Jing-chun ZHOU, De-huan ZHANG, Wei-shi ZHANG, 2020. Classical and state-of-the-art approaches for underwater image defogging: a comprehensive survey. *Frontiers of Information Technology & Electronic Engineering*, 21(12):1745-1769.
https://doi.org/10.1631/FITEE.2000190

Classical and state-of-the-art approaches for underwater image defogging: a comprehensive survey

Key words: Underwater image defogging; Restoration approaches; Enhancement approaches; Evaluation metrics

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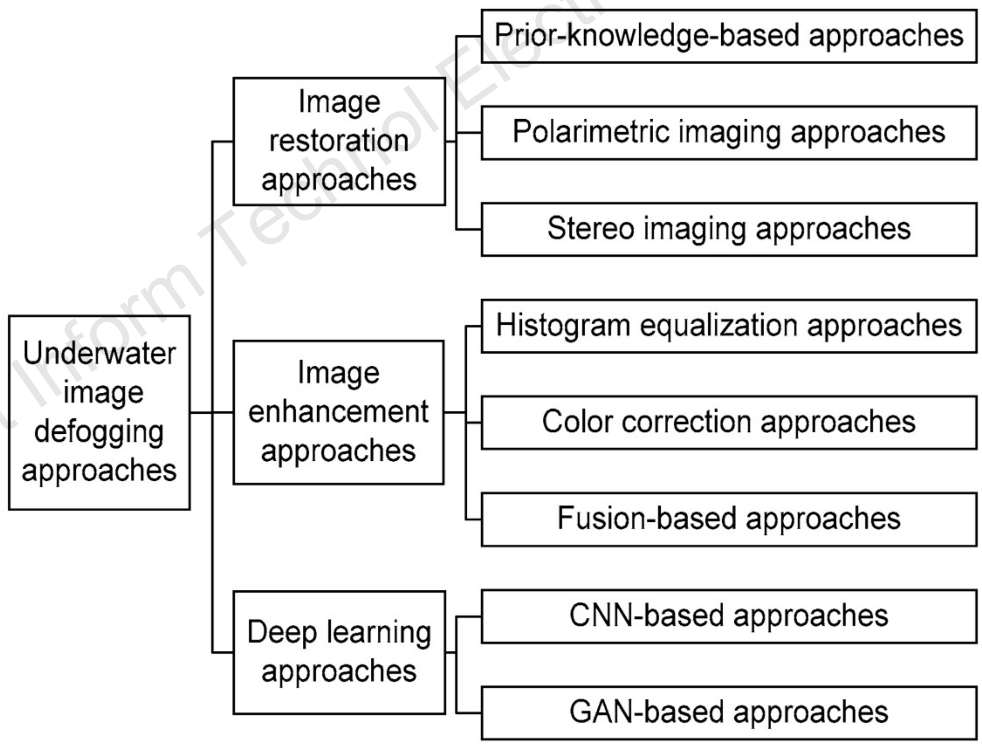
Tendency and challenges

- To date, underwater optical imaging has been one of the challenging fields in computer vision research. Due to the limitations of the environment and the imaging equipment, the underwater images obtained have noise, blurring, and low contrast [1][2].

Samples of underwater degraded images

Motivation

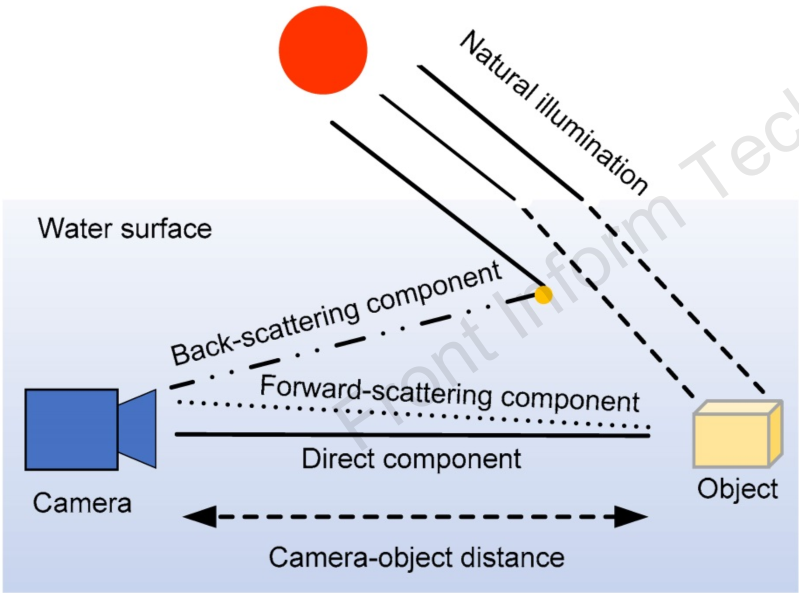
- Study on underwater images enhancement is fundamental and vital for machine vision research and development, especially considering the new applications and techniques.
- Combining recent progress on deep learning, creating a data set is essential for training the model.



