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A Retinex-based Method for Underwater Image Enhancement

CONTENTS

1. Introduction

1.1 Background

- The ocean covers approximately 71% of the Earth's surface and is a vast repository of biological and chemical resources essential for human survival.

- The advancement of underwater image enhancement will facilitate the development of marine scientific research and engineering construction.

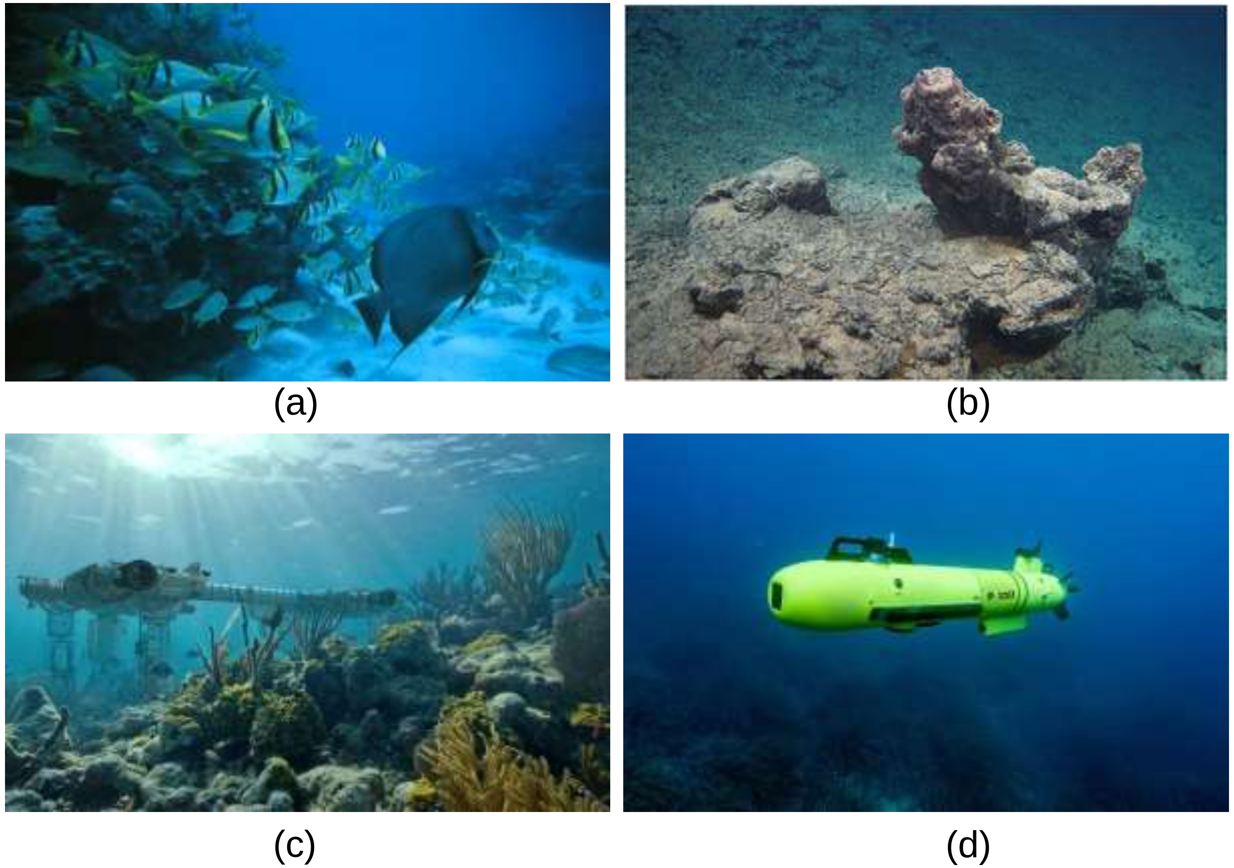

Fig. Humanity's explorations of the underwater world.
(a) Coral reef ecosystem. (b) Polymetallic sulphide slot. (c) Deep-sea mining facility. (d) Autonomous underwater vehicle (AUV).

1.2 Challenges

The field of underwater imaging faces a number of challenges, including:

- Absorption and scattering of natural light by water.
- Underwater images often face problems such as color distortion, low contrast, and blur.
- Specifically designed hardware is usually expensive and requires a significant amount of power.

Fig. Degraded underwater images.

1.3 Objectives

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It is necessary to propose an effective underwater image enhancement method.

- Propose a Retinex-based method for simulating the human visual perception system that is intended to enhance the contrast of underwater images.

- In consideration of the inherent optical properties underwater, employ an improved color correction technique to avoid introducing artifacts.

- In the case of hazy or blurred images, use morphological operations to improve the visibility of details.

2. Related Work

2.1 Underwater Imaging Theory

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

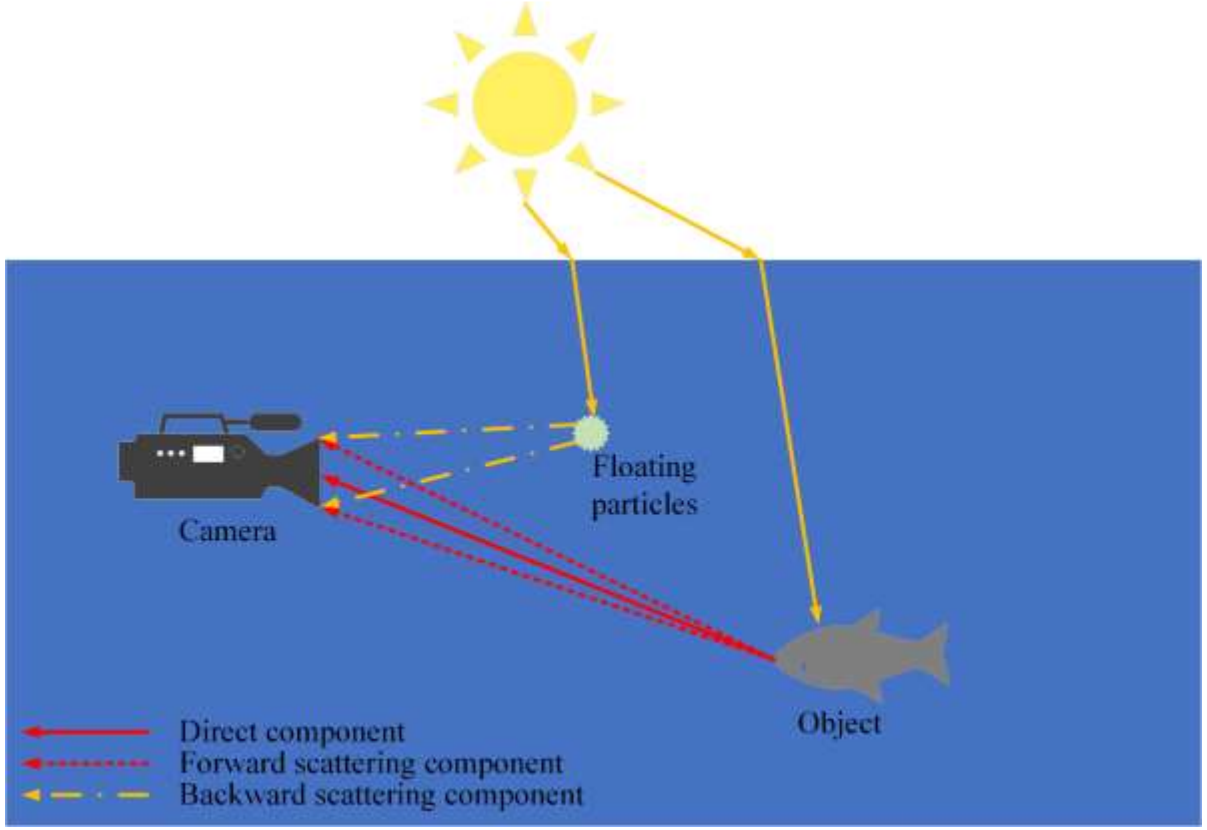

Fig. Jaffe-McGlamery underwater imaging model.

