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Underwater image enhancement with fuzzy histogram equalization and adaptive color correction

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ABSTRACT

Marine exploration continues to increase as new technologies, such as computer vision implemented in underwater vehicles and robots, develop. Identifying underwater objects is challenging due to environmental conditions, including poor lighting and color absorption in the viewed image. Underwater image enhancement has been widely applied to overcome these obstacles. Therefore, this study presents a new workflow for improving the quality of underwater images. A combination of the fuzzy histogram equalization (FHE) and adaptive color correction (ACC) methods is used to increase contrast and restore absorbed colors. This study proposes combining FHE and ACC to improve underwater image quality, using the FHE method with the FHEACC method. The results of the UIQM and ENTROPY metrics obtained the highest values, while UCIQE ranked third. This shows that the image quality improved using the FHEACC combination method is objectively better than that achieved with the HE, AHE, CLAHE, FHE, IBLA, RCP, and UDCP methods, especially in maintaining color balance. This research can introduce a new workflow to improve the quality of underwater images by combining Fuzzy Histogram Equalization and Adaptive Color Correction methods, thereby supporting the optimization of underwater image identification systems in wild environments using computer vision technology.

1. Introduction

In recent years, underwater imaging has become a research topic attracting the attention of many researchers due to its crucial role in various applications such as marine resource exploration, underwater autonomous navigation, ecological research, target tracking, and ocean monitoring [1]–[5]. However, major challenges arise due to image quality degradation caused by wavelength-dependent light intensity reduction, scattering by suspended particles, and the dominance of certain colors (blue/green) due to the loss of the red channel [6]–[8]. This significantly affects machine vision-based tasks, including underwater object recognition, making image quality enhancement a crucial step in the pre-processing process of underwater applications [9], [10]. Unlike regular photography, underwater visibility is very blurred due to water molecules and suspended particles that distort light rays and cause differential absorption at different color wavelengths [11]. In underwater images, color intensity fades with increasing depth. This necessitates techniques to enhance color and contrast to better reflect the lighting [12].

Various image enhancement methods have been developed to address this issue. One popular technique is histogram equalization (HE), which smooths the pixel intensity distribution. However, conventional HE methods tend to produce local distortions and are less adaptive to brightness variations [13]. To overcome these limitations, a number of developments have been made, such as histogram equalization methods with a probabilistic approach to preserve entropy and fine details [14], adaptive segmentation with quadruple clipping [15], and contrast-constraint-based local adaptive approaches such as CLALHE [16].

Besides histogram methods, fuzzy-based approaches have also attracted attention due to their ability to represent pixel uncertainty and increase flexibility in image manipulation, especially in low-light conditions [13]. For example, Chunmeng [17] proposed a multi-histogram equalization based on adaptive fuzzy clustering and optimized cropping, while Manivasagan [18] used Pythagorean fuzzy sets for low-contrast image enhancement. Other studies used intuitionistic fuzzy approaches to preserve contrast and color constancy [19]–[21]. Fuzzy logic-based approaches were also developed [22]–[24], which utilize the average intensity and contrast parameters in the HSV color space. Reman Kumar [25] and Mayathevar [26] implemented a fuzzy clustering model and a weighted fuzzy histogram to preserve natural colors and enhance contrast details.

To address color dominance caused by red-channel loss, adaptive color correction has become an important component of underwater image enhancement. Several approaches have been proposed, such as by Li [9], who utilizes backlight estimation, color detection, and color compensation, and Qiang [7], who developed an adaptive multichannel compensation algorithm based on gray world and local entropy constraints. Other approaches include combining the enhanced Retinex algorithm with adaptive color correction [27], [28] and the use of algorithms such as Adaptive Gray World and Unsharp Masking in a deep learning framework (FFA-Net) [29]. Fan [30] also proposed an innovative method combining adaptive color compensation and image pyramid fusion to enhance underwater microscopic images.

This study proposes a combined method of Fuzzy Histogram Equalization and Adaptive Color Correction for more effective and adaptive underwater image enhancement. By leveraging fuzzy logic to improve local contrast and adaptive color correction to restore spectral balance, this approach is expected to produce underwater images with better, more realistic visual quality, while still maintaining fine details important for underwater object recognition and analysis.

2. Method

To address the phenomenon of color bias and visual degradation in underwater images, this study proposes a workflow called Fuzzy Histogram Adaptive Color Correction (FHEACC) as shown in Fig. 1. The FHEACC algorithm begins with an input image that still experiences color distortion, then a Fuzzy Histogram Equalization (FHE) stage is carried out to balance the intensity distribution adaptively to the pixel intensity membership [25], [26] so that the contrast increases without causing excessive artifacts.

