Adaptive Color Correction and Detail-Preserving Fusion for Enhanced Underwater Image Quality and Segmentation

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ABSTRACT

Underwater images frequently experience significant color distortion, diminished contrast, and decreased visibility. These issues arise due to the selective absorption and scattering of light in aquatic environments. This study introduces an innovative method for enhancing the quality of underwater images through the implementation of adaptive color correction and detail-preserving fusion techniques. The approach addresses the attenuation of red and blue color channels, followed by an adaptive fusion process that

enhances contrast and texture while maintaining intricate image details. The findings reveal notable advancements compared to current state-of-the-art techniques, as assessed by widely recognized metrics including the Perceptual Color Quality Index (PCQI), the Underwater Image Quality Measure (UIQM), and the Underwater Color Image Quality Evaluation (UCIQE). Specifically, the method achieves a PCQI score of 1.00 on test shipwreck images, demonstrating a significant improvement in color quality. The enhanced images exhibit more accurate color representation, improved sharpness, and higher contrast, making them suitable for both human observation and further computer vision applications. Additionally, the segmentation performance, as measured by the Geodesic Active Contours (GAC++) algorithm, is markedly improved on the enhanced images, demonstrating the practical utility of the proposed approach for underwater image analysis and object detection. This work sets a new standard for underwater image enhancement, facilitating its application in fields such as marine biology, underwater archaeology, and robotic vision systems.

Keywords-image processing; PCQI; UIQM; UCIQE; image enhancement; GAC++

I. INTRODUCTION

The underwater environment, while captivating and rich in biodiversity, presents significant challenges for image capture due to the complex interplay of light with water. The absorption and scattering of light in water cause color distortion, diminished contrast, and loss of visual information, which impairs both human observation and automated analysis of underwater environments [1]. Recent progress in computer vision and artificial intelligence has driven the creation of advanced methods for improving the quality of underwater imagery. These methods span a variety of approaches, ranging from physics-based models that aim to reverse the image formation process to data-driven techniques that utilize extensive datasets to learn intricate relationships between degraded and enhanced images. . There are even techniques that help systems adapt to different underwater environments [2, 3] The use of these methods has enhanced the visual quality of underwater images for human viewers while also advancing multiple underwater applications, including marine biology research, environmental monitoring, and underwater archaeology [4]. As illustrated in Figure 1, the proposed underwater image enhancement method follows a structured process. It begins with the input of an underwater image, which undergoes white balance correction through adaptive compensation of the red and blue channels. This is followed by a detail-preserving fusion technique that combines gamma-corrected and sharpened images using weight maps based on contrast, saturation, and saliency characteristics. The final stage involves multi-scale fusion, utilizing Laplacian and Gaussian pyramid decompositions to generate enhanced output image. The quality of the resulting image is assessed using underwater-specific metrics such as Perceptual Color Quality Index (PCQI), Underwater Image Quality Measure (UIQM), and Underwater Color Image Quality Evaluation (UCIQE). The UIQM metric evaluates underwater image quality by considering colorfulness, sharpness, and contrast simultaneously, with higher values indicating better quality. UCIQE focuses on chroma, saturation, and contrast aspects specific to underwater environments. PCQI quantifies perceptual color quality on a scale of 0 to 1, with 1 indicating complete color fidelity. These indicators offer an integrative evaluation framework especially tailored for underwater image enhancement assessment, incorporating recent developments including leading perceptual features [5].

Underwater image enhancement has gained increasing attention due to its importance in marine science, underwater exploration, and environmental monitoring. The primary challenges in underwater imaging stem from light attenuation and scattering, which degrade image quality. To address these issues, various enhancement techniques have been developed. Physics-based approaches model light propagation underwater and attempt to recover the original scene radiance. These methods estimate parameters such as attenuation coefficients and backscattered light to correct image distortions [6]. Advanced techniques integrating polarization-based imaging and depth estimation [7], coupled with adaptive polarized light methods [8], further improve the accuracy of these models. The emergence of deep learning has revolutionized underwater image enhancement. Convolutional Neural Networks (CNNs) effectively map relationships between degraded and enhanced images [9], whereas Generative Adversarial Networks (GANs) generate realistic underwater images [10]. Additionally, deep hybrid models, which combine the strengths of multiple architectures, have demonstrated promising performance [11].