2.1 Underwater Imaging Theory

Absorption of light during underwater propagation

- 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 having mostly green or blue tones.

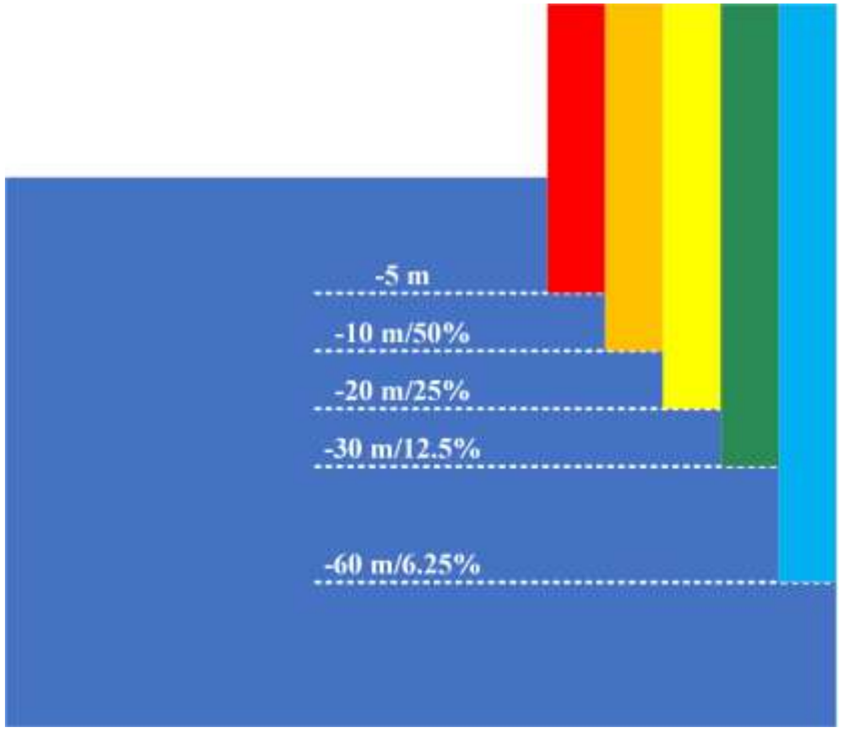

Fig. The selective attenuation of light.

2.2 Underwater Image Processing Technology

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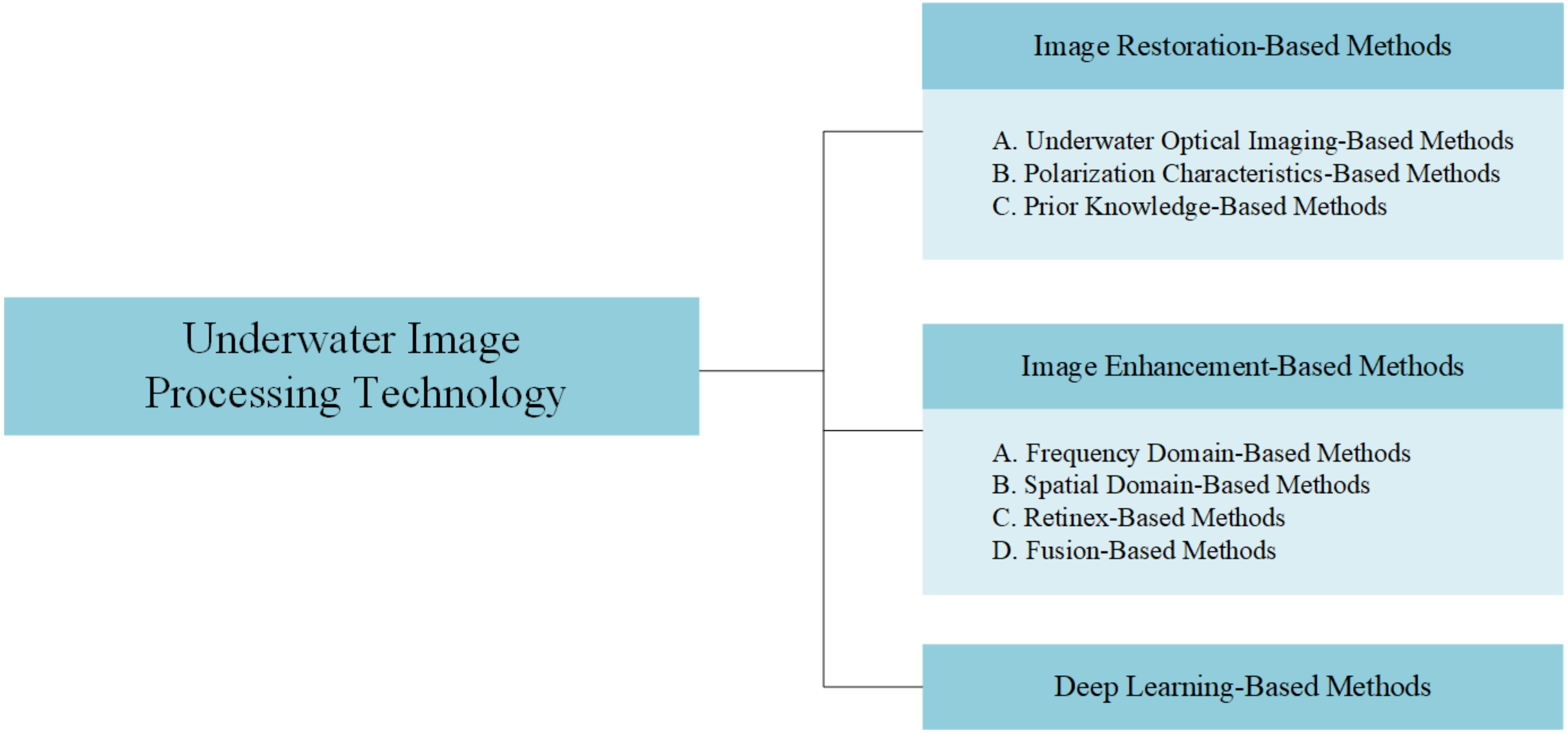

Fig. Underwater Image Processing Technology.

2.2.1 Image Restoration-Based 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.

- These methods follow simplified image formation models, but real scenes are more complex, and parameter estimation is also a big challenge.

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

2.2.2 Image Enhancement-Based 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.
- Over-exposure and over-enhancement also occur frequently.

Method	Principle
Frequency Domain-Based Methods	Convolution or spatial transformation
Spatial Domain-Based Methods	Grayscale mapping
Retinex-Based Methods	Color Constancy
Fusion-Based Methods	Gaussian Pyramid or Laplacian Pyramid

2.2.3 Deep Learning-Based methods

- This kind of method aims to use network models with rich structures to learn nonlinear representations of training data.

- The lack of high-quality training datasets limits the development of deep learning based methods.