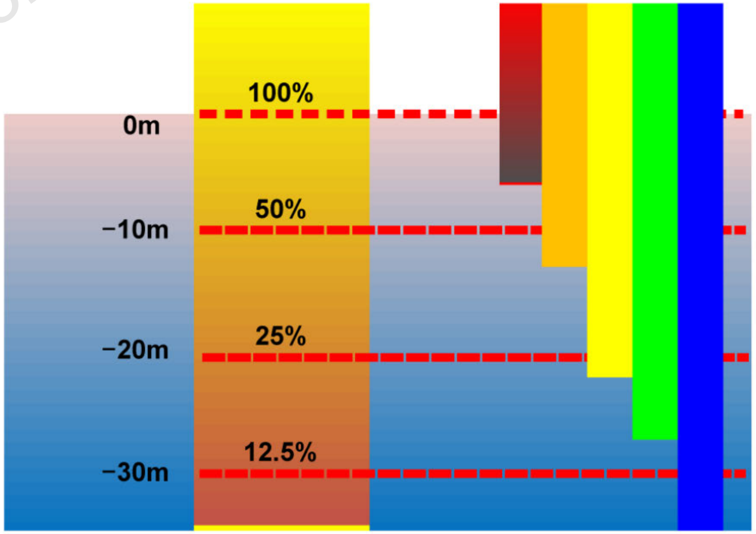
Categories of underwater image defogging approaches

1) Underwater optical imaging model

- The light received by the camera is linearly composed of three parts: direct component, forward-scattering component, and back-scattering component. A linear combination of these three components can be used to describe the underwater optical imaging model.



Schematic of the underwater optical imaging model

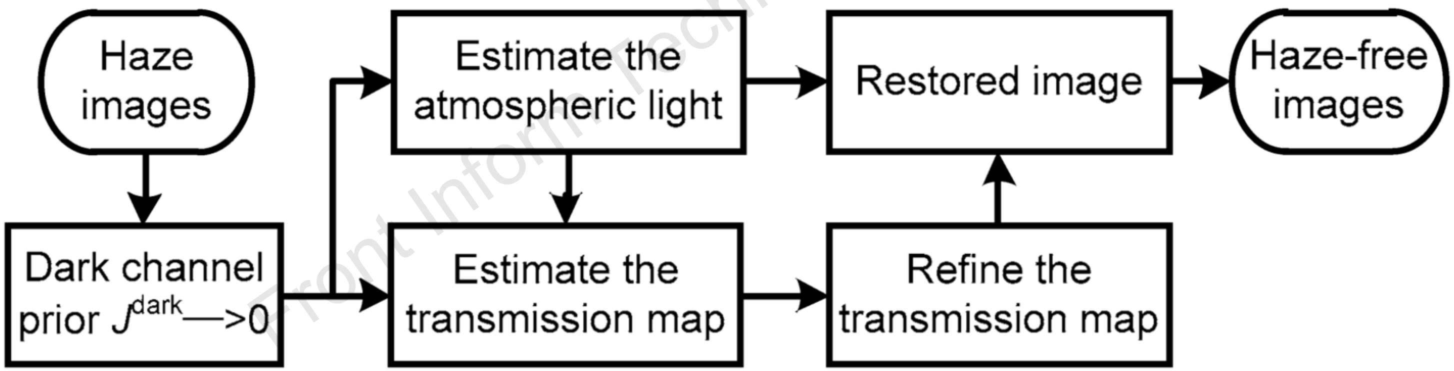


Selective attenuation model of underwater light

2) Underwater image restoration approaches

A) Prior-knowledge-based approaches

The software methods introduced here are dark channel prior (DCP) and DCP-based variants. DCP technology is an effective defogging method based on the Jaffe-McGlamery model. The aim of this model is to improve the accuracy in the estimated background light (BL) and transmission map (TM) [3].