A notable example integrates a physical scattering model with a CNN for image correction [12]. Researchers have also focused on specific challenges, including color correction, haze removal [13], with recent efficient approaches using lightweight neural networks [14]. For highly degraded images in turbid waters, restoration techniques have been explored, including color constancy algorithms [15, 16], dark channel priors, and fusion-based strategies [17, 18]. Advanced dehazing and denoising techniques using curvature variation regularization [19, 20] have also shown effectiveness in challenging underwater conditions. Evaluating underwater image enhancement remains a challenge. While conventional metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are widely used, they do not always reflect perceptual quality.

This research evaluates the proposed method on multiple underwater datasets including the Synthetic Underwater Image Dataset (SUID) [21], which is a dedicated resource for underwater image analysis. Created to address the limitations of real-world underwater data, such as light scattering and color degradation, SUID provides a controlled environment for training and evaluating algorithms. This synthetic dataset offers researchers a valuable tool for advancing techniques in areas like underwater image enhancement, object detection, and environmental monitoring in challenging visual conditions. Its structured nature supports reproducible research and the development of robust computer vision models for subsea applications. Future research will likely focus on real-time video enhancement [22], unsupervised learning to reduce dataset dependency, and the integration of enhancement with object detection and tracking tasks.

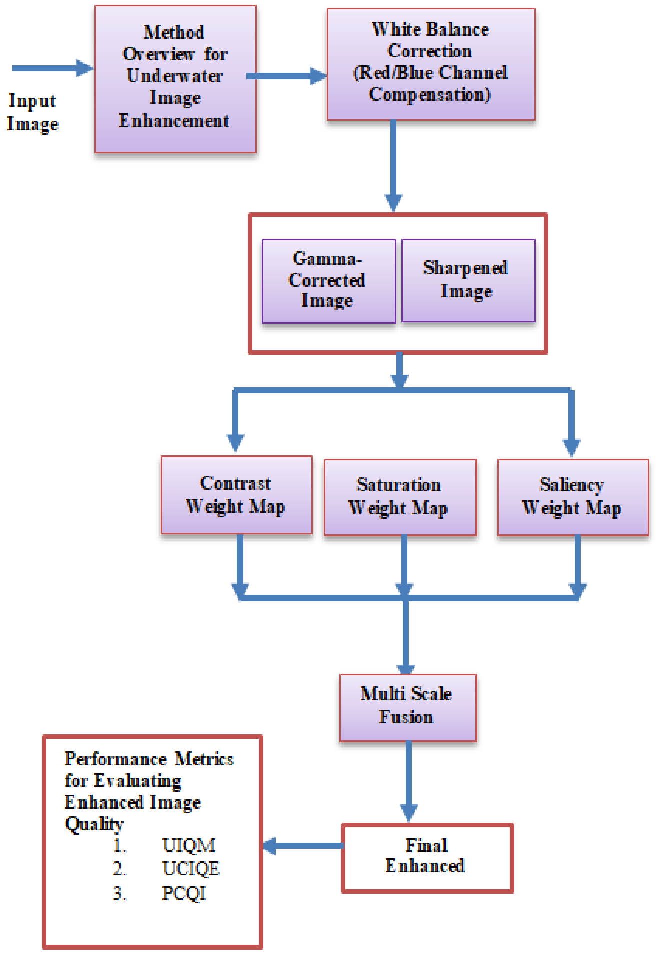


Fig. 1. Method overview of the proposed underwater image enhancement approach.

