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# A Survey of Restoration and Enhancement for Underwater Images

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**ABSTRACT** Images captured underwater usually suffer from color distortion, detail blurring, low contrast, and a bluish or greenish tone due to light scattering and absorption in the underwater medium, which in turn the visibility is adversely affected by these factors seriously. Over the last decades, various image restoration and enhancement methods have been developed by many researchers to improve the quality (visibility and highlight richer details) of underwater images. This paper introduces the overview of state-of-the-art underwater image restoration and enhancement techniques and classifies the approaches in two categories: image restoration (physical-based model) and image enhancement (nonphysical-based model). Furthermore, the classification of these two methods is elaborated. Then, the typical underwater image restoration and enhancement methods are discussed in detail, as well as a comprehensive study and fair evaluation of the methods is carried out from both qualitative and quantitative perspectives. Finally, the research process of underwater image restoration and enhancement is summarized and the suggestions for future research are prospected.

**INDEX TERMS** Underwater image degradation, underwater image restoration, underwater image enhancement, underwater image quality evaluation, transmission map estimation.

## I. INTRODUCTION

The exploitation and utilization of rich mineral resources in the marine environment is beneficial to national defense security and economic construction. Researchers often use underwater videos or images to obtain valuable information when studying underwater environments. However, the environment of underwater optical imaging (UOI) is more complex than the atmospheric because the scattering and absorption of underwater medium often results in degradation of the quality of underwater videos or images. In general, these complex underwater environments seriously affect the quality of underwater videos or images. However, clear underwater images are widely used in the fields of UOI [1]–[3], underwater detection [4]–[7], underwater target tracking [8], marine biology research [9], marine surveillance [10], and underwater environmental protection [11].

A clear image is a crucial prerequisite for understanding real-world scenarios in the turbid underwater environment.

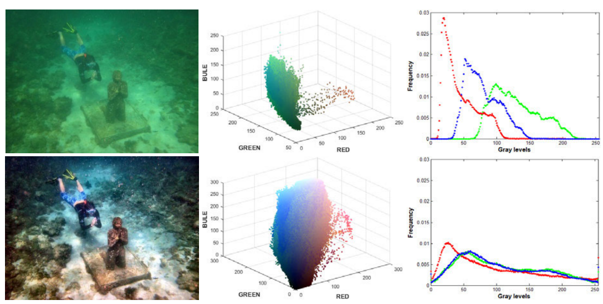


**FIGURE 1.** Comparison of 3D color spaces and RGB tricolor histograms for underwater image and underwater enhanced image.

For example, Fig. 1 shows the 3D color space diagrams and RGB tricolor histograms of underwater image and enhanced underwater image, respectively. It can be observed from the first row of Fig. 1 that the underwater degraded image seriously affects the perceptions and recognition abilities of the human eyes, the distribution of 3D colors is relatively concentrated and tends to GREEN coordinate space, and the

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dynamic range distribution of RGB tricolor gray value is narrow, as well as the histogram distribution is concentrated, respectively. Likewise, it can be found from the second row of Fig. 1 that the underwater image enhanced by Ancuti's method [12] provides the advantages of having a superior visual quality and more clear details, providing a more extensive 3D color distribution, and acquiring a more homogeneous distribution of RGB tricolor histogram. As a result, the method of underwater image restoration or enhancement has significant research implications and application value for improving the visibility of underwater images.

1) UOI cannot obtain satisfactory results due to scattering and absorption process of the light during the propagation of underwater medium. Scattering can easily result in fogging and detail blurring of underwater images [13], [14]. Absorption easily results in color distortion, contrast and brightness reduction of underwater images [15], [16]. According to the imaging model of Jaffe-McGlamey [17] shown in Fig. 2, where the direct component and the forward scattering component are derived from reflected light of the object in the underwater media, and the back-scattering component is formed by the interaction between underwater ambient light and underwater suspended particles.

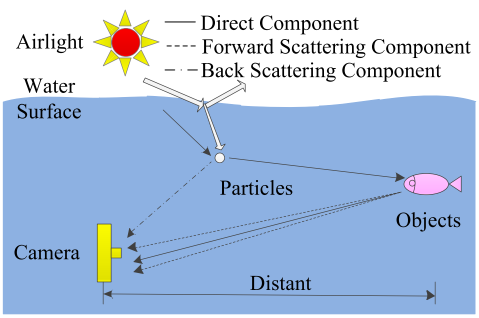


**FIGURE 2. Underwater optical imaging model from [73].**

2) Recent studies have shown that the light of different wavelengths with different attenuation rates during the propagation of underwater medium, which will lead to blurring and color distortion of underwater images [18], [19]. The absorption of light by water is shown in Fig. 3, where red light with longer wavelength and lower frequency is preferentially

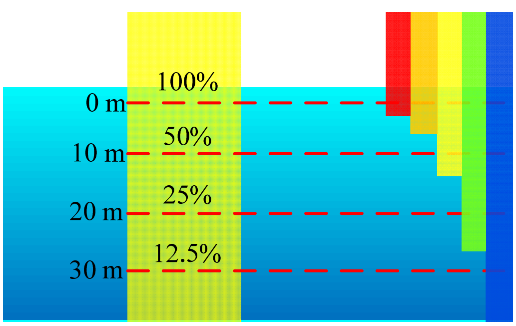


**FIGURE 3. Absorption of light water from [50].**

absorbed by water, followed by orange, yellow, green and blue. As a result of this uneven absorption by water most captured underwater images will take on a cyan coloration.

3) Usually, artificial light sources are often used as auxiliary light sources to extend the range of underwater imaging [20], [21]. However, the nonuniform artificial illumination result in bright spots in the center of the captured underwater image and the brightness of the entire image is nonuniform.

At present, underwater image sharpening technology is divided into the method based on physical model and the method based on image enhancement. On the basis of [22]–[25], we have mainly reviewed the latest advances, current challenges and applications of underwater image restoration and enhancement. We summarize the major contributions include three aspects.

1) This paper provides a comprehensive summary of recent advances in underwater image restoration and enhancement. We describe in detail the types of underwater image degradation, such as scattering, absorption, color distortion and the effects of artificial light sources.

2) We outline the state-of-the-art methods and select representative methods for discussion, and we also compare and analyze these methods from both qualitative and quantitative perspective.

3) We analyze the application of underwater image in various fields, such as underwater autonomous navigation and underwater target tracking. Finally, we summarize application of underwater video and super-resolution of underwater image.

The rest of the paper is organized as follows. Section II introduces the underwater image restoration method based on physical model. Section III describes the underwater image enhancement method based on image enhancement. Section IV compares and analyzes these state-of-the-art methods qualitatively and quantitatively. Section V presents the application of underwater images. Finally, in section VI we summarize the research process and future development direction of underwater image sharpening technology.

## II. UNDERWATER IMAGE RESTORATION METHODS

In this section, we focus on the underwater image restoration method based on physical model. The kind of method builds an appropriate physical model by studying the physical mechanism of underwater image degradation. The effects of illumination and fog on underwater images are offset or removed after understanding the reasons for the impact of underwater complex environments on image quality.

### A. UNDERWATER OPTICAL IMAGING-BASED METHODS

The UOI model can obtain optimal estimation of clear and natural underwater image by establishing an approximate optical imaging model and inverting the degradation process [26]. According to the physical characteristics of light transmission in underwater environment, the UOI model can

**TABLE 1. Overview of underwater optical imaging methods.**

| Method | Advantages | Disadvantages |
|---|---|---|
| [27] | Automatically optimizes the estimated parameter values | Excessive optimization parameters increase the computation complexity |
| [28] | Point spread function is introduced into underwater image restoration | Necessary to estimate the illumination scattering parameters |
| [29] | A standard smoothing inverse method is applied to degraded underwater color images | Cannot improve the image contrast significantly |
| [30] | Improve the perception of underwater images or video frames | Poor adaptability and flexibility |
| [31] | Effectively correct color and remove haze | Ignorance of artificial lighting source |

be expressed as:

$$I(x, y) = J(x, y)\, t(x, y) + A(1 - t(x, y)) \tag{1}$$

where $I(x, y)$ is the underwater image captured by the camera, $J(x, y)$ is the scene residual at point $(x, y)$, $t(x, y)$ is the medium transmittance, and A is the background light coefficient, $J(x, y)\, t(x, y)$ and $A(1 - t(x, y))$ are direct component and back scattering component, and $t(x, y)$ is the transmittance, respectively.

Trucco and Antillon [27] presented a self-tuning underwater image restoration method based on simplified Jaffe-McGlamery UOI model [17], [26]. It was based on two ideal assumptions that the underwater image was subject to homogeneous illumination and affected by forward scattering. Despite the method could reduce the effect of light scattering on underwater images, its wide application was limited due to the assumed conditions were vulnerable to the impact of the external environment. Hou *et al.* [28] combined UOI with a traditional image restoration method, they assumed that the blurring of underwater images was caused due to scattering of water bodies and suspended particles. The method restores the underwater image by deconvolution method based on estimating the light scattering parameters. Boffety *et al.* [29] described the effects of spectral discretization on underwater color image and restored color on the basis of underwater optical imaging model. Wen *et al.* [30] proposed a new underwater optical imaging model and estimated the scattering rate and background light. Zhao *et al.* [31] founded that degraded underwater images related to the optical characteristics of water. The optical characteristics of the underwater transmission medium obtained by the background color of underwater images, and then a clear underwater image obtained by the inversion process. Ahn *et al.* [32] applied underwater optical imaging to autonomous underwater vehicles, which improved the accuracy of underwater target detection.

Table 1 summarizes the advantages and disadvantages of the above underwater-optical-imaging-based methods. The analysis results show that although these methods are enabled to recover images close to actual scene, it is necessary to consider the effect of underwater scattering and the distance from the underwater light source to the shooting camera on the imaging distance.