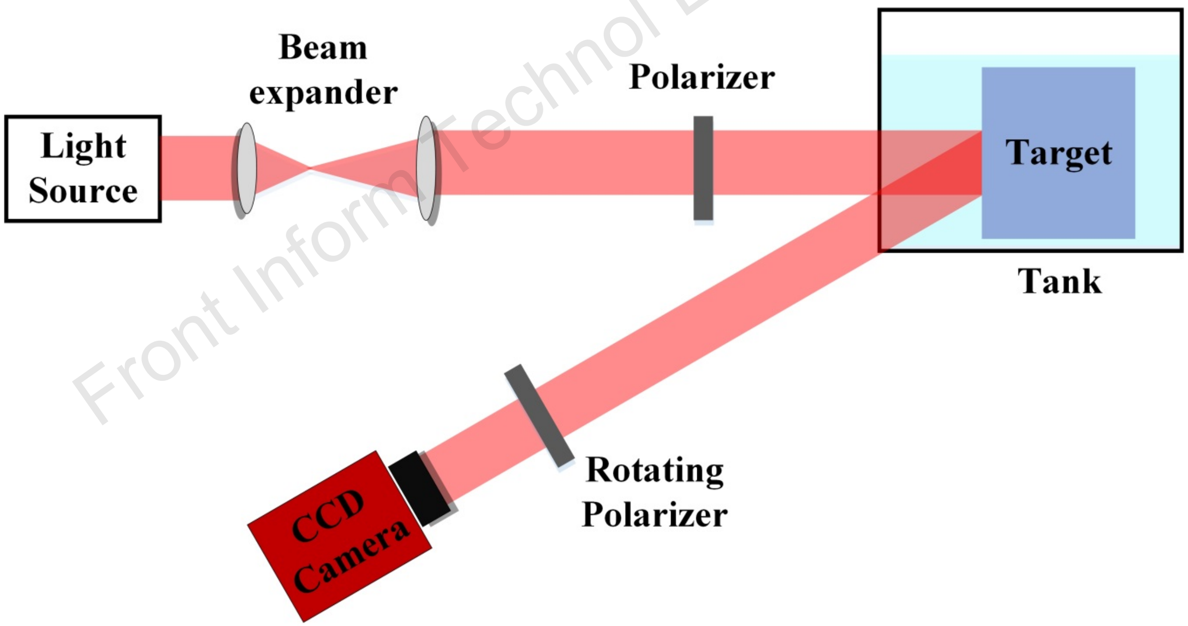


The dark channel prior (DCP) defogging model

2) Underwater image restoration approaches

B) Polarimetric imaging approaches

Polarization is an inherent attribute of light, and it can provide more valuable information than the scene spectrum (color) and intensity distribution. Images processed by polarization methods hold higher visual contrast than those processed by traditional images [4].



