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Improved GCC Technique: A Comprehensive Approach to Color Cast Rectification and Image Enhancement

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ABSTRACT

The domain of underwater imaging is riddled with multifarious challenges, such as light attenuation, scattering, and color distortion, which can have a detrimental impact on the quality of images. In order to address these challenges, the Generalized Color Compensation (GCC) technique has been introduced, which utilizes color compensation and color mean adjustment to rectify color cast while integrating contrast enhancement via the Contrast Limited Adaptive Histogram Equalization (CLAHE). Nevertheless, the performance of GCC is limited due to the production of bright and smooth images. To overcome this challenge, we have introduced the improved GCC approach, which employs color compensation and color mean adjustment to rectify color cast. Subsequently, a contrast-enhanced image is generated through CLAHE to improve image contrast, while the detail-enhanced image is produced via a cumulative distribution function. Furthermore, image fusion between the detail-enhanced and contrast-enhanced images yields a superior-quality image. Our experimental results demonstrate the effectiveness of our proposed technique in improving the visual quality of underwater images. Objective metrics such as Underwater Image Quality Measure (UIQM) demonstrate that our technique surpasses GCC in terms of image sharpness, colorfulness, and contrast.

Keywords: Color cast, GCC, underwater image enhancement

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INTRODUCTION

As the demand for underwater exploration intensifies, the significance of underwater computer vision has correspondingly escalated in acquiring crucial information.

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However, the inherent lack of visibility in an underwater environment presents a substantial limitation to the potential of underwater computer vision, given that clear underwater imagery is an indispensable prerequisite. Consequently, mounting interest has been in augmenting the quality of underwater images to address this burgeoning need.

In contrast to images captured in an atmospheric environment, where light scattering effects pose the primary obstacle, underwater image quality is primarily impacted by light absorption induced by the water medium. Light energy exponentially dissipates as it penetrates deeper into the water, with the attenuation rate varying based on the wavelength of the light. Notably, different colors of light exhibit distinct penetration ranges, with red light, having the longest wavelength, attenuating more rapidly than the shorter wavelengths of green and blue light as it descends further into the water.

A digital image can be defined as a matrix of pixels, each assigned a unique color intensity value that represents color information, including RGB colors. However, underwater image quality is susceptible to degradation caused by light absorption, leading to color attenuation, especially red. This color attenuation issue causes the remaining colors to dominate, leading to color casts such as blueish, yellowish, or greenish tones.

In addition to color casts, color attenuation also leads to distortion, wherein irregular color regions appear in the images. Furthermore, underwater images are prone to various forms of degradation, including poor visibility range, loss of image contrast, image noise, and haze effects. The Generalized Color Compensation (GCC) technique (Yao et al., 2022) has been recognized for its impressive ability to remove color cast from images. However, the output images from GCC often exhibit undesired qualities such as excessive brightness and loss of texture. In light of this, the present study endeavors to address this issue by proposing a novel solution to enhance the performance of the GCC technique.

Literature Review

Underwater image enhancement has a long history dating back to the inception of the Underwater Image Formation Model (UIFM) (Jaffe, 1990). The primary objective of underwater image enhancement techniques is to optimize the visual quality of underwater images. Research in this field has been broadly categorized into image enhancement, restoration, fusion, and learning-based enhancement. The former refers to optimizing the visual quality of images directly, while the latter strives to recover clean images from degraded ones by employing physical image formation models. Image fusion involves integrating image features from multiple sources, and learning-based enhancement employs machine learning algorithms to optimize the underwater image enhancement process.

Spatial domain and transform domain techniques are sub-categorized under image enhancement techniques, offering different approaches to enhance the quality of underwater images. Spatial domain techniques, typically low in complexity and suitable for real-time implementation, are widely used for enhancing underwater images by adjusting the pixel intensity. Various spatial domain techniques have improved underwater images, such as image equalization, smoothing, and sharpening. However, these techniques often result in undesired effects, such as reddish or abnormal color regions. To address the color cast problem in underwater images, various color balance techniques, such as the Grey World algorithm and Underwater White Balance (UWB) (Ancuti et al., 2018), have been introduced. However, they sometimes introduce other degradation, such as color distortion and oversaturation.

Transform domain techniques differ from spatial domain techniques by initially converting the underwater image into a different domain before implementing further enhancements. These techniques have lower complexity and enable manipulation of the image frequency component, but automation poses challenges and may not improve every image component simultaneously. Common transformation techniques such as Empirical Mode Decomposition (EMD) (Çelebi & Ertürk, 2010) and Wavelet Transform (WT) (Singh et al., 2015) have been utilized in enhancing underwater images.

