

Retinex Underwater Image Enhancement

With Multiorder Gradient Priors

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1. Introduction

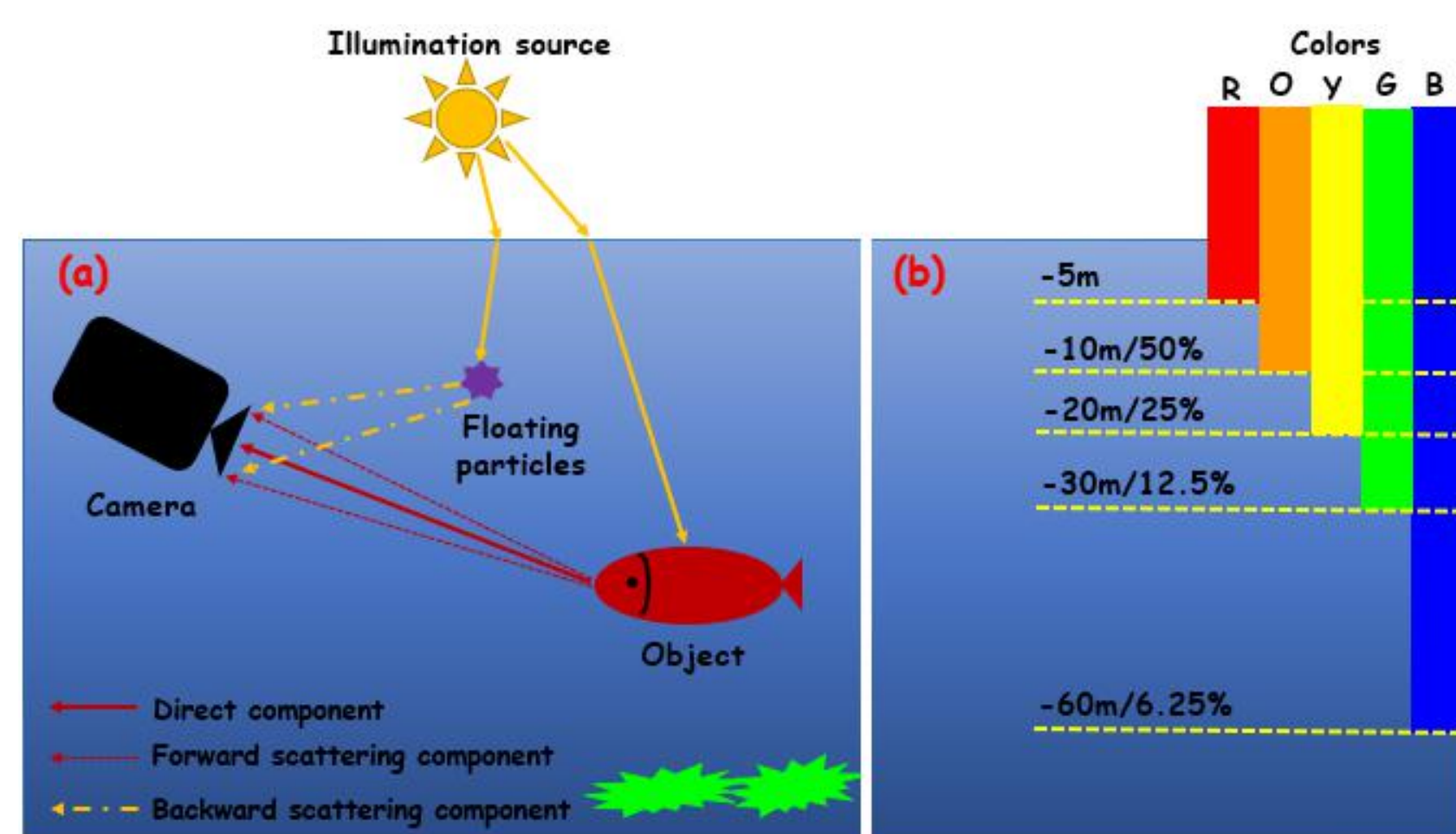


Figure 1. Schematic diagrams of underwater imaging model (a) and light absorption (b).



Due to complicated physical property of underwater image environment, underwater images suffer from **color distortion and contrast degradation** when light travels in water.