Schematic of the experimental setup for underwater imaging

3) Underwater image enhancement approaches

A) Histogram equalization approaches

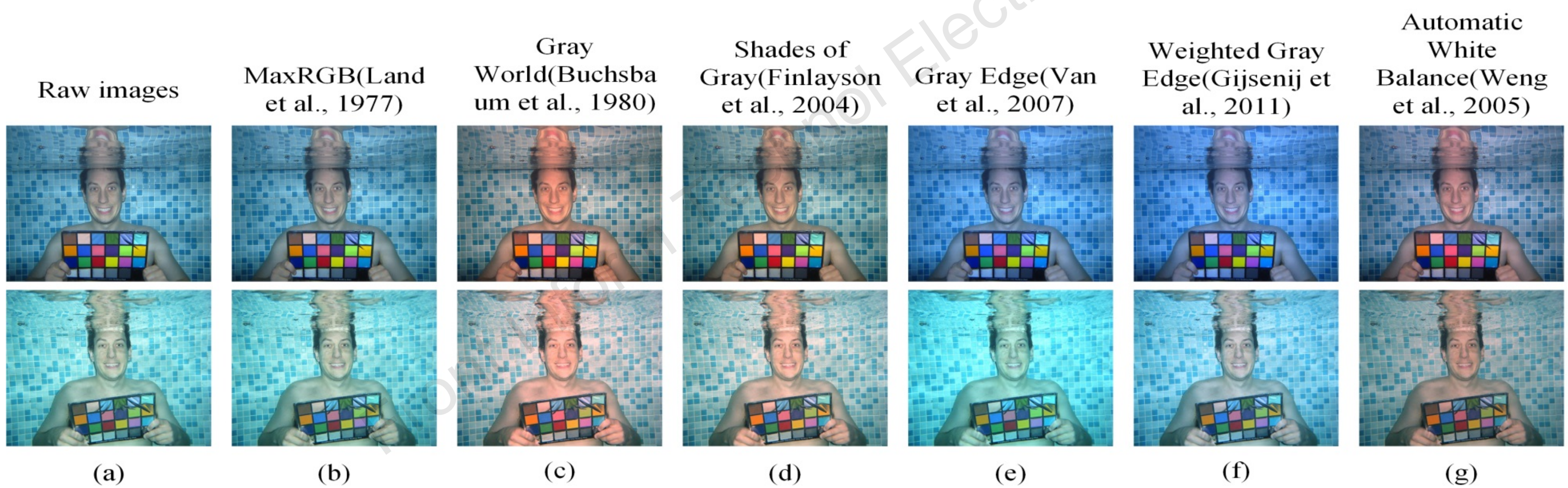
Histogram indicates the distribution of the image tone [5]. Histogram equalization is a typical image enhancement approach; it is used to solve the problem of low contrast. Compared with images acquired on land, the distribution of the underwater image pixel histogram is more concentrated. Thus, the dynamic range of image histograms is amplified to enhance the contrast of the degenerated images [6].

Histogram equalization and its evolutionary approaches ignore the underwater optical imaging model, which can enhance the contrast; histogram equalization introduces artifacts and noise. In applications where the contrast of the underwater image needs to be enhanced, histogram equalization can be added to the underwater optical imaging model based method as post-processing.

3) Underwater image enhancement approaches

B) Color correction approaches

White balance is used to improve the color cast of the image. In water, the perception of color is related to depth, and a crucial problem is the blue-greenish effect that needs to be corrected.



Results of different white balance methods: (a) raw images; (b) MaxRGB [7]; (c) gray world [8]; (d) shades of gray [9]; (e) gray edge [10]; (f) weighted gray edge [11]; (g) automatic white balance [12]

4) Deep learning approaches

Recently, deep learning technology has been extensively applied to underwater image defogging, and it can improve the quality of underwater images to some extent. Deep learning based methods can reduce errors caused by invalid priors by training a neural network to study the relationship between the image sets and relevant transmission maps.

Deep learning approaches:

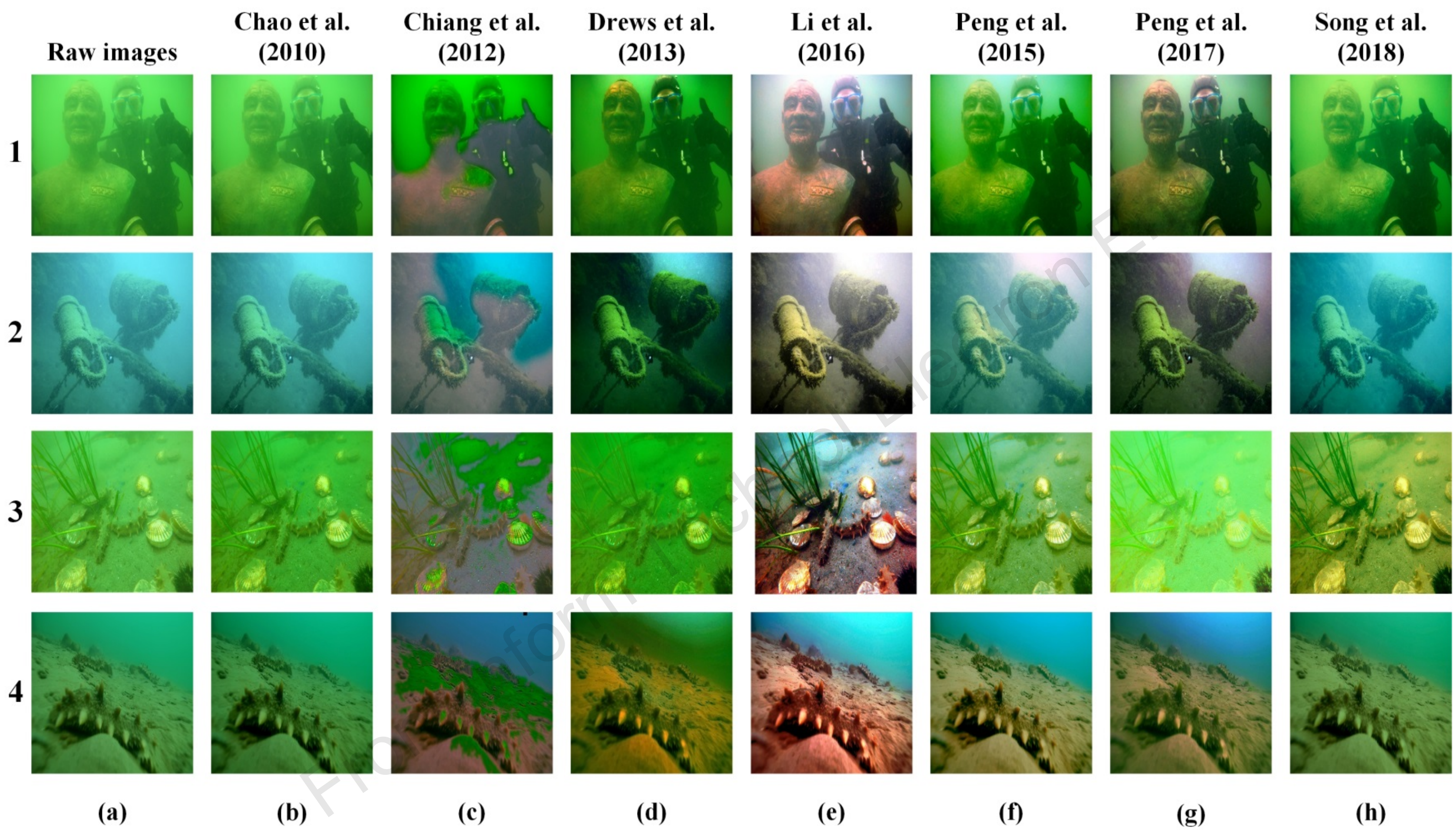
1) CNN-based approaches

DehazeNet [13], DSDH [14], UWCNN [15], etc.

2) GAN-based approaches

CycleGAN [16], UGAN [17], WaterGAN [18], UWGAN [19], GAN_RS [20], etc.

Subjective evaluation



Comparison of underwater image restoration methods: (a) underwater raw images; (b–h) images obtained using Chao and Wang (2010), Chiang and Chen (2012), Drews et al. (2013), Li CY et al. (2016), Peng et al. (2015), Peng and Cosman (2017), and Song et al. (2018)'s methods, respectively