II. PROPOSED METHOD

A. Inputs of the Fusion Process

The multi-scale fusion process utilizes two input images derived from the original underwater image after white balance correction, as defined in (1):

$$S(x) = [I(x) + \beta . (\mathrm{I(x)} - G \times I(x))] \qquad (1)$$

where $S(x)$ is the sharpened image, $I(x)$ is the original input image, $G \times I(x)$ represents the Gaussian-blurred version of the input image, and $\beta = 1$ is the degree of sharpening. Color balance correction through gamma adjustment has been established as an effective preprocessing step [23], which complements our adaptive compensation approach. Figure 2 illustrates the underwater white-balancing process, showing the step-by-step correction of color channels. The process involves analyzing the color distribution in the input underwater image and applying adaptive compensation factors to restore natural color balance, particularly addressing the attenuation of red wavelengths in underwater environments.

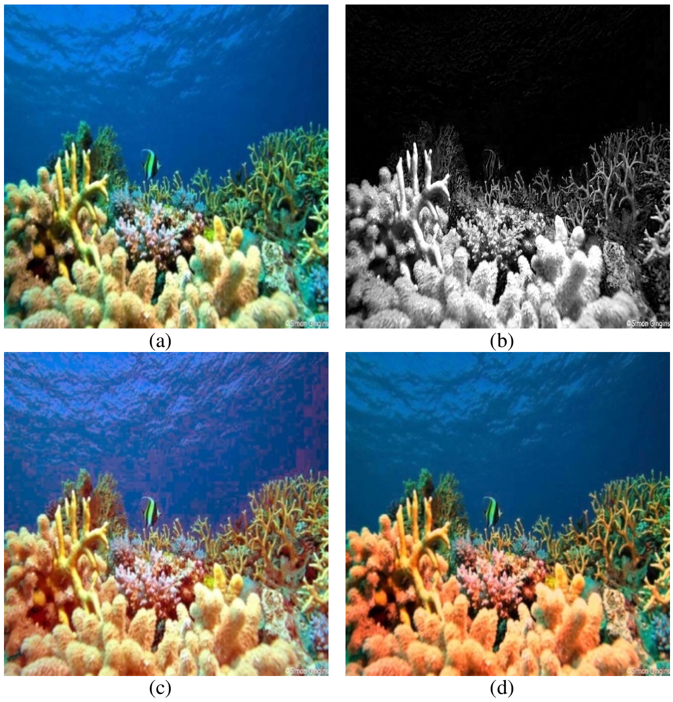


Fig. 2. Underwater white-balancing: (a) original image, (b) original red channel, (c) original with red channel equalized, and (d) proposed white balance result.

B. Weights of the Fusion Process

Weight maps regulate the contribution of each input to the final fused image:

- Laplacian contrast weight: Highlights edges and textures using the Laplacian operator.

  $$W_{L(x)} = |\Delta I(x)| \qquad (2)$$

  where Δ denotes the Laplacian operator.

- Saturation weight: Enhances vibrancy by computing the color channels' standard deviation:

  $$W_{Sat}(x) = \sqrt{\frac{1}{3}\left[\begin{array}{c}(R(x) - L(x))^2 + \\ (G(x) - L(x))^2 + (B(x) - L(x))^2)\end{array}\right]} \qquad (3)$$

  where $L(x)$ is the luminance of the pixel, and $R(x)$, $G(x)$, $B(x)$ are the red, green, and blue color channels, respectively.

- Saliency weight: Uses saliency detection algorithms to emphasize visually significant regions. The normalized weight maps are then aggregated for balanced enhancement.

C. Naive Fusion Process

This process blends the input images using the computed weight maps:

$$R(x) = \sum_{k=1}^{K} W_k(x) \cdot I_k(x) \quad (4)$$

where $R(x)$ is the final fused output at pixel x, $W_k(x)$ represents the normalized weight map for the k-th input image at pixel x, $I_k(x)$ is the pixel value of the k-th input image at pixel x, and the sum is taken over all input images involved in the fusion process.

