SGUIE-Net: Semantic Attention Guided Underwater Image Enhancement with Multi-Scale Perception (Supplementary Material)

Qi Qi, *Student Member, IEEE*, Kunqian Li*, *Member, IEEE*, Haiyong Zheng, *Member, IEEE*, Xiang Gao, Guojia Hou, *Member, IEEE*, Kun Sun, *Member, IEEE*

***Abstract*—This supplementary material provides more details of the newly constructed SUIM-E dataset and more visual comparisons on various benchmarks, including UIEB [1] challenging set, RUIE [2], EUVP [3] and SQUID [4].**

In addition to the source code and SUIM-E dataset, more multimedia supplement materials are also available at: https://trentqq.github.io/SGUIE-Net.html.

I. More Details about the Proposed SUIM-E Dataset

The SUIM-E dataset is created by supplementing the SUIM [5] dataset with the corresponding enhancement references. Inspired by [1], we used 12 underwater image enhancement methods to generate candidate reference images, including CE [6], Fusion [7], GCHE [8], HistogramPiror [9], HUE [10], IBLA [11], Retinex [12], TwoStep [13], UCM [14], ULAP [15]), DCP [16] and a commercial application for enhancing underwater images (i.e., dive+ [1]). With the raw underwater images and their enhancement candidates, we invited 10 volunteers to independently select the best result from the 12 enhanced results corresponding to each raw underwater image. Then, for each raw underwater image, we count the number of votes for its corresponding 12 enhancement candidates and select the result with the highest number of votes as the final reference image. In Figure 1, we present the enhancement candidates on four underwater images, which are generated by different methods. The chosen reference images are marked with red boxes. During the whole voting phase on SUIM dataset, the distribution of votes received by different underwater enhancement methods is shown in Figure 2. Besides, the percentages of the reference images from the results of different methods are presented in Figure 3.

In summary, the SUIM-E dataset contains a total of 1635 real-world underwater images, along with the corresponding high-quality reference images and the pixel annotations for eight object categories: fish (vertebrates), reefs (invertebrates), aquatic plants, wrecks/ruins, human divers, robots, and sea-floor are in it. To the best of our knowledge, it is the first real-world underwater dataset that contains both corresponding enhancement reference and semantic segmentation map.

Q. Qi and H. Zheng are with Faculty of Information Science and Engineering, Ocean University of China, Qingdao 266100, China (qiqi2013@stu.ouc.edu.cn; zhenghaiyong@ouc.edu.cn).

K. Li and X. Gao are with College of Engineering, Ocean University of China, Qingdao 266100, China (likunqian@ouc.edu.cn; xgao@ouc.edu.cn).

G. Hou is with the College of Computer Science and Technology, Qingdao University, Qingdao 266071, China (hgjouc@126.com).

K. Sun is with School of Computer Science, China University of Geosciences, Wuhan 430078, China (sunkun@cug.edu.cn).

* Corresponding author: Kunqian Li (likunqian@ouc.edu.cn)

[1] https://diveplus.cn/app

II. More Visual Comparisons with Perceptual Scores

To provide a more intuitive comparison of the performance of each method on different datasets, more visual comparison results on UIEB [1] challenging set, RUIE [2], EUVP [3] and SQUID [4] datasets are shown in Figures 4, 5, 6 and 7, respectively. The perceptual score of each enhancement is marked on its upper right corner, which further demonstrates the superiority of our method.

References

[1] 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.

[2] R. Liu, X. Fan, M. Zhu, M. Hou, and Z. Luo, "Real-world underwater enhancement: Challenges, benchmarks, and solutions under natural light," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 30, no. 12, pp. 4861–4875, 2020.

[3] 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.

[4] D. Berman, D. Levy, S. Avidan, and T. Treibitz, "Underwater single image color restoration using haze-lines and a new quantitative dataset," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 43, no. 8, pp. 2822–2837, 2021.

[5] M. J. Islam, C. Edge, Y. Xiao, P. Luo, M. Mehtaz, C. Morse, S. S. Enan, and J. Sattar, "Semantic segmentation of underwater imagery: Dataset and benchmark," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2020, pp. 1769–1776.

[6] Y. Wang, W. Song, G. Fortino, L.-Z. Qi, W. Zhang, and A. Liotta, "An experimental-based review of image enhancement and image restoration methods for underwater imaging," *IEEE Access*, vol. 7, pp. 140 233–140 251, 2019.

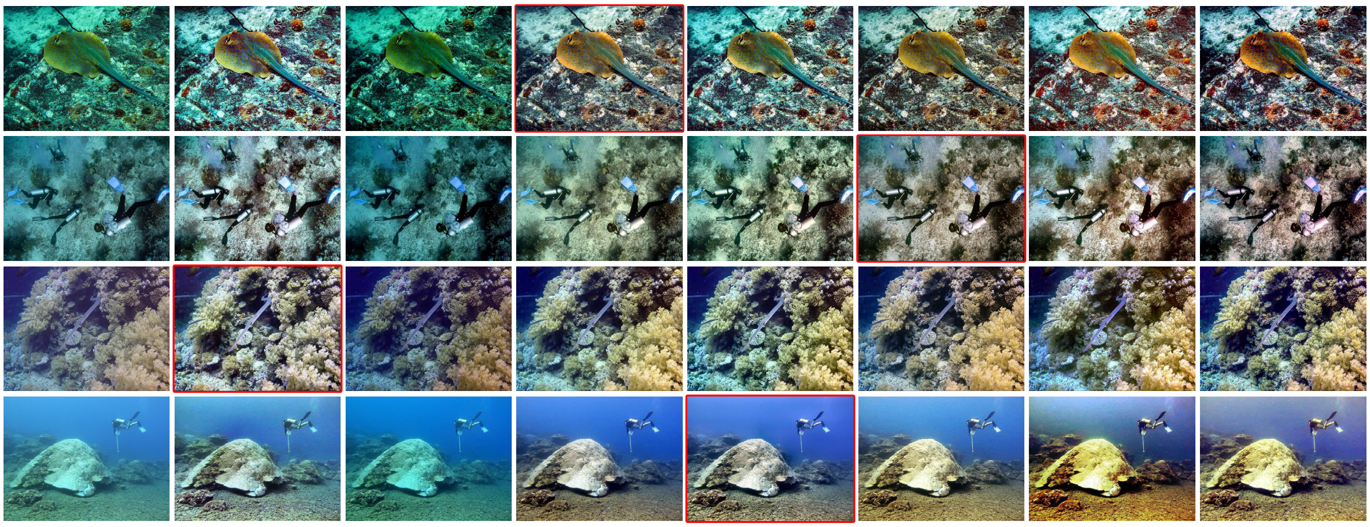
[7] C. Ancuti, C. O. Ancuti, T. Haber, and P. Bekaert, "Enhancing underwater images and videos by fusion," in *IEEE Conference on Computer Vision and Pattern Recognition*, 2012, pp. 81–88.

[8] X. Fu and X. Cao, "Underwater image enhancement with global–local networks and compressed-histogram equalization," *Signal Processing: Image Communication*, vol. 86, p. 115892, 2020.

[9] C.-Y. Li, J.-C. Guo, R.-M. Cong, Y.-W. Pang, and B. Wang, "Underwater image enhancement by dehazing with minimum information loss and histogram distribution prior," *IEEE Transactions on Image Processing*, vol. 25, no. 12, pp. 5664–5677, 2016.

[10] X. Li, G. Hou, L. Tan, and W. Liu, "A hybrid framework for underwater image enhancement," *IEEE Access*, vol. 8, pp. 197 448–197 462, 2020.

[11] Y.-T. Peng and P. C. Cosman, "Underwater image restoration based on image blurriness and light absorption," *IEEE Transactions on Image Processing*, vol. 26, no. 4, pp. 1579–1594, 2017.



(a) Raw (b) CE (c) DCP (d) dive+ (e) Fusion (f) GCHE (g) HistogramPiror (h) HUE

Fig. 1. Results generated by different methods. From left to right are raw underwater images, and the results of CE [6], DCP [16], dive+, Fusion [7], GCHE [8], HistogramPiror [9] and HUE [10]. Red boxes indicate the images which are chosen as references.

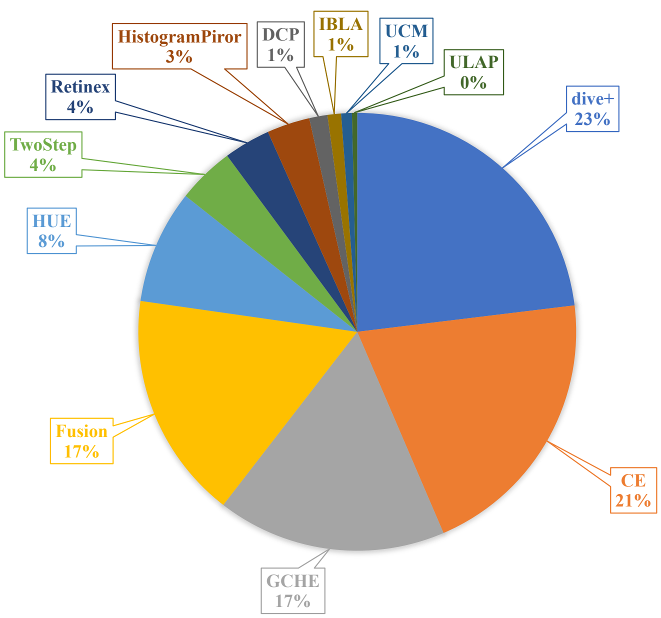


Fig. 2. The percentages of votes received by different underwater enhancement methods in the vote on the whole dataset.

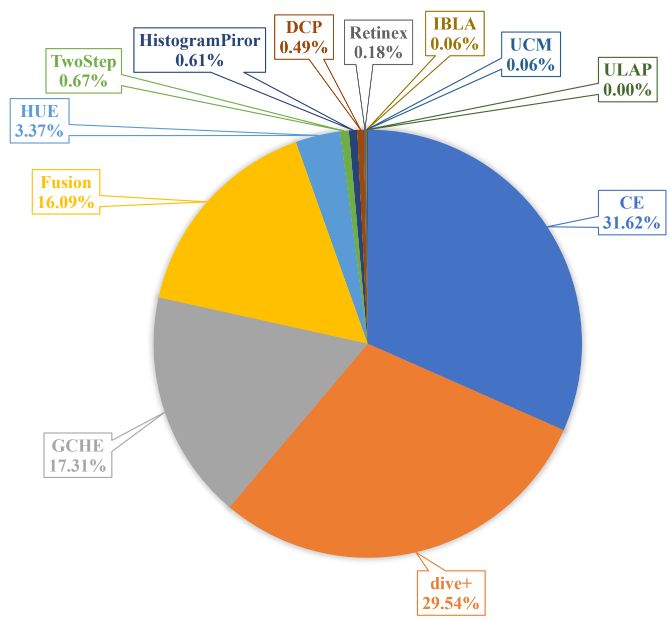


Fig. 3. The percentages of the reference images from the results of different methods.

[12] X. Fu, P. Zhuang, Y. Huang, Y. Liao, X.-P. Zhang, and X. Ding, "A retinex-based enhancing approach for single underwater image," in *IEEE International Conference on Image Processing*, 2014, pp. 4572–4576.

[13] X. Fu, Z. Fan, M. Ling, Y. Huang, and X. Ding, "Two-step approach for single underwater image enhancement," in *IEEE International Symposium on Intelligent Signal Processing and Communication Systems*, 2017, pp. 789–794.

[14] K. Iqbal, M. Odetayo, A. James, Rosalina Abdul Salam, and Abdullah Zawawi Hj Talib, "Enhancing the low quality images using unsupervised colour correction method," in *IEEE International Conference on Systems, Man and Cybernetics*, 2010, pp. 1703–1709.

[15] W. Song, Y. Wang, D. Huang, and D. Tjondronegoro, "A rapid scene depth estimation model based on underwater light attenuation prior for underwater image restoration," in *Pacific Rim Conference on Multimedia*, 2018, pp. 678–688.

[16] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 12, pp. 2341–2353, 2010.

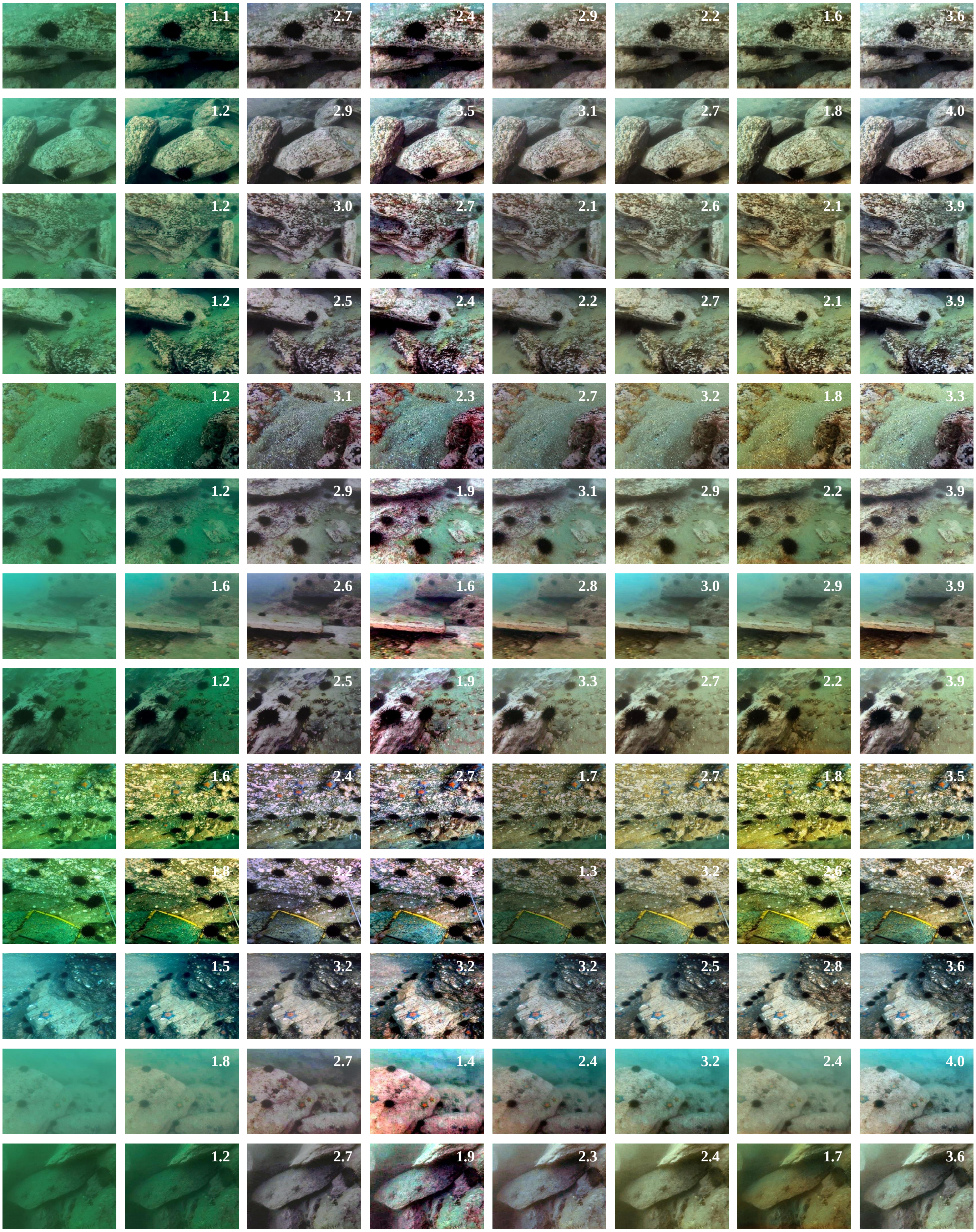
[17] C. O. Ancuti, C. Ancuti, C. De Vleeschouwer, and P. Bekaert, "Color balance and fusion for underwater image enhancement," *IEEE Transactions on Image Processing*, vol. 27, no. 1, pp. 379–393, 2018.

[18] C. Li, S. Anwar, J. Hou, R. Cong, C. Guo, and W. Ren, "Underwater image enhancement via medium transmission-guided multi-color space embedding," *IEEE Transactions on Image Processing*, vol. 30, pp. 4985–5000, 2021.

[19] Q. Qi, Y. Zhang, F. Tian, Q. M. Jonathan 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*, pp. 1–1, 2021.

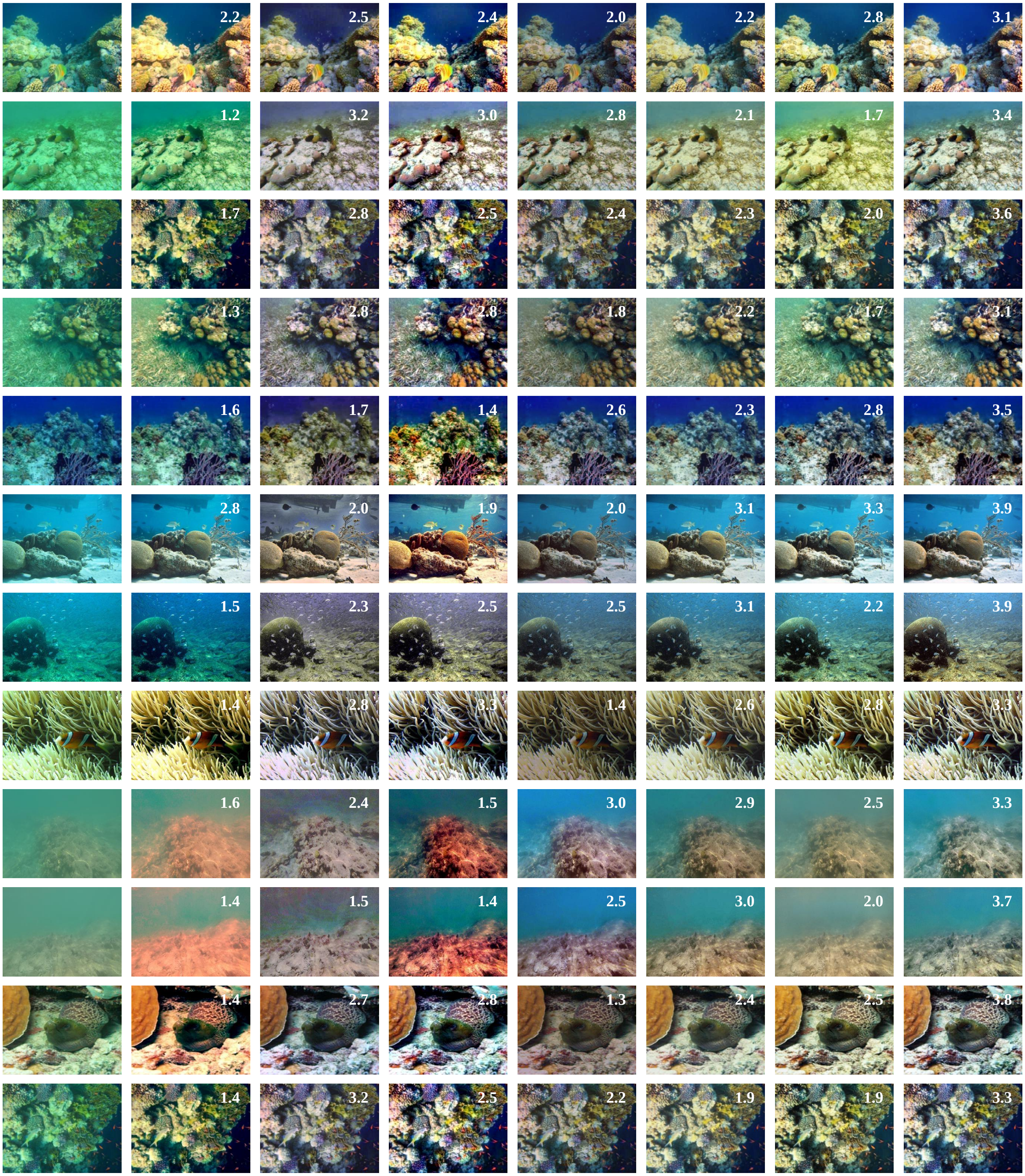
(a) Raw (b) ULAP (c) CBF (d) HUE (e) Water-Net (f) Ucolor (g) UICoE-Net (h) SGUIE-Net

Fig. 4. Visual comparisons on underwater images from UIEB challenging dataset. From left to right are raw underwater images and the results of ULAP [15], CBF [17], HUE [10], Water-Net [1], Ucolor [18], UICoE-Net [19] and the proposed SGUIE-Net. Perceptual scores are marked on the upper right corner.



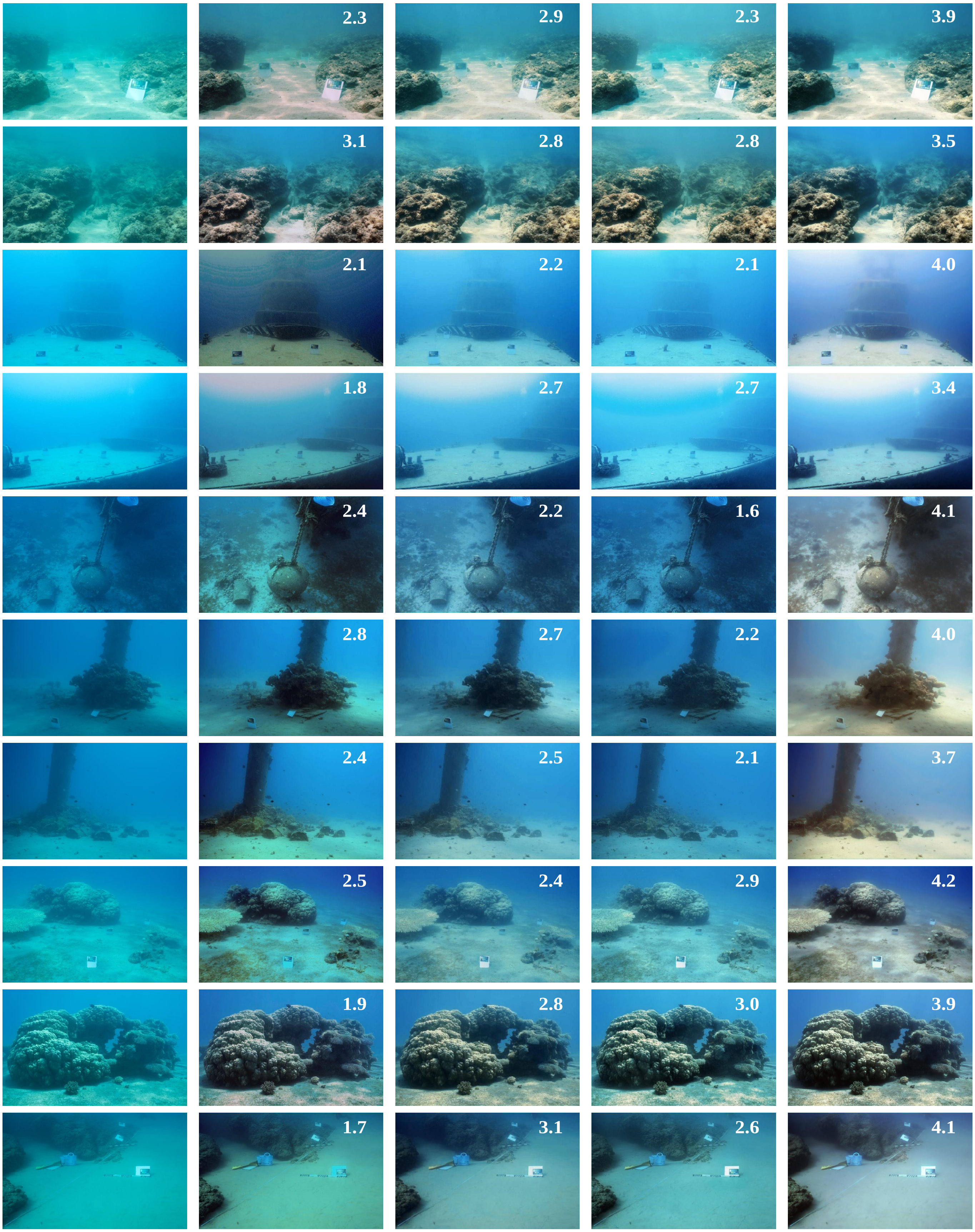
(a) Raw (b) ULAP (c) CBF (d) HUE (e) Water-Net (f) Ucolor (g) UICoE-Net (h) SGUIE-Net

Fig. 5. Visual comparisons on underwater images from RUIE dataset. From left to right are raw underwater images and the results of ULAP [15], CBF [17], HUE [10], Water-Net [1], Ucolor [18], UICoE-Net [19] and the proposed SGUIE-Net. Perceptual scores are marked on the upper right corner.



(a) Raw (b) ULAP (c) CBF (d) HUE (e) Water-Net (f) Ucolor (g) UICoE-Net (h) SGUIE-Net

Fig. 6. Visual comparisons on underwater images from EUVP dataset. From left to right are raw underwater images and the results of ULAP [15], CBF [17], HUE [10], Water-Net [1], Ucolor [18], UICoE-Net [19] and the proposed SGUIE-Net. Perceptual scores are marked on the upper right corner.



(a) Raw (b) Water-Net (c) Ucolor (d) UICoE-Net (e) SGUIE-Net

Fig. 7. Visual comparisons on underwater images from SQUID dataset. From left to right are raw underwater images, and the results of Water-Net [1], Ucolor [18], UICoE-Net [19] and the proposed SGUIE-Net. Perceptual scores are marked on the upper right corner.