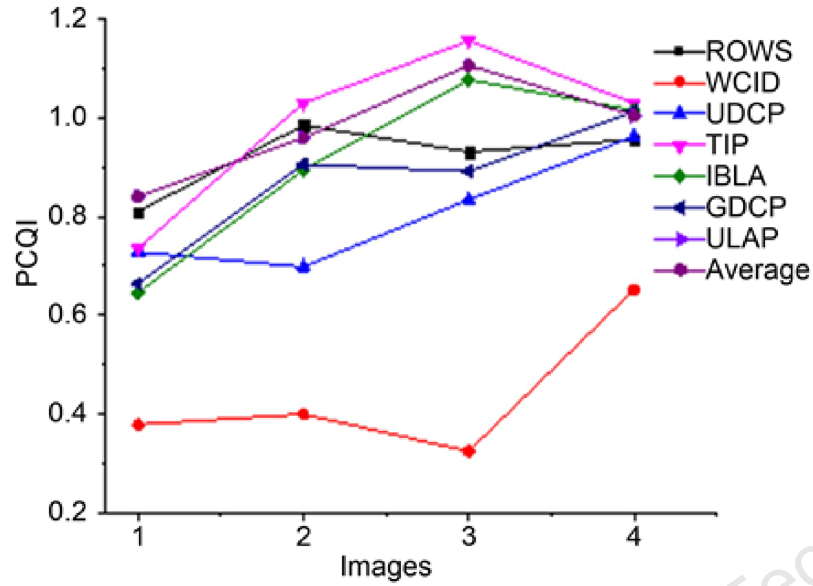
Objective evaluation metrics

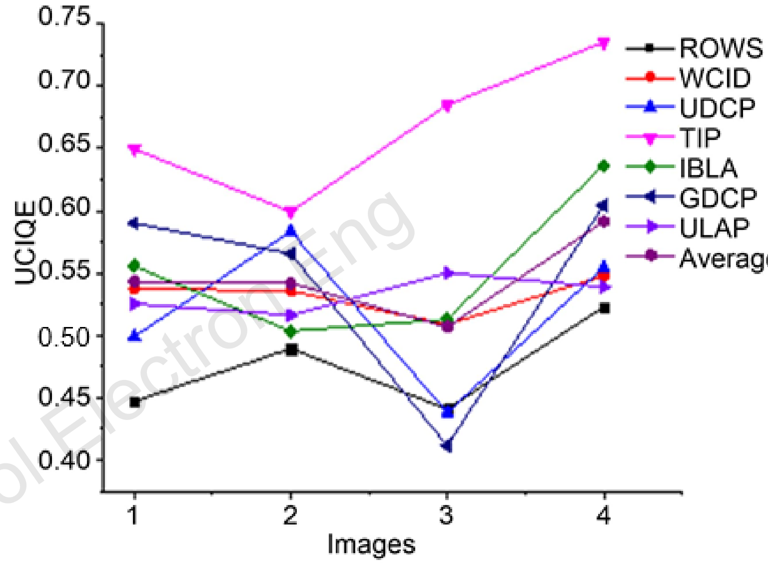
Table 2 Objective evaluation metrics

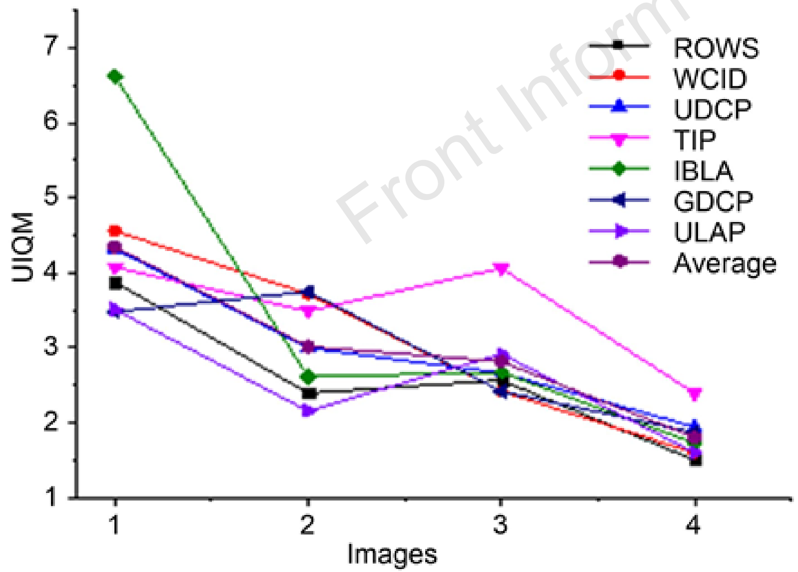
Metric	Formula	Significance
AG	$\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\sqrt{\frac{1}{2}\left(\left[\frac{\partial F(x,y)}{\partial x}\right]^2+\left[\frac{\partial F(x,y)}{\partial y}\right]^2\right)}$, where M and N represent the sizes of the image	Higher AG reflects better image clarity
IE	$\sum_{i=0,p(i)\neq 0}^{255} p(i)\log\left(\frac{1}{p(i)}\right)$, where $p(i)$ (i=0, 1, …, 255) represents the probability distribution	Higher IE indicates more information of an image
MSE	$\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[I_1(i,j)-I_2(i,j)]^2$, where I_1 is the original image and I_2 is the defogging image	Lower MSE represents better recovery
PSNR	$10\lg\left(\max\left(\frac{(I_1,I_2)^2}{\mathrm{MSE}}\right)\right)$, (I_1, I_2)=255	Higher PSNR represents better quality of the restored image
SSIM	$\frac{2\mu_x\mu_y+C_1}{\mu_x^2+\mu_y^2+C_1}\frac{2\sigma_x\sigma_y+C_2}{\sigma_x^2+\sigma_y^2+C_2}$, where μ_x and μ_y are means, σ_x and σ_y are standard deviations, and C_1 and C_2 are constants	Higher SSIM means more restoration information of the raw image
e	$(n_r-n_0)/n_0$, where n_0 and n_r denote the numbers in the sets of visible edges in I_0 and I_r, respectively	Higher e shows more restored edges
σ	$n_s/(MN)$, where n_s represents the number of saturated pixels	Lower σ shows better contrast
$\bar{\gamma}$	$\exp\left(\frac{1}{n}\sum_{p_i\in\vartheta_r}\log\gamma_i\right)$	Higher $\bar{\gamma}$ shows better contrast restoration
PCQI	$\frac{1}{M}\sum_{i=1}^{M}q_i(x_i,y_i)q_c(x_i,y_i)q_s(x_i,y_i)$, where M indicates the total number of patches in the image, $q_i(x_i, y_i)$ is the mean intensity, $q_c(x_i, y_i)$ is used to determine the structural distortion, and $q_s(x_i, y_i)$ represents the changes in contrast	Higher PCQI represents better contrast of the image