### B. POLARIZATION CHARACTERISTICS-BASED METHODS

The polarization characteristics of light are stable and predictable in the underwater environment [33]. Polarization imaging has become an important technology for underwater image restoration due to its advantages of avoiding scattering and absorption of light. Based on the atmospheric scattering model [35], Treibitzr and Schechnerl [36] used a homogeneous turbid medium of active illumination to form the physical model of underwater imaging. The radiation image received by the detector can be expressed as:

$$I(x, y) = D(x, y) + B(x, y) \tag{2}$$

where $D(x, y)$ is derived from the irradiance of the target signal, which is attenuated due to the absorption and scattering of the turbid medium. $B(x, y)$ is backscatter, which comes from light scattered onto the detector by scattered particles in water. Therefore $D(x, y)$ and $B(x, y)$ can be defined as:

$$D(x, y) = L(x, y)\, t(x, y) \tag{3}$$

$$B(x, y) = A_\infty[1 - t(x, y)] \tag{4}$$

where $L(x, y)$ is the irradiance of the object without attenuation, $A_\infty$ is the backscatter value of the infinite distance in the water. $t(x, y)$ is the medium transmittance, which can be defined as:

$$t(x, y) = e^{-\beta(x,y)\rho(x,y)} \tag{5}$$

where $\beta(x, y)$ is the attenuation coefficient, and $\rho(x, y)$ is the underwater part of the optical path between the object and the detector. From (2), (3), and (4), $L(x, y)$ can be redefined as follows:

$$L(x, y) = \frac{I(x, y) - A_\infty[1 - t(x, y)]}{t(x, y)}. \tag{6}$$

It is generally considered that the objects are highly depolarized and that the degree of polarization of the object can be ignored [34], [39]. In general, $D^{\parallel}(x, y) = D^{\perp}(x, y) = D(x, y)/2$. In this case,

$$\begin{aligned} I^{\parallel}(x, y) &= \frac{D(x, y)}{2} + B^{\parallel}(x, y) \\ I^{\perp}(x, y) &= \frac{D(x, y)}{2} + B^{\perp}(x, y) \end{aligned} \tag{7}$$

where $I^{\parallel}(x, y)$ and $I^{\perp}(x, y)$ correspond to the two orthogonal directions of the polarization filter obtained by the camera. Thereby the degree of polarization of the backscatter can be defined as:

$$P_{scat}(x, y) = \frac{B^{\parallel}(x, y) - B^{\perp}(x, y)}{B^{\parallel}(x, y) + B^{\perp}(x, y)} = \frac{\Delta B(x, y)}{B(x, y)}. \tag{8}$$

**TABLE 2.** Overview of underwater polarization methods.

| Method | Advantages | Disadvantages |
|---|---|---|
| [36] | Enhancement visibility and estimation distance in scattering media | Enhanced image appears blurry in multi-scatter conditions |
| [37] | Without using multi-directional lighting to estimate the 3D scene structure | Non-uniform backscatter is not considered. |
| [38] | Remove artificial light interference and region-varied changes in the ambient light are taken into consideration | Red artifacts and overexposure |
| [40] | Backscatter is suppressed and extracting accurate edges | No experiments are conducted in real-life conditions |
| [41] | Enhancement visibility and the computation is less time consuming | No effectively remove noise and no application to underwater color images |
| [42] | DOP and intensity of backscatter are considered simultaneously | Difficulty in solving spatial distribution of $A_\infty$ and $P_{scat}$ |
| [43] | Bio-inspired optimization metaheuristics introduced to estimates the model parameters | High time complexity and red artifacts |
| [44] | Enhancing contrast of objects with different materials and different imaging distances in turbid water | Amplifies noise and no application to underwater color images |

Finally, from (2) and (6), $t(x, y)$ can be redefined as follows:

$$t(x,y) = 1 - \frac{\Delta B(x,y)}{P_{scat}A_\infty} = 1 - \frac{\Delta L(x,y)}{P_{scat}A_\infty}. \tag{9}$$

where the object irradiance $L(x, y)$ is obtained by formula (4). $P_{scat}$ and $A_\infty$ can be constants, or the optimal spatial distribution of $P_{scat}$ and $A_\infty$ can be estimated according to the solution method of [43] to obtain the best transmission estimate $t(x, y)$.

Over the recent years, polarization-based methods have been widely applied to underwater image restoration [35]–[44]. Schechner and Karpel [35] proposed that the degradation of underwater images was related to light polarization. Treibitz and Schechner [36] estimated the degree of polarization of the background light from two or more images of the same scene taken by adjusting an artificial light source or polarizer. Although this method could restore the image and the 3D information of the scene, it was more complicated to collect images. Treibitz *et al.* [37] pointed out that the effects of uneven illumination and natural light in multiple directions could cause local contrast reduction of underwater images, where the images were acquired by changing the position of the light source, and then using a fusion rule to obtain a clear underwater image. Chen *et al.* [38] proposed to divide an underwater image into artificial illumination areas and non-artificial illumination areas for nonuniform illumination issues, which compensated the artificial illumination area to remove the interference of artificial light. Han *et al.* [40] dealt with backscatter by adjusting the light source and to obtain two images under orthogonal polarization. They introduced a point spread estimation method and the restored image with a nice property of edge-preserving. Hu *et al.* [41] proposed an underwater image restoration method based on transmittance correction by changing the transmittance of low polarization. The method could effectively improve the quality of underwater images, whether it was a high depolarization object or a low depolarization object. Hu *et al.* [42] proposed an underwater image restoration method for estimating the degree of polarization and backscatter intensity of different positions of underwater image based on the consideration of non-uniform illumination. Ferreira *et al.* [43] presented a restoration method that estimates the parameters of the restoration model by bio-inspired optimization metaheuristics, where a no-reference image quality metric as a cost function. The method has a good applicability to the restoration of underwater images, but the solution of cost function is complicated. Yang *et al.* [44] presented an underwater image enhancement method using active unpolarized illumination. Compared with traditional polarization imaging, the use of non-polarized illumination can ensure that the polarization effect of the signal light is neglected.

Table 2 summarizes the advantages and disadvantages of the above polarization-characteristics-based methods. The analysis results show that although the methods can effectively improve the quality of underwater images, they need to obtain two or more images of different degrees of polarization by specialized hardware. Unfortunately, these complex hardware systems are very expensive and consume a lot of energy.

### C. PRIOR KNOWLEDGE-BASED METHODS

He *et al.* [45] proposed that the dark channel prior (DCP) applied to fog-degraded image restoration [46], [47]. They pointed out that for each local area of a fog-free image there will be at least one-color channel with some pixel values close to zero. For any input image J, the dark channel is defined as:

$$J^{dark}(x) = \min_{C\in\{r,g,b\}}\left(\min_{y\in\Omega(x)} J^C(y)\right) \approx 0 \tag{10}$$

where $J^C$ is the $C^{th}$ channel of the image $J$, $\Omega(x)$ is the window centered on $x$, and $J^{dark}$ is the dark channel of the image $J$. Then, the minimum value operation on both sides of the equation (1):

$$\min_{C\in\{r,g,b\}}(\min_{y\in\Omega(x)}\frac{I^C(y)}{A^C}) = \tilde{t}(x)\min_{C\in\{r,g,b\}}(\min_{y\in\Omega(x)}\frac{J^C(y)}{A^C}) + 1 - \tilde{t}(x). \tag{11}$$

From equation (10) and (11), the transmission image $\tilde{t}(x)$ can be obtained as:

$$\tilde{t}(x) = 1 - \min_{C\in\{r,g,b\}}(\min_{y\in\Omega(x)}\frac{I^C(y)}{A^C}). \tag{12}$$

Since the underwater imaging environment is similar to the foggy environment, thereby the DCP

**TABLE 3. Overview of underwater prior knowledge methods.**

| Method | Advantages | Disadvantages |
|---|---|---|
| [48] | Not require any specialized hardware or prior of the scene | May produces an overly-bright background and ignorance of artificial lighting source |
| [49] | Wavelength compensation and image dehazing | Accuracy decreases at high-salinity and turbid scenes |
| [52] | Trilateral filter introduced to overcome the gradient reversal artifacts issues | Ignorance of artificial lighting, no quantitative evaluation |
| [53] | Handles gracefully artificially illuminated areas | Requires more additional information |
| [54] | Statistical priors can restore the visibility of the images | Lacking in terms of reliability and robustness |
| [55] | Not require complex information about the underwater scenes and user interaction. | Red artifacts are easy to be introduced for blue-green strong degraded underwater images. |
| [56] | Use both image blurriness and light absorption to estimate depth | Estimates of depth scenarios are complex |
| [57] | Introduced intensity attenuation difference prior | Poor quality of the restored in non-uniformly lighting |
| [58] | Reduces to several DCP variants, suitable for a variety of scene images | Not applicable to images with multiple illumination sources |
| [59] | Recover more complex 3D scenes, collected a new dataset of underwater images | Estimation of the transmission map is complex |
| [60] | Exhibit the characteristics of the color-line prior | Introduction of too many optimization parameters |

gradually applied to underwater image restoration [48]–[60]. Carlevaris-Bianco *et al.* [48] proposed a difference between the maximum value of the R, G and B channels, which is not the minimum value directly selected in the DCP. The method achieved an excellent performance when R channel is strongly attenuated. Chiang *et al.* [49] proposed an underwater image restoration method based on wavelength compensation and DCP. Lu *et al.* [51] addressed the problem of light scattering and color correction of underwater images via employing a guided trigonometric bilateral filter method and a color correction method. Serikawa and Lu [52] compensated for the illumination based on Lu *et al.* [51], and proposed a DCP underwater image dehazing method with trilateral filter. The method improved exposedness of the dark regions and global contrast. Galdran *et al.* [53] proposed an automatic red-channel underwater image restoration method, which reduced the attenuation of the red channel and the influence of the artificial light source on the transmittance estimation. Drews *et al.* [54] proposed that the R channel attenuation of underwater images is serious; thereby the method only considers G and B channels. Compared with DCP [45] and MDCP [50], this method with a better recovery performance. However, its reliability and robustness are insufficient to the limitations of the assumptions. Li *et al.* [55] applied the classical DCP to a color corrected underwater image. Peng and Cosman [56] proposed an underwater image restoration method based on image blurriness and light absorption, which could estimate the depth of underwater scene more accurately. Zhang and Peng [57] proposed a new underwater image formation model, which introduced intensity attenuation difference prior based on UDCP. Peng *et al.* [58] proposed a single image restoration method based on generalization of the DCP, where the ambient light was estimated using the depth-dependent color change, and then the scene transmission was estimated by calculating the difference between the observed intensity and the ambient light. Berman *et al.* [59] reduced the underwater image restoration problem to a single image dehazing by estimating the attenuation ratios of the blue-red and blue-green color channels. Zhou *et al.* [60] presented an underwater image restoration method using color-line model, which could produce high-quality underwater image with relatively genuine colors and natural appearance.

Table 3 summarizes the advantages and disadvantages of the above prior-knowledge-based methods. The analysis results show that although the methods effectively improve the quality of underwater images, they need to use dark channel prior, haze-line or color-line. Unfortunately, the prior knowledge directly determines the result of recovery; thereby the acquisition of prior knowledge is the crucial for these underwater image methods based on prior knowledge.

## III. UNDERWATER IMAGE ENHANCEMENT METHODS

In this section, we mainly introduce the underwater image enhancement methods. This kind of method does not consider the actual physical process of image degradation in complex underwater environment, but rather on the degraded image. The enhanced image with higher contrast, richer detail information, and better visual effects by enhanced processing.

### A. FREQUENCY DOMAIN-BASED METHODS

In the field of underwater image enhancement, the frequency-domain method processes underwater images by convolution or spatial transformation to achieve enhancement. It mainly includes quaternion [61], low-pass filter [62], high-pass filter [63], homomorphic filter [64], and wavelet transform [65], [66].

Quaternion [61] compressed and transformed the image color space and used the optical attenuation characteristics to achieve color correction and contrast enhancement. Low-pass filtering is used to remove noise by suppressing high-frequency information. High-pass filtering is used to preserve details by suppressing low-frequency information. Homomorphic filtering is based on the illumination component $i(x, y)$ and the reflection component $r(x, y)$. It designed corresponding high and low pass filters according to different requirements, and it's expressed as follows:

$$f(x, y) = i(x, y)\, r(x, y) \tag{13}$$

**TABLE 4.** Overview of frequency-domain methods.

| Method | Advantages | Disadvantages |
|---|---|---|
| [61] | Improve underwater image contrast and better separation between objects (foreground) and the water (background) | The saturation decreases of the water and produces an overly-bright background |
| [62] | Effectively recovery underwater images while eliminating the influence of absorption and scattering | Artificial light source and red channel attenuation are not considered |
| [63] | Effectively remove underwater backscatter noise | Experimental environment is not real enough. |
| [64] | Improved global contrast, detail and visibility | Introducing too many processing methods |
| [65] | Effectively denoise and improve contrast | No experiment on underwater color images |
| [66] | Using an adaptive retinal mechanism and not require the specialized prior | Parameters solution of adaptive neural mechanisms are complicated |

where $i(x, y)$ and $r(x, y)$ represent low-frequency components and high-frequency components, respectively. Then, the logarithm of both sides of the equation (13) can be obtained:

$$z(x, y) = \ln(f(x, y)) = \ln(i(x, y)) + \ln(r(x, y)) \tag{14}$$

Homomorphic filter [64] achieved the fusion of high-frequency components and low-frequency components by logarithmic transformation. Wavelet transform [65], [66] was employed to decompose images to obtain images of different scales or unequal amounts of information.

