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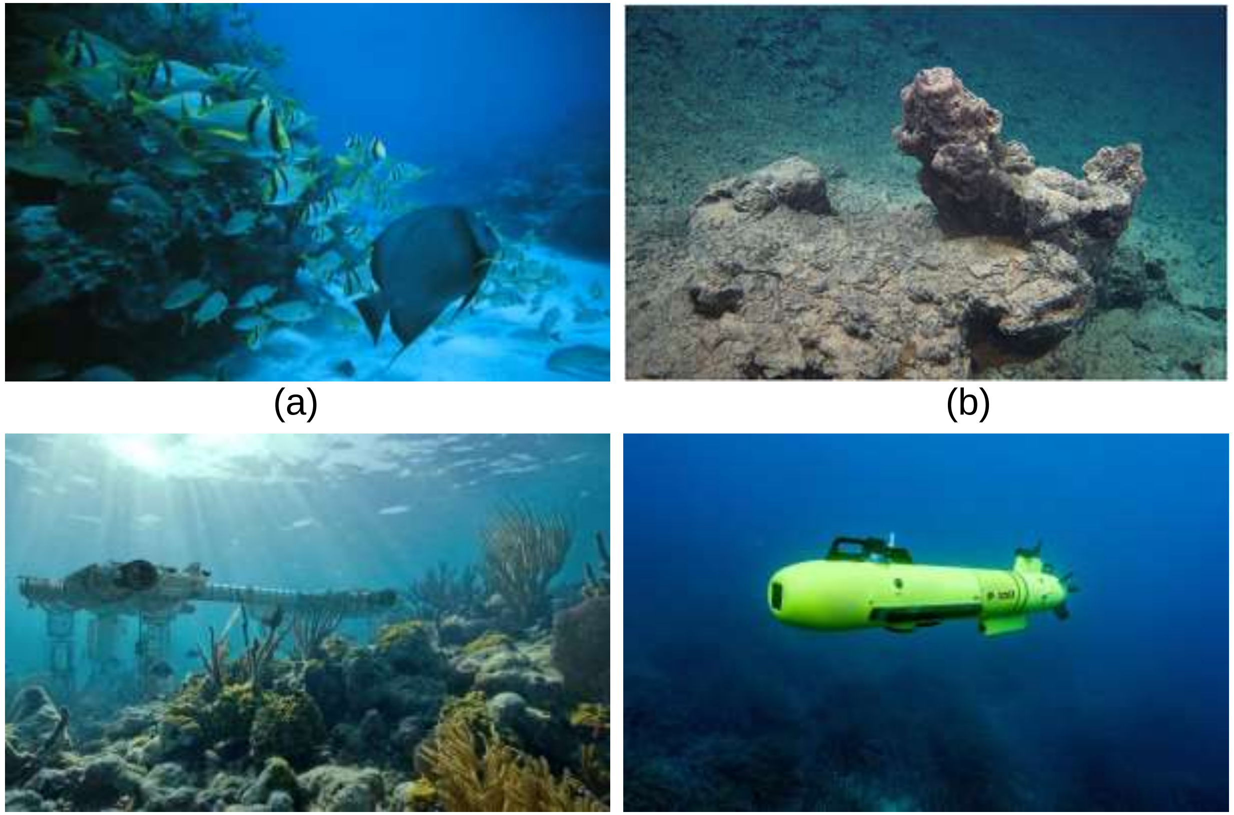
A Retinex-based Method for Underwater Image Enhancement

CONTENTS

1. Introduction

1.1 Motivation

- Deep sea and ocean exploration have increasingly attracted human attention.
- Fields such as marine ecological research, deep-sea facility monitoring, naval military applications, and underwater environmental protection are developing rapidly.
- High-quality underwater images are needed to obtain valuable information.



(a) (b)

(c) (d)

Fig1. Humanity’s exploration of the underwater world. (a) Coral reef ecosystem. (b) Polymetallic sulphide slot. (c) Deep-sea mining facility. (d) Autonomous underwater vehicle (AUV).

1.1 Motivation

- The complexity of underwater environments can lead to the degradation of underwater images.
- Degraded underwater images often face problems such as color distortion, low contrast, and blur, which limit the development of the underwater field.
- Therefore, it is necessary to propose an effective underwater image enhancement method.

