An Overview of Underwater Image Enhancement Techniques

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ABSTRACT: *As one of the important carriers for understanding the underwater environment, underwater images have important research significance in the fields of marine ecology, marine resources and marine environment monitoring. However, the degradation inherent in underwater images, such as color distortion due to light absorption and scattering, severely hampers their effectiveness in downstream applications, including object detection, recognition and tracking. Therefore, underwater image enhancement methods are crucial for restoring image quality and enhancing visual information. This paper aims to introduce several diverse enhancement approaches, including image-based, physics-model-based, and deep-learning-based. Additionally, we discuss relevant underwater image datasets and quality evaluation metrics. By doing so, we aim to provide insights into the landscape of underwater image enhancement research and its implications for advancing underwater vision systems.*

KEYWORDS -*Underwater Image Enhancement, Underwater Image Dataset, Quality Evaluation Metrics*

I. INTRODUCTION

Recently, underwater imaging technology has gained widespread attention in various fields, including marine biology research, underwater archaeology, ocean exploration, and underwater robotics, due to its wide range of applications [1]. However, capturing high-quality images in underwater environments is inherently challenging due to the unique optical properties of water, such as absorption, scattering, and attenuation of light. This degradation can result in color distortion, low contrast, and blurred details, seriously hindering subsequent image analysis and interpretation tasks.

To address these challenges, numerous underwater image enhancement techniques have been developed to restore and improve the visual quality of underwater images. These methods aim to mitigate the effects of light attenuation, enhance contrast, correct color distortion and sharpen image details, ultimately promoting more accurate and reliable image-based analysis and decision-making in underwater applications.

This paper aims to provide a comprehensive overview of the current representative underwater image enhancement methods. We categorize these methods into three approaches: image-based methods, physical model-based methods, and deep learning-based methods [2]. The classification strategy is shown in the Fig. 1. Image-based methods enhance contrast, sharpen edges, and correct colors by manipulating pixel values without explicitly modeling the underwater imaging process. Physical model-based methods utilize mathematical models to describe the light propagation and attenuation processes in water, enabling the reversal of these effects to restore image quality. In recent years, deep learning-based methods have shown remarkable performance in underwater image enhancement by learning complex mappings from degraded underwater images to their enhanced counterparts.

Furthermore, underwater image datasets play a crucial role in the development and evaluation of underwater image enhancement methods. This paper presents several publicly available underwater image datasets that have been widely utilized by the research community. These datasets encompass a wide range of underwater environments and imaging conditions, providing a valuable resource for training and testing underwater image enhancement algorithms.

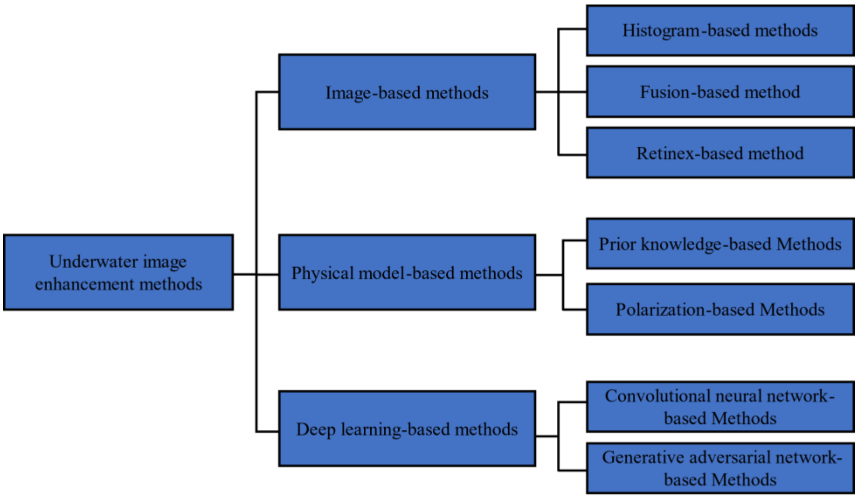

Fig. 1The classification strategy of underwater image enhancement methods.

Evaluating the quality of enhanced underwater images is a crucial step in assessing the performance of different enhancement methods. This paper reviews several underwater image quality assessment metrics, including fully referenced and non-referenced metrics, which have been proposed to quantitatively assess the visual quality and fidelity of enhanced underwater images. These metrics enable an objective comparison of different enhancement techniques and contribute to the development of more efficient algorithms.