Petit *et al.* [61] proposed a quaternion attenuation coefficient inversion method to restore underwater images, which could improve the contrast of the object, but there was color distortion. Cheng *et al.* [62] designed a simple and effective low-pass filter method to enhancement the degraded underwater image by analyzing the physical characters of the point spread function of underwater images. However, the effects of artificial light source and red channel attenuation on underwater images are not considered. Sun *et al.* [63] proposed an underwater image denoising method based on wavelet decomposition and high-pass filter, it removed underwater backscatter noise. Ghani *et al.* [64] combined a homomorphic filter method; a recursive-overlapped contrast limited adaptive histogram equalization (CLAHE) method and a dual-image wavelet fusion role to achieve the enhanced visibility of deep underwater images. Firstly, in order to uniform the illumination of the entire image by homomorphic filter, and then the recursive-overlapped CLAHE to separate and stretch the overlapped blocks and adjacent overlapped blocks of the image channel. Finally, the two images after stretching were fused by wavelet transform. Priyadharsini *et al.* [65] proposed a contrast underwater acoustic image enhancement method based on wavelet transform. Li *et al.* [66] proposed an underwater image enhancement method via adaptive retinal mechanisms. The method to correct the nonuniform color cast by the feedback from color-sensitive horizontal cells to cones and red channel compensation.

Table 4 summarizes the advantages and disadvantages of the above frequency-domain-based methods. The analysis results show that the frequency-domain method effectively remove noise, but the contrast enhancement and color correction of underwater images cannot achieve better results. As a result, these methods are slowly progressing and less studied.

### B. SPATIAL DOMAIN-BASED METHODS

The spatial-domain method is based on grayscale mapping, which can enhance the contrast and detail information of images by changing the dynamic range of image grayscale. In other words, the process of spatial-domain enhancement is histogram equalization [67]. Since it performs a same processing for all pixels, thereby local features are ignored usually. To handle this issue, CLAHE [68] first saved the details of the original image before implementing histogram equalization, and then these details are added to the histogram equalization process. Finally, the equalization equation is defined as:

$$x^*(i, j) = \begin{cases} T(x(i,j)) + k(x(i,j) \\ \quad -m(i,j)) & 0 \leq x(i,j) \leq 255 \\ T(x(i,j)) & other \end{cases} \tag{15}$$

where $m(i, j)$ is the mean value centered on $x(i, j)$, $T$ is the transform function applied to $x(i, j)$. As can be seen from the above equation, the role of $T$ is to adjust the dynamic range of the histogram. $k(x(i, j) - m(i, j))$ is equivalent to a high-pass filter that introduces high-frequency noise while enhancing detail. It is known from $k(x(i, j) - m(i, j))$ that the choice of $k$ value is crucial to enhancing detail and avoiding the increase of the high-frequency noise.

The spatial-domain method has achieved productive development in the field of image enhancement [67], [68]. Recently, it has gradually applied to underwater image enhancement [69]–[77]. Iqbal *et al.* [69] proposed a method based on slide stretching, which first using a contrast stretching method to equalize the contrast of the image, and then the saturation and intensity stretching of HIS to increase the true color. Iqbal *et al.* [70] proposed an unsupervised color correction method based on [69]. In order to correct the color, the method stretches the red histogram to the right to improve red and stretches the blue histogram to the left to restrain the blue. Hitam *et al.* [71] proposed a Mixture CLAHE method that conducted CLAHE processing on RGB and HSV color models and employed Euclidean norm to fusion both results. Ahmad *et al.* [72] proposed a dual-image Rayleigh-stretched CLAHE method, which not only enhanced image contrast but also enhanced image detail by considering global and local contrast correction. Li *et al.* [73] proposed a method of underwater image enhancement with minimum information loss and histogram distribution prior, which improved the contrast

**TABLE 5.** Overview of spatial-domain methods.

| Method | Advantages | Disadvantages |
|---|---|---|
| [69] | Low computational complexity and equalize colour contrast | No quantitative evaluation and red over-enhanced |
| [70] | Efficiently removes the bluish color cast and improves the low red colour | No quantitative evaluation and red artifacts |
| [71] | Improves the visual quality, as well as reduce noise and artifacts | Poor performance in low-light conditions |
| [72] | Improve image contrast and reduce image noise | Exhibit color image distortion when an image has a low color percentage |
| [73] | Achieves better visual quality and more accurate color restoration | Poor performance in low-light conditions, cannot totally remove noise |
| [74] | Considers overlapped and column-wise modification of image histogram | Introduction of recursive adaptive histogram modification increases the complexity of the algorithm |
| [75] | Improve contrast and color, reduce artifacts, low complexity | Red artifacts and noise are easy to be introduced for red and blue severely degraded underwater images |
| [76] | Improved global contrast, introduced percentile methodologies | Lost details, cannot effectively remove noise |
| [77] | Introduced YIQ and HIS color spaces | High complexity, cannot effectively remove noise |

and brightness of underwater images. Ahmad *et al*. [74] proposed a recursive adaptive histogram method based on [72], which improved the contrast and color of underwater images. Fu *et al*. [75] proposed a two-step underwater enhancement method for color correction and contrast enhancement of underwater images. Garg *et al*. [76] proposed a method of blending CLAHE and percentile to enhance underwater images, which improved the visual effect of the image. Ma *et al*. [77] proposed a fusion method based on CLAHE for different color spaces. Firstly, the original image was converted to YIQ and HIS color spaces, and the YIQ and HIS color spaces were enhanced by CLAHE, respectively. Then the enhanced images were converted back to RGB space. Finally, the YIQ-RGB and HSI-RGB images were fused into the final enhanced image by self-adaptive weight selection nonlinear image enhancement via a 4-direction Sobel edge detector.

Table 5 summarizes the advantages and disadvantages of the above spatial-domain-based methods. The analysis results show that the image enhancement method based on spatial-domain is mature and simple to implement. The kind of method can effectively improve the contrast of the image when it is directly applied to underwater image enhancement. However, since the color cast is not considered and the noise cannot be suppressed well, which will result in red artifacts and noise amplification in the enhanced image. Therefore, such methods often require a combination of color correction or noise reduction methods to achieve better enhancement.

### C. COLOR CONSTANCY-BASED METHODS

Color constancy mainly includes white balance and Retinex. White balance is mainly to solve the problem of color casts of objects under different lighting conditions. Retinex is an automatic application based on the theory of color constancy allows humans to perceive the world under different lighting conditions.

White balance includes Gray Edge [78], Shades of Gray [79], Max RGB [80], Gray World [81], Weighted Grey Edge [82], Ancuti *et al*. [12] and Ancuti *et al*. [83]. Fig. 4 shows the color correction effect of seven white balance methods by experiments, and the light of the original image gradually decreases from top to bottom. Gray Edge, Shades of Gray, Max RGB, Gray World, and Weighted Grey Edge improve the visual quality of the image when the light is sufficient, but worse than Ancuti *et al*. [12] and Ancuti *et al*. [83]. With the light fades, the balance results of Gray Edge, Shades of Gray, Max RGB, Gray World, and Weighted Grey Edge are getting worse, while Ancuti *et al*. [12] and Ancuti *et al*. [83] still with better results. Regardless of whether the lighting is sufficient, Shades of Gray and Gray World have color casts and Gray World is serious. Ancuti *et al*. [83] introduced the compensation of red and blue channels on basis of Ancuti *et al*. [12], which makes the balanced image have better color fidelity and clarity.

Retinex's basic idea is that the human eyes perceive the color and brightness of a certain point not only depends on the absolute light that the point enters the human eyes, but also on the color and brightness around it. Jobson *et al*. [84] proposed a single-scale Retinex method by introducing a Gaussian kernel function based on Retinex. The observed image is divided into luminance and reflection components, as shown in equation (16):

$$\log(S(x,y)) = \log(L(x,y)) + \log(R(x,y)) \tag{16}$$

where $S(x,y)$ is the observed image, $L(x,y)$ and $R(x,y)$ are luminance and reflection components, respectively. In order to preserve color and details well, Rahman *et al*. [85] used Gaussian kernels with three different scales to convolution $S(x,y)$ to extract finer features to estimate the luminance components, as shown in equation (17):

$$\begin{cases} MSR(x,y) = \sum_{n=1}^{N} w_n\{\log(S(x,y)) \\ \quad -\log(G_n(x,y) * S(x,y))\} \\ G_n(x,y) = \frac{1}{2\pi\sigma_n^2}\exp \\ \quad \frac{-\left((x-x\_center_w)^2+(y-y\_center_w)^2\right)}{2\sigma_n^2} \end{cases} \tag{17}$$

where $MSR(x,y)$ is the enhanced image, $N$ is the number of the scales, $w_n$ is the weight, and $\sigma$ is the coefficient of the Gaussian function. In order to solve the problem of MSR with

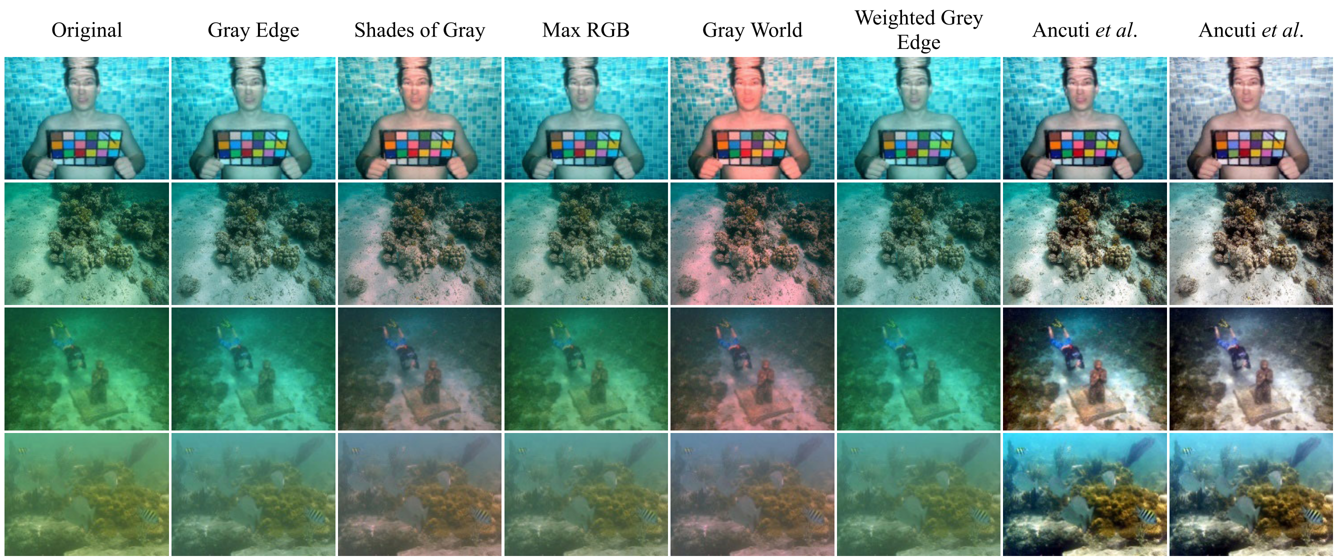


**FIGURE 4.** Comparison of results of different white balance methods. From left to right: 1. The original underwater images; 2. Gray Edge [78]; 3. Shades of Gray [79]; 4. Max RGB [80]; 5. Gray World [81]; 6. Weighted Grey Edge [82]; 7. Ancuti *et al.* [12]; 8. Ancuti *et al.* [83].

insufficient edge sharpening and local detail color distortion, Rahman *et al*. [86] proposed a MSRCR method (Multiple-scale Retinex color restore, MSRCR) by introducing a color recovery factor to compensate for color distortion, as shown in equation (18) :

$$\begin{cases} MSRCR(x,y) = \sum_{i\in\{r,g,b\}} (C_i \times MSR_i(x,y)) \\ C_i = \beta \log(\alpha \times \dfrac{S_i(x,y)}{\sum_{j\in\{r,g,b\}} S_j(x,y)}) \end{cases} \tag{18}$$

where $C_i$ is the color recovery factor of each channel, $\beta$ is the gain constant, and $\alpha$ is the control nonlinear intensity coefficient.