Method	Example
Convolutional Neural Network, CNN	WaterNet, UWCNN, UColor
Generative Adversarial Network, GAN	WaterGAN, UGAN, TACL
Vision Transformer, ViT	URSCT-SESR

3. Methodology

3 General Framework

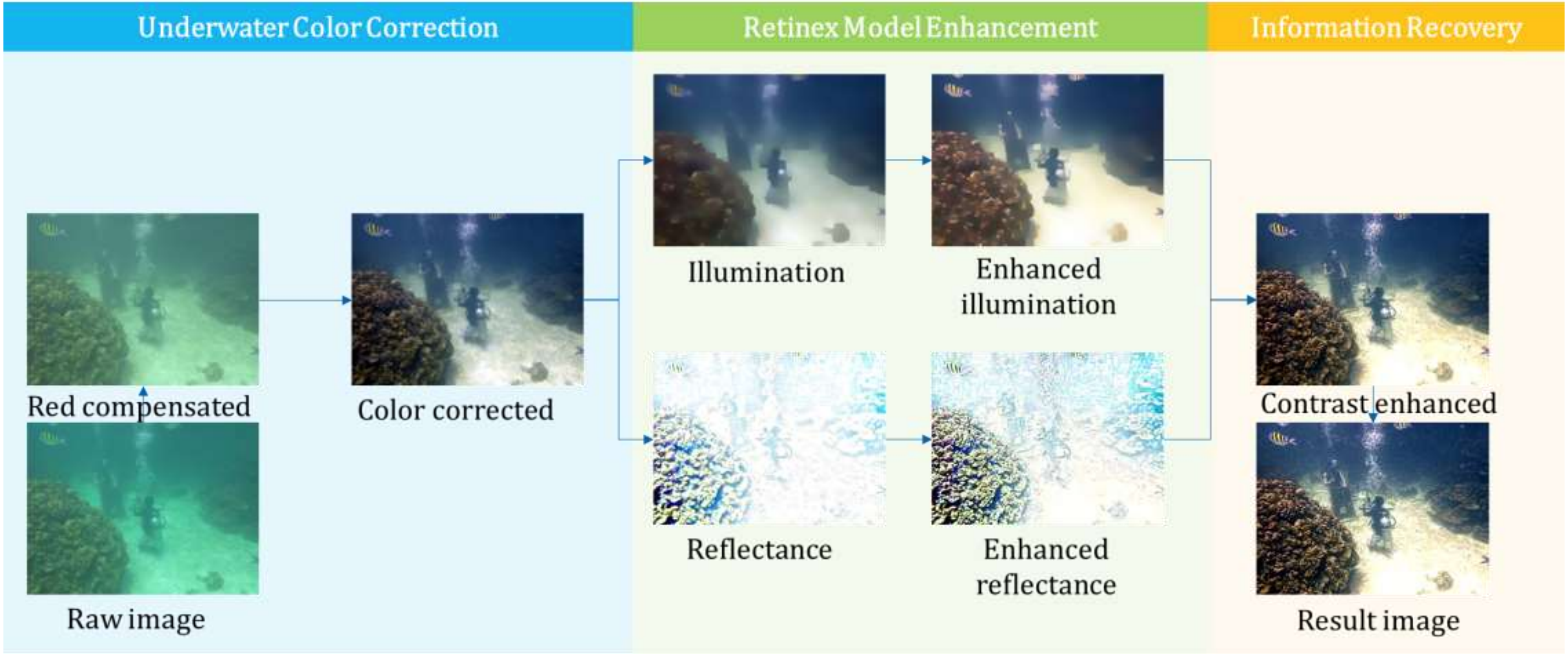

Fig. Flowchart of the proposed method.

3.1 Underwater Color Correction

Red channel compensation equation

$$R_{comp} = R + \rho \times (\bar{G} - \bar{R}) \times (1 - R) \times G$$

R, G - Red and green channels
$\bar{R}, \bar{G}$- The mean value of R, G
ρ - a constant parameter
R_{comp} - Red compensated channel

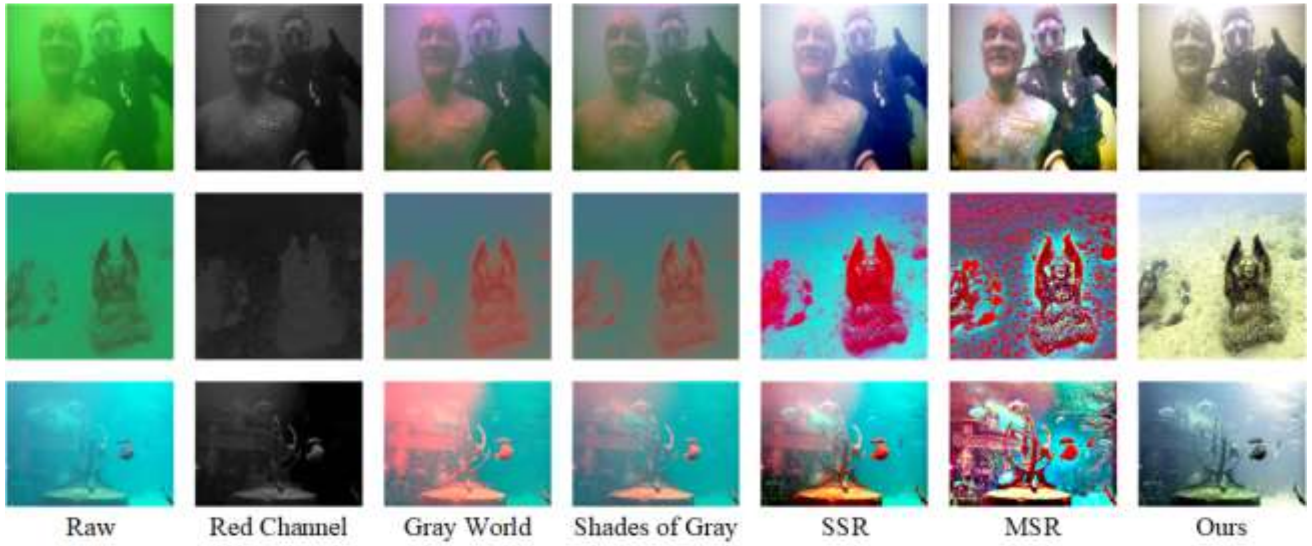

Fig. Underwater color correction results. Applying color correction directly will produce severe red artifacts.