In summary, this paper presents a comprehensive review of underwater image enhancement methods, underwater image datasets, and underwater image quality assessment metrics. By synthesizing information from these three areas, this paper aims to provide researchers and practitioners with a comprehensive understanding of the current state of underwater imaging research and identify potential directions for future work. This review hopes to contribute to the development of underwater imaging technology and its applications in various fields.

II. UNDERWATER IMAGE ENHANCEMENT METHODS

In this section, we provide an overview of various representative underwater image enhancement methods.

2.1 Image-based Methods

The image-based method does not depend on the underwater imaging model, and improves the brightness and contrast of the underwater image by directly adjusting the pixel value of the image. Image-based underwater image enhancement methods can be subdivided into the following methods: histogram-based method, fusion-based method and retinex-based method.

2.1.1 Histogram-based Methods

The histogram equalization-based algorithm [3] is an effective and straightforward method for image enhancement. This method's principle involves recalculating the gray world map of the image and transforming the histogram from a narrow single-peak distribution to a uniform distribution, ensuring that the image has an approximately equal number of pixels across the gray level range, thereby enhancing the image's brightness and contrast [4].

In the early stages of underwater image enhancement technology research, researchers attempted to directly apply the aerial histogram equalization method to process underwater images. However, the enhancement effect was poor due to the neglect of the distinct differences between underwater and airborne imaging. Iqbal et al. [5] proposed an unsupervised color correction method in the field of underwater image enhancement, which is based on color correction and adaptive histogram stretching. This algorithm employs a color balancing method and adjusts the histogram distribution of the red and blue channels in the RGB color space, effectively removing color bias and correcting saturation and brightness in underwater images. Ahmad et al. [6][7] successively proposed an adaptive histogram enhancement method using Rayleigh stretching limit contrast enhancement and a recursive histogram correction method. The former method improves image contrast, enhances detail, and reduces over-enhancement, over-saturation, and noise introduction. However, if the color proportion in the image is low, the image may become distorted. The latter method modifies the image color in the HSV color space, enhancing the contrast of the background region, but also increasing the algorithm's complexity. Li et al. [8] proposed a prior histogram distribution algorithm based on underwater image dehazing, which significantly improved the brightness and contrast of underwater images and greatly reduced the inference time. The disadvantage is that the enhancement effect is not significant when the degraded image has low brightness. While this method is effective in enhancing image quality, it can potentially overstretch the gray levels, leading to excessive enhancement and the introduction of artifacts. Consequently, this may result in a loss of detail or an unnatural appearance in the enhanced image.

2.1.2 Fusion-based Methods

The fusion-based method complements the information of different images by fusing multiple images of the same scene, so that the degraded image has richer and more accurate information.

Ancuti et al. [9][10] used the complementary information between multiple images to optimize the acquisition process and the definition of weight information of fused images, which improved the exposure of enhanced images and retained the edge information of images. However, this algorithm cannot perform selective compensation. Pan et al. [11] obtained atomization image and color correction image of the original image through dehazing network and white balance, used the fusion strategy of Laplace pyramid for fusion, and used hybrid wavelet to achieve denoising and edge enhancement. The disadvantage of this algorithm is that it can not significantly improve the contrast of the image. Chang et al. [12] proposed an adaptive fusion algorithm for underwater image restoration. Based on optical characteristics and image processing knowledge, the algorithm extracts the background light and transmission images of underwater images, and performs adaptive weighted fusion according to their respective salient images. The algorithm can effectively restore the clarity and color information of the image, but the blurring still exists in the background area and the contrast is insufficient. Gao et al. [13] proposed an underwater image enhancement method based on Local Contrast Correct and multi-scale fusion. The multi-scale fusion method effectively addresses the issues of low contrast and color distortion in underwater images by fusing the locally contrast-corrected image with the sharpened image. Song et al. [14] introduced a method called Multiscale Fusion and Global Stretching of Dual-model (MFGS). MFGS utilizes white balance to correct color bias and incorporates contrast and spatial cues into a significance weight sparse strategy for achieving high-quality fusion. Furthermore, MFGS globally stretches all channels in the RGB color space to enhance color contrast. However, this algorithm exhibits limitations in enhancing color richness and reducing inference time.

These fusion methods generally mitigate noise, thereby enhancing the overall contrast and refining edge and detail clarity. However, these methods necessitate the acquisition of multiple images and the fusion of weights.

2.1.3 Retinex-based Methods

The underwater image enhancement method based on Retinex simulates the human eye's adaptive light adjustment mechanism by disentangling color and brightness information from the image, and subsequently enhancing image quality through the adjustment of their relative proportions. Retinex theory, rooted in color constancy, mitigates the impact of irradiation components on object color, thereby eliminating degradation under uneven illumination and revealing the true scene depiction.

