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

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***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 supplementary 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[1] with the corresponding enhancement references. Inspired by [1], we used 12 typical underwater image enhancement methods to generate enhanced images as the candidates for the enhancement references, 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+[2]).

With the raw underwater images and their enhancements, we invited 10 volunteers with basic knowledge of image processing to independently select the best result from the 12 enhanced images corresponding to each raw underwater image. Specifically, each volunteer will see a raw underwater image and the corresponding 12 enhanced images under the same type of monitor (with 2560*1440 resolution). For the volunteers, there is no time limit on the evaluation and zoom-in operation is allowed. The order of the images presented to each volunteer is randomized. Moreover, the 12 enhanced images corresponding to each image are randomly shuffled and are anonymous to the volunteers.

When all the volunteers have finished voting, for each raw underwater image, we count the number of votes for its corresponding 12 candidates and select the one with the highest number of votes as the final enhancement reference. 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(a). Besides, the percentages of the enhancement references from the results of different methods are presented in Figure 2(b).

Figure 3 presents more raw images and semantic segmentation maps from SUIM dataset with their corresponding enhancement references given by our SUIM-E dataset. We can find that the raw underwater images from SUIM dataset are taken from diverse real underwater scenarios, which have different degrees of degradation, including severe color deviation, blurred details, low lightness, etc. The corresponding enhancement references have effectively corrected the color cast and have improved visibility and brightness. 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 semantic categories: background, fish/vertebrates, reefs/invertebrates, aquatic plant/sea-grass, wrecks/ruins, human divers, robots and sea-floor/rocks. To the best of our knowledge, it is the first real-world underwater dataset that contains both corresponding enhancement reference and semantic segmentation map. SUIM-E dataset has been made publicly available at https://github.com/trentqq/SUIM-E.

To validate the quality of our proposed dataset, we propose to train recently proposed deep enhancement models with SUIM-E and UIEB datasets [1], separately. Then, we test their enhancement performance on other datasets, including UIEB Challenging set [1], RUIE [2] and EUVP [3]. By comparing the performance of the models trained on UIEB with the models trained on SUIM-E, we can notice that their overall performance are close. Considering that UIEB is a widely recognized and adopted benchmark, the quality of our SUIM-E dataset can thus be validated, since the deep models trained on SUIM-E achieve performance comparable to that of the models trained on UIEB dataset.

II. More Visual Comparisons with Perceptual Scores

To provide a more intuitive performance comparison of different approaches, more visual comparison results on UIEB

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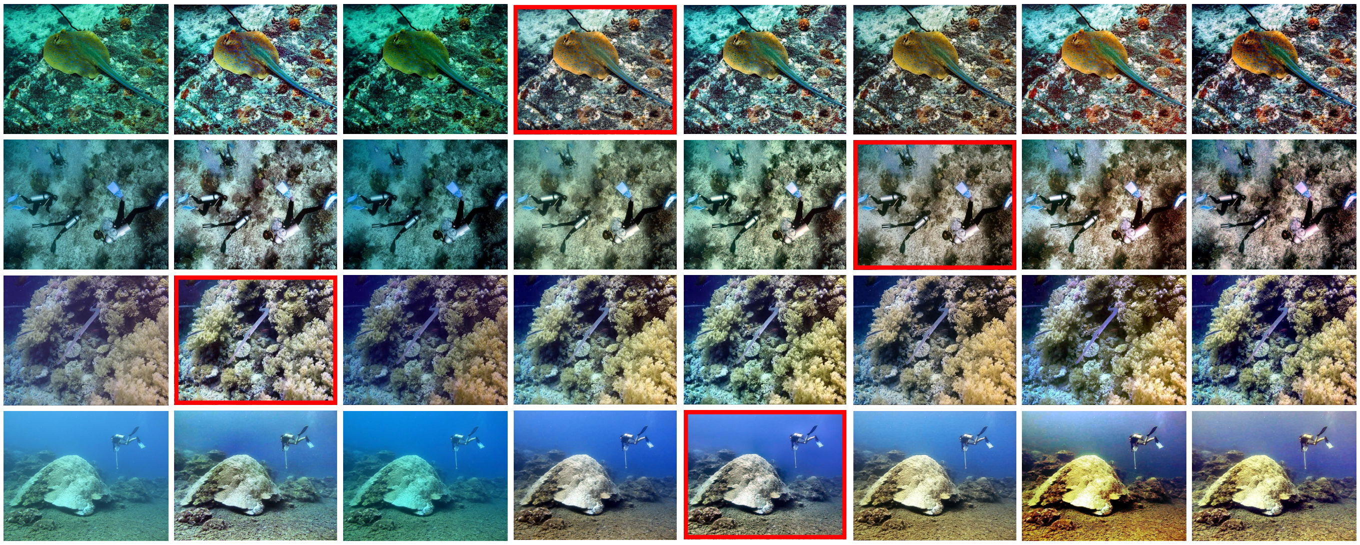
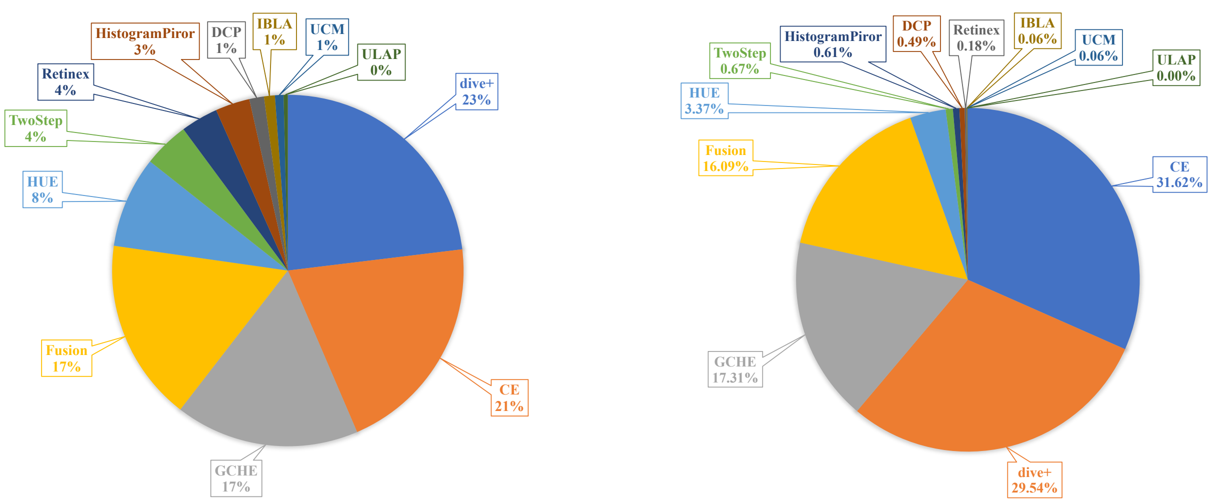
[1] https://irvlab.cs.umn.edu/resources/suim-dataset

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



(a) input (b) CE [6] (c) DCP [16] (d) dive+ (e) Fusion [7] (f) GCHE [8] (g) HistogramPiror [9] (h) HUE [10]

Fig. 1. Results generated by different enhancement methods. Red boxes indicate the images which are chosen as references.



(a) Distribution of votes (b) Source distribution of enhancement references

Fig. 2. Statistics for the SUIM-E dataset. (a) The percentages of votes received by different underwater enhancement methods in the vote on the whole SUIM-E dataset. (b) The percentages of the enhancement references from the results of different enhancement methods.

[1] Challenging dataset, 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. We can notice that the enhancements of SGUIE-Net are rated higher by volunteers on different datasets, which further demonstrates the superiority and good generalization of our method.

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TABLE I
QUALITY VALIDATE OF THE PROPOSED SUIM-E DATASET BY COMPARING THE ENHANCEMENT PERFORMANCE OF DEEP MODELS TRAINED ON SUIM-E AND UIEB DATASETS. UIEB CHALLENGING, RUIE AND EUVP DATASETS ARE USED FOR PERFORMANCE EVALUATION AND COMPARISON.

Method	Training Dataset	UIEB Challenging		RUIE		EUVP	
		UIQM↑	UCIQE↑	UIQM↑	UCIQE↑	UIQM↑	UCIQE↑
Water-Net [1]	UIEB	0.248	**0.549**	**0.628**	**0.545**	**0.738**	**0.564**
	SUIM-E	**0.350**	0.540	0.590	0.526	0.709	0.534
Ucolor [17]	UIEB	0.265	0.520	0.554	0.523	0.726	0.547
	SUIM-E	**0.316**	**0.536**	**0.621**	**0.526**	**0.814**	**0.561**
UICoE-Net [18]	UIEB	0.312	**0.539**	0.367	0.516	0.880	**0.586**
	SUIM-E	**0.407**	0.532	**0.517**	**0.518**	**0.910**	**0.586**
SGUIE-Net	UIEB	**0.524**	**0.578**	**0.706**	0.552	0.985	**0.609**
	SUIM-E	0.462	0.571	0.688	**0.556**	**1.007**	0.603

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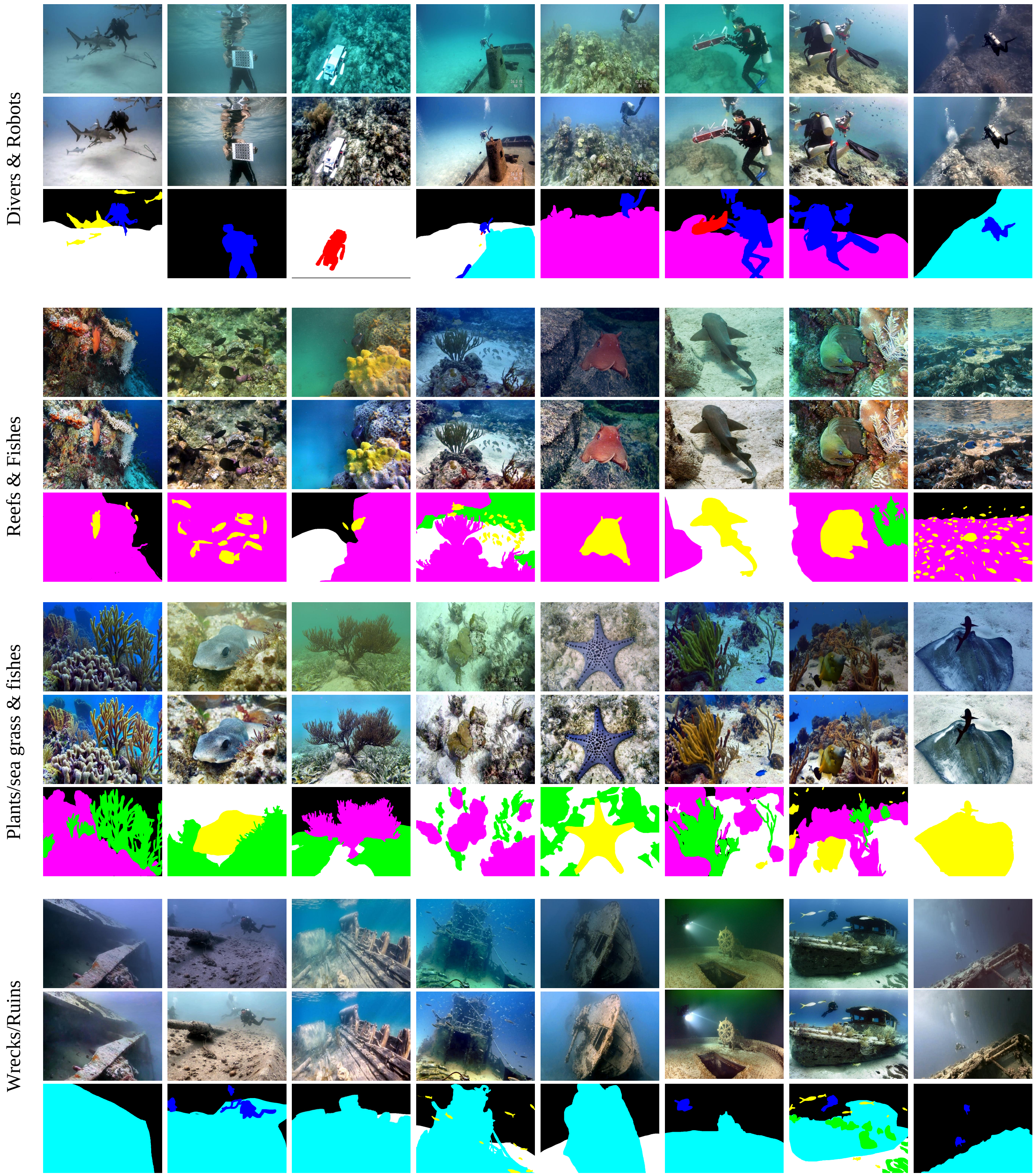
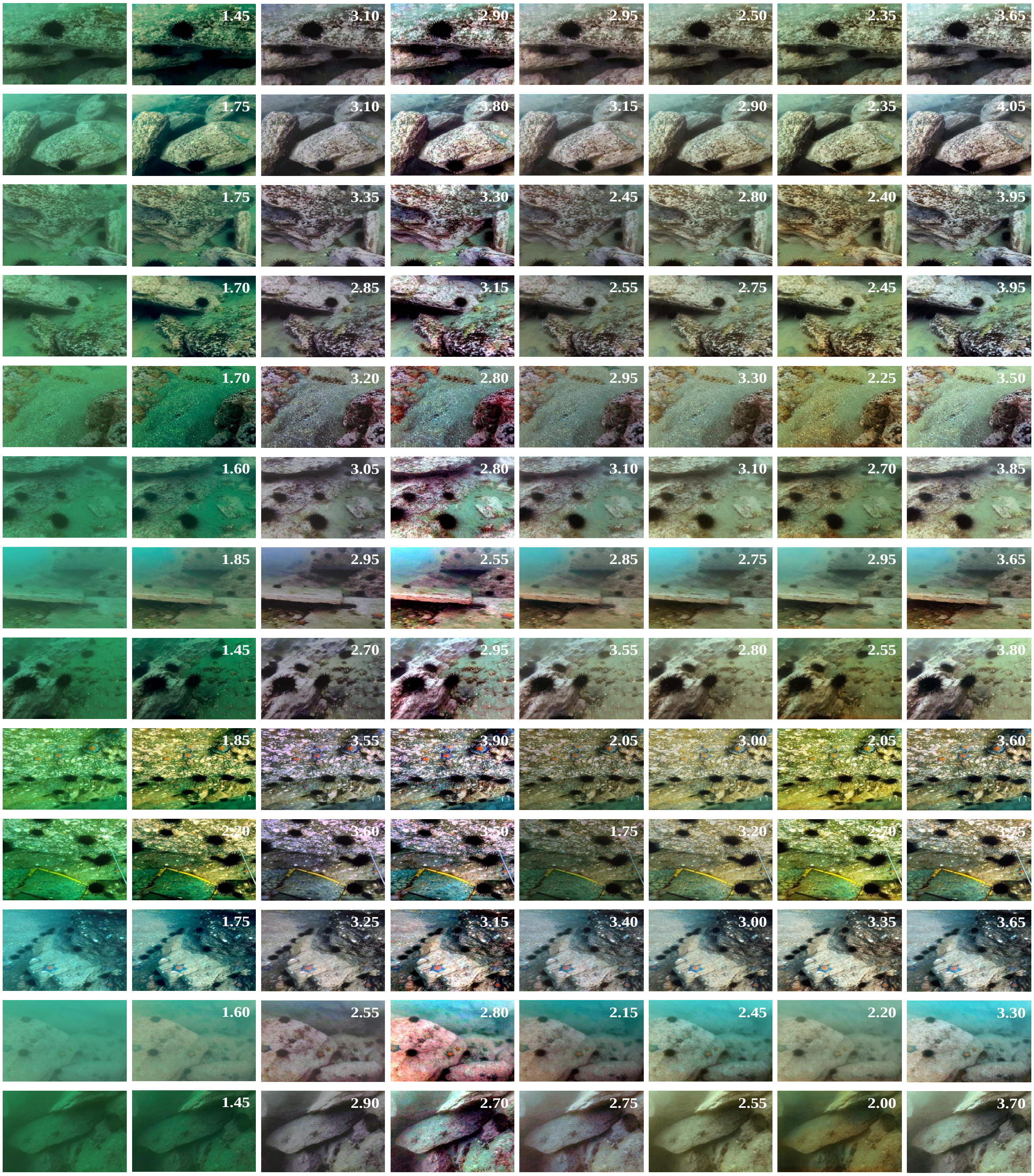


Fig. 3. More raw images and semantic segmentation maps from SUIM dataset [5] with their corresponding enhancement references given by our SUIM-E dataset. Four groups of images with different dominant contents are presented. From top to bottom in each group, the images are raw underwater images, their corresponding enhancement references and semantic segmentation maps, respectively.

(a) input (b) ULAP[15] (c) CBF[19] (d) HUE[10] (e) Water-Net[1] (f) Ucolor[17] (g) UICoE-Net[18] (h) SGUIE-Net

Fig. 4. Visual comparisons on underwater images from UIEB Challenging set. The perceptual score is marked on the upper right corner of each enhancement.



(a) input (b) ULAP[15] (c) CBF[19] (d) HUE[10] (e) Water-Net[1] (f) Ucolor[17] (g) UICoE-Net[18] (h) SGUIE-Net

Fig. 5. Visual comparisons on underwater images from RUIE dataset. The perceptual score is marked on the upper right corner of each enhancement.

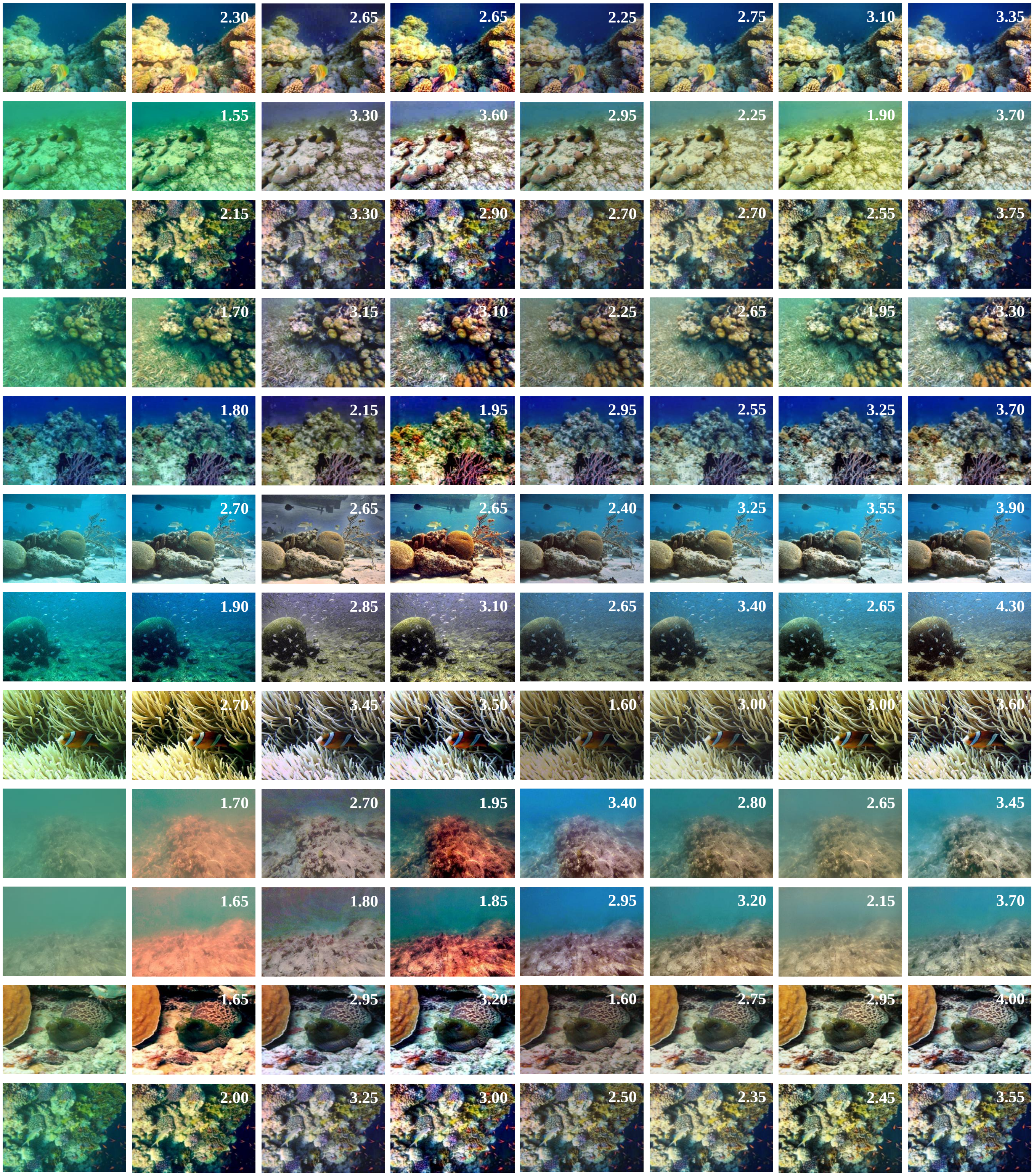
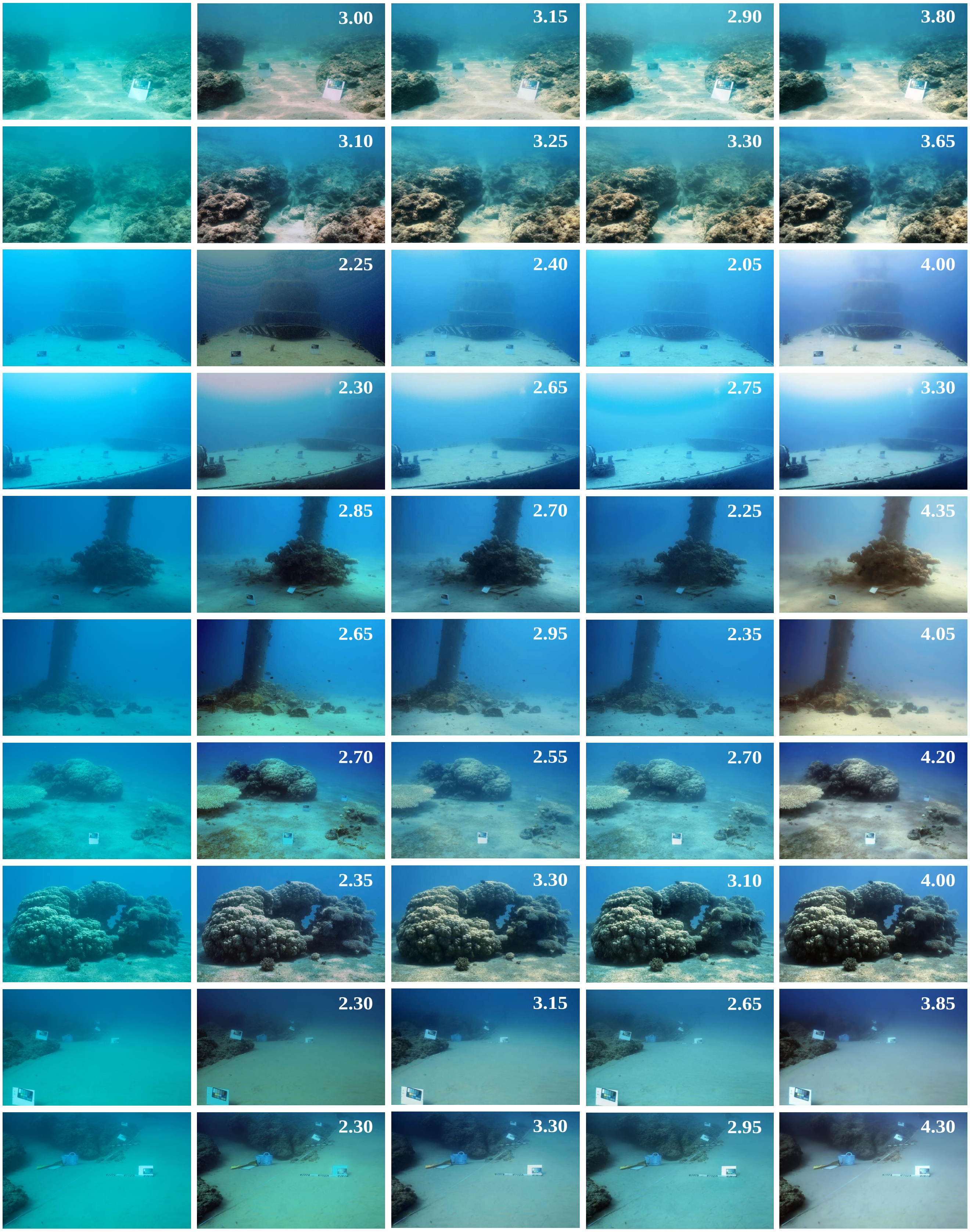


Fig. 6. Visual comparisons on underwater images from EUVP dataset. The perceptual score is marked on the upper right corner of each enhancement.



(a) input (b) Water-Net [1] (c) Ucolor [17] (d) UICoE-Net [18] (e) SGUIE-Net

Fig. 7. Visual comparisons on underwater images from SQUID dataset. The perceptual score is marked on the upper right corner of each enhancement.