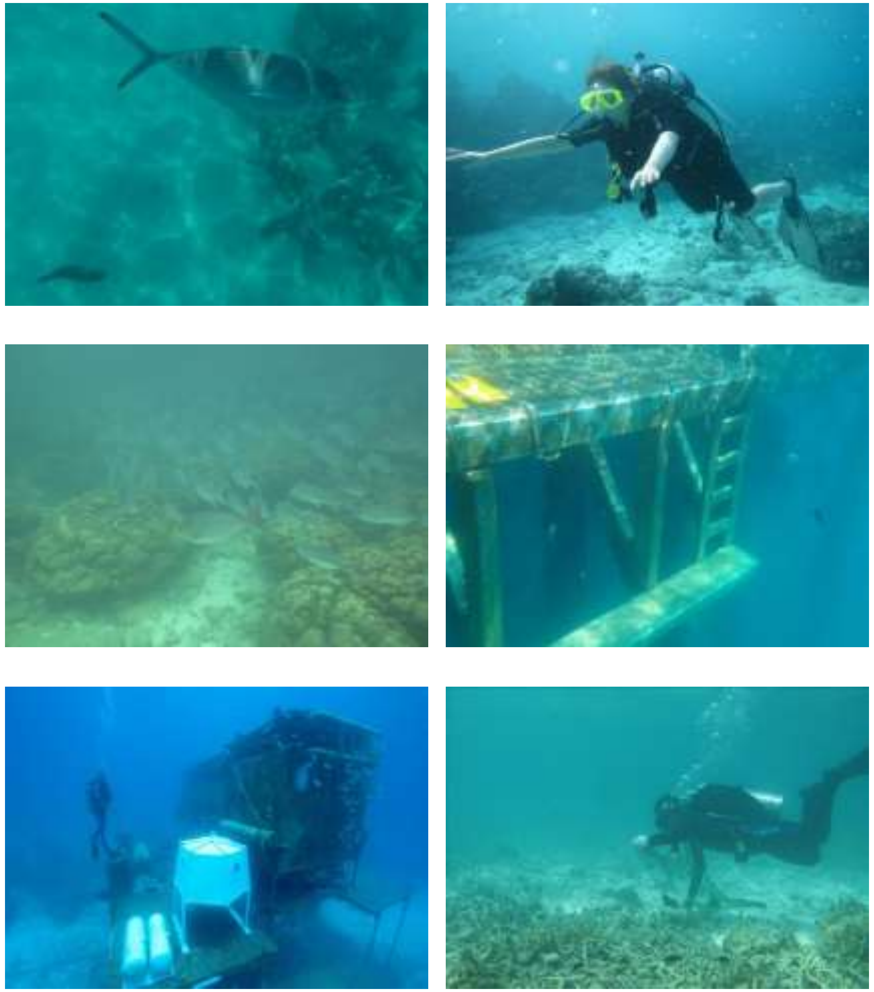


Fig2. Degraded underwater images face problems of color distortion, low contrast, and blur.

1.2 Description of Underwater Environment

Jaffe-McGlamery underwater image model

$$E_T = E_d + E_f + E_b$$

E_T - Total irradiance which enters the camera
E_d - Direct component
E_f - Forward scattering component
E_b - Backward scattering component

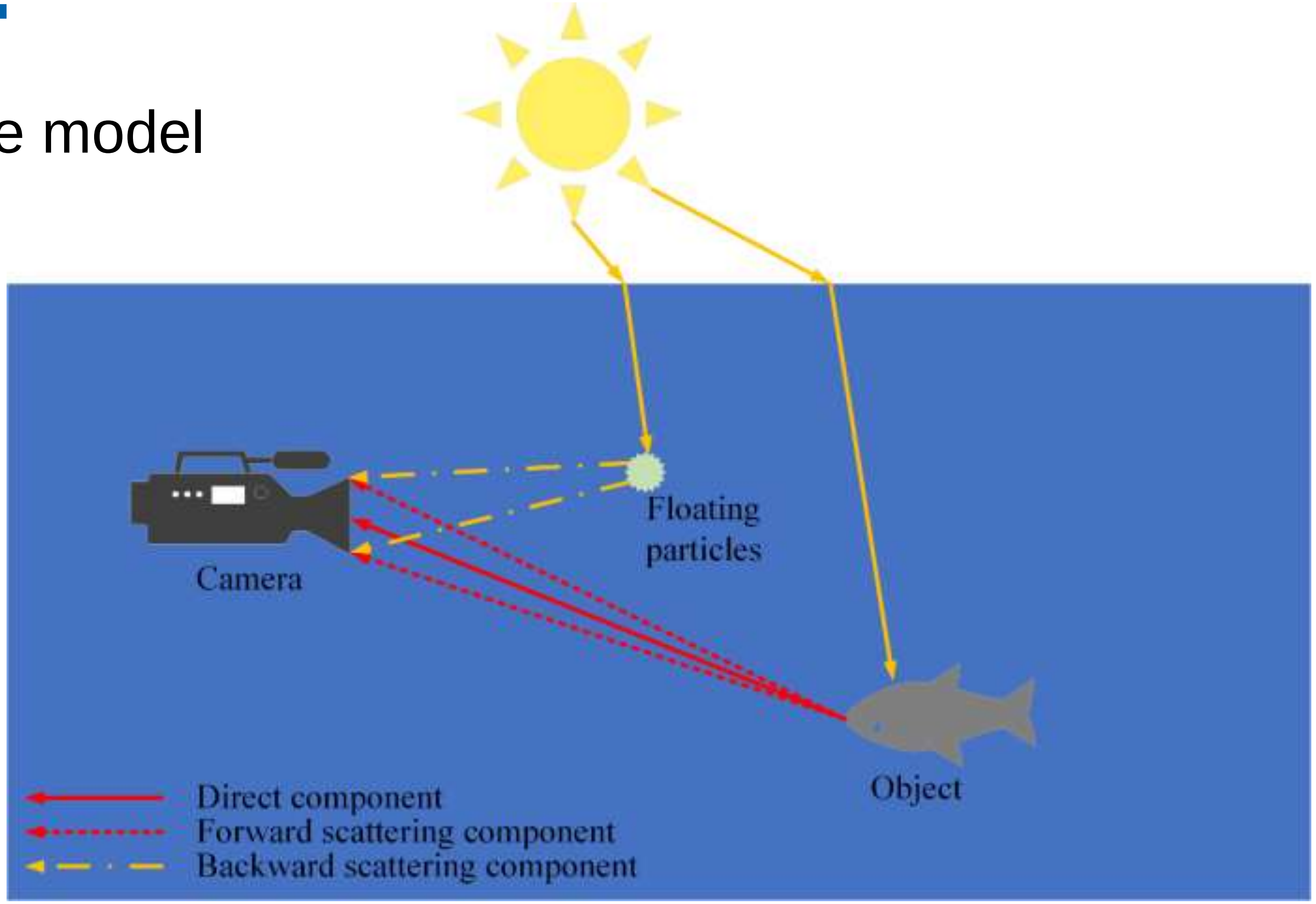


Fig3. Jaffe-McGlamery underwater imaging model.