In image restoration, various techniques are used to correct common issues such as color cast, loss of contrast, and haze effects in images. Among these techniques are polarization-based, prior-based, and model modification techniques. Model modification techniques aim to improve the accuracy of image restoration by creating a more precise physical model. The Atmospheric Scattering Model (ASM) (Narasimhan & Nayar, 2002) is widely used to describe image formation; however, it neglects the absorption effects that significantly affect underwater image formation. Therefore, there is a need to develop a more accurate mathematical model for underwater image formation.

The Sea-Thru model (Akkaynak & Treibitz, 2019) is a model that considers the coefficient governing the increase in backscatter with distance and the signal attenuation coefficient, which depends on object range and reflectance. This model has successfully removed the color cast, restored accurate colors in underwater images, and recovered depth dependency. Besides, Pei and Chen's revised underwater image formation model (2022) has been proposed to remove the underwater effects while tackling the haze issues. However, further research is necessary to precisely define underwater image formation, as the development of model modification techniques has shown.

Underwater images often suffer from loss of contrast, color cast, and haze effects. Many haze removal techniques have been developed to address these issues, including polarization-based and prior-based techniques. Polarization-based techniques (Schechner & Karpel, 2004) involve using polarizers to capture images and exploit the relationship between underwater image degradation and partially polarized scattered airtight to restore image visibility. Prior-based techniques like Dark Channel Prior (DCP) (He et al., 2009) and Intensity Attenuation Difference Prior (IADP) (Carlevaris-Bianco et al., 2010) leverage statistical observations made on images to restore image quality. However, prior-based techniques have limitations in removing absorption effects due to a lack of a comprehensive mathematical model.

The improvement of underwater images has a rich history in utilizing image fusion techniques. The Multi-scale Fusion (MSF) technique (Ancuti et al., 2012) is one such technique that combines a color-corrected image with a contrast-enhanced image through MSF. While image fusion techniques can integrate desired features from different images, they can also result in distortion. For example, the UWB technique occasionally produces color distortion despite removing the color cast. Unlike traditional image fusion, which involves contrast-enhanced image and color-balanced images, Non-Subsampled Shearlet Transform (NSST) based fusion (Lin et al., 2023) involves the fusion of detail-enhanced image and edge-enhanced images to deal with color distortion and low contrast issues.

Learning-based enhancement techniques have recently gained popularity for optimizing underwater image enhancement processes. These techniques rely on training data extracted from features to select and extract the optimal information for enhancement. Several learning-based enhancement techniques have been developed for underwater image enhancement, including dictionary learning, Convolutional Neural Networks (CNN), and Generative Adversarial Networks (GAN). For example, adaptive color mapping with a learning-based technique (Farhadifard et al., 2015) sharpened images based on sparse representation using learned dictionaries. CNNs have been commonly used for training underwater image enhancement processes, including UIE-net, Encoding-decoding deep CNN (Sun et al., 2017), and Underwater Residual CNN (URCNN) (Hou et al., 2018). Moreover, GAN-based techniques such as Feature-based Conditional GAN (MLFcGAN) (Liu et al., 2019) for multi-scale feature extraction and Cast-GAN (Li & Cavallaro, 2020) for color cast removal have also been developed. Both CNN and GAN have shown effectiveness in feature extraction and training to obtain optimal parameters for underwater image enhancement processes. Nonetheless, these techniques' efficacy heavily depends on the chosen enhancement approach.

MATERIALS AND METHODS

The Generalized Color Compensation (GCC) technique recently stabilized the color compensation process, and no more color distortion appears as an aftereffect. Nevertheless, the GCC technique tends to smooth and brighten the image. The improved GCC technique has been proposed to rectify the color cast and improve the image detail to address these issues of the GCC technique. Figure 1 shows the process of the proposed technique.

The initial step in underwater image enhancement involves obtaining the input underwater image. However, due to the light attenuation in water, the resulting image often has a color cast that needs to be rectified. Color compensation is employed to ensure that the image accurately represents the natural colors of the scene to tackle this issue. The proposed technique recompenses the color through Equation 1, where I_c' and I_c represent the compensated and color intensity, respectively. Moreover, I_{max} is the highest intensity among the color channels, C.

$$I_c' = I_c + (\overline{I_{max}} - \overline{I_c})\left(1 - \frac{c}{255}\right)\left(\frac{I_{max}}{255}\right), c \in \{r, g, b\} \quad (1)$$