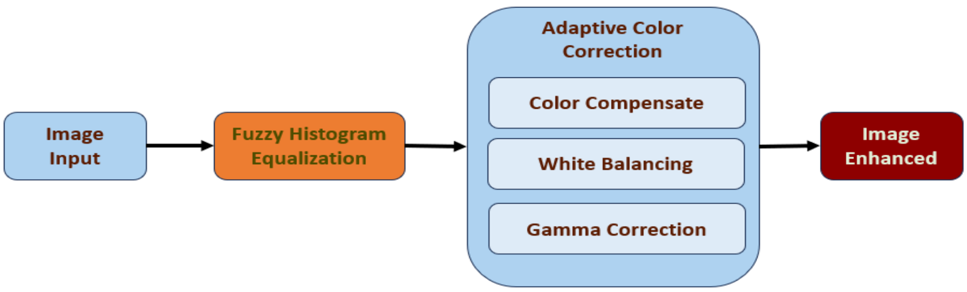

Fig. 1. Diagram of the FHEACC technique

The FHE image is then processed through Adaptive Color Correction (ACC) which consists of three main steps: reducing the dominance of certain colors, applying color compensation is applied, to normalize the color distribution to be more neutral, white balancing is applied [31]–[33], and to improve the brightness level and emphasize visual details, gamma correction is applied. The final result is a more natural, sharper, and information-rich image, with high UIQM and IE values, while remaining computationally efficient, making it suitable for real-time underwater image enhancement applications.

This study uses two main data sources. First, primary data was obtained from direct documentation in the waters of the Seribu Islands, North Jakarta, Indonesia, using a Canon PowerShot G15 camera by divers at depths between 1 and 20 meters above sea level. Image capture was conducted through photos and videos of the real conditions of coral reefs in the sea. Second, the UIEB (Underwater Image Enhancement Benchmark) dataset [31] was also used, which provides a range of underwater images with different characteristics, including greenish, bluish, yellowish, low-light, and turbid. Fig. 2 shows 40 sample images of coral reefs in greenish conditions with a resolution of 512 × 384 pixels used in experiments to test the effectiveness of the FHEACC method.

Fig. 2. The samples of 40 objects underwater images in greenish conditions

2.1. Fuzzy Histogram Equalization

Fuzzy Histogram Equalization (FHE) is a development of the traditional histogram equalization method that aims to overcome weaknesses such as the appearance of edge artifacts or edge ringing that commonly occur due to global equalization of pixel intensities [20], [23]–[26]. To reduce these effects, FHE builds local histograms using a weighted-neighbor-based approach, where each pixel has its own histogram computed from the intensities of its surrounding pixels. This approach produces a smoother contrast equalization that is adaptive to local structures in the image. In forming a fuzzy histogram, a fuzzy membership function is used that accounts for the intensity distance between pixels. This fuzzy function is defined as.

$$F(p) = 1/(1 + \beta d) \tag{1}$$

Where: p is the intensity of the pixel being processed, d is the difference in intensity between the pixel and the reference point (seed point), and β is a parameter that controls the rate of propagation of the fuzzy membership function [24]. This function gives higher weight to pixels with similar intensities and reduces the influence of pixels that are very different, thus preventing unwanted contrast propagation. The following formula calculates the pixel intensity increase in FHE:

$$I'_{FHE}(x,y) = Ar(x,y) + \{I(x,y) - Ar(x,y)\}\, F\{|I(x,y) - Ar(x,y)|\} \tag{2}$$

In this equation, $I(x,y)$ is the original intensity of the pixel at coordinates (x,y), while $Ar(x,y)$ is the average gray level of the pixels located within a certain radial distance r from that point. A fuzzy function F is applied to the difference of intensity values to produce a new intensity I' FHE (x,y) that better matches the local structure and preserves fine details.

With this approach, FHE not only enhances image contrast more subtly than traditional methods but also preserves the naturalness of colors and avoids excessive artifacts that can damage visual quality.

2.2. Adaptive Color Compensate

Adaptive Color Compensation is an important step in the Adaptive Color Correction process, which aims to restore the natural color of underwater images by dynamically adjusting the intensity distribution of color channels. Underwater images often exhibit color shifts (color casts), such as bluish or yellowish dominance, due to reduced light intensity at depth. Therefore, an adaptive color-compensation approach based on the RGB or CIELab color model is used to accurately and contextually restore color balance in underwater environmental conditions [32], [33].

The Adaptive Color Compensation method proposed in this study is inspired by a previous approach [34] and is designed to provide more comprehensive color correction. Adaptive Color Compensation consists of two main components: color channel compensation and overall color balancing. Unlike the previous approach [35], which only focuses on red channel compensation with a constant value, this method considers the spectral complexity of the underwater environment to produce more realistic and natural color correction.

The first step of this process is to calculate the average intensity for each of the red (R), green (G), and blue (B) color channels using the following equations:

$$R_{avg} = \frac{\sum R}{N}\ ,\ G_{avg} = \frac{\sum G}{N}\ ,\ B_{avg} = \frac{\sum B}{N} \tag{3}$$

where R, G, B are the intensity values of the red, green, and blue channels for all pixels in the image, and N is the total number of pixels.

Next, the total average value of the three color channels is defined as $K = R_{avg} + G_{avg} + B_{avg}$. If the proportion of $\frac{G_{avg}}{K} > {}^{2}/_{3}$, then the image is considered to have a fairly good color balance, and only normalization is performed to the range 0–255. However, if this condition is not met, channel compensation is performed using the parameters α, β, and γ, which are calculated logarithmically from the intensity difference between the channels.