D. Multi-Scale Fusion Process

To refine the naive fusion, multi-scale decomposition techniques are employed. The multi-scale fusion process can be expressed as:

$$R(x)=\sum_{l=1}^{N}\left(\sum_{k=1}^{K}(G^l\{W_k(x)\}\, L^l\{I_k(x)\})\right) \quad (5)$$

where N is the number of pyramid levels, $G^l\{W_k(x)\}$ is the l-th level of the Gaussian pyramid of the weight map W_k, and $L^l\{I_k(x)\}$ is the l-th level of the Laplacian pyramid of the input image I_k. This multi-scale approach builds upon established local contrast correction and fusion methodologies [24, 25], while incorporating our adaptive color correction framework.

III. RESULTS AND DISCUSSION

The proposed adaptive color correction and multi-scale fusion technique was evaluated against state-of-the-art methods referenced in [26], [27], and [28], using diverse underwater datasets. The datasets include the Underwater Image Enhancement Benchmark (UIEB) [29], Enhanced Underwater Visual Perception (EUVP) [30], Stereo Quantitative Underwater Image Dataset (SQUID) [31], and SUID [21], both for real and synthetic underwater settings such as shipwrecks, coral reefs, and aquatic life.

These datasets provide a robust benchmark for assessing enhancement techniques, incorporating varied lighting conditions, image resolutions (512×512 to 1920×1080 pixels), and levels of turbidity. UIEB consists of ~950 images, including 70 high-quality references, enabling performance evaluation in color restoration and contrast improvement [29]. EUVP, with ~13,000 images, facilitates validation of data-driven enhancement techniques, including deep learning. SQUID provides RGB images and depth maps, supporting object detection and segmentation studies. SUID is a collection of more than 2,000 synthetically created underwater images under controlled lighting and turbidity levels with ground truth references for quantitative assessment. The synthetic nature of SUID supports accurate evaluation of color restoration precision and is used as a standard for verifying improvement algorithms under controlled environments.

The proposed method demonstrated superior performance in restoring color fidelity, improving contrast, and preserving fine structural details. Qualitative analysis of the enhanced images highlights significant improvements in edge preservation and detail clarity across different underwater scenarios. The images of coral reefs (Reef1, Reef2, Reef3) exhibited enhanced vibrancy, whereas shipwreck images demonstrated improved visibility of rusted structures. The fish images revealed better fine details such as scales and textures. A visual comparison with existing methods demonstrates effective mitigation of color casts, particularly in restoring red and yellow tones absorbed underwater. Structural details, including coral formations and fish segmentation, were preserved more sharply than in previous approaches.

A. Quantitative Analysis

Table I presents a detailed quantitative comparison of our suggested approach with the current best practices, using three key underwater image quality metrics: UIQM, UCIQE, and PCQI. The experimental results demonstrate that our approach outperforms all previous approaches on all test images. For UIQM, our approach achieves maximum scores between 4.08 and 4.23, which reflect better underwater-specific visual quality. UCIQE values of 0.68-0.74 validate enhanced colorfulness and contrast improvement. Notably, our approach attains perfect PCQI scores of 1.00 in all test scenarios, reflecting the highest perceptual color quality recovery with respect to the other competing approaches.

