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A Review on Underwater Image Enhancement Models, Datasets and Metrics

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Abstract: Exploration of the underwater world is still the direction we are heading. Underwater imaging remains challenging due to blurred visibility, color deviation, and low contrast. Underwater image enhancement (UIE) represents a fundamental yet critical research challenge in the field of computer vision. Despite continuous advancements in hardware and algorithmic methodologies, there remains a lack of comprehensive summaries in this domain. To address this, we provide an overview of the research progress in UIE from the following perspectives. First, we introduce the three mainstream categories of UIE algorithms, along with the construction of datasets, including paired and unpaired datasets. Second, we conduct model training and evaluate the performance on a unified dataset, presenting results from both quantitative and qualitative perspectives. Finally, by utilizing the enhanced datasets for object detection tasks, we observe that the evaluation metrics of image enhancement and object detection do not exhibit a positive correlation.

Keywords: Underwater image enhancement; UIE models; Underwater dataset; Metrics; Object detection.

1. Introduction

The ocean covers approximately 71% of the Earth's surface[1], and as terrestrial resources become increasingly depleted and explored, the importance of investigating the resources of the underwater world is steadily growing. In the context of aquaculture, fish farmers are tasked with monitoring the health and growth of cultured organisms by assessing characteristics such as size, shape, and color. This enables the early detection of diseases and abnormalities, allowing farmers to implement effective strategies to optimize production and minimize losses[2]. However, the use of low-quality underwater imagery presents a significant challenge for biomonitoring applications[3]. To address this, marine engineering and research increasingly depend on underwater imagery captured by Underwater Vehicles (UVs), allowing researchers to efficiently and accurately analyze complex underwater situations. In the face of possible damage to pipeline facilities on the seabed, such as gas[4] or oil pipeline leaks[5] or submarine cable breaks[6][7], operators can use UVs to locate and analyze the damage, so that the necessary measures can be taken early to reduce economic losses and environmental impacts. UIE can also be used for surveys of seabed topography and geological features as well as underwater archaeological excavations[8]. The color of underwater images and the contour of the target serve as important information, so how to improve the quality of the images is closely related to many fields of underwater research.

When light spreads in water, it will be selectively absorbed, especially in red. So, the color deviation is serious[9]. And there are always floating particles, plankton, dust, which lead to light scattering during underwater propagation, making the image appears blurred and turbid[10][11]. Combining the effects of the above points, the underwater image obtained by UVs using camera often have serious color distortion, and blurred images with poor contrast, which makes it difficult to be directly applied to related underwater research fields.

In addition to above factors, another major difficulty in UIE techniques is lack of corresponding reference images. Due to the dynamic nature of underwater objects, it is almost impossible to capture blurry and clear image pairs at the same location[12], which makes supervised learning extremely difficult. Most of the current underwater datasets use the captured underwater images to be processed by enhancement algorithms to obtain the corresponding reference images.

The subsequent chapters of this paper are structured as follows: Chapter 2 describes the UIE models; Chapter 3 introduces the underwater datasets; Chapter 4 conducts image enhancement experiments, target detection task experiments and analyses the results; Chapter 5 concludes the contents of this paper and presents an outlook.

2. UIE Models

While advancements in underwater camera technology have improved image quality to some extent, digital image processing remains a more cost-effective and practical solution, as it can be implemented in software at a significantly lower cost compared to sophisticated imaging hardware. Since the introduction of digital image processing, significant progress has been made in the field of underwater image processing, enabling enhanced visual quality and broader applications. Currently, common UIE models are mainly classified into three categories according to generating clear image methods: non-physical models, physical models, and deep learning models.

2.1. Non-physical Models

Non-physical models are usually computing faster and performing operations at the pixel level.

