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A Comprehensive Study of Underwater Image Enhancement Techniques

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ABSTRACT

Low contrast, blurring details, colour deviations, non-uniform lighting, and other quality issues are common in underwater images. The enhancement of underwater images is a critical problem in image processing and computer vision for a variety of practical applications. Underwater enhancement has attracted a growing amount of research effort over the last few decades. However, a thorough and in-depth survey of related accomplishments and improvements is still lacking, especially a survey of underwater image datasets, which is a key issue in underwater image processing and intelligent applications. To promote a thorough understanding of underwater image enhancement, this paper examines the contributions and shortcomings of current approaches.

Keywords - Blurring, Enhancement, Histogram Distribution, Denoising

I. INTRODUCTION

Underwater optical imaging systems usually involve an optical camera or employ polarisation, stereo / panoramic, and spectral imaging techniques. Other than optical cameras, each technique has its own set of limitations, such as a small field of view, restricted depth, complex and skilled operation, and so on. As light travels through water, the absorption and scattering caused by the water's internal optical property (IOP) affect the underwater imaging process. Forward scattering happens as light is transmitted from the target objects and then enters the receiver. Forward scattering causes a blur circle to form around the point light source, resulting in blurred images. In an underwater image, backscattering reduces contrast and causes foggy veiling. Underwater picture quality is also influenced by dissolved organic matter and small floating particles known as "sea snow," whose concentration and species differ greatly. Depending on the wavelengths of light, the colours of light fade as the depth of the water increases. While artificial lighting may be used to increase the visible distance, it results in a bright spot in the image surrounded by a dark region, exacerbates the scattering caused by suspended matter, and makes the scattering caused by suspended matter more severe. Furthermore, the inherent noise of underwater imaging systems is a significant factor that affects the image quality. As a result, to improve the visual quality of the optical images collected from water, additional enhancement processing is needed.

II. UNDERWATER IMAGING MODEL

Understanding the underwater optical imaging model can aid in the development of more robust and effective enhancement strategies. The underwater optical imaging method and selective light attenuation are depicted in Fig. 1, which was drawn and updated using the model proposed by Huang et al. [1]. On the right side of Figure. 1, the selective attenuation characteristics are shown. When travelling through water, red light absorbs faster than green and blue wavelengths due to its longer range (which are shorter). As a result, underwater pictures often have green-bluish colours.

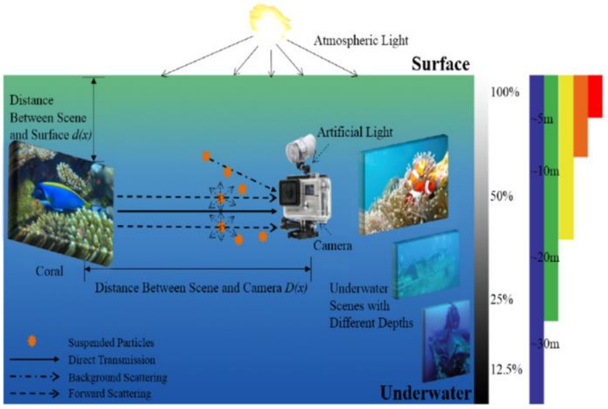

Figure 1: Underwater optical imaging

Figure 1, shows the interaction between light, transmission medium, camera and scene. The camera receives three types of light energy in line of sight (LOS): the direct transmission light energy reflected from the scene captured (direct transmission); the light from the scene that is scattered by small particles but still reaches the camera (forward scattering); and the light coming from atmospheric light and reflected by the suspended particles (background scattering) .

