MCSF-Net: A Multi-Color Space Fusion Network for Underwater Image Enhancement (Supplementary Material)

Yijian Wang, Peixian Zhuang *Member, IEEE,* Zhenqi Fu, and Jiaquan Yan

***Abstract*—In the supplementary material, we provide more experimental results to complement our main manuscript, including experimental results as follows: 1) comparison of enhancement performance, visual results and data distributions between our LSMU and raw datasets [1]–[8], 2) visual comparison of different thresholds, 3) different types of real underwater images from Challenge-60 [2] and NUID [9], 4) different types of synthetic underwater images from Test-S1000 [3], [7], 5) ablation study on underwater images with yellow color degeneration [2], 6) visual comparison on low-light [10] and sandstorm images [11].**

I. More experimental results

References

[1] C. Fabbri, M. J. Islam, and J. Sattar, "Enhancing underwater imagery using generative adversarial networks," in *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 7159–7165, 2018.

[2] C. Li, C. Guo, W. Ren, R. Cong, J. Hou, S. Kwong, and D. Tao, "An underwater image enhancement benchmark dataset and beyond," *IEEE Transactions on Image Processing*, vol. 29, pp. 4376–4389, 2020.

[3] C. Li, S. Anwar, and F. Porikli, "Underwater scene prior inspired deep underwater image and video enhancement," *Pattern Recognition*, vol. 98, p. 107038, 2020.

[4] M. J. Islam, Y. Xia, and J. Sattar, "Fast underwater image enhancement for improved visual perception," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 3227–3234, 2020.

[5] M. J. Islam, P. Luo, and J. Sattar, "Simultaneous enhancement and super-resolution of underwater imagery for improved visual perception," in *Robotics: Science and Systems (RSS)*, July 2020.

[6] Q. Qi, Y. Zhang, F. Tian, Q. J. Wu, K. Li, X. Luan, and D. Song, "Underwater image co-enhancement with correlation feature matching and joint learning," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 32, no. 3, pp. 1133–1147, 2021.

[7] G. Hou, X. Zhao, Z. Pan, H. Yang, L. Tan, and J. Li, "Benchmarking underwater image enhancement and restoration, and beyond," *IEEE Access*, vol. 8, pp. 122078–122091, 2020.

[8] L. Peng, C. Zhu, and L. Bian, "U-shape transformer for underwater image enhancement," *IEEE Transactions on Image Processing*, vol. 32, pp. 3066–3079, 2023.

[9] G. Hou, N. Li, P. Zhuang, K. Li, H. Sun, and C. Li, "Non-uniform illumination underwater image restoration via illumination channel sparsity prior," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 34, no. 2, pp. 799–814, 2024.

[10] S. Zhou, C. Li, and C. Change Loy, "LEDNet: Joint low-light enhancement and deblurring in the dark," in *European Conference on Computer Vision (ECCV)*, pp. 573–589, 2022.

[11] J. Huang, H. Xu, G. Liu, C. Wang, Z. Hu, and Z. Li, "SIDNet: A single image dedusting network with color cast correction," *Signal Processing*, vol. 199, p. 108612, 2022.

[12] Z. Fu, W. Wang, Y. Huang, X. Ding, and K.-K. Ma, "Uncertainty inspired underwater image enhancement," in *European Conference on Computer Vision (ECCV)*, pp. 465–482, 2022.

[13] J. Zhou, J. Sun, C. Li, Q. Jiang, M. Zhou, K.-M. Lam, W. Zhang, and X. Fu, "HCLR-Net: Hybrid contrastive learning regularization with locally randomized perturbation for underwater image enhancement," *International Journal of Computer Vision*, pp. 1–25, 2024.