1.2 Description of Underwater Environment

- Another property of light propagation underwater is absorption.
- The absorption of light in water varies with wavelength.
- Red light with longer wavelengths is absorbed first by water, followed by orange, yellow, green, and blue.
- Underwater images mostly have green or blue tones.

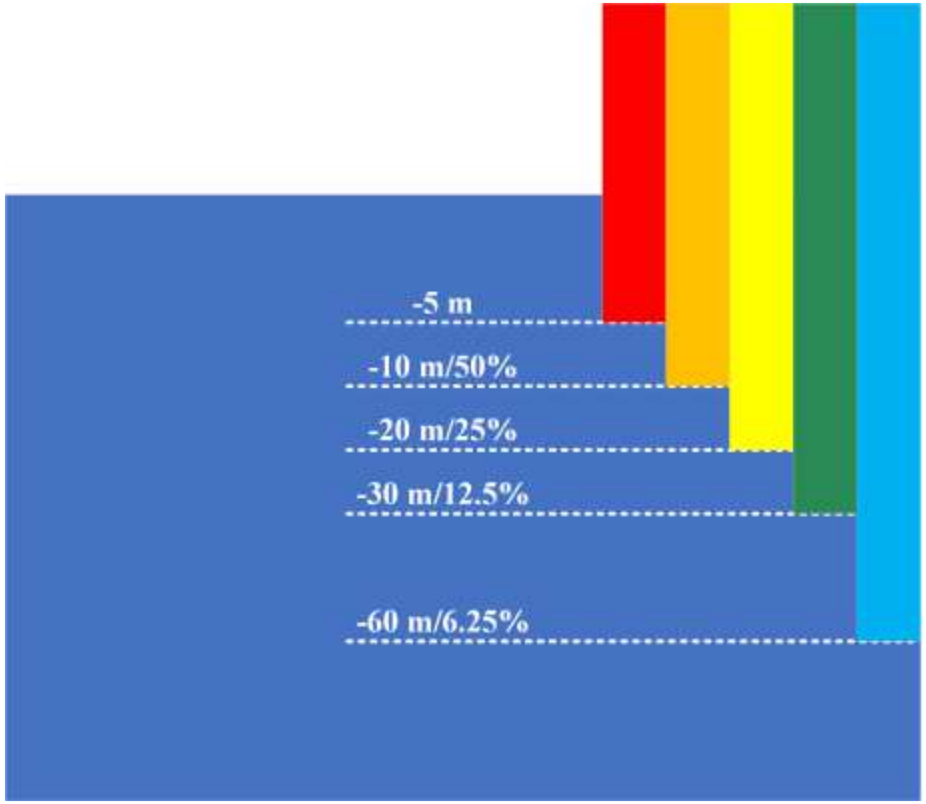


Fig4. The selective attenuation of light.

2. Related Work

2.1 Underwater Image Restoration Methods

- This kind of method **builds an appropriate physical model** by studying the physical mechanisms of underwater image degradation.

- These methods usually follow the same pipeline:

  1) building a physical model of the degradation;
  2) estimating the unknown model parameters;
  3) addressing this inverse problem.

Method	Principle
Underwater Optical Imaging-Based Methods	$I(x,y) = J(x,y)t(x,y) + A(1 - t(x,y))$
Polarization Characteristics-Based Methods	$I(x,y) = D(x,y) + B(x,y)$
Prior Knowledge-Based Methods	$J^{dark}(x) = \min_{C\in\{r,g,b\}}(\min_{y\in\Omega(x)} J^C(y)) \approx 0$

2.2 Underwater Image Enhancement Methods

- This kind of method does **not consider the actual physical process** of image degradation, but rather the degraded image.

- The enhanced image with higher contrast, richer detail information, and better visual effects by enhanced processing.

Method	Principle
Frequency Domain-Based Methods	Convolution or spatial transformation
Spatial Domain-Based Methods	Grayscale mapping
Color Constancy-Based Methods	White balance and Retinex
Fusion-Based Methods	Gaussian Pyramid or Laplacian Pyramid
Deep Learning-Based Methods	Deep network structure has better feature extraction ability