Artificial light sources tend to intensify the negative impact of background scattering in a real-world underwater scene. The particles suspended underwater created unnecessary noise and made dimming images more visible. This paper categorizes the quality improvement methods of IFM-free underwater

Image enhancement methods as shown in figure 2

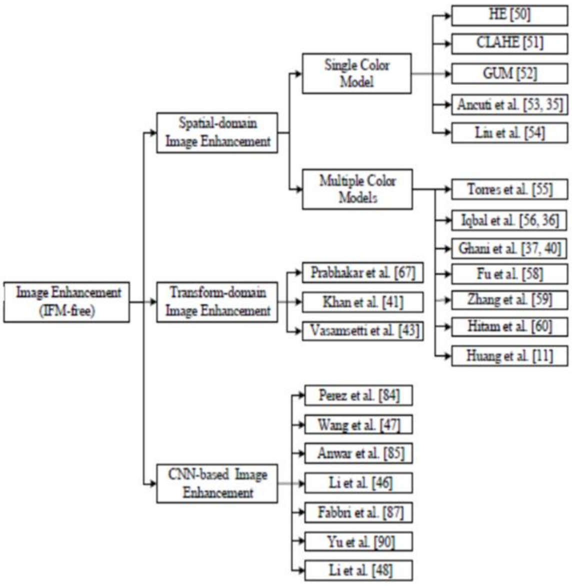

Figure 2. Categories of quality improvement of single underwater image

III. IFM-FREE IMAGE ENHANCEMENT

Without taking into account the basic underwater imaging concepts, underwater image enhancement methods boost the contrast and colour of images primarily by pixel intensity re-distribution. Early underwater image enhancement study often applied outdoor image enhancement techniques to underwater images.

Later approaches are adapted to the particular charact eristics of underwater images, such as hazing, colour c ast, and low contrast.These methods modify the values of pixels in the spatial or transformed domains. Deep learning models, especially convolutional Neural Networks (CNN), have recently been used for image enhancement, based on the concept that hidden features can be learned to improve image quality. The image enhancement approaches are classified as spatial-domain image enhancement, transform-domain image enhancement, and CNN-based image enhancement.

A. Spatial-Domain Image Enhancement

Underwater image histograms show a more concentrated distribution of pixel values than natural image histograms. As a result, increasing the dynamic range of the image histogram provides a method for improving the visibility of underwater images. Based on grey mapping theory, spatial-domain image enhancement methods complete an intensity histogram redistribution by expanding grey levels [2]. This can be done in a variety of colour models. Color models that are commonly used include Red-Green-Blue (RBG), Hue-Saturation-Intensity (HSI), Hue-Saturation-Value (HSV), and CIE-Lab.

We can divide spatial-domain image enhancement methods into SCM-based and MCM-based image enhancement based on whether a single colour model (SCM) or multiple colour models (MCM) is used in the histogram redistribution process.

1) SCM-based image enhancement

The RGB colour model is used by many methods. Histogram Equalization (HE) [3], Contrast Limited Adaptive Histogram Equalization (CLAHE) [4], Gamma Correction, and Generalized Unsharp Masking (GUM) [5] are common contrast enhancement methods used to improve the overall visibility of low-light images. Traditional colour correction methods include Gray-World Assumption (GWA), White Balancing (WB), a nd Gray-Edge Assumption (GEA). Because of the low energy of RGB components of underwater images (lack of illumination in underwater environments), it is common to introduce serious artefacts and halos, amplify image internal noise, and even cause colour distortion when HE, GWA, WH, and their variations are used directly for underwater image enhancement. GEA frequently fails to enhance underwater images because the contrast is low and the edge features are hazy. Fusion is a powerful underwater image enhancement strategy in a single colour model.

Ancuti et al. [6] proposed a fusion-based method in 2012. First, two fusion images are created from the input image: the first is colour corrected using white balance, and the second is contrast enhanced using local adaptive histogram equalisation. The contrast, salient features, and exposure of the two fused images are then used to calculate four fusion weights.