The green channel (G) is corrected based on Algorithm 1 (Fig. 3).

```
Algorithm 1
if B_Mean - G_Mean > 0.1:
    gamma = -np.log(B_Mean - R_Mean)
G = G + (B_Mean - R_Mean) * (1 - G) * B * gamma
```

Fig. 3. Green channel (G) algorithm

If the difference between the blue and green averages exceeds 0.1, the gamma value is calculated and applied to the green channel (G), taking into account changes in the blue channel (B). The Blue channel (B) is corrected based on Algorithm 2. If the difference between the green and blue averages exceeds 0.1, the beta value is calculated using Algorithm 2 (Fig. 4).

```
Algorithm 2
if G_Mean - B_Mean >= 0.1:
    beta = -np.log(G_Mean - B_Mean)
if R_Mean - B_Mean <= 0.1:
    beta = 1 / (1 + beta)
    elseif R_Mean - B_Mean > 0.1:
        beta = 1 + beta
  alpha = 0
```

Fig. 4. Blue channel (B) algorithm

The beta value is then used to change the blue channel (B), so that the blue color is more balanced with green.

B = B + (G_Mean - B_Mean) * (1 - B) * G * beta

While the red channel (R) is compensated as in Algorithm 3. The alpha value is calculated based on the difference between the green mean (G_Mean) and the red mean (R_Mean). If this difference is greater than zero, color compensation is applied using Algorithm 3 (Fig. 5).

```
Algorithm 3
if G_Mean - R_Mean > 0:
    alpha = 1 - np.log(G_Mean - R_Mean)
else:
    alpha = 0
R = R + (G_Mean - R_Mean) * (1 - R) * G * alpha
```

Fig. 5. Red channel (R) algorithm

After all channels are corrected, the adaptive color compensation image is represented as:

$$I_{ACC}(x, y) = [R(x, y), G(x, y), B(x, y)] \tag{4}$$

The Adaptive Color Correction (ACC) process in FHEACC begins by normalizing a uint8 RGB image to the [0,1] range to maintain numerical stability, then averaging each color channel to evaluate the initial balance. If the difference between channels is small (≤0.05), the image is considered balanced and subjected to final normalization. Otherwise, adaptive compensation (ΔT=0.1) is applied through stepwise adjustments to the green, blue, and red channels. The green channel is corrected when blue is dominant, using a logarithmic gamma factor to reduce blue cast; the blue channel is adjusted to green using a dynamic beta parameter to reduce an excess bluish hue; and the red channel is boosted proportionally via an alpha parameter to restore color warmth. The values of each channel are then clamped to [0,1], renormalized, and merged back to the [0,255] format, resulting in a final image with balanced lighting, natural colors, and improved contrast. Adaptive color compensation is applied to the output image resulting from the Fuzzy histogram equalization (FHE) process

2.3. White Balance

White balance is the process of removing unwanted color nuances in an image so that white remains white under various lighting conditions. In underwater imaging, white balance is very important because uneven lighting can cause color shifts (color casts). The most commonly used white balance algorithm is the Gray World (GW) method, which works on the assumption that the average color in the scene should be gray [30], [36], [37]. Thus, each color channel (red, green, and blue) in the image is balanced to approach its combined average value.

The pixel location index is indicated by an image with dimensions $M \times N$ represented as $I(x, y)$, where (x, y) indicates the pixel location index. The initial stage of the GW algorithm is to find the average of each red, green, blue channel.

Where, $I_r(x, y)$, $I_g(x, y)$, $I_b(x, y)$, respectively, are the values of the red, green, and blue color channels for each pixel. $Tvag$ is calculated by averaging the three channels.

$$T_{avg} = (R_{avg} + G_{avg} + B_{avg})/3 \tag{5}$$

Finally, the color values for each pixel are adjusted according to the equation given below to achieve the assumptions of the GW theory:

$$I_r^{'}(x, y) = I_r(x, y) \times T_{avg}/R_{avg}$$

$$I_g^{'}(x, y) = I_g(x, y) \times T_{avg}/G_{avg}$$

$$I_b'(x,y) = I_b(x,y) \times T_{avg}/B_{avg} \quad (6)$$

Where, $I_r'(x,y)$ $I_r'(x,y)$ dan $I_b'(x,y)$ are the adjusted channel values of each pixel by the gray world method.

$$I_a'(x,y) = I_a(x,y) - \left((A_{avg} - 128)I_l(x,y)/255\right)$$

$$I_b'(x,y) = I_b(x,y) - \left((B_{avg} - 128)I_l(x,y)/255\right) \quad (7)$$

Where, $I_a'(x,y)$ and $I_b'(x,y)$ are the adjusted channel values of each pixel by the modified gray world method $I_l(x,y)$, $I_a(x,y)$ and $I_b(x,y)$ are the respective channel values of each pixel intensity, A_{avg} and B_{avg} are the averages of each channel calculated using (8). To eliminate the chroma distance shift, 128 is subtracted from the average. White balancing is applied to the output image of the Adaptive Color Compensate process.

2.4. Gamma Correction

Gamma correction is a nonlinear operation used to adjust image brightness by changing the distribution of pixel intensities [38]–[40]. This technique is important because human visual perception of brightness is logarithmic, not linear. In overexposed images, gamma correction can selectively darken bright areas. Conversely, in dark images, this technique can enhance detail by brightening dim areas [41].

Mathematically, gamma correction is defined as:

$$I_{out}(P) = \left(I(P)\right)^{\gamma}, \gamma > 0 \ and \ I(P) \in [0,1] \quad (8)$$

where $I(P)$ and $I_{out}(P)$ are the normalized pixel intensities at the input and output, respectively. Fig. 6 shows the behavior of the gamma curve as a function of different values of γ. $\gamma > 1$ produces a darker image while $\gamma < 1$ produces a brighter image. Gamma correction is applied to the output image of the white balancing stage in the previous process. In this study, a gamma value of 1.2 was used.