3. Methodology

3 Methodology

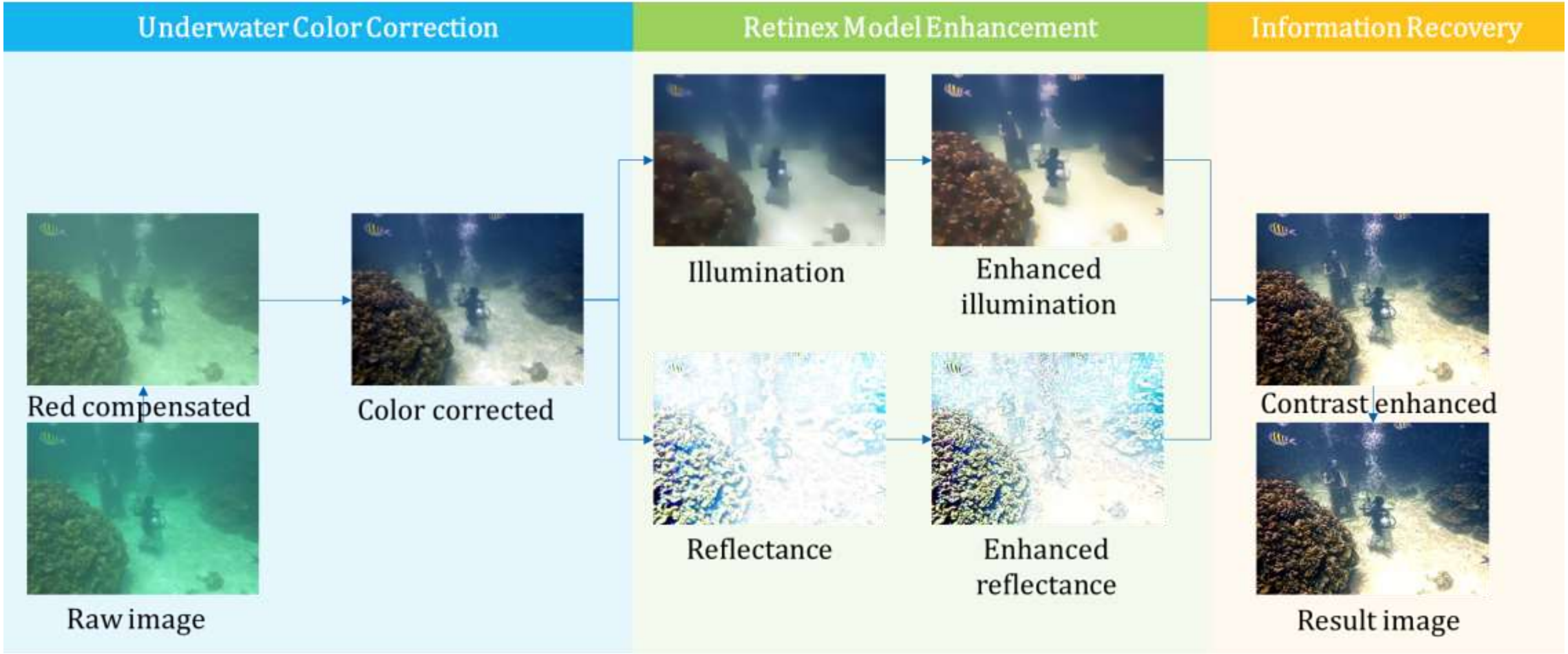


Fig5. Flowchart of the proposed method.

3.1 Underwater Color Correction

Red channel compensation equation

$$I_{rc}(x) = I_r(x) + \alpha\left(\bar{I}_g - \bar{I}_r\right)\left(1 - I_r(x)\right) I_g(x)$$

I_r, I_g - Red and green color channels of image I

$\bar{I}_r, \bar{I}_g$ - The mean value of I_r, I_g

α - a constant parameter

I_{rc} - Red corrected color channel

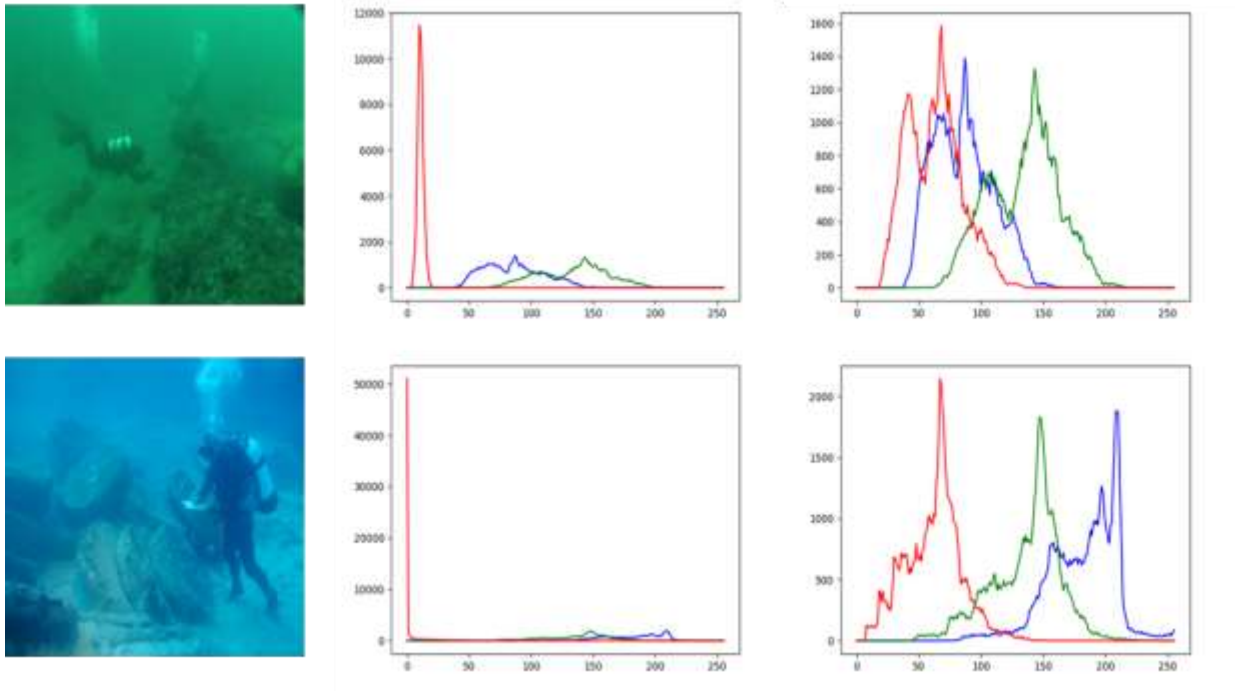
(a) Raw (b) Red channel (c) SSR[1] (d) MSR[2] (e) Ours

