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 the details of the SUIM-E dataset and more visual results on various benchmarks to complement the main manuscript, including real-world underwater images sampled from UIEB [1] challenging set, RUIE [2], EUVP [3] and SQUID [4].**

The code and proposed dataset are available at: https://github.com/trentqq/SGUIE-Net

I. SUIM-E

The SUIM-E dataset is created by supplementing the SUIM [5] dataset with the corresponding reference enhanced images. Inspired by [1], we used 12 underwater image enhancement methods to generate candidate reference images, including 10 underwater image enhancement methods (i.e., CE [6], Fusion [7], GCHE [8], HistogramPiror [9], HUE [10], IBLA [11], Retinex [12], TwoStep [13], UCM [14], ULAP [15]), 1 image dehazing methods (i.e., DCP [16]) and 1 commercial application for enhancing underwater images (i.e., dive+ [1]). With the raw underwater images and the enhanced results, 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 candidate reference images and select the result with the highest number of votes as the final reference image. As shown in Figure 1, we present some cases that the results of some methods are shown and mark the final reference images with red boxes. The votes received by the different underwater enhancement methods during the voting phase are shown in Figure 2. Furthermore, the percentage of the reference images from the results of different methods is presented in Figure 3.

In summary, the SUIM-E dataset contains a total of 1635 real 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 ground truth and semantic segmentation map.

Q. Qi and H. Zheng are with College 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 ith 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. Visual Comparisons

More visual comparison results are shown in Figures 4, 5, 6 and 7, which further demonstrate the superiority of our method.

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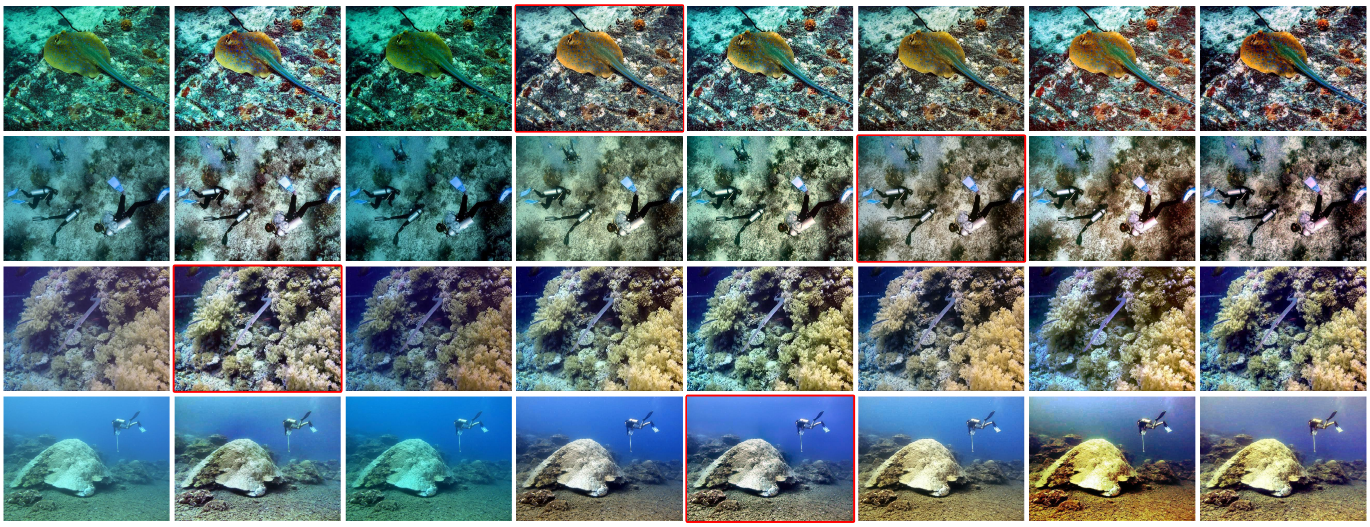

(a) Raw (b) CE (c) DCP (d) dive+ (e) Fusion (f) GCHE (g) HistogramPiror (h) HUE

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 final reference images.

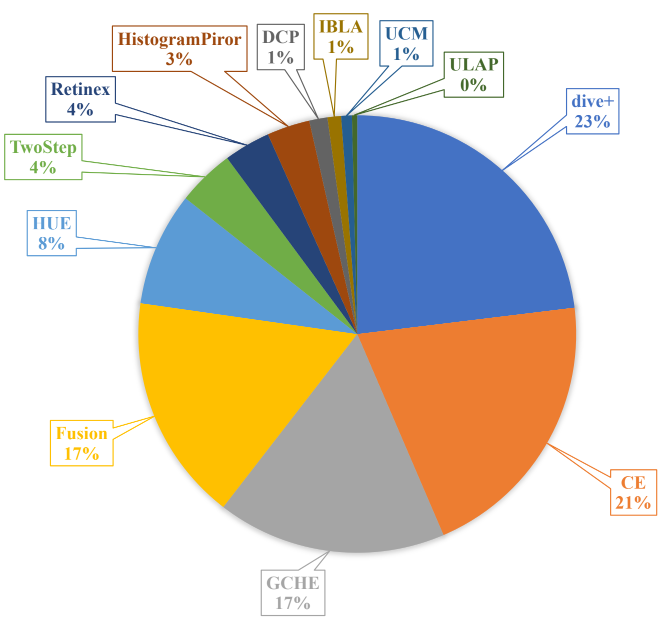

Fig. 2. The percentage of votes received by each underwater enhancement method in the voting process.