Without accounting for the underwater imaging process, enhancement techniques may inadvertently distort the image structure and introduce artifacts[13]. A basic enhancement approach involves first restoring the colors through white balance correction[14], followed by the application of Histogram Equalization (HE) to improve contrast[15]. Zhang proposed an enhancement method that compensates for specific color channels and performs local white balance adjustment, followed by histogram stretching of the RGB and intensity channels[16]. However, due to the relatively uniform contrast variation in underwater images, traditional HE tends to amplify noise. To address this issue, Hitam applied Contrast Limited Adaptive Histogram Equalization (CLAHE) to the RGB and HSV color models, subsequently fusing the results to enhance image quality[17]. Ghani and Iqbal introduced a novel approach combining Rayleigh distribution with the Integrated Color Model (ICM) and Unsupervised Color Correction Method (UCM) to enhance image contrast, while mitigating over-enhancement and noise artifacts[18][19].

Despite the advantages of non-physical models in terms of processing speed, they usually suffer from problems such as over-enhancement, color distortion, and image shifting.

2.2. Physical Models

Physical models start from the principle of image degradation and derive clear images from mathematical expressions for blurry images.

According to the Jaffe-McGlamery underwater imaging principle[20], the imaging process is shown in Fig.1. The camera receives the light by three components: 1) Direct Attenuation, the light reflected directly from the object to the camera; 2) Forward Scattering, the light offset from the original direction, randomly reflected back to the camera; 3) Backward Scattering, the light encounters particles that scatter the light before it is reflected back to the camera. The multiple scattering process during transmission further scatters the beam into a uniform background light.

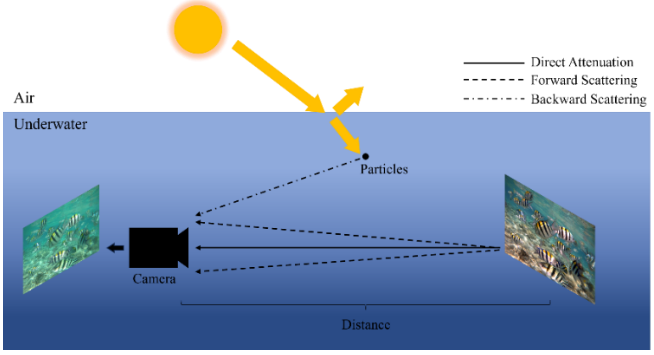


Fig.1 Underwater imaging process

He[21] firstly proposed Dark Channel Prior (DCP) model to perform the enhance operation, which is shown in Eq. (1).

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

I shows a blurry image, J shows a clear image, t shows the percentage of scene brightness that reaches the camera after reflections from objects, and A shows the global atmospheric light in the scene, (x, y) is pixel position. So, J is recovered by backpropagating, which is shown in Eq.(2).

$$J(x,y) = \frac{I(x,y) - A(1-t(x,y))}{t(x,y)} \tag{2}$$

Given the similarities in light scattering effects between underwater and terrestrial environments, the principles of underwater imaging can be extended to land-based scenarios. As a result, many researchers have proposed UIE methods based on DCP.

Red has a longer wavelength than green and blue light. Consequently, the fastest absorbed light underwater is red and the most retained is blue, as shown in Fig.2, which is the reason underwater images appear blue-green. Consequently, unlike blurry images captured in terrestrial environments, the red channel pixels in underwater images are often near zero, which results in inaccurate transmission maps when estimated using the DCP method. Drews proposed UDCP applied to the blue-green channel to enhance image, but it is prone to over-enhancement[22]. Fayaz proposed Modified Underwater Dark Channel Prior (MUWDCP) to calculate global atmospheric light based on the degraded image[23]. Guan proposed an improved polarization-based DCP method to obtain both intensity and polarization information to enhance the difference between the target and its surrounding environment[24]. Song proposed a fast and effective scene depth estimation model based on Underwater Light Attenuation Prior (ULAP) and trained the model coefficients using the learning-based supervised linear regression for underwater images[25].