Fig6. Underwater color correction. (a) Raw. (b) Red light is absorbed underwater. (c) SSR results. (d) MSR results. (e) Our results.

3.1 Underwater Color Correction

Red channel compensation equation

$$I_{rc}(x) = I_r(x) + \alpha\left(\bar{I}_g - \bar{I}_r\right)\left(1 - I_r(x)\right) I_g(x)$$



(a) Raw

(b) Before red compensation

(c) After red compensation

Fig7. Underwater Red channel compensation.

Fig8. The result of color correction.

3.2 Retinex Model Enhancement

A simplified Retinex model can be expressed as

$$\boldsymbol{I} = \boldsymbol{L} \odot \boldsymbol{R}$$

$\boldsymbol{I}$ - The observed image
$\boldsymbol{L}$ - The illumination component
$\boldsymbol{R}$ - The reflectance component
$\odot$ - The element-wise multiplication

The objective function that estimates illumination and reflectance components

$$\min_{\boldsymbol{L},\boldsymbol{R}} \left\|\boldsymbol{I} - \boldsymbol{L} \odot \boldsymbol{R}\right\|_F^2 + \alpha\left\|\boldsymbol{S}_0 \odot \nabla\boldsymbol{L}\right\|_F^2 + \beta\left\|\boldsymbol{T}_0 \odot \nabla\boldsymbol{R}\right\|_F^2$$

$\boldsymbol{S}_0$, $\boldsymbol{T}_0$ - The weighting matrices of $\boldsymbol{L}$ and $\boldsymbol{R}$
α, β - Constant parameters

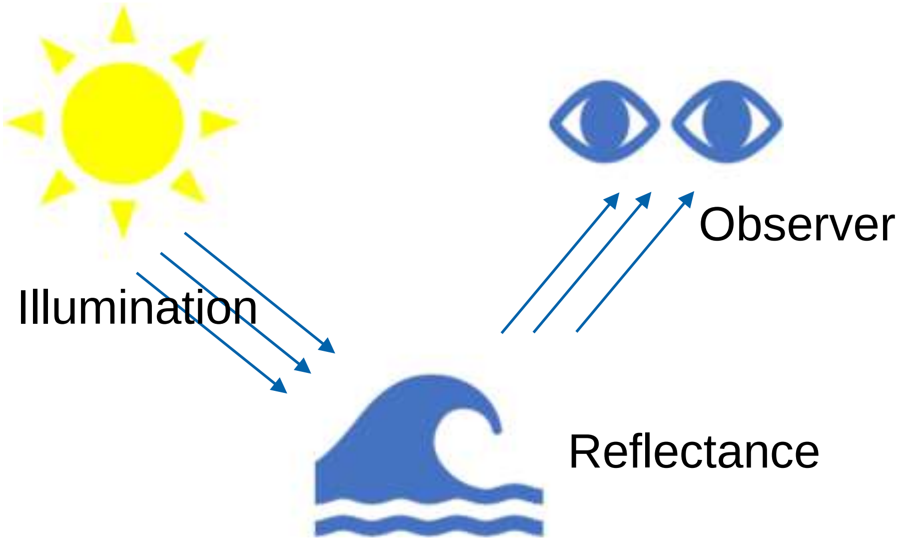


Fig9. Retinex theory model.