2. Motivation

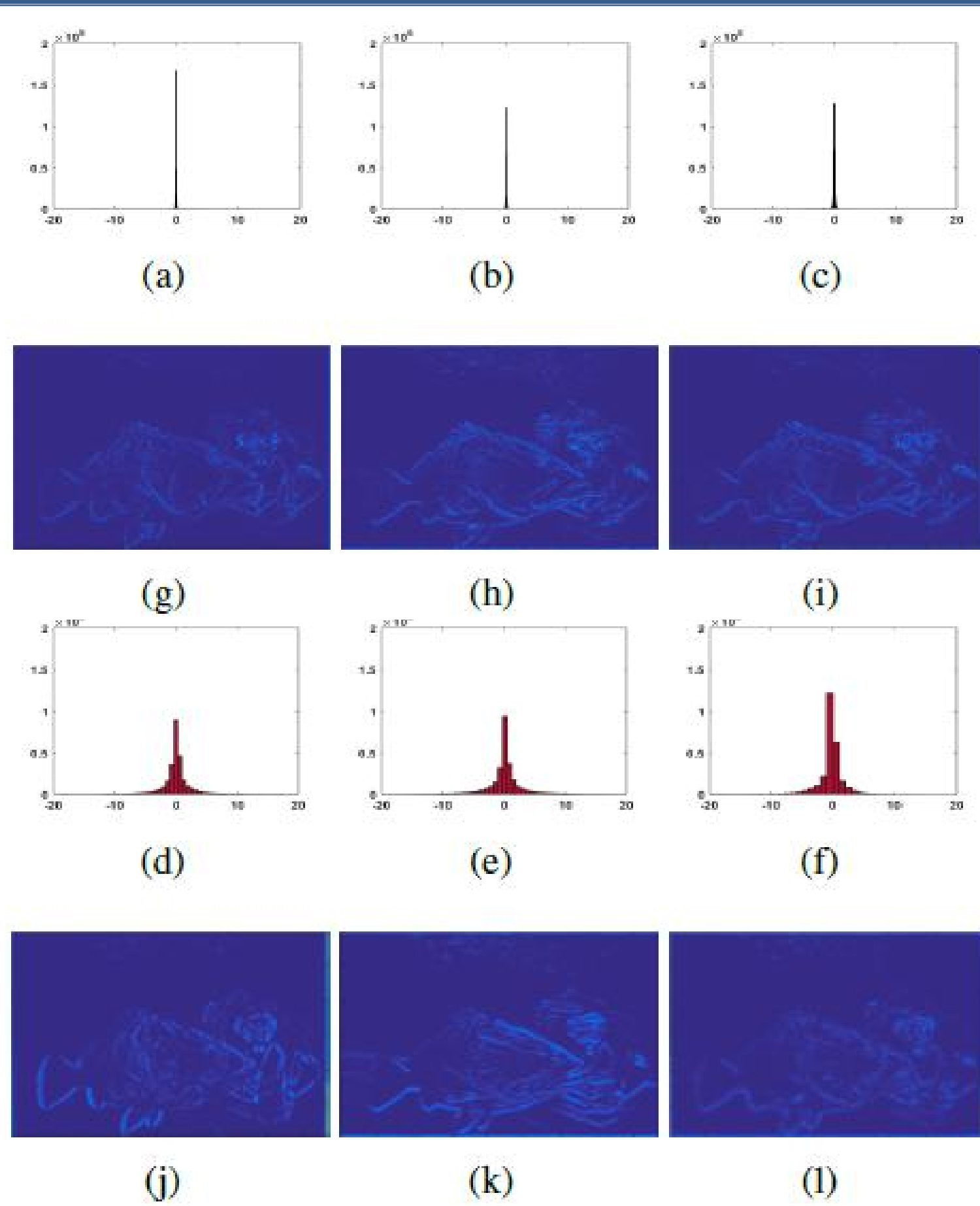


Figure 2. Average multi-order gradient histograms of reflectance (a-c) and illumination (d-f) on 100 high quality underwater images. (a)(b) and (d)(e): average histograms of first-order gradients of reflectance and illumination at horizontal and vertical directions. (c) and (f): average histograms of second-order gradients of reflectance and illumination.