Finally, using the multi-scale fusion strategy, the two fused images and the defined weights are combined to produce enhanced images with improved global contrast and detail information. Ancuti et al. [7] published a new method for colour balance and fusion for underwater image enhancement in 2017. Taking into account underwater optical imaging theory, the proposed underwater white balancing, which aims to compensate for colour cast caused by light with selective attenuation, is gamma corrected and sharpened to generate two fusion images and associated weight maps, which are merged using the standard multi-scale fusion strategy. Their proposed enhanced images and videos are distinguished by improved dark region exposure, global contrast, and edge sharpness.

To estimate the illumination of underwater images, Liu et al. [8] proposed Deep Sparse Non-negative Matrix Factorisation (DSNMF) in 2017. The observed images were first segmented into small blocks, then each channel of the local block was reconstructed into a [R, G, B] matrix, and the depth of each input matrix was decomposed into multiple layers by the DSNMF method's sparsity constraint. The patch is illuminated by the last layer of the factorization matrix, and the image is adjusted with sparse constraints. To obtain the enhanced image, the local block illumination of the original image is estimated after factorization.

2) MCM-based image enhancement

Torres-Méndez et al. used Markov Random Field (MRF) to describe the correlation between underwater images before and after distortion, and improved the colour of images based on the maximum a posteriori in 2005. When calculating image patch dissimilarity, the image is transformed to CIE-Lab colour space to represent equal perceived differences. The experimental data collected from various underwater scenes confirmed the method's feasibility and effectiveness. In 2007, Iqbal et al. [10] proposed an Integrated Color Model-based underwater image enhancement algorithm (ICM). To begin, the RGB colour model's heavily attenuated GB channels are stretched across the entire range [0, 255]. The image is then converted to the HSI colour model, and the S and I components are finally stretched with sliding histogram stretching to improve the output image's saturation and brightness. In 2010, Iqbal et al. proposed an unsupervised Color correction method based on Von Kries hypothesis (VKH) and contrast optimization of selective histogram stretching.

UCM can effectively remove blue-greenish cast and improve the brightness of low components. Ghani et al. used the Rayleigh distribution function in 2015 to redistribute the input image in conjunction with the variation of ICM and UCM, improving image contrast and reducing over-enhancement, over-saturation region, and noise introduction.

The Retinex theory models the mechanism by which the human vision system perceives the world. The term Retinex is derived from the words "retina" and "cortex." It tries to achieve colour constancy when the scene is dominated by a specific illumination, which is similar to the situation in the underwater environment.Fu et al. were the first to propose a simple RGB colour cast correction algorithm for underwater images in 2014. Then, in the CIE-Lab colour model, a new frame was proposed based on retina cortex theory to separate direct light from reflected light. Finally, various strategies were employed to highlight the separated light components in order to improve the contrast of underwater images.

Zhang et al. improved the aforementioned methods and extended the Retinex framework for underwater image enhancement in 2017. To remove luminance in the Lab colour model and suppress halo artefacts, the brightness L and colour a, b components are filtered by bilateral and trilateral filters.

In 2013, Hitam et al. improved the visibility of underwater images by adjusting CLAHE and developing the mixture contrast limited adaptive histogram equalisation (Mix-CLAHE). The CLAHE was applied to the RGB and HSV colour models to generate two images, which were then combined using the Euclidean norm. The results of the experiments show that Mix-CLAHE can significantly improve the visual quality of underwater images by increasing contrast and decreasing noise and artefacts.

Huang et al. introduced relative global histogram stretching (RGHS) in the RGB and CIE-Lab colour models in 2018. The pre-processed image, based on Gray-World theory, used adaptive histogram stretching in the RGB colour model based on RGB channel distribution characteristics and selective attenuation of light propagating under water. Finally, in the CIE-Lab colour space, the brightness L and colour a, b components are optimised as linear and curve adaptive stretching, respectively.

By avoiding blind enhancement due to underwater image characteristics, RGHS can improve the visual effect of the image and retain available information.