Jobson et al. [15][16] introduced the Multiscale Retinex enhancement algorithm to enhance image quality. Joshi et al. [17] applied Retinex theory to underwater images for enhancing degraded image, albeit with limited improvement in visual effect despite advances. Fu et al. [18] presented a Retinex-based variant that utilizes an alternate direction optimization strategy to address reflectivity and illuminance issues, while incorporating color correction to mitigate underexposure and blur. However, the complexity of this algorithm is heightened by the iterative optimization process. Bianco et al. [19] pioneered the use of color space for color correction in underwater images. The method manipulates the color component, adjusting its distribution around white balance and histogram cutoffs, and enhances image contrast by stretching the brightness component. Mercado et al. [20] introduced a deep-sea dark image enhancement technique based on MSRCR (Multi-Scale Retinex with Color Restoration), aimed at mitigating color loss and addressing the issue of uneven illumination. Zhang et al. [21] developed an underwater image enhancement algorithm based on extended multi-scale Retinex, incorporating both bilateral and trilateral filtering to mitigate the halos. The disadvantage of trilateral filtering is its lengthy processing time and limited contrast enhancement effect. Zhang et al. [22] presented an MSRCR-based single image dehazing method utilizing multi-channel convolution, capable of enhancing the global contrast and detail information of underwater images while mitigating noise interference. However, this method occasionally fails to prevent the occurrence of overexposure. Tang et al. [23] developed an underwater video image enhancement method. This method initially achieves even pixel distribution through preprocessing, followed by the application of multi-scale Retinex with intensity channels to the preprocessed images, further enhancing contrast and color. However, the algorithm's real-time performance is constrained by its intricate steps.

In conclusion, Retinex-based underwater image enhancement techniques effectively enhance the clarity and visibility of underwater images. However, their design and calculation processes are intricate, necessitating the integration of color correction, detail enhancement, and histogram equalization methods for optimal image enhancement.

2.2 Physical Model-based Methods

Different from image-based methods, physical model-based underwater image enhancement methods mimic the light propagation process underwater by constructing an optical model specific to underwater imaging. Subsequent to establishing the underwater imaging model, this approach utilizes prior knowledge and additional methodologies to approximate the model's parameters and reverse the degradation process, thereby yielding a clearer underwater image. Currently, the physical model-based methods include polarization-based methods and prior knowledge-based methods.

2.2.1 Polarization-based Methods

The polarization-based method exploits the polarization attributes of scattered light to discern between scene light and scattered light, thereby enhancing the underwater image through the estimation of the scattered light's intensity and transmission coefficient.

Schechner et al. [24] harnessed the polarization of light scattering in water to restore the visibility, contrast, and color fidelity of underwater images. Nonetheless, in the case of images exhibiting severe scattering, the enhancement outcomes may suffer from blurriness. Based on independent component analysis, Namer et al. [25] first approximated the intensity and polarization level of background light from polarization images. Then, the depth map of the underwater image is derived to facilitate the restoration of the degraded image. Chen et al. [26] segmented the underwater image according to whether it was an artificial illuminated area, compensated the artificial illuminated area in the image, eliminated the influence of artificial lighting on the underwater image, and solved the problem of uneven illumination. But this method may result in overexposure. Han et al. [27] considered the influence of backscattering in imaging and mitigated its effect by altering the light source, acquiring two orthogonally polarized images. This method effectively preserves edge information. Ferreira et al. [28] utilized particle swarm optimization to estimate polarization parameters and employed an unreferenced mass measure as the cost function for image recovery, resulting in improved visual quality. However, the parameter optimization process increases the time complexity of the algorithm.

In summary, while these methods enhance underwater image quality, they require multiple images of the same scene captured at different polarization angles as prior information, thereby restricting their applicability.

2.2.2 Prior knowledge-based Methods

The prior knowledge-based methods utilize the existing knowledge of underwater environment features to estimate the parameters of the underwater image degradation model and invert the degradation process to obtain a clear underwater image.