3.2 Retinex Model Enhancement

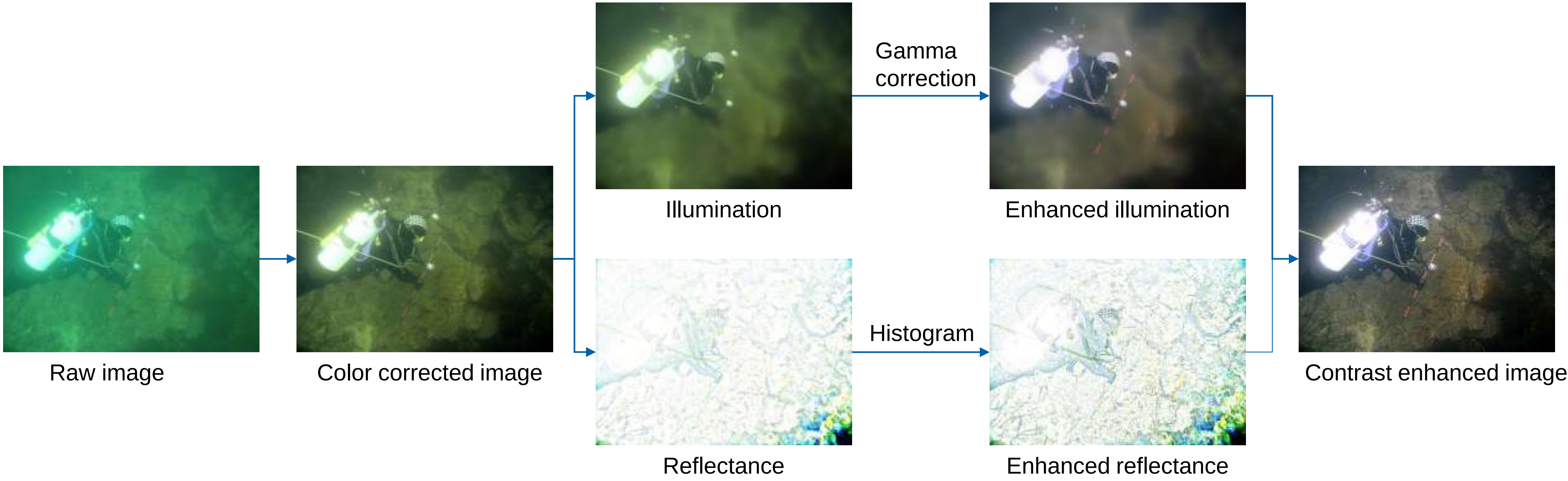


Fig10. Retinex Model Enhancement.

3.3 Underwater Information Recovery

- Recover missing details through morphological operations, overcoming blur caused by scattering.

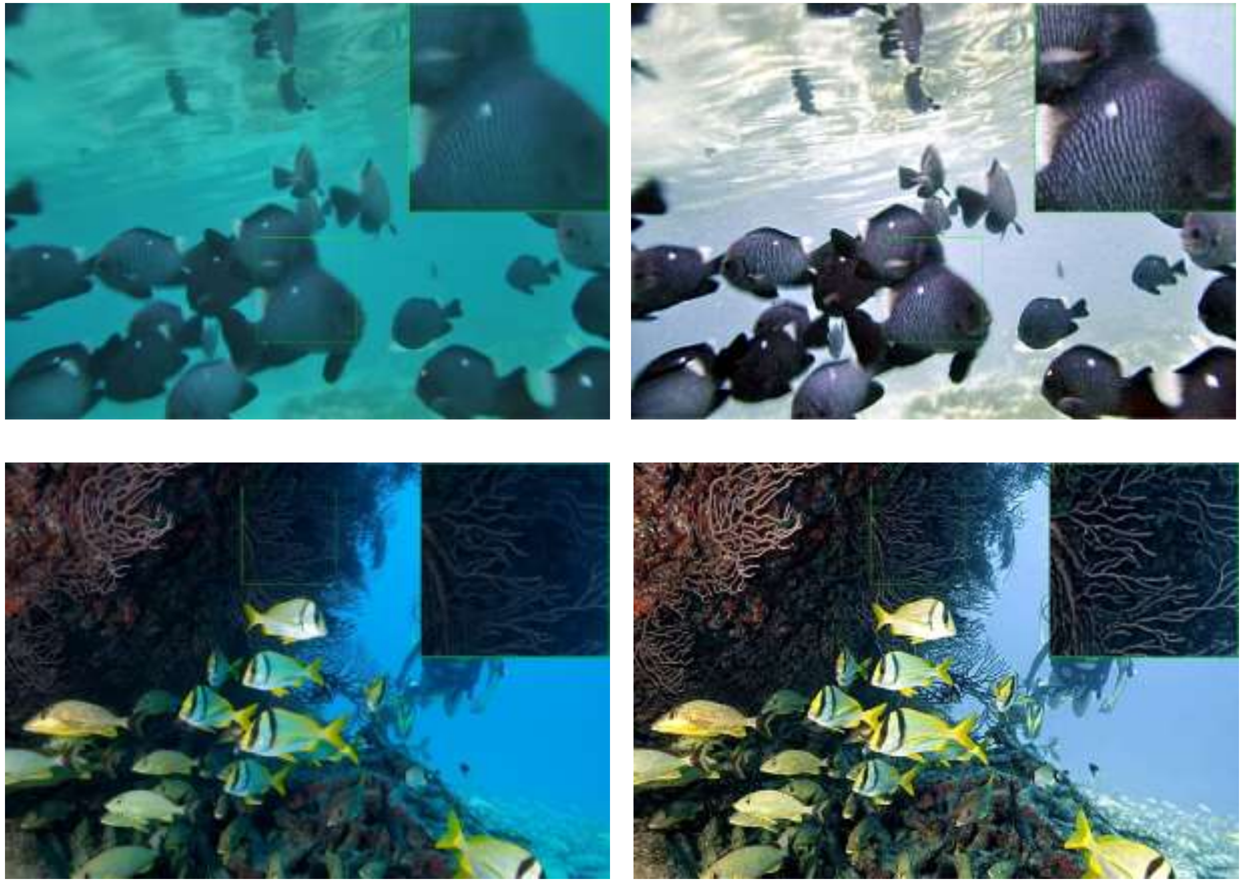
- Through an appropriate combination of morphological opening and closing operations, missing texture details can be filled in and unwanted noise eliminated.

