Just Scratching the Surface: Exploring Underwater Image Enhancement with CLIP Jingwen Wang, Zixuan Hu Department of Computer Science, University of Toronto

Motivation

- Improving underwater images is essential for marine research and exploration.
- Conventional techniques like WaterNet[1] depend on raw-reference image mapping, where the enhancement quality is limited by reference images.
- With fixed references, there is a significant challenge in modifying enhancements to align with specific or new requirements.
- Recent advancements with the **CLIP[2]** model showcase its ability to bridge images and text, understanding and correlating visual content with linguistic descriptions.

Prompt design:

Methods

- 1. Colorfulness: "Vibrant and Vivid", to restore the natural color often dimmed by water.
- 2. White Balance: "Accurate Color representation", to correct the prevalent blue/green color cast.
- 3. Exposure: "Well-lit and clear", to discern fine details and ensure the scene's clarity.



Figure 2. the distribution of positive scores for contrastive pairs, comparing raw and reference images from the **UIEB** dataset.

Overview of the Mode:

Our approach employs a pretrained WaterNet as the base model, subsequently enhanced through a dual loss strategy with CLIP's contrastive pair and perceptual losses. The model is trained on the **UIEB** dataset with various contrastive pairs and then evaluated using the **LSUI** dataset [4].



Figure 1. CLIP model: Assessment of image quality by contrasting pairs.

- The pretrained CLIP model can effectively assess image quality, distinguishing between high-quality and low-quality images, due to its training on extensive and diverse datasets [3].
- We intend to enhance WaterNet by incorporating CLIP, aiming to improve image colors, precisely adjust white balance, and evenly balance exposure, solely using the **UIEB dataset[1]**.



- WaterNet[1] was proposed alongside the UIEB dataset. It excels in reconstructing underwater images to closely match reference images.
- The CLIP[2] model represents a breakthrough in contextual understanding of images. Trained on extensive image-text pairs, it has the unique ability to correlate visual content with textual descriptions.



Experimental Results

model	psnr	ssim	$\operatorname{colorfulness}$	white balance	exposure
base	22.154	0.850	0.489	0.354	0.548
Color-Enhanced	20.421	0.822	0.682	0.310	0.558
WhiteBalance-Enhanced	20.490	0.839	0.332	0.549	0.559
Exposure-Enhanced	21.202	0.830	0.407	0.230	0.618

Table 1. the performance metrics of various models on the LSUI dataset. It uses PSNR and SSIM for comparative analysis with reference images. It also includes positive scores for colorfulness, white balance, and exposure, based on contrastive pairs of images produced by each model.



- The CLIP-LIT[3] underscores CLIP's potential in unsupervised backlit image enhancement.
- LSUI Dataset[4]: Encompassing 4,279 paired underwater images, LSUI offers a comprehensive range of scenes, lighting conditions, water types, and target categories.

References

[1] Li et al., *An underwater image enhancement benchmark dataset and beyond.* IEEE Transactions on Image Processing, 29:4376–4389, 2019.
[2] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. *Learning transferable visual models from natural language supervision.* In International conference on machine learning, pages 8748–8763. PMLR, 2021

[3] Zhexin Liang, Chongyi Li, Shangchen Zhou, Ruicheng Feng, and Chen Change Loy. *Iterative prompt learning for unsupervised backlit image enhancement.* In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 8094–8103, 2023.
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