Early Retinex was mainly applied in image defogging [92] and image enhancement [87]. In recent years, Retinex-based methods have gradually applied to underwater image enhancement [88]–[93]. Joshi *et al*. [88] analyzed the main causes of color distortion for haze and the underwater degraded image and applied Retinex to achieve enhancement. Despite the underwater image visual effects were improved, the enhancement effect was limited. Fu *et al*. [89] proposed application of Retinex to underwater image enhancement by analyzing three imaging problems of underwater image color distortion, insufficient illumination and visual fuzz. Although the enhanced underwater image had better visual effects and more accurate color recovery, it requires 4-6 iterations with a higher time complexity. Zhang *et al*. [90] converted the degraded underwater image from RGB color space to LAB color space, and then the L channel was enhanced by the MSR of bilateral filter, and the A and B channels were enhanced by the MSR of trilateral filter. Finally, the enhanced LAB color space was fused and converted into RGB color space to obtain the final enhanced image. Wang *et al*. [91] converted the degraded underwater image from RGB color space to HSV color space, and then used Retinex to decompose the V-channel into illumination layer and detail layer, and used different methods to enhance them. Finally, the enhanced V, H and S channels were converted into RGB color space to obtain the final enhanced image. Zhang *et al*. [92] proposed MSRCR image defogging method based on multi-channel convolution and successfully applied to underwater image enhancement. Tang *et al*. [93] presented a Retinex-based underwater image and video enhancement method, which was suitable for underwater images of various scenes, but the processing process and filtering techniques were inefficient.

Table 6 summarizes the advantages and disadvantages of the above color-constancy-based methods. The analysis shows that the use of Retinex alone has limited improvement in the quality of underwater images. Therefore, the RGB color space needs to be converted to LAB or HSV color space, and enhance the underwater image by contrast stretching, histogram equalization, color correction, and other methods.

### D. FUSION-BASED METHODS

Fusion methods are mainly from color correction, detail enhancement, contrast stretching, color balance and other aspects of consideration. The fusion rules are mainly based on Gaussian Pyramid or Laplacian Pyramid [12], [83]. Recently, a fusion method for underwater image and video enhancement was proposed by Ancuti *et al*. [12]. First, a color corrected image and a contrast enhanced image obtained from the original underwater image, and the two images were used as fusion components. Then, four fusion weight maps were obtained from a degraded underwater image. Finally, the multi-scale fusion method was performed with four different weight components and fusion components to reconstruct the final enhanced image. Recently, Lu *et al*. [94]

**TABLE 6.** Overview of underwater color constancy methods.

| Method | Advantages | Disadvantages |
|---|---|---|
| [88] | Balance between the human vision and machine vision system | Low contrast and color distortion |
| [89] | Improve contrast and color, enhance edges and details | High time complexity |
| [90] | Reduce image noise, details and edges are enhanced significantly | Cannot enhance the image contrast apparently, the MSR of trilateral filter with high time consumption |
| [91] | Improve image quality and balance color | High time complexity and introduced noise |
| [92] | Multi-Channel Convolution is introduced into Retinex and with edge-preserving and denoising well | Enhanced underwater images may be overexposed |
| [93] | Intensity channel is introduced in multi-scale Retinex | Processing process and filtering techniques are inefficient |

**TABLE 7.** Overview of underwater fusion methods.

| Method | Advantages | Disadvantages |
|---|---|---|
| [12] | Introduced write balance and fusion rule | Ignorance of artificial lighting source |
| [83] | Introduced red-green color compensation, can recover important faded features and edges | Selective compensation cannot be implemented |
| [97] | Reduce image noise, details and edges are enhanced significantly | Cannot enhance the image contrast apparently |

conducted descattering and color correction on underwater images to improve the contrast of underwater images, and it had been well applied in [95]. They first denoised the original underwater image by the descattering method [94], then the high-resolution image of the denoised and descattered images obtained by the self-exemplars super-resolution method [96], and finally the two high-resolution images were fused by a fusion strategy. The fusion was designed to preserve the edges and detailed information of the high-resolution image without affecting the color rendering of [94]. Ancuti *et al.* [83] provided an alternative to [95], which first obtained the gamma corrected image and the white balanced image from the original underwater image, then defined the weight maps associated with the fused image, and finally used a fusion method to fusion the two versions of the underwater image. It could effectively improve the brightness of the dark area, global contrast and edge detail, and improves the accuracy of image segmentation and points matching. Pan *et al.* [97] first obtained a defogged image and a color corrected image from the original underwater image, where the defogged image was acquired by Dehazenet and the color corrected image was obtained by white balance. It was fused by the fusion strategy of the Laplacian pyramid, and the final fused image was denoised and enhanced edge by hybrid wavelets and directional filter banks domain.

Table 7 summarizes the advantages and disadvantages of the above fusion-based methods. The analysis results show that the fusion method can effectively improve the quality of underwater images, reduce noise and recover edge. However, these methods need to obtain multiple fusion images and fusion weights; thereby their acquisition is the difficulty and focus of the fusion method.

### *E. DEEP LEARNING-BASED METHODS*

Deep learning method has better feature extraction ability due to deep network structure. Therefore, it is widely used in the field of image segmentation [98], target detection [99], and image defogging [100]. In recent years, deep learning has been gradually applied to underwater image enhancement [101]–[107]. Wang *et al.* [101] proposed an underwater image enhancement method based on the Convolutional Neural Network (CNN), which improves the brightness and contrast of the underwater image, but the red over-enhanced. Fabbri *et al.* [102] proposed an underwater image enhancement model based on Generative Adversarial Networks, which improved the visual effect and contrast of underwater images as well as the accuracy of underwater diver tracking. Anwar *et al.* [103] proposed a CNN-based underwater image enhancement model (UWCNN). UWCNN used an end-to-end automatic data-driven training mechanism to reconstruct clear underwater images. Li *et al.* [104] presented a correction method based on weakly supervised color transfer, which designed a multi-term loss function including adversarial loss, cycle consistency loss, and structural similarity index measure loss. Li *et al.* [105] first proposed a comprehensive analysis and research on underwater image enhancement using degraded images in large-scale real world and constructed an underwater image enhancement benchmark dataset. In addition, they built a deep underwater image enhancement network based on benchmark dataset. Pritish *et al.* [106] proposed to use adversarially learning the features of the underwater images by disentangling the unwanted nuisances corresponding to water types, so as to solve the different types of water on the impact of enhanced results. Li *et al.* [107] designed a deep underwater image convolutional neural network method based on underwater scene prior, it is well used in different underwater scenes and easily extended to underwater videos for frame-by-frame enhancement.

Table 8 summarizes the advantages and disadvantages of the above deep-learning-based methods. The analysis results show that the enhanced images by early deep learning have low contrast and color distortion, and these problems have been better solved with the continuous development of deep learning. However, these methods have higher requirements on hardware devices and training dataset.

**TABLE 8.** Overview of underwater deep learning methods.

| Method | Advantages | Disadvantages |
|---|---|---|
| [101] | UIT-net is trained with color correction and haze removal | Red over- enhancement |
| [102] | Generate more visually appealing images, and provide increased accuracy for a diver tracking method | Limited training dataset, cannot effectively remove noise |
| [103] | Improve the visual effect of the image without changing the color cast | Higher requirements for training dataset |
| [104] | A cross domain mapping function introduced between underwater images and air images | Difficulty solving the loss function |
| [105] | Constructed an underwater image enhancement benchmark dataset | Quantitative evaluation is not best, both network architectures and task-related loss functions need improvement |
| [106] | Nicely Handles the diversity of water during the enhancement | Construction of Loss function is difficult and highly dependent on training data |
| [107] | Generalizes well to different underwater scenes | UWCNN cannot realize the prediction of single model |

## IV. EVALUATION RESULTS OF TYPICAL METHODS

In this section, we evaluate and compare typical underwater image restoration and enhancement methods. The evaluation method of underwater image quality is divided into qualitative and quantitative. The qualitative evaluation is mainly to observe an image by the tester and make qualitative evaluation and analysis on the quality of the image. Strictly speaking, the qualitative evaluation method is that multiple testers perform repeated observation experiments for images. Quantitative evaluation method uses mathematical methods to calculate the evaluation results of image quality.

### A. QUALITATIVE EVALUATION METHODS

At present, there is no uniform evaluation standard for different underwater image restoration and enhancement methods. Researchers usually use qualitative evaluation methods or quantitative evaluation methods for ordinary images [108]–[112]. Because the underwater environment is more complex than the rain, fog and natural environment, it is difficult to evaluate the quality of underwater images. Therefore, the traditional method of quantitative evaluation of images is not suitable for underwater images. Shechner *et al.* [36] used global contrast to quantitatively evaluate the quality of underwater images, but the evaluation results are not satisfactory. In recent years, qualitative evaluation methods for underwater images had been proposed [113]–[116]. In terms of quantitative evaluation, we compare and analyze the experimental results of different methods from five quantitative evaluation metrics of full-reference metrics: average gradient (AG) [92] and information entropy (IE) [92], and non-reference metrics: patch-based contrast quality index (PCQI) [112], underwater image quality measure (UIQM) [115] and underwater color image quality evaluation (UCIQE) [116].

1) AG mainly represents the rate of change in the tiny details of the image, which can be used to represent the sharpness of the image. It is expressed as:

$$AG = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \sqrt{(\nabla xF(i,j))^2 + (\nabla yF(i,j))^2} \tag{19}$$

where $\nabla xF(i,j)$ and $\nabla yF(i,j)$ are the difference of $F(i,j)$ toward the $x$ and $y$ directions, $M$ and $N$ denote the width and height of the image, respectively.

2) IE mainly represents the amount of average information that can be used to describe the richness of the image color, it can be defined as:

$$IE = -\sum_{i=0}^{255} p(i) \log_2 p(i) \tag{20}$$

where $i$ is the pixel value, $p(i)$ is the probability of the occurrence of pixels with a pixel value of $i$ in the image.