- The top-hat transformation can be expressed as

$$Wh(I, b_1, b_2) = I - M_c((M_o(I, b_1)), b_2)$$

$$Bh(I, b_1, b_2) = M_o\left((M_c(I, b_1)), b_2\right) - I$$

Wh - The white top-hat transformation
Bh - The black bottom-hat transformation
M_0 - The morphological opening operation
M_c - The morphological closinging operation
b_1, b_2 - Two different structural elements



(a) (b)

Fig11. Underwater information recovery results. (a) Original images. (b) Morphological enhanced results.

4. Experimental Results

4 Experiment

- Comparison Methods. Including UDCP[3], GDCP[4], TACL[5], WWPF[6], PUIE-Net[7], and SGUIE-Net[8].

- Benchmark Datasets. Testing on the UCCS and UIEB datasets.

- Evaluation Metrics. Underwater color image quality evaluation (UCIQE), underwater image quality measure (UIQM), and patch-based contrast quality index (PCQI).

4.1 Color Correction Comparisons

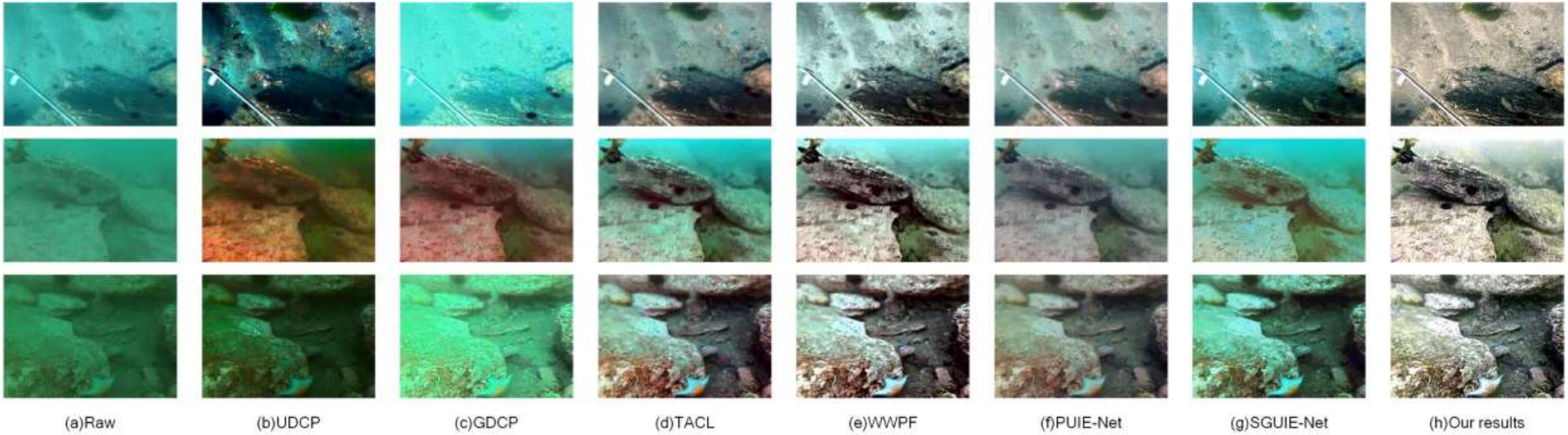


Fig12. Visual comparisons on the UCCS dataset. From top to bottom are the raw underwater images sampled from the Blue, Blue-green, and Green subsets of UCCS, respectively.