B. Transform-Domain Image Enhancement

In the frequency domain, the high-frequency image component usually corresponds to the edge region where the pixel values change a lot, whereas the low-frequency component represents the image's flat background. Transform-domain image enhancement methods commonly transform the spatial domain image into the frequency domain (e.g., using the Fourier Transform) [9], and improve the quality of underwater images by simultaneously amplifying the high-frequency component and suppressing the low-frequency component [10]. The difference between the high-frequency component of the edge region and the low-frequency component of the background region is often small in hazed underwater images [11]. As a result, underwater image quality can be improved by employing transformdomain methods [12], such as the homomorphic filter, highboost filter, wavelet-transform, and so on. Prabhakar et al. used a homomorphic and an anisotropic filter to correct non-uniform illumination and smooth the image in 2010. Finally, to implement de-noising, they used adaptive wavelet sub-band thresholding with a modified BayesShrink function. Underwater image enhancement methods based on Wavelet transformation have recently become more popular. Amjad et al. proposed a wavelet-based fusion method in 2016 to improve the contrast and colour alteration of hazy underwater images. First, two fusion images are created from the original image by stretching the value component of the original image across the entire range in the HSV colour model and then enhancing them with CLAHE. The wavelet-based fusion method then consists of a series of low-pass and high-pass filters to eliminate unwanted low and high frequencies in the image, as well as separately acquiring details of approximation coefficients to make the fusing process more convenient.

Vasamsetti et al. proposed a wavelet-based perspective enhancement technique for underwater images in 2017. Because changing the sign of a wavelet coefficient can cause unwanted image changes, they used the discrete wavelet transform (DWT) on the RGB channels to generate two decomposition levels and collect the approximation and detailed responses for these parts to reconstruct the grey scale images for R-G-B channels.

Meanwhile, this method can be used to improve the accuracy of high-level underwater computer vision tasks by pre-processing underwater detection and tracking techniques. Although transform-domain underwater image enhancement methods can improve visibility and contrast in hazy images, they have a tendency to over-amplify noise and cause colour distortion.

C. CNN based Image Enhancement

Many studies in recent years have demonstrated the effectiveness of deep learning methods in various application fields, such as image segmentation and speech recognition.

Convolutional neural networks (CNN) perform particularly well in image-based tasks; indeed, CNN is the foundation of several advanced deep learning models. Many results have been obtained using various CNNs on low-level vision tasks , such as image de-blurring, image de-raining, image de-noising, low-light image enhancement, and image dehazing. However, only a few methods are effective for improving underwater images.

In 2017, Perez et al. [13] proposed a CNN-based underwater image enhancement method that uses pairs of degraded and recovered underwater images to train an end-to-end transformation model between the hazed images and the corresponding clear images. Meanwhile, Wang et al. proposed UIE-net (Underwater Image Enhancement-net), an end-to-end CNN-based underwater image enhancement framework for colour correction and haze removal. To extract the inherent features of local patches of the image, the UIE-net employs a pixel disrupting strategy, which greatly accelerates model convergence and improves accuracy.

In 2018, Anwar et al. [14] trained a convolutional neural network (UWCNN) on a database of synthetic underwater images created in an indoor environment, and then used the UWCNN to directly reconstruct the clear underwater latent image. This model's generality was validated using real and synthetic underwater images from a variety of underwater scenes. However, in deep sea environments, a large amount of training data is difficult to compile, so researchers used generative adversarial networks (GANs) [15] to generate realistic underwater images in an unsupervised pipeline. WaterGAN was proposed by Li et al. to generate synthetic real-world images from in-air image and depth maps, and then both raw underwater and true colour in-air, as well as depth data, were used to feed a two-stage deep learning network for color-cast underwater image correction. Fabbri et al. like waterGAN, used GANs to improve underwater image. They first used CycleGAN to reconstruct distorted images based on undistorted images, and then the pairs of underwater images were fed into the training of a novel Underwater-GAN, which can transform hazy underwater images into clear and high-resolution images. Li et al. proposed a weakly supervised underwater colour correction model that primarily consists of adversarial networks and a multi-term loss function that includes adversarial loss, cycle consistency loss, and SSIM loss to alleviate the need for paired underwater images for network training and allow the use of unknown underwater images. This method preserves the content and structure of the input underwater image while correcting the colour distortion. Yu et al. proposed Wasserstein GAN with gradient penalty term as the backbone network in 2019, designed the loss function as the sum of generative adversarial network loss and perceptual loss, and used a convolution patchGAN classifier as the discriminator of Underwater-GAN. Uplavikar et al. proposed a domain-Adversarial learning-based underwater image enhancement method in 2019 that can handle multiple types of underwater images and generate clear images by learning domain-agnostic features.