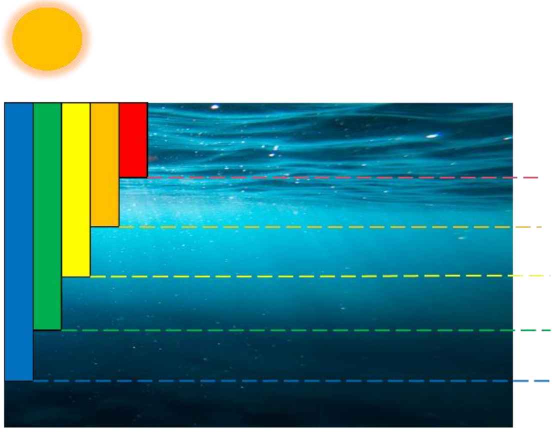


Fig.2 Depth of absorption of different colors underwater

Physical models enhance image clarity by simulating the physical processes of light scattering and absorption underwater. While they produce more accurate results, these models involve complex optical and physical computations, which demand substantial computational resources and depend on precise parameter configurations. Variations in parameter selection can significantly impact the model's performance, leading to limited robustness

2.3. Deep Learning Models

There is three UIE models based on deep learning.

2.3.1. CNN-based model

The first one is CNN-based model, which refers to the use of convolutional kernel to extract hierarchical features from the input image. Perez first introduced CNN into the field of UIE[26]. Cai proposed DehazeNet, which is a combination of CNN and physical models, to recover the clear images[27]. GCAnet used the gating mechanism to solve the grid artifact problem in the generated images[28]. Shallow-UWnet based on deep residual networks and a self-attention mechanism to improve the contrast and saturation of underwater images without losing details[29]. Liu proposed a supervised adaptive learning LANet to solve the image degradation problem[30]. Guan proposed DiffWater based on a conditional DDPM, which takes advantage of DDPM to train stable and well-converged models that are capable of generating high-quality and diverse samples[31].

2.3.2. GAN-based model

The second is GAN-based model, which employs the Generator and the Discriminator to be trained iteratively to generate more realistic and clear images. Cong proposed a physical model-guided GAN with dual-discriminators for UIE[32]. Zhang proposed a GAN with hierarchical attention aggregation and multi-resolution feature learning[33]. WaterGAN use images with Depth Map to correct the colors[34]. Most GAN-based models require paired clear and blurry images for training. CycleGAN innovatively provides an unsupervised learning model to train model from unpaired images[35]. CycleGAN network with dual discriminators and dual generators, as shown in Fig.3. Generators generate corresponding clear or blurry images. The task of the Discriminators is to distinguish whether the input images are from the real dataset or generated by generators. Wang proposed a novel unsupervised Red Channel Attention Optimized CycleGAN (RCA-CycleGAN) using two local discriminators to enhance the performance of the locally degraded part[36]. Sun proposed Underwater Multiscene GAN (UMGAN) using a feedback mechanism and a noise reduction network to address noise and artifacts in generated images[37].

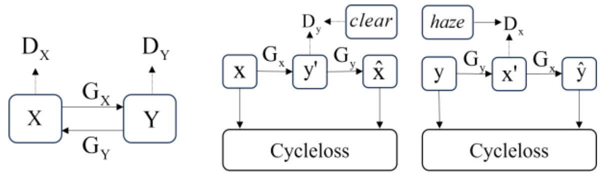


Fig.3 CycleGAN network structure

UIE is the process of transforming a blurred domain into a clear domain. As shown in Fig.3, X(x)domain to Y(y) domain. We define the X(x) domain as the original underwater image, and the overall characteristics of this domain are blurring, low contrast, and tonal deviation. The Y(y) domain is defined as the image after enhancement, and this domain is higher contrast and clearer outlines of each target object within the image.

2.3.3. Transformer-based model

The third one is Transformer-based model. Transformer was first applied to natural language processing and sequential Tasks. Later, the improved Vision Transformer (ViT) was applied to Computer Vision (CV)[38]. Traditional CNN is limited by their local receptive fields, whereas Transformers are capable of modeling long-range dependencies within an image, making them particularly advantageous for capturing relationships between objects in complex underwater environments. Transformer-based underwater image enhancement models leverage their self-attention mechanism, which, in conjunction with feature extraction and enhancement, is especially effective in addressing common underwater image issues such as low contrast, color distortion, and blurring.