3) PCQI is mainly used to predict the perceived distortion of the human eyes for the contrast of image, it can be defined as:

$$PCQI(x,y) = \frac{1}{M} \sum_{i=1}^{M} q_i(x_i,y_i) \cdot q_c(x_i,y_i) \cdot q_s(x_i,y_i) \tag{21}$$

where $M$ is the total number of patches in the image, $q_i$, $q_c$, and $q_s$ are the three comparison functions. The higher the value of the PCQI represents the better the contrast of the image.

4) UIQM uses underwater image colorfulness measure (UICM), underwater image sharpness measure (UISM), and underwater image contrast measure (UIConM) as the basis for evaluating the quality of underwater images for the degradation mechanism and optical imaging characteristics of underwater images. The method is similar to the traditional non-reference image quality evaluation method, which uses the measuring component or feature of the image to represent the visual quality of the image. Finally, the underwater image quality evaluation method is expressed as a linear combination of the above three measurement components:

$$UIQM = c_1 \times UICM + c_2 \times UISM + c_3 \times UIConM \tag{22}$$

And, $c_1 = 0.0282$, $c_2 = 0.2953$ and $c_3 = 3.5753$ in [115].

5) UCIQE is a linear combination of chroma, saturation and contrast. It converts underwater images from RGB color space to CLELAB color space that is closer to the visual perception of the human eyes. Based on the calculation of

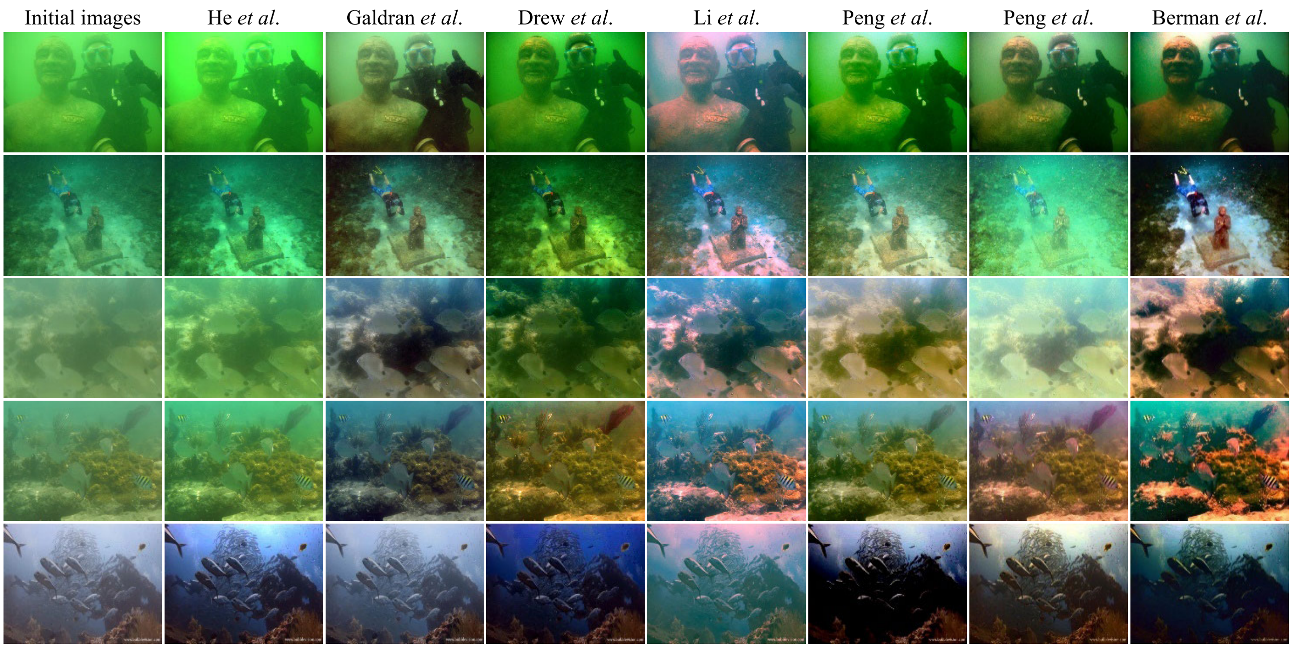


**FIGURE 5.** Comparison of the above underwater image restoration methods on DataA. From left to right are input images, the enhanced underwater images obtained by He *et al.* [45], Galdran *et al.* [53], Drew *et al.* [54], Li *et al.* [55], Peng *et al.* [56], Peng *et al.* [58], and Berman *et al.* [59], respectively.

each measurement component of the underwater image quality, UCIQE can be defined as:

$$UCIQE = c_1 \times \sigma_c + c_2 \times con_l + c_3 \times \mu_s \tag{23}$$

where $\sigma_c$ is the standard deviation of chroma, $con_l$ is the contrast of luminance, and $\mu_s$ is the average of saturation. And, $c_1 = 0.4859$, $c_2 = 0.2745$ and $c_3 = 0.2576$ in [116].

### B. QUALITATIVE EVALUATIONS

In this section, we used two read-world underwater image datasets DataA and DataB to qualitatively evaluate typical underwater image restoration and enhancement methods. DataA provided by [12], [83] and downloaded from the Internet, which includes 53 degraded underwater images. DataB provided by [105], which includes 890 underwater image enhancement benchmark dataset. Typical underwater image restoration methods include: He *et al.* [45], Galdran *et al.* [53], Drew *et al.* [54], Li *et al.* [55], Peng and Cosman [56], Peng *et al.* [58], and Berman *et al.* [59]. Typical underwater image enhancement methods mainly include: Ancuti *et al.* [12], Iqbal *et al.* [70], Li *et al.* [73], Fu *et al.* [75], Fu *et al.* [89], Zhang *et al.* [92] and Pan *et al.* [97]. Due to the limited space, we only show parts of experimental results of DataA and DataB.

#### 1) QUALITATIVE EVALUATION OF REAL-WORLD UNDERWATER IMAGE DataA

Fig. 5 presents the results of seven classic underwater image restoration methods for DataA. The traditional image restoration method He *et al.* [45] can improve the contrast, but it is not able to restore the color and improve the contrast significantly due to the degradation mechanism of the underwater image is not fully considered. Compared with some specialized underwater image restoration methods Drew *et al.* [54], Li *et al.* [55], Peng *et al.* [56] and Peng *et al.* [58] considering the effects of scattering and absorption on degraded underwater images. These methods improve contrast and highlight detail, but without considering color compensation. However, these methods introduce red artifacts for some challenging underwater images. Berman *et al.* [59] fully considered the effects of different types of water bodies on light scattering and absorption, which can restore image color well, improve contrast and enhance details. Nevertheless, the method does not fully consider the color compensation caused some images to appear red artifacts. Galdran *et al.* [53] considered that the compensation of red channel can restore the color well, but did not consider the effect of different types of water bodies on underwater degraded images, so that the details of a few images aren't highlighted. It can be seen that the restoration results based on the physical model method are directly related to the tested images and different types of water bodies. At present, the underwater recovery model established by restoration methods is quite ideal, so that the adaptive ability and robustness of such methods are insufficient.

Fig. 6 presents the results of seven classic underwater image enhancement methods for DataB. The traditional image enhancement method Iqbal *et al.* [70] could improve the contrast, but the red artifact was introduced due to the magnified noise. In contrast, the specialized underwater image enhancement methods Li *et al.* [73], Fu *et al.* [75] and Fu *et al.* [89] not only improved the visual effect of

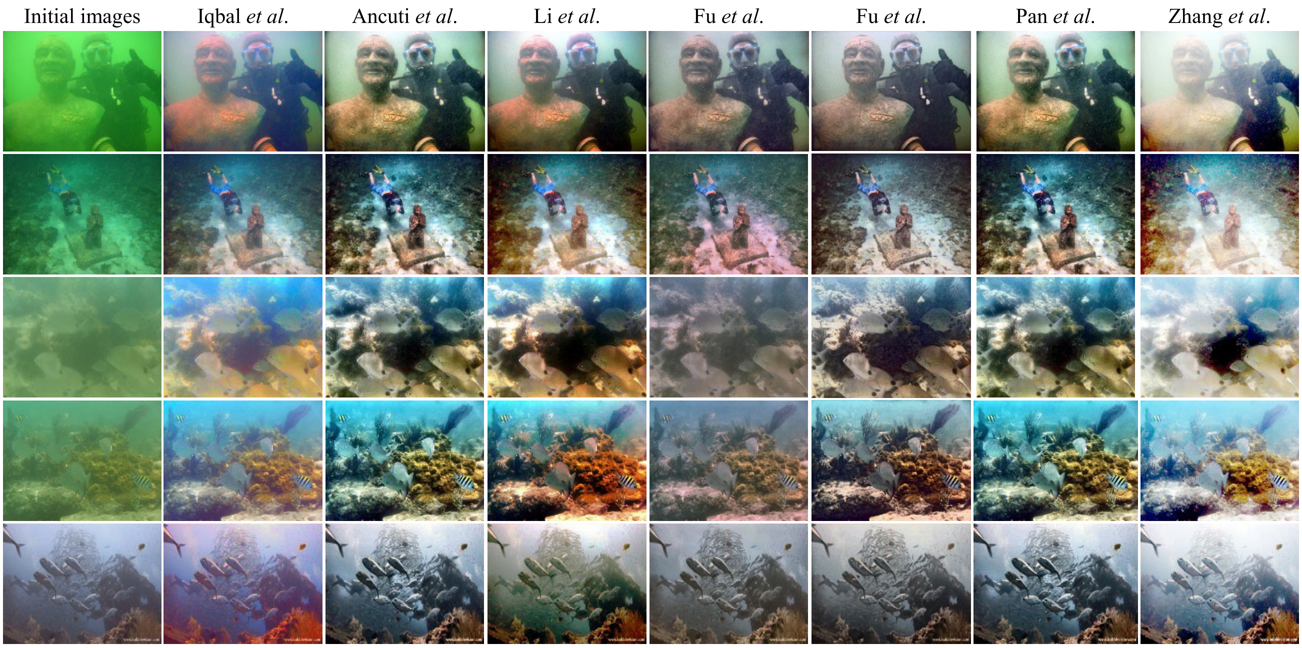


**FIGURE 6. Comparison the above underwater image enhancement methods on DataA. From left to right are input images, the enhanced underwater images obtained by Iqbal *et al.* [70], Ancuti *et al.* [12], Li *et al.* [73], Fu *et al.* [75], Fu *et al.* [89], Pan *et al.* [97], and Zhang *et al.* [92], respectively.**

underwater images and highlighted the details of images, but also introduced fewer artifacts and noises. However, Ancuti *et al.* [12] and Pan *et al.* [97] proposed underwater image enhancement methods based on fusion to remove noise and highlight image details. Zhang *et al.* [92] improves contrast and corrects color, but the enhanced image overexposure. Despite this kind of method can effectively remove noise while improving the contrast and restoring color of underwater images, but they do not adequately consider the physical imaging model of underwater images, therefore there are over-enhanced and under-saturated areas in some enhanced underwater images. In conclusion, the fusion methods have superior performance in terms of improving contrast, recovering color and removing noise, but the capability of depth scene enhancement is less than that of the physical model-based restoration methods.