3.1 Underwater Color Correction

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Red channel compensation equation

$$R_{comp} = R + \rho \times (\bar{G} - \bar{R}) \times (1 - R) \times G$$

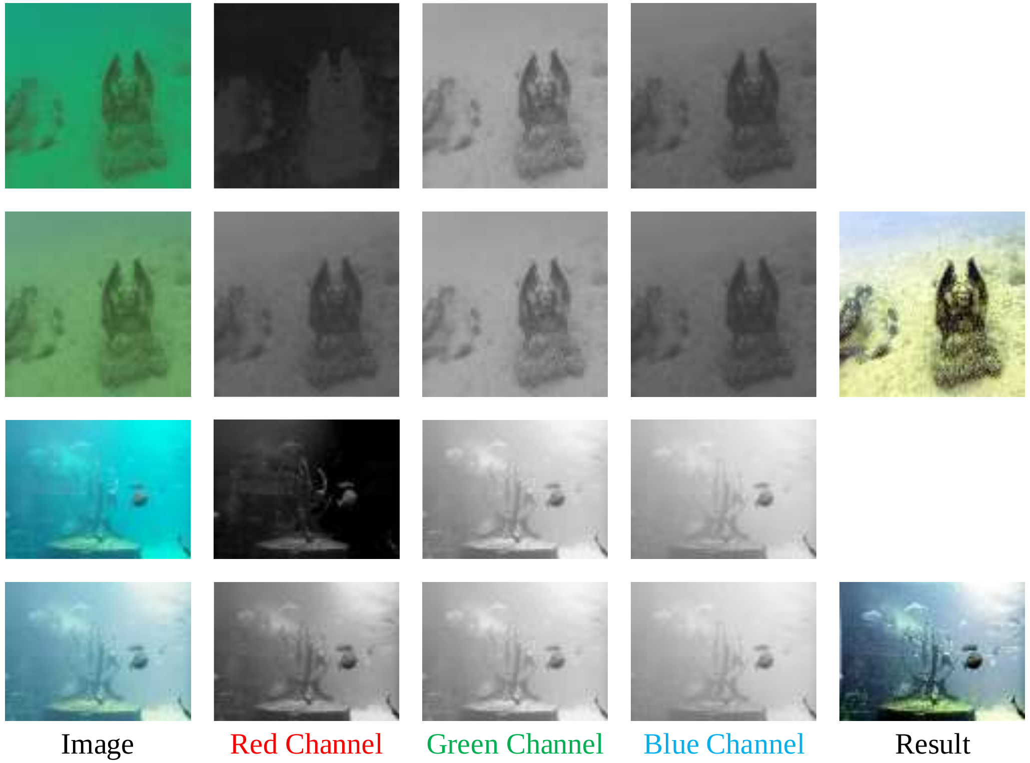


Fig. Red channel compensation.

Fig. Color correction results under different background colors.

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

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

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

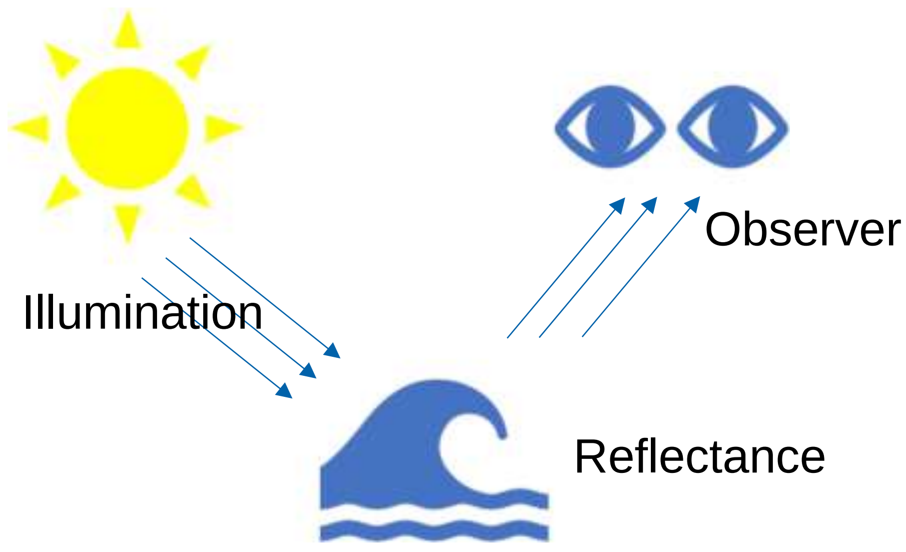


Fig. Retinex theory model.

3.2 Retinex Model Enhancement

Algorithm 1 Retinex Model Decomposition

Input: Input image $\boldsymbol{I}$, parameters α, β, maximum iteration number k;

while $k = 0, 1, 2, \ldots, K-1$ **do**

Update $\boldsymbol{L}_{k+1}$ by

$$\boldsymbol{L}_{k+1} = \arg\min_{\boldsymbol{L}} \|\boldsymbol{I} - \boldsymbol{L} \odot \boldsymbol{R}_k\|_F^2 + \alpha \|\boldsymbol{S}_0 \odot \nabla \boldsymbol{L}\|_F^2 \tag{3.1}$$

Update $\boldsymbol{R}_{k+1}$ by

$$\boldsymbol{R}_{k+1} = \arg\min_{\boldsymbol{R}} \|\boldsymbol{I} - \boldsymbol{L}_{k+1} \odot \boldsymbol{R}\|_F^2 + \beta \|\boldsymbol{T}_0 \odot \nabla \boldsymbol{R}\|_F^2 \tag{3.2}$$

if Converged **then**

Stop

end if

end while

Output: Estimated illumination $\widehat{\boldsymbol{L}}$ and reflectance $\widehat{\boldsymbol{R}}$

3.2 Retinex Model Enhancement

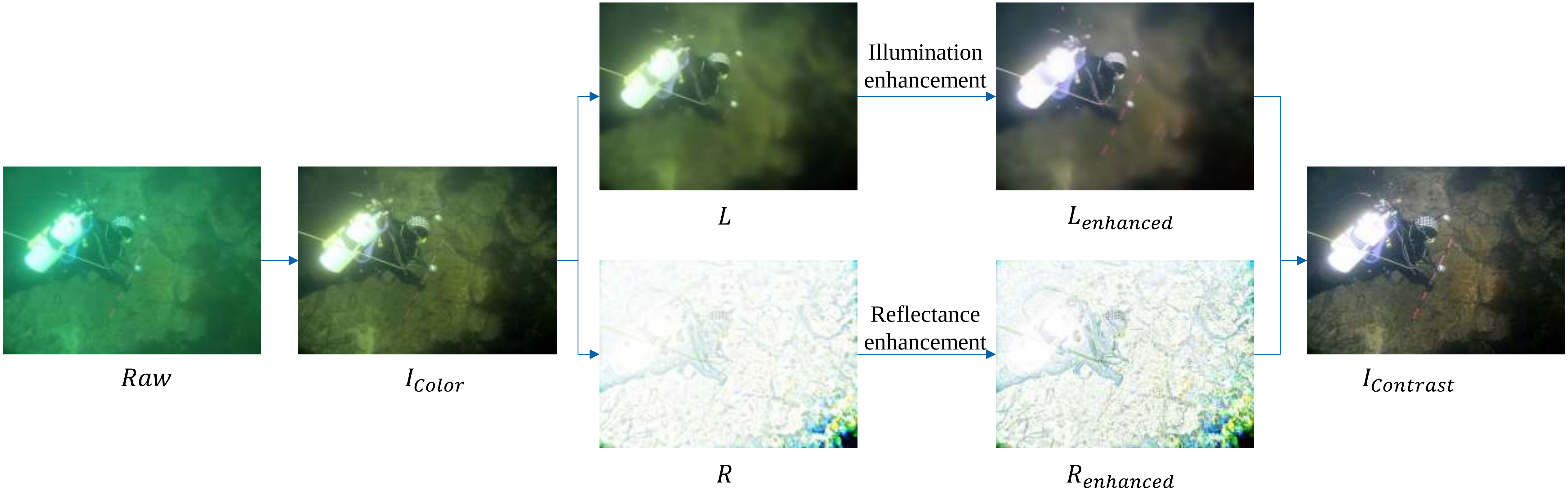


Fig. The process of enhancing underwater image based on Retinex.