Peng first introduced the Transformer model to UIE task by proposing U-shape Transformer[39]. Swin Transformer proposed with Shifted Windows Multi-Head Self-Attention (SW-MSA) to transfer information between neighboring windows while significantly reducing computation[40]. For image enhancement task, the image edge is as important as middle. DehazeFormer changed the cyclic shift based on Swin Transformer to reflection pad to process the edge pixels[41]. MB-TaylorFormer proposed with a multi-branch linear Transformer[42]. DFC-dehaze introduced DehazeFormer blocks into CycleGAN instead of CNN for image enhancement[43]. However, Transformer models typically involve a large number of parameters, leading to significantly higher computational and memory demands compared to conventional CNNs, particularly when applied to image processing tasks.

Deep learning-based UIE models are capable of generating more realistic and clearer images; however, they require extensive datasets for effective training. The limited availability of underwater image datasets presents a significant challenge for the development and performance of these models. The advantages and disadvantages of the three UIE models are shown in Table 1.

Table 1. Overview of three UIE models

	Non-physical model	Pyhsical model	Deep learning model
Advantage	processing speed fast	particular scenario works well	images realistic and clearer
Disadvantage	over-enhancement color distortion image shifting	large computational resources precise parameter settings	a large dataset for training

3. Underwater Image Datasets

The complexity of the underwater environment makes the collection of underwater datasets become extremely difficult. The following underwater image datasets are widely utilized in UIE research due to their distinctive characteristics and suitability for various tasks. These datasets provide diverse image qualities and conditions, serving as critical benchmarks for evaluating and comparing enhancement methods. They typically include paired and unpaired datasets designed to test different models in terms of color correction, contrast improvement, and visibility restoration under varying underwater conditions. By encompassing a range of scenarios, such as turbid water, varying depths, and lighting conditions, these datasets play a pivotal role in advancing the development and validation of UIE algorithms.

3.1. UIEB Dataset

The UIEB[44] dataset is a widely recognized benchmark for evaluating underwater image enhancement (UIE) methods. It consists of 950 underwater images, including 890 raw underwater images and 60 high-quality reference images. The UIEB dataset utilizes twelve algorithms to generate a variety of reference images. Subsequently, a selection process involving 50 volunteers is employed to determine the final reference image, with the most effective enhancement for each scene chosen. Making the dataset particularly useful for supervised learning and evaluation tasks.

The dataset is designed to address common underwater imaging challenges, such as color distortion, low contrast, and reduced visibility caused by scattering and absorption in water. It encompasses diverse underwater conditions, including varying depths, water types, and lighting scenarios, ensuring broad applicability for real-world tasks.

3.2. EUVP Dataset

The construction of the EUVP[45] dataset is driven by the requirements of various underwater image processing tasks. It involves the collection and organization of underwater image data from diverse sources, including both paired and unpaired datasets, to support tasks such as image enhancement, color correction, and restoration. The paired dataset consists of 5,550 pairs of underwater dark images, 2,185 pairs of underwater scene images, and 3,700 pairs of imagenet images for training. The unpaired dataset includes 3,195 images of poor quality and 3,140 enhanced or high-quality images for training.

During the dataset creation process, the FUnIE-GAN model was employed to generate ground truth (GT) for the paired data. For the unpaired images, they were classified into different quality levels based on their visual characteristics. The dataset includes images captured from a variety of underwater environments, such as coral reefs, deep-sea settings, and artificial underwater scenes, to simulate the real-world challenges encountered in underwater image processing.

3.3. RUIE Dataset

RUIE[46] dataset is divided into three subsets, Underwater Image Quality Set (UIQS), Underwater Color Cast Set (UCCS), and Underwater Higher-level Task-driven Set (UHTS).