#### 2) QUALITATIVE EVALUATION OF REAL-WORLD UNDERWATER IMAGE DataB

Fig. 7 further presents the recovery performance of these restoration methods on underwater image enhancement benchmark dataset. He *et al.* [45] and Peng *et al.* [58] have poor performance in contrast enhancement and color correction. Although Galdran *et al.* [53] and Drew *et al.* [54] are superior to He *et al.* [45] and Peng *et al.* [58] in terms of improving contrast and correcting color, the visual effect of restored images is not ideal. Peng *et al.* [56] can output an image with good visual effect, but the details of the image are blurred. Li *et al.* [55] and Berman *et al.* [59] are superior to them in improving contrast and correcting color, but red artifacts still exist for some challenging scenes. The problems with these restoration methods in DataA are still evident in DataB. It can be seen that not all restoration methods are universally applicable to underwater images of different challenge scenes.

Fig. 8 further demonstrates the enhanced performance of these enhancement methods on the underwater image enhancement benchmark dataset. By comparing the results of these enhancements on DataA and DataB, we found that that their advantages and disadvantages in DataA still exist in DataB and follow the rules in DataA.

### C. QUANTITATIVE EVALUATIONS

In this section, we used five quantitative evaluation methods named AG, IE, PCQI, UIQM and UCIQE to evaluate the results of the typical methods in Fig. 5-8. Table 9 and Table 10 show the mean quantitative evaluation of each typical underwater image restoration and enhancement method for DataA and DataB.

#### 1) QUANTITATIVE EVALUATION OF REAL-WORLD UNDERWATER IMAGE DataA

For the underwater image restoration method in Table 9: He *et al.* [45] has the lowest AG, UIQM, and UCIQE metrics, which demonstrate that the method shows the worst recovery results. Peng *et al.* [56] has the minimum IE metric, which indicates that the method recovers less color information of underwater images. Berman *et al.* [59] has the lowest PCQI metric, which indicates that the method has a poor result in improving contrast. Li *et al.* [55] has the highest IE and PCQI metrics, which demonstrates that the method has superior performance in restoring color and improving

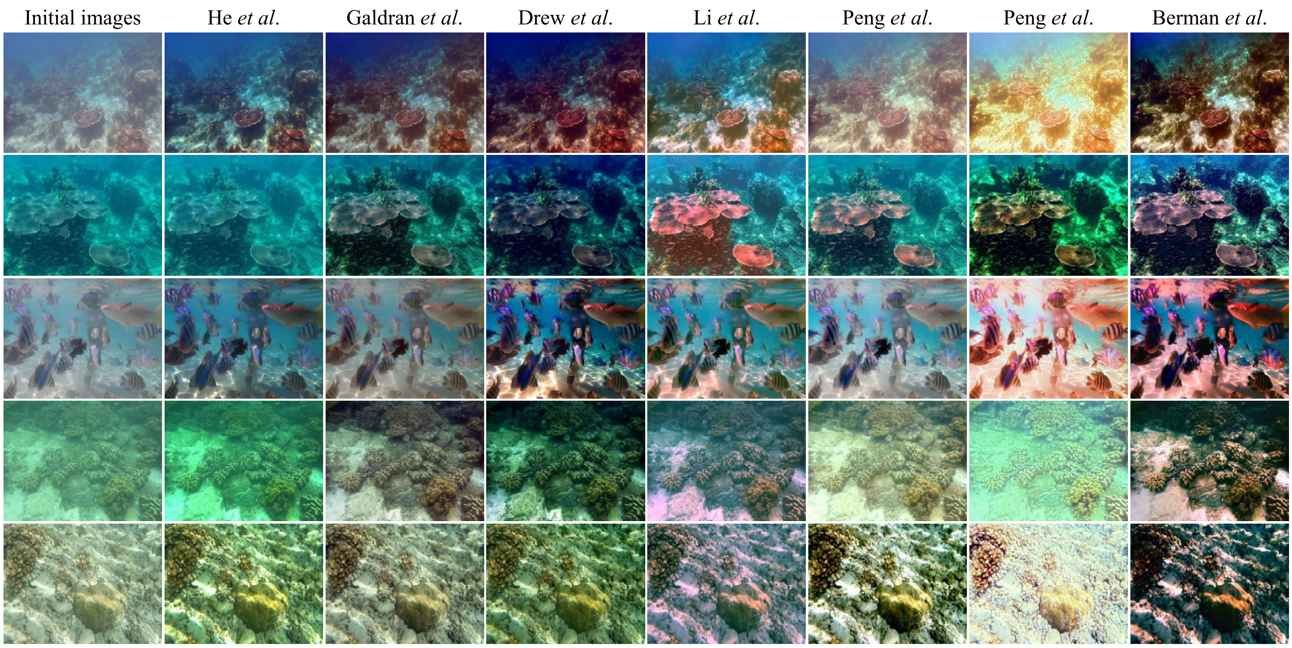


**FIGURE 7.** Comparison of the above underwater image restoration methods on DataB. From left to right are input images, the restorated underwater images obtained by He *et al.* [45], Galdran *et al.* [53], Drew *et al.* [54], Li *et al.* [55], Peng *et al.* [56], Peng *et al.* [58], and Berman *et al.* [59], respectively.

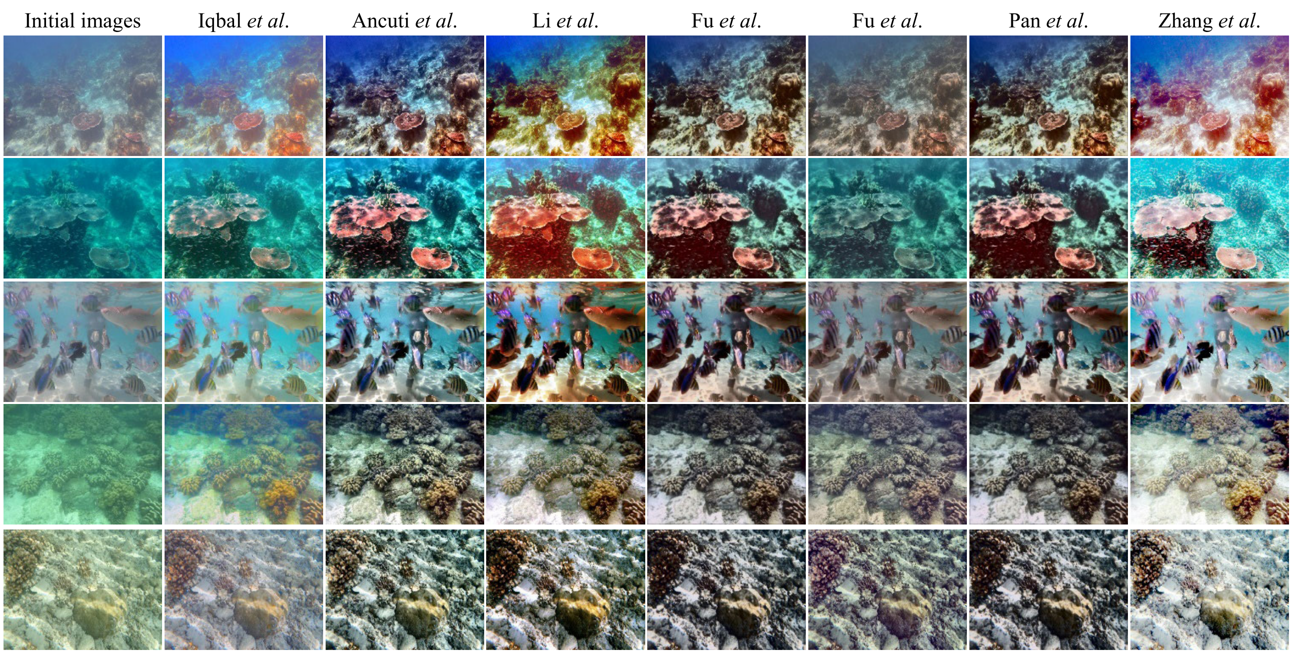


**FIGURE 8.** Comparison the above underwater image enhancement methods on DataB. From left to right are input images, the enhanced underwater images are obtained by Iqbal *et al.* [70], Ancuti *et al.* [12], Li *et al.* [73], Fu *et al.* [75], Fu *et al.* [89], Pan *et al.* [97], and Zhang *et al.* [92], respectively.

contrast. Berman *et al.* [59] can obtain the highest AG, UIQM and UCIQE metrics, which shows that the method can balances hue, saturation and contrast well. As shown in Fig. 5, although Berman *et al.* [59] has the highest AG, UIQM and UCIQE values, the restored image does not provide the best visual effect with a small amount of green block effect in the underwater image recovered by Berman et al. For the average evaluation metric, the quantitative metrics of Li *et al.* [55] are higher than the average, which indicates that Li *et al.* [55] not only improves the subjective visual results, but also has a better quantitative evaluation.

For the underwater image enhancement method in Table 9: Zhang *et al.* [92] has the lowest PCQI and UCIQE metrics, it shows that the method has poor performance in terms of

**TABLE 9.** The average values of the evaluation metrics of AG, IE, PCQI, UIQM and UCIQE of the restoration methods on DataA.

| Compared methods | | Quality evaluation metrics of underwater images | | | | |
|---|---|---|---|---|---|---|
| | | AG | IE | PCQI | UIQM | UCIQE |
| Underwater image Restoration methods | He *et al.* | 1.8301 | 7.3423 | 1.0161 | 1.6880 | 0.4924 |
| | Galdran *et al.* | 2.1231 | 7.3650 | 1.0551 | 3.4706 | 0.5492 |
| | Drew *et al.* | 2.2757 | 7.0841 | 0.9611 | 3.3282 | 0.5220 |
| | Li et al. | 2.8599 | **7.6023** | **1.0819** | 3.2273 | 0.5716 |
| | Peng *et al.* | 2.5422 | 6.6732 | 1.0099 | 2.6485 | 0.5619 |
| | Peng *et al.* | 2.8300 | 7.3542 | 1.0401 | 3.0996 | 0.5442 |
| | Berman *et al.* | **3.2299** | 7.3071 | 0.9229 | **4.6692** | **0.6500** |
| Average | | 2.5272 | 7.2468 | 1.0124 | 3.1616 | 0.5559 |
| Underwater image Restoration methods | Iqbal *et al.* | 2.3893 | 7.5548 | 1.0210 | 3.4424 | 0.5642 |
| | Ancuti *et al.* | **4.5962** | **7.8658** | **1.2398** | 4.0223 | 0.6337 |
| | Li *et al.* | 3.5861 | 7.3248 | 1.1512 | 4.1893 | **0.6688** |
| | Fu *et al.* | 3.4859 | 7.7452 | 1.0816 | **4.3136** | 0.5791 |
| | Fu *et al.* | 3.1641 | 7.2424 | 1.1320 | 4.1225 | 0.5122 |
| | Pan *et al.* | 4.5613 | 7.8568 | 1.1057 | 4.0722 | 0.6330 |
| | Zhang et al. | 3.7693 | 7.5114 | 0.8092 | 3.3174 | 0.6338 |
| Average | | 3.6304 | 7.5983 | 1.1218 | 4.0270 | 0.5985 |

**TABLE 10.** The average values of the evaluation metrics of AG, IE, PCQI, UIQM and UCIQE of the enhancement methods on DataB.