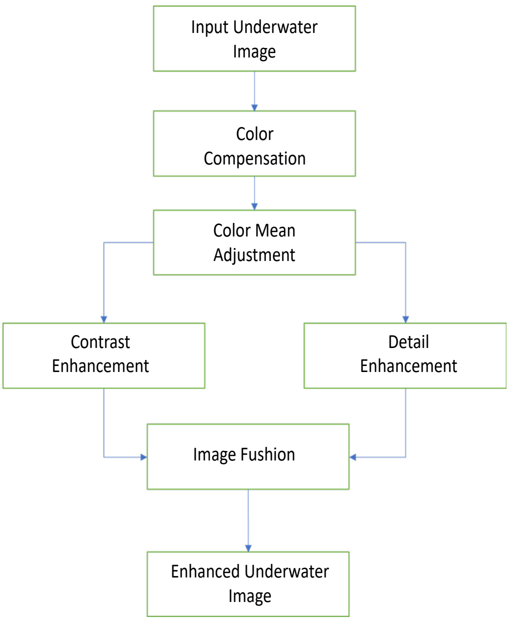


Figure 1. Improved GCC technique

Furthermore, to guarantee a balanced color representation, the image's color mean is adjusted to achieve color consistency throughout the image. It will help to rectify the color cast in underwater images. The proposed technique adjusts the color means through Equation 2, where the I_c^{ma} and I_{max}' are the color mean adjusted intensity and the highest intensity among the compensated color channels, respectively.

$$I_c^{ma} = I_c' - \overline{I_c} + \overline{I_{max}'} \quad (2)$$

A contrast-enhanced version, $I_c^{contrast}$ is produced through CLAHE to enhance the image's contrast. In addition, a detail-enhanced version, I_c^{detail}, is produced to improve the image detail. The z score for each color channel of the contrast-enhanced image is first computed, where the z scores will be used to compute the cumulative distribution function, $pvalue_c$. The detail-enhanced version image is computed as Equation 3.

$$I_c^{detail} = (I_c^{ma})(pvalue_c) \quad (3)$$

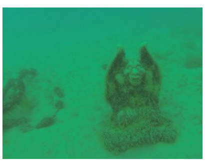
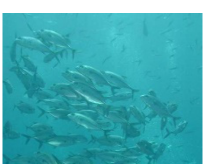
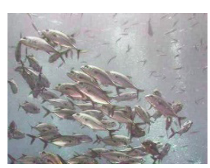
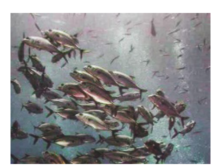
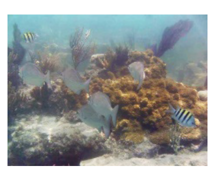
Finally, the contrast-enhanced and detail-enhanced versions are fused into a single enhanced underwater image to produce an improved image with greater visual clarity and detail.

RESULTS AND DISCUSSION

The Underwater Image Enhancement Benchmark Dataset (UIEBD) (Li et al., 2019) is a publicly available dataset of underwater images that has been widely used for testing and benchmarking image enhancement algorithms. The dataset includes 950 images with varying levels of degradation captured in different underwater environments with various cameras. Therefore, the UIEBD was chosen as the dataset for the performance evaluation.

Table 1 presents the findings of the Visual Comparison Analysis. Our proposed technology demonstrates proficiency in eliminating color casts, including bluish, greenish, and yellowish. In comparison to the GCC technique, the proposed technique yields sharper images. Notably, for input images 1 and 4, the proposed technique outperforms the UWB technique by preserving the image's color vibrancy and delivering a more authentic representation.

Table 1
Visual comparison analysis

	Input	UWB	GCC	Proposed technique
1				
2				
3				
4				
5				

In order to evaluate the performance of the proposed technique, the Underwater Image Quality Measure (UIQM) (Panetta et al., 2016) was selected to evaluate the image quality in terms of sharpness, colorfulness, and contrast. The sharpness component of UIQM, Underwater Image Sharpness Measure (UISM), measures the level of detail and focus on the image, while the colorfulness component, Underwater Image Colorfulness Measure UICM), measures the vividness and saturation of colors. The contrast component, Underwater Image Contrast Measure (UIConM), measures the difference between the lightest and darkest parts of the image, indicating the overall visual clarity and definition.

Table 2 presents the results of the UIQM for five different input images processed by three distinct image processing techniques: UWB, GCC, and the proposed technique. Notably, the UIQM value indicates the level of image quality, whereby a higher UIQM value corresponds to superior image quality in terms of three key factors: sharpness, colorfulness, and contrast.