Note that **multi-order gradient histograms of the reflectance (a-c) are more sparse than those of the illumination (d-f)**. Meanwhile, take one image for example, it is observed that **first-order (j-k) and second-order (l) gradients of the illumination are relative smoother than first-order (g-h) and second-order (i) of the reflectance**.

3. Proposed Method

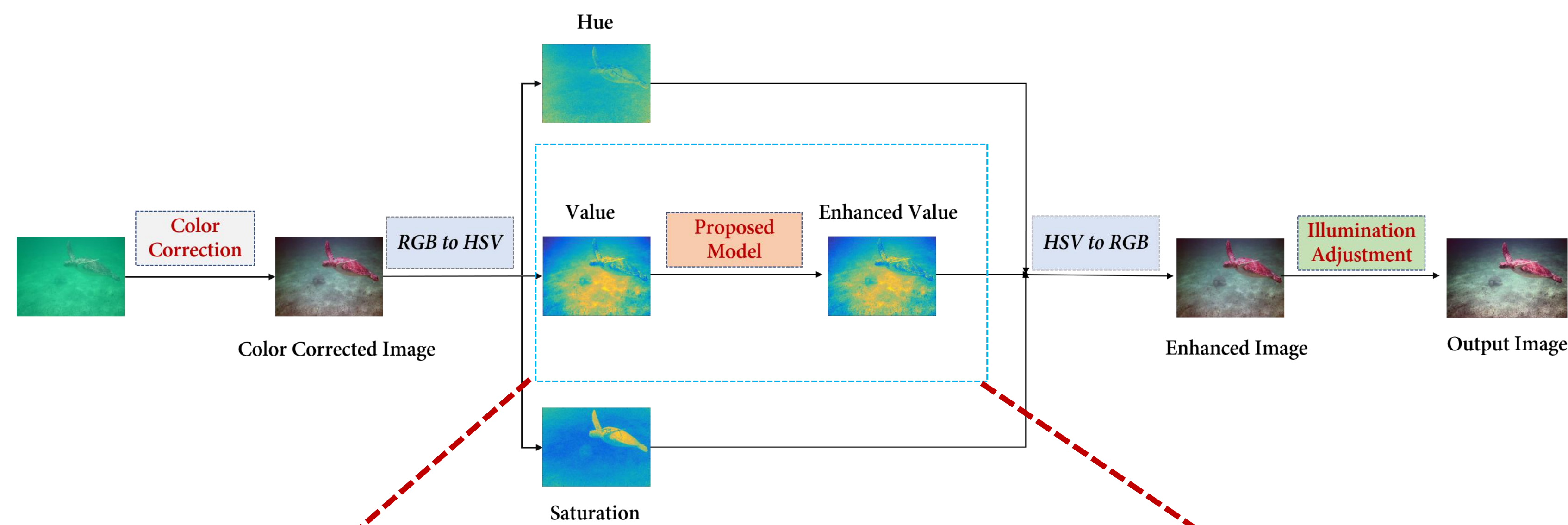


Figure 3. The flowchart of the proposed method.

$$E(\mathbf{I}, \mathbf{R}) = \|\mathbf{I} \cdot \mathbf{R} - \mathbf{V}\|_2^2 + v_1 \|\nabla \mathbf{R}\|_1 + v_2 \|\Delta \mathbf{R}\|_1 + \lambda_1 \|\nabla \mathbf{I}\|_2^2 + \lambda_2 \|\Delta \mathbf{I}\|_2^2 \quad \text{s.t. } \mathbf{V} \leq \mathbf{I}$$

Annotations for the equation:

- Data fidelity uses l_2 norm to minimize error.
- first-order and second-order gradient priors use l_1 norm to enforce piecewise continuous and piecewise linear continuous on \mathbf{R} .
- first-order and second-order gradient priors use l_2 norm to enforce piecewise continuous and piecewise linear continuous on \mathbf{I} .
- Constraint guarantees that \mathbf{R} is ranged from 0 to 1.