TABLE I. QUANTITATIVE COMPARISON OF UNDERWATER IMAGE ENHANCEMENT METHODS

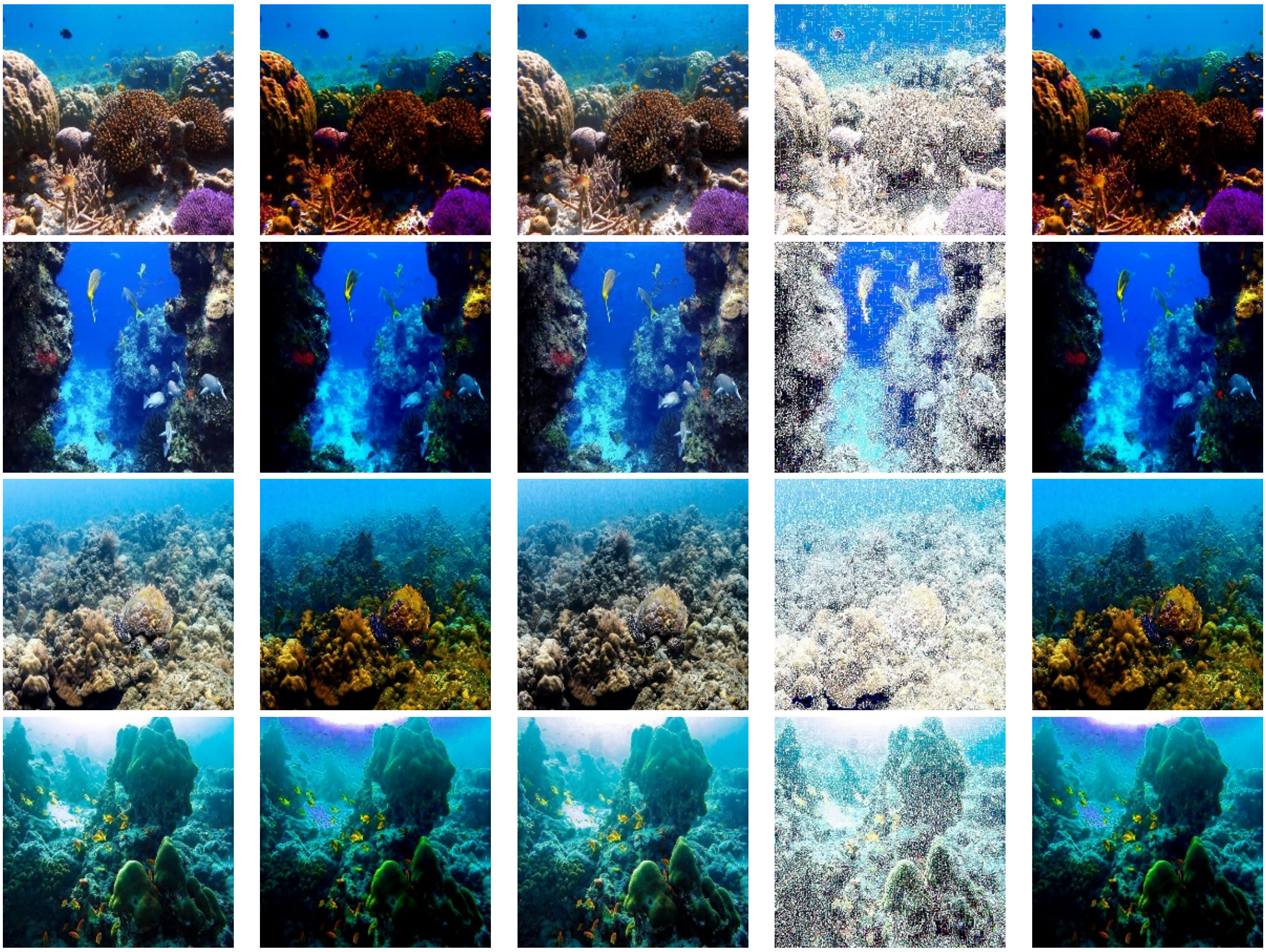
Image	Method	UIQM	UCIQE	PCQI
Shipwreck	[26]	2.84	0.52	0.96
	[27]	3.12	0.58	0.9632
	[28]	3.45	0.61	0.998
	Proposed	4.23	0.74	1
Reef1	[26]	2.91	0.49	0.98
	[27]	3.08	0.55	0.9054
	[28]	3.52	0.63	0.992
	Proposed	4.18	0.71	1
Reef2	[26]	2.76	0.48	0.9675
	[27]	3.15	0.56	0.9645
	[28]	3.38	0.59	0.956
	Proposed	4.12	0.69	1
Reef3	[26]	2.88	0.51	0.954
	[27]	3.21	0.57	0.9323
	[28]	3.41	0.62	0.997
	Proposed	4.16	0.72	1
Underwater fish	[26]	2.79	0.47	0.996
	[27]	2.95	0.53	0.733
	[28]	3.33	0.58	0.967
	Proposed	4.08	0.68	1