So far, the reality of the generated underwater images has received little scrutiny.

To address the difficulty in developing CNN-based underwater image enhancement, Li et al. created a large-scale and real-world underwater image enhancement benchmark dataset (UIEBD) in 2019, which was used to train a DUIENet that uses a gated fusion network architecture to learn three confidence maps.

IV. QUALITY IMPROVEMENT METHODS FOR UNDERWATER IMAGES:EXPERIMENTAL COMPARISONS

To investigate the current state of quality improvement methods for underwater images, we first introduce image quality assessment metrics before conducting comprehensive comparisons on mainstream IFM-free underwater image enhancement methods from both subjective and objective perspectives.

A. The Methods to be included

HE, CLAHE , integrated colour model (ICM), unsupervised colour correction method (UCM), Fusion-based underwater image enhancement method (Fusion-based, FB), underwater image enhancement method based on Rayleigh distribution (RD)and relative global histogram stretching (RGHS) are among the IFM-free image enhancement methods compared.

B. Metrics for Image Evaluation

The optical performance of imaging equipment, instrument noise, imaging conditions, image processing, and other factors can all have an impact on image quality.

Image quality assessment (IQA) is frequently divided into two categories: subjective qualitative assessment (SQA) and objective quantitative assessment (IQA) (OQA). SQA relies heavily on the human visual system (HVS) to obtain subjective impressions of images. A proper SQA necessitates repeating a number of experiments (varying the factors that affect image quality) to generate a dataset, which is then scored by human observers in order to achieve statistical significance. Due to the low efficiency and complicated operation of SQA, we simply present representative results from various image enhancement/restoration methods as the basis for subjective analysis in this paper. OQA develops a mathematical model based on the HSV in order to calculate a quality index. This method is significantly more efficient than SQA if accurate models are used, because a larger dataset can be automatically scrutinised.

OQA methods are commonly classified into three types: fullreference (FR), reduced-reference (RR), and nonreference (NR). FR and RR image quality metrics require or partially require a high-quality reference image when evaluating image quality. Unfortunately, in a complex underwater environment, a dehazed and natural reference image cannot be obtained unless synthetic images or colour boards from the terrestrial scene are brought into the underwater scene. Furthermore, due to the complex underwater environment and optical imaging mechanism, underwater image evaluation metrics are limited. To fully comprehend the performance of the compared underwater image quality improvement methods, we selected multiple NR metrics developed for both specific underwater images and general images, taking into account aspects such as information richness, naturalness, sharpness, and the overall index of contrast, chroma, and saturation.

Entropy is defined as the average degree of uncertainty in information. Entropy, when applied to images, represents the abundance of information observed in the image. When the image's contrast is more uniform, the entropy is relatively higher; the higher the entropy, the better the image's quality and clarity; otherwise, an image with low contrast, whose pixel values are distributed within a narrow range, has a lower entropy and appears hazy. The natural image quality evaluator (NIQE) was developed based on human vision sensitivity to high-contrast areas in images. It establishes the feature model of sensitive areas using multivariate gaussian (MVG), with the larger the values of these parameters, the higher the image quality. A lower NIQE score indicates better perceptual quality.