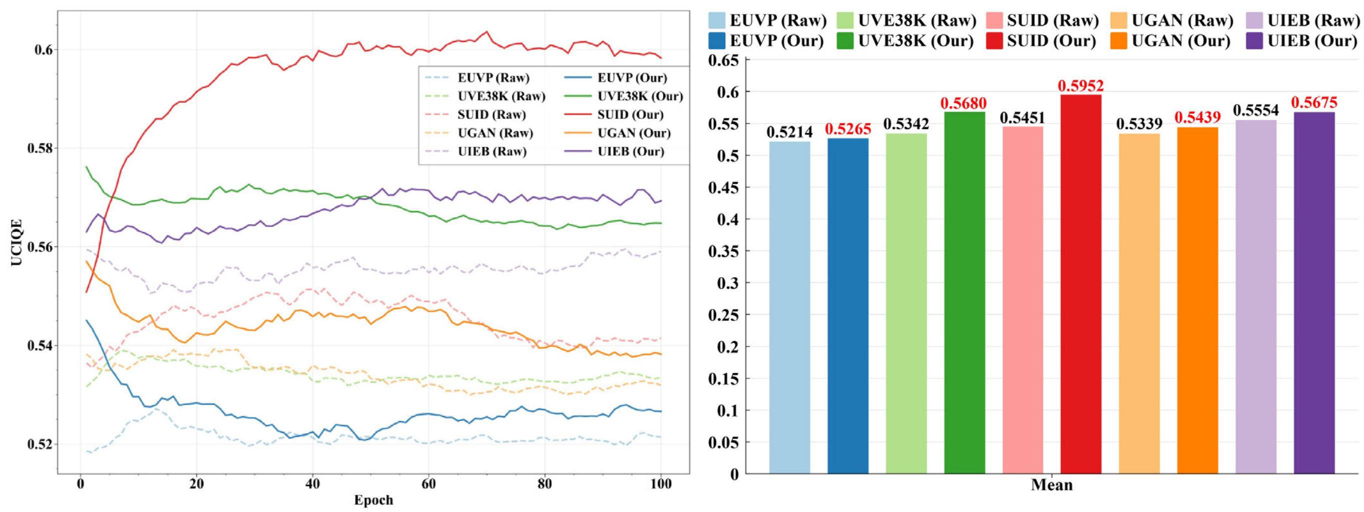


Fig. 1. Comparison of enhancement performance between raw and our LSMU datasets. Higher UCIQE curves are shown with our LSMU datasets, and better mean values confirm our superiority. The best results are marked in red under each case.

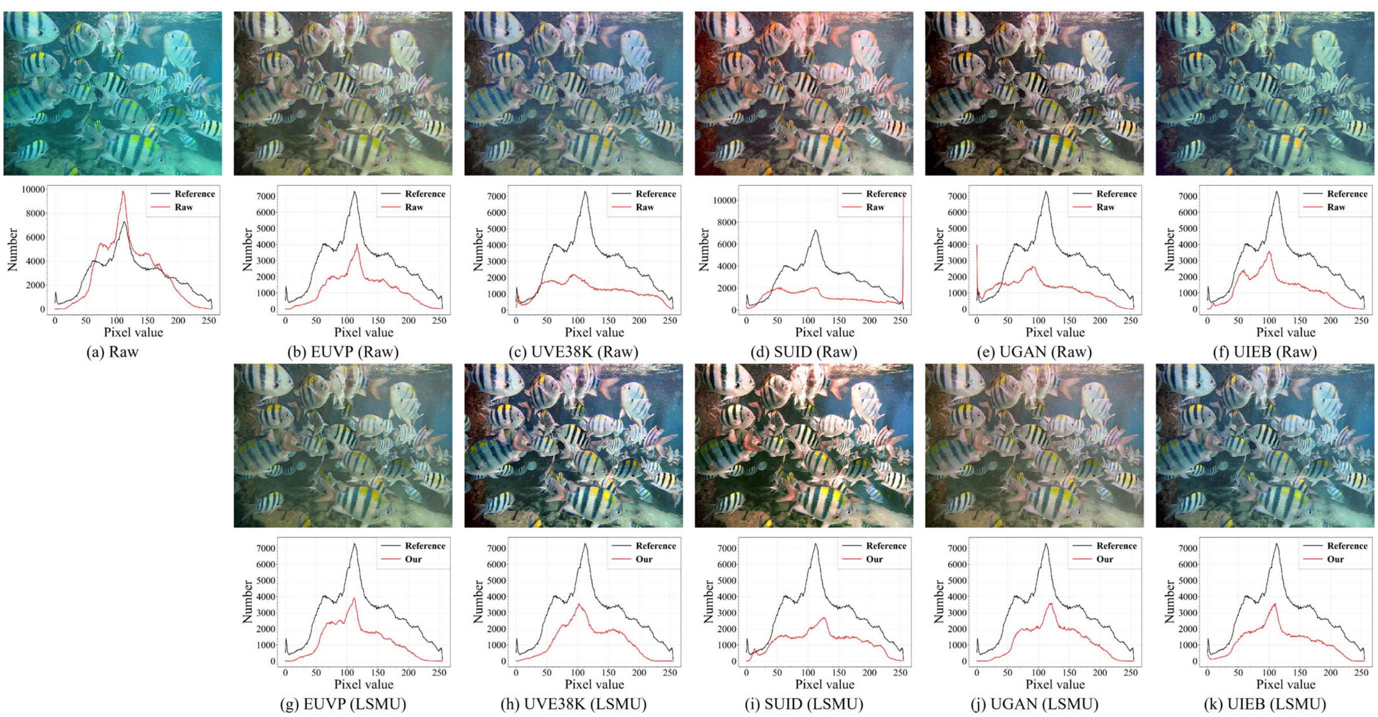


Fig. 2. Comparison of visual results and data distributions between PUIE-Net methods [12] trained with raw datasets and our LSMU datasets on a sample from UIEB dataset [2]. The PUIE-Net method [12] trained with our LSMU datasets yields better visual quality and more consistent data distributions.