UIQS subset is used to test UIE algorithms to improve image visibility. According to the UCIQE values, it was equally divided into 5 subsets according to their descending order, denoted as (A, B, C, D, E). UCCS subset is intended to evaluate the ability of the algorithm color correction. It contains 3 subsets of 100 images with blue, green and blue-green hues. UHTS subset investigates the effectiveness of the UIE algorithm for target detection tasks from the perspective of high-level tasks. It contains 5 subsets of 60 images.

4. Experimental Results and Discussion

We conducted comparative image enhancement tests on the UIEB and RUIE datasets to evaluate the performance of the generated images using both subjective and objective metrics. Additionally, we performed target detection task on the enhanced UHTS subset to validate that the enhanced images are better suited for high-level CV tasks.

The experiments were carried out in an environment equipped with an Intel Core i7-12700F CPU, an Nvidia GeForce RTX 3080 GPU, Python 3.9.0, and Pytorch 1.9.0. The input images size is 256 × 256, the initial learning rate set to 0.0002, the batch size is 1, and 300 epochs.

4.1. Subjective Evaluation and Qualitative Analysis

In the field of UIE, the final recipients of the generated clear underwater images are human or subsequent high-level CV task, making qualitative and subjective analysis particularly important. Rather than relying on a single image quality metric, a more comprehensive evaluation of image quality can be achieved including contrast, color fidelity, and detail preservation. The enhancement results of the various models are presented in Fig. 4.