He et al. [29] introduced the Dark Channel

Prior (DCP) technique, originally designed for dehaze removal in images, which has gradually been adapted for enhancing underwater image scenes. This method employs the DCP theory to solve for the transmitted image and atmospheric light value, while utilizing the atmospheric scattering model to restore the image. However, when Liu et al. [30] directly applied the DCP method to underwater image enhancement, the enhancement effect was minimal, and even led to degradation. To address this, Yang et al. [31] proposed a rapid underwater image restoration method based on DCP, which utilized median filtering to estimate the depth of field information and introduced a color correction method to enhance image contrast. Nevertheless, this approach was unable to recover underwater images with low brightness and color deviation. Chiang et al. [32] overcame these limitations by proposing an underwater image enhancement method that combined wavelength compensation with DCP dehazing. This method not only corrected image blur and distortion caused by artificial light sources but also improved image quality by compensating for the varying attenuation characteristics of the RGB channels. Drews et al. [33] introduced the Underwater Dark Channel Prior (UDCP) method. This method solely focuses on the blue and green channels, resulting in a more precise underwater transmission map compared to the DCP algorithm, thereby enhancing the image recovery performance. Galdran et al. [34] devised an automatic red channel underwater image restoration method. This approach utilizes the red channel prior and incorporates saturation information to modulate the impact of artificial light sources. Li et al. [35] presented a method that combines red channel correction with blue and green channel dehazing. This method employs the gray world algorithm and adaptive exposure images to adjust the red channel's color, simultaneously addressing issues of overexposure and underexposure areas, thereby enhancing visibility and contrast. However, for underwater images captured in uneven lighting conditions, the quality of recovered images remains suboptimal. Meng et al. [36] introduced an underwater image enhancement technique that integrates color correction with image sharpening. When the value of red channel is approximates approaching the blue channel, a color balance method is employed for image restoration. Furthermore, the algorithm utilizes the Maximum a Posteriori Probability (MAP) method to sharpen the image subsequent to color correction. This algorithm enhances image visibility while preserving foreground texture details, albeit at the cost of introducing numerous parameters.

While these methods can effectively enhance image quality, they rely heavily on obtaining precise prior information. Obtaining this information, however, poses significant challenges and necessitates the estimation of prior knowledge through the utilization of mathematical or statistical models. Accurately estimating prior knowledge is pivotal in achieving high-quality recovery of underwater images.

2.3 Learning-based Methods

In recent years, deep learning has garnered significant attention in the field of computer vision owing to its robust feature learning capabilities. Furthermore, deep learning-based underwater image enhancement techniques have garnered the interest of researchers in the field. The objective of deep learning-based underwater image enhancement is to learn the mapping between degraded and clear underwater images, leveraging extensive training data. Based on varying network architectures, it can be categorized into two enhancement approaches: Convolutional Neural Networks-based (CNN-based) methods and Generative Adversarial Networks-based (GAN-based) methods.

2.3.1 CNN-based Methods

CNN is a classical type of deep feed forward artificial neural network, comprising multiple convolutional layers designed to efficiently extract feature representations, ranging from low-level details to high-level semantic information, enabling the processing of diverse computer vision tasks.

Gai et al. [37] proposed DehazeNet, a deep neural network that utilizes convolutional neural networks to extract media-transmitted images and employs an atmospheric scattering model to restore degraded images, achieving end-to-end image de-hazing. However, this network proves ineffective when directly applied to underwater image processing tasks. Shin et al. [38] introduced a universal convolution structure to recover underwater images by learning both the transmission pattern and the background light of underwater images. Although the model exhibits effective performance in removing haze, it suffers from color overcompensation. Ding et al. [39] addressed distorted images using an adaptive color correction algorithm. This algorithm employs a CNN network to estimate the depth map of the image after color correction and converts it directly to the transmission map for restoration. Nevertheless, the adaptability and real-time performance of the algorithm require improvement. Li et al. [40] constructed a large-scale underwater image enhancement dataset encompassing various water types based on the physical model of images and the optical characteristics of underwater scenes. Bseides, they proposed UWCNN, an underwater image enhancement model based on underwater scene priori. UWCNN trains multiple networks on different degradation types of underwater image datasets and employs multiple loss functions for joint optimization to reconstruct clear underwater images while preserving the original structure and texture. Uplavikar et al. [41] employed encoder-decoder network to reconstruct clear underwater images and utilized an independent CNN as a water classifier to determine the water types. To address the diversity of underwater image distribution, they incorporated adversarial training, forcing the model to learn agnostic features of the water types from degraded underwater images. This method enhanced the generalization performance of the model by reducing the interference of domain distribution diversity, albeit with a challenging optimization process. Naik et al. [42] introduced a shallow neural network comprising a fully connected convolutional network and three densely connected convolutional blocks. This network effectively avoided overfitting through skip connections and exhibited well generalization performance and real-time efficiency. However, the enhancement effect requires further improvement. Yang et al. [43] proposed integrating RGB and HSV color spaces into a CNN network. RGB pixel block operations facilitated denoising and chromatic aberration correction, while HSV enabled adjustment of color, brightness, and saturation in underwater images.