3.3 Underwater Information Recovery

- Recover missing details through morphological operations, overcoming blur caused by scattering.
- Through appropriate combinations of morphological opening and closing operations, missing details can be filled in and unwanted noise eliminated.
- Introduce two different-sized structural elements to reconstruct missing details of underwater images.
- The new proposed morphological operations can be expressed as

$$\mathbb{W}(I, \varepsilon_1, \varepsilon_2) = I - [(I \circ \varepsilon_1) \bullet \varepsilon_2]$$

$$\mathbb{B}(I, \varepsilon_1, \varepsilon_2) = [(I \bullet \varepsilon_1) \circ \varepsilon_2] - I$$

$\mathbb{W}$ - The white top-hat transformation
$\mathbb{B}$ - The black bottom-hat transformation
$\circ$ - The morphological opening operation
$\bullet$ - The morphological closinging operation
$\varepsilon_1, \varepsilon_2$ - Two different structural elements

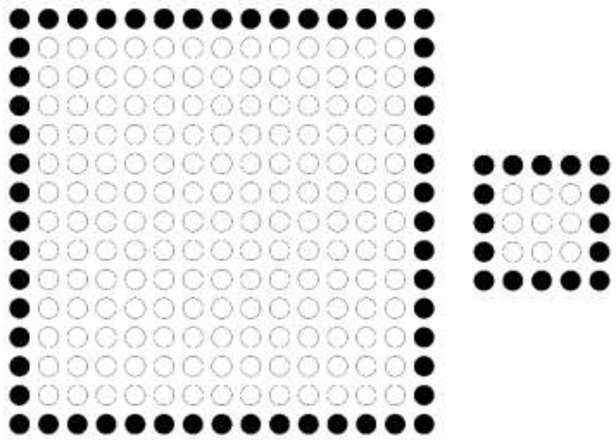


Fig. Structure elements. $\varepsilon_1 = 15 \times 15, \varepsilon_2 = 5 \times 5$.

3.3 Underwater Information Recovery

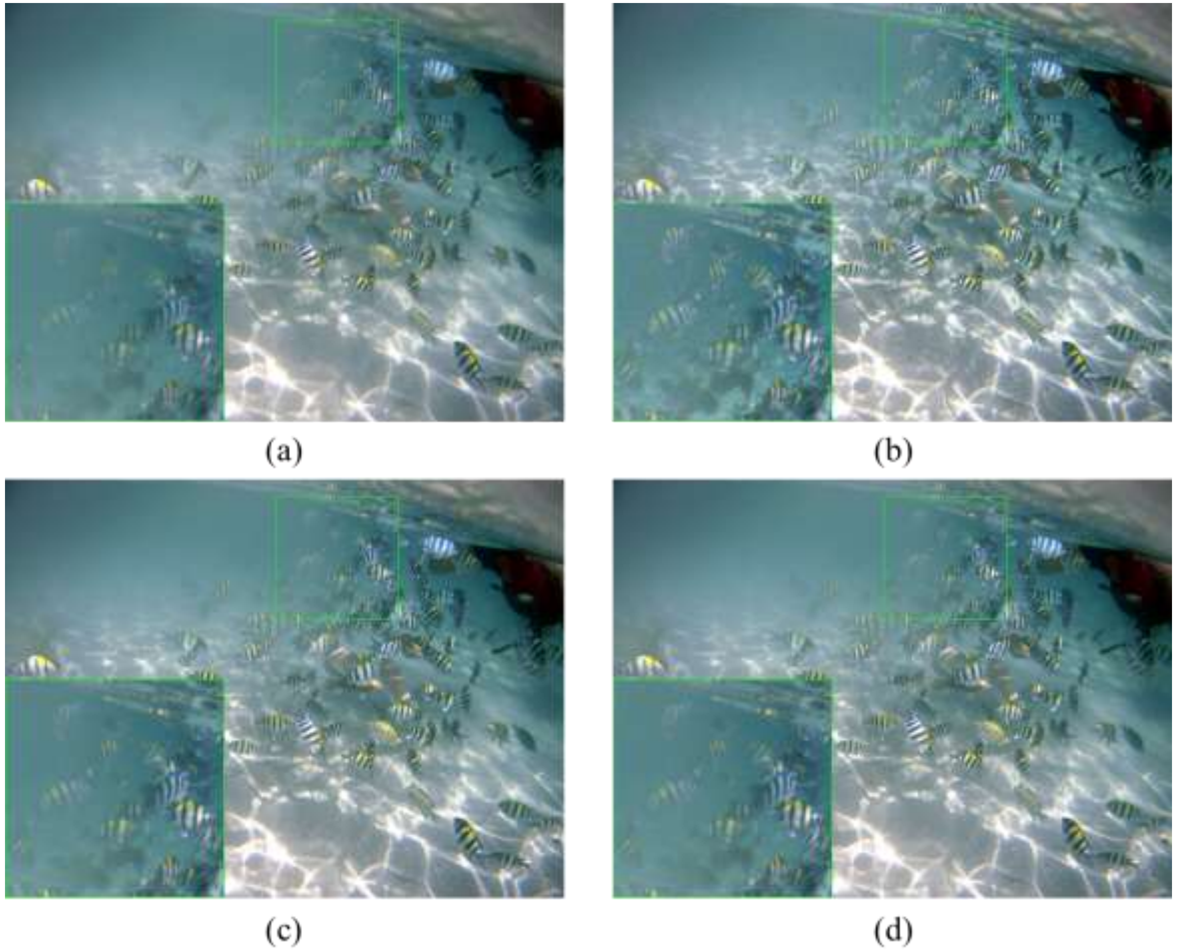


Fig. Detail enhancement results using different structure elements. (a) Blurred image. (b) $\varepsilon_1 = 15 \times 15, \varepsilon_2 = 5 \times 5$. (c) $\varepsilon_1 = 10 \times 10, \varepsilon_2 = 10 \times 10$. (d) $\varepsilon_1 = 5 \times 5, \varepsilon_2 = 15 \times 15$.

Fig. Detail enhancement results.

4. Experiment Results

4.1 Experiment Settings

- Comparison Methods. Comparison with 10 other methods, including UDCP, GDCP, BRUIE, Shallow-UWnet, SGUIE-Net , TACL, PUIE-Net, WWPF, MSPE, CMSFFT.

- Benchmark Datasets. Testing on the UCCS, UIEB and U45 datasets.

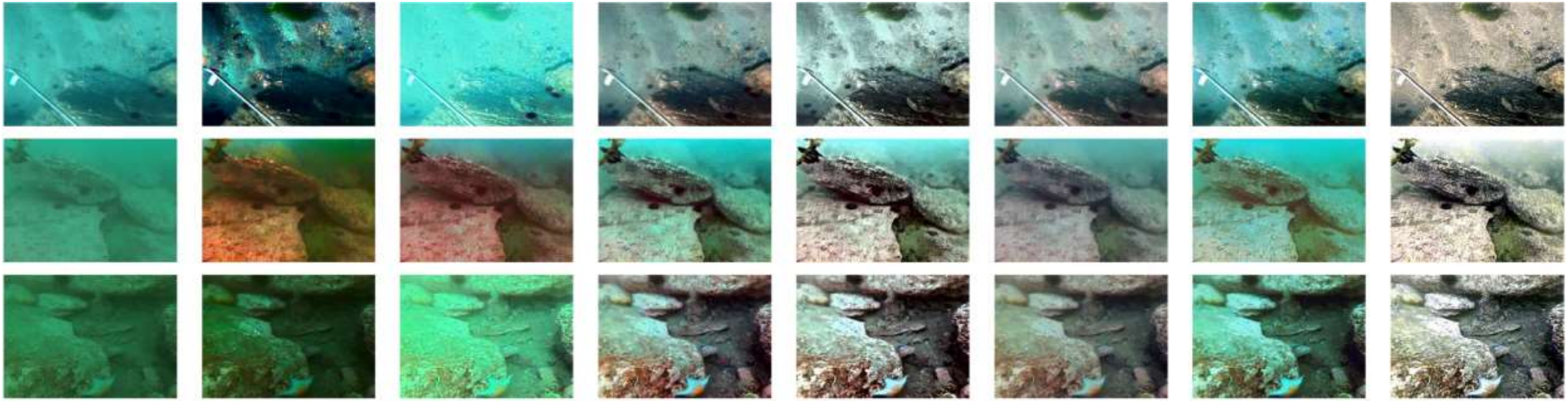
- Evaluation Metrics. Underwater color image quality evaluation (UCIQE), underwater image quality measure (UIQM), and frequency domain underwater measure (FDUM).