| Compared methods | | Quality evaluation metrics of underwater images | | | | |
|---|---|---|---|---|---|---|
| | | AG | IE | PCQI | UIQM | UCIQE |
| Underwater image Restoration methods | He *et al.* | 5.4007 | 7.2990 | 1.0027 | 2.3604 | 0.5091 |
| | Galdran *et al.* | 5.7887 | 7.2999 | 1.0622 | 3.7036 | 0.5454 |
| | Drew *et al.* | 6.4375 | 7.1366 | 0.9756 | 4.0392 | 0.5890 |
| | Li et al. | 7.6025 | **7.6158** | 1.1589 | 3.6351 | 0.5982 |
| | Peng *et al.* | 7.4481 | 7.3427 | **1.1865** | 3.1515 | 0.5558 |
| | Peng *et al.* | 8.2718 | 7.2190 | 1.1082 | 3.5265 | 0.5505 |
| | Berman *et al.* | **9.8269** | 7.4320 | 1.0780 | **4.0898** | **0.6664** |
| Average | | 7.2537 | 7.3350 | 1.0817 | 3.5008 | 0.5734 |
| Underwater image Restoration methods | Iqbal *et al.* | 5.4468 | 7.3960 | 1.0289 | 2.8302 | 0.5154 |
| | Ancuti *et al.* | **10.9255** | **7.8249** | **1.2870** | 4.1237 | 0.6236 |
| | Li *et al.* | 9.7037 | 7.3251 | 1.1990 | 4.5200 | **0.6664** |
| | Fu *et al.* | 8.3022 | 7.7365 | 1.0698 | **4.9288** | 0.6011 |
| | Fu *et al.* | 7.1839 | 7.3035 | 1.1331 | 4.2492 | 0.5150 |
| | Pan *et al.* | 8.2951 | 7.7357 | 0.8939 | 4.8020 | 0.6017 |
| | Zhang et al. | 9.5510 | 7.4166 | 0.8658 | 3.5808 | 0.6143 |
| Average | | 8.4868 | 7.5340 | 1.0682 | 4.1478 | 0.5910 |

colorfulness, sharpness and contrast. Iqbal *et al.* [70] has the lowest AG value, which indicates that the method has the worst performance in improving contrast. The IE and UCIQE values of Fu *et al.* [89] are the lowest, which indicates that the enhanced underwater image of the method has less color information and does not balance the chroma, saturation and contrast well. The AG, IE and PCQI metrics of Ancuti *et al.* [12] are the highest, which demonstrates that the underwater image enhanced by the method has better performance in terms of sharpness, color and contrast. Li *et al.* [73] can obtain the highest UIQM and UCIQE values, which indicates that this method can balances hue, saturation and contrast well. Fu *et al.* [75] can obtain the highest UIQM value, which indicates that this method can improve the colorfulness, sharpness and contrast well. For the average evaluation metric, the quantitative metrics of Ancuti *et al.* [12] and Pan *et al.* [97] are both higher than the average scores, which indicates that they not only improve the subjective visual results, but also have better quantitative evaluation.

The analysis results found that the underwater image restoration method has better performance in depth scene estimation and denoising. The underwater image enhancement method has good performance in improving contrast and restoring color. Despite some methods have the highest quantitative metrics, they do not necessarily have the best

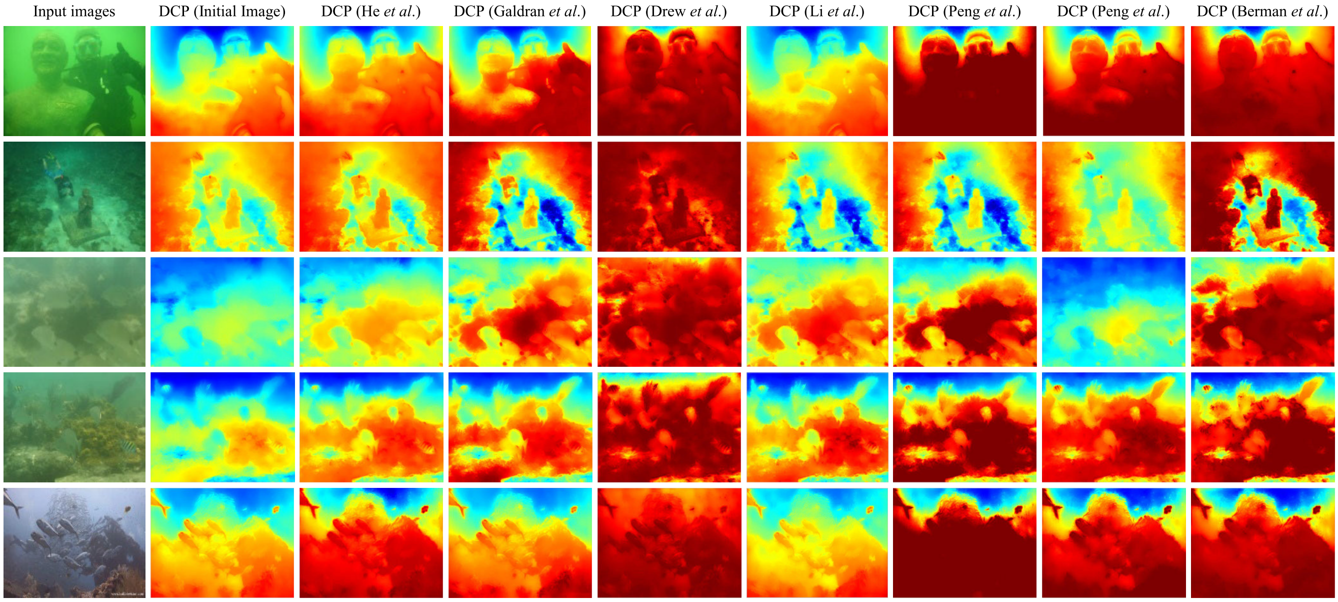


**FIGURE 9. Compared with the transmission map estimation obtained by the classical underwater image restoration methods applied to DataA. From left to right are input images, the transmission estimation map based on DCP applied on the input images but also from versions obtained by several typical underwater restoration methods (He *et al.* [45], Galdran *et al.* [53], Drew *et al.* [54], Li *et al.* [55], Peng *et al.* [56], Peng *et al.* [58], and Berman *et al.* [59]).**

visual effects. Therefore, the quantitative metric of underwater images needs to be further improved.

#### 2) QUANTITATIVE EVALUATION OF REAL-WORLD UNDERWATER IMAGE DataB

For underwater image restoration methods in Table 10: The minimum values of AG, UIQM and UCIQE in Table 10 still follow the rules in Table 9. However, the lowest values of IE and PCQI in Table 10 are obtained by Drew *et al.* [54]. The highest values of AG, IE, UIQM and UCIQE in Table 10 still follow the rules in Table 9. However, the highest value of PCQI in Table 10 is obtained by Li *et al.* [55].

For underwater image enhancement methods in Table 10: The lowest and highest values of each metric in Table 10 still follow the rules in Table 9. However, the UIQM value of Ancuti *et al.* [12] is lower than the average value of the evaluation metric, and the PCQI value of Pan *et al.* [97] is also lower than the average value of the evaluation metric.

It is found that the same method has some differences in quantitative and quantitative evaluation of underwater images applied to different scenes. Compared with underwater image restoration methods, underwater image enhancement methods have higher robustness for underwater images of different scenes.

### *D. TRANSMISSION MAP ESTIMATION*

In this section, we use DCP-based transmission map estimation to evaluate the performance of the above selected classical methods for deep scene estimation on DataA and DataB.

#### 1) TRANSMISSION MAP ESTIMATION ON REAL-WORLD UNDERWATER IMAGE DataA

Fig. 9 shows the DCP-based transmission map estimation corresponding to the seven underwater image restoration methods to verify the accuracy of the transmission map estimation. The accuracy of the transmission map estimation obtained by Drew *et al.* [54], Peng *et al.* [56], and Peng *et al.* [58] is poor and the information of depth scene cannot be well estimated. The estimation performance of the transmission map of He *et al.* [46] is slightly better than that of the original image. Galdran *et al.* [53], Li *et al.* [55] and Berman *et al.* [59] have good estimation performance and clear deep scene contour. In summary, it was found that the better the recovery performance of underwater image restoration method (the better qualitative and quantitative evaluations), the better the estimated transmission map.

Fig. 10 shows the DCP-based transmission estimation maps corresponding to the seven underwater image enhancement methods to verify the accuracy of the transmission map estimation. The accuracy of the transmission map estimation obtained by Iqbal *et al.* [70], Fu *et al.* [75], Fu *et al.* [89] and Zhang *et al.* [92] is poor and the information of depth scene cannot be well estimated. Li *et al.* [73] has depth scene estimation performance, but some details of the deep scene are lost. Ancuti *et al.* [12] and Pan *et al.* [97] have good estimation performance and clear contour of deep scene. In summary, the better the enhancement performance of the underwater image enhancement method (the better qualitative and quantitative evaluations), the better the estimated transmission map.

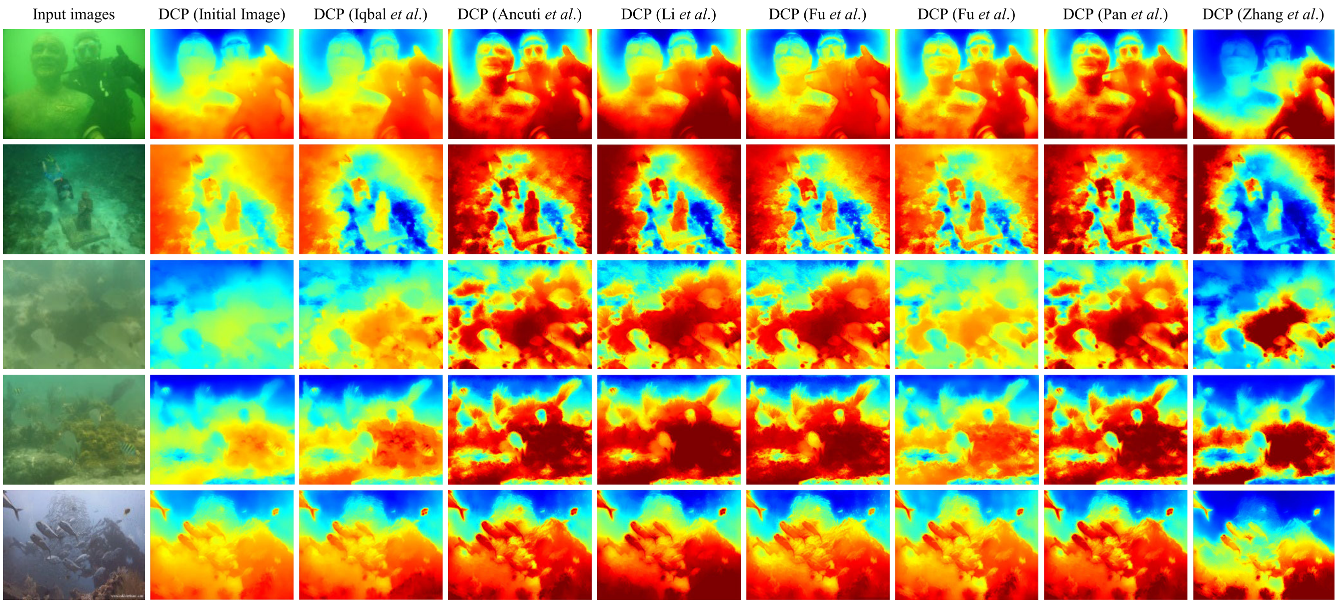


**FIGURE 10.** **Compared with the transmission map estimation obtained by the classical underwater image enhancement methods applied to DataA. From left to right are input images, the transmission estimation map based on DCP applied on the input images but also from versions obtained by several typical underwater enhancement methods (Iqbal *et al.* [70], Ancuti *et al.* [12], Li *et al.* [73], Fu *et al.* [75], Fu *et al.* [89], Pan *et al.* [97], and Zhang *et al.* [92]).**

#### 2) TRANSMISSION MAP ESTIMATION ON REAL-WORLD UNDERWATER IMAGE DataB

Fig. 11 presents the DCP-based transmission map estimation obtained by seven underwater image restoration methods applied to the DataB and verifies the accuracy of the transmission map estimation. The accuracy of most transmission map estimation and the completeness of deep scene estimation follow the rule presented in Fig. 9. The transmission estimation maps obtained by Li *et al.* [55] and Drew *et al.* [54] applied to DataB are different from the results presented in DataA.