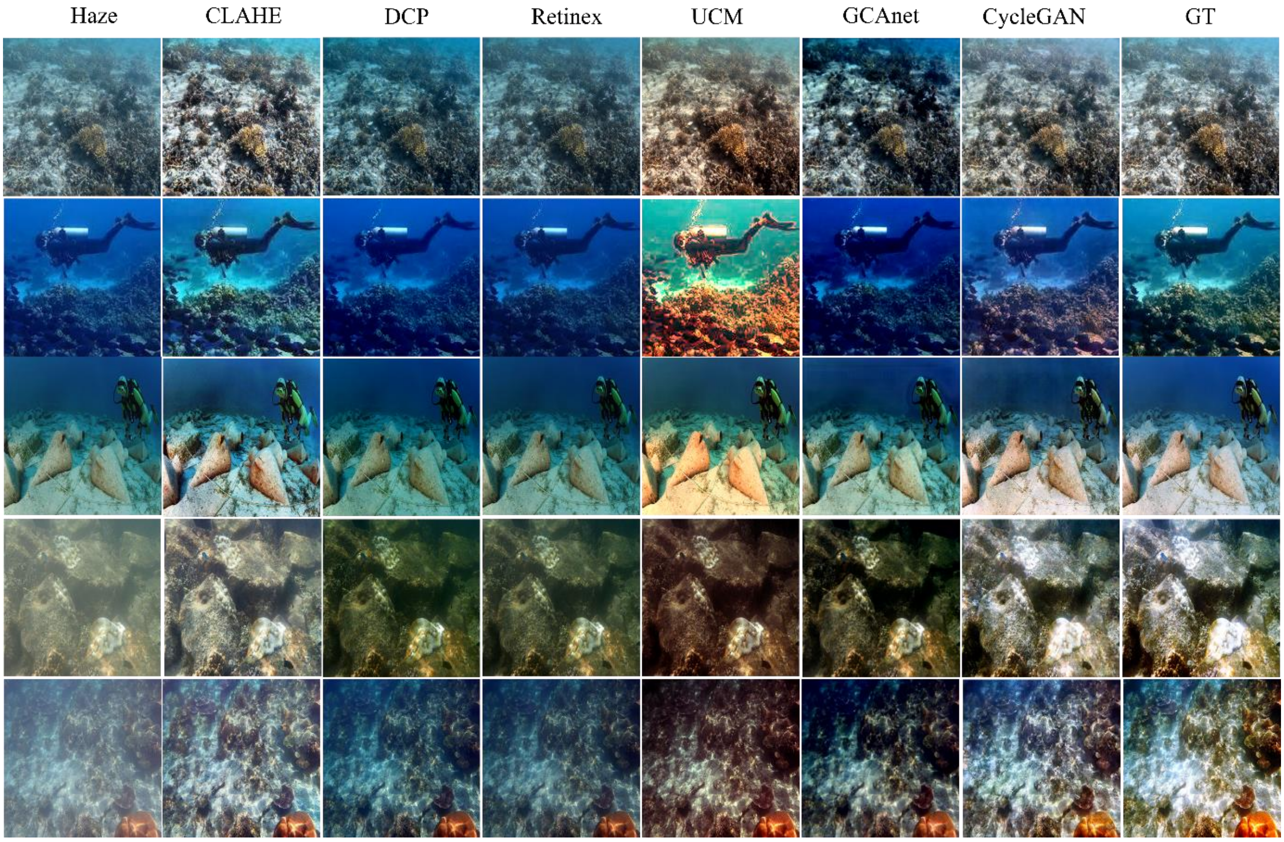


Fig.4 The enhancement effect of different models

As shown in Fig. 4, the DCP, Retinex, and GCAnet models produce enhanced images with dark blue or green tones similar to the original hazy image, though with improved contrast. The CLAHE model enhances color but still exhibits some color distortion. The UCM model leads to overcorrection, resulting in a reddish hue. In comparison, CycleGAN provides a more noticeable improvement in both color and contrast, though the generated image exhibits some exposure issues.

However, due to the existence of a certain degree of variability in the subjective perception of images by different people, the judgement of the same image may be different. Therefore, objective evaluation and quantitative analysis were conducted along with subjective evaluation to improve the objectivity of the assessment.

4.2. Objective Evaluation and Quantitative Analysis

Based on reference image as a judgement criterion for the generated image, the existing objective evaluations mainly have two metrics: Full-reference and Non-reference.

4.2.1. Full-reference

Full-reference evaluation necessitates the use of reference images as a benchmark for comparison. This metric assesses the quality of the generated image by comparing it to the reference image. We conducted evaluations using PSNR and SSIM on the paired UIEB dataset.

PSNR measures the image similarity by comparing the mean square error MSE between the images. A higher PSNR value, which means a smaller mean square error between images, indicates a better effect after enhancement. However, it only considers the MSE and ignores the image structure and perceptual factors, which cannot fully reflect the image quality.

SSIM evaluates an image from three perspectives: luminance, contrast and structure. Compared with PSNR, SSIM can provide a more human judgement of the image in terms of image quality and restoration effect. The result value of SSIM is in the range of (-1, 1), and the larger the result, the closer the enhanced clear image is to the reference image and the better the enhancement effect is.

4.2.2. Non-reference

When enhancing a blurry image without a reference image, it is not possible to evaluate the enhancement using full-reference metrics. In such cases, non-reference metrics, which can independently evaluate image quality, are more appropriate for practical applications. Underwater Image Quality Measure (UIQM) evaluates the degradation mechanism and imaging characteristics of underwater images purely from the perspective of generating image quality. It includes three underwater image attribute measurements: Underwater Image Colour Measurement (UICM), Underwater Image Sharpness Measurement (UISM), and Underwater Image Contrast Measurement (UIConM).

4.3. Models Compare Experiment

The results of objective metrics of different UIE models on different datasets are shown in Table 2.

Table 2. Test results of different models for objective metrics

Dataset	Models / Metrics	Haze	CLAHE	DCP	Retinex	UCM	GCANet	CycleGAN
UIEB	PSNR	21.1013	21.1114	17.9582	18.7871	21.3441	16.9085	20.4965
	SSIM	0.7786	0.8483	0.7097	0.7663	0.8187	0.6984	0.7432
	UIQM	2.6582	3.1046	2.1468	2.5688	2.7427	2.1865	3.0732
UIQS	UIQM	2.5837	3.0776	1.8898	2.4041	3.0127	2.3970	3.3095
UCCS		2.4656	3.0557	1.7665	2.3236	3.0919	2.2423	3.3201
UHTS		2.9381	3.2847	2.2970	2.7897	3.1370	2.6128	3.3585

(1. The UIEB dataset contains reference images, so three evaluation metrics were tested; 2. UIQS, UCCS, and UHTS are sub-datasets of RUIE and do not contain reference images, so only a single metric, UIQM, was tested.)