$$UCIQE = c_1 \times \sigma_{chroma} + c_2 \times l_{contrast} + c_3 \times \mu_{saturation}$$

$$UIQM = \gamma_1 \times D_{UICM} + \gamma_2 \times D_{UISM} + \gamma_3 \times D_{UIConM}$$

$$FDUM = \lambda_1 \times c_{Colorfulness} + \lambda_2 \times c_{Contrast} + \lambda_3 \times s_{Sharpness}$$

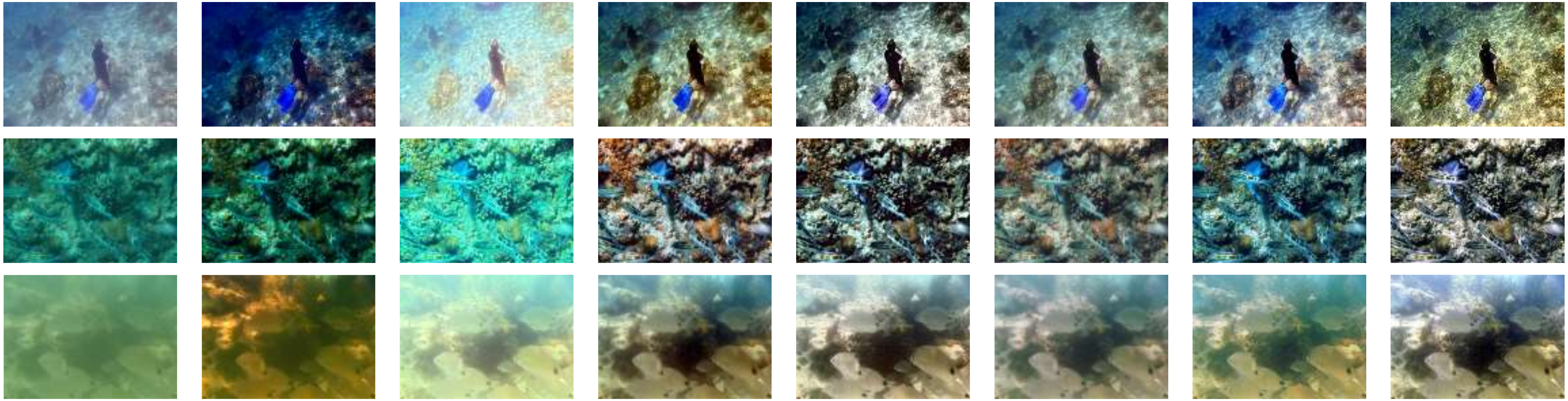
4.2 Comparison of Color Correction



(a)Raw (b)UDCP (c)GDCP (d)TACL (e)WWPF (f)PUIE-Net (g)SGUIE-Net (h)Our results

Fig. Comparative analysis of color correction techniques. From top to bottom are the raw underwater images from the Blue, Blue-green, and Green subsets of UCCS, respectively.

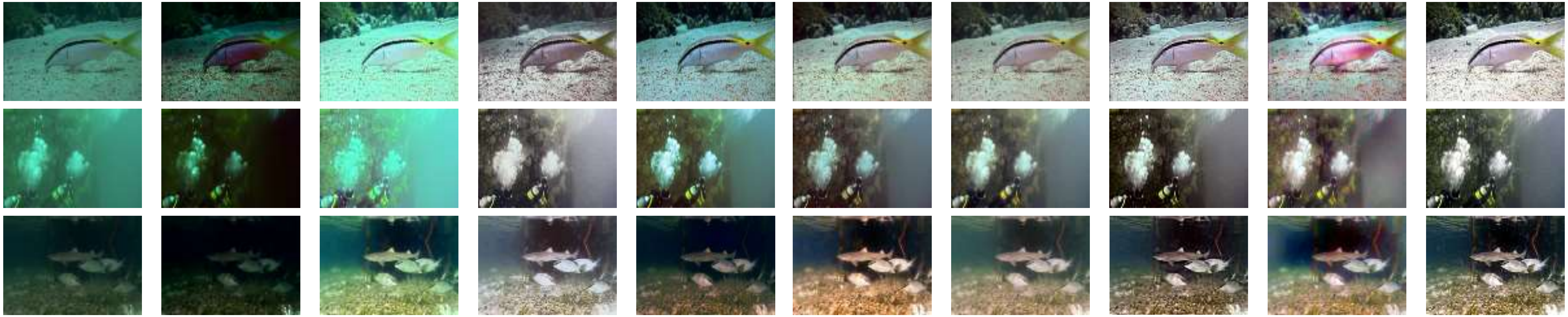
4.3 Comparison of Different Scenarios



(a)Raw (b)UDCP (c)GDCP (d)TACL (e)WWPF (f)PUIE-Net (g)SGUIE-Net (h)Our results

Fig. Comparative analysis based on the UIEB-890 dataset. Images presented from top to bottom demonstrate hazy,color distortion and poorly visible underwater images, respectively.

4.3 Comparison of Different Scenarios



(a) Raw (b) UDCP (c) GDCP (d) BRUIE (e) SGUIE-Net (f) TACL (g) PUIE-Net (h) WWPF (i) CMSFF (j) Proposed

Fig. Comparative analysis based on the UIEB-60 dataset.

