

Where α is the fusion weight, and I_{SR} corresponds to the image enhanced through Rayleigh distribution stretching.

This strategy ensures that the image retains global contrast improvements while simultaneously enhancing local details, producing a sharper and more naturally enhanced visual representation.

3. Experimental results and analysis

To assess the effectiveness of the proposed algorithm, comparative evaluations were performed from both subjective and objective perspectives in comparison with existing methods. The experiments were conducted on datasets collected from two representative underwater environments. The first dataset originates from the Jingyuan Shipwreck site in the Yellow Sea, where the seafloor is primarily composed of silty sand, a condition that promotes suspended particle formation, resulting in high turbidity and low visibility. The second dataset was collected from the Xisha underwater trench, where images predominantly suffer from severe color distortion. A total of 246 images were processed, all standardized to a 1024 × 1024 pixel resolution. Performance evaluation was conducted using both qualitative and quantitative approaches. Qualitative assessment involved visual comparisons to subjectively evaluate image quality, whereas quantitative analysis utilized a comprehensive set of evaluation metrics to objectively assess the algorithm’s effectiveness.

Four existing underwater image enhancement methods were selected for comparison with the proposed approach: Retinex, UW-CycleGAN, UDCP, and UWCNN. These methods provide a comprehensive evaluation of the impact of different underwater image processing techniques on image quality.

To ensure objective assessment, three quantitative evaluation metrics were employed: Patch-Based Contrast Quality Index (PCQI), Underwater Color Image Quality Evaluation Metric (UCIQE), and Underwater Image Quality Measure (UIQM).

Five representative images were selected for visualization. The first dataset, as illustrated in **Figure 2**, was collected from the Jingyuan Shipwreck site.

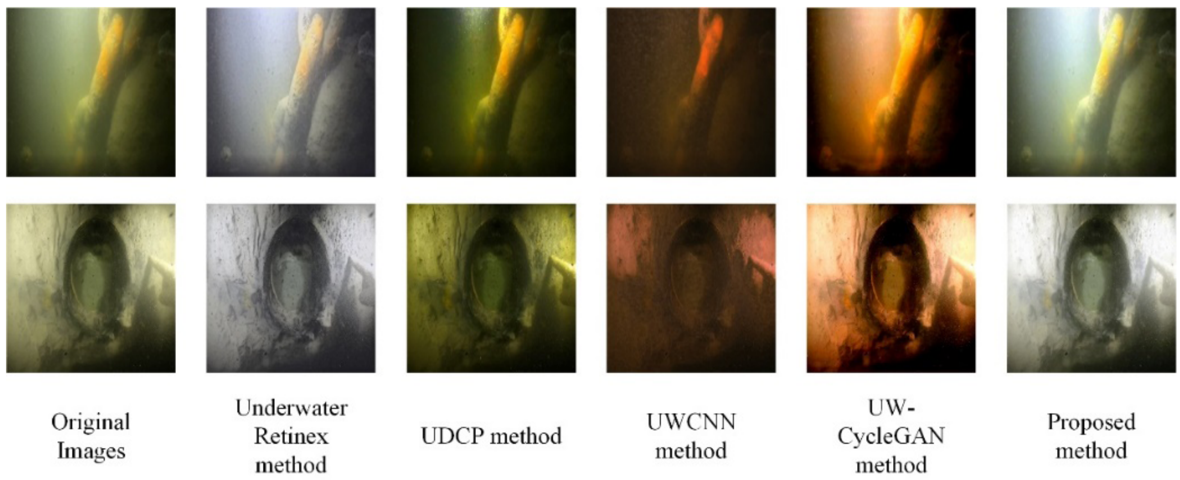

Figure 2. Images enhancement results of the proposed method compared to other methods

The turbidity of the underwater environment, combined with the presence of artificial light sources, causes significant light scattering, leading to a notable reduction in image details and contrast while also affecting color fidelity. Furthermore, overexposure artifacts are observed near the artificial light sources on both sides of the image. The UWCNN method leads to a complete loss of fine details. The Retinex method demonstrates limited effectiveness in underwater environments, with some images exhibiting noticeable sharpness degradation. The UDCP method results in the over-enhancement of colors in specific regions, while the UW-CycleGAN method suffers from excessive color amplification, causing color distortion. In contrast, the proposed method, specifically optimized for underwater conditions, effectively enhances text clarity, preserves image details and contrast, and improves color fidelity, while minimizing over-enhancement artifacts (**Figure 3**).