Fig. 12 presents the DCP-based transmission map estimation obtained by seven underwater image enhancement methods applied to the DataB and verifies the accuracy of the transmission map estimation. The accuracy of most transmission map estimation and the completeness of deep scene estimation follow the rule presented in Fig. 10. The analysis found that the subjective and objective results of enhancement or restoration methods determine the quality of the transfer map estimation, which has a good visual evaluation of the effect of deep scene restoration.

## V. APPLICATION OF UNDERWATER IMAGE CLARITY

In this section, we describe the research significance of underwater images or underwater video with high-quality in the field of underwater autonomous navigation and underwater target tracking.

### A. UNDERWATER AUTONOMOUS NAVIGATION

Underwater autonomous navigation is an important means for human beings to explore the ocean word. People pay more and more attention to its development and application, especially its underwater vision part has become the focus of research in the field of science.

Autonomous underwater vehicle is an intelligent multi-functional integrated system, and it has been widely used in marine resource exploration, underwater facility inspection, marine rescue and underwater communication construction [117]–[119]. At present, the research of underwater vehicles mainly focuses on underwater data acquisition and underwater vehicle navigation [120], [121]. Underwater enhanced images play an important role in implementing path planning and obstacle avoidance functions. In this process, visual navigation is the core technology for underwater vehicles to sail autonomously on the seabed. It requires automatic generation of high-quality underwater images as a true representation of the underwater scene [122]. Enhanced underwater images are helpful for underwater vehicle to draw real-world scenes [123], [124]. Building clear underwater videos or images faces huge challenges due to the complexity of the underwater environment. Therefore, there is an urgent need for highly accurate and clear underwater videos or images for underwater autonomous navigation services.

### B. UNDERWATER TARGET TRACKING

Underwater target tracking is to extract target information from complex background and realize target tracking by a series of image sequences. As a research hotspot in the field of computer vision, underwater target tracking is widely used in the fields of visual surveillance, human-computer interaction and robot navigation [125]–[127].

The two main challenges of underwater target tracking are the uncertainty of underwater target and the uncertainty of measurement. In view of these problems, tracking

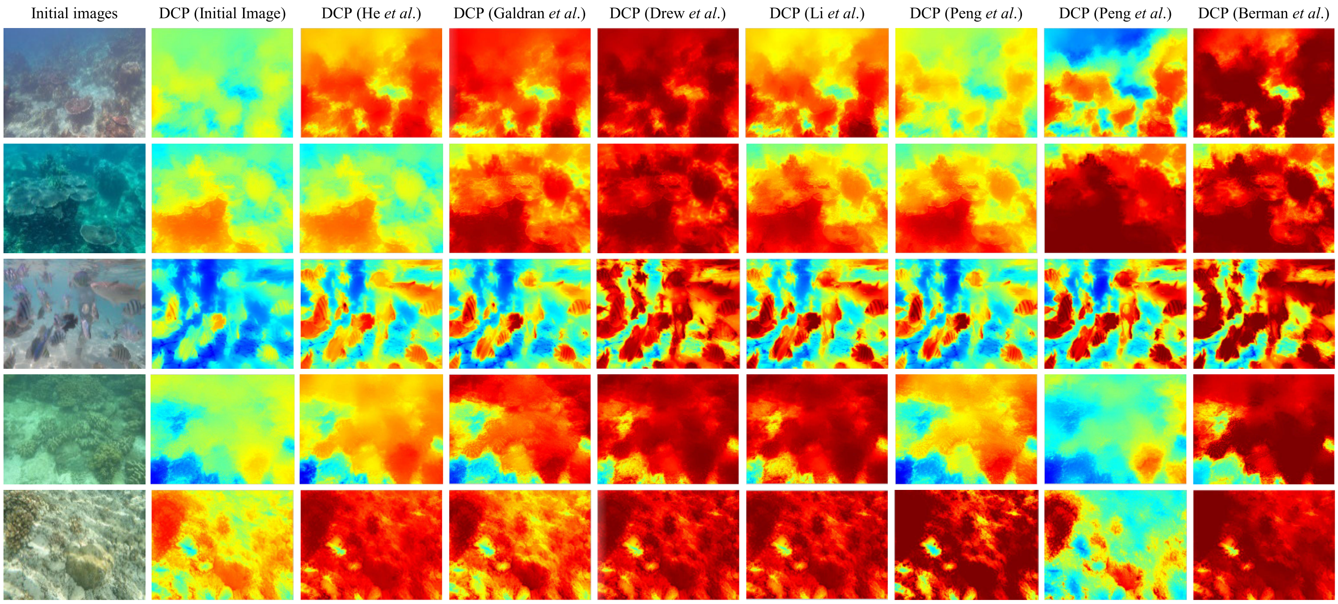


**FIGURE 11. Compared with the transmission map estimation obtained by the classical underwater image restoration methods applied to DataB. From left to right are input images, the transmission estimation map based on DCP applied on the input images but also from versions obtained by several typical underwater restoration methods (He *et al.* [45], Galdran *et al.* [53], Drew *et al.* [54], Li *et al.* [55], Peng *et al.* [56], Peng *et al.* [58], and Berman *et al.* [59]).**

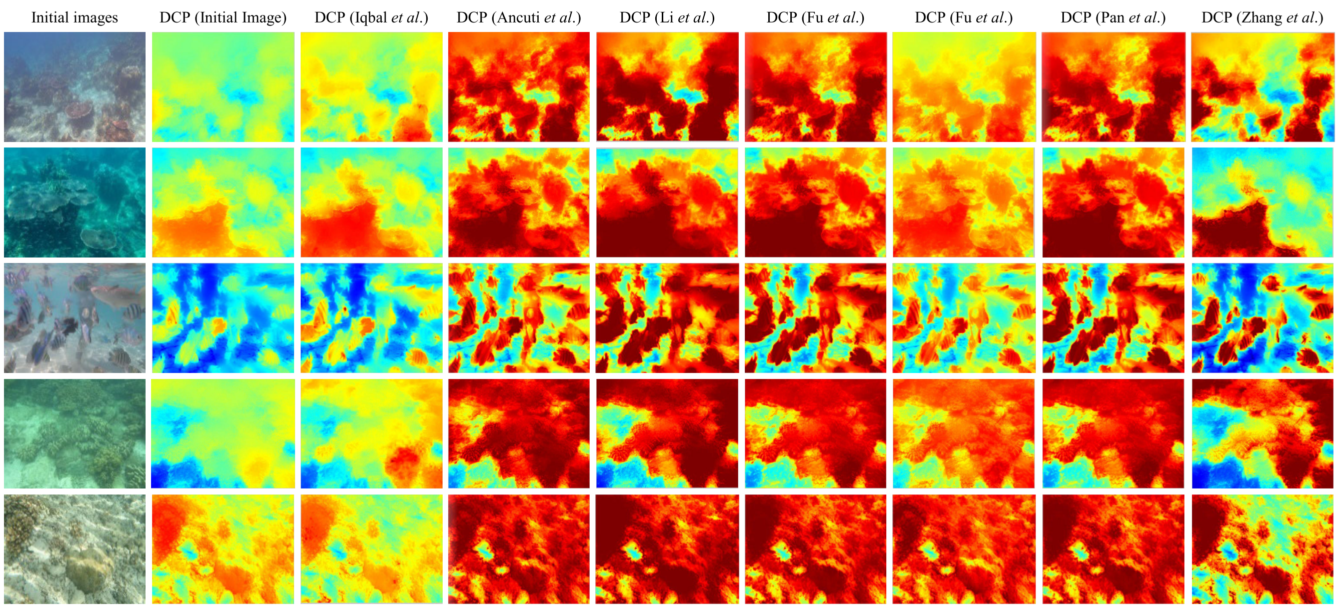


**FIGURE 12. Compared with the transmission map estimation obtained by the classical underwater image enhancement methods applied to DataB. From left to right are input images, the transmission estimation map based on DCP applied on the input images but also from versions obtained by several typical underwater enhancement methods (Iqbal *et al.* [70], Ancuti *et al.* [12], Li *et al.* [73], Fu *et al.* [75], Fu *et al.* [89], Pan *et al.* [97], and Zhang *et al.* [92] ).**

methods [128], [129] based on data association, tracking methods [130], [131] based on probability hypothesis density and tracking methods based deep learning have been proposed [132]–[134]. However, these methods are difficult to extract target features in complex underwater environments, which will lead to the accuracy of tracking method is reduced. Therefore, it is of great significance to study the clear method of underwater image or video to improve the accuracy of underwater target tracking. In practical applications, these methods should have the advantages of low consumption, low complexity and ease application.

## VI. CONCLUSION

In this survey, we mainly introduce the research advances of underwater image restoration and enhancement methods. This paper points out the main reasons for the degradation of underwater images, discusses the classification of existing methods and summarizes the advantages and disadvantages.

In addition, we also introduce the current evaluation system of underwater image quality and point out the shortcomings of the evaluation system. Finally, the performance and characteristics of typical methods are evaluated qualitatively and quantitatively. In summary, underwater image restoration and enhancement researchers should focus on the following aspects in the future:

1) Improve the stability and applicability of the method. Existing methods aren't suitable for all images or tasks, and parameter optimization is complex, thereby the actual application cannot be satisfied. The ideal method can be applied to degraded images in different scenes and achieve the need of underwater image sharpening.

2) The complexity of the algorithm and the quality of the underwater enhanced image still need to be improved. In particular, the method based on physical model generally has high time complexity. The ideal method can improve the quality of underwater images and has lower time and space complexity.

3) The quantitative evaluation system of underwater image quality needs to be improved, and there is less research on the underwater image enhancement reference dataset. Although Li *et al*. [105] have constructed an underwater image enhancement benchmark dataset, the number and scene of the dataset are limited. Therefore, the establishment of a standard quantitative evaluation system and an underwater image enhancement benchmark dataset is the focus of future research.

4) At present, researchers are mainly focusing on single underwater image, but underwater video and super-resolution of underwater image should be pay more attention. Although Ancuti *et al*. [12] and Lu *et al*. [95] have studied on underwater video and super-resolution of underwater image, respectively, its development is relatively slow. Therefore, how to effectively address the problem of underwater video and super-resolution of underwater image needs to pay more efforts.

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