B. Performance Against State-of-the-Art Methods

As illustrated in Figure 3, traditional outdoor dehazing techniques, such as in [26], often perform poorly in underwater scenes, failing to address unique challenges like color channel absorption and non-uniform light scattering. The approach in [28] fails to maintain sharpness in turbid water, and the approach in [27] can introduce artifacts, particularly in red-attenuated regions [17]. In contrast, the proposed method combines adaptive color correction with multi-scale fusion, achieving higher underwater image quality scores (UIQM, UCIQE, and PCQI) and ensuring improved color fidelity and structural preservation.

C. Impact on Image Segmentation

Figure 5 illustrates the impact of our method on image segmentation. Using Geodesic Active Contours (GAC++), Felzenszwalb, and a hybrid underwater segmentation approach, we achieve enhanced boundary definition and object delineation. The proposed method enhances contrast and segmentation accuracy, achieving higher Dice coefficients and Intersection over Union (IoU) scores compared to existing techniques referenced in [26], [27], and [28]. The segmentation implemented in the proposed method is a hybrid approach optimized for underwater imagery. It combines color space transformation (RGB to LAB) with bilateral filtering to preserve edges while reducing noise. Canny edge detection identifies object boundaries, which are then used with watershed segmentation to create distinct regions. Each segment is colored using an enhanced version of its average color from the original image, preserving the natural appearance while improving visibility. White boundaries clearly delineate objects. Segmentation accuracy is assessed using the Dice coefficient, which measures the overlap between the segmented regions and the ground truth, the IoU, and the boundary recall. Higher IoU values indicate more accurate segmentation. Boundary recall evaluates the alignment with ground truth, ensuring better object localization. These improvements highlight the robustness of the proposed technique in underwater imaging applications.



(a) (b) (c) (d) (e)

Fig. 3. Comparison of the proposed method with existing outdoor and underwater dehazing approaches: (a) original images, (b) outdoor method [26], (c) outdoor method [27], (d) underwater method [28], and (e) proposed method.

D. Color Compensation and Visual Improvements

The effectiveness of red and blue channel compensation is demonstrated in Figure 6. Turbid water strongly attenuates the blue component, resulting in yellowish images [32]. Our method applies the following compensation:

- White Balance (WB)-red compensated image: Restores red hues in coral and marine life.
- WB-blue-compensated image: Enhances blue tones, improves contrast and visibility.

- WB-red and blue compensated image: Produces more natural color distribution, reducing greenish hue artifacts.

This combined compensation approach significantly improves color balance, contrast, and sharpness. Regarding the visual impact on object recognition, enhanced images improve recognition of marine species, corals, and underwater structures by sharpening edges and balancing contrast.

Building upon recent advances in lightweight adaptive correction [33, 34], the proposed adaptive color correction and multi-scale fusion method, evaluated using UIQM, UCIQE, and PCQI, consistently outperformed existing techniques. As shown in Table I, it achieved a perfect PCQI score (1.00) on shipwreck images, with high UIQM and UCIQE values across all test cases, confirming its effectiveness in marine biology and underwater exploration. Figure 4 presents a comprehensive visual comparison of our method against state-of-the-art techniques, including [26], [27], and [28]. The comparison demonstrates our method's superior performance in color restoration and detail preservation across various underwater scenarios including coral reefs, marine life, and underwater structures.