UCIQE	$c_1\sigma_c+c_2\mathrm{con}_l+c_3\mu_s$, where σ_c, con_l, and μ_s indicate the standard deviation of chroma, the contrast in brightness, and the average value of saturation, respectively, and c_1, c_2, and c_3 denote the weighting coefficients	Higher UCIQE means better image quality in chroma, saturation, and contrast
UIQM	c_1UICM+c_2UISM+c_3UIConM, where c_1, c_2, and c_3 denote the weighting coefficients	Higher UIQM means better comprehensive performance in color, contrast, and sharpness

AG: average gradient; IE: information entropy; MSE: mean squared error; PSNR: peak signal-to-noise ratio; SSIM: structural similarity; e: rate of visible edges; σ: saturation; $\bar{\gamma}$: quality of contrast restoration; PCQI: patch-based contrast quality index; UCIQE: underwater color image quality evaluation; UIQM: under-water image quality measure

Objective evaluation metrics







The PCQI, UCIQE, and UIQM values of the underwater image restoration methods

ROWS (Chao and Wang, 2010); WCID (Chiang and Chen, 2012); UDCP (Drews et al., 2013); TIP (Li CY et al., 2016); IBLA (Peng et al., 2015); GDCP (Peng and Cosman, 2017); ULAP (Song et al., 2018)

Outlook

In future research on underwater image enhancement and restoration, researchers may carry out work from the following perspectives:

- Improve the robustness and adaptivity of the algorithms.
- Decrease the complexity of methods and improve the processing results.
- Design a comprehensive underwater image solution suitable for multiple scenarios.
- Design special deep learning methods for underwater images, such as network structures or loss functions [21].
- Establish a standard system for evaluation of underwater image quality and data sets of underwater images.
- Further improve the underwater video processing technologies.
- Synthesize underwater images using the text-to-image method.

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