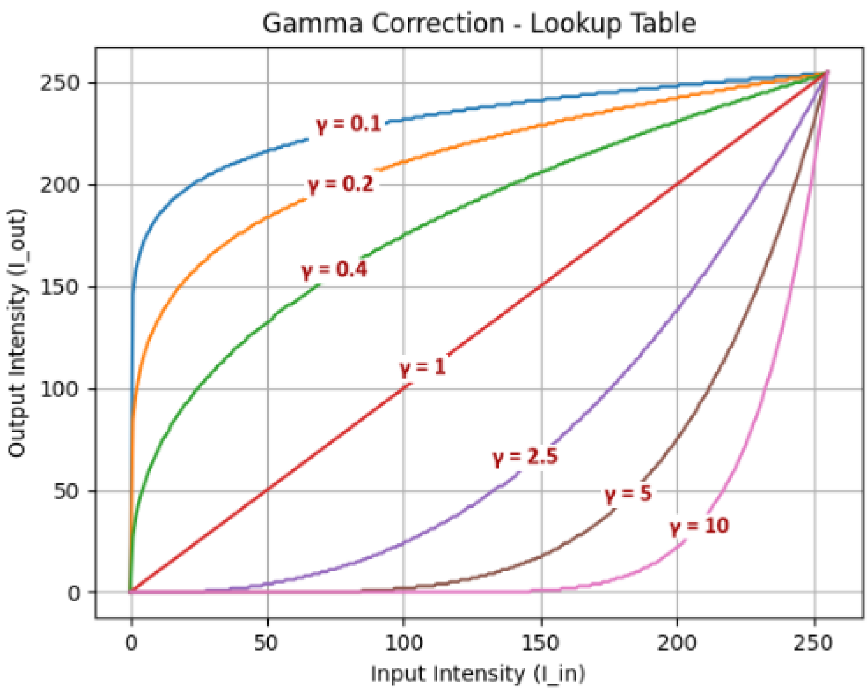

Fig. 6. Gamma Correction Lookup Table

3. Results and Discussion

A major problem in underwater imagery is visual degradation caused by the optical characteristics of water, such as selective absorption of light wavelengths and scattering by suspended particles. This results in the dominance of certain colors, such as greenish or bluish, as well as reduced contrast and loss of important details. Fig. 2 shows examples of images captured at various depths under low-light conditions and a predominance of greenish colors, illustrating common challenges in underwater imaging.

To address these issues, this study proposes an underwater image enhancement algorithm based on Fuzzy Histogram Equalization (FHE) and Adaptive Color Correction (ACC). The proposed method uses a structured process that starts with RGB contrast stretching to equalize the intensity distribution across color channels. Next, the image is converted to the HSI (Hue, Saturation, Intensity) color space to obtain a broader color representation, with separate channels for intensity and chromaticity. After manipulation in the HSI space, the image is converted back to RGB for processing with the ACC method, which adaptively corrects color distortion and adjusts white balance. A complete working diagram of the method is shown in Fig. 1.

The main novelty of FHEACC lies in the simultaneous integration of Fuzzy Histogram Equalization (FHE) and Adaptive Color Correction (ACC) using dynamic logarithmic parameters (γ, β, α), which enables contextual color adjustment across channels (R, G, B). In contrast to the Retinex method based on adaptive color correction [28], [30] which is capable of achieving high contrast but requires large computational costs, as well as the fuzzy clustering/fusion based approach [17], [18] which can increase local contrast but risks introducing color distortion, this study introduces FHEACC as a simpler yet effective solution. FHEACC works directly in the color domain to adaptively balance channel intensities via a ΔT threshold, preserve local texture, and reduce color cast without increasing computational complexity. This integration results in natural color enhancement, stable lighting, and high efficiency, making it a lightweight yet effective solution for visual enhancement of underwater images or unbalanced light environments.

Performance evaluation was conducted by comparing the proposed method against other benchmark methods popular in the literature. This process includes a combination of FHE [24]–[26] which is used to equalize the color and enhance the contrast of coral reef images, and ACC [32]–[35], which restores the RGB color balance disturbed by underwater conditions. ACC also improves dark and light areas while sharpening the contours of objects in the image. The combination of these two approaches proved effective in producing more natural, clear, and informative image quality.

The experiment was conducted using 45 underwater images covering a variety of visual conditions. Forty images were obtained from field documentation in the waters of the Seribu Islands, Indonesia, at varying depths and angles. The remaining five images came from the UIEB dataset [31], which covers five types of underwater conditions: bluish, greenish, yellowish, lowlight, and turbid. The variety of objects, dominant colors, and lighting quality in this dataset allows for comprehensive testing of the effectiveness of the proposed image enhancement method. Experimental results show that the FHEACC algorithm significantly improves contrast, restores realistic colors, and clarifies the structure of underwater objects compared to conventional methods.