Based on Table 2, the proposed technique consistently yields the highest UIQM scores across most input images, indicating superior image quality compared to the other two techniques. For example, for image 1, the proposed technique yielded a quality metric score of 2.976, which is higher than the scores for UWB and GCC (2.704 and 2.077, respectively). Similar trends were observed for the other input images, underscoring the proposed technique's superior image processing capabilities in sharpness, contrast, and colorfulness.

Table 2
UIQM

Image	Input	UWB	GCC	Proposed technique
1	-1.397	2.704	2.077	**2.976**
2	0.121	3.208	3.671	**3.788**
3	0.845	1.728	2.151	**2.237**
4	-1.133	**3.901**	3.119	3.770
5	1.061	3.211	3.272	**3.652**

The outcomes of the UISM are presented in Table 3. Although the proposed approach did not manifest significant advantages over the other two techniques in relation to boosting image sharpness, it demonstrated comparable levels of improvement for the sharpness metric. It strongly implies that the proposed technique holds substantial potential as a feasible alternative for enhancing image sharpness—the proposed technique obtained better results for inputs 2, 3, 4, and 5 than UWB. The proposed technique outperformed inputs 1, 4, and 5 compared to the GCC technique. Therefore, the proposed technique may not outperform the UWB and GCC in every scenario, but its performance in improving the sharpness was considerably balanced.

Table 3
UISM

	Input	UWB	GCC	Proposed technique
1	1.379	**3.660**	2.739	3.531
2	3.011	3.633	**4.137**	4.074
3	0.897	1.290	**1.650**	1.535
4	2.029	4.176	3.685	**4.204**
5	2.052	**3.960**	3.680	3.742

Table 4 shows the results of UICM that measure image colorfulness. It is also worth noting that the GCC and proposed techniques have varying results across the different inputs. For instance, the GCC technique performs better than the proposed technique for inputs 2 and 3 but worse for inputs 1, 4, and 5. Therefore, the effectiveness of the proposed technique and GCC in producing colorful images seems to depend on the specific input image. The UWB technique also manifests variable outcomes, displaying superior performance only for inputs 1 and 5. Conversely, the proposed technique illustrates a more stable and predictable performance than the other two.

Table 4
UICM

	Input	UWB	GCC	Proposed technique
1	-116.363	**-6.287**	-13.020	-12.181
2	-104.545	-10.200	**-2.776**	-3.696
3	-22.472	-10.195	**5.500**	1.804
4	-71.359	-22.583	-0.495	**0.376**
5	-40.806	-30.592	-7.375	**-6.060**

Table 5
UIConM

	Input	UWB	GCC	Proposed technique
1	0.413	0.504	0.457	**0.637**
2	0.610	0.678	0.707	**0.752**
3	0.339	0.457	0.422	**0.485**
4	0.868	**0.919**	0.875	0.841
5	0.779	0.812	**0.845**	0.806

Table 5 presents the results of the UIConM, which assesses the contrast quality of images. The UIConM values are higher for images with better contrast quality. The table shows that the proposed technique consistently outperforms the other techniques for three out of five inputs in terms of contrast quality, with the highest UIConM values for each input. Furthermore, the UWB and GCC techniques exhibit varying outcomes across the inputs. For instance, the UWB technique performs better than the GCC technique for inputs 1, 3, and 4 but worse for inputs 2 and 5. It is because the UWB technique had recovered an imbalanced color, especially for inputs 1 and 4, where the images do not preserve the underwater color well but left the difference between intensities become bigger, which eventually led to the conclusion of obtaining higher contrast. The proposed technique, on the other hand, preserves the underwater color and, at the same time, obtains better contrast.

CONCLUSION

Based on the evaluations conducted, it can be concluded that the proposed technique performs better than the other two techniques (UWB and GCC) in terms of overall image quality, as measured by the Underwater Image Quality Measure (UIQM). The proposed technique consistently yields the highest UIQM scores across most input images, indicating superior image quality in sharpness, colorfulness, and contrast. The UISM results also suggest that the proposed technique has comparable levels of improvement for image sharpness, indicating that it holds potential as a feasible alternative for enhancing image sharpness. The UICM and UIConM results show that the proposed technique produces colorful and high-contrast images that are more stable and predictable than the other two techniques, which exhibit varying outcomes across different input images.

Overall, the proposed technique appears to be a promising image processing technique for eliminating color casts and enhancing overall image quality. Our proposed improved GCC technique has preserved the capability of the GCC technique, which can remove the various color casts like bluish, yellowish, and greenish tones without further distorting the image color. Meanwhile, the proposed method overcomes the smoothing image issue held by the GCC method.

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