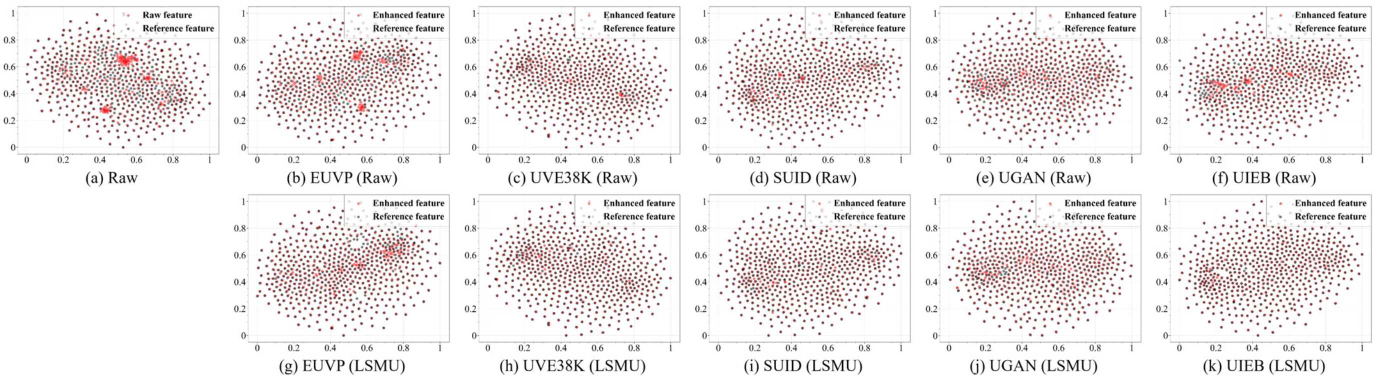


Fig. 3. Comparison of feature distributions [13] between the PUIE-Net [12] method (trained with raw datasets and our LSMU datasets respectively) on the UIEB dataset [2]. The red and black dots represent the distributions of raw/enhanced feature and reference feature, respectively. PUIE-Net methods [12] trained with our LSMU datasets significantly improve the mapping accuracy of data distributions between raw and reference features.

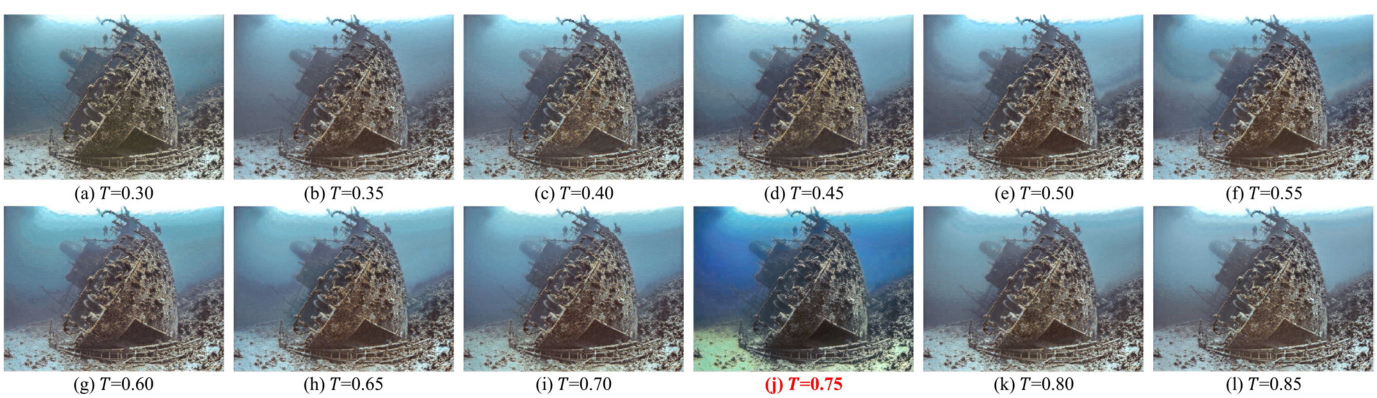


Fig. 4. Visual comparison of different thresholds T. When the threshold reaches 0.75, enhanced underwater images are visually decent, and thus the threshold T is recommended to set as 0.75.

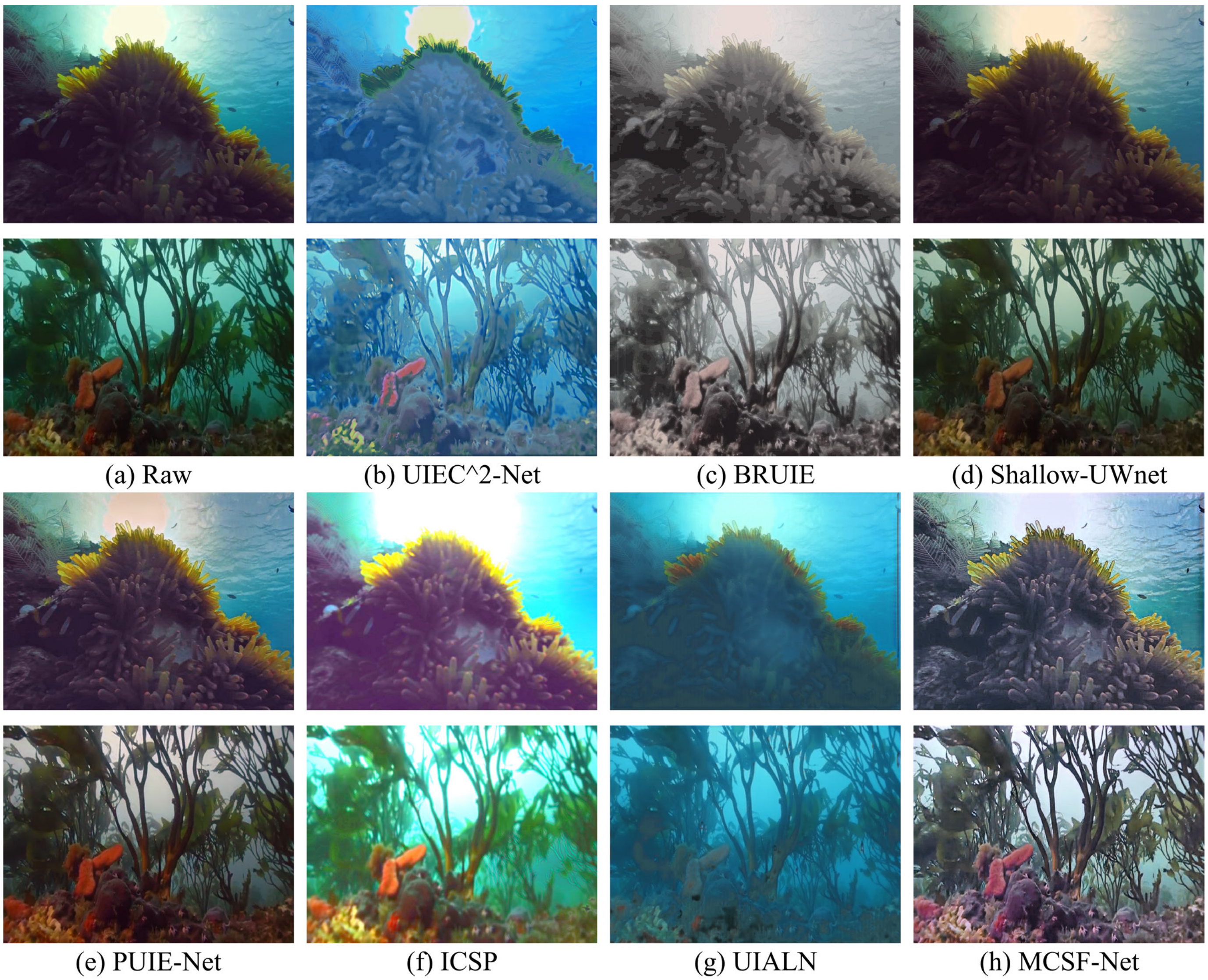
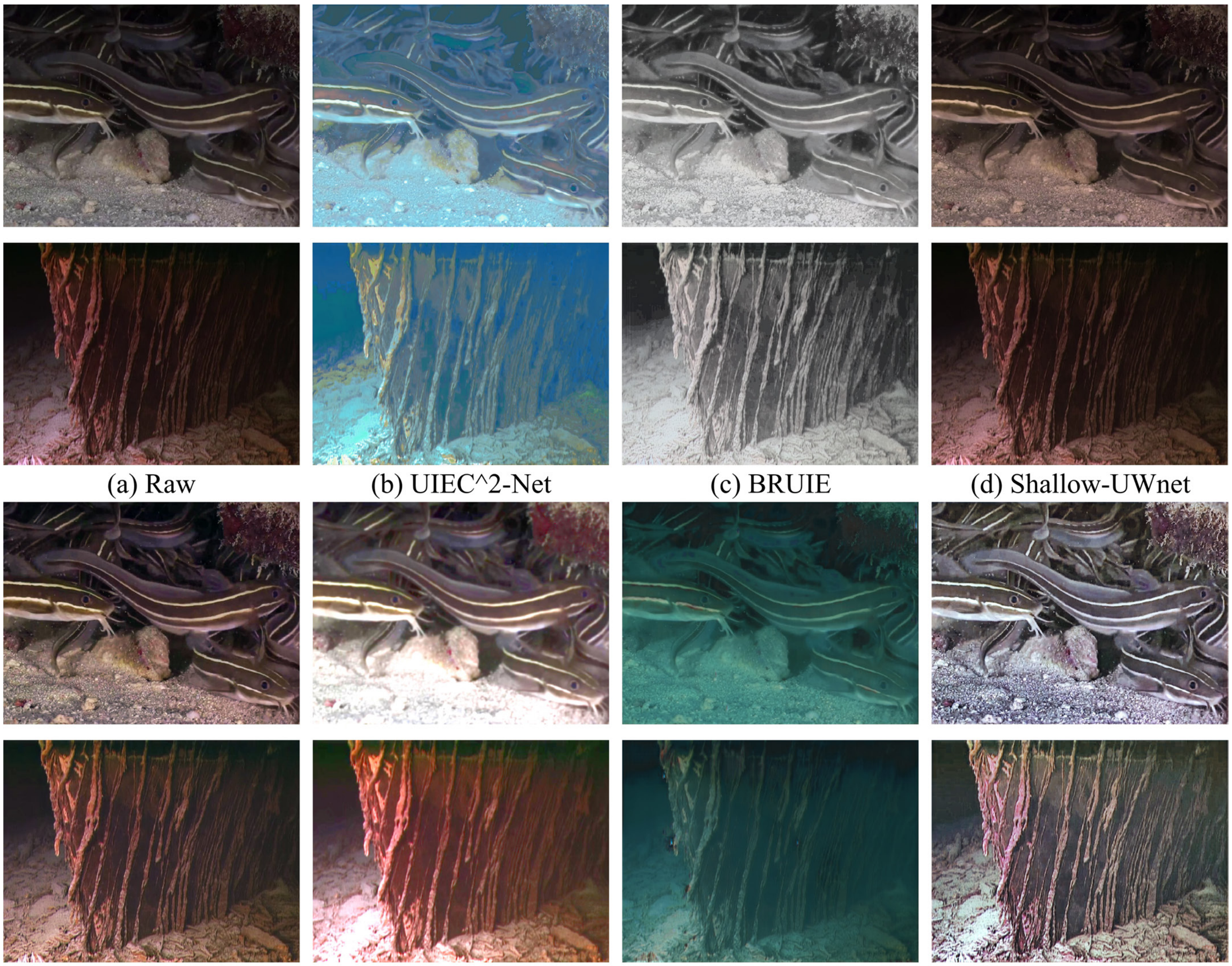


Fig. 5. Visual comparison of different methods on two real underwater images from Challenge-60 [2] and NUID [9].



(a) Raw (b) UIEC^2-Net (c) BRUIE (d) Shallow-UWnet

(e) PUIE-Net (f) ICSP (g) UIALN (h) MCSF-Net

Fig. 6. Visual comparison of different methods on two real underwater images from NUID [9].

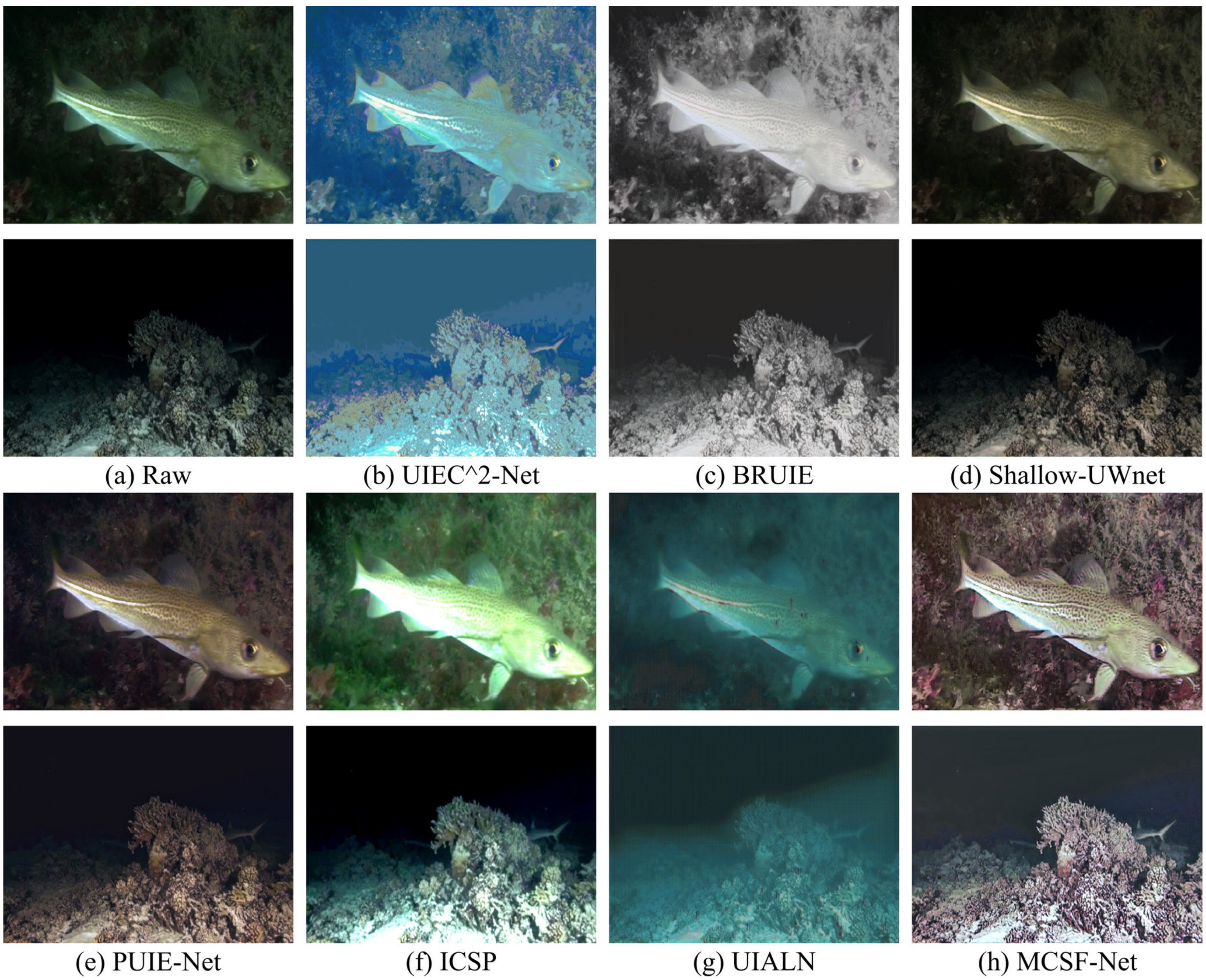


Fig. 7. Visual comparison of different methods on two real underwater images from NUID [9].

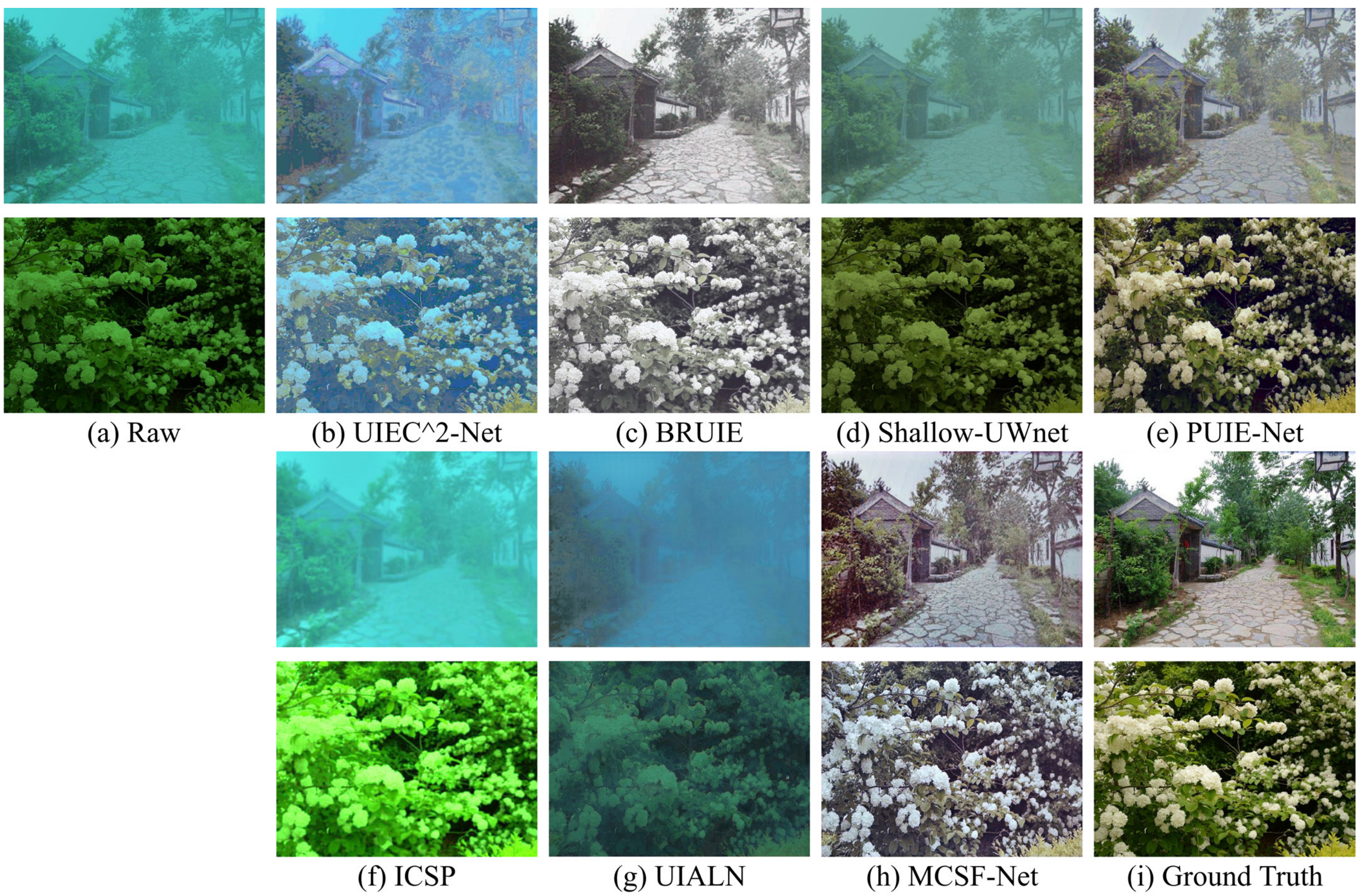


Fig. 8. Visual comparison of different methods on two synthetic underwater images from SUID [7]. Our MCSF-Net can restore both finer details and better visibility of synthetic underwater images.

Fig. 9. Visual comparison of different methods on two synthetic underwater images from NUY-U [3]. Our MCSF-Net can restore both finer details and better visibility of synthetic underwater images.

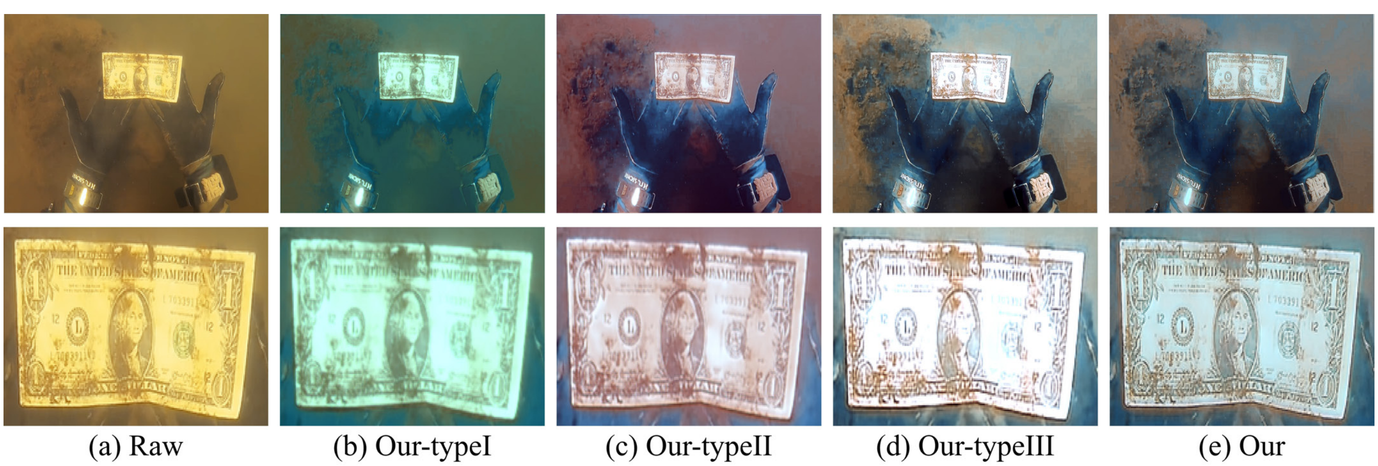


Fig. 10. Ablation study on an underwater image with yellow color degeneration. Bottom row: zoomed-in views of red box regions of the top row. Our full method (Our) not only yields more authentic colors and richer image details, but also suppresses undesirable results of local over-brightness.

(a) Raw (b) UIEC^2-Net (c) BRUIE (d) Shallow-UWnet

(e) PUIE-Net (f) ICSP (g) UIALN (h) MCSF-Net

Fig. 11. Visual comparison of different methods on two sandstorm images from [11]. our MCSF-Net achieves both better visibility and clearer details, which indicates better generalization of MCSF-Net on enhancing sandstorm images.

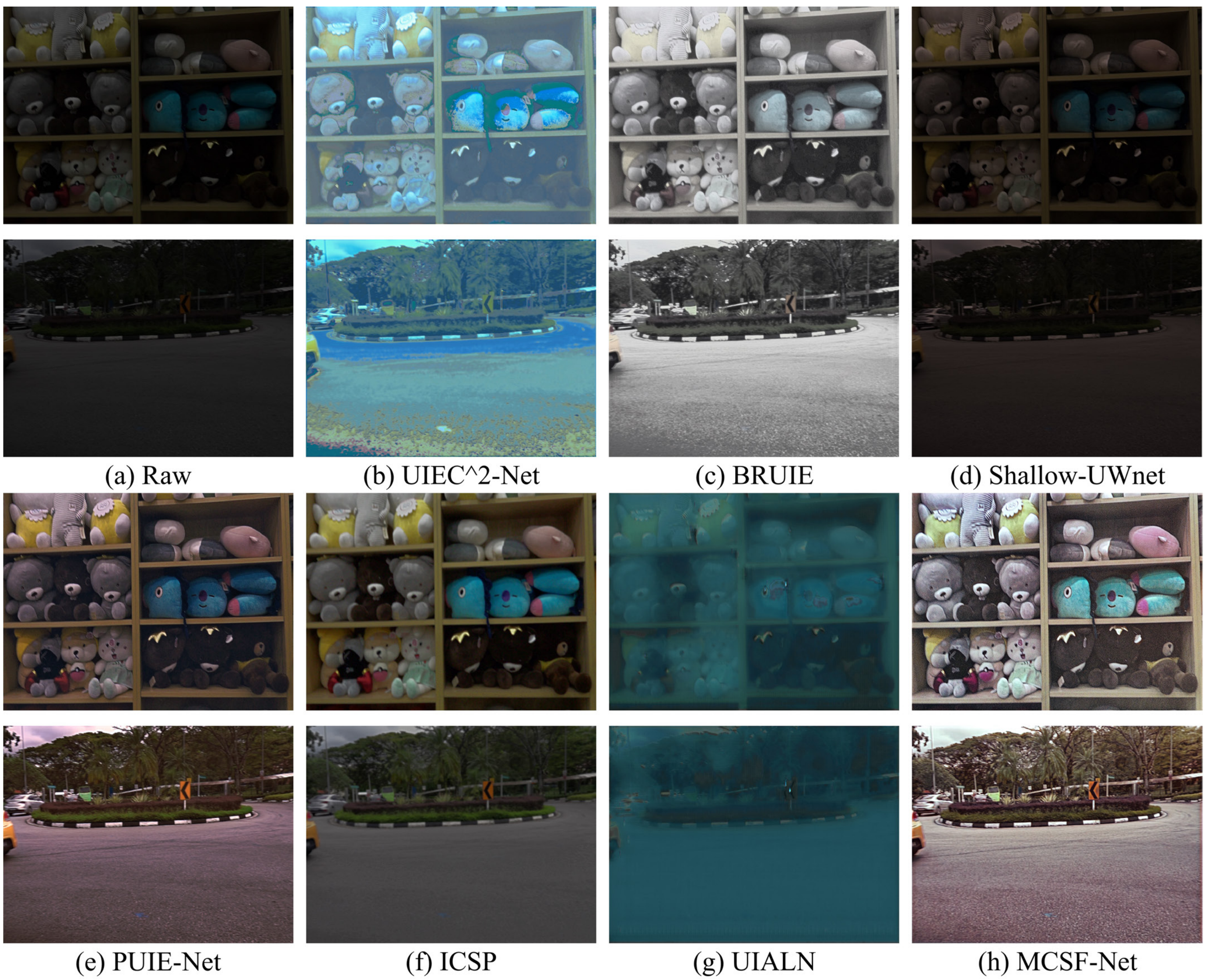


Fig. 12. Visual comparison of different methods on two low-light images from [10]. our MCSF-Net achieves better visibility and clearer details, which indicates better generalization of MCSF-Net on enhancing low-light images.