Image with no context/reference The Spatial Quality Evaluator (BRISQUE) assesses image naturalness by measuring deviations from a natural image model based on natural scene statistics. BRISQUE can represent the potential loss of image naturalness caused by distortion, with a value ranging from 0 to 100, and the higher the value, the poorer the image quality.

Yang et al.discovered a relationship between image sharpness and colour and subjective image quality perception in 2015 and proposed an image quality evaluation method specifically for underwater images, the underwater colour image quality evaluation (UCIQE). In CIELab colour space, UCIQE is a linear model of contrast, chroma, and saturation that can be expressed as:

$UCIQE = c_1 \times \sigma_c + c_2 \times con_l + c_3 \times \mu_s$.

where σ_c, con_l, μ_s represents the standard deviation of image chromaticity, con represents the contrast of image brightness, and c represents the average of image saturation, and c_1, c_2, c_3 represents the weights of these parameters. Underwater image quality measure (UIQM) is similar to UCIQE in that it is a linear combination of underwater image colorfulness measure (UICM), underwater image sharpness measure (UISM), and underwater image contrast measure (UIConM). As a result, the larger the UCIQE and UIQM, the better the underwater colour image quality.

C. Evaluation and Discussion Of the Overall Performance Of Underwater Image Enhancement

As a baseline, we used a dataset with four types of un derwater images that is commonly used in the literatu re. This includes one relatively clear scene and three difficult underwater images in a greenish, turbid, and low-visibility scene (Figure. 3).