In the proposed FHEACC method, parameter selection was empirically optimized through visual assessment and quantitative evaluation using UIQM, UCIQE, and IE metrics to balance contrast enhancement, color naturalness, and computational efficiency. In the Fuzzy Histogram Equalization (FHE) stage, the parameter β (1.5–2.0) effectively controlled the fuzziness of histogram distribution, preventing over-enhancement while preserving fine details. In the Adaptive Color Correction (ACC) stage, the gamma factor (γ = 0.85) adjusted global brightness and midtone visibility, improving image realism and contributing to the highest IE score (6.870). Meanwhile, an adaptive color balance threshold (ΔT = 0.05–0.10) regulated inter-channel compensation strength, applying stronger correction only when the color imbalance exceeded the threshold. Collectively, these parameter settings enable FHEACC to achieve stable color enhancement and perceptual quality under varying underwater lighting conditions while maintaining computational efficiency without iterative processing.

3.1. Visual Experiments

Visual experiments are conducted to assess method clarity. Fig. 7 to Fig. 11 show some visual results. These experiments are conducted on selected images to demonstrate each method's ability to improve display quality by optimizing contrast and color.

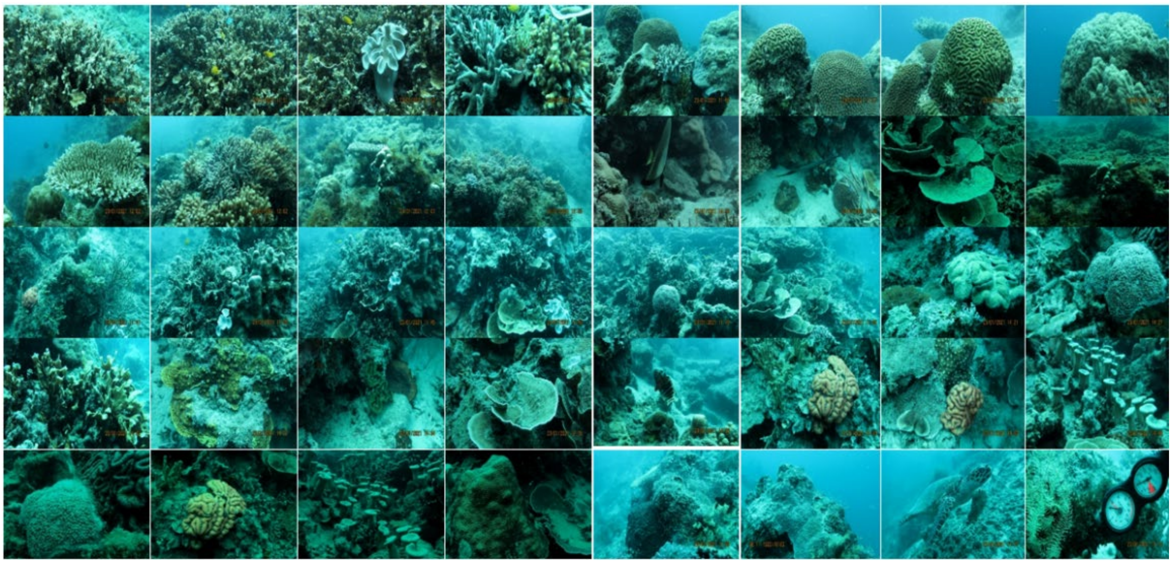

Fig. 7. Enhancement by FHE of 40 underwater images

Fig. 7 shows the visual results of the 40 underwater image data in Fig. 2 that have been applied to the Fuzzy Histogram Equalization (FHE) method. This experiment shows that the FHE method can increase contrast in the image, but it cannot visually reduce the dominant color. To overcome this, in the next stage, we apply the ACC method to restore underwater images with colors close to the actual ones. Fig. 8 shows the images after processing with the FHEACC method proposed in this paper.