4.4 Comparison of Detail Improvement

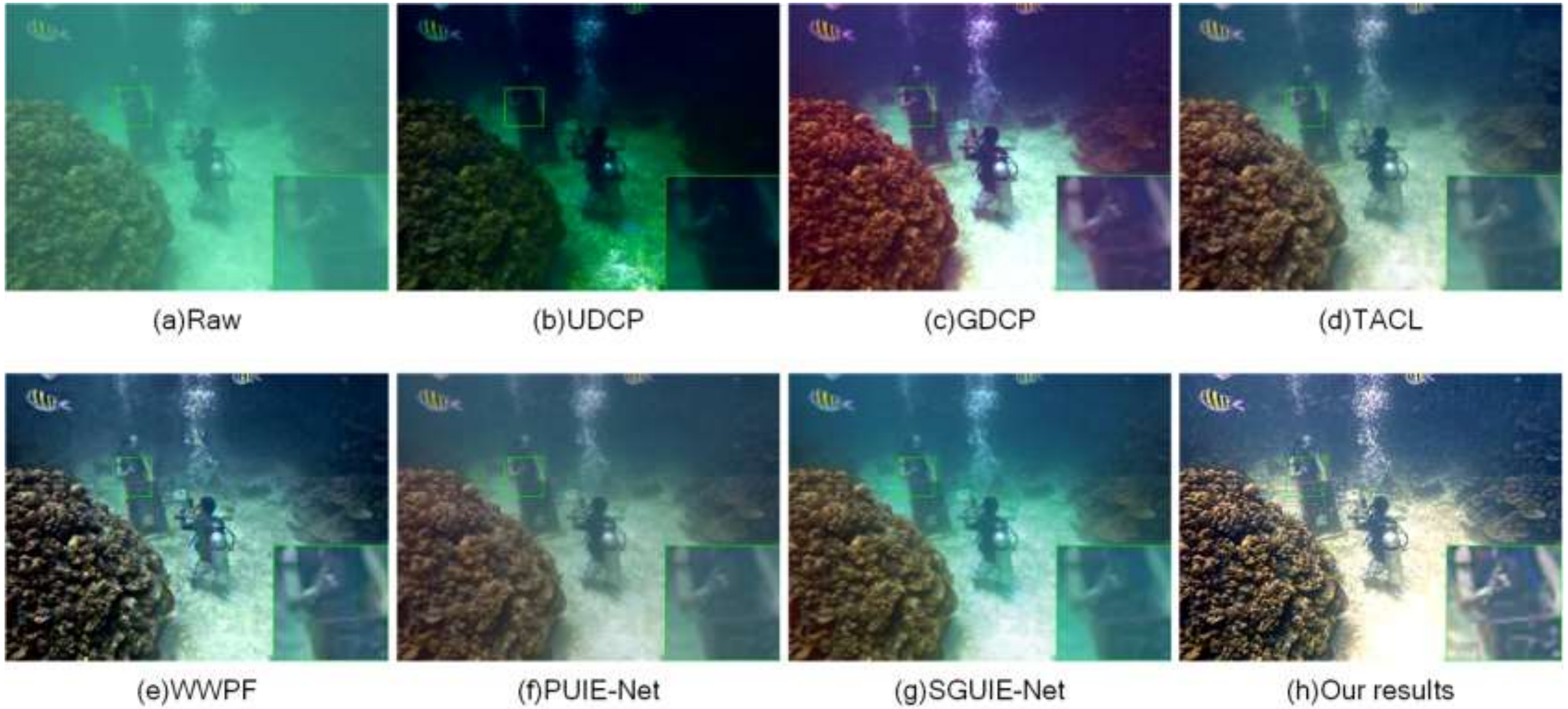


Fig. Comparative analyses of detail improvement.

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4.5 Quantitative Comparisons

Table1. Quantitative comparison on UIEB-890.

Method	UCIQE	UIQM	FDUM
UDCP	0.5980	1.5724	0.6042
GDCP	0.6044	1.4695	0.7383
BRUIE	0.5881	1.5020	0.6815
Shallow-UWnet	0.5214	1.1088	0.4127
SGUIE-Net	0.6192	1.3463	0.5967
TACL	0.6125	1.3600	0.5892
PUIE-Net	0.5852	1.2704	0.5239
WWPF	0.6181	1.5405	0.7166
MSPE	0.6286	1.3366	0.6493
CMSFFT	0.5644	1.4175	0.6270
Proposed	0.6333	1.5658	0.7466

Table1. Quantitative comparison on U45.

Method	UCIQE	UIQM	FDUM
UDCP	0.5990	1.5648	0.6534
GDCP	0.5634	1.2384	0.4733
BRUIE	0.5911	1.5764	0.7320
Shallow-UWnet	0.4881	1.0388	0.3529
SGUIE-Net	0.5992	1.1606	0.4022
TACL	0.6297	1.5300	0.6918
PUIE-Net	0.5661	1.3480	0.5109
WWPF	0.6039	1.5853	0.6932
MSPE	0.6262	1.5051	0.7416
CMSFFT	0.5530	1.3462	0.5218
Proposed	0.6306	1.5790	0.7827

4.6 Ablation Study

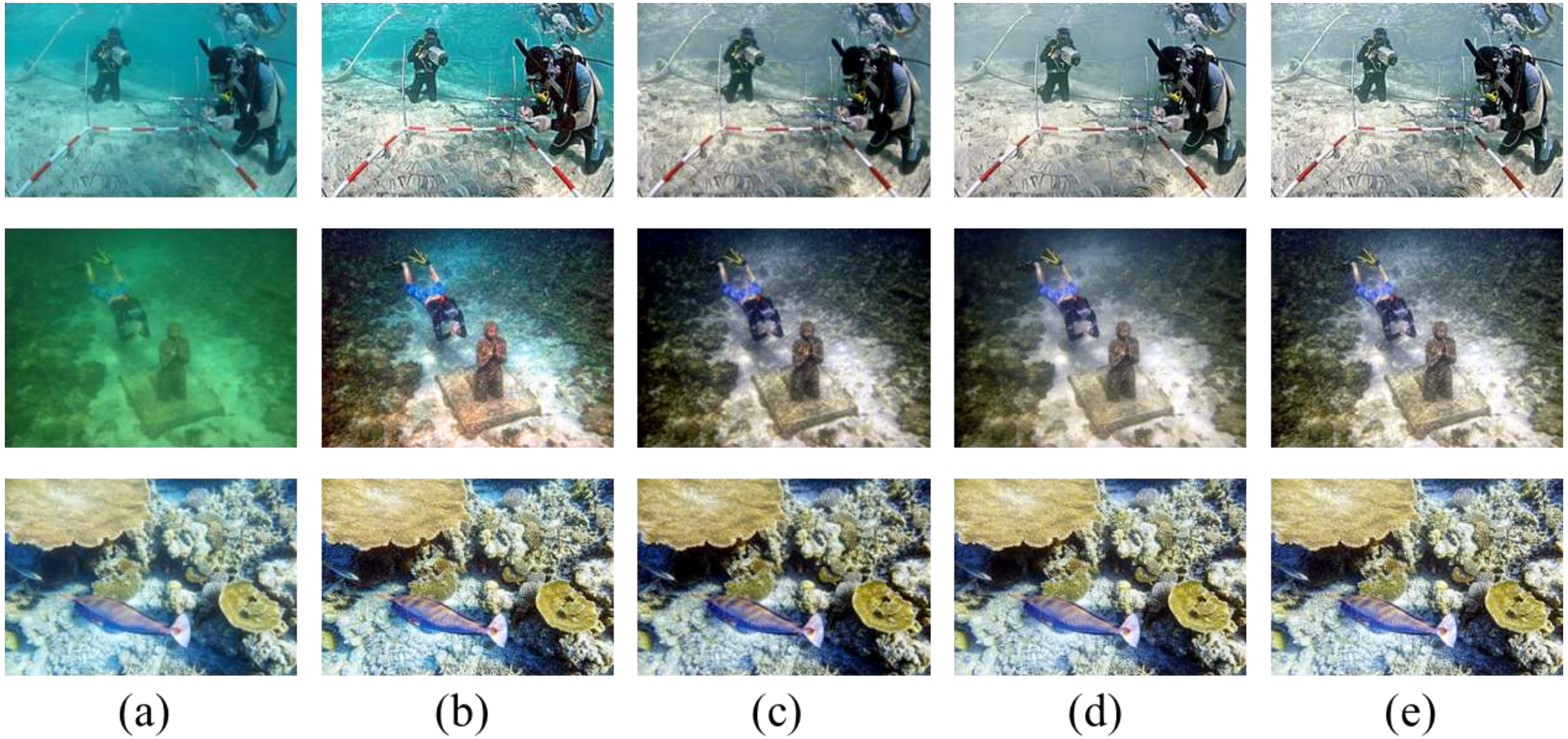

Fig. (a) Raw images. (b) Results without red light compensation. (c) Results without Retinex illumination enhancement. (d) Results without morphological transformation for detail enhancement. (e) Proposed results.