4. Results

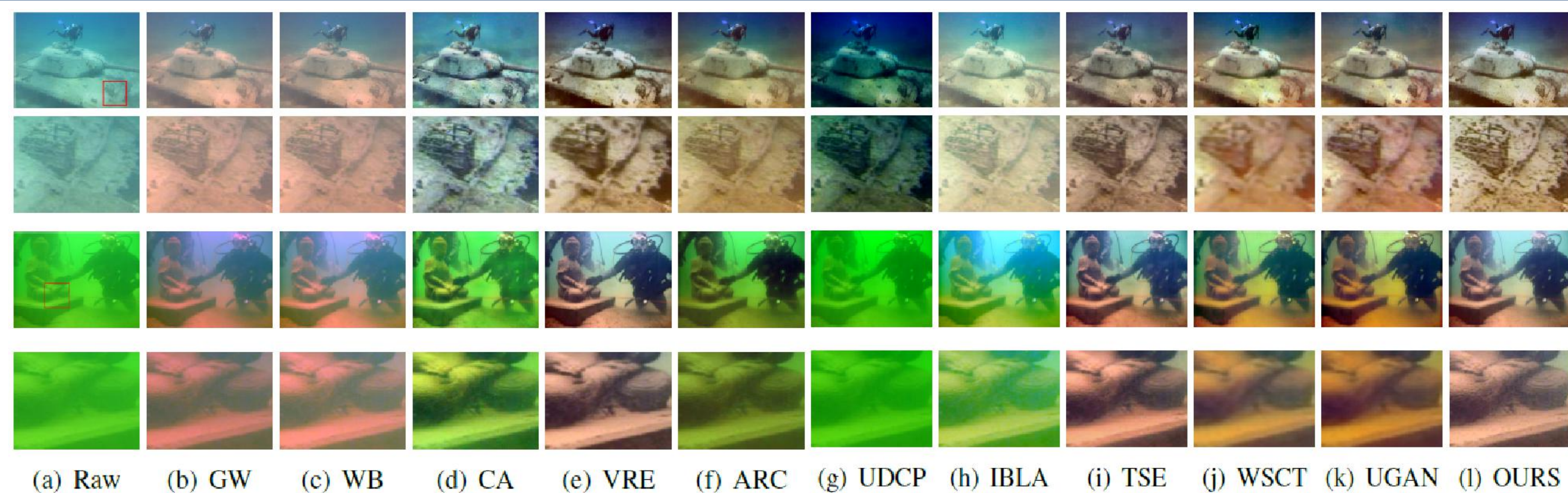


Figure 4. Enhanced and zoomed-up results of different methods.

Table 1. Average metrics on 50 underwater images

Methods	UIQM \uparrow	UIConM \uparrow	UICM \uparrow	UCIQE \uparrow	CCF \uparrow
GW	3.0056	0.4743	-8.3827	0.5115	18.5482
WB	3.0168	0.4705	-7.1783	0.5092	18.1135
CA	2.4496	<u>0.7123</u>	-64.154	0.5246	16.2955
VRE	<u>4.1724</u>	0.6976	-1.8649	0.5724	<u>37.1042</u>
ARC	2.7998	0.6269	-36.240	0.5422	16.3227
UDCP	2.2087	0.6386	-52.541	0.4745	20.9495
IBLA	3.8097	0.5498	-0.2852	0.5686	32.7881
TSE	3.4320	0.6662	-23.336	0.5334	22.4793
WSCT	2.2766	0.6426	-60.083	0.5659	16.8319
UGAN	4.0091	0.6278	<u>3.3558</u>	<u>0.5728</u>	20.8231
OURS	<u>4.4722</u>	<u>0.7209</u>	<u>1.3907</u>	<u>0.5730</u>	<u>37.1664</u>

5. Conclusion

- ① A variational retinex model with **multi-order gradient priors of reflectance and illumination** is proposed for underwater image enhancement, which captures fine-scale and complete structures of underwater images.
- ② **L_1 norm** is accurate to model multi-order gradients of the reflectance, since its multiorder gradients are **more sparse** than those of the illumination. **L_2 norm** is used to model multi-order gradients of the illumination, since its multiorder gradients are **smoother** than those of reflectance.
- ③ A complex underwater enhancement issue is turned into simple subproblems that their **convergence proof** is provided, and an **efficient alternating optimization** method is derived to address them, along with fast pixel-wise operations and no extra underwater prior knowledge.

Contact

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More details can be found in <https://github.com/zhuangpeixian/Supple>