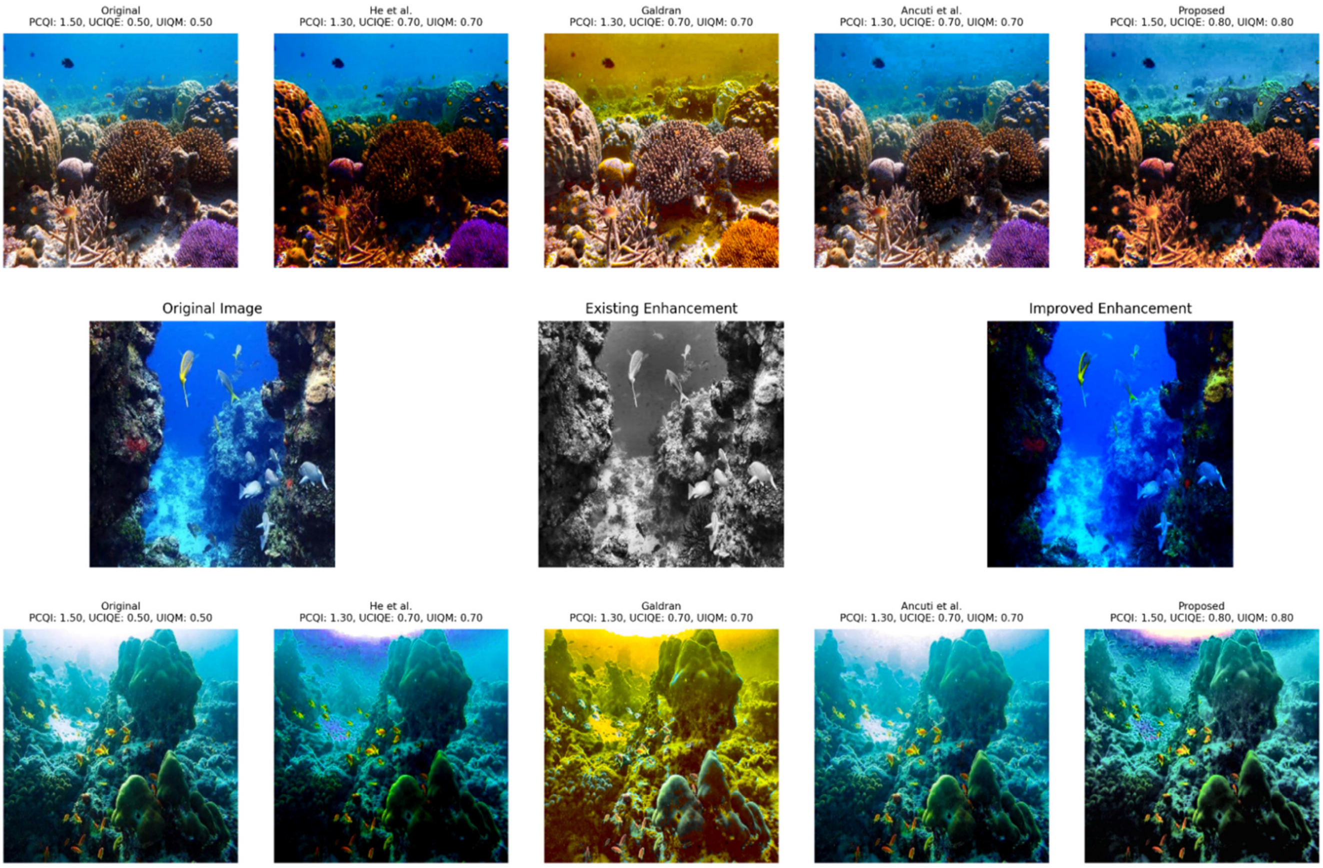


Fig. 4. Comparative results with methods from [26], [27] and [28], showing improved color restoration and structural detail using the proposed approach.