Overall, CNN-based methods should consider the underwater imaging process during design to enhance interpretability and better meet practical application needs.

2.3.2 GAN-based Methods

GAN is a neural network structure consisting of generator and discriminator. The objective of the generator is to learn to produce high-quality underwater images, while the discriminator identifies differences between generated and real underwater images. Through iterative training, the generator progressively enhances its ability to generate underwater images, approximating the effect of real underwater images as closely as possible.

Due to the difficulty in obtaining pairs of underwater images, relevant researchers [44][45] employed GAN networks to generate a substantial amount of underwater images, addressing the issue of limited underwater image enhancement datasets. Li et al. [46] proposed an underwater image generation adversarial network that utilizes aerial and synthetic underwater images as training data for real-time color correction of a single underwater image. Fabbri et al. [47] proposed an underwater image enhancement model based on a generative adversarial network, which restores underwater images by incorporating absolute error loss and gradient loss. Guo et al. [48] proposed a multi-scale dense generative adversarial network for underwater image enhancement, utilizing multi-scale, dense cascade, and residual learning operations to enhance model performance. Liu et al. [49] proposed a multi-scale fusion adversarial network that fuses local and global features to obtain more discriminative feature expressions, facilitating more efficient network learning. Yang et al. [50] proposed an underwater image enhancement method with dual discriminators that captures local and global semantic information, constraining the generator to produce real and natural results. Lu et al. [51] embedded prior knowledge into the cycle generation adversarial network and used depth information to guide multi-scale calculation, achieving good performance in contrast enhancement and color correction. Li et al. [52] proposed a fusion adversarial network for underwater image enhancement, utilizing multiple target loss functions to correct color bias and spectral normalization to enhance image quality. Park et al. [53] added a pair of additional discriminators based on the cyclic adversarial generation network, and introduced an adaptive weighting method to limit the loss of the two discriminators.

In general, GAN-based methods mainly rely on high quality training data, reasonable network structure and effective training methods.

III. UNDERWATER IMAGE ENHANCEMENT DATASETS

Underwater image enhancement method needs a lot of underwater image data to train or optimize. In the process of training and testing, the underwater image dataset adopted by the model should not only consider the diversity of underwater scenes and the richness of content, but also consider whether the amount of underwater image data is sufficient. We introduce a variety of underwater image datasets, including the paried real world datasets UIEB [49], UFO [54], and EUVP [55], and unparied real world dataset RUIE [56], as well as the synthetic and paried underwater image dataset [40].

These datasets all collect a large number of real or synthetic underwater images from different domains and different imaging equipment, covering multiple types of degradation and rich image content. Most of them also provide corresponding reference images or images that have been processed by specialized underwater image enhancement algorithms in order to evaluate and compare the effects of different underwater image enhancement methods. UIEB contains 890 original underwater images and corresponding high-quality reference images, as well as 60 challenging underwater images. This dataset contains multiple underwater scenes, a wide range of image content and a different range of colors, and also provides high-quality reference images that can be used to guide image quality evaluation and end-to-end learning. The UFO dataset contains 1500 training samples and 120 test samples and can be used for salient object detection, super-resolution reconstruction, and underwater image enhancement. Underwater images of this dataset were collected at different locations and under different water types, and significant foreground pixels were manually marked. The EUVP dataset consists of 20K underwater images with 12K paired instances and 8K unpaired instances. The EUVP dataset was shot with a variety of different cameras, covering different visibility and sea areas. Some of the images were taken from publicly available Youtube videos to accommodate the wide range of natural variations in the data. The RUIE dataset consists of three subsets: UIQS, UCCS and UHTS. UIQS is divided into five quality levels, each containing 726 underwater images, totaling 3,630 images. The UCCS subset consists of 300 underwater images, including 100 blue distorted, 100 green distorted, and 100 blue-green distorted images. The UHTS subset consists of 300 underwater images of different species of Marine life for evaluation of classification and detection methods. And Li et al. [40] used attenuation coefficients to characterize different water scenes and constructed 10 different types of image datasets using the RGB-D NYU-v2 indoor dataset [57].