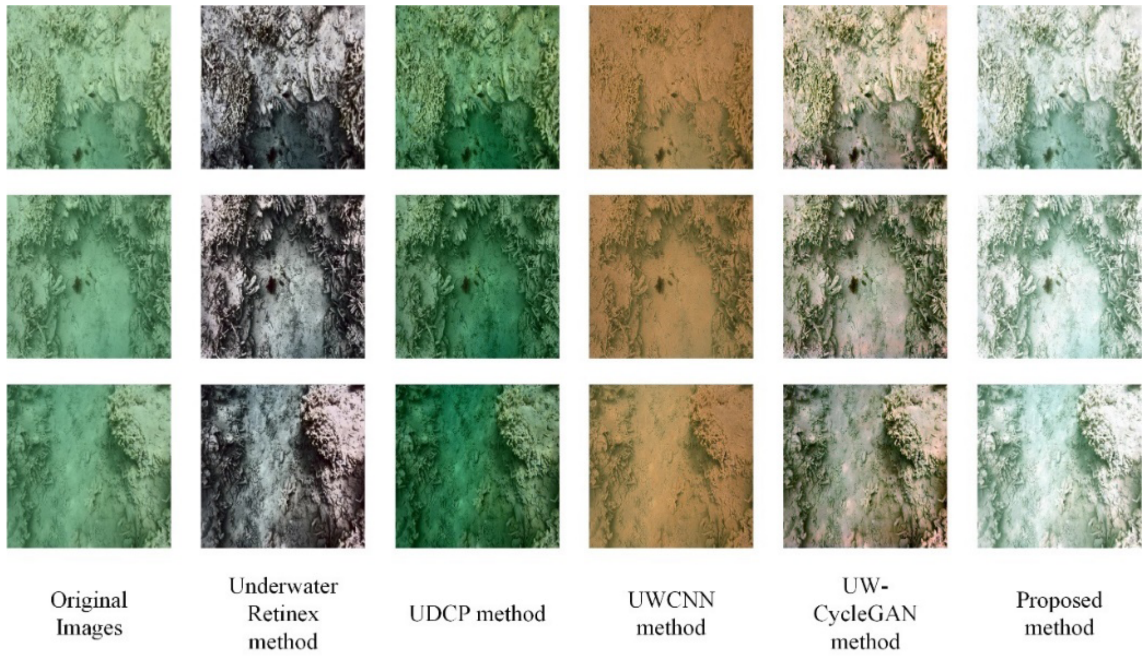

Figure 3. Images enhancement results of the proposed method compared to other methods

In the Xisha underwater trench, the optical properties of light absorption and scattering result in significant color distortions, predominantly characterized by a strong cyan-green tint, which substantially degrades color fidelity and visual clarity. Various enhancement methods exhibit distinct advantages and limitations in addressing this issue. The UWCNN method applies excessive compensation to the red channel, leading to oversaturated red regions. The UDCP method overcorrects the green channel, causing the image to appear unnaturally greenish. The Retinex method over-enhances dark regions, resulting in underexposure and loss of fine details. Similarly, the UW-CycleGAN method suffers from overcompensated red hues, distorting the overall color balance. By comparison, the proposed method demonstrates superior performance in color correction and image enhancement, effectively alleviating underwater color distortions, improving overall visual quality, and achieving a more natural and realistic restoration.

To quantitativelyw assess image quality, UIQM, UCIQE, and PCQI values were computed for the five selected images. The results are summarized in **Table 1**.

Table 1. Performance of evaluation metrics for different image processing methods

Images	Methods	UIQM	UCIQE	PCQI
1	Retinex	7.5709	24.2249	0.4744
	UDCP	6.3653	33.6903	0.5135
	UWCNN	1.6955	18.9805	0.3197
	UW-CycleGAN	4.9672	32.6752	0.4904
	Ours	7.4270	33.9983	0.6329
2	Retinex	7.3989	23.7096	0.5133
	UDCP	4.3207	21.5981	0.4306
	UWCNN	1.7468	17.1665	0.3547
	UW-CycleGAN	4.8150	21.5271	0.5017
	Ours	7.4704	24.4932	0.6250
3	Retinex	7.6713	26.0896	0.4855
	UDCP	3.2267	32.9838	0.5318
	UWCNN	6.4588	15.8973	0.4200
	UW-CycleGAN	7.0313	31.6088	0.7346
	Ours	7.7864	33.0733	0.7470
4	Retinex	7.5230	25.0243	0.5369
	UDCP	4.0981	24.9454	0.617
	UWCNN	5.2463	15.2347	0.4844
	UW-CycleGAN	7.7680	25.7651	0.7790
	Ours	7.8279	25.0277	0.7857
5	Retinex	4.8094	26.9719	0.5062
	UDCP	3.9349	25.3797	0.5339
	UWCNN	5.3996	16.5229	0.4460
	UW-CycleGAN	8.3393	30.7937	0.7238
	Ours	8.7182	30.4943	0.7119

The experimental results reveal significant differences in evaluation metrics among the tested image processing methods. Notably, the proposed method consistently outperforms others across all metrics. In particular, for the first test image, the Retinex method achieves a relatively high UIQM score, indicating its effectiveness in enhancing image details and overall visual quality. However, its lower performance in UCIQE and PCQI suggests limitations in color restoration and contrast optimization, highlighting areas for further improvement. Meanwhile, the UW-CycleGAN method exhibits distinctive performance trends in the fourth and fifth test images. It attains higher scores in UCIQE and PCQI, demonstrating strong capabilities in color enhancement and perceptual contrast improvement. Nevertheless, its relatively low UIQM scores expose deficiencies in overall image quality enhancement and detail preservation, indicating challenges in achieving a well-balanced and comprehensive enhancement.

4. Conclusion and future directions

This study presents LACC-RCE, a novel underwater image enhancement framework that combines LACC with adaptive Rayleigh distribution stretching and CLAHE-based contrast enhancement. Experimental results indicate that the method exhibits strong adaptability in color correction, contrast enhancement, and detail preservation, leading to a notable improvement in the visual quality of underwater images. Additionally, in terms of quantitative evaluation metrics, the proposed approach demonstrates consistent and superior performance across diverse underwater environments. Nevertheless, under extreme conditions, such as high turbidity or low-light environments, the proposed method may still exhibit insufficient enhancement in certain local regions or color shifts, suggesting that its performance in highly complex underwater scenarios requires further improvement. Future research can focus on the following directions, Refining color correction and contrast enhancement strategies to improve the method's adaptability and robustness in varying underwater conditions. Incorporating deep learning approaches to explore data-driven enhancement techniques, thereby improving the model's generalization capability across different underwater environments.

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Disclosure statement

The author declares no conflict of interest.

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