4.2 Detail Enhancement Comparisons

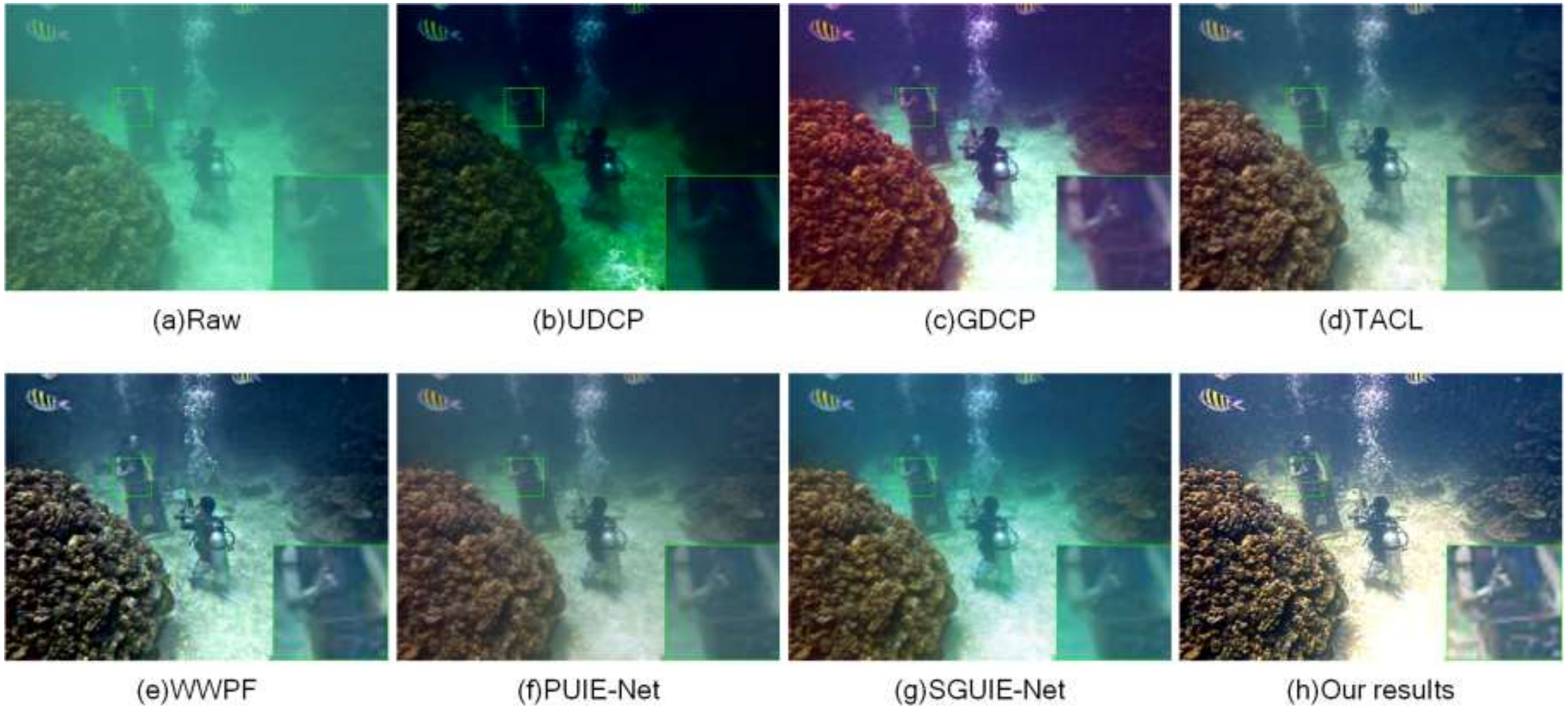


Fig13. Visual comparisons of detail enhancement.

4.3 Comprehensive Comparisons on UIEB

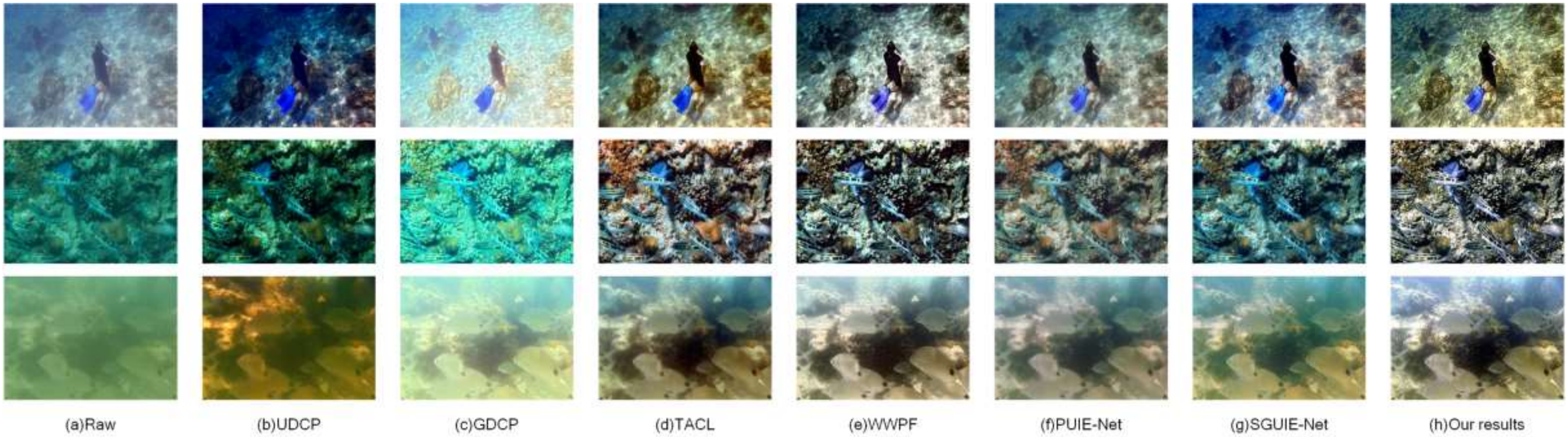


Fig14. Visual comparisons on the UIEB dataset. From top to bottom are hazy, color distortion and low visibility underwater images, respectively.

4.3 Comprehensive Comparisons on UIEB

Table1. Quantitative Comparisons of Different Methods on the UIEB dataset.
The best result is in red, while the second best result is in blue under each case.

Method	UCIQE	UIQM	PCQI
UDCP	0.5980	1.5724	0.8518
GDCP	0.6044	1.4695	0.8611
TACL	0.6125	1.3600	0.9838
WWPF	0.6181	1.5405	1.1947
PUIE-Net	0.5852	1.2704	1.0715
SGUIE-Net	0.6192	1.3463	1.0004
Proposed	0.6419	1.5895	1.2037

5. Remaining Work

5 Remaining Work

Table2. Schedule.

Period	Tasks
January 2024	Complete a proposal for an image enhancement method.
February 2024	Obtain results from the proposed algorithm and analyze them.
March 2024	Improve the algorithm.
April 2024	Begin writing the thesis.
May and June 2024	Test the final algorithm and complete the writing of the thesis.

Thank you!

References

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