From the data in Table 2, it can be noticed that: (1) In the UIEB dataset, UCM achieved the best performance in terms of PSNR, while CLAHE delivered the best results in both SSIM and UIQM. Additionally, CycleGAN achieved the second-best performance in UIQM. (2) In the three subsets of the RUIE dataset, CycleGAN consistently achieved the best performance in terms of UIQM across all subsets.

4.4. High-level Computer Vision Task Evaluation

The object detection task was carried out after the image enhancement UHTS dataset to further verify the effectiveness of image enhancement for subsequent high-level computer vision tasks. The five subsets of UHTS were enhanced with different models and then target detection was performed on the YOLOv7[47]. The detection accuracy results are shown in Table 3 and Fig.5, and the corresponding target detection visualization with label block is shown in Fig.6 below.

As shown in Table 2, Table 3, Fig. 5, and Fig. 6, it is important to note that, despite not achieving the highest scores in objective metrics such as PSNR, SSIM, and UIQM, the Retinex model performs the best in terms of target detection. This suggests that higher objective metric values do not necessarily correlate with better image quality for computer vision tasks.

Table 3. Comparison of mAP for UHTS dataset

Models / Subsets	Haze	CLAHE	DCP	Retinex	UCM	GCAnet	CycleGAN
	mAP (%)						
A	0.468	0.438	0.46	0.502	0.453	0.476	0.451
B	0.566	0.541	0.559	0.555	0.572	0.575	0.511
C	0.615	0.581	0.609	0.706	0.589	0.59	0.518
D	0.556	0.524	0.532	0.551	0.55	0.52	0.551
E	0.828	0.802	0.843	0.843	0.778	0.817	0.751