IV. QUALITY EVALUATION METRICS

Image quality evaluation is an important index to measure image quality. According to the situation with or without reference images, quantitative evaluation can be divided into reference image quality evaluation and non-reference image quality evaluation.

4.1 Reference Evaluation Metrics

For reference evaluation metrics, the widely employed full-reference image quality evaluation methods include Peak Signal to Noise Ratio (PSNR) [58] and Structural Similarity (SSIM) [59].

Images processed through neural networks or other technical approaches differ from their original counterparts, and the PSNR value is commonly utilized to assess whether the quality of the processed image satisfies the desired standards. For an image of size $m \times n$, the calculation process of PSNR can be expressed as follows:

$$PSNR(x,y) = 10 \times \log_{10} \frac{255^2}{E_{MS}} \#(1)$$

$$E_{MS}(x,y) = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{n=0}^{n-1} \|x(i,j) - y(i,j)\|^2 \#(2)$$

Where x represents the processed image, y represents the clear reference image, and E_{MS} is the mean square error. Higher PSNR values indicate a lesser degree of image distortion.

SSIM evaluates the similarity between two images based on three components: luminance similarity, contrast similarity, and structural similarity. The SSIM calculation formula is presented as follows:

$$SSIM(x,y) = \left[l(x,y)^{\alpha} \times c(x,y)^{\beta} \times s(x,y)^{\gamma}\right] \#(3)$$

$$l(x,y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \#(4)$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2\sigma_y^2 + c_2} \#(5)$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3} \#(6)$$

here, $\boldsymbol{x}$ represents the processed image, whereas $\boldsymbol{y}$ represents the clear reference image. The mean values of $\boldsymbol{x}$ and $\boldsymbol{y}$ are denoted by $\boldsymbol{\mu_x}$ and$\boldsymbol{\mu_x}$, respectively, and their variances are denoted by $\boldsymbol{\sigma_x^2}$ and $\boldsymbol{\sigma_y^2}$ .Constants $\boldsymbol{c_i}$ ($\boldsymbol{i=1,2,3}$) are introduced to prevent the denominator from being zero.The value of SSIM ranges from 0 to 1, with higher values indicating greater similarity between the two images.To simplify the calculation, the common choice is to set $\boldsymbol{\alpha=\beta=\gamma=1}$ and $\boldsymbol{c_2=2c_3}$. The simplified SSIM formula can expressed as:

$$SSIM(x,y)=\frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)}\#(7)$$

4.2 Non-reference Evaluation Metrics

For evaluating image quality without reference images, two non-reference metrics can be employed: Underwater Color Image Quality Evaluation (UCIQE) [60] and Underwater Image Quality Measurement (UIQM) [61].

UCIQE evaluates an image's chroma, saturation, and contrast, with chroma quantifying color bias, contrast measuring local contrast of targets, and the mean saturation indicating color purity. The calculation formula for UCIQE can be defined as:

$$UCIQE=c_1\times\sigma_c+c_2\times c_l+c_3\times\mu_s\#(8)$$

where $\boldsymbol{c_1}$, $\boldsymbol{c_2}$, $\boldsymbol{c_3}$ are weight coefficients, and $\boldsymbol{\sigma_c}$, $\boldsymbol{c_l}$, and $\boldsymbol{\mu_s}$ represent the standard deviation of chromaticity, luminance contrast, and mean saturation, respectively.Higher UCIQE values indicate better image quality.

UIQM comprises three components: Underwater Image Colourfulness Measure (UICM), Underwater Image Sharpness Measure (UISM), and Underwater Image Contrast Measure (UIConM).The calculation formula for UIQM as follows:

$$U\quad QM=c_1\times U_{ICM}+c_2\times U_{ISM}+c_3\times U_{IConM}\#(9)$$

where $\boldsymbol{c_1}$, $\boldsymbol{c_2}$, and$\boldsymbol{c_3}$ are the weight coefficients for UICM, UISM, and UIConM, respectively. Higher UIQM values indicate better image quality.

V. CONCLUSION

At present, the mainstream underwater image enhancement technology is aimed at a single water scene. Although there are relevant technologies that can cope with multiple types of degraded underwater images, it is still difficult to take into account the effectiveness, universality and robustness of the method. Therefore, it is of great significance to study the diversity of underwater image degradation and achieve a universal and robust underwater image enhancement method for different degradation types. At the same time, research on the multi-frequency of underwater image information, design underwater image sharpening methods that can generate high-quality enhanced results, and then promote the application of underwater image sharpening technology in underwater survey, marine biological research and underwater rescue.

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