4.7 Convergence Analysis

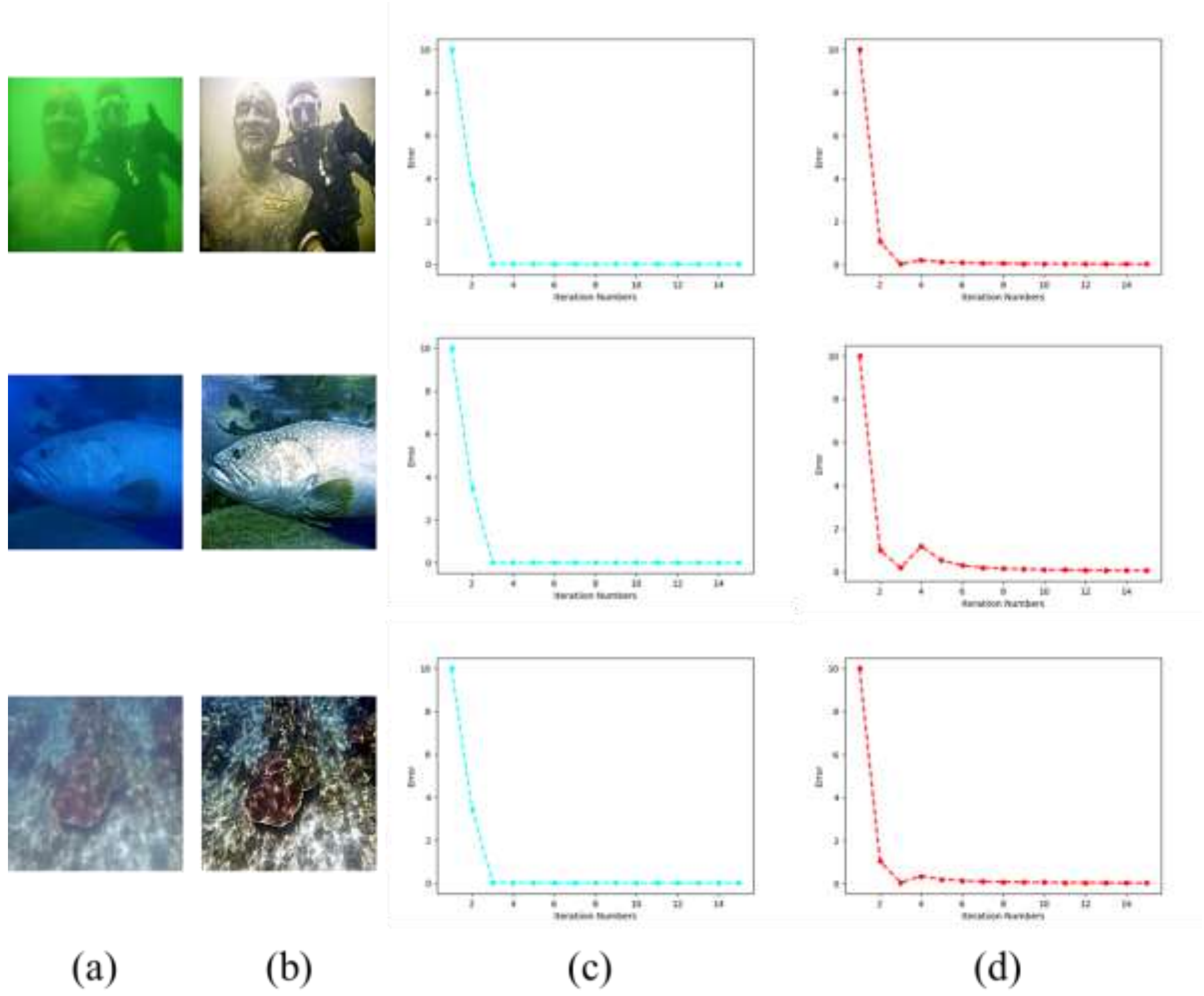

Fig. (a) Raw images. (b) Results. (c) L error shrinkage. (d) R error shrinkage.

4.8 Applications

Fig. Underwater image key point detection.

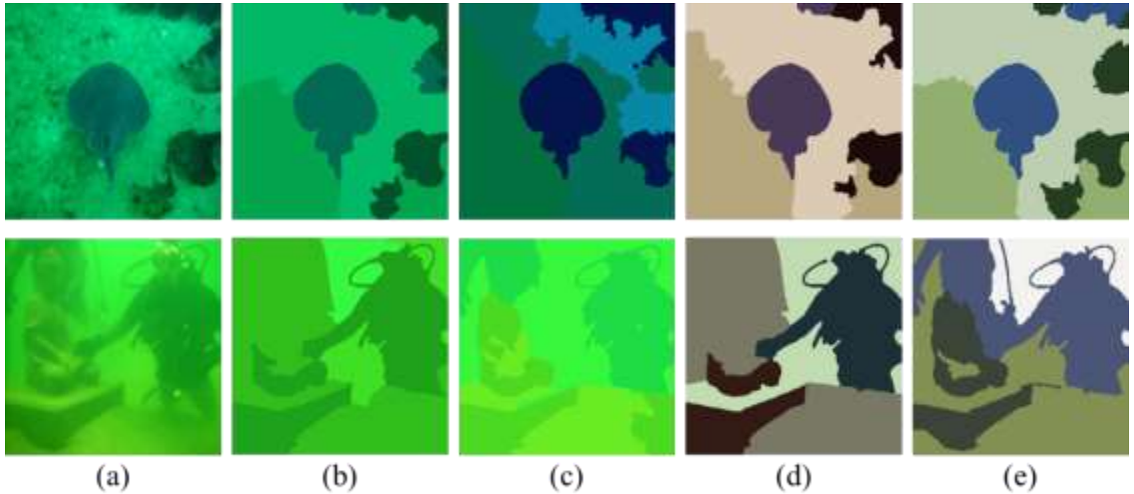

Fig. Underwater image segmentation. (a) Raw. (b) Original rsults. (c) GDCP. (d) WWPE. (e) Proposed.

Fig. Underwater scene enhancement.

5. Conclusion and Future Work

5.1 Conclusion

- Underwater Image Color Correction. Presented a color correction approach that compensates for the absorption of red light in water.

- Retinex Model Enhancement. Employed the Retinex framework to decompose underwater images into reflectance and illumination. It effectively enhances underwater images by simulating the way the human eye perceives light and shadow.

- Underwater Image Information Recovery. Used morphological operations to recover missing details and enhance information.

5.2 Future Work

- Algorithm Optimization. The algorithm proposed currently takes a long time to process complex underwater images. Future work should focus on optimizing the algorithm for faster execution and reduced time complexity.

- Addressing Additional Challenges. While this thesis successfully tackles color difference, low contrast, and blur issues in underwater images, the real underwater environment may present more serious challenges. Researchers should explore solutions for various other underwater image problems beyond the ones addressed here.

- Practical Application and Validation. To validate and improve the proposed algorithm, it needs to be applied in practical production and manufacturing scenarios. Real-world testing will provide valuable insights and guide further enhancements.

Thank you!