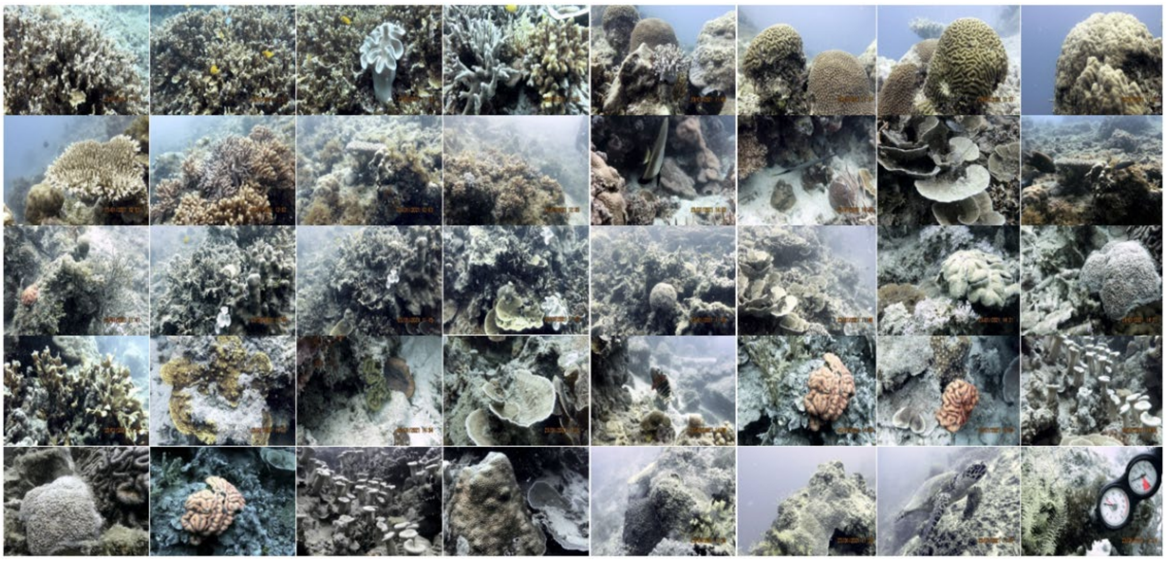

Fig. 8. Enhancement by FHEACC of 40 underwater images

A set of statistical measures is calculated for each image generated using FHE and ACC. Fig. 9 shows the histogram of one underwater image from the 40 used in our experiment. From left to right, the original image shows that the pixel distribution tends to be concentrated in the low (dark) intensity range. This lack of intensity distribution indicates low contrast, which is common in underwater images that experience color degradation. Blue and green colors dominate with little variation in bright areas. Meanwhile, in the histogram of the FHE-enhanced image, the pixel intensity distribution is more uniform than in the original image, but it tends to be concentrated in the low (dark) intensity range. Compared to the FHEACC method, the contrast increases as the intensity range widens. The pixel intensity that was previously concentrated in the dark area is now spread across the range, indicating increased visibility and detail. Then, in the histogram of the image with the FHEACC method, the pixel intensity distribution is wider than that of the FHE method. The contrast enhancement is more aggressive, as indicated by the histogram, which is more even and spans a wider intensity range. Image details are clearer with more balanced colors, reducing the effect of blurring or the dominance of certain colors.

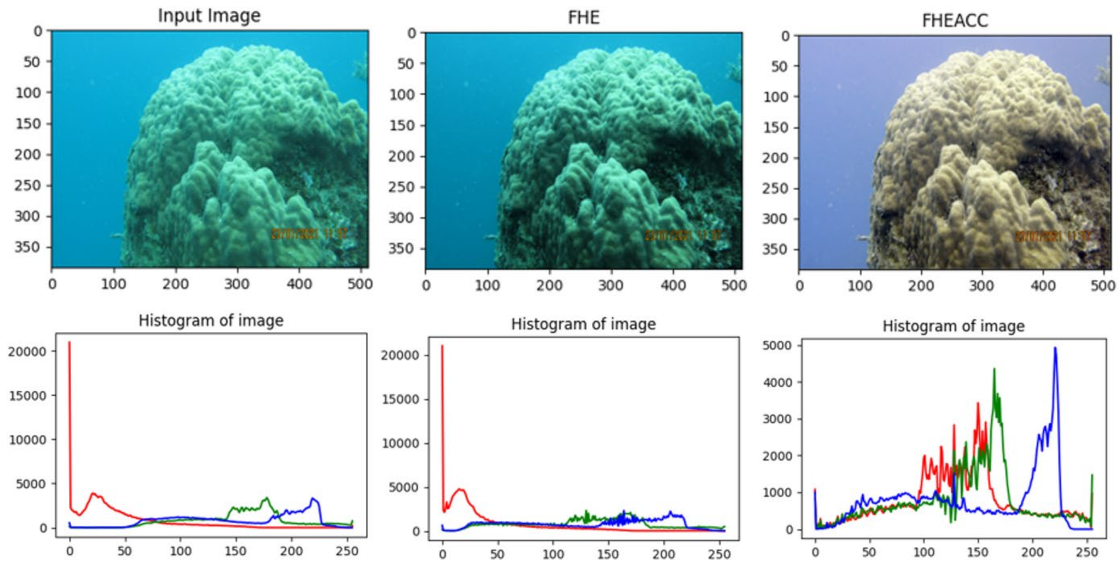

Fig. 9. Comparison of underwater image histogram graphs from left to right of original, FHE, FHEACC

Fig. 10 shows examples of 4 underwater images from the 40 images used in our experiments. From left to right, the input image is shown, followed by the enhanced images from various comparison algorithms tested on the dataset. Visually, IBLA produces greenish images under low-light conditions but does not fully eliminate the greenish tint. RCP under greenish conditions can slightly increase brightness, but still cannot reduce the greenish tint. HE, AHE, CLAHE, and UDCP in greenish conditions sharpen the image but produce dark conditions on the dominant color according to each color condition. The results of our proposed method, FHEACC, can visually correct colors under greenish conditions, eliminate haze, and clearly and sharply enhance image details. Through several visual comparisons, it can be seen that the proposed algorithm effectively corrects colors and produces visually appealing results.

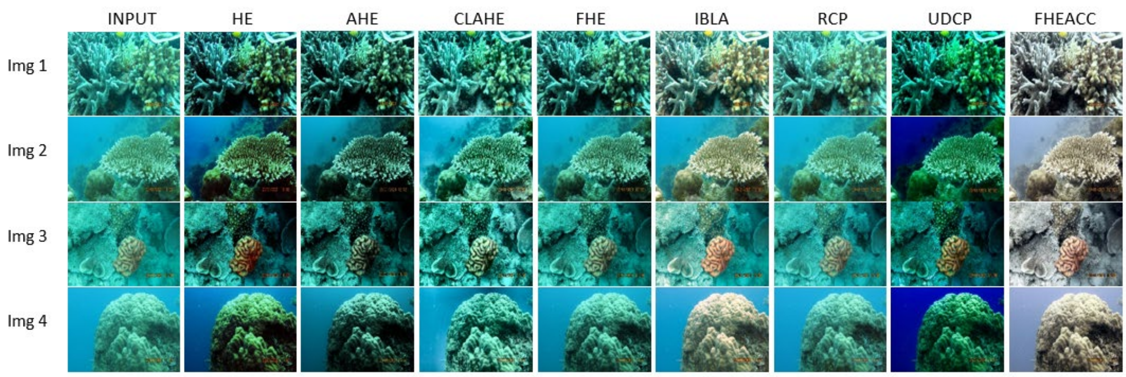

Fig. 10. Subjective comparisons of greenish, low-light underwater images. From left to right are raw underwater images and the results of input: HE, AHE, CLAHE, FHE, IBLA, RCP, UDCP, and OUR method.