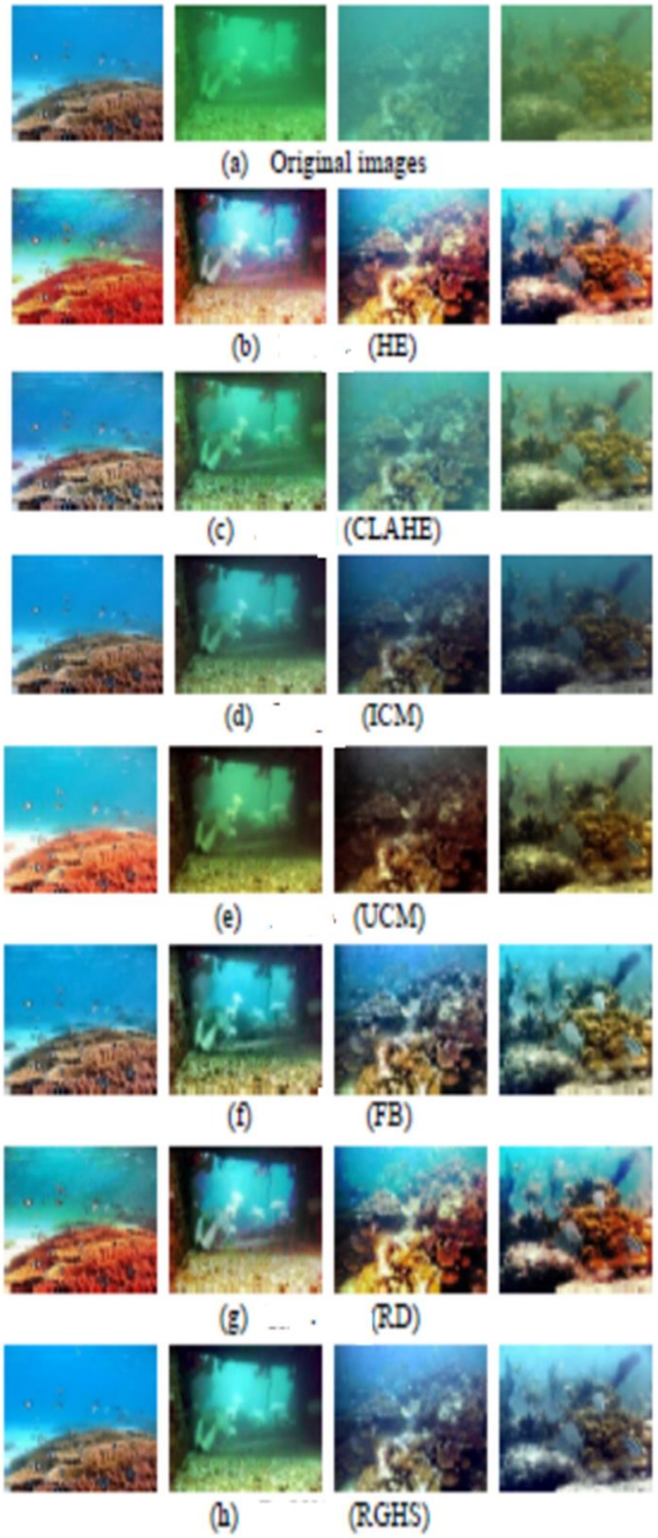

Figure 3: Comparisons on results of IFM-free image enhancement methods.

1) Subjective Analysis

The results of IFM-free image enhancement methods are shown in Figure. 3 (b-h). The HE-enhanced images (Figure. 3 (b)) have an overwhelming red tone and amplify the noises in the original image. Both CLAHE and RGHS use adaptive parameters to avoid global histogram stretching or blind pixel redistribution, both of which reduce sharpness.

As a result, their results in Figure. 3 (c) and Figure. 3 (h) are not exaggerated. RGHS outperforms CLAHE in terms of dehazing. As shown in Figure. 3, ICM and UCM redistribute the S and I components in HSI colour space, which can result in under- and over-saturated images (d-e). In the HSV colour model, RD combined ICM and UCM with Rayleigh distribution to minimise under- and over-enhanced areas of output images. However, RD conceals the enhanced images' local detailed information. Although the Fusion-based (FB) image enhancement method can significantly improve image contrast and chromaticity, noise is unavoidably introduced into the enhanced images.

2) Objective Analysis

The goal of underwater image restoration/enhancement is to improve the visibility, colour, and saturation of images while also revealing detailed information for feature extraction and computer vision analysis. Because reference underwater images (ground truth) are not available, this review selects five types of non-reference image quality metrics to quantify information entropy, distortion, and the balance of brightness, contrast, and colour for underwater images. ENTROPY, BRISQUE, NIQE, UIQM, and UCIQE are the five metrics.

TABLE 1. QUANTITATIVE ANALYSIS OF ENHANCED RESULTS BASED ON DIFFERENT METHODS

Compared methods	Image Quality Assessment Metrics				
	ENTROPY	BRISQUE	NIQE	UIQM	UCIQE
HE	7.8139	28.6079	3.9654	4.0399	0.6818
CLAHE	7.1132	27.3445	3.6338	2.0644	0.6567
ICM	6.9117	33.1758	3.4253	2.2999	0.5872
UCM	7.2643	28.2424	3.6339	3.3228	0.6131
FB	7.5269	32.9730	3.9176	2.7567	0.6684
RD	7.7487	29.0286	3.7631	3.2654	0.6721
RGHS	7.4759	28.3178	3.5161	2.0116	0.6176
Avg (Var)	7.04 (0.09)	29.67 (4.86)	3.69 (0.03)	2.82 (0.49)	0.64 (0.001)

Table 1, shows the average values of the five quantitative evaluations of the enhanced images, highlighting the best results in bold.

V. CONCLUSION

To assist researchers in better exploring this unknown underwater world, quality improvement methods for single underwater images based on image enhancement are thoroughly reviewed. In this review, we will first discuss the fundamental principles of underwater imaging models and selective light absorption characteristics under water. This paper presents an experimental comparison of state-of-the-art quality improvement methods using multiple quality assessment metrics, which leads to a discussion of the problems encountered by current IFMfree underwater image quality improvement methods. Overall, it provides a comprehensive overview of the progress and challenges of single underwater image quality improvement, which can aid researchers in the future development of this field.

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