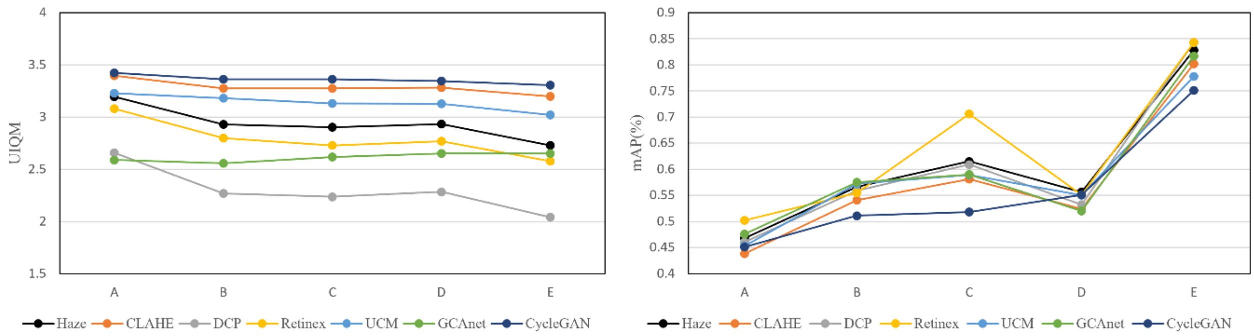
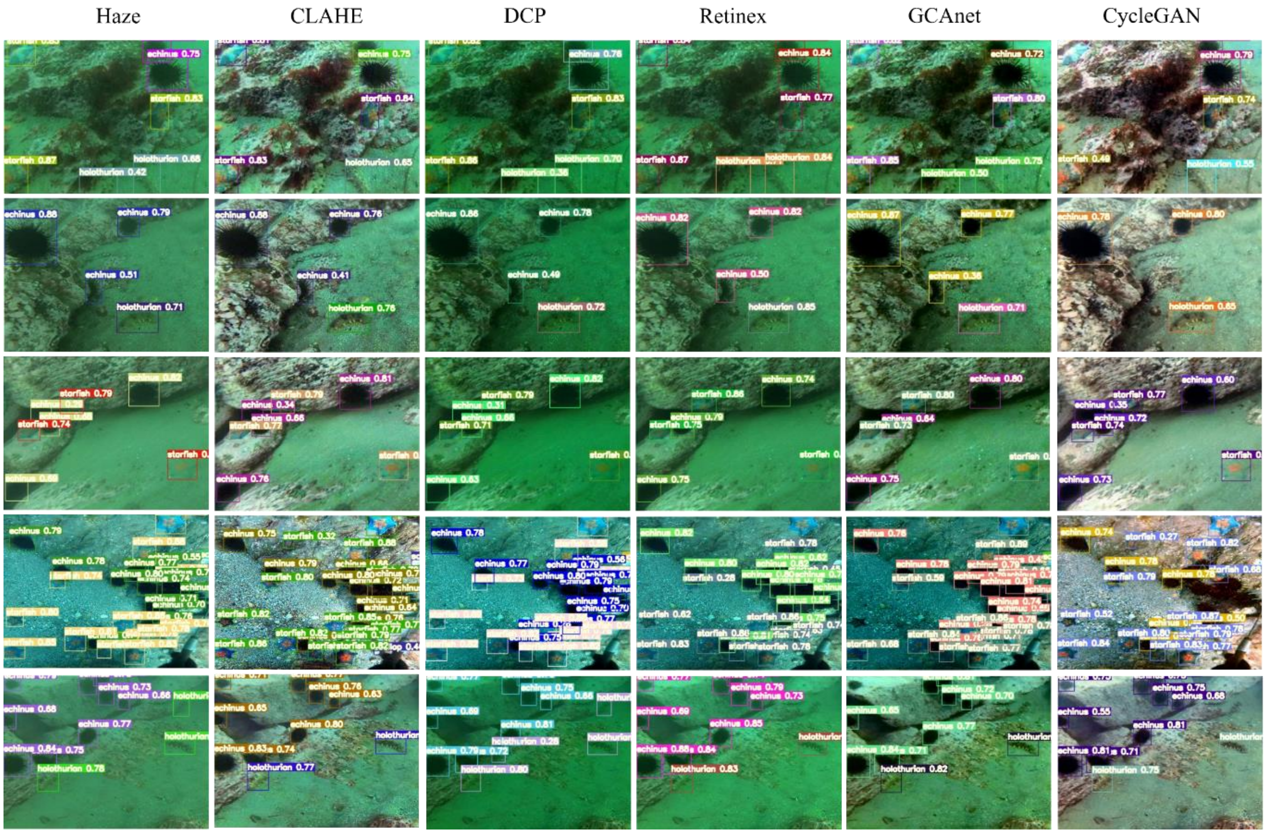


Fig.5 Comparison of UIQM and mAP for UHTS dataset



(The five rows in the figure from top to bottom are in order of the ABCDE subset.)

Fig.6 Visualization of target detection results

5. Conclusion and Outlook

In this work, we provide an overview of the research in the field of UIE. Firstly, we introduce three categories of UIE algorithms: non-physical models, physical models, and deep learning models, and present representative algorithms for each category, followed by an analysis of their respective advantages and disadvantages. Secondly, we discuss underwater image datasets, including paired and unpaired image datasets. Subsequently, we review the primary evaluation metrics for UIE, categorized into non-reference and full-reference types. Finally, we conduct training on various models and perform both quantitative and qualitative evaluations. The enhanced images are then applied to a target detection task to demonstrate the effectiveness of UIE in supporting subsequent high-level CV tasks.

However, we also observed an issue where some models, despite achieving higher scores in objective image enhancement metrics, yielded lower accuracy in subsequent target detection tasks compared to unenhanced images. This highlights that objective metrics alone are insufficient for determining whether enhanced images will improve performance in high-level computer vision tasks. We aim to explore this further by developing a metric that more accurately reflects the perceptual quality of images for computer vision applications.

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