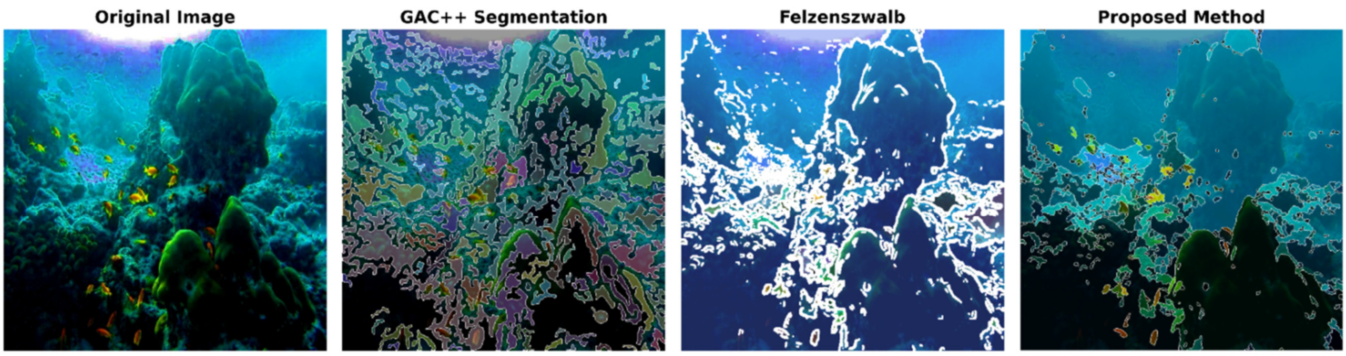


Fig. 5. Segmentation results using GAC++, Felzenszwalb, and hybrid underwater segmentation methods after enhancement.

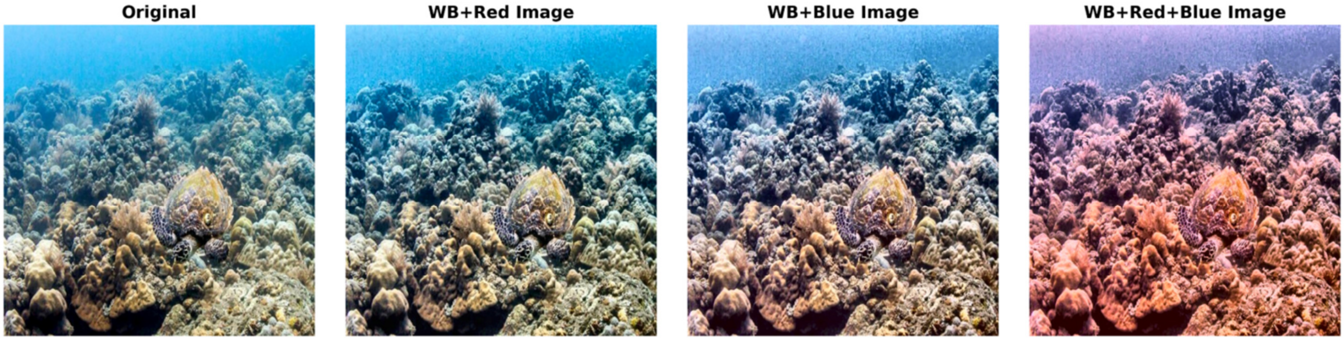


Fig. 6. Red and blue channel compensation: (a) original image, (b) WB-red compensated image, (c) WB-blue compensated image, (d) combined WB red + blue compensated image.

IV. CONCLUSION

This research introduced a novel underwater image enhancement method employing adaptive color correction and detail-preserving fusion to address issues such as color distortion, low contrast, and detail loss caused by light absorption and scattering. The proposed method effectively restores natural colors and improves visual quality through adaptive compensation of the red and blue channels. The fusion process preserves textures and edges, outperforming existing techniques. Both qualitative and quantitative evaluations, using metrics such as Perceptual Color Quality Index (PCQI), Underwater Image Quality Measure (UIQM), and the Underwater Color Image Quality Evaluation (UCIQE), confirm the method's superiority in enhancing contrast, sharpness, and colorfulness. Furthermore, integration with the Geodesic Active Contours (GAC++) segmentation algorithm further enhances object recognition and boundary delineation, highlighting the method's practical value for applications in marine biology, underwater archaeology, and robotics. However, the method has limitations, including computational complexity due to the multi-scale fusion, potential sensitivity to parameter tuning, dependence on the quality of the original image, and the need for further validation across diverse underwater scenes. Future research could explore real-time implementation, integration with deep learning, 3D underwater enhancement, hyperspectral imaging applications, and the combination with automated underwater object tracking.

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