Fig. 11 shows a comparison of underwater images in several color conditions, namely bluish, low light, greenish, cloudy, and yellowish, which have their image color quality improved with several image enhancement methods, namely (b) IBLA, (c) RCP, (d) UDCP, and (e) the proposed method. Visually, across all image conditions, only the method we proposed (FHEACC) removes the color that dominates image visualization, leaving the image looking like an image without color dominance, which can obscure the actual image.

Subjective comparisons on bluish (1), low light (2), greenish (3), turbid (4), and yellowish underwater images. From left to right are raw underwater images UIEB [31], and the result of the distorted image, IBLA, RCP, UDCP, and the proposed method.

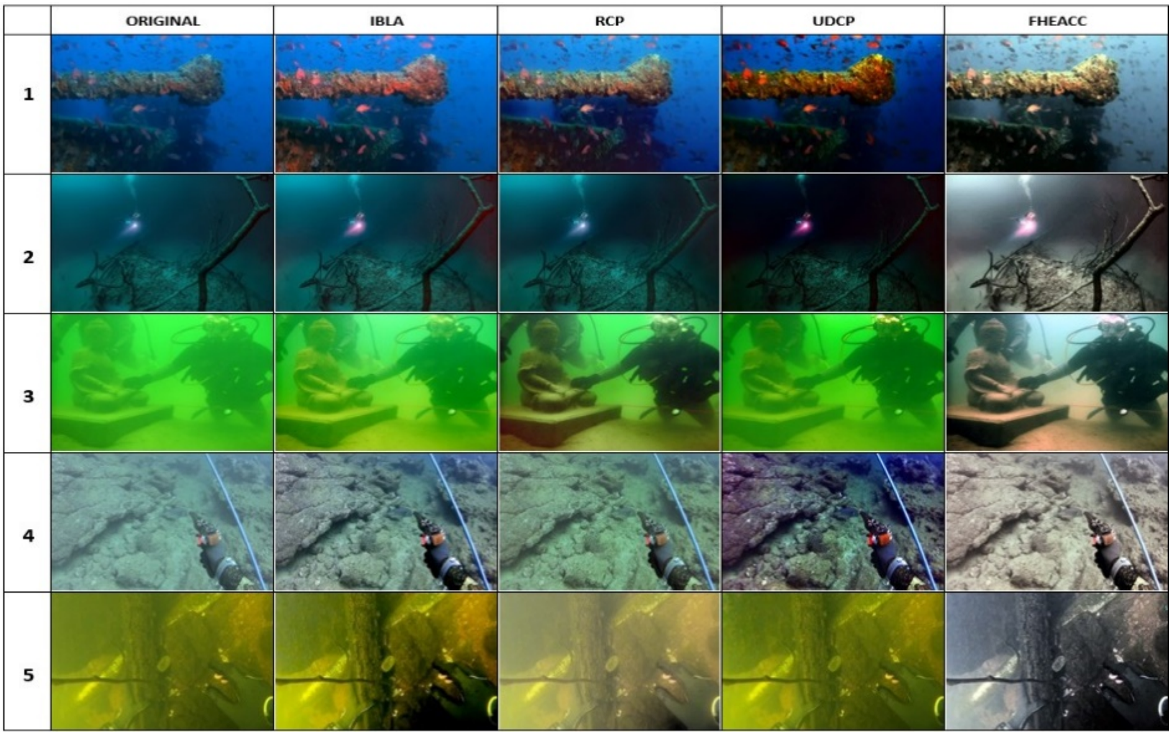

Fig. 11. Subjective comparisons on bluish (1), low light (2), greenish (3), turbid (4), and yellowish underwater images. From left to right are raw underwater images UIEB [31], and the result of the distorted image, IBLA, RCP, UDCP, and the proposed method

3.2. Statistical Experiments

To evaluate the underwater image enhancement results and demonstrate the effectiveness of our proposed algorithm objectively, we choose three non-reference metrics, including information entropy (IE), underwater image quality measure (UIQM) [42], and underwater color image quality evaluation metric (UCIQE) [43] to evaluate the underwater image quality shown in Table 1. Information Entropy (IE) primarily represents the average amount of information reflecting the color richness of underwater images, while UIQM assesses image quality based on three components, the Underwater Image Colorfulness Measure (UICM), Underwater Image Sharpness Measure (UISM), and Underwater Image Contrast Measure (UIConM). UIQM can be expressed as $UIQM = c1 \times UICM + c2 \times UISM + c3 \times UIConM$, where c1= 0,0282, c2 = 0,2953 and c3 = 3,5753 or c1 = 0,4859, c2 = 0,2745 and c3 = 0,2576 in [43]. UCIQE is a comprehensive evaluation metric that combines chroma, saturation, and contrast through a linear formulation to assess overall underwater image quality. UCIQE can be defined as $UCIQE = c1 \times \sigma c + c2 \times conl + c3 \times \mu s$, where σc is the standard deviation of chroma, con1 is the luminance contrast, and μs is the average saturation. Hence, this metric is considered a holistic assessment of the effectiveness of different enhancement methods.

Table 1 shows that, compared with other methods such as HE, AHE, CLAHE, FHE, IBLA, RCP, and UDCP, the FHEACC method achieves the best performance in terms of UIQM (3.176) and IE (6.870). This confirms that the combined approach of Fuzzy Histogram Equalization and Adaptive Color Correction can produce sharper, more natural, and information-rich images without losing important visual details. However, the UCIQE score (1.255) obtained by FHEACC is lower than HE (3.743) or AHE (3.779). This low UCIQE value is caused by the adaptive color correction and white-balancing mechanism in FHEACC, which suppresses saturation and extreme contrast, resulting in a more realistic display for human perception but statistically reducing the chromatic and luminance differences that form the basis of the UCIQE measurement. On the other hand, the simple operation of FHEACC, which utilizes only global fuzzy histogram transformation and channel-based color correction, makes this method more computationally efficient than the Retinex approach or multi-scale fusion methods, which require longer processing times due to more complex iterations. Thus, the optimal compromise between visual quality and efficiency provided by FHEACC makes it well-suited for the implementation of real-time underwater image enhancement. However, further development is needed to improve chromatic contrast.

Table 1. Values of different methods on the greenish, low-light underwater images.
(The bold values represent the best results)

	Average		
	UCIQE	*UIQM*	*IE*
HE [6]	3.743	2.525	6.867
AHE [44]	**3.779**	2.466	6.833
CLAHE [16]	0.816	2.195	6.837
FHE [26]	1.541	2.487	6.815
IBLA [45]	0.780	2.274	6.687
RCP [46]	0.718	2.746	6.641
UDCP [47]	2.048	2.149	6.777
FHEACC (our)	1.255	**3.176**	**6.870**

The high entropy value in FHEACC is achieved because Fuzzy Histogram Equalization (FHE) is not like HE or CLAHE, which can sometimes make the intensity distribution too extreme; the fuzzy approach increases contrast more adaptively and smoothly, so that details are preserved. Then, I added the color compensation module, white balancing, and gamma correction, ensuring a more even distribution of intensity across all channels (R, G, B) to prevent any one channel from dominating and to maintain rich color information. As a result, the image histogram is more balanced, the distribution of information improves, and details are not lost, leading to a higher IE value.

Meanwhile, the UIQM value assesses the image from three aspects: sharpness, naturalness, and color diversity. Because color compensation reduces the dominance of certain colors (for example, blue or green in underwater images or low-light conditions), the color becomes more natural and realistic. White balancing normalizes color distribution, preventing the image from becoming too biased toward one spectrum and thereby increasing colorfulness and naturalness. Gamma Correction optimizes global brightness without losing detail, thereby increasing perceptual sharpness. Ultimately, it makes the image more natural and clearer, and the contrast is in accordance with human perception.

The relatively lower UCIQE value in FHEACC is due to the adaptive color correction mechanism that focuses on visual naturalness through logarithmic adjustment of the γ, β, and α parameters, which suppresses the dominance of certain channels but indirectly reduces the global chromatic contrast. This approach results in a more uniform color distribution, reducing saturation variations between channels and weakening the UCIQE metric, while the UIQM and IE values increase due to more natural colors and sharper local details. To improve UCIQE without sacrificing UIQM and IE, this method can be adjusted by adding a light color contrast reinforcement stage after ACC or optimizing the ΔT threshold and the logarithmic function of the γ and β parameters to maintain differences between channels without producing a color cast, thereby increasing global color contrast while maintaining efficiency and tonal balance.

4. Conclusion

This study proposes an adaptive color correction method based on contrast enhancement, using a fuzzy histogram equalization approach that preserves the entropy of the enhanced image, as in the original, and maintains the color balance. The proposed method decomposes the occurrences and gray-value histograms of the original image. Then, the cropped occurrences and histograms are equalized. Finally, new pixel values are calculated with the proposed transfer function. To improve FHE performance, adaptive color correction (ACC) is applied to enhance contrast more aggressively, as evidenced by a more even histogram and a wider intensity range. Image details are clearer with more balanced colors, reducing blurring and the dominance of any single color. Experiments using public and private UIEB datasets, as well as UCIQE, UIQM, and IE measurements, are conducted to assess performance. The results show that the proposed method can maintain information and details in the enhanced image as in the original image. In addition, the results of UIQM and IE measurements indicate that the proposed method outperforms other techniques across all datasets, although its UCIQE score remains third among seven methods. The proposed method (FHEACC) is generally successful at improving low contrast, particularly in maintaining the image's color balance without causing side effects. This research is expected to develop the proposed method further, particularly to improve contrast without compromising the original image's color balance. Although experimental results show significant improvements in visual quality, validation of the FHEACC method remains limited to the UIEB dataset and a small number of live-capture test images. This limitation may affect the model's generalizability to more extreme underwater conditions, such as high turbidity, depth variations, or non-uniform light distribution. Therefore, further research is needed, including testing on more diverse and challenging scenarios to assess the algorithm's robustness to various underwater optical conditions and ensure consistent performance in real-world environments.

Declarations

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