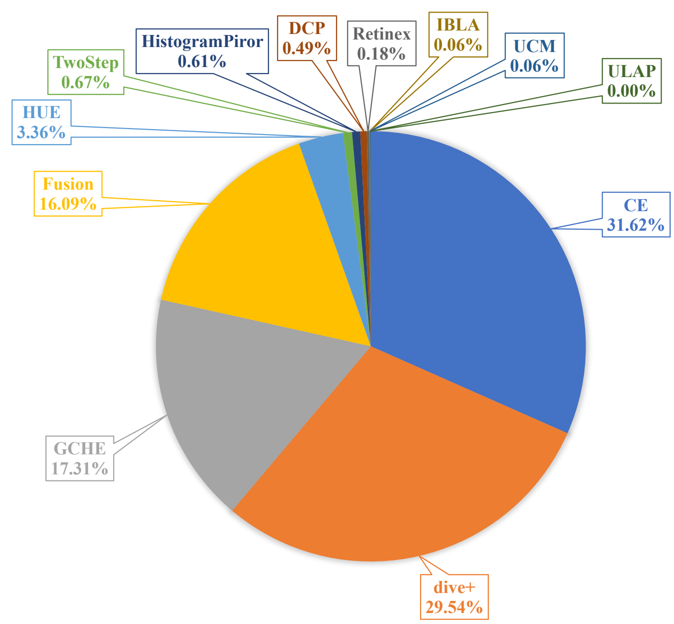

Fig. 3. Percentage of the reference images from the results of different methods.

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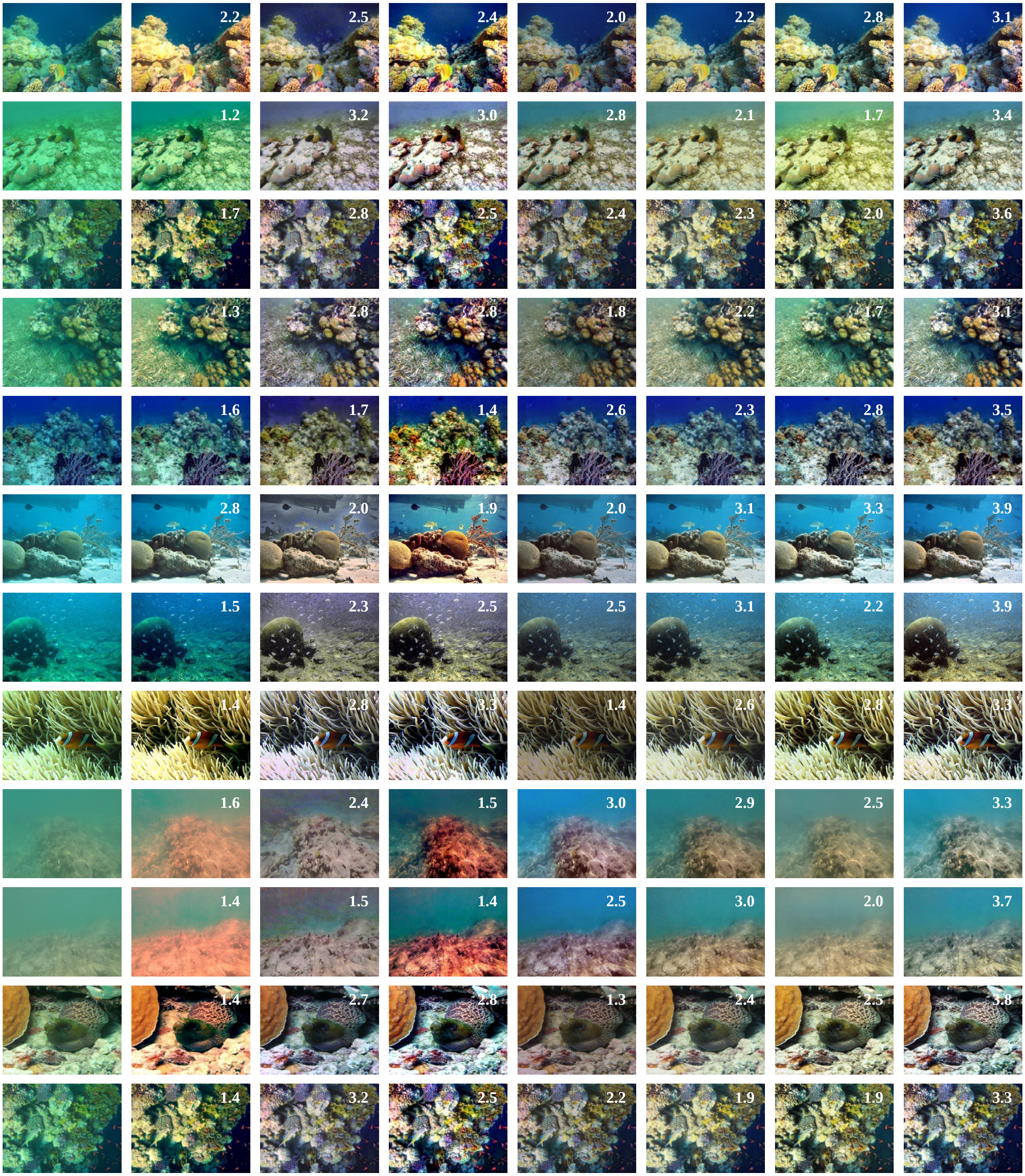
(a) raw (b) ULAP (c) CBF (d) HUE (e) Water-Net (f) Ucolor (g) UICoE-Net (h) SGUIE-Net

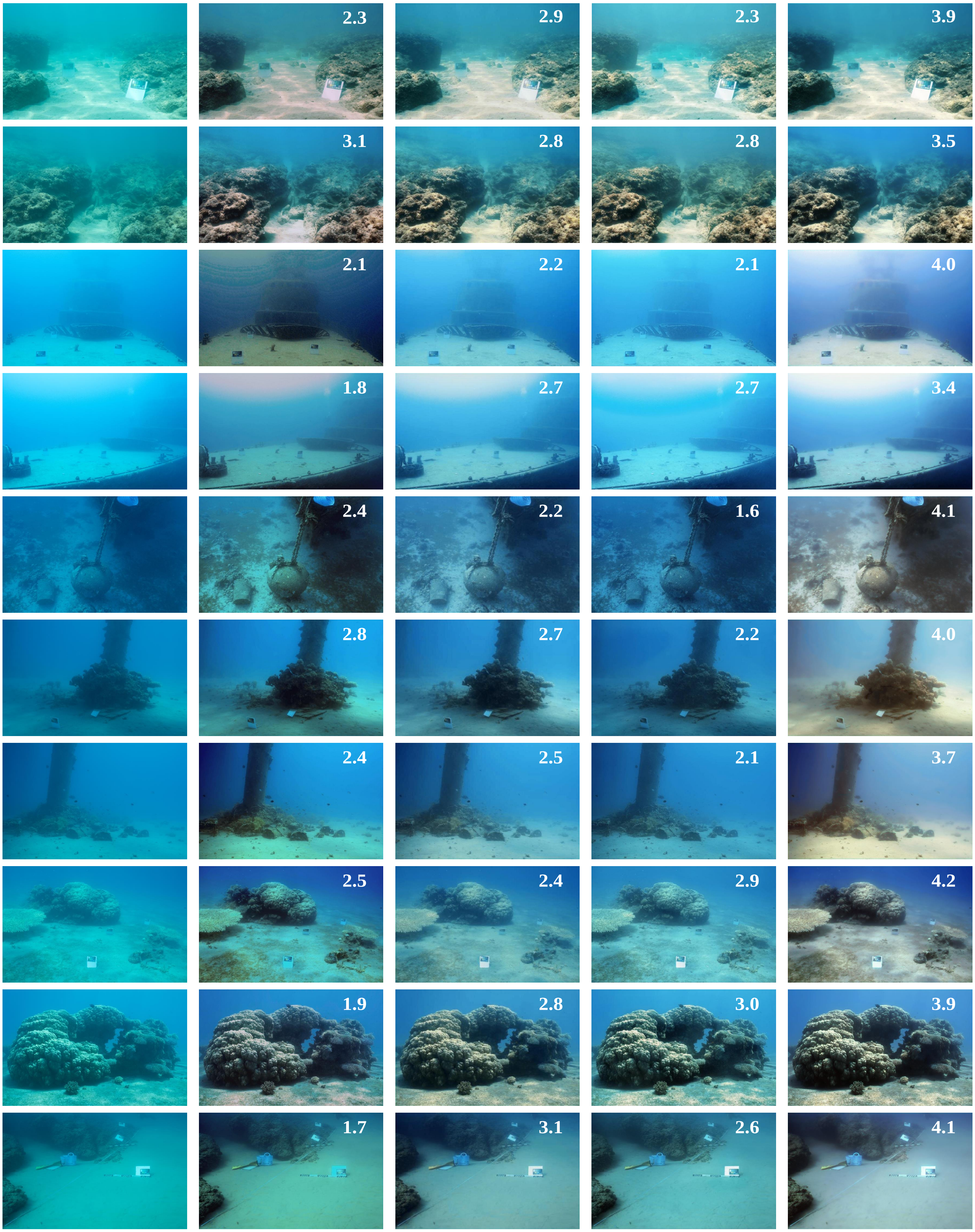
Fig. 4. Visual comparisons on underwater images from UIEB challenging dataset. From left to right are raw underwater images and the results of ULAP [15], CBF [17], HUE [10], Water-Net [1], Ucolor [18], UICoE-Net [19] and the proposed SGUIE-Net. Perceptual